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Toward a thematic documentation of heritage features

Digital data segmentation for comparative, critical-interpretative analysis within the scan-to-BIM process

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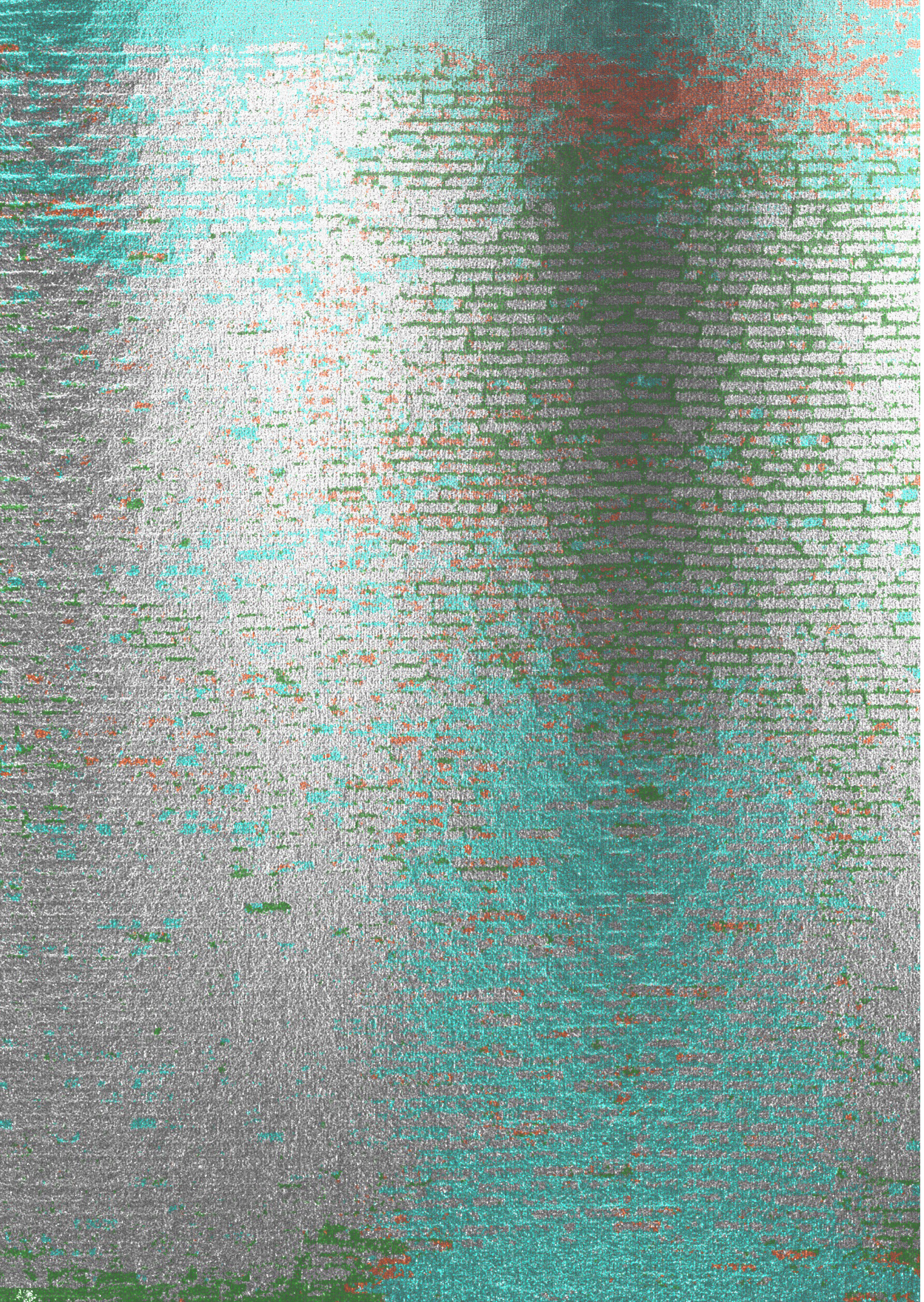

Toward a thematic documentation of heritage features

Digital data segmentation for comparative,
critical-interpretative analysis
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Abstract ENG

The research investigates innovative methodologies for the digital documentation, analysis, and interpretation of architectural heritage through the segmentation and classification of point cloud models, with the aim of optimizing their integration into H-BIM (Heritage Building Information Modelling) processes. The thesis addresses one of the most pressing challenges in the framework of the current digital transition: to add semantic meaning to the large amount of three-dimensional survey data, converting them into interoperable and queryable information for heritage conservation, restoration, and management purposes.
The aim is to provide a methodological and procedural model for the thematic management of digital data, leveraging Artificial Intelligence to support interpretation. The object of the research is the analysis of historic architectural surfaces, specifically classifying them according to materials, construction techniques and state of conservation.
The methodology is developed thorough the investigation of different topics, from surveying procedures to Scan-to-BIM modelling. Laser scanner intensity value is analysed in-depth, assessing its relation to architectural surface properties, experimentally tested under different acquisition conditions to evaluate its potential in surface characterization. The research prioritises on Supervised Machine Learning approaches, allowing domain-specific expertise (Architectural, historical, and conservation knowledge) to guide classification, thus ensuring that automatic processes support rather than replace critical interpretation. The experimentations were applied both on point clouds and images, leading to the development of an integrated workflow leveraging the potentialities of the two methods, according to the required needs. Moreover, the evaluation of different Scan-to-BIM strategies for the integration of semantically enriched point clouds into BIM environments is explored, as well as the development of future scenarios. Case studies were selected according to macro indicators that identify categories and levels of response of buildings to the context in which they are located. Moreover, selected buildings belong to different historical periods, to ensure heterogeneity materials, construction techniques, and state of conservation.
The results demonstrate that point cloud thematic segmentation trough integrated workflows provide reliable classification, adapted to different categories of investigation. In this process, point cloud intensity values, if critically controlled and contextualized, represent a valuable parameter for surface analysis.
Main impact of this research lies in its contribution to support and solve some issues related to the acceleration of the digital transition in cultural heritage documentation, by bridging the gap between massive survey data and usable, interoperable information for conservation purposes, including H-BIM resources. It proposes a replicable yet adaptable methodological model, applicable across different heritage contexts, allowing a, scalable solution with critical-interpretative orientation, to enhance accessibility, usability, and long-term management of digital heritage assets.

Abstract ITA

La ricerca si focalizza su metodologie innovative per la documentazione digitale, l'analisi e l'interpretazione del patrimonio architettonico attraverso la segmentazione e la classificazione di modelli a nuvola di punti, per ottimizzarne l'integrazione nei processi H-BIM (Heritage Building Information Modelling). La tesi affronta una delle sfide più rilevanti della transizione digitale in corso: attribuire un significato semantico alla grande quantità di dati acquisiti tramite rilievo tridimensionale, trasformandoli in informazioni interoperabili e interrogabili a supporto delle attività di conservazione, restauro e gestione dei beni culturali. L'obiettivo è definire un modello metodologico e procedurale per la gestione tematica dei dati digitali, utilizzando processi di Intelligenza Artificiale a supporto della loro interpretazione. Oggetto della ricerca sono le superfici architettoniche storiche, analizzate e classificate in base ai materiali, alle tecniche costruttive e allo stato di conservazione.
La metodologia sviluppata comprende diverse fasi, dalle procedure di rilievo alla modellazione Scan-to-BIM. Il dato di riflettanza acquisito tramite laser scanner è stato analizzato approfonditamente, studiando la sua correlazione con le proprietà delle superfici architettoniche, e testato sperimentalmente in differenti condizioni di acquisizione, per valutarne il potenziale nella caratterizzazione materico-conservativa. La ricerca predilige gli approcci di apprendimento automatico supervisionato, che consentono agli esperti del settore (e alle competenze storico-architettoniche e conservative), di orientare la classificazione, garantendo che i processi automatici supportino, senza sostituirla, l'interpretazione critica. Le sperimentazioni sono state sviluppate sia sulle nuvole di punti sia su immagini, definendo un workflow integrato che sfrutta le potenzialità di entrambi i metodi, in funzione delle finalità. Sono state inoltre valutate diverse strategie Scan-to-BIM per l'integrazione delle nuvole di punti semantiche all'interno di ambienti parametrici, ipotizzando inoltre possibili sviluppi futuri. I casi di studio sono stati selezionati in base a macroindicatori che identificano le categorie e i livelli di risposta degli edifici al contesto in cui si trovano. L'appartenenza degli edifici selezionati a diversi periodi storici garantisce l'eterogeneità dei materiali, delle tecniche costruttive e dello stato di conservazione.
I risultati ottenuti dimostrano che la segmentazione tematica delle nuvole di punti attraverso workflow integrati fornisce una classificazione affidabile, adattabile a diverse categorie di indagine. In questo processo, i valori di riflettanza delle nuvole di punti, se analizzati criticamente e contestualizzati, costituiscono un parametro significativo per lo studio delle superfici.
Il principale impatto della ricerca risiede nel suo contributo al supporto e alla risoluzione di alcune criticità che la transizione digitale sta portando nella documentazione del patrimonio culturale, colmando il divario tra i dati di rilevamento massivi e le informazioni utilizzabili e interoperabili per la conservazione, anche in ambiente H-BIM. Il modello metodologico proposto è replicabile ma flessibile, adattabile a differenti contesti del patrimonio culturale, e fornisce una soluzione scalabile e dalla forte valenza critico-interpretativa, per migliorare l'accessibilità, l'usabilità e la gestione a lungo termine dei beni.

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List of acronyms and abbreviations

2D	Two dimensional
3D	Three dimensional
AI	Artificial Intelligence
AR	Augmented Reality
BIM	Building Information Model
CAD	Computer-Aided Design
CDE	Common Data Environment
CH	Cultural Heritage
CNNs	Convolutional Neural Networks
CV	Cross Validation
DAP	Data Acquisition Protocol
DL	Deep Learning
DT	Digital Twin
DTr	Decision Tree
HDR	High Dynamic Range
HSV	Hue Saturation Value
H-BIM	Heritage Building Information Modelling
GS	Grid Search
GSCV	Grid Search Cross Validation
ICCROM	International Centre for the Study of the Preservation and Restoration of Cultural Property
ICOMOS	International Council on Monuments and Sites
ID	Identification
IFC	Industry Foundation Classes
IFC	Industry Foundation Classes
IT	Information Technology
LIDAR	Light Detection and Ranging or Light Imaging, Detection, And Ranging
MiC	Ministero della Cultura (Ministery of Culture)
ML	Machine Learning
ML	Multi Level
MLMR	Multi Level Multi Resolution
NeRF	Neural Radiance Fields
nm	nano meter
NORMAL	Normalizzazione Materiali Lapidei (Normalization of Stone Materials)
OOB	Out Of Bag error
PND	Piano Nazionale di Digitalizzazione del patrimonio culturale
PNRR	Piano Nazionale di Ripresa e Resilienza
PS	Phase-Shift
RF	Random Forest
RGB	Red Green Blue

SfM	Structure from Motion
SICaRweb	Sistema Informativo per i Cantieri di Restauro web
SIGECweb	Sistema Informativo Generale del Catalogo web
SIRA	Società Italiana per il Restauro dell'Architettura
SLAM	Simultaneous Localisation And Mapping
SVM	Support Vector Machines
TLS	Terrestrial Laser Scanning
TWS	Trainable Weka Segmentation
TOF	Time-Of-Flight
UAV	Unmanned Aerial Vehicles
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNI	Ente Nazionale Italiano di Unificazione (Italian National Unification Body)
UV	In texture's coordinate system: U is the horizontal axis and V the vertical
VPL	Visual Programming Language
VR	Virtual Reality
WP	Work Package

Projects developed during the PhD research period

The PhD. candidate, as member of DIAPReM/TekneHub research centre of the University of Ferrara, is involved in some research activities, where issues related to those of the present research are investigated, such as:

1. "AIM-eBIM - Adapted Information Management for existing Buildings Information Modeling" project, funded under the PR-FESR Emilia-Romagna 2021-2027 (*Bando per Progetti di Ricerca Industriale Strategica rivolti agli ambiti prioritari della Strategia di Specializzazione Intelligente 2023-2024*). CUP: F97G22000480003. The project is focused on the creation of a new workflow based on finalizing digital data from integrated survey toward "adaptive" BIM modelling through segmentation of the source data by Artificial Intelligence processes on specific thematic (documentation, analysis, monitoring, design) and criteria (materials, techniques, components, structures, preservation). The thematic analysis of the segmented point cloud allows for hierarchy, extraction and management of specific parameters within the BIM model. Scientific coordinator: Prof. Federica Maietti.

2. "Digital and parametric analysis of the church of Cristo Obrero y Nuestra Señora de Lourdes. A modern architecture designed by Eladio Dieste, UNESCO World Heritage Site" project, funded under the "*Bando per il finanziamento della Ricerca Scientifica – Fondo per l'incentivazione alla ricerca dipartimentale (FIRD 2023), Dipartimento di Architettura*". The research aims to digitally survey the church of Cristo Obrero y Nuestra Señora de Lourdes through the use of integrated methodologies, using the point cloud as the basis for the production of a three-dimensional parametric elaboration, in order to compare the existing building-in its current state-with Eladio Dieste's original design, a study never before carried out on his works. Scientific coordinator: Luca Rossato.

3. "Digital documentation for HBIM modelling of urban spaces: a pilot study on a protected Brazilian historic centre" project, funded under the "*Bando Giovani anno 2024 per progetti di ricerca finanziati con il contributo 5x1000 anno 2022*". The project aims to develop, test and evaluate a speditive data acquisition methodology, using low-cost technologies, for the documentation of the widespread heritage of minor Brazilian historic centres, with the aim of representing it through a digital information model to support the management of historical heritage. The case study is a portion of the historic centre of the city of Amparo (state of São Paulo, Brazil). Scientific coordinator: Gabriele Giau. This project is part of a larger pilot project, conducted by UNICAMP University (Campinas, Brazil) in collaboration with the DIAPReM centre of the University of Ferrara, which aims to define protocols for the protection of cultural heritage through the application of innovative digital technologies in minor urban historical contexts.

4. "3D geometric surveying services using integrated geomatic methods for the Colosseum", call by Invitalia S.p.A. (the national agency for attracting investment and business development) in 2021. The project was coordinated by the Colosseum Archaeological Park and carried out by the temporary consortium consisting of Consorzio Futuro in Ricerca (CFR) of Ferrara (lead partner), Geograà Srl, ETS Srl and Janus Srl. Expert consultants in various fields of analysis were also involved, including the Bruno Kessler Foundation (FBK). The service included topographic, laser scanner and photogrammetric surveying, two-dimensional geometric, thematic (materials, construction techniques and state of conservation) and specialist (masonry stratigraphic units and crack pattern) restitution of plans and radial and annular sections on a scale of 1:50, as well as a BIM model and a historical report. The operation, completed in 2024, resulted in the complete documentation of the monument. Within the project, PhD candidate has been ATI coordinator of the Scan-to-cad process and CFR coordinator for the integrated survey.

5. "Survey of the geometric-morphological features and analysis of the degradation and state of conservation of the former Colonia Varese in Milano Marittima". Project funded by the Emilia-Romagna Region, Heritage, Logistics, Security and Procurement Sector, General Directorate of Resources, Europe, Innovation and Institutions. Responsible Manager: Elettra Malossi. Sole Project Manager: Elisa Tommasini. Working Group: Annalisa Loccioni, Irene Cavallari. The survey and analyses were carried out by the Department of Architecture of the University of Ferrara, DIAPReM Centre. Scientific coordinators: Marcello Balzani, Luca Rossato, Guido Galvani. Techincal coordinators: Guido Galvani (3D survey), Federica Maietti (diagnostic analyses), Ing. Andrea Giannantoni (structural analyses), Fabiana Raco (2D representation). Working group: Martina Suppa (diagnostic analysis and representations), Gabriele Giau (three-dimensional survey support), Fabio Planu (CAD extraction support), Agnese Chianella, Luisa Pandolfi, Gabriele Giannantoni (structural analysis support). The activities of this project were developed during the collaboration period with the Cultural Heritage Department of the Emilia-Romagna Region as Host Institution.

Summary

1. Introduction

Abstract
This chapter frames the research within the broader European and national context of cultural heritage digitization. In recent years, the increasing availability of large-scale survey data has created both opportunities and challenges: while technologies such as 3D laser scanning and photogrammetry allow for extremely accurate documentation, they also generate datasets that are difficult to interpret and reuse effectively. The study addresses this gap by exploring how Artificial Intelligence can support the enrichment of point cloud data with semantically structured information. Specifically, it focuses on segmentation and classification techniques that aim to recognize architectural features according to their material, construction techniques, and state of conservation. The proposed methodology is organized into six work packages that combine the study of the current scenario in data processing with practical experimentation, guiding the process from initial survey to Scan-to-BIM modelling. Through specific objectives (among others, the evaluation of the reliability of AI assisted segmentation workflows, the assessment of laser scanner intensity value contribution in semi-automatic classification) the research contributes to define a procedural model for managing thematic data in heritage documentation, fostering knowledge extraction and enhancing interoperability, accessibility, and long-term usability of digital data.

1.1 Research framework and topic

The research presented in this thesis was developed under a position financed by the Italian PNRR (*Piano Nazionale di Ripresa e Resilienza*), D.M. 351/2022, M4C1 I. 4.1 (*Missione 4, Componente 1, Investimento 4.1*), measure aimed at increasing the number of innovative PhDs for the Cultural Heritage. This action is part of a broader framework that has its foundations at European level, linked to the need to promote the digitisation of cultural heritage in order to improve the effectiveness of documentation.

For several years, the European Union (EU) has been developing an integrated framework to promote the digitization of cultural heritage, combining guidelines, technological infrastructure, and funding. Among the former, it is worth to mention the "European data space for cultural heritage," launched in 2021 by the European Commission, that recommends Member States to accelerate the digitization of cultural heritage assets. These include "all cultural heritage monuments and sites, objects and artefacts, to protect and preserve those at risk, and boost their reuse in domains such as education, sustainable tourism and cultural creative sectors". Moreover, it encourages "to digitize by 2030 all monuments and sites that are at risk of degradation and half of those highly frequented by tourists" (European Commission, 2021).

Regarding the technological infrastructures, it is worth mentioning the Europeana platform (Europeana, n.d.), launched by an initiative of the European Union, that provides access to Europe's digital cultural heritage. It is indicated in the "European data space for cultural heritage" recommendations as the basis for sharing and reusing digital content, including 3D models and high-resolution scans.

In terms of funding, the EU, through the Horizon Europe program, allocates economic resources to the development of advanced digital technologies for cultural heritage: 3D modelling, virtual museums, and conservation, following up on what was developed with Horizon 2020 program, which ended in 2020 (https://digital-strategy.ec.europa.eu/en/policies/cultural-heritage).

To monitor progress in the digitization of cultural heritage as outlined in the document "European data space for cultural heritage", the European Commission has published the report "The Future of Europe's Past – Why Member States must do more to advance digitization for Cultural Heritage" (European Commission, 2024), which covers the first two years since the publication of the guidelines. The report shows that, although Member States have made progress during this period, the ambitious digitization targets for 2025 and 2030 remain well out of reach. To achieve these targets, the report calls on Member States to step up their efforts to expand the digitization, including 3D digitization, of cultural heritage and to adopt advanced technologies such as Artificial Intelligence (AI) and Virtual Reality (VR).

In this context, Italian *Piano Nazionale di Ripresa e Resilienza - PNRR* (National Recovery and Resilience Plan) also aims to accelerate the digitization of cultural heritage, dedicating a strategic axis to this for the period 2022–2026. In particular, through measure M1C3-Tourism and Culture, which provides for an acceleration of digitization for the restoration and renovation of physical cultural heritage in order to increase knowledge, accessibility, enjoyment, and dissemination, as well as more efficient management of the country's enormous cultural heritage (PNRR Cultura, 2025).

The strategic context of reference for the achievement of the objectives of the PNRR measure is the P*ND - Piano Nazionale di Digitalizzazione del patrimonio culturale* (National plan for the digitisation of cultural heritage). Drafted by the *Istituto centrale per la digitalizzazione del patrimonio culturale – Digital Library* (Central Institute for the Digitisation of Cultural Heritage – Digital Library) of the Italian Ministry of Culture, it is the result of a process of sharing and discussion with various cultural institutions (Digital Library, 2022). The Plan constitutes the strategic vision with which the Ministry intends to promote and organise the digital transformation process in the five-year period 2022-2026, addressing in the first instance the bodies that own, protect, manage and enhance cultural heritage, acting as a useful methodological and operational reference. The PND is divided into three sections: the first (the vision) outlines the transformation and opportunities for change, indicating long-term objectives; the second (the strategy) defines the path for implementing and achieving the objectives; the third (the guidelines) outlines the operational tools that support the planning and execution of activities. With reference to this document, the objective is to create an interoperable digital ecosystem. Digital platforms play a crucial role as systems for data exchange and control, with a view to ensuring transparency and optimising the work of public administrations and stakeholders.

Digitization is thus a priority both at international and national level, it is the core of current and future actions within the cultural heritage conservation sector. Documentation is the first and crucial step and technological advances involving not only tools and processes, but also the specific skills required, also involve theoretical aspects of architectural discipline. Digitization, in fact, should not be seen as the computerization of traditional procedures, but as a renovation of processes to achieve higher quality and efficiency objectives (SIRA, 2023).

The current trend therefore sees the increasingly widespread use of tools and procedures for the digitization of historic buildings. The evolution of 3D surveying technologies has led to the availability on the market of tools capable of acquiring sufficiently accurate point clouds in a very short time. This has undoubtedly facilitated the production of metric models with a certain ease compared to the past, even if they are not always accompanied by metadata certifying their degree of reliability for future use and reuse. However, despite the obvious advantages of speed and metric accuracy during *in situ* acquisition, the issue of processing the acquired data remains unresolved, as this can be a very long, complex and costly process. These 3D point cloud models have a high potential information density: they can provide an insight into the heritage site in terms of its metric, morphological, structural, material, and conservation characteristics. The effort of European policies to applied research is to propose guidelines and standards to find common ground towards ever greater data "quality" and reliability (Maietti, 2023). One possible strategy is to develop new digital data management processes that allow "raw" data to be segmented and discretized through semantic classifications with high critical and interpretative value. Considering this, it is essential to explore Artificial Intelligence (AI) processes in order to complement irreplaceable cultural and interpretative expertise with new tools for processing the large amounts of data available. Automatic procedures can provide support for hierarchizing data according

to different levels of knowledge necessary for making decisions about conservation actions on cultural heritage.
Therefore, the general scenario of heritage digitization is already growing exponentially and it is favoured by choices addressed at creating the conditions for innovation, development, and enhancement of digital documentation possibilities. The expected impacts of a further acceleration of the process are significant, but many questions regarding the management, interpretation, and preservation of digital data remain unanswered. The present research is intended to fit into this context, exploring strategies for the thematic segmentation and classification of point clouds, toward H-BIM modelling, supported by the application of artificial intelligence algorithms. The reason for the interest in using AI lies in the fact that such procedures aim to solve the complexity of direct and repeated extractions, transferring analytical skills to self-learning algorithms, making the feasibility of diagnosis and the time management of processes more efficient. The hierarchized models resulting from the automated procedures become a valuable support for further processing and facilitation to all actors involved in the very topical issue of heritage digital survey and data interpretation. This way, the research can help accelerating the digital transition of cultural heritage processes and it is applicable at different scales.
The research aims at applying algorithms capable of recognizing architectural features, in order to propose new data management and sharing processes to combine critical-interpretative skills with automatic procedures for hierarchizing data according to different knowledge levels. Classification algorithms can be applied to identify various categories of interest according to different criteria, for example to perform semantic segmentation that detects architectural elements (such as walls, columns, capitals, beams, etc.). This research aims to test these procedures on one of the most complex aspects of architectural analysis: the analysis of surfaces degradations for conservation purposes. This topic allows to work on many related aspects connected to the material consistency of buildings. Specifically, experiments has been developed to discretize:

- materials,
- construction techniques,
- state of conservation.

The thematic models produced can be valuable tools for the informative implementation of the H-BIM model, which, populated with parameters derived from them, becomes increasingly comprehensive and interdisciplinary, aiming to validate an improvement in data interpretation and parametric modelling.

1.2 Research objectives

The project aims at improving the efficiency of the management of the extensive and articulated architectural heritage by deepening the semantic interrogation of digital models of historic buildings, including the widespread heritage. The project is intended to support and address issues related to the acceleration of the digitization for the conservation and renovation of the physical cultural heritage to increase knowledge, accessibility, use and dissemination, through the processing of digital resources.
The main objective of the research is to contribute to the establishment of a methodological-operational workflow that facilitates the effective employment of digital tools, which very often remain unused or underused but that can improve the conservation of cultural heritage, by professionals and management bodies.
Specific objectives of the research are:

a. to test and evaluate current procedures for automatic and semi-automatic segmentation and classification processes, leveraging AI algorithms applied on different data sources, such as point cloud models and images, in order to identify case-specific best strategies in order to outline and describe the characteristics of historic surfaces (materials, construction techniques, state of conservation);
b. to establish a point cloud semantization process aimed at thematizing architectural surface data through segmentation and classification algorithms that take into account the best suited method to the descriptive requirement, possibly combining procedures to achieve the pursued objective;
c. in point cloud processing, to take into account and asses the intensity value feature, whose effectiveness has already been leveraged by other analysis and methodologies but not implemented in AI processes in a meaningful way. Few studies explored the reflectance data that remains thus underutilised in relation to its potential;
d. to assess different Scan-to-BIM strategies and methodological processes for connecting data obtained from automated point cloud analysis to the semantic H-BIM model in order to make the management of cultural heritage not only more meaningful, but also faster, more productive, efficient, and sustainable.
e. All these objectives contribute to provide a procedural model for the thematic management of digital data in the framework of the critical-interpretative processes, towards applications accessible via databases or platforms. Thematic analysis of the segmented point cloud will enable the hierarchization, extraction, and management of different levels of knowledge within the BIM process, allowing to foster accessibility and querying of complex information content.

1.3 Research limitations

The increasingly widespread use of survey tools in architectural documentation has become well established practice, but it should always be remembered that the construction sector in general, and the cultural heritage conservation field in particular, is not a direct producer of technological development issues, but rather a "second-level" user. With the exception of diagnostic technologies, some of which are also developed considering applications on heritage, few of the remaining technologies, from measuring instruments to software, including Digital Twin platforms, were originally designed for architecture. These are "borrowed" and applied, and this condition stimulates a research context that aims to enter into the logic of the system in order to modify it according to disciplinary needs. While it is true that, over time, specific needs have guided and adapted the development of software and processes tailored to the construction field, such as BIM modelling, it is equally true that when dealing with existing building environments, issues arise that go beyond contemporary production needs and are connected to a multiplicity of cultural meanings that are not always easy to understand.

This basic consideration also applies to AI processes, the experimental focus of this research, whereby different types of Machine Learning (ML) models are applied and tested on data representing architectures. This gives rise to a series of limitations more closely related to the research topic.

Some of these are primarily practical and operational in nature. As is well known, AI processes generally need large amounts of data to train, test, and validate algorithms. These processes often require considerable hardware capacity. Therefore, case studies on which to test algorithms have been chosen primarily according to the purpose and the objectives of the research, considering the characteristics of the buildings, but at the same time so that they are controllable and manageable in IT dimensions without requiring excessive software and hardware capabilities. The research was modulated on the computational capabilities available in the Home and Host Institutions.

Moreover, in this research, Machine Learning algorithms are preferred rather than Deep Learning (DL), since the latter require large databases already annotated, which at the moment are not sufficient to guarantee a satisfactory result for the thematic components that the research aims to identify, as outlined in paragraph 4.3. Further technical and conceptual considerations, described in the same paragraph, contribute to restricting the range of action to supervised learning procedures. These workflows have been tested and implemented in depth to have input data instructed with critical-interpretive knowledge peculiar to the specialist (architect, conservator, etc.), specifically for the selected case studies, in order to obtain a reliable result that takes into consideration the boundary conditions that make each building unique. Supervised learning allows the predictive model to be trained on a case-by-case basis; unsupervised learning, on the other hand, is based on pre-trained models that, at the moment, do not provide the expected answers to specific needs.

There are many possibilities for classifying and segmenting point cloud models, determined by a wide variety of documentation requirements. However, the focus of the research is on architectural surfaces, and this leads to the exclusion of, for example, those algorithms applied for architectural elements recognition. These were tested for a deeper understanding of the state of the art in ML processing, and applied only if preparatory steps to the analysis of materials, construction techniques and degradation, leveraging hierarchic processing strategies.

A specific objective of the research is to assess whether, and how, reflectance data (or intensity) can be used in a meaningful and useful way within AI processes, whether it can therefore lead to an improvement in results, and under what conditions. To evaluate the link between the intensity and the characteristics of the surfaces to which it belongs, one section investigates the outcomes obtained using different instrumental sensors on different materials, detected as certain boundary conditions vary, in order to record any differences in the information obtained. As specified in more detail in paragraphs 4.1 and 4.4.1, analysing reflectance data requires methodological and operational precautions that take into account multiple factors that can influence and modify this type of data. Furthermore, in order to evaluate univocally the variations in reflectance data based on exogenous factors (such as distance and angle of incidence with respect to the surface surveyed, surface humidity and temperature, environmental humidity and temperature, etc.), acquisitions should be performed in a controlled laboratory environment, a closed system that allows the variables to be analysed to be isolated one at a time. However, it was not possible, from an operational point of view, to create such acquisition conditions. There were controlled the operator-dependent factors as much as possible (e.g., the position of the scanner), managing certain conditions (e.g., saturating the surface to modify its humidity conditions), or simply noting the values of those factors not dependent on the operator. The measures taken were nevertheless considered sufficient to obtain a meaningful result that could be analysed and from which conclusions could be drawn. Furthermore, it is more compatible with field survey practice, in which some specific conditions remain difficult, if not impossible, to control.

1.4 Research methodology and structure

The methodology of the thesis was developed through a study that involved both theoretical-critical and applied aspects of the discipline of architectural surveying and representation, through an interdisciplinary comparison necessary both when dealing with built heritage and when addressing the issue of digitisation. For this reason, two research periods of six months each were spent, at the Settore Patrimonio Culturale (Cultural Heritage Department) of the Emilia Romagna Region, and at the Scott

Sutherland School of Architecture & Built Environment of the Robert Gordon University of Aberdeen, Scotland. Research involves complex processes that require cross-disciplinary skills. For example, IT skills are not secondary, and this is evidenced by the fact that working effectively with documentation increasingly requires multidisciplinary teams, in which experts from various fields contribute with their expertise. Responsible for heritage conservation or professionals must understand the technology, its potential and its limitations in order to use it effectively, asking technical specialists for what is necessary to manage the entire process.
The research methodology was developed thorough No. 6 Work Packages (WPs):

- WP1 – State-of-the-art analysis and identification of digital models on which to apply segmentation processes;
- WP2 – Investigation of point cloud radiometric features, focusing in particular to intensity value, in order to test its significance in surface description;
- WP3 – Point cloud and image processing thorough supervised ML methodologies, in order to develop an effective pipeline for thematic segmentation and classification;
- WP4 – Study of the Scan-to-BIM process for evaluation of strategies to integrate the results of the classified point cloud within the informative model.
- WP5 – Assessment of the overall process, from 3D survey to semantic segmentation, included the analysis of possible BIM model implementations according to the identified parameters.
- WP6 – Dissemination, referring to FAIR data and open access principles.

WP1 – State of the art analysis. The step included the analysis of the main methods of three-dimensional surveying, in particular laser scanning and digital photogrammetry, to identify the characteristics of the models that can be obtained, and the study of the most relevant current research in the field of AI applications for point cloud segmentation and classification. Once the most significant algorithms have been identified, digital models were selected to test them, choosing from point clouds surveyed by the PhD candidate during the three-years research period, or in the years before. Moreover, the databases available in the archive of the DIAPReM / Teknehub research centre of the University of Ferrara were considered, too. This research unit carries out activities in the field of integrated three-dimensional surveying, as well as in H-BIM modelling and in the development of semantic web platforms for data management. Its extensive set of databases consist of documented and digitized heritage buildings on the national and international territories, surveyed thorough different instruments and methodologies, from which it was possible to draw the most relevant case studies concerning the research needs. This wide range of datasets allow for a greater number of various tests in terms of the types of input data and categories to be researched.

WP2 – Investigation of point cloud radiometric features. This stage focused in particular to the intensity value, in order to use it within an algorithmic process. There are two prerequisites for doing so: the first is that reflectance has actual significance in surface description, and the second is to associate a robust colour data with the point clouds surveyed by laser scanners. Regarding the first issue, experiments have been conducted to study the correlation between intensity data and surface features, such as materials and states of conservation. The tests, carried out partly on existing databases (among the case studies selected in WP1) and partly on point clouds acquired *ad hoc*, made it possible to study the responses obtained with different laser wavelengths, associated with different instrumental sensors. In addition, it was analysed how certain external factors can influence intensity data. With regard to the second issue, it was evaluated three strategies for associating robust colour data with laser scanner clouds: using laser scanner built-in cameras, leveraging reprojection from point clouds obtained thorough photogrammetry, and through recolouring using images aligned within the photogrammetric dataset.

WP3 – Point cloud and image processing thorough supervised ML methodologies. After identifying the most suitable predictive models based on the characteristics of the input data, as well as the categories to be mapped and the boundary conditions, the point clouds of the selected case studies were processed in order to develop a workflow for segmentation and thematic classification, optimized in relation to the various variables involved: purpose, type of data available, characteristics to be mapped, etc. In this phase, the importance of geometric and radiometric features, including intensity value, were evaluated. Classification strategies were explored directly on point cloud models or via image segmentation. The latter option generally allows for greater detail, so a procedural model was developed that defines an integrated method combining the advantages of both, should it be necessary to achieve a comprehensive description of the building.

WP4 – Study of the Scan-to-BIM process. The classified point cloud model can serve as a working tool in the Scan-to-BIM process, as it carries semantic levels that can both facilitate the BIM specialist's interpretation of the characteristics of the building under analysis and constitute, at least in part, the information content. Therefore, for materials, construction techniques, and state of conservation, various strategies for integrating thematic data into parametric modelling software were explored and tested for their evaluation according to different criteria, ranging from geometric accuracy to informational accessibility.

WP5 – Assessment of the process. The entire workflow, developed in the previous WPs, was applied to the Former Colonia Varese in Milano Marittima (Ravenna) case study. The activities in this case study were developed during the research period at the Settore Patrimonio Culturale (Cultural Heritage Department) of the Emilia Romagna

Region, the institution that owns and manages the property. The activities involved all phases of the process covered by this research, from 3D survey to semantic segmentation, including the implementation of the BIM model according to the identified parameters. Part of the process was also applied to the case study of Christo Obrero Church in Atlantida, Uruguay, from the *in situ* survey to the semantic segmentation of the surfaces of the point cloud model. The BIM model can be developed in the future, as an additional in-depth activity.

WP6 – Dissemination. During the development of the research, sharing the process and the results achieved were pursued according to different actions. Dissemination activities were carried out thorough presentations at academic research events, as well as papers on the most relevant issues were published in national and international scientific journals. In addition, during the research abroad period at the Scott Sutherland School of Architecture & Built Environment of the Robert Gordon University of Aberdeen, Scotland, several presentations were held, sharing the research with the research community of that host institution.
The Ph.D. candidate is affiliated with the UID - Unione Italiana Disegno (Italian Drawing Union). UID is a nonprofit scientific and cultural association, which aims to develop, promote, coordinate the activity of scientific research in the field of Drawing 08/E1 (CEAR-10/A - former ICAR 17) and to promote the coordination and development of teaching activities in the disciplines of Drawing, in the wake of scientific innovations including through multidisciplinary contributions. Within this association, he has been part of the "Innovation" commission, subgroup Artificial Intelligence.
The Ph.D. candidate is affiliated with the REAACH (Representation Advances And Challenges) association, which mission is to organize annual or biennial conferences, workshops, seminars, summer/winter schools, and itinerant events on the national and international territory. The primary purpose of the association is to foster the mutual exchange of knowledge and multidisciplinary research related to the advances and challenges of representation increasing the network of research interconnections. It also aims to support the dissemination of representation topics related to advances and challenges in the discipline, including the use of artificial intelligence, through international publications.

Although the WPs described had a logical sequence, their development overlapped in certain phases, allowing for the modification and verification of previous phases in light of any observations that emerged as the project progressed. Like communication and dissemination, the study of the state of the art also continued as in progress activity throughout the research. The development of what has been briefly described above is reported in the chapters of this thesis.

Structure of the Thesis

Chapter 2 deals with the methodological approach followed, contextualising the research within the field of heritage survey, documentation and representation for enhancement, conservation and restoration, focusing on the interpretation criteria of digital data. The overall proposed methodology for architectural heritage digital data management deepened in the thesis is traced, the concept of architectural surface, the characteristics to be mapped (materials, construction techniques and state of conservation), and the methodological approach for thematic abacuses elaboration are described.

Chapters 3 and 4 describe, respectively, the state of the art in data acquisition and processing, reporting on what has been developed during WP1. The first focuses on integrated 3D methodologies for the surveying of cultural heritage, while the second includes a description of intensity data analysis, thematic classification of point clouds using artificial intelligence, and segmentation towards an optimized Scan-to-BIM process. It also reports how these survey data analysis processes were applied in the integrated survey with geomatic procedures of the Colosseum.

Chapter 5 presents the case studies. It illustrates the selection criteria and describes briefly their history and their features, focusing especially on the characteristics of the surfaces, such as materials, construction techniques and state of conservation. Moreover, 3D survey activities carried on for each building are described.

Chapter 6 describes the analysis carried on the radiometric features of the point clouds, reporting on what was developed during WP2. First, it focuses on the colour data, exploring three methods for the robust association of RGB data to laser scanner point clouds. Second, studies the intensity value, sampling on avaiable point cloud databases, in order to test the reliability of this information for surface description. Third, it deeply analyses the intensity value surveyed on *ad hoc* acquisitions, in order to test the link between this feature and the characteristics of the surfaces. In this step it was evaluated the incidence of some factors, such as surface temperature and humidity, or other boundary conditions.

Chapters 7 and 8 describe the experiments on segmentation and thematic classification of point cloud models, using supervised machine learning procedures applied to three-dimensional data or images, which are mainly the subject of WP3. Specifically, Chapter 7 presents the methodology and theoretical workflows, while Chapter 8 presents the experimental applications on selected case studies. In this section, the different pipelines have been adapted to the specific characteristics of each building. Each case study application is characterised by specific objectives. Where necessary, an integrated procedure has been applied and developed, using both three-dimensional and two-dimensional segmentation methods in order to achieve the level of detail required for the various levels of thematization. The first experiments described report the workflow actually carried out, also recording the critical issues that emerged and the failed tests, from whose analysis of the causes the method was corrected for subsequent applications.

Chapter 9 is dedicated to the study of the Scan-to-BIM process, developed in WP4, analysing and evaluating different possible options for transferring the results obtained in the thematic point cloud model into a BIM model, also accessible through collaborative web platforms to larger categories of users.

Chapter 10 presents the results obtained, defining the reliability levels of the methods tested, both those involving semi-automatic processing with the support of artificial intelligence and those involving reflectance data analysis to aid in the interpretation of architectural surface characteristics. It also evaluates the different scan-to-BIM strategies tested in relation to modelling effort, informative level and purpose. It then incorporates all these procedures into a comprehensive methodological model for the documentation of cultural heritage.

Chapter 11 draws conclusions, describing the impacts on the architectural heritage documentation field, highlighting the key issues that emerged concerning the discipline of architectural surveying and the digitisation of cultural heritage, and outlining possible scenarios for innovation and applicability. This section summarizes the limitations that emerged during the experimental phases of the research and hypothesises further developments.

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Summary

2. Methodological approach

Abstract
This chapter outlines the methodological framework guiding the thesis, concerning the digital documentation and interpretation of architectural heritage for conservation purposes. The research is grounded within the disciplinary fields of drawing and surveying, emphasizing their evolution from traditional documentation to integrated, data-driven digital processes. The chapter critically examines the role of digital tools, such as CAD, GIS, and H-BIM, in enhancing knowledge production while addressing the challenge of interoperability. A semi-automatic methodological approach is proposed, integrating AI-assisted segmentation and classification of point clouds with expert interpretation. This approach aims balance automation and critical awareness, ensuring that technology supports, rather than replaces, the interpretative process. The research focuses on the analysis of architectural surfaces, interpreted as complex and historical palimpsests, through categories of materials, construction techniques, and states of conservation, structured via thematic abacuses. Architectural surfaces are intended as places where phenomena manifest, offering valuable insights into the understanding of the building as a whole. Thematic abacuses serve as frameworks linking geometric and semantic data within the Scan-to-BIM process, advancing reproducible and meaningful workflows for heritage documentation and conservation management

2.1 Architectural heritage documentation for conservation: digital data interpretation criteria

The disciplines of drawing and surveying are central to the documentation process aimed at conservation and restoration. Considering surveying as ‘the science that teaches us to read and document architecture’ (Migliari, 1999), it is an essential tool for knowledge.
In fact, since the first documents summarising the key points of architectural restoration regulations, from the ‘Athens Charter for the restoration of historic monuments’ (The

International Museums Office, 1931) and the ‘Carta Italiana del Restauro’ (Consiglio Superiore per le Antichità e Belle Arti 1931), both from 1931, there has been a need to document the state of conservation of the work before, during and after the restoration. Initially, the scientific community's interest focused mainly on documenting what had been done to the property undergoing intervention, but subsequently, acquiring information on its state of conservation became increasingly important as a basis for design choices. This value was confirmed in the guidelines subsequently developed at international level (ICOMOS, 1964), considering that it serves to identify, preserve and transmit to future generations the cultural and natural heritage through the development of scientific and technical studies (UNESCO, 1972; UNESCO, 2025).

Nowadays, documentation does not only cover activities of collecting “information regarding monuments, buildings, and sites, including their physical characteristics, history, and problems”, but also “the process of organizing, interpreting, and managing that information” (Leblanc & Eppich, 2005). The documentation of cultural heritage is therefore the first and fundamental step in planning actions for its conservation, maintenance and renovation (Fiorani, 2009). It must provide a series of essential data to designers and decision-makers, and must be both holistic and concise in order to provide knowledge of the asset on which conservation practices can be structured, right up to the restoration project. The quality of the documentation determines that of the restoration project, and the purpose of the restoration project and its requirements determine the purpose for which an artefact is documented. This point is fundamental, as it defines the scope of the fields of investigation in relation to the objectives of the specific project. In fact, the activities that can be carried out to acquire the correct knowledge for restoration purposes could be almost limitless. The possibilities increase if the digitisation process is considered as an opportunity to increase knowledge, rather than merely a reproduction of existing “paper-based” procedures. The digital models and tools available and in use offer ever-increasing potential (De Sanctis, 2015).

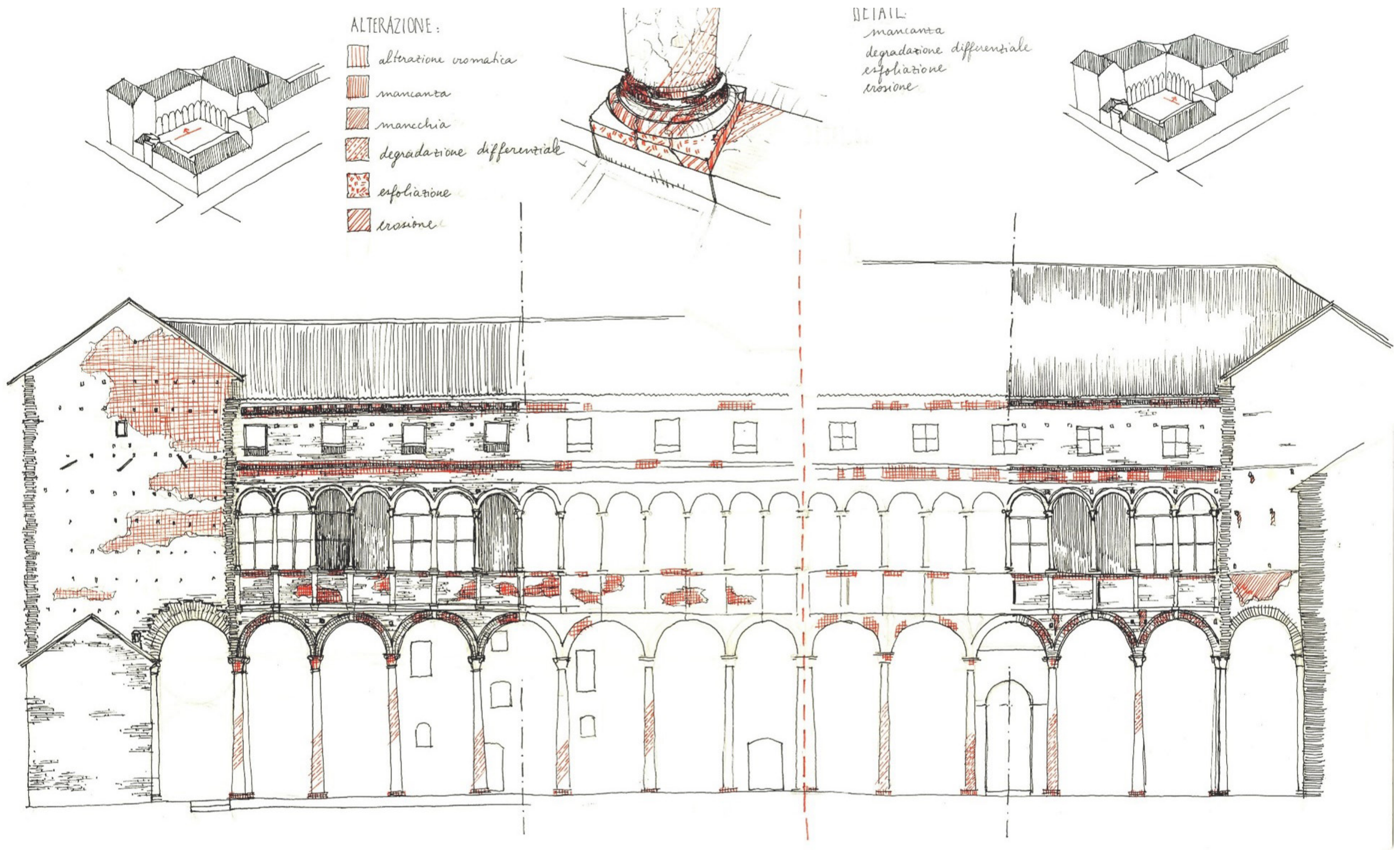
While not wishing to deny the autonomous nature of drawing as a discipline, there is no doubt that it constitutes a powerful tool for documentation and knowledge in its application to the restoration of cultural heritage (Fig. 2.02). Surveying, in particular, serves as a means of analysis and control, non-destructive pre-diagnostic investigation and historical-critical understanding of the artefact (Carbonara, 1989). Metric surveying is the first step in documentation, to which other data can then be added, such as those derived from diagnostic investigations. These activities describe and focus attention on the materiality of the work, which is the object of the physical action of restoration (Brandi, 1963). The renewal of surveying methodologies has been one of the main drivers of the digital transition of understanding historical architecture; the greater completeness and high accuracy that can be achieved leads to a level of knowledge that was previously difficult to attain. However, knowledge is not limited to geometry, but includes other information, elevating surveying to an activity characterised by

Fig. 2.01.

Guidelines developed at national and international level for the conservation and restoration of cultural heritage emphasise the role of documentation as a basis for understanding artefacts and promote digitisation as a tool for increasing knowledge.

Fig. 2.02.

Drawing of the visual survey of the materials and state of conservation of the surfaces of Palazzo Constabili in Ferrara (Source: Maietti, 2023).



multidisciplinary collaboration for the production of documents of extraordinary authenticity on the building under study, which in turn produce knowledge (Carbonara, 2012). It is therefore a complex issue that goes beyond representation, nowadays in the direction of informative digital modelling (SIRA, 2023) . The use of CAD, GIS and BIM (in its H-BIM heritage version) to draw up restoration plans is in some cases standard practice, in others a horizon that is being approached (Figg. 2.03, 2.04, 2.05 and 2.06). The research framework at both international and national levels is pushing for digitization. In fact, several organizations dealing with conservation, in their references and most up-to-date guidelines, place particular importance on digital tools as a means of effectively improving the understanding of cultural heritage artefacts (ICOMOS & ICCROM, 2023). At the Italian level, it is worth mentioning the initiatives undertaken by the Ministry of Culture (MiC), that has developed two platforms for cataloguing and digitisation: SIGECweb and SICaRweb[1]. However, the management of the information in the digital archives is still challenging, mainly due to the increasing number of complex and heterogeneous data produced by the use of continuously innovative surveying and investigation techniques, which add to the “traditional” types of information. This multiplying of digital data is not a minor issue and also raises questions relating to digital heritage preservation[2].

1. SIGECweb (https://www.sigecweb.beniculturali.it/it.iccd.sigec.axweb.Main/), created for the Central Institute for Catalogue and Documentation (ICCD) (http://www.iccd.beniculturali.it/), manages the entire cataloguing process, from the production and dissemination of cataloguing standards to the assignment of unique catalogue codes, the cataloguing of tangible and intangible heritage assets, and the publication of catalogue sheets for the use on the Catalogo generale dei beni culturali (General cultural heritage catalogue) website (https://www.catalogo.beniculturali.it/). SICaRweb (http://sicar.beniculturali.it:8080/) is an online information system for the documentation, design and management of restoration sites, which integrates the geometric representation of the asset and the respective thematic maps with the management of heterogeneous information organised in a database structured into dedicated files. It is possible to map and consult the measurable representation of the property, areas of deterioration and intervention with all the accompanying technical and documentary information. In this way, SICaRweb aims to be a decision-making support for the economic and temporal planning of the works and subsequent monitoring. Once the site is completed, all the documentation collected remains organised and archived on the platform.

2. “Digital heritage is made up of computer-based materials of enduring value that should be kept for future generations. Digital preservation consists of the processes aimed at ensuring the continued accessibility of digital materials” (National Library of Australia, 2003). The size and ephemeral nature of Digital Heritage make it difficult to preserve, and many international organization focused in developing and implementing selection criteria and collecting policies as a means to ensuring digital heritage preservation for the current and future generations (UNESCO/PERSIST, 2016). For further details, see also Myers, D., Hansen, J. (2024). Inventories and Surveys for Heritage Management, Lessons for the Digital Age. Getty Conservation Institute, Los Angeles.

Furthermore, given the new possibilities offered by these digital systems, critical issues arise from the adaptation for technological transfer to cultural heritage of tools not originally designed for the field of conservation. These issues are of an applicative nature and, at the same time, have significant implications from a disciplinary point of view. The most obvious examples are in the use of BIM systems applied to existing buildings, where limitations in geometric modelling can lead to excessive simplification of conservation issues, or the lack of dedicated IFC (Industry Foundation Classes) for certain elements prevents the association of specific semantic sets during export, generating problems of interoperability, availability and accessibility of information[3]. Research is focusing on the development of domain ontologies[4], which aim to address these shortcomings with specific sets of properties with useful categories designed for restoration (Acierno & Fiorani, 2025), representing the diverse forms of knowledge involved in the restoration process, supporting the creation of a digital archive and related services (Carmeliti & Catalano, 2025).
It is therefore necessary to develop a critical awareness of the potential and limitations of digital tools: no system is definitive, no model is optimal for meeting the needs of each disciplinary sector. The best approach is to develop interoperable Common Data Environments (CDEs) to enable the exchange of data and information. Based on open formats and ontologies, they must follow rules shared among the various actors in the field of documentation, preservation and enhancement, in order to bring about effective improvement in the overall process. In these activities, too, the issue of simplification is central and raises questions about the level of “compromise” that ontology schemes inevitably entail and about the control by domain experts over the formalisms that organise the structure of digital knowledge (Salonia, 2023).
Within the analyses aimed at understanding the historic building, in addition to defining its historical and cultural aspects, meaning and values, as well as its architectural,

3. IFC (Industry Foundation Classes) is an international standard for data exchange in Building Information Modelling (BIM), which ensures that different software programmes can exchange information about objects in a 3D model in a consistent and structured manner. Each type of architectural element should have a specific IFC class that defines its role and semantic meaning in the model. For many elements that refer to specific components of historic buildings, particularly deterioration, there is no appropriate class, as BIM is conceived for new buildings. If, during export, when the information has to be translated into the standard IFC language, the proper class is missing, it is not possible to associate a specific semantic set with the object, i.e. a set of information describing what it is, what it is used for, what properties it has, etc.

4. An ontology in computer science is a formal, shared and explicit representation of a conceptualisation agreed into a domain. For further details, see Gruber, T. (1993). Toward principles for the design of ontologies used for knowledge sharing, Formal Ontology. In Conceptual Analysis and Knowledge Representation, Kluwer Academic Publishers, Deventer, The Netherlands.

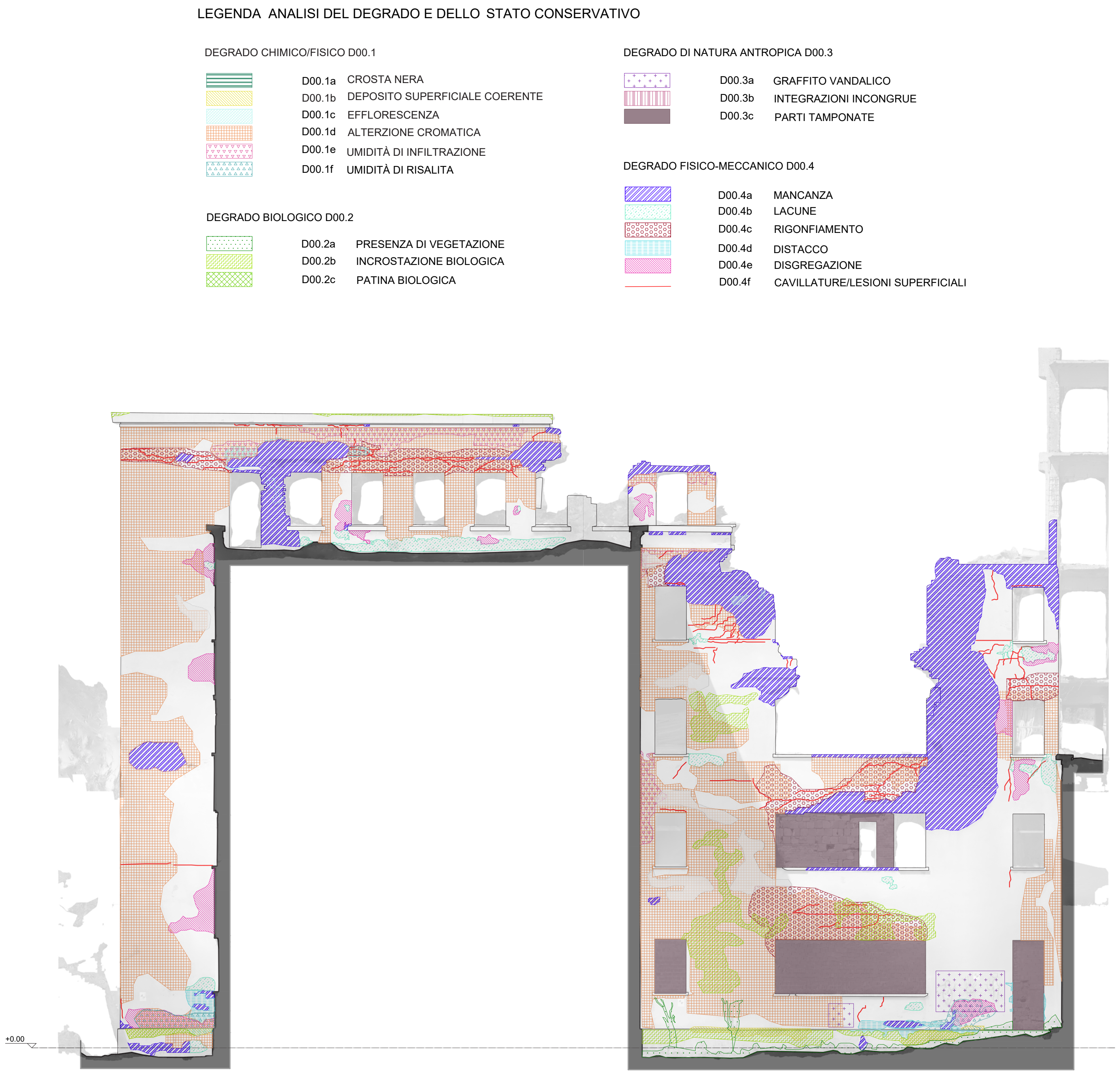


Fig. 2.03.

Example of 2D degradation mapping on the surfaces of an elevation, with degradations represented in vector format for computational purposes. The building is Former Colonia Varese, to deepen see paragraph 5.3.

Fig. 2.04.

Example of 2D mapping of surface degradation on an architectural elevation in GIS environment (Source: Tsilimantou et al., 2020).

Fig. 2.05.

Example of 3D mapping of surface degradation in BIM software (Source: Chiabrando et al., 2017).

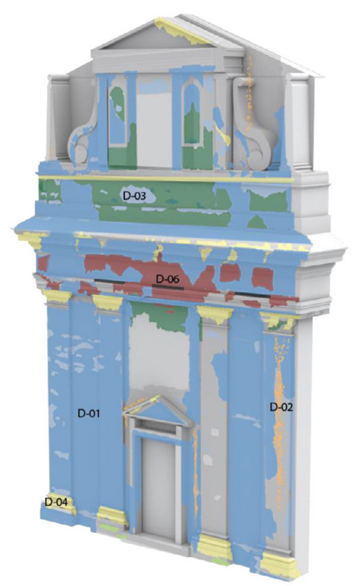


Fig. 2.06.

Example of 3D mapping of surface degradation on an architectural elevation in BIM software (Source: Malinverni et al., 2019).

typological and technical-constructive aspects, the description of the surfaces, which is the subject of this research, plays an important role. In general, the study of architectural surfaces, the materials they are made of and their state of conservation requires an interdisciplinary approach, which maintains the protection of the asset as its fundamental objective. It is necessary to consider that analytical data, although fundamental, cannot be the sole basis for decision-making, but must be interpreted critically in their results (SIRA, 2023). The challenges involved in surveying and diagnosing historical surfaces highlight both the need and the opportunity to systematise procedures, optimise the use of collected data, create stronger connections between surveying and thematic representation, and integrate this information into parametric models aimed at supporting restoration projects.

This research, pertaining to the disciplinary sector CEAR-10/A Drawing, is situated within this framework, focusing particularly on documentation through integrated three-dimensional surveying procedures, point cloud data classification, and their representation, as a support to conservation processes ranging from monitoring and maintenance to restoration interventions. The specific aim is to investigate methods for translating analytical data and information into forms that are accessible and usable by professionals. Within this perspective, the documentation process has a distinctly multidisciplinary character, involving references to related sectors such as diagnostics and restoration. However, the research itself primarily focused in the field of drawing and surveying.

Thus, the main objective of the research is to contribute to the establishment of a methodological-operational workflow that facilitates to the effective employment of digital tools, which very often remain unused or underused but that can improve the effectiveness of the actions for conservation of cultural heritage, by professionals and management bodies.

In the framework of digital data processing for the characterization of historical surfaces, digital modeling discretization processes are increasingly aimed at “decomposing” massive datasets through segmentation, handling architectural complexity by assigning hierarchical meanings to specific subsets of the digital model (Russo et al., 2021). At the same time, efforts are being made to accelerate the process by exploiting automatic classification methods based on AI techniques, aimed at addressing unresolved issues closely tied to the morphological complexity of shapes or, as in this study, to the characterization of architectural surfaces. The central research question underpinning this work concerns the need for a point cloud processing and data segmentation workflow capable of taking advantage of current automatic or semi-automatic methods for the analysis of heritage surfaces.

Beyond the technological dimension, this research also addresses the growing gap between the vast quantity of data produced and its practical usability. Large datasets are collected, yet in some cases the specific information required for a given analytical problem is missing, or the geometric data acquired is not linked to meaningful attributes. In the context of digital surface surveys, therefore, the amount of data does not always correspond to its quality.

What emerges is the necessity for a more informed and structured representation, supported by semantic classification. This implies not only recognizing architectural elements, but also enriching them with non-geometric information related to surface characteristics.

2.2 A workflow for digital data management

The current scenario of architectural heritage documentation is highly fragmented, encompassing a wide range of tools and processes that vary according to specific needs. Among these, one of the areas concentrating the greatest amount of innovation is the so-called scan-to-BIM process, although its application differs from case to case depending on the required level of knowledge and the intended purpose of intervention. Clearly, based on what has been outlined in the previous paragraph, the critical issues and complexities of the existing architecture must always be taken into consideration. On the one hand, such a statement risks oversimplifying a very broad issue, but on the other hand, it is necessary in order to codify an operational practice on which to build elements of development and improvement.

The starting point is the building itself, the primary document of itself (Boito, 1893), and the end point is (or should be) one (or more) coordinated digital models representing the characteristics necessary to manage the life of the building in question. This model, Digital Twin (DT), must be accessible, interoperable and updatable through platforms that allow all stakeholders to perform their respective operations on the model. In between, there are several phases which, for the topic and objectives of this research, can be grouped into three macro steps. The first is integrated three-dimensional surveying, primarily metric, but accompanied by research on other sources, such as archives, and fact-finding investigations where necessary. A second phase involves the organisation of this data, which in the case of point cloud models may include segmentation and semantic classification processes. The third phase is that of actual parametric modelling, in which an informative digital model is developed to contain all the documentation collected in a three-dimensional relational database.

The specific scope of this research is the second phase, in which the most recent studies show how quantitative data analysis operations can be supported and facilitated by the application of AI algorithms. There are many algorithms available, with different application characteristics. The State of the Art presents various experiments focused on identifying historical materials and architectural elements, construction techniques, and decay pathologies by processing different types of raw data, including point clouds, images, orthophotos, and UV textures. In this research, these processes are tested

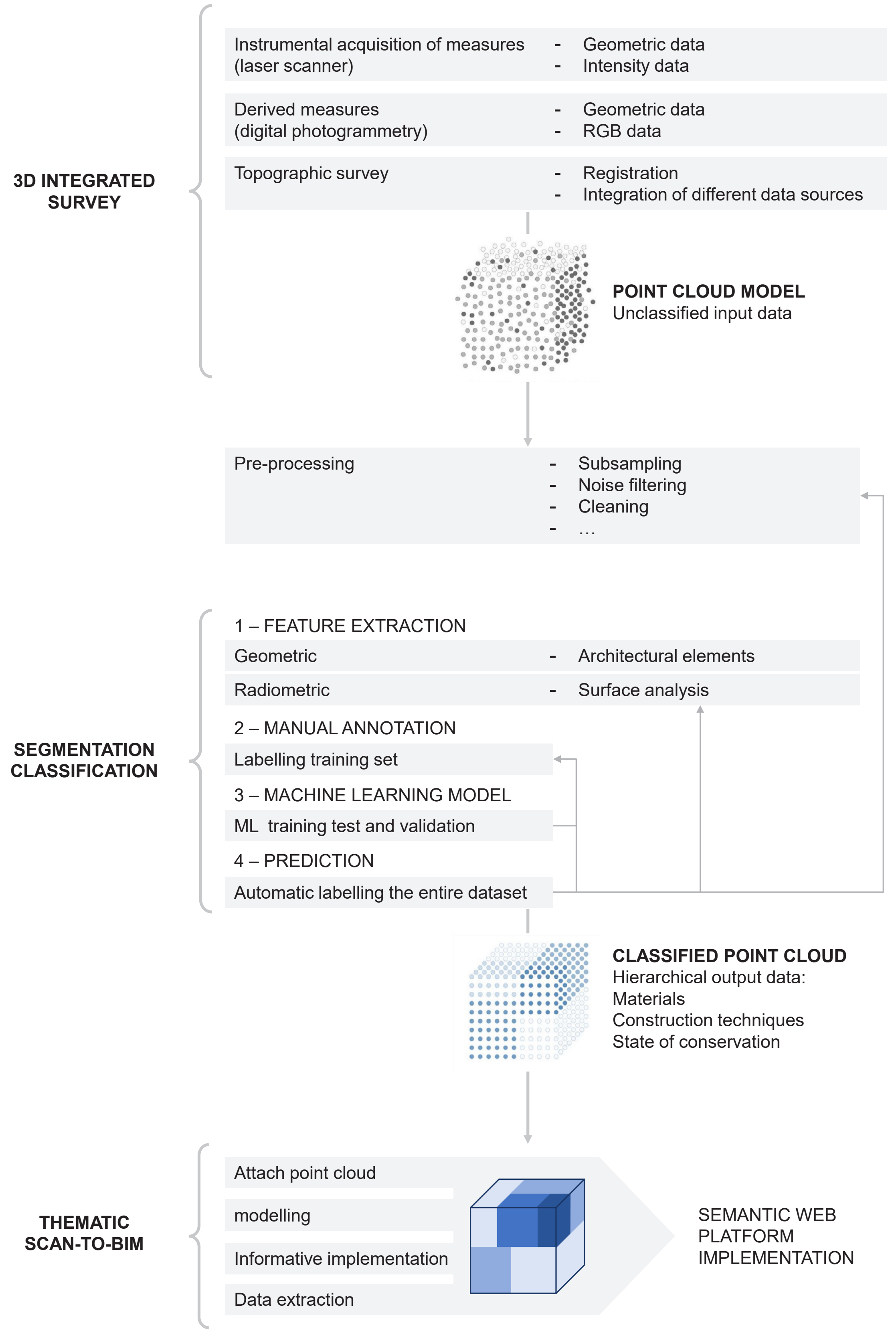


Fig. 2.07.

Methodological workflow for the documentation of architectural cultural heritage

in order to systematise a workflow specifically suited to surface analysis, possibly combining multiple methodologies to achieve the optimal result (Fig. 2.07). A further focus introduced in this pipeline aims at analysing possible in-depth uses of the intensity value as a benchmark for historical surface assessment.

In this process, the transition from data acquisition to knowledge is the result of an interpretative mechanism, which is also linked to the operator's skills (Docci & Maestri, 2020). The introduction of automatic or semi-automatic procedures into the workflow of segmentation and classification of survey data must take this aspect into account, favouring tools in which specialist control is present at various stages. There is a growing reliance on AI within DTs to simulate interpretative and decision-making scenarios, but its uncritical use can lead to risky situations in a sensitive context such as cultural heritage (Salonia, 2023). For this reason, in this research, AI is intended to be used as a tool for reiterating quantitative operations, not as a generative tool. Interpretation, the selection of categories of interest, final validation of results, and other operations that require more advanced, complex, and interdisciplinary knowledge are still entrusted to human intelligence. At present, there are no signs of convincing results regarding the introduction of a completely autonomous process in the segmentation of architectural heritage data. Therefore, given the objective of providing effectively applicable tools, the proposed direction is a semi-automatic hybrid approach, with a human critical-interpretative component that remains fundamental.

The interpretative aspects that AI, understood in this way, can improve and renew are those related to features with the most repeated and repeatable characteristics, where any interpretation is based exclusively on objective parameters, even if not immediately distinguishable to the naked eye, or on associations of features that are difficult, if not impossible, to correlate with each other. As the result of statistical calculations, each response resulting from procedures of this type is linked to a certain degree of reliability. Just as every result of a measurement is not an absolutely exact data, but a value with a surround of uncertainty, it is essential to know the extent of this uncertainty, with the aim of reducing it as much as possible. The thesis therefore aims to raise greater awareness among future users of semi-automatic processes (which may become automatic in the future), emphasising that a critical approach must remain central, identifying at which stages.

2.3 Historical surfaces as a source of knowledge

Among the definitions that can be given of "surface", in the present research it is considered not as an abstract geometric entity but as a concrete component of architecture, as it is the "external part of an object or entity materialized as a layer of a certain thickness" (Maietti, 2023). However, architectural surfaces, particularly those of historic buildings, cannot be reduced to mere material boundaries or envelopes. Rather, they constitute a space of representation, a conceptual and perceptual place in which multiple values are condensed, including aesthetic, historical and constructive ones. Each surface is, in fact, a palimpsest of traces, revealing natural and anthropogenic events and the transformations that affect the material of which it is composed. Plaster, coatings, colours and finishes preserve the signs of periods, techniques and languages that overlap over time, making the surface a document, a source for interpreting the processes of construction and transformation (Fiorani, 1995). As such, it possesses several characteristics, each related to different reading and interpretation categories, which describe not only the envelope but can extend to the entire building.

The analysis of architectural surfaces is thus one of the themes of the historic buildings survey. Primarily, surveying allows the exploration of the three-dimensional complexity of artifacts. Whether carried out thorough traditional methods or advanced instrumental surveying procedures, the representation of surfaces plays a fundamental role as they define architectural volumes and spaces. In addition, the architectural surface is the exposed part of the material, the manifestation of its depth, and their study is fundamental to a deep and comprehensive understanding of buildings. Their documentation is preparatory and functional to the preservation of the whole building. Therefore, the ultimate goal tends to be restoration and preservation (Docci & Maestri, 2020), so the aspects to be analysed can be multiple and case-specific: geometries of the elements, materials, construction aspects, state of conservation, cracking and collapsing occurrences, etc. At a second stage, what is represented must be critically interpreted in the broader perspective knowledge that also includes historical and context-related aspects, in order to identify causes of phenomena and strategies to be implemented. At this stage, diagnostics assumes an important role in enabling analytical insights. Therefore, the surface is the threshold for accessing a complex system of relationships and, at the same time, a tool for critical interpretation: by reading it, it is possible to acquire information about architecture. The architectural surface is thus a source of knowledge of the whole building (Maietti, 2023).

Integrated digital surveying is the first step in understanding an artifact. Point clouds obtained from three-dimensional acquisition procedures are models in which spaces are surveyed and described through the surfaces of architectural components. The measured points belong to the surfaces and, in addition to geometric information, can carry that qualitative information that experts of many fields, such as architects, conservators, and archaeologists, can read on the surface. This massive informative possibility is anchored in the three-dimensional metric structure of the survey, offering greater potential for documentation and representation for conservation purposes. The mapped three-dimensional datum can be extracted into traditional two-dimensional representations but also studied in its spatiality, allowing for an extension of interpretive support tools (Fig. 2.08).

The categories considered in this research are materials, construction techniques and state of conservation. Each of them is defined on a case-by-case basis by appropriate abacuses, drawn up according to the specifics of the buildings studied. These three categories describe the material manifestation of heritage corresponding respectively to its constituent materials, how they are arranged, and the condition in which they have been transmitted to the present day. With regard to materials and construction techniques, their historical and geographical context is often of fundamental importance, as it serves to define the level of compatibility of the materials introduced by the restoration in the pre-existing material context. Due to the layered nature of historic buildings, different construction methods often coexist within a single structure, creating localised critical issues or vulnerabilities that need to be identified and addressed. Considering the susceptibility of architecture to degradation and damage, including from a structural point of view, it is essential to document its state of conservation in order to intervene and prevent, as far as possible, the recurrence of certain phenomena. Clearly, in certain cases, diagnostic investigations would also be required to determine the precise nature of certain phenomena, but in this research, for the elaboration of the category abacuses, it was proceeded as described in the following paragraph.

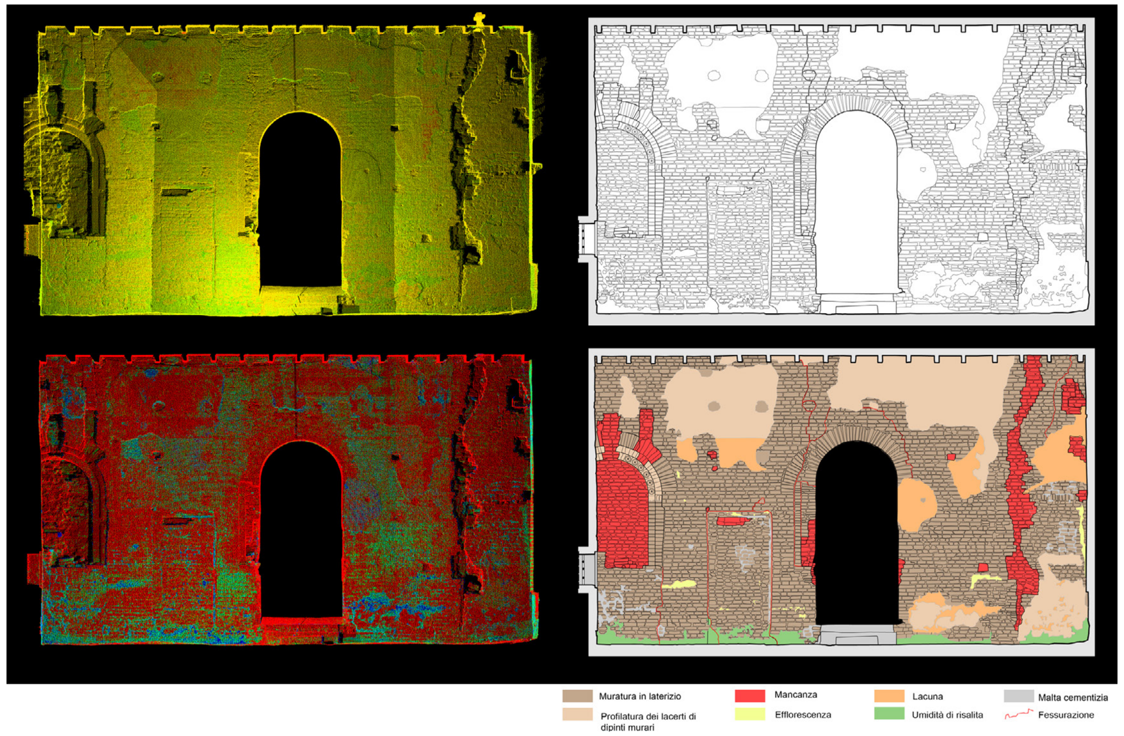


Fig. 2.08.

From integrated surveying to the representation of architectural surface characteristics, such as materials and state of conservation. Elevation of a room of the Palazzo del Podestà in Mantua (Source: Maietti, 2023).

2.4 Development of thematic classification tools for critical assessment

Segmentation and classification aims to compose a point cloud model as a queryable informative system composed of data layered according to different levels of information. This can be a powerful tool to support the interpretation and study of historical artifacts and a facilitation in H-BIM modelling. In each case, the classes must be uniquely coded, with the possibility of tracing them back to further, more detailed and in-depth information. This is managed through abacuses (Fig. 2.09).

Thematic abacuses make explicit the characterization by materials, construction techniques and state of preservation of all surfaces that are being analysed. In a multi-category characterization, the abacuses must be structured in a consistent and coordinated synoptic framework between the different thematic readings.

Considering the direction in which the digitisation of historic architecture is heading, namely towards relational and interoperable databases, the structuring of common dictionaries and ontologies in which classes, subclasses and properties are hierarchised, specifically to describe the domain of conservation and restoration, represents a very active line of research that requires a great effort (Acierno & Fiorani, 2025). The abacuses of categories to be identified in the point cloud model can, and hopefully should, be part of ontologies of this kind, with a view to developing increasingly integrated and efficient methods for cultural heritage documentation.

Fig. 2.09.

Extract from the abacus of survey and analysis of materials, finishes, colours and the state of conservation of the architectural surfaces of the historic centre of Mesola, Ferrara (Source: Maietti, 2007).

The construction of the abacus necessarily involves a phase of in-depth study and critical analysis of the different typologies that have emerged from the visual readings of the surfaces carried out *in situ*, combined and supported by historical knowledge of the building and the context in which it is located. This process, can be conducted through the three methodological guiding principles described below.

Objective/subjective reading. This principle concerns the distinction between the characters referable to a datum that can be attributed thanks to visual analysis of the artifact and those that can be deducted thanks to a critical interpretation. For instance, regarding construction techniques, historical-archaeological aspects often intervene in their proper identification. This aspect must be taken into account since the purpose of the abacus is to identify classes that are useful for documentation, and therefore necessary for describing the object of study according to aspects that are useful for guiding intervention or conservation decisions. However, artificial intelligence procedures are used to support the automatic identification of the classes, two considerations must be made:

- the algorithms work by means of the distinguishable and detectable geometric and radiometric characters on the input data (point cloud or images);
- on the contrary, what arises exclusively from critical interpretation of visible traces is not mappable by automatic procedures.

Accordingly, the abacuses should take into account all the classes needed, but it is reasonable to expect that only those related to the first of the two categories mentioned will be successfully identified. For this reason, classes susceptible to critical interpretation can be identified and segmented upstream or downstream of automatic processing. In this way, the classified point cloud model fulfils the function of a tool to support critical assessment, without replacing it. The distinguishability of the classes to be mapped thorough algorithms is particularly critical for the category of the state of conservation. In fact, many degradation pathologies occur in an overlapping manner with each other or with very similar colorimetric characters. Since algorithms need parameterizable radiometric and morphological features to lead to a result, where there are no such features distinctive enough to allow algorithmic training of the mapping, it is convenient that these classes constitute macro-morphologies, which must necessarily be critically interpreted later.

a. **Surface/Structure**. This principle concerns the object of mapping and is connected to the nature of point clouds. These, in effect, consist of groups of adjacent points that describe surfaces (Docci et al., 2017), which in turn delimit three-dimensional components. The geometric entity (the point) belongs to the surface of the three-dimensional element, which often has its own internal stratigraphy. For example, many masonry construction techniques in historical and archaeological architecture consist of external surfaces of a certain material and a core of a different material (sack masonry). The fundamental question is how to classify the elements, and the criterion usually adopted is based on the identification of each of the layers visible on the surface. Again, the choice is also determined by whether the procedure can be pursued through algorithmic prediction, which allows the identification of homogeneous areas that are recognizable as such from the point of view of colour and shape.

b. **2D/3D annotation**. This principle concerns the choice of documentary medium. It is not necessarily true that point clouds are always and in every case the best means of achieving the expected representation. While for materials and construction techniques there are no particular problems in achieving the same levels of detail on both two- and three-dimensional representations, for the state of conservation often the information content reported by 2D graphical mapping reaches more detailed scales. This is true both for completely manual procedures (in vectorizing two-dimensional polylines, the control and accuracy in tracing is greater than in segmenting a three-dimensional point cloud) and for algorithmic procedures, which are more mature on images than on 3D data (Grilli et al., 2018). In defining the abacus of the state of conservation, thus, one must contextually take into account the purpose of analysis and consequently define the segmentation methodology to be followed, in order to achieve at a satisfactory result for the requirements (Fig. 2.10).

c. **References to existing documentation**. To draw up the abacuses, it has been assumed as a basic reference existing documents that allow the coding of identified pathologies and their cataloguing in a shared system. Regarding the state of conservation, for example, in the present research, the UNI 11182/2006 document was used. The document UNI 11182/2006 Beni Culturali. Materiali lapidei naturali ed artificiali. Descrizione della forma di alterazione - Termini e definizioni, is based on former Normal 1/88 Alterazioni macroscopiche dei materiali lapidei: lessico (UNI 11182/2006 Cultural Heritage. Natural and artificial stone materials. Description of the form of alteration - Terms and definitions, former Normal 1/88 Macroscopic alterations of stone materials: definition). In an integrated logic, the abacus of degradation morphologies is subordinate to the macroscopic identification of the building's materials and construction techniques, as certain phenomena occur on certain materials, or may affect surfaces depending on the building's construction characteristics. In addition, the study of morphological aspects such as overhangs and niches from the main surface is also functional in defining certain encountered phenomena (Maietti, 2023).

For these reasons, it is clear that in many cases the abacuses of interest for documenting architectural heritage surfaces are not perfectly compatible with the categories that automatic or semi-automatic procedures can identify. Therefore, the strategy adopted involves defining two levels of abacuses: the first containing the classes to be included in the final model, and the second containing the classes recognisable by the algorithm. A common example is that of categories of materials and construction techniques,

Fig. 2.10.

From detailed abacus of deteriorations to two-dimensional mapping. Extract from the representation of the citadel of Gozo in Malta survey (Source: Balzani, 2010).

which can form a mixed abacus for the automatic procedure, as components of the same material can have very different geometric morphologies determined by the construction techniques used. This characteristic makes it convenient to assign these areas to two different categories (construction techniques) and group them together to obtain the material class at a later stage, manually.

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Summary

3. A framework for architectural survey

Abstract
This chapter describes the theoretical and methodological framework of architectural surveying as a core discipline for documenting and conserving cultural heritage. It traces the transition from traditional "direct" surveys to technologically advanced "indirect" methods, showing how the introduction of digital tools, such as laser scanning and photogrammetry, have transformed documentation into a data-rich, three-dimensional process. The chapter highlights the importance of integrated survey methodologies that combine laser scanning, photogrammetry, and topographic networks to ensure geometric accuracy, completeness, and error control. These methods constitute the foundation, especially geometric, of current Scan-to-BIM workflows. A detailed section describes the difference between the kind of data obtained thorough laser scanning or photogrammetric processes, followed by an overview of sensor technologies (Time-of-flight, phase-shift and SLAM), discussing their operating principles and suitability for diverse heritage contexts. The final section mentions main digitization protocols and European guidelines, emphasizing the current need for standardization, quality control, and long-term data preservation.

3.1 A foreword about a changing scenario

The documentation of cultural heritage, in its broadest sense, is recognized as a fundamental aspect of preservation strategies, serving as a critical tool for generating and sharing knowledge, fostering public engagement, and ensuring its long-term conservation. In the case of architectural heritage, the transmission of knowledge relies on thorough analysis of both current and historical conditions, including the reconstruction of form, geometry, and visual characteristics (Docci & Maestri, 2020). Central to this process is surveying, which involves not only the measurement of structures but also their graphic representation, and encompasses a multifaceted process of observation, selection, synthesis, and codification of built environments.

Graphical representations function as layered interpretive tools that support different levels of understanding. They serve as knowledge models to analyse and interpret architectural and urban contexts (Docci & Chiavoni, 2017).

The advances in technology and in computer science, made possible the transition from traditional methods of surveying, called “direct”, to the ones based on technologies, called “indirect”. The former involve manual instruments to record dimensions on-site, taken by placing tools directly on building surfaces to determine lengths; then measures are reported on drawings, which would be the basis for graphic representation of the architecture. The latter rely on sensors to acquire massive data remotely, resulting in the creation of digital models of built environments (Docci & Maestri, 2020).

As a result, for several years, in the discipline of architectural surveying have been widely used technologies, tools and procedures capable of digitizing the built heritage with a higher level of automation. These are non-invasive methods, such as laser scanners and photogrammetry, which produce 3D point cloud models characterized by high metric and morphological accuracy (Remondino & Rizzi, 2010). The digital models of the buildings, leveraging the third dimension, offers significant benefits in representing their morphological complexity, providing a comprehensive description of the architecture, capturing its overall condition at a specific moment in time. For this reason, these information-dense databases are now becoming essential not only for the documentation of the existing but also for the development of more effective projects and interventions on heritage buildings. On the point cloud models, in fact, it is possible to “read” morphological, structural, textural, and conservation features, and to extract descriptive 2D drawings or 3D models (Bianchini et al., 2012), including H-BIM - BIM related to historic buildings - (Murphy et al., 2009), through the so-called Scan-to-BIM process (Dore & Murphy, 2013; Laing et al., 2015; Liu & Li, 2024; Li et al., 2025). The relevance of considering the application within the BIM modelling lies in the fact that Building Information Modelling (BIM) is the ultimate frontier of 3D architectural representation, design and management of digital data. It is about to become mandatory in building processes[1], but there is a lack of standard procedures and data aggregation for Heritage applications. These practices are gaining ground also because of the significant advantages they bring, starting with the speed of surveying (given the increasingly shorter acquisition times) to the management of even complex buildings over time, which is possible thanks to approaches finalized to semantic BIM models and web platforms.

This shift from “direct” to “indirect” survey arise changes in the moment of observation and interpretation of existing buildings. In the first case, selection of parts or elements to be measured, represented and, consequently, analysed, is strictly linked to on-site operation, while in the second case, these operations are demanded to a subsequent phase in the digital environment, made possible by the large amount of data that can be acquired (Bianchini et al., 2012). However, even if the analytical step appears to be separate from the acquisition phase, the latter must take into account the purposes of the survey and the reasons for carrying it out, since these determine the methods to be applied.

1. Mention is made to Legislative Decree 36/2023, Article 43 (D.Lgs. 36/2023, art. 43), which is the main updated regulatory reference for the adoption of BIM in Italian public administration. The legislation implements a gradual transition by progressively lowering the economic threshold above which BIM design must be used for public contracts. However, for interventions on cultural heritage, the obligation only applies to values above the EU threshold of €5,538,000.

3.2 3D integrated survey for aimed data mining

Surveying techniques using digital tools are several, each with specific characteristics, and the selection of the most appropriate one is often influenced by the object's scale and the required level of accuracy (Fig. 3.01). Then, the chosen measurement method determinates the complexity of the resulting digital model (Remondino & Campana 2014). In the context of architectural heritage, laser scanning and photogrammetry are commonly employed due to their ability to capture detailed geometric and visual information across varying scales. Nevertheless, these methods are not mutually exclusive for a comprehensive description. In fact, representing both geometry and surface texture typically requires their integration, since no single technique usually offers the ideal balance of accuracy, portability, cost, acquisition time, and flexibility, etc. (Remondino, 2011). This integration is often complemented by a topographic

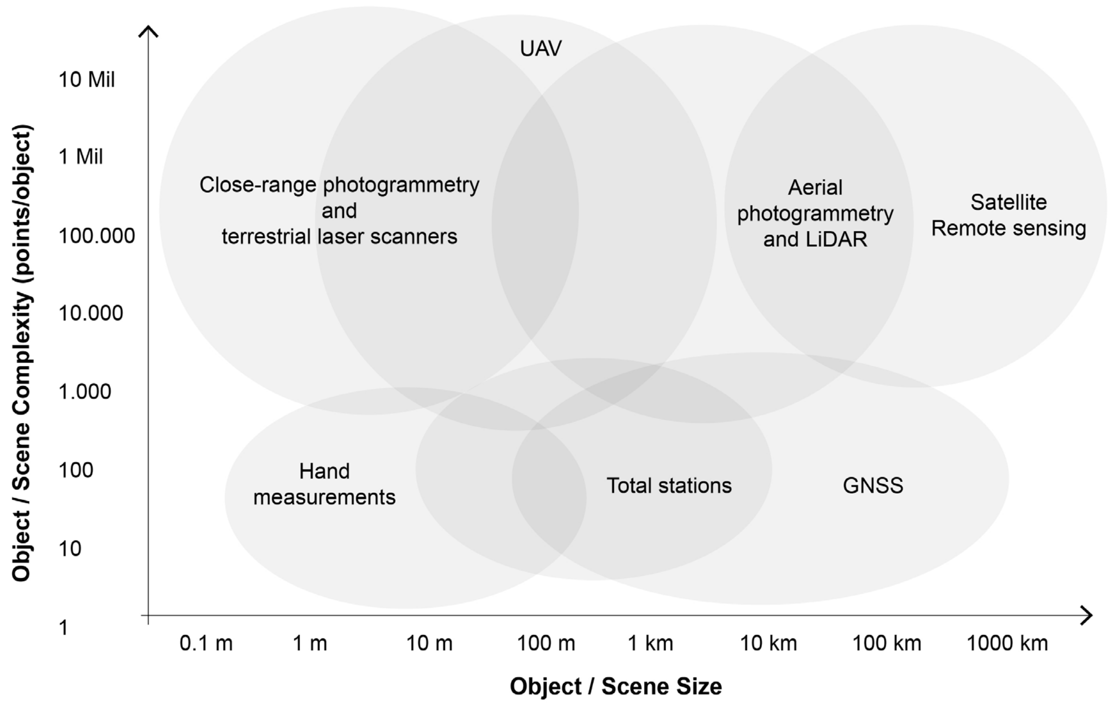


Fig. 3.01.

Geomatics techniques for 3D data acquisition, shown according to the object/ scene dimensions and complexity of the reconstructed digital model (Image by the author adapted from Remondino & Campana, 2014).

survey capable to ensure a strong geometric error control, optimizing both acquisition and data registration (Bianchini et al., 2022). In the state of the art for cultural heritage documentation, the synergistic use of terrestrial laser scanning and photogrammetry has emerged as a robust approach across diverse application areas. Several applications were developed during the years, well documented in a wide scientific literature: the buildings interested by surveying campaigns are not only historical monuments of particular importance (Balzani, 2006; Fassi et al., 2011; Pritchard et al, 2017; Rinaldi et al., 2025), but also historic urban areas (Remondino et al, 2016), modernist buildings (Balzani et al., 2017), minor and rural historic centres (Lin et al., 2021; Piccinini et al, 2022), archaeological sites (Benedetti et al., 2010: Russo et al., 2022), and historic infrastructure (Pepe et al., 2019). The topographical and hierarchical approach to data structuring also allows for the management of complex databases (Balzani et al, 2023; Parrinello et al., 2024). Most of the 3D surveys led to de development of HBIM models, where generally laser scanner point clouds remains the backbone of HBIM workflows, with photogrammetric data essential for completeness, texture, and cost-efficiency (Liu & Li, 2024). Integrated survey is essential in Scan-to-BIM process to document geometric, material, and historical data for preservation management (Baik & Alshawabkeh, 2024). Comparative studies on different point clouds evaluated laser scanning superior in accuracy, yet photogrammetry effective for filling laser scanning data gaps in low-tolerance geometries (Liu et al., 2023), demonstrating how the latter complements the former in occluded zones (Luhmann et al, 2024). Given that point clouds can also be used for surface analysis for conservation purposes (Maietti, 2023), also H-BIM models can leverage them for material degradation analysis (Tysiac et al., 2023; Aricò et al., 2024).
Also in archaeology workflows, the combination of laser scanner and photogrammetry is used often in relation to GIS and HBIM (Limongiello et al., 2025), since it is effective in modelling multiscale spatial data at archaeological sites (Banfi et al., 2022), even considering stratigraphic units (Lombardi & Rizzi, 2024). Integrated 3D survey methodologies have significantly enhanced not only the digital documentation and conservation, but also the valorisation and public accessibility of cultural heritage buildings (Banfi, 2021; Zachos & Anagnostopoulos, 2023), sometimes developing comprehensive “scan-to-HBIM-to-VR” workflows (Tini et al., 2024).
Among the various purposes for which an integrated survey may be executed, this research focuses specifically on documentation aimed at the conservation and restoration of architectural surfaces. The morphometric model enables assessments of the material composition and state of preservation of buildings, as well as the production of metrically accurate mapping. These maps can also be projected directly onto the model, generating three-dimensional representations. The output of the integrated survey therefore has a crucial role as it constitutes the primary material used both for interpretative analysis and as digital support for documentation.

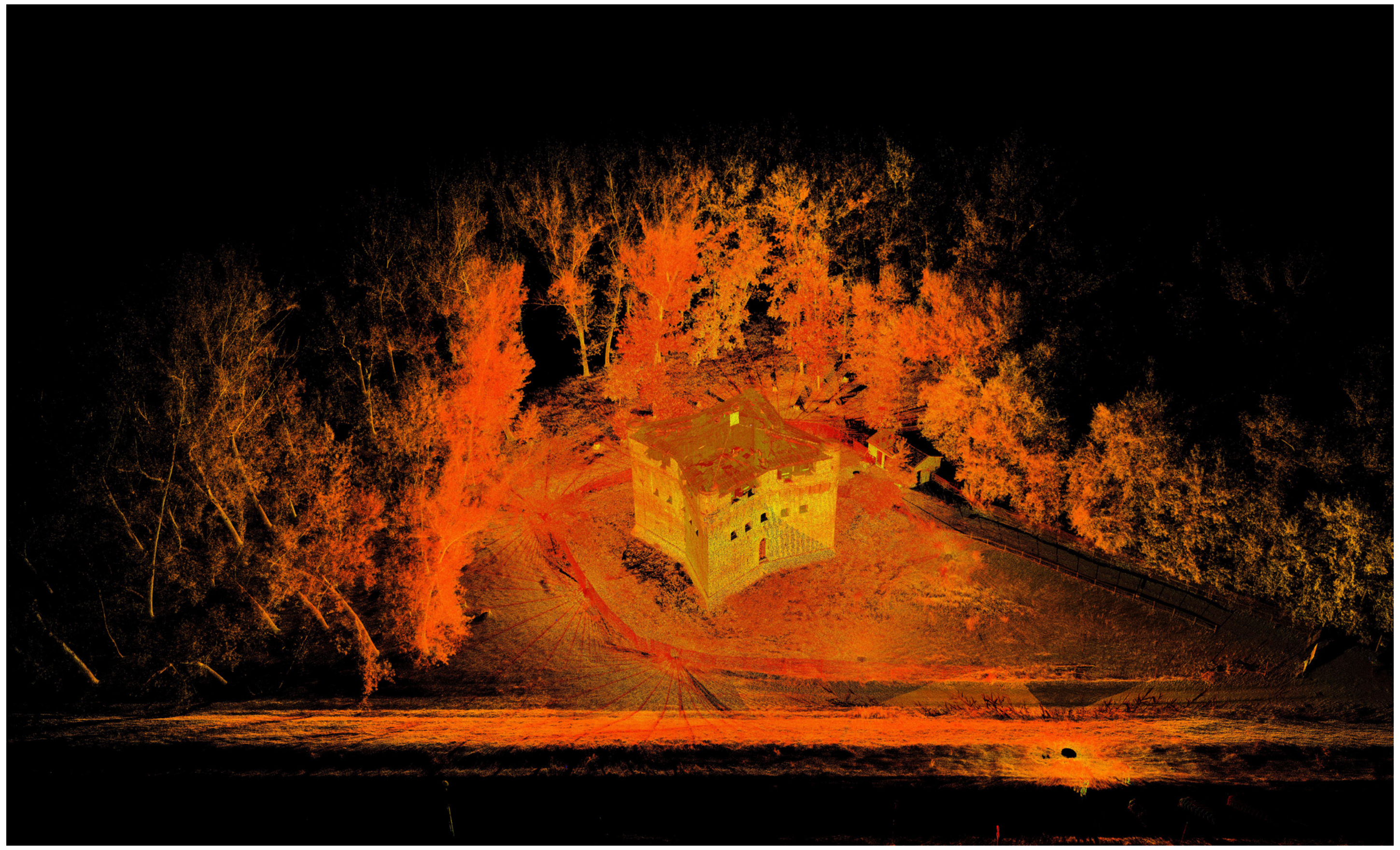
3.3 Dataset acquisition methodologies: laser scanning and photogrammetry

The connection between the data acquisition phase and the theory of drawing is inseparable, as the geometric principles underlying surveying instruments are rooted in projective and descriptive geometry. For instance, the theodolite, the total station and the 3D laser scanner exploit a polar coordinate system: the object is recorded from a known position by measuring angles and distances relative to that fixed point. In digital photogrammetry, both for image capture via photographic sensors and for the restitution algorithms, rules of perspective are exploited: projective rays extending from the projection center through the object intersect a perspective plane, thereby rendering the object onto a two-dimensional surface (Remondino & Campana 2014).
These two different geometric operating characteristics are also accompanied by a classification frequently found in the literature between “active” and “passive” sensors (Grussenmeyer et al., 2008; Russo et al., 2011; Remondino & Campana 2014). This refers to the fact that an instrument can either emit and receive radiation, in the first case, or only receive it, in the second case. According to this distinction, laser scanners belong to the first category, since they emit an electromagnetic pulse which, once it reaches the surface to be detected, returns to the sensor providing metric information (Remondino & Rizzi, 2010). Digital photogrammetry, on the other hand, is classified as a surveying method that uses “passive” sensors, since cameras exploit the light radiation in the environment to capture images without emitting light pulses. Consequently, these sensors do not acquire measurements, but the spatial coordinates of what is detected are subsequently derived through mathematical algorithms based on probabilistic calculations (Remondino & Rizzi, 2010). This last aspect is fundamental in choosing the methodology to be adopted for surveying and also in the critical use of the data produced. In fact, in general, net of the correct design and application of on-site survey procedures, a point cloud derived from a digital photogrammetry process has a lower geometric accuracy than one measured with a laser scanner (Grussenmeyer et al., 2008; Mora et al. 2019). On the contrary, a photogrammetric point cloud provides better colour fidelity in the visible spectrum than a point cloud from a laser scanner. These differences are gradually diminishing, thanks to the improvement of photogrammetric calculation algorithms on the one hand, and the improvement of built-in cameras in laser scanner devices on the other. However, it is unlikely that the two final products will be equivalent, due to the methodological differences described above. Beyond integrating data from different acquisition sources, also the number of cases in which data acquired from different devices is fused has increased (Luhmann et al., 2020; Konstantakis et al., 2024; Aricò et al., 2024). In this process, it is good to keep track of the source of the data, as it is linked to a certain accuracy related to the adopted methodology as described below.
Laser scanning captures 3D coordinates by recording the reflected light from a laser

beam projected onto object surfaces. The system includes a laser emitter with movable mirrors and optical sensors to collect the return signal. The laser scanner measures zenith and azimuth angles, along with range, thus defining point positions in polar coordinate system, which are converted to Cartesian coordinates (Docci & Maestri, 2020). Based on their operating principles, laser scanners are classified as Time-of-Flight (TOF), phase-shift (PS) or triangulation-based, and research has been addressed in comparative analyses of their accuracy and application purposes (San José Alonso et al., 2011; Carraro et al, 2020). Considering TOF and PS laser scanners, most used in building survey, the acquisition methodology involves positioning the instrument in strategic locations to acquire architectural surfaces. The instrument measures 360° coordinates on the horizontal and vertical planes (with the exception of the shadow cone beneath the instrument itself) with a range that depends on the type of instrument. The result is a dense point cloud based on the set resolution (Fig. 3.02). To obtain the complete point cloud model of the surveyed building, the various scans must be registered with each other, i.e. undergo a translation process that places them in a common reference system (Docci & Maestri, 2020). This can be done through common targets between scans, which in turn can be detected with a total station to ensure greater geometric control or allow georeferencing. Another registration approach is the so-called cloud-to-cloud method, which exploits the overlap between adjacent scans

Fig. 3.02.

Point cloud obtained using laser scanner methodology of Rocca Possente in Stellata (To deepen, see Paragraph 5.4).

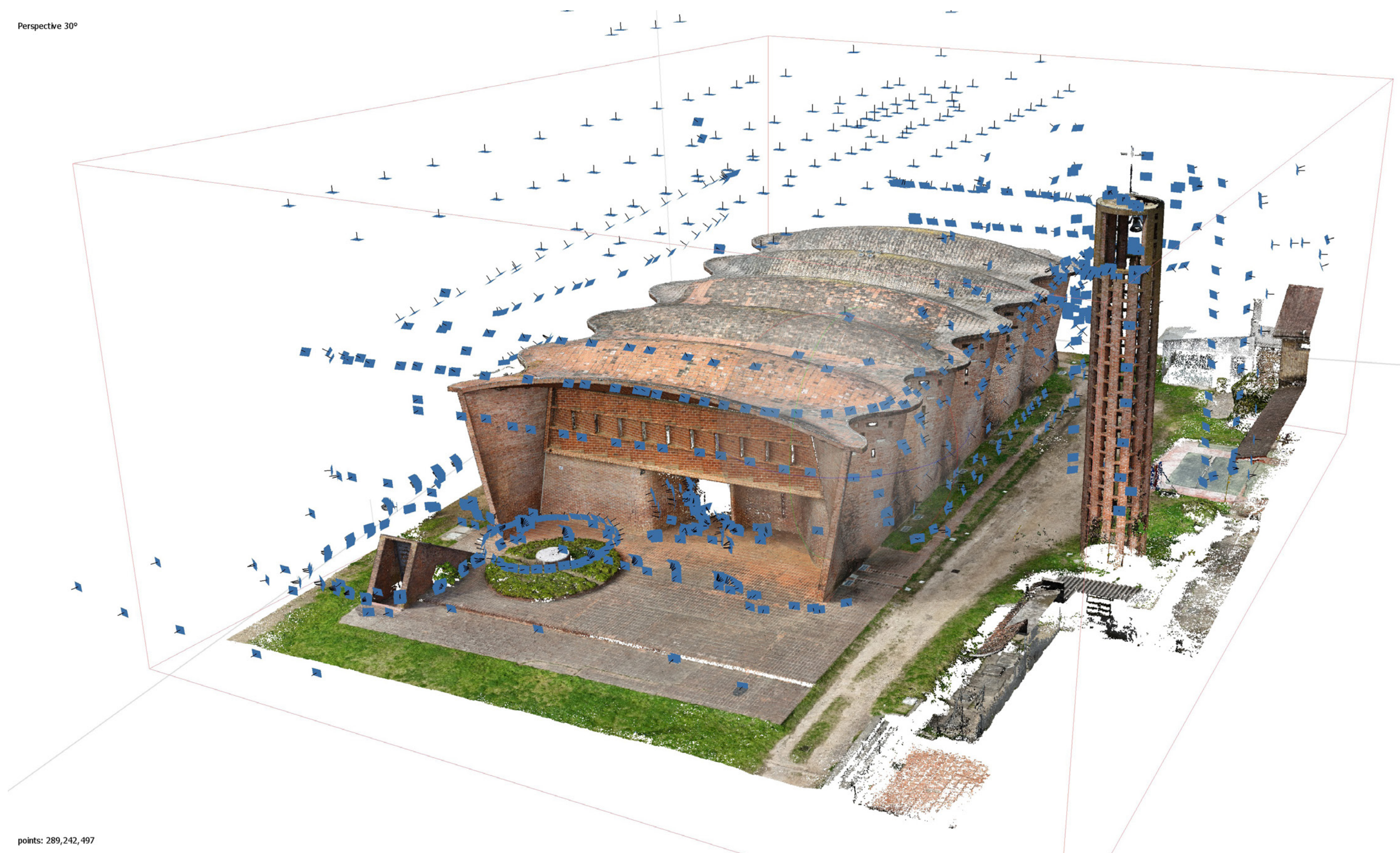


for alignment. The widespread use of this technique in recent years has been made possible by advances in alignment algorithms and the introduction of tools with reduced acquisition times. Therefore, in the same amount of time, it is possible to increase the number of stations to capture the complexity of spaces and, as a result, the overlapping areas between scans are also larger (Pritchard et al., 2023). This method therefore allows time savings onsite by avoiding the positioning of targets, but on the other hand, although highly reliable results can be achieved especially for indoor surveys, there is not the same control over error as with the topographic registration (Bonora et al., 2021; Teppati Losè & Rinaudo, 2025).

Photogrammetry is basically the process of reconstructing the dimensions of an object starting form a set of photos properly taken (Fig. 3.03). Graphic and optical-mechanical procedures have been replaced by analytical and digital ones, which allow the spatial coordinates (x, y, z) of the points in the surveyed scenes to be determined by exploiting the projective relationships between two-dimensional images and the three-dimensional objects represented. The spread of software based on structure-from-motion principles has automated the application of photogrammetric processes, making this surveying technique popular, also given the lower costs of the necessary equipment compared to laser scanners (Bianchini, 2014). The underlying principle is collinearity, according to which the point in space, the projection centre (camera lens) and the projection of that

Fig. 3.03.

Point cloud obtained using photogrammetric process of Cristo Obrero Church, showing the aligned photographic images (To deepen, see Paragraph 5.5).



point on the image lie on the same straight line. If the projection of the point appears in two or more images, it is possible to determine its coordinates by intersecting the straight lines (Russo et al., 2011). To achieve this, it is necessary to know or determine the internal and external orientation parameters using probabilistic calculations. The former are, for example, the focal length and lens distortion parameters, while the latter are the coordinates of the point of capture relative to a reference system and the angles of rotation of the frame around the axes. By photographing a scene from different angles, with sufficient overlap between the images, the software is able to estimate the unknown parameters, positioning and orienting the cameras in space and materialising significant points in space. To do this, it first identifies the key points common to the images, then determines the coordinates of the key points (Historic England, 2017). At the end of this alignment phase, the relative orientation and positioning between the photos and the key points is resolved, but not the absolute orientation or the correct dimensioning. To do this, topographic support is required, based on which the coordinates of certain specific points, which are easily recognisable and appropriately positioned in the surveyed scene, are known, i.e. surveyed with other instruments, such as a total station. In the absence of this information, the model does not have metric value (Remondino & Rizzi, 2010). With this approach, the model can also be georeferenced. To generate dense point clouds and meshes, each pixel in each image is assigned a depth value, creating what are known as depth maps. The images can also be used to produce mesh textures and orthophotos depending on the areas of interest. These images, as well as the RGB values of the dense cloud points (derived from the photographic pixels), enrich the models with high-quality colorimetric information. Due to the complexity and completeness of the three-dimensional reconstruction that is possible, the entire process is referred to in the literature as photomodelling (Paris, 2012).

Laser scanner and photogrammetric acquisition methodologies therefore both produce three-dimensional models, but with different metric and colorimetric qualities that are closely linked to the technologies and acquisition procedures used. Since the survey results are the input data for classification processing, these may differ based on the characteristics of this data. There may be artificial intelligence–based methods that are more or less suitable for a given type of source data, and that consequently yield algorithmic predictions of varying reliability. Understanding surveying methods allows a more aware and effective application of automatic (or semi-automatic) segmentation techniques.

3.4 The influence of laser scanner sensors on surface digitization: an overview

In a point cloud surveyed thorough a laser scanner, the reflectance data (or intensity value) is of great importance and will be discussed in detail in paragraph 4.1. In fact, it can also be used for surface analysis purposes. Consequently, an important section of this research is dedicated to its study, with the aim of achieving one of the set objectives, namely the use of this value in artificial intelligence processes. The value of the reflectance data is determined by multiple factors, including the type and wavelength of the sensor. The characteristics of the various types of laser scanner sensors are listed below. Beyond reflectance data, it should be acknowledged that each laser scanning technology differs in its suitability for specific applications (Tab. 3.01).

In Time-Of-Flight (TOF) laser scanners, the range is calculated by measuring the time elapsed between the emission of the signal and its reception, given that the speed of the laser is known. In addition to the geometric data, the reflectance data is also acquired. It is possible to add colour data to the coordinates, either directly using the cameras integrated into the instruments or, for some instruments, in post-processing, by collimating spherical photos produced by external cameras on special calibrated instruments (White & Jones, 2008).

In phase-shift (PS) laser scanners, distance is determined by assessing the phase

Scanning System		Usage	Typical Accuracies (mm)	Typical Range (m)
Triangulation	Rotation stage	Small objects taken to scanner. Replica production	0.05	0.1 - 1
	Arm mounted	Small objects. Lab or field. Replica production	0.05	0.1 - 3
	Tripod mounted	Small objects in the field. Replica production	0.1 - 1	0.1 - 2.5
	Close range handheld	Small objects. Lab. Replica production	0.03 - 1	0.2 - 0.3
	Mobile (handheld, backpack)	Awkward locations eg building interiors, caves	0.03 - 30	0.3 - 20
Pulse (TOF)	Terrestrial	Building exteriors/interiors. Drawings, analysis, 3D models	1 - 6	0.5 - 1000
	Mobile (vehicle)	Streetscapes, highways, railways. Drawings, analysis, 3D models	10 - 50	10 - 200
	UAS	Building roofscapes, archaeological sites. Mapping and 3D models	20 - 200	10 - 125
	Aerial	Large site prospecting and mapping	50 - 300	100 - 3500
Phase	Terrestrial	Building exteriors/interiors. Drawing, analysis, 3D models	2 - 10	1 - 300
SLAM	Terrestrial	Building exteriors/interiors. Drawing, 3D models	10 - 40	1 - 120

Tab. 3.01.

Laser scanning systems and their uses, in blue sensors used in this research (Elaboration by the author based on Historic England, 2018).

difference between the emitted and received modulated signal. Compared to TOF scanners, these devices offer significantly greater accuracy but are limited in long distance measuring. For this reason, they are typically employed in medium-range contexts, particularly where small-scale heritage documentation is required and, until recently, TOF laser scanners were preferred for architectural surveys involving the buildings and monuments. However, advancements in phase-shift technology have significantly reduced performance differences. As a result, phase-shift scanners have become widely adopted, also due to their generally high data acquisition speed.
Regardless of the scanner type, the quality of laser scanning outputs is affected by several factors: the device's specifications (such as calibration and measurement technique), the properties of the scanned object (including surface reflectivity, colour, and how it diffuses or absorbs light), environmental conditions, and the nature of the backscattered signal (Remondino & Rizzi, 2010). PS laser scanners also acquire intensity and may have associated colour data with the same methods as TOF laser scanners.
Other types of laser scanners are triangulation-based and structured light. Characterised by a low measurement range, these scanners, rather than buildings, are generally used for small and medium-sized object surveying, such as statues, capitals, and other types of fragments. Since this research focuses on architectural scale, point clouds produced by these sensors were not used[2].
In recent years, laser scanners based on SLAM (Simultaneous Localisation And Mapping) algorithms have become increasingly widespread. This describes the process by which an instrument can move around in an unknown environment while mapping that environment and localising itself within that map. Usually composed of a LIDAR (Light Detection and Ranging or Light Imaging, Detection, And Ranging) sensor and an inertial measurement unit, the instrument estimates the path trajectory, while raw clouds are continuously measured and aligned, reconstructing the 3D space according to the surface best match. To minimise error generation, closed paths are preferred, with a logic comparable to that of closed polygons in topography, which offer greater control than open ones. These sensors are used in various applications, such as robotics and autonomous driving (Wang et al., 2024), but, thanks to the very short acquisition times in the field, interest in their application in architecture has grown, proving useful and effective for certain purposes (Campi et al. 2024), always considering that the results in terms of accuracy are lower than those of a static laser scanner (Trzeciak & Brilakis, 2021). Research is making progress on the reliability of

1. For more information on the working principle, refer to: Docci, M., Maestri, D. (2020). Manuale di rilevamento architettonico e urbano. Laterza, Roma-Bari, p. 221, or Russo, M., Remondino, F., Guidi, G. (2011). Principali tecniche e strumenti per il rilievo tridimensionale in ambito archeologico. Archeologia e Calcolatori. 22. pp. 169-198.

SLAM algorithms, developing methods to improve real-time acquisition effectiveness under limited computing resources and higher precision and stability performance. (Sheng et al., 2024). In cultural heritage field, these portable sensors are usually installed on trolleys, backpacks, or handheld. These systems are suitable for short-range mapping, especially for interior spaces with poor accessibility, or in conditions of risk and damaged heritage. Scientific literature compared portable mobile mapping systems each other or with static terrestrial laser scanners highlighting a significantly changing scenario (Conti et al., 2024).
Not only SLAMs, but also other range-based sensors in the latest generation of instruments make it more difficult to calibrate reflectance data, which is acquired with different 'quality' than in the past, as well as being 'dirtier' in the final model, as a result of cloud-to-cloud registration methods that involve the multiplication of stations. The data is therefore less "pure" and more "contaminated", surveys are increasingly integrated (so, from a technological point of view, different sensors are used simultaneously), and the photorealistic image returned by photogrammetric models plays a growing role: all these factors may lead to the need to develop different methods for selecting surface information (Maietti, 2023).

3.5 The demand for digitization protocols and guidelines

The variety of tools on the market, in recent years also available at increasingly lower prices, lead more and more actors to be involved in the surveying field. The almost natural consequence is a multiplication of digital products that tend to be heterogeneous among themselves and not systematized according to common criteria. For these reasons, research panorama has focused not only on optimizing the case-specific application of tools and methods, but also in the direction of standardization to lead to greater interoperability. Also thorough several European funding programs and the Italian PNRR (Piano Nazionale di Ripresa e Resilienza), the digitization of cultural heritage has been boosted. In this innovation contest, the need arose to define some shared methodological protocols.
Several projects and initiatives have proposed and are developing guidelines to improve data quality and present methodological protocols (Fig. 3.04).
These include the "Basic principles and tips for 3D digitisation of cultural heritage" (European Commission, 2020), developed in 2020 by The Expert Group on Digital Cultural Heritage and Europeana. This guidelines include 10 basic principles, each followed by a number of tips, relevant for the 3D data capture workflow, specifically for tangible Cultural Heritage. In the document emerges the importance of the purpose of the 3D digitization project as a guide for planning the whole process, considering the final users and how they will use the data. The concept of "quality" in 3D digitization is

Fig. 3.04.

Guidelines developed at international level to improve data quality in the cultural heritage digital documentation, thorough the establishment of standards and methodological protocols.

highlighted, focusing not only about accuracy and resolution, but also about fitness for purpose and the range of data and metadata generated. Emerges the importance to follow standards and best practices both for acquisition stage and, where possible, for the use of open and/or commonly used formats. A urgent issue is in fact digital long term preservation, that is where to store, process, manage 3D datasets, to make them available for their use and reuse.

Another relevant study is "Study on quality in 3D digitization of tangible cultural heritage - VIGIE 2020/654" (European Commission 2022), coordinated by Cyprus University of Technology and aimed to map and list the parameters, formats, standards, methodologies and guidelines related to 3D digitization of tangible immovable or movable cultural heritage. Different possible purposes such as preservation, reconstruction, reproduction, research and visualization are considered in the study. One section delves into the concept of complexity, in relation to the stakeholder's requirements, the location and the condition of the cultural heritage site. In 3D digitization process planning, complexity is crucial as well as the intended use of the 3D model. The Study includes other aspects of particular relevance both for planning and for execution of digital surveys, such as accuracy and precision, level of detail, object size, and parameters for measuring data quality. Furthermore, a number of cultural heritage digitization projects are identified as benchmark best practices.

An interesting synthesis work was carried out by Historic England, that produced a series of publications that collect technical advice for surveying historic sites with best standard possible (Historic England, 2024). The specifications are intended to ensure that geospatial survey data is both appropriate and 'fit for purpose'. For this reason, Historic England has developed a suite of standard survey specifications for measured building and topographic survey. Different topics are explored, covering a variety of surveying technologies including laser scanning (both static and mobile mapping systems (Historic England, 2018), multi-image and Structure-from-Motion photogrammetry (Historic England, 2017a). The guidance offers user-friendly guidelines and advice on recording cultural heritage, and it is supported by a number of case studies in archaeology and architecture. Moreover, issues surrounding the use of BIM for historic buildings are addressed (Historic England, 2017b). The aim is to support professionals, such as architects, archaeologists, researchers and those who manage the historic environment, to evaluate whether these technologies will actually be beneficial for their purposes, how the data can be acquired properly and used effectively.

Some of these protocols are not limited to the purpose to guide the processes of digitization of cultural heritage, but are also connected to the BIM (or H-BIM) modelling. This is the case of the Data Acquisition Protocol (DAP) developed as part of the EU INCEPTION project, where the aim was related to the data management into a parametric environment for data enrichment within a semantic web platform (Maietti et al., 2020). The DAP is intended to be both a methodological procedure and a workflow specification. It can be followed for the planning and execution of a 3D integrated survey and it

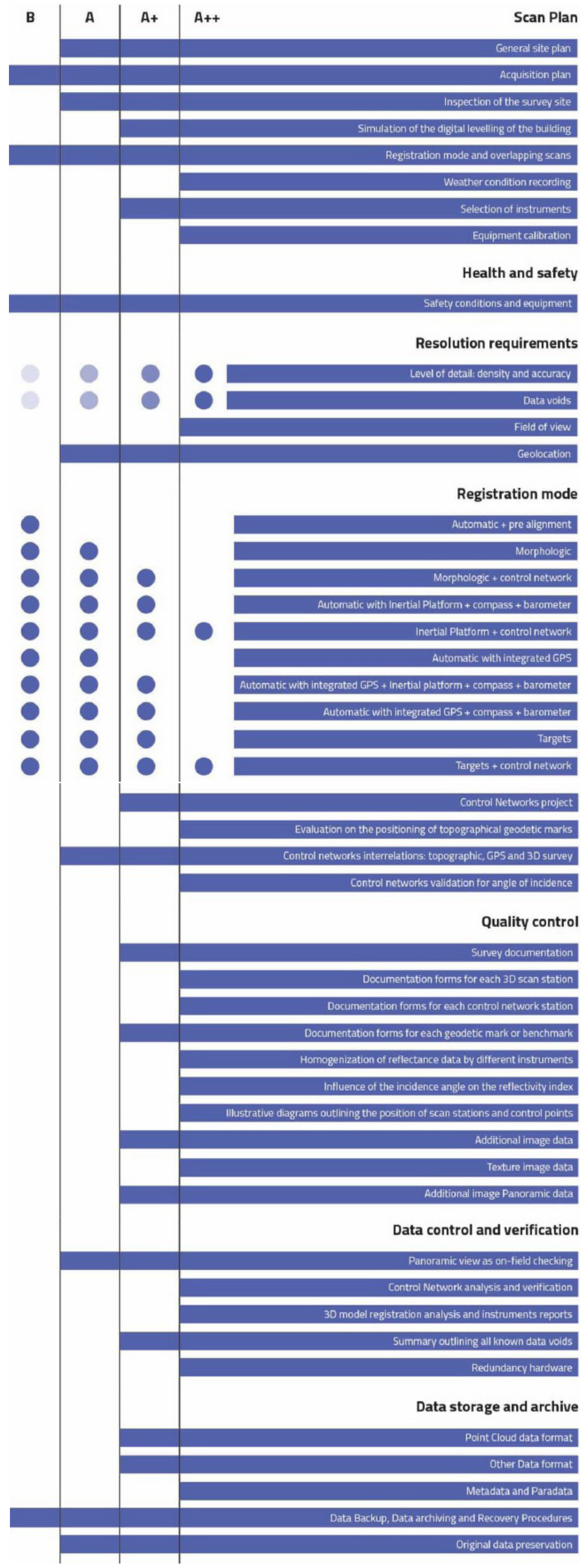


Fig. 3.05.

Activity indicators and their metrics for each phase foreseen by the INCEPTION Data Acquisition Protocol (Maietti et al., 2020).

is flexible to adapt to specific cases and needs. Moreover, it includes specifications for to data management (scan registration, data verification), storage and archive (Di Giulio et al., 2017). The protocol defines 4 incremental categories for survey evaluation, based on different activity indicators.

The current scenario is inevitably oriented toward continuous innovation in digital documentation, and at the same time keeps open the issues described, in a recurring manner we must address the new possibilities that arise. Among these, is not insignificant the impact that artificial intelligence is having, where advanced algorithms such as Neural Radiance Fields (NeRF) are beginning to be compared to photogrammetry for 3D reconstruction in the cultural heritage domain (Croce et al., 2024; Trizio et al., 2024). For these reasons, all these proposed guidelines and standards aim to define criteria for adequate quality, reliability, and optimization in relation to the purpose of the collected data, taking into consideration the storage of digital data aimed at their maximum usability.

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Summary

4. Current scenarios in heritage digital data processing

Abstract

This chapter explores current developments in digital data processing for architectural heritage, focusing on the interpretative potential of radiometric and geometric information derived from 3D surveys. It first discusses the critical use of laser intensity (reflectance) data, considering how it varies according to surface characteristics, angle of incidence, and environmental factors, and its possible role as a qualitative indicator for material and decay analysis when properly calibrated and interpreted. The chapter then examines the increasing use of Artificial Intelligence, particularly Machine Learning and Deep Learning, for point cloud segmentation and classification. These methods enable the enrichment of 3D models with semantic information, facilitating the identification of components or for surface analysis. Issues concerning input data reliability, accurate annotation, and the uniqueness of heritage surfaces are highlighted, leading to the use of supervised approaches tailored to each context. Thereafter, the chapter frames segmentation within the broader Scan-to-BIM process, explaining how semantically classified point clouds can optimize interpretation and modelling workflows for conservation-oriented documentation. Finally, a practical application of the described methodology within the project of the 3D survey of the Colosseum is reported, which represents the execution of classification procedures in a complex heritage environment.

4.1 The intensity value and its critical interpretation

One of the objectives of this research is to take into account and assess the intensity value (or reflectance) as a feature in point cloud AI processing. Even if few studies explored the contribution of data in algorithmic procedures, its potential in surface analysis is demonstrated in literature.

LIDAR (Light Detection and Ranging or Light Imaging, Detection, And Ranging) surveying methods use a laser beam emitted by the sensor of the tools to measure angles and distances. Once the beam reaches a surface, part of it is reflected and returns to the sensor, which records its energy with a numerical value. As a result, each point detected is defined by the three coordinate values x, y, and z, and by the reflectance data. Therefore, the instrument acquires not only geometric information but also radiometric data, which depends on the wavelength of the laser.

According to Lambert's law, a rough surface reflects incoming rays diffusely, scattering energy in all directions, including back toward the source, allowing part of it to return to the instrument sensor. In contrast, a smooth surface reflects the ray specularly, mirroring it across the surface normal. Architectural surfaces, in most cases, exhibit a hybrid rough-smooth behaviour, whereby part of the ray is reflected in all directions and part specularly. Consequently, the reflectance value also depends on the angle of incidence of the laser beam with the detected surface. As the angle varies, the intensity of the reflected signal varies, resulting in a higher value the closer the incident ray is to the normal of the surface. (Kashani et al., 2015).

The intensity also varies depending on the composition of the surface of the object reflected by the pulse, which is very interesting for the analysis of architectural surfaces as it is related to their features, such as the materials or the state of conservation. From this perspective, the reflectance data constitutes potential information for the reading and interpretation of the surfaces to be investigated. (Maietti, 2023a).

However, while the geometric values measured by laser scanners are uniquely determined, the reflectance data is not. In fact, this also varies depending on the distance of the laser instrument from the object to be scanned, the surface temperature and humidity, atmospheric or environmental conditions in general, etc. (Kashani et al., 2015). Based on these considerations, reflectance cannot be considered as data to be used for diagnostic purposes. Consequently, variations in intensity can only be used to deduce information on materials and degradation if critically interpreted through visual and photographic comparison, or with other information acquired through other instrumental investigation techniques. Given that its reliability is influenced by the many factors listed, in a survey campaign all these variables cannot be controlled. However, if the aim is to obtain meaningful reflectance responses, they must be taken into account in order to make the different scans as homogeneous as possible.

The intensity values vary from 0 to 1 and can be displayed on the point cloud through so-called "false colours," which are colours not related to the "real" chromatic characteristics of the object. Generally, a colour scale ranging from red (low values) to blue (high values) is used, but it can be set by the user depending on the software used. In any case, this feature is of considerable interest, since it is possible to clearly visualize the surface areas that have different responses in the reflection of the laser beam (Fig. 4.01). The colour scale can be reduced to specific ranges, and it allows to visualize colour maps of the different levels of reflectance intensity (Maietti, 2015). Therefore, all points corresponding to a particular material or state of conservation that has the same intensity value will be represented in the point cloud model with the

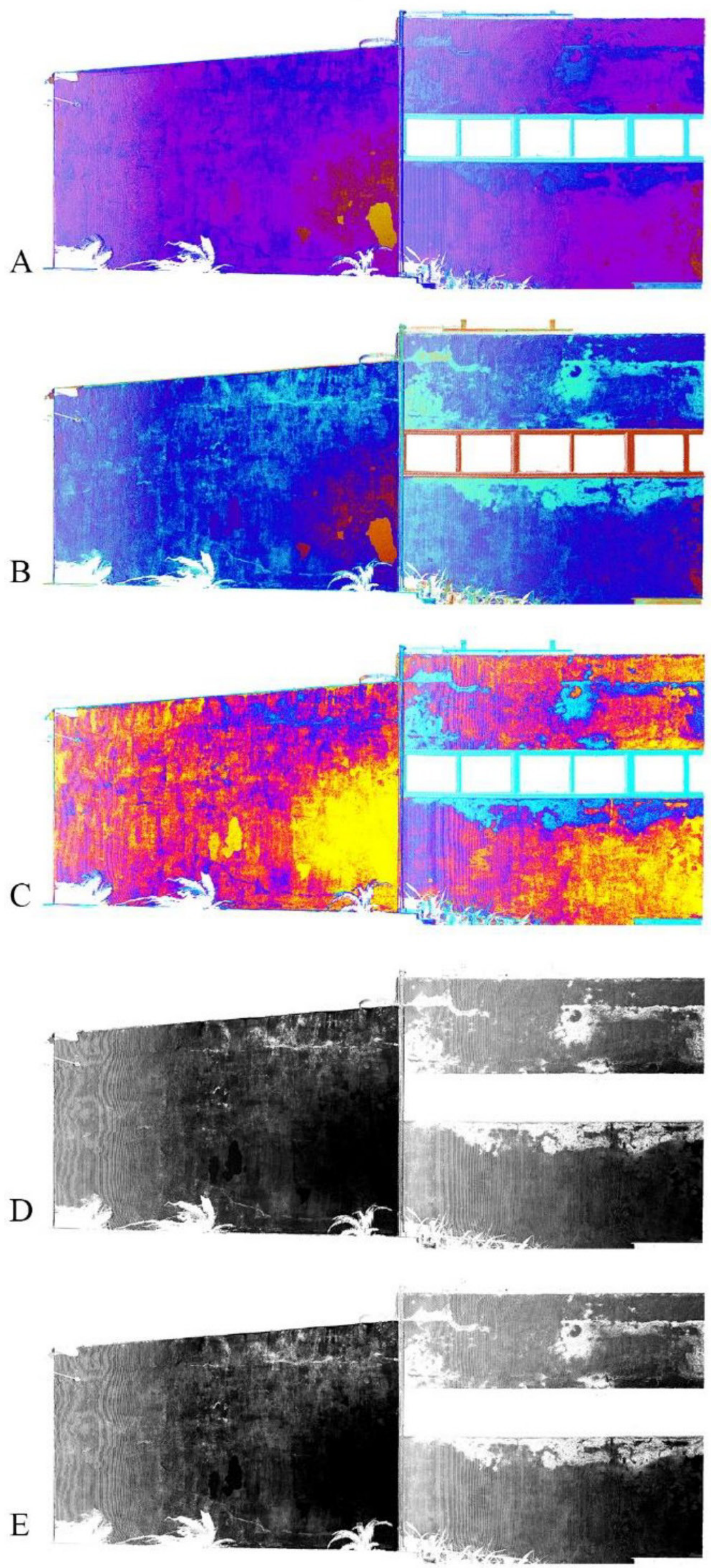


Fig. 4.01.

Elaboration of intensity values of the point cloud of Lina Bo Bardi's Casa de Vidro (São Pulo, Brazil), visualized with different colour ranges, useful to support the analysis of surface specifications (Source: Balzani et al., 2019).

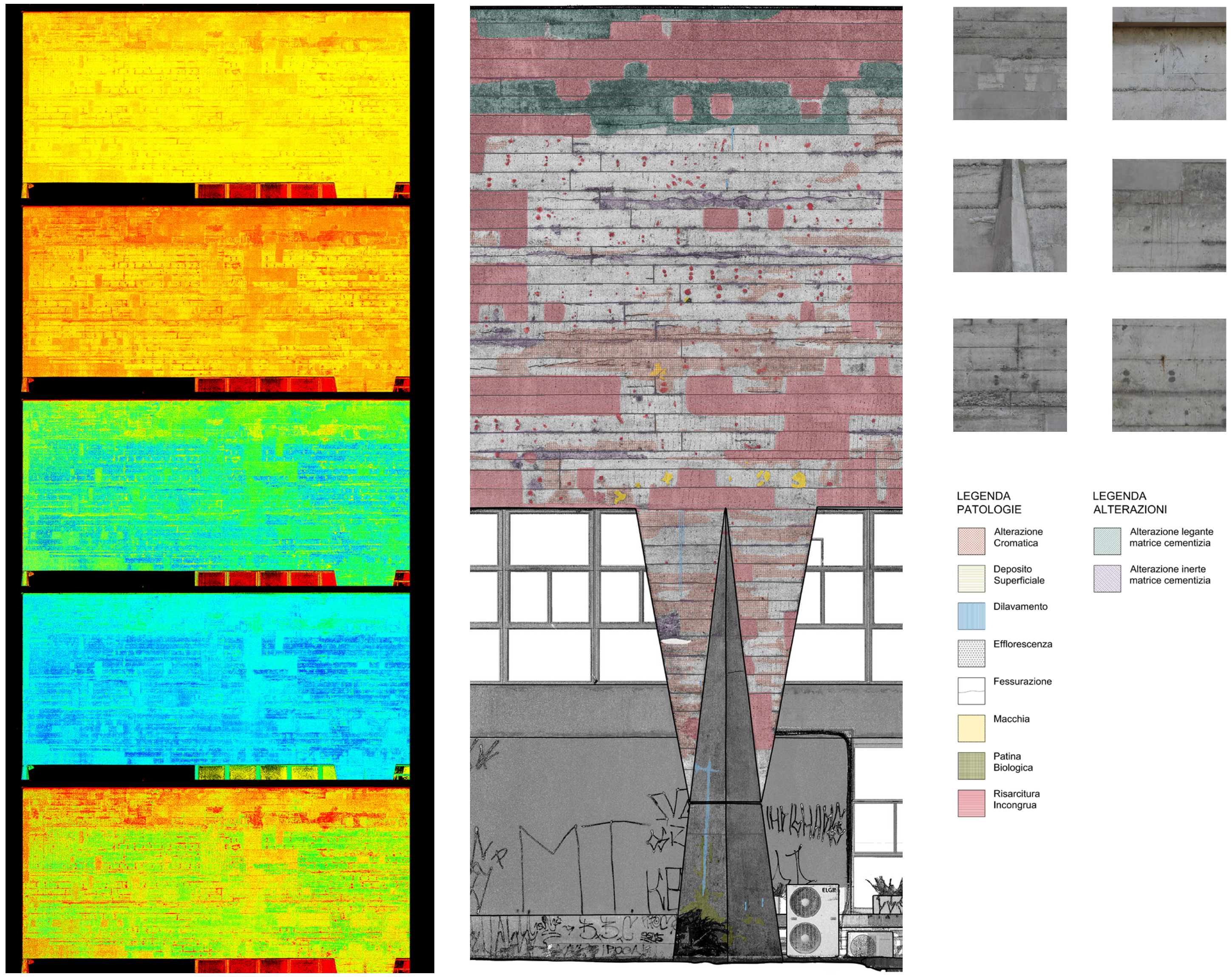
same colour (Maietti et al., 2021). Several examples in the literature expound on the advantages of analysing this data (Fig. 4.02), which helps the specialist to recognize materials and especially degradation pathologies on surfaces detected by a laser scanner, as if a mapping was already available not only for a visual analysis but also metrically very accurate, depending on the accuracy and precision of the survey (Mulahusić et al, 2020). Furthermore, there are cases in which surfaces that appear homogeneous in terms of materials and survey conditions exhibit different reflectance values, immediately revealing inconsistencies that are not perceptible to the naked eye (Docci & Docci, 2005).

Based on these data, interpretative hypotheses can be formulated regarding the behaviour of the material. Viewing reflectance maps is not sufficient to assess the state of conservation, but further analysis is required (Balzani et al., 2019). Intensity can therefore provide support in identifying certain areas for further investigation. The potential of its use lies in the fact that the qualitative surface data is precisely linked to the three-dimensional metric data (Maietti, 2023a). Its use is particularly useful in the absence of photogrammetric surveying, where the absence of colorimetric data can make it difficult to read the surfaces of historic buildings in the digital model (Balaguer-Puig et al., 2017).

According to this, the reflectance data collected for analysis requires a highly critical and targeted approach: interpretation by a specialist is necessary (Maietti, 2023b). Qualitative knowledge of the surface specifications must be obtained through other methods of investigation and interpretation, including traditional ones, while their "quantitative" detection on the three-dimensional model can be done with the support of reflectance data. Assuming the use of automatic artificial intelligence procedures for quantitative and repetitive operations, it is reasonable to ask whether intensity data can be used for this purpose.

Fig. 4.02.

From intensity value analysis to degradation and alterations mapping, example of a portion of the façade of Vilanova Artigas' FAU-USP - Faculty of Architecture and Urbanism, University of São Paulo. (Source: Balzani et al., 2017).



4.2 AI segmentation and classification in the heritage field

Point cloud models are a reliable morphometric database, but potential uses are not limited to the representation of geometric, colorimetric, or reflectance data information. These models can be enriched with additional levels of reading by adding information to their points. This operation is easily enabled at the computer level, since the structure of a 3D point cloud consists of .csv (comma separated values) data in which the rows are the points and the columns are the features describing these points. A point cloud always has a minimum number of three columns corresponding to the X, Y and Z coordinate values, which define the position of the points in space with respect to an origin. The other features may occur in varying numbers in different point clouds.

For example, they may depend on the type of tool used and on the acquisition method that led to the generation of the point cloud model (paragraph 3.3). If the point cloud is surveyed by laser scanning, each point also has the intensity datum (paragraph 4.1). If the point cloud is derived by digital photogrammetry processes, the intensity datum is not present. The representation of the colour datum is obtained through three additional values: R, G, B. In point clouds from photogrammetry these are derived directly from the photographic images used for three-dimensional reconstruction of the model, in those from laser scanning they can be associated with different methodologies. Three other values, calculated in post-processing are the components of the vector normal to the surface that the point forms with its neighbours.

By adding more columns, thus more attributes for points, new information can be provided, depending on a variety of categories of interest. This increases the possibilities of using point clouds and simplifies their interpretation. In the literature, these procedures are called segmentation and classification, and are very active research topics, especially in cultural heritage field, due to the complexity and variety of objects surveyed. Segmentation refers to the task of grouping points in subsets characterized by common features; classification consists on the assignment of the points to specific classes (Grilli et al., 2017). Classification can also be considered as the “labelling” of a segmentation. Both segments and classes are defined according to different user-defined criteria, based on the objectives of the project, that could be, among others, documentation and study of historic architecture (Vandenabeele et al, 2024), conservation (Valero et al, 2019), BIM modelling (Croce et al., 2021), valorisation or support for building maintenance (Teruggi et al., 2021). Segmentation and classification techniques have, in addition, the potential to be applied at different scales, and that is a great value in the field of cultural heritage, since it can be used from objects to entire sites (Grilli & Remondino, 2019).

This operation enriches a point cloud model with semantic information that is otherwise absent, but this step, together with the other management and analysis phases, can still be quite time-consuming and complex (Terruggi et al., 2020; Lo Turco et al., 2017). Indeed, data segmentation and classification tasks according to subsequent work steps still require manual procedures by specialists in the field who are able to correctly interpret the source material (Pierdicca et al., 2020). These activities are therefore costly in terms of economic resources, time and qualified professionals involved.

In the direction of optimizing these steps, several research is being developed by applying Artificial Intelligence (AI) processes, such as Machine Learning (ML) and Deep Learning (DL) algorithms, in order to automate the hierarchization of data (Grilli et al., 2017). These techniques allow computers to make predictions based on sample data. Specifically, ML exploits mathematical algorithms to process a dataset with given features and learn how to classify new and unseen observations from that data. DL is a subset of ML that generates an artificial neural network, which learns the features itself and makes predictions on new data (Croce et al., 2021). Specialists should not be overloaded by quantitative operations delegated to AI but focus on qualitative ones: the instruction of algorithms and the assessment and validation of the results obtained.

Applications of automatic procedures for the segmentation and semantic classification of point clouds started on airborne data analysed at urban scale (Mallet et al., 2011; Weinmann et al, 2014), and then focused on historic buildings. In literature the use of various algorithms can be found and can be grouped into two main categories based on purpose. Some deal with the recognition of architectural elements (Fig. 4.03) (Croce et al., 2021; Matrone et al., 2020a; Morbidoni et al., 2020; Pierdicca et al., 2020; Grilli & Remondino, 2020), others are related to surface analysis, with recognition of materials, construction techniques, and decay morphologies (Fig. 4.04) (Grilli et al, 2018; Valero et al., 2019; Ibrahim et al., 2020, Musicco et al., 2021; Trivi et al., 2024). Generalizing, the adopted algorithms mainly act on two macro properties of point clouds: geometric features and radiometric characteristics (such as RGB values and HSV). The former are mostly used for the identification of architectural elements, the latter for those related to

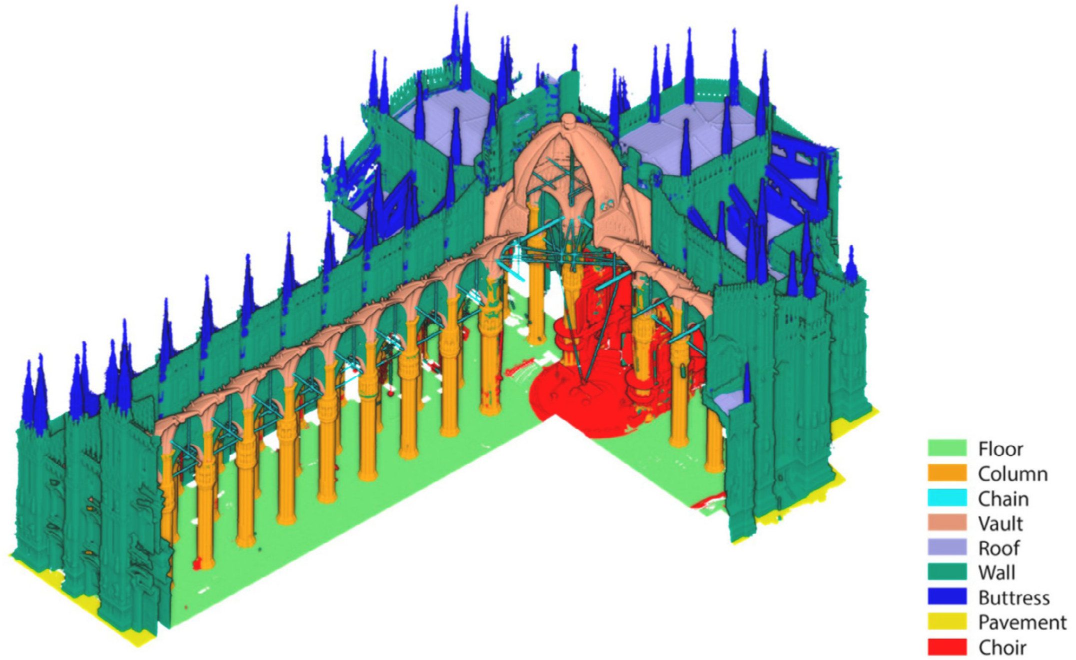


Fig. 4.03.

Classified point cloud model of the Milan Cathedral according to the architectural elements (Source: Teruggi et al., 2020).

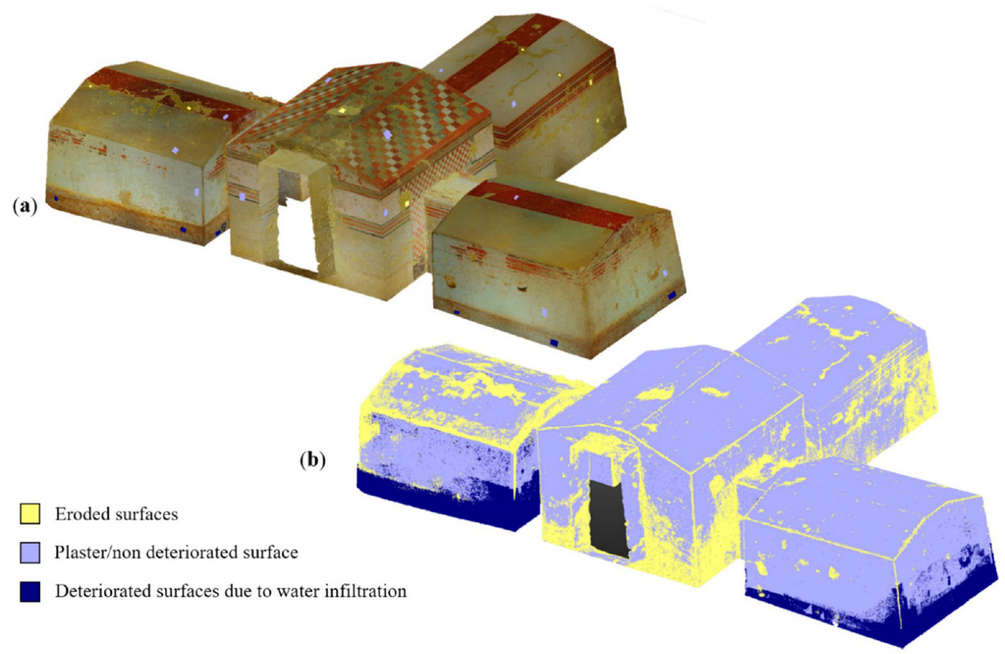


Fig. 4.04.

Texturized (a); and classified (b) 3D model of the Bartoccini's Tomb in Tarquinia according to state of conservation of the surfaces (Source: Grilli & Remondino, 2019).

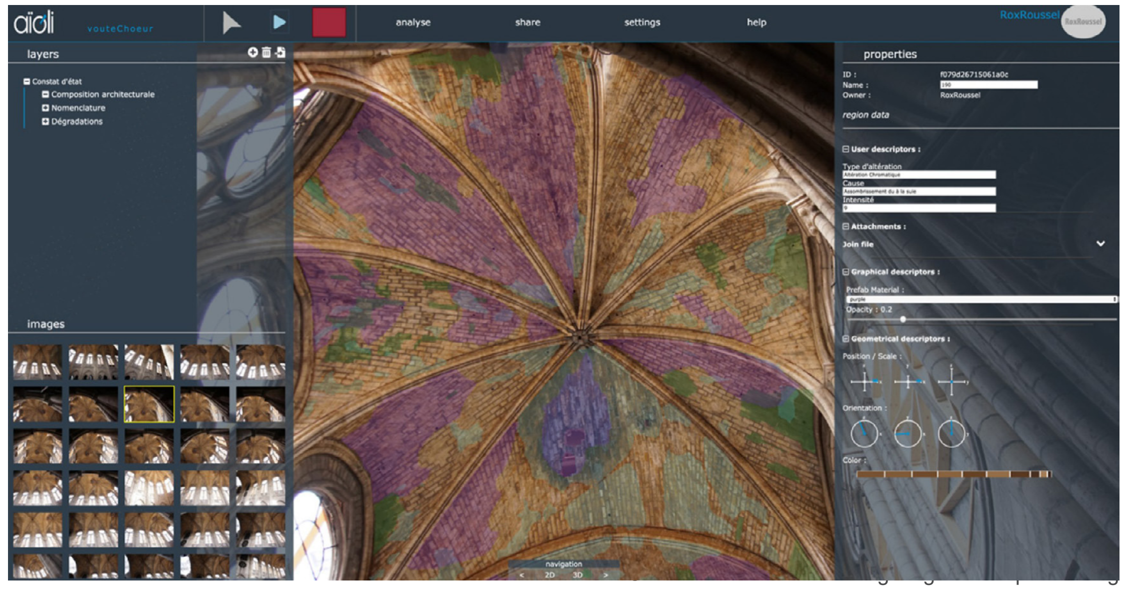


Fig. 4.05.

Aïoli platform allows 2D/3D annotation of the alterations. This example shows the vaults of the choir of the Notre-Dame de Paris, after the fire of April 15, 2019, for the architectural diagnosis before the restoration (source: Abergel et al, 2023).

surface analysis. In any case, the association is not so clear-cut and schematic because radiometric parameters affect the recognition of architectural elements. Conversely, geometric features are also employed to describe the morphology of surfaces.
Although the required end product is always a point cloud model, classification can also take place in other media. This is the case with experiments for the recognition of materials, construction techniques, and degradation, that in many cases have been carried out not by acting directly on the point cloud but on images, orthophotos, and UV textures (Grilli & Remondino, 2019). The algorithmic training and prediction are made on two-dimensional data, and the results are reprojected onto the three-dimensional model. This workflow is followed to leverage the higher level of maturity of AI algorithms on images, most robust and reliable, allowing to achieve more accurate results.
This correspondence between two- and three-dimensional environments, characteristic of photogrammetric surveying processes, is a key strategy used to transfer a segmentation on images to a 3D model (Murtiyoso et al., 2022). The web collaborative reality-based annotation platform Aïoli (Aïoli, 2017), leverages this concept, too, and it is developed to allow a multidisciplinary semantically-enriched 3D descriptions of heritage artefacts from simple images (Abergel et al, 2023). It allows to transfer information from 2D to 3D, for documentation and restoration purposes (Fig. 4.05). 2D annotations are spatialized, displayed and mapped in real-time on the 3D model. Although in this case the annotations are designed to be carried out manually, it is possible to supplement the workflow with semi-automatic procedures supported by AI (Croce et al., 2023).

4.3 Machine and Deep Learning algorithms, supervised and unsupervised learning

Various Various AI approaches have been proposed in the architectural and cultural heritage context. Whether applied to images or point clouds, there are many types of algorithms that have been tested in literature: image-based classifiers, k-nearest neighbour (kNN) classification techniques, Convolutional Neural Networks (CNNs). Other algorithms are used to automatically identify edges (contour detection), areas with shared attributes (region detection), or features that match the shape and structure of a predefined geometric model (model-based fitting).
Machine Learning methodologies have been widely used in recent research in the field. As anticipated, this branch of artificial intelligence is devoted to setting up algorithms that enable computer systems to "learn" from input data through statistical methods. Then, based on the learned information, these models are able to make decisions or predictions on unseen data, improving their performance over time. ML can be divided into supervised and unsupervised learning (Sindhu Meena & Suriya, 2020).
In the first case, the algorithm is trained with a labelled dataset, that is a dataset where each sample has an answer associated with it, called a "class." The goal is for the model to learn how to map inputs to correct outputs. Training labels are manually assigned by an user on a part of the overall dataset, and this step is called "manual annotation". In this way, the predictive model should be able to recognize the class associated with the inputs, and the trained model is then used to provide semantic classification of the entire dataset.
In the second case, the algorithm tries to classify the data without having predefined answers. An example of this type is clustering, where data are grouped into categories based on similarities, patterns or structures found independently in the raw data. The K-means algorithm is an unsupervised algorithm widely used both for its simplicity of use and speed.
In general, in the case of cultural heritage classification the operation of supervised ML is based on the following basic steps:

a. Data collection, such as images or point clouds.
b. Data pre-processing: raw data are analysed and cleaned to remove errors, handle missing data, and transform them into a format suitable for computer analysis. For point clouds, this stage may include outlier removal, noise reduction, subsampling, etc. This is the phase where features extraction is performed. Features are the characteristics on the basis of which the ML model will learn, at first, and predict, after. The selection of appropriate features for defining classification is crucial. Optimized feature extraction enhances the performance of predictive models, both in terms of training time and the accuracy of the resulting prediction (Weinmann et al., 2014; Grilli et al, 2019).
c. Model Selection: among the various existing ML algorithms, the one best suited to the classification or segmentation problem being addressed should be identified. Typical supervised ML algorithms include Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF).
d. Model Training: during this phase, the algorithm is trained using a subset of the available data, called the training set. The algorithm "learns" to recognize patterns in the data, adjusting its internal parameters to minimize error and improve its predictions. The training set is manually annotated.
e. Validation and Testing: after training, the model is validated and tested on another subset of data (test set). This allows to assess how well the model generalizes to new data. The test set is also manually annotated.
f. Prediction: once the model has been tested and optimized, it can be applied to generate predictions on previously unseen data, namely, the unannotated portion of the original dataset.

Advancements in deep learning (DL) and neural networks are progressively enabling the automatic generation of information, becoming more reliable tools for solving very complex problems. DL is based on Artificial Neural Networks (ANNs), referred to as "deep" neural networks (DNNs) because they are composed of many layers of artificial nodes or “neurons,” each of which processes information and passes the output to the next layer until the final prediction is made. During training, the model is exposed to a vast number of labelled examples, and the weights of the links between the neurons are adjusted and modified autonomously by the algorithm until the model can minimize the error in its predictions. A neural network can learn highly abstract and complex representations of data. As in ML, after training, the network is tested on new data and then should be able to make accurate predictions on new data.

DL algorithms, considering their rapid technological development, are shaping up as the horizon toward which automatic segmentation and classification processes are heading, including in applications in the field of cultural heritage. However, at this stage, some of their operating peculiarities limit their use (Fiorucci et al., 2020).

First, the DL inherently needs a very large amount of pre-annotated, available data from which it can learn and make predictions to new data. For architectural heritage, there is not the availability of this data in sufficient quantity (Grilli et al., 2018), although some research aims, among others, to form databases available for this purpose (Matrone et al., 2020a). The main difficulty is related to the complexity of the elements in a building, and their variation (morphological, dimensional, colorimetric) makes the data from different buildings very heterogeneous, thus difficult to generalize (Morbidoni et al., 2020). In addition, all the elements of the urban or natural context in which the buildings are located (cars, signs, street furniture, etc...) or the vast types of objects within them (furniture, people, etc...), “noisy” the purely architectural data being analysed, and, of course, a removal of them in the data pre-processing phase involves extremely time-consuming operations, which makes such an assumption effectively impractical.

Second, since these algorithms have great decision autonomy during the process, theoretical and methodological questions rise, especially about the extent and actual necessity of critical-interpretive input in these procedures. This question is greatly amplified in the case of unsupervised learning, where there is a higher probability that the result may not align with the user's intentions (Barni & Inglese, 2024).

4.4 Issues and limitations to surfaces’ features segmentation

Although tthe application of AI methods for point cloud classification has been thoroughly investigated in geospatial contexts, their use in Cultural Heritage is a relatively recent development. Within the geomatics field, many benchmark have been reached, offering labelled terrestrial and aerial datasets for users to test and evaluate their algorithms, such as those in Semantic3D (www.semantic3d.net) (Hackel et al., 2017). Most of these datasets feature classified natural, urban, or street environments where object categories and labels are largely standardized (e.g., ground, roads, vegetation, and buildings). In contrast, classifying elements in the cultural heritage domain is significantly more complex. Depending on the specific study objective, the same building may be divided into different categories, and architectural semantic labels do not always correspond clearly to specific shapes or colours. (Croce et al., 2020).

As for segmentation according to building elements, this can refer to the grammar defined in centuries of theoretical treatment on architecture (Matrone et al., 2020a; Barni & Inglese, 2024), as well as on a shared coded language among industry operators, based on classes of technological elements (UNI, 1981). These logics were translated in authoring software thorough the development of ontologies and libraries of architectural elements to accurately represent the components of a building (Felicetti & Niccolucci, 2025). For this reason, the classified point cloud is configured as a functional interpretation tool for the modelling itself. This model is not only a geometric reference but also carries a basic semantization, according to a pre-selected hierarchical structure, propaedeutic to the study of the architectural artifact.

However, for surface analysis there are more elements of complexity. First, the searched categories have pronounced characters of uniqueness. In addition to the inherent characteristics of each building, the boundary conditions and contexts in which they are located, as well as their history, are all components that affect the characteristics of surfaces. Although there are, for example regarding deterioration morphologies, documents shared by professionals in the field of conservation and restoration of architectural heritage, such as UNI 11182:2006 - former NORMAL 1/88 (UNI, 2010), it is very difficult for these morphologies to appear with exactly the same formal and colorimetric features.

Then, the quality of the dataset under analysis is even more crucial. Also contributing to the complexity and inhomogeneity of the data described in section 4.3, especially in relation to the radiometric characteristics of the surfaces, are the environmental conditions at the time the survey was performed, e.g., for a photogrammetric survey, the lighting conditions. If the purpose is to be surface analysis, these conditions are crucial to the success of the prediction.

Further conditions of complexity for degradation may be, for instance the presence of several possible interpretations for the same phenomenon, or the association of different phenomena with a single response, that makes it difficult to rely on automated processes for this analysis. In addition, the overlapping of multiple degradation morphologies on the same area also complicates the analysis, whether it is carried out by traditional or algorithmic methods (Fig. 4.06).

It often happens, therefore, that for surface analysis, segmentation is achieved through computerized procedures with varying degrees of automation, and where methods assisted by machine learning are not sufficient to guarantee the searched result, manual segmentation is employed. Manual segmentation is particularly useful in archaeological models, for instance, in distinguishing stratigraphic layers or isolating key areas for restoration analysis (Barba et al, 2022). This method is especially effective when the

Fig. 4.06.

Examples of architectural exterior surfaces, showing texture complexities due to material composition and their conservation condition. Overlapping and fine detailed decay morphologies may often be subjectively interpreted.

semantic structure depends on a careful interpretation of the object, making it difficult to identify features that can be automatically processed, or when there is no sufficient quantity of samples to set up a ML procedure. Similarly, surface analysis, too, requires a strong critical-interpretive reading component, which is better explored in paragraph 5.3.

For these reasons, and for those exposed in paragraph 4.3, in this research, supervised Machine Learning algorithms have been tested and implemented in-depth to have input data instructed with critical-interpretive knowledge peculiar to the specialist (architect), specifically for the case studies, in order to obtain a correct result that takes into consideration the boundary conditions that make each building unique. Using supervised machine learning algorithms, the model is trained on a case-by-case basis, allowing it to be tailored to the characteristics of the specific building and the corresponding dataset under analysis. Furthermore, since the class labelling procedure must be planned before segmenting the model, it is the specialist who defines the analysis categories and not the algorithm that determines them (Grilli et al., 2019).

To achieve good results with DL, it would be needed to generalize as much as possible, thus providing a very large number of already annotated buildings (Pierdicca et al., 2020). In this context, studies have begun to develop online libraries capable of training neural networks to recognize architectural elements of buildings, with encouraging results (Matrone et al., 2020b). Nevertheless, for the thematic components that the present research aimed to identify, such as materials, construction techniques and states of conservation, the quantity of these databases, at the moment, is not sufficient to guarantee a satisfactory result. As a result, DL algorithms are not deepened in this research.

4.4.1 The intensity value in automatic segmentation and classification

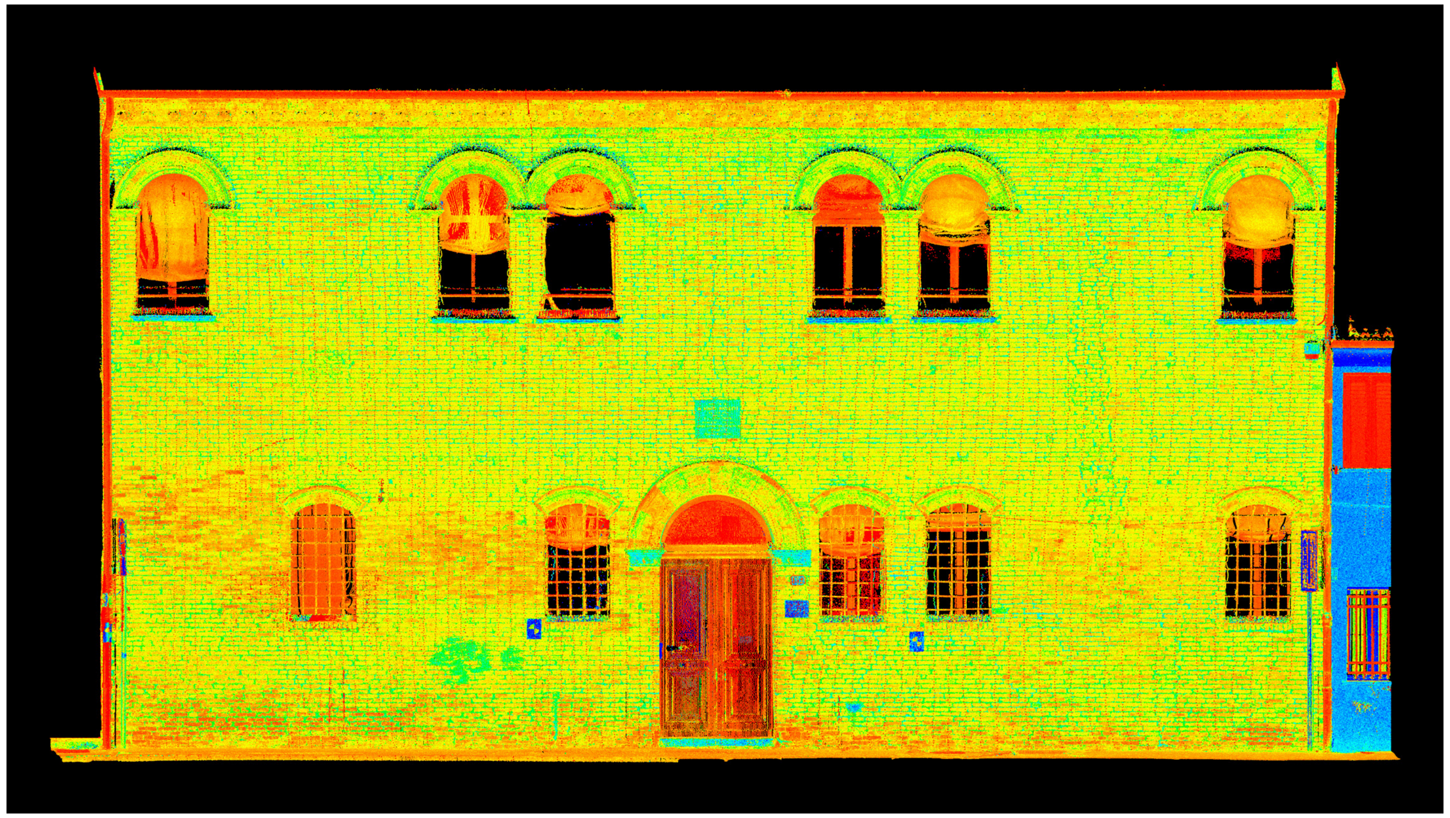
The interest in testing the prediction algorithm with the inclusion of intensity values stems from the concept that, under certain conditions, these values can provide useful insights: if intensity value reveals continuities and discontinuities in the surfaces (Fig. 4.07), since it is determined by variations and different decay morphologies (Suchocki et al, 2020), it can contribute to a more effective prediction. Another relevant reason in leveraging intensity data is that it is a radiometric feature proper of direct, measured point clouds, that are, in general, geometrically more reliable than the ones derived from photogrammetry (Mora et al., 2019; Peterson et al., 2019).

However, few segmentation tests based on Machine Learning and Deep Learning techniques appear to have been carried out using the reflectance data as a benchmark, even if interesting results were achieved especially in brick or stone masonry analysis (Riveiro et al, 2016; Dreier et al., 2025). Probably, this is due to two main reasons.

First, the source dataset needs more control. As described, it is well established that the reflectivity dataset varies depending on many factors, including the survey tool used and the inhomogeneity of single scan characteristics (angle of incidence, distance, boundary conditions, etc.). Consequently, to develop and apply an algorithm

Fig. 4.07.

Elevation view of the point cloud of Biagio Rossetti's House in Ferrara, with intensity values visualized in false colour, highlighting material differences and several decay phenomena. Stone elements appear in green/cyan, metal components in red. Bricks affected by degradation are shown in orange, while the not affected ones appear in green/yellow. Since the colours correspond to distinct numerical values, digital attributes of the point-cloud model, they are potentially valuable for AI-based workflows (Source: Maietti, 2023b).



that considers this parameter, the input point cloud must be obtained from an integrated 3D survey carried out for this purpose.
Second, to set up an algorithm that considers both the geometric features of the points and their colorimetric datum, the point clouds must contain both. Since acquiring the RGB data from laser scanners generally does not yield satisfactory results, there is a tendency not to acquire this feature (Croce et al., 2021). Therefore, point clouds from photogrammetry are preferred for applying the algorithms. These, being obtained from methodologies that do not involve a laser measurement system but being derived from image-matching and 3D reconstruction algorithms, lack the reflectance data proper for laser scanner acquisitions.
Furthermore, another issue emerges from previous research, often developed with specific case-by-case applications (Balzani et al., 2017). These show that in order to systematically rely on reflectance data as an interpretative aid, it is necessary to produce comparative data by 'sampling' the reflectance ranges on different materials, measured with different sensors and in environments with different boundary conditions (Wu et al., 2025). The ambitious goal is to associate specific reflectance values with specific materials, or at least to understand its actual limits of application. On the one hand, this is aimed at being able to reliably use the reflectance value within artificial intelligence algorithms, but on the other hand, it may be precisely thanks to automatic data segmentation processes that advances and further comparisons can be made on a massive scale.
This research addresses these concerns, such as the use of 3D survey of historical architecture as a foundational method for the assessment of historical surfaces, the degree of reliability of intensity data for diagnostic purposes, the accuracy of automatic (or semi-automatic) mapping of surface specifications directly onto the point cloud (Maietti, 2023b).

4.5 Segmentation toward an optimized Scan-to-BIM process

The possibility of representing architectural assets through 3D models has increased the potential for documenting cultural heritage, as it would led to a comprehensive and holistic description, which is inherent to any architecture (Apollonio et al., 2018). The shift from the 2D to the 3D based model, leveraging integrated 3D survey methodologies, was initially undertaken for complex three-dimensional objects where two-dimensional representations were limiting in describing certain aspects, and the 3D model would be used effectively for restoration activities (Fassi et al., 2011). This advancement has reached its current peak in BIM modelling applied to existing heritage buildings and sites (Murphy et al., 2009). By exploiting parametric modelling and the possibility of implementing, annotating, and linking various types of information that these systems allow, it is also possible to carry out management and design activities on existing buildings, aimed at preservation, conservation, retrofitting, renovations, etc. (Dore & Murphy, 2013). Documentation using integrated surveying methodologies is the most effective way to acquire the geometries on which to develop the BIM model, through the so-called Scan-to-BIM process, that articulates in three main steps: data acquisition, data processing and parametric modelling (Dore & Murphy, 2013; Laing et al., 2015).
While data acquisition and processing, despite ongoing technological developments, can rely on established protocols and practices (paragraph 3.5), the main reference model for parametric modelling is International Standard ISO 19650 (ISO, 2018), which standardizes all procedures and ensures information management. However, having to deal with existing buildings introduces elements of complexity that research and professionals in this field are constantly struggling with (Li et al., 2025). Indeed, BIM techniques have been originally developed to design new constructions, managing the information of each building component embedding it in the digital objects that form their 3D geometric representation. First, this arises challenges related to the geometric limitations in authoring software in representing the diversity of complex, irregular forms and architectural details typical of heritage structures. These difficulties often stemming from the absence of predefined libraries of parametric objects (Dore & Murphy, 2017) and their limited free-form geometry modelling functions, since new buildings require regular and standardized components (Bruno & Roncella, 2019). Consequently, the simplifications that must be applied introduce approximations with respect to the point cloud survey model, which must be carefully defined within a tolerance level in relation to the purpose of the model. Second, issues involving critical-interpretive and deductive reasoning characterize the whole modelling phase, since architectural elements have to be represented geometrically and semantically (Bianchini et al., 2021). Indeed, having 3D survey data as reference involves accurately identifying and defining the components of the architecture, their relationship, and consequently assigning them into appropriate object categories (Fig. 4.08).
These issues are not only inherent in the reading and representation of the geometric-formal and compositional elements of historical architecture, but also in the characterization of surfaces. In this case, greater critical issues arise on both levels, both in terms of representation and annotation, and in terms of interpretation. The former is linked to the fact that most authoring software lack of specific tools for modelling surface characteristics, and that it is often necessary to annotate only part of the BIM object, for instance when it is necessary mapping degradation, decay conditions or materials. Since parameters can only be assigned to the entire object, it becomes complicated to insert localized information. The second is determined by the skills required to perform a task that demands a high level of knowledge both in IT tools and in conservation domain. Usually, most professionals involved in conservation do not have sufficient knowledge and training in H-BIM technology, while BIM specialists do not have skills to interpret the complexities of the architectural surfaces. Furthermore,

for BIM specialists, it is difficult not only to attribute meaning to non-standard historical components (e.g., construction techniques or deterioration), but also to identify them correctly in the digital source data, such as the point cloud, as they do not have specific training in the field of conservation. Clearly, in cases of cultural heritage buildings, the support material for the modeler is not limited to a point cloud, as might be sufficient for a building of no particular historical or artistic significance. Indeed, it is often integrated by photo or video support, including 360° images for a thorough inspection of spaces and surfaces. In many cases, this helps but does not completely resolve semantic attribution questions. All these limitations stem from the lack of established standards, shared regulatory references, and guidelines for H-BIM modelling.
Research is attempting to address these issues with a view to improving, standardizing, and consequently reducing the time required for H-BIM modelling. The tasks are mostly manual, albeit with the use of parametric object libraries developed specifically for historical contexts (Dore & Murphy, 2013) and advanced ontological models (Colucci et al., 2021), but semi-automatic Scan-to-BIM methods are being tested. A first approach uses primitive fitting algorithms able to recognize and then reconstruct planar elements, as floors and walls, or other simple volumetric objects (Macher et al., 2017). Another technique is based on generating meshes from survey models: this provides greater accuracy for the morphology of more complex elements, but they remain geometrically non-editable within authoring software, and must be handled with care so as not to excessively increase the file size (Andriasyan et al., 2020). In order to automate more, BIM reconstruction by generative modelling leverages Visual Programming Language (VPL) where the objects of the 3D model are generated thorough instructions given by a set of nodes (algorithms), connected together (Pepe et al., 2020). Similar approaches have been tested for surface characterization too, especially addressing the issue of mapping decay on a part of the 3D object. Some research propose to locally adding a new object over the surfaces of each parametric element, thorough the use of simplified patches (Barontini et al., 2022; Li et al., 2025), or adaptive components, in Autodesk Revit (Chiabrando et al., 2017; Malinverni et al, 2019). These are elements created from scratch by the user to suit the shape needed and carry on the related information, but they have operational limitations due to the fact that they are not made with instruments designed for this purpose for the documentation of structural and material decay (Fig. 4.09). To overcame this issue, a possible strategy is the one adopted in the collaboration between the University Federico II of Naples and the software house ACCA, that developed a specific toolbar to enrich H-BIM modelling with degradation and crack representation (Lanzara et al, 2021). Difficulties concerning times and

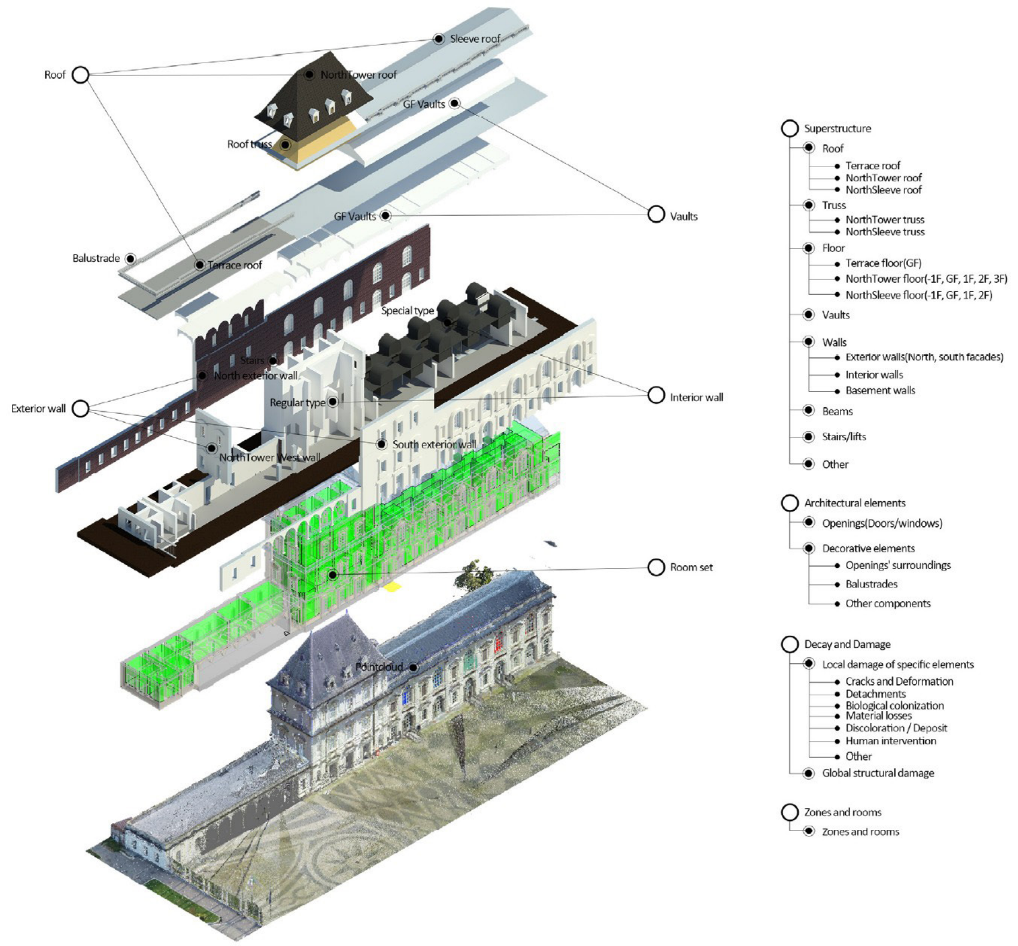


Fig. 4.08.

Explosion diagram of different types of architectural elements' geometric modelling in HBIM, starting from the point cloud as a geometric reference (Source: Li et al., 2025).

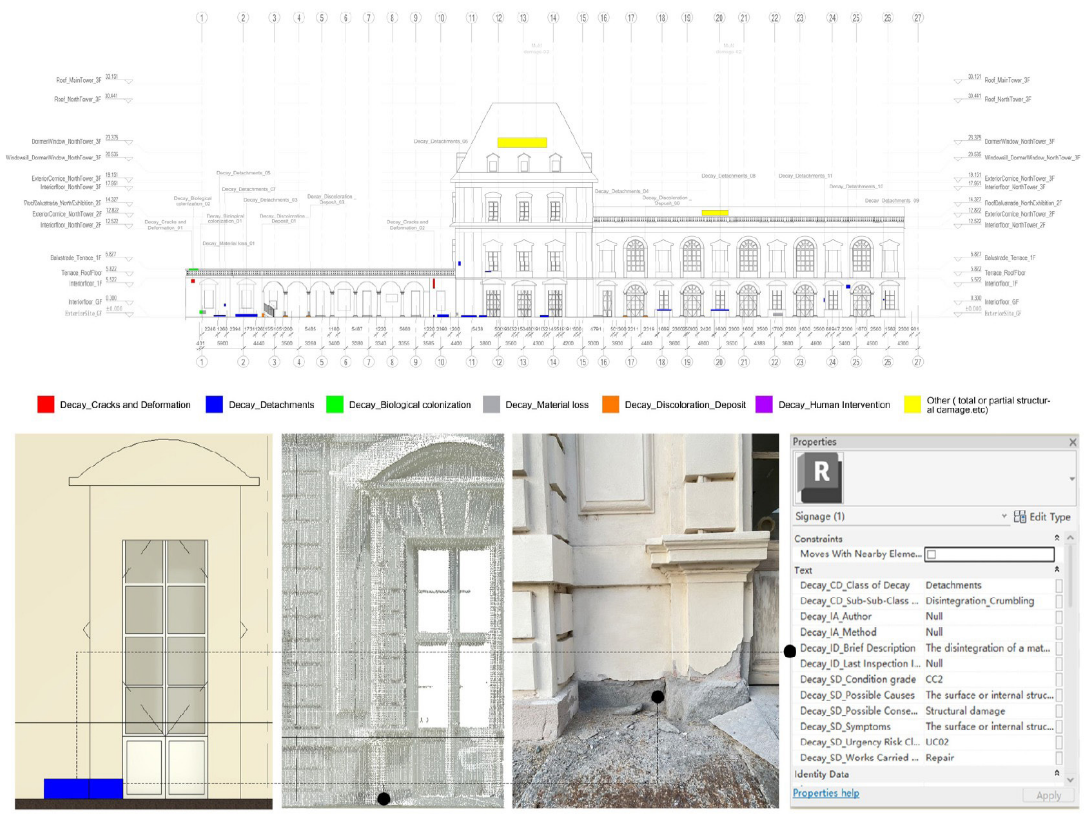


Fig. 4.09.

H-BIM decay representation thorough geometrically simplified patch-type objects (Source: Li et al., 2025).

procedures persist, since significant manual intervention is still required to perform mapping. Greater automation has therefore been sought by exploiting the flexibility and interoperability that VPL tools allow with BIM software (Lanzara et al, 2022).
In this context, a segmented and classified point cloud model becomes an additional tool for improving the entire workflow, both because it allows individual components to be isolated, studied, and modelled, and, above all, because it is a model with semantic information. As a result, it is no longer a formal geometric reference, but also a tool to attributing meaning to the various components and interpreting the parts. In this sense, as far as surface characterization is concerned, many interpretation difficulties on the part of BIM specialists can be resolved, speeding up modelling and avoiding incorrect or ambiguous attributions. Strategies have been tested to automate and improve BIM pipeline based on point clouds segmented by construction elements (Buldo et al., 2023), also exploiting both primitive fitting methods and parametric objects defined by VPL (Croce et al., 2021). Similarly, segmentation according to surface characteristics can support the modelling of material and conservative components (Nieto-Julián et al., 2025), for which strategies are also being tested to automate the generation of BIM objects using meshes and VPL (Avena et al., 2024).
In this framework, the direction of BIM modelling is toward interoperability and multidisciplinarity. For this reason, information protocols were established to guide the construction of object-based models. For example, Industry Foundation Classes (IFC) is an open global standard aiming to guarantee information exchange between different BIM software through a standardized and open data structure (buildingSMART International, 2025). Conceived for new constructions, it is also a reference for existing buildings, and has led to the possibility of opening BIM models through web platforms capable of organizing, using ontology structures, the various information related to the different levels of knowledge useful for maintenance, conservation, decision making, etc., around the 3D geometric representation of a building (Maietti et al., 2018). For this reason, open BIM is extremely interesting for platforms that are as accessible and user-friendly as possible, allowing more operators with different levels of IT knowledge to operate and annotate models (Scandurra & Di Luggo, 2023). There are several examples of applications in the field of documentation for conservation and restoration purposes, capable of collecting and hosting models that can be parameterized according to BIM logic even if generated with different modelling procedures (Fassi et al., 2020), or directly derived from survey models (Apollonio et al., 2018; Teruggi et al., 2021). These elements can therefore also be generated by more automatic processing of point clouds, such as mesh models resulting from digital source segmentation (Scandurra et al., 2024).

4.6 A benchmark in point cloud thematization: the case of the Colosseum digital documentation

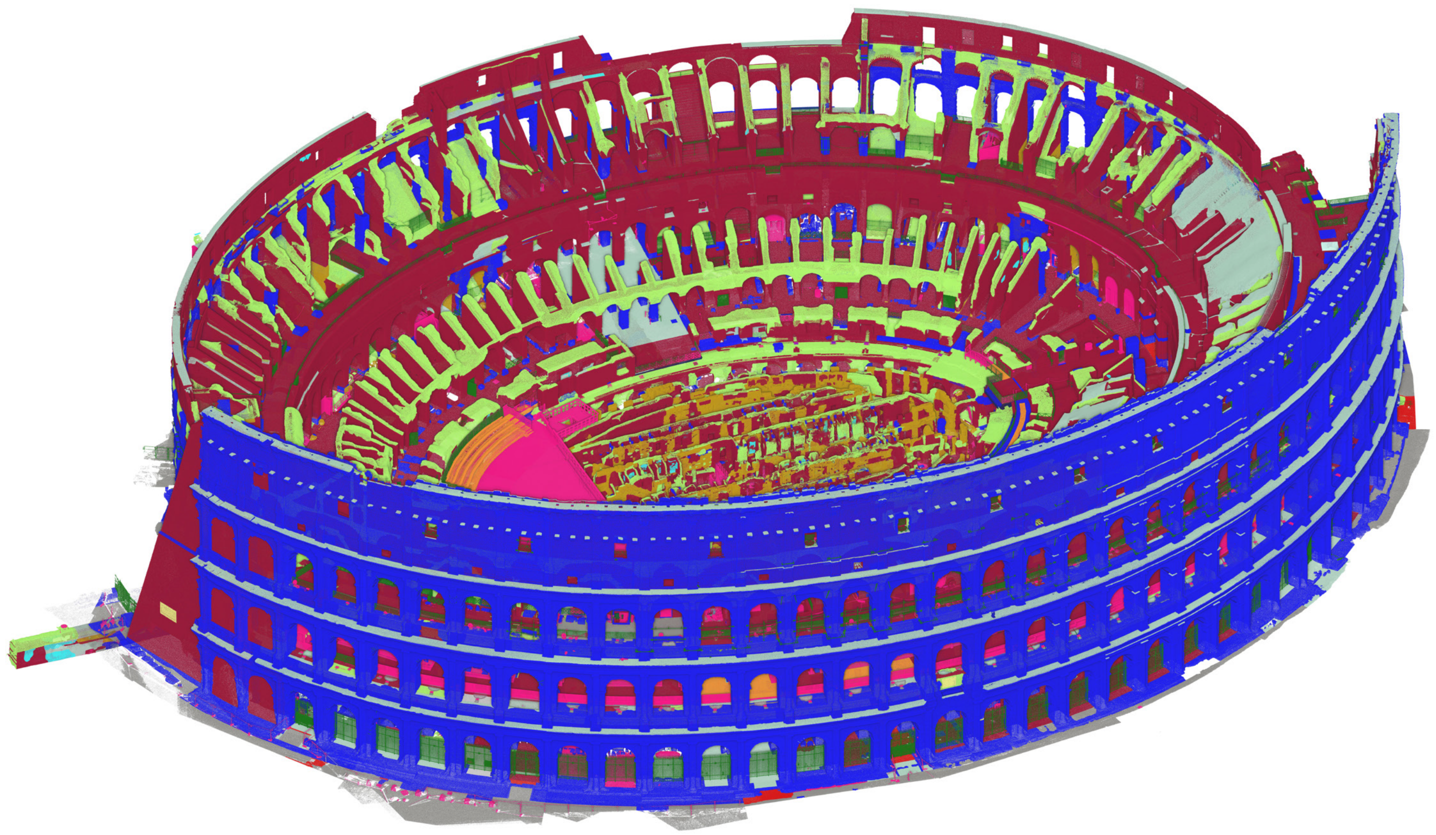
In 2021, the competition for the service of “3D geometric surveying services using integrated geomatic methods for the Colosseum” was lounched[1]. The aim was to produce comprehensive digital documentation of the monument, through a high-resolution metric model and a BIM information model that could serve as a knowledge repository, to be used in the future as a database for the development of restoration and maintenance projects, in particular the seismic vulnerability one. The service included topographic, laser scanner and photogrammetric surveying, two-dimensional geometric, thematic (materials, construction techniques and state of conservation) and specialist (masonry stratigraphic units and crack pattern) restitution of plans and radial and annular sections on a scale of 1:50, as well as a BIM model and a historical report. The work, completed in 2024, resulted in the complete documentation of the monument, which had previously been surveyed only in relation to individual portions or themes.
This was therefore a project of extraordinary importance for the documentation and, consequently, for the preservation of the Colosseum, providing essential documentation for any study, maintenance, restoration or enhancement work (Rinaldi et al., 2026). As part of the project, it was developed a thematic point cloud model according to surface analysis categories such as materials, construction techniques and state of conservation[2] (Fig. 4.10). This work, therefore, represents one of the first applications of automatic or semi-automatic point cloud segmentation and classification procedures on a large scale in a professional context and not exclusively in research.
The methodological approach adopted involved a long and in-depth phase for the preparation of abacuses (materials, construction techniques and types of deterioration), which took into account the characteristics and critical issues specific to the thematic mapping of architectural surfaces, the specific features of the monument, the purposes of the analysis, the type of source data and the feasibility in terms of IT. From a methodological point of view, the considerations made can also be applied in other

1. The competition was launched by Invitalia S.p.A. (the national agency for attracting investment and business development) and the development of the project was coordinated by the Colosseum Archaeological Park. The temporary consortium awarded the contract was composed of Consorzio Futuro in Ricerca (CFR) of Ferrara (lead partner), Geogrà Srl, ETS Srl and Janus Srl. Expert consultants in different fields of analysis were also involved, including the Bruno Kessler Foundation (FBK), a research centre that develops and applies AI procedures for the documentation of cultural heritage.

2. Within the group, Janus Srl, a start-up from Sapienza University of Rome, was responsible for formulating the reference abacuses of classes, manual annotation, evaluation and validation of results, as well as correction of prediction errors. FBK was responsible for the computational phases: training, testing and prediction.

cases of cultural heritage and are described in detail in paragraphs 2.3 and 2.4, having also been taken as a reference for the development of this research.
The developed thematic point cloud model served both as a working tool and as a representative support for the visualisation of thematic characterisations in the BIM model, as well as being itself a visualisable and queryable deliverable product.
The classified point cloud model was an efficient and versatile working tool, as it provided support for the design of two-dimensional maps (Fig. 4.11 and 4.12). Just as it is possible to extract plans and sections from a point cloud for the vectorisation of geometries, sections can be derived from a thematic point cloud with homogeneous areas already identified morphologically and identified with the category to which they belong. This has speeded up both the interpretation and vectorisation of the various categories. In BIM modelling, the criterion adopted for the decomposition of objects was that of the prevailing material: each material corresponds to a different object, except for small elements that are considered negligible overall. Consequently, the point cloud classified according to materials was an indispensable tool for BIM specialists, who were able to rely on a semantic model that spared them from having to interpret the source data directly. Since the same thematic point cloud was used both for the production of two-dimensional drawings and for BIM modelling, it was possible to minimise interpretative discrepancies attributable to the subjectivity of operators, which are normally encountered due to individual sensitivity. Another example of how

Fig. 4.10.
General thematic point cloud of the Colosseum visualized according to material category, homogeneous areas are represented in false colours.



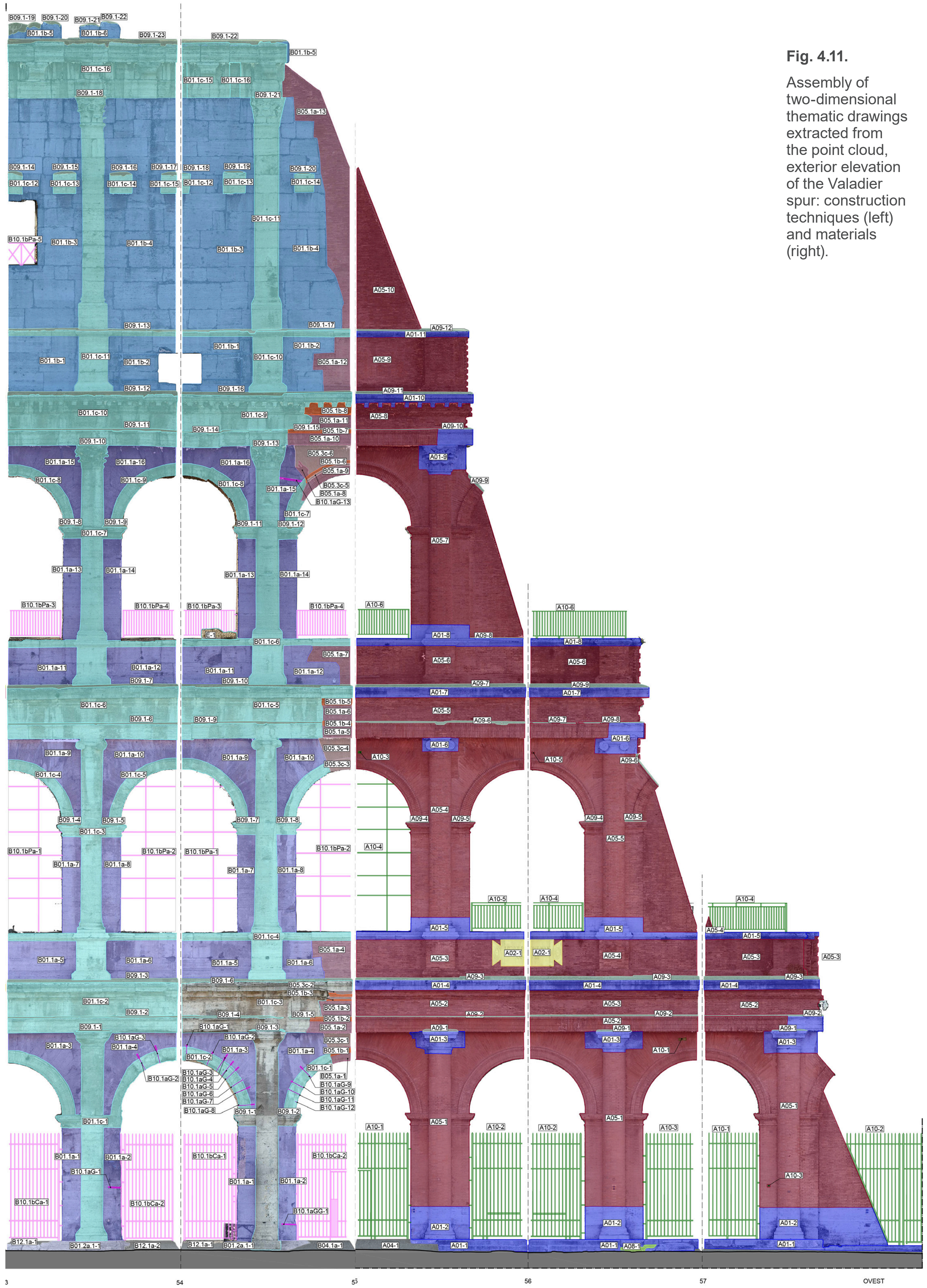


Fig. 4.11.
Assembly of two-dimensional thematic drawings extracted from the point cloud, exterior elevation of the Valadier spur: construction techniques (left) and materials (right).

Fig. 4.12.

Portion of a radial section mapped according to state of conservation.

this model has accelerated and optimised BIM modelling can be described in relation to the modelling of existing structural supports, such as chains, clamps, hoops, etc. The segmented cloud allows homogeneous components for a given category to be isolated. The construction techniques model includes the “structural supports” class. By isolating it, only the relevant elements remain visible, always spatialised in the same reference system. This makes them easy to identify.

The classified point cloud model also provided the representative support for the visualisation of thematic characterisations in the BIM model (Fig. 4.13). In fact, the three categories (materials, construction techniques and state of conservation) were attached into the BIM model via links that allow them to be connected and displayed superimposed on the parametric model in the Revit environment. This is particularly useful for construction techniques, which are not always identified by a specific object, as in the case of materials, and for types of deterioration, which can then be visualised on which elements they occur and what their geometric extent is.

Finally, the classified point cloud model is a deliverable product that can be viewed and queried using the open source software Cloudcompare (Cloudcompare, 2024). It consists of layers of information that are organised and correlated. The basic metric and geometric structure consists of a point cloud from photogrammetry, completed in some parts by laser scanning, subsampled to regularise its resolution and make the file size manageable.

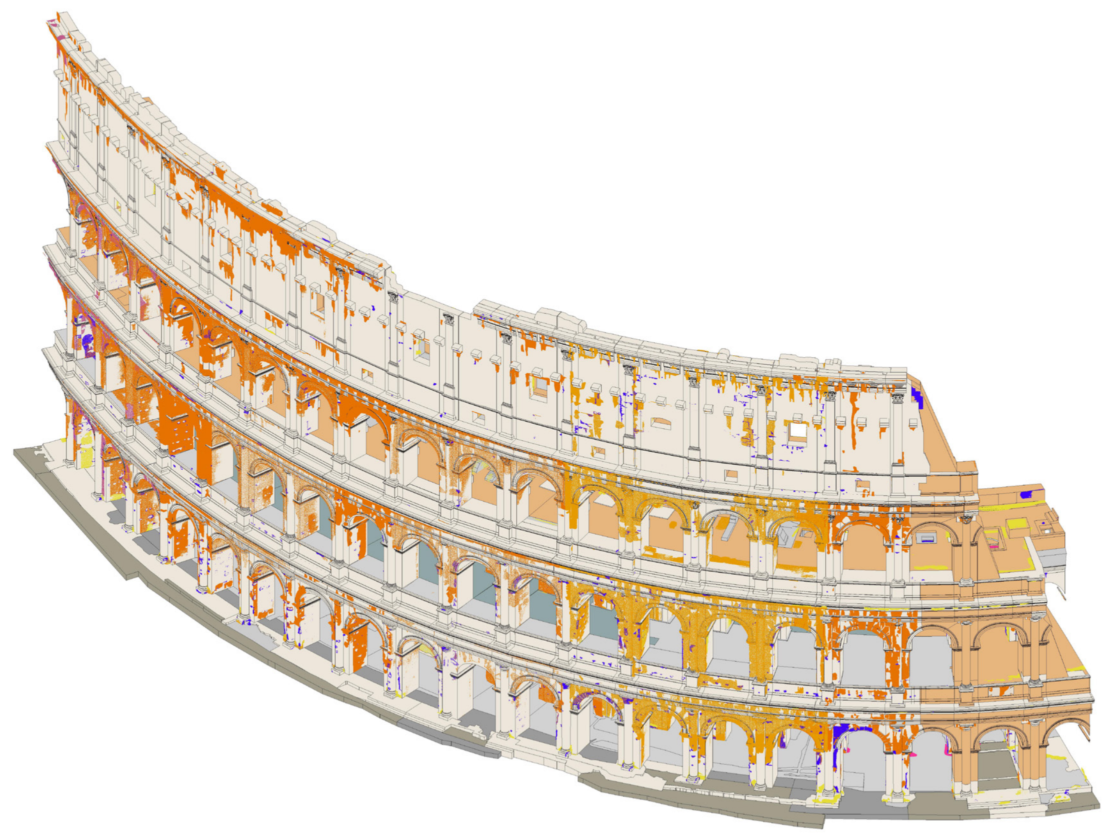


Fig. 4.13.

Section of the BIM model with visualization of the state of conservation thematic point cloud superimposed. Each degradation morphology is represented with a specific point cloud.

In the mapping of materials and construction techniques, each layer shows a thematic category, associated with a scalar field (Fig. 4.14). The information is queried by selecting the scalar field corresponding to the topic to be investigated. In this way, the coordinates of the point cloud take on a false colouring corresponding to a colour scale with reference to the legend of the reference abacus and common to that shown in the two-dimensional drawings. Therefore, homogeneous areas are displayed with the same colour value. This allows for immediate visualisation and interpretation of the surfaces, which can also be queried numerically, thanks to the assignment of a unique ID for each class, again with reference to the abacus. Using this ID, it is possible to perform additional operations, such as partializing the display and segmenting the cloud by type, exploiting the numerical value assigned to each individual point. The IDs are ascending natural numbers and have been assigned taking into account the future implementability of the model. Thanks to this query option, it is possible to view the spatial distribution of elements made from a specific material or construction technique within the point cloud model of the monument. Although it may seem elementary, this is an operation that would otherwise be impossible and completely unprecedented. By deepening the investigation, it is also possible to isolate a specific construction technique, thanks to the uniqueness of the ID codes assigned to the classes. For example, it is possible to isolate the blocks that constitute the vertical load-bearing structure, observing, in an overall view of the building, where it is still present and where it is missing, and therefore where it has been replaced or rebuilt in subsequent interventions. This can also help in the study of the monument from a historical point of view, leading to advances in the knowledge of the monument.
In mapping the state of conservation, each layer represents a single degradation, with a binary code 0/1 to indicate its presence or absence. Since it is not possible, within a scalar field, to assign more than one ID to the same point, it is not possible to produce a single layer to represent the entire “state of conservation” category. Therefore, in the event of one or more decays overlapping, it would have been necessary to define a number of IDs for each combination of pathologies, which would have made the model very difficult to read. Alternatively, it would have been necessary to choose one pathology that prevailed over the others, leading to greater problems of critical interpretation and producing an excessive simplification of the description of the monument. By generating a scalar field dedicated to each type of deterioration, it is possible to fully represent their complexity as they stratify among themselves. Considering the fact that specific types of deterioration affect specific materials, layers of the state of conservation were generated in association with the segmented clouds of the respective materials. This approach allows for a combined reading of the material and the deterioration, which is useful for the overall analysis of the monument. A specific layer for cracks was also dedicated to the point cloud. Unlike the other themes, where the point cloud guided the BIM modelling, for the cracking pattern the process was the opposite, i.e. it was re-projected onto the point cloud starting from the three-dimensional elements traced in the parametric model.
During the point cloud segmentation operation, in a context of practical applicability, the issues described in paragraph 4.4 were encountered. In particular, problems had to be addressed relating to the large number of classes, especially for construction techniques, and to critical interpretation, mainly for macro-morphologies of degradation. As a result, the level of automation of the process increased during the course of the project. Initially, segmentation was performed manually, with a view to labelling training datasets for supervised learning. Then, the procedures began to provide reliable answers, first with the materials category and then with the construction techniques category. The approach adopted is image-based, and the correction of misclassification areas was performed directly on the 3D point cloud model. This intervention was always necessary in order to meet the contracting authority's requirements. Every automatic process is indeed associated with a statistical error rate, which was reduced by manual validation in post-processing. In the case of conservation mapping, this was done entirely manually.

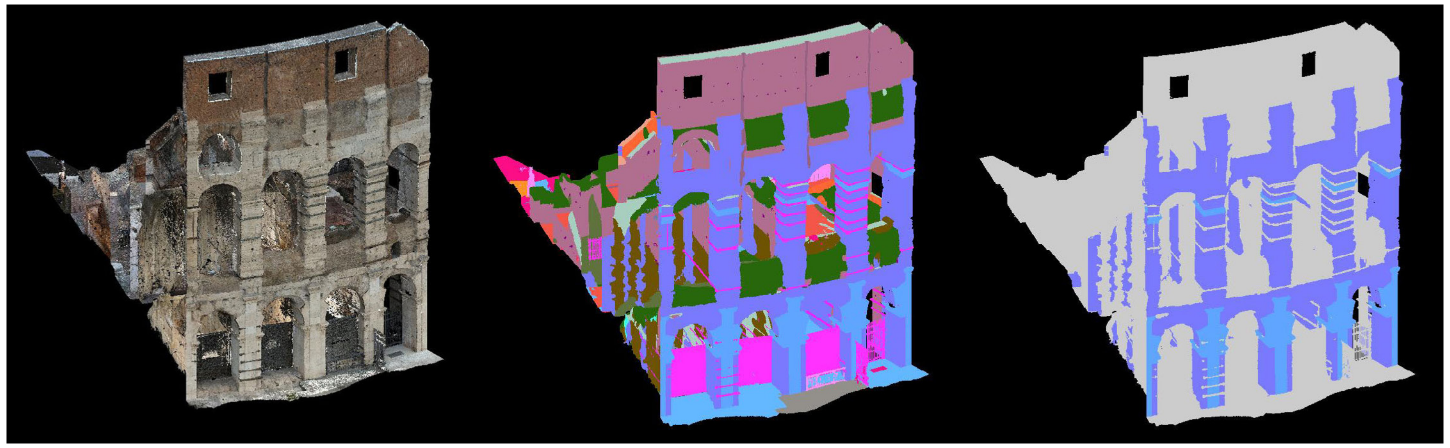


Fig. 4.14.
Thematic point cloud of a group of 4 fornixes of the south front of the Colosseum. Visualization of the photorealistic colour data (left), according to the category of construction techniques (center) and example of interrogation, in which the travertine components are isolated, thus being able to study their spatial location in the monument on the 3D model.

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Summary

5. Data processing addressing conservation issues: selected case studies

Abstract

This chapter presents the selection of five heritage buildings used to test the methodological framework for digital survey and data processing thorough Artificial Intelligence processes for surfaces interpretation, in addition to other datasets used for specific tests and analysis throughout the research development. Case studies range from medieval to modernist and contemporary contexts, and were chosen considering some macro indicators that identify categories and levels of response of buildings to the context in which they are located, to ensure heterogeneity materials, construction techniques, and state of conservation. Selected architectures are: Former Monastery of St Agostino in Verucchio (Italy), Former Colonia Varese in Milano Marittima (Italy), Rocca Possente in Stellata (Italy), Cristo Obrero Church in Atlantida (Uruguay), and St Margaret's Church in Braemar (Scotland). Each of them was surveyed through integrated procedures combining terrestrial laser scanning, and digital photogrammetry, both terrestrial and drone-based. These datasets, moreover, support comparative analyses for intensity data reliability, as well as feature extraction for semantic interpretation.

Working with documentation of cultural heritage buildings involves a wide range of activities spanning multiple domains, which are necessary to achieve a holistic understanding of the manufact, sufficient and necessary to provide professionals and decision-makers with useful guidance on the actions to be taken to ensure its preservation. At a methodological level, therefore, it is clear that each case study analysed in this research requires a variety of actions, such as bibliographic, iconographic and historical-archival research, metric surveys, fact-finding investigations where necessary, etc. Furthermore, analysis of the context and its impact on the building is of great importance. This section summarises data providing a general overview of each case study from a historical point of view, the characteristics of the surfaces and the

survey procedures applied. Consequently, a framework is provided that sets out data and information required for the specific research developments.
The first paragraph illustrates the criteria for selecting the case studies, after which each case study is described in a dedicated paragraph.

5.1 Conservative macro indicators as selection criteria

Experimentations about AI algorithms need a consistent number of different point clouds to be carried on with significance (Pierdicca et al., 2020).
The databases used were primary produced by the PhD candidate during the research period, while others derive from surveys performed by the candidate in previous years. To broaden the range of case studies and enable more comprehensive experimentation, additional point clouds were selected from the database of the DIAPReM/TekneHub research centre of the Department of Architecture of the University of Ferrara. This research unit has a recognized experience in the field of integrated three-dimensional surveying, which also carries out activities in the field of H-BIM modelling and the development of semantic web platforms for data management. The extensive set of databases of documented and digitized heritage buildings at national and international scales, surveyed thorough different instruments and methodologies offers a wide range of possibilities among which select significant test-beds. This research indeed also foresees the reuse of databases, capitalizing unexploited data for the specific purposes of the research. Moreover, given the PhD candidate's study abroad period at The Scott Sutherland School of Architecture & Built Environment of Robert Gordon University of Aberdeen, Scotland, also the set of databases present in the research unit that deals with surveying at this institution was analysed in order to expand the range of cases to be examined.
Relevant and suitable datasets were chosen according to the criteria of different levels of complexity of historical surfaces in terms of materials and conservation conditions.
The first criterion taken into consideration is the historical period. Digital surveying methods, and the possibility of analysing the point clouds produced, can be applied to a wide variety of architecture built throughout human history. This ranges from prehistoric archaeological remains to contemporary buildings (Tafuri, 1968). For the purposes of this research, five macro periods have been identified, in relation to their influence on the categories of analysis (materials, construction techniques and states of conservation):

- Period 1, from prehistory to Roman antiquity
- Period 2, from the Middle Ages to the Second Industrial Revolution
- Period 3, from the Second Industrial Revolution to the 20th century
- Period 4, first half of the 20th century
- Period 5, second half of the 20th century

The first period is strongly characterised by its archaeological component. These artefacts and construction techniques are linked to wall stratigraphic layers, and their inclusion in the application section would have required their specialistic analysis, which would have required an interdisciplinary approach not feasible within the scope of this research. However, this does not exclude the possibility of future in-depth studies on this topic, expanding the applicability tests of the proposed procedural model. In any case, Paragraph 4.6 describes the application of segmentation and classification procedures in an artefact strongly characterised by its archaeological component, namely the Colosseum.
The second period includes buildings characterised by traditional construction methods, while the third represents a period in which buildings were constructed using methods that differed from those of the master builders, with the introduction of the first machine-made elements, which became predominant, where technology was aimed at improving the construction process and evolved rapidly during the 20th century (Periods 4 and 5). This evolution of processes produced evident changes in materials and construction techniques employed and, therefore, also in the forms of deterioration affecting buildings.
A second criterion considered consists of a set of macro indicators identifying categories and levels of response of buildings to the context in which they are located. Each building can be scored from 1 to 5 for each macro indicator:

- Environmental impact, as the effect that the context has on the building, ranging from mild (1) to aggressive (5);
- Risk level, from low (1) to high (5);
- Level of surface degradation, from none (1), for example for buildings recently restored, to severe (5);
- Level of structural damage, from none (1) to collapse (5)
- Degree of accessibility, from completely inaccessible (1) to completely accessible (5);
- Hybridisation, from an asset built in a specific period and never altered (1) to layered palimpsests, even with alterations and incongruous interventions (5).

Across these macro-indicators, it is also necessary to consider the context in which the buildings are located, both in terms of their geographical setting, which influences the use of specific materials and construction techniques, and their urban or rural environment, which affects, in different ways, the morphologies and extent of degradation phenomena.
Although these different thematic areas do not represent all the components that influence and describe historical architecture, they help to identify buildings that are representative of a sufficient variety of conditions that may be faced in the documentation of built heritage. It is possible to apply and test segmentation and classification procedures more comprehensively on these buildings, taking into account more variables. The

different categories identified by the macro indicators represent the conditions of the buildings visible on their surfaces, which are also linked to the temporal dimension. In this way, the number of materials, construction techniques and decay morphologies were as diversified as possible. Regarding the state of conservation, both isolated and superimposed degradation conditions on historical surfaces were considered.

A third criterion is the type of source data. Buildings that had been surveyed using different methodologies such as laser scanning and digital photogrammetry were taken into consideration. Each of these surveys were designed for different aims and objectives, according to the specific needs and requests of the specific research project. However, the present research explores the possibility of exploiting digital 3D metric-morphological models to apply new data assessment methodologies regarding surface features and conservation aspects. In such direction, point clouds could be enriched with informative layers, according to specific categories of interest. Results can be cross-referenced to achieve a greater and more meaningful definition of the components searched. Point cloud surveyed with different tools and related methodologies, led to the opportunity to compare different sensors, which is a part of this research.

The fourth criterion specifically concerns reflectance data. Indeed, some of the selected case studies were used also for preliminary experiments regarding the reliability of intensity data in point cloud databases for algorithmic processing (Paragraph 6.3). Since intensity value depend on many factors (Paragraph 4.1), using DIAPReM/TekeneHub databases allows to experiment on datasets where some conditions were known and case-specific variations could be better controlled and compared, increasing methodological relevance in the analysis of different outcomes on different contexts (Giau & Maietti, 2024). Moreover, on some surveys by DIAPReM, characterized by a high control of systematic error and a consequent optimization of the database, surface analyses have already been carried out using the point cloud intensity values (Maietti, 2023). Whole buildings, if significant, were not considered in the early stages of testing. Instead, limited samples have been used to allow for a greater number of various tests in terms of input data and, consequently, the categories to be researched. To establish a set of common conditions and a set of different features and specifications able to support the definition of parameters to classify intensity value ranges, further specific tests on intensity data were carried out on samples surveyed *ad hoc* with different tools, hence with different sensors (Paragraph 6.4). This case study is a layered wall, whose surface is partly plastered, partly exposed brick masonry, located on the Department of Architecture of the University of Ferrara.

5.2 Material complexity of Former Monastery of St. Agostino in Verucchio

Environmental impact	●●○○○
Risk level	●●●○○
Level of surface degradation	●○○○○
Level of structural damage	●○○○○
Degree of accessibility	●●●●●
Hybridisation	●●●●○

The municipal Former Monastery of St. Agostino (Fig. 5.01) is located just outside the medieval walls and dating back to the 12th century (Rossato et al., 2023). Transformation works involved the building during the 17th century included the construction of the church and spinning mills. The complex was then used for different purposes until it was abandoned in the 1970s. The Verucchio area was interested in archaeological campaigns between 1893 and 1894, then resumed in 2005, since the presence of a flourishing Etruscan civilization of Villanovan phase (10th-7th centuries B.C). Former Monastery of St. Agostino was chosen to expose the archaeological finds, especially rich funeral kits from the nearby necropolis (Von Eles, 1998). Restoration of the building took place in the 1980s and the Archaeological Museum was inaugurated in 1985.

Fig. 5.01.

Former Monastery of St Agostino in Verucchio.

Construction period

Period 2: Original monastery 12th century ca.; transformation works 17th century; restoration 1980s.

Materials and construction techniques

The building is an example of traditional local architecture and main construction technique that characterizes exterior surfaces is exposed mixed stone and brick masonry. While brick areas shows a more regular layout, stone ones appear to be constructed according to random uncoursed rubble technique, made of poorly shaped ashlars. The building features a portico, where there are more refined elements: such as eight stone columns. Portico's walls are plastered, with cornerstones, while only an external minor facade is plastered. The upper part of the façades is decorated with a simple brick moulding. Other materials are present to a lesser extent, such as metal for structural reinforcements and wood in some lintels and in portico's ceiling.

State of conservation

Overall, surfaces are in a good state of conservation, given the recent restoration works. This allows for the analysis of material components and construction techniques without the "interference" of factors that alter their perceptual characteristics.

3D integrated survey

The aim for the development of the point cloud model was the definition of a database to be used for extraction of 2D CAD drawings and as a geometric basis for a future H-BIM model. The Museum has been surveyed by applying integrated procedures (Tab. 5.01): a Total Station Leica TPS 1202 for the topographic network, a laser scanner Leica BLK360 for the detail acquisition of exterior and interior (Fig. 5.02), and a UAS drone DJI mini 2 for the North façade (not accessible) and roofs (Fig. 5.03) (Giau & Maietti, 2024).

Credits

The 3D survey was carried out in 2020 as part of the research project:

Definition of protocols for the integrated digital, geometric-morphological survey and HBIM modelling of the cultural heritage located in Verucchio, with reference to the Rocca Malatestiana and the Civic Archaeological Museum of Verucchio, by means of integrated three-dimensional survey and digital modelling technologies, aimed at the knowledge, documentation and modelling for the technological transfer and integrated management of the cultural heritage.

Partners: Municipality of Verucchio, Department of Architecture of the University of Ferrara - DIAPReM/TekneHub Laboratory.

Scientific coordinators: Prof. Marcello Balzani and Dr. Fabiana Raco (DIAPReM/TekneHub); Engineer Marino Pompili, Head of the Technical, Culture and Sport Sector (Municipality of Verucchio).

DIAPReM/TekneHub responsible for the survey and processing of the overall data model: Guido Galvani.

DIAPReM/TekneHub research group: Fabio Planu, Luca Rossato, Dario Rizzi, Greta Montanari, Gabriele Giau, Federica Maietti, Francesco Viroli.

Area	Surveying tool	Aim	Coordinates number
Exterior	Total Station Leica TPS 1202	Overall topographic network	-
Exterior	Laser scanner Leica BLK360	Geometric detail survey	7.800.000.000
Interior	Laser scanner Leica BLK360	Geometric detail survey	780.000.000
Exterior	DJI mini 2 Drone	Inaccessible areas survey	19.000.000

Tab. 5.01.

Survey data of Former Monastery of St Agostino in Verucchio.

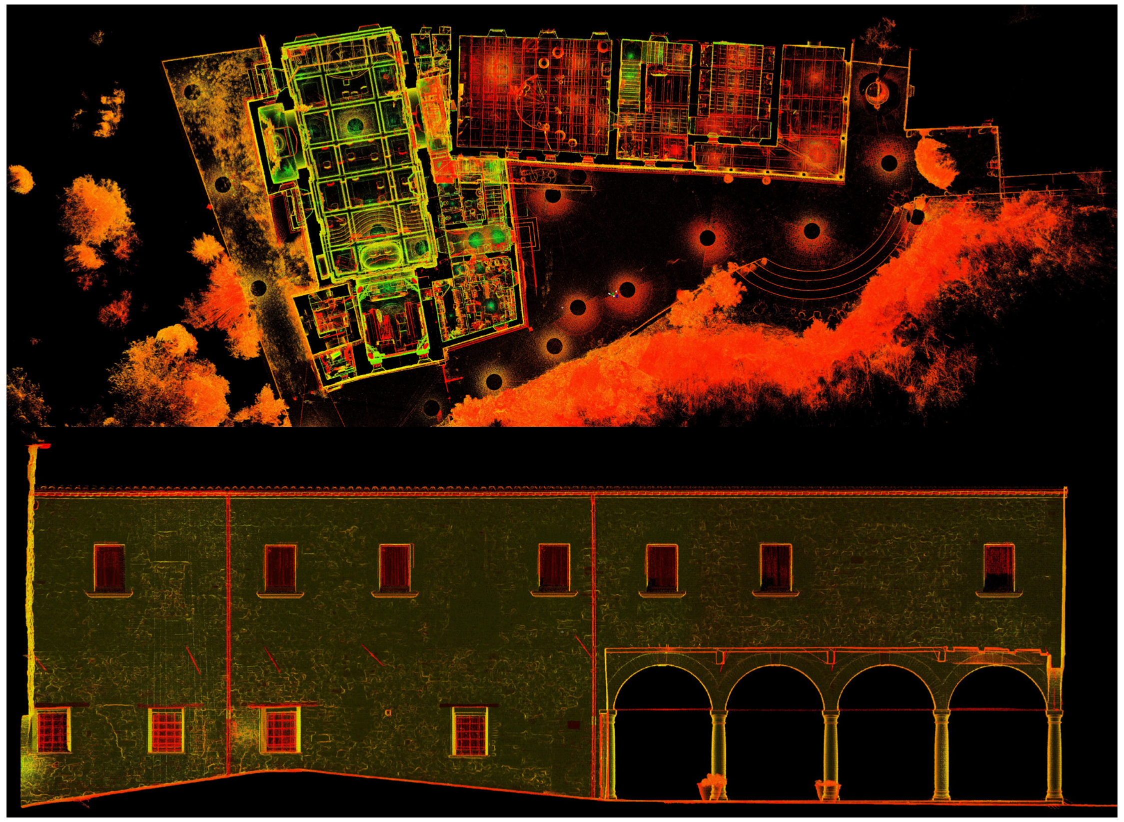


Fig. 5.02.

Laser scanner point cloud model of Former Monastery of St Agostino. Plan (top) and main elevation (bottom) visualization.

Fig. 5.03.

Photogrammetric point cloud model of the North Façade of the Former Monastery of St Agostino.

5.3 The critical state of conservation of Former Colonia Varese in Milano Marittima

Environmental impact	●●●●●
Risk level	●●●●○
Level of surface degradation	●●●●●
Level of structural damage	●●●●○
Degree of accessibility	●○○○○
Hybridisation	●●○○○

The Colonia Varese was built in Milano Marittima, Cervia (Ravenna), in the 1930s as a colony for children on the Adriatic Sea. The modernist building, designed by Mario Loreti in a rational Italian architecture style (Figg. 5.04, 5.05, 5.06, 5.07, 5.08), was then used as a prison and hospital during World War II. In the post-war years some restoration works involved building, to repair war damages (Bartolomei and Morganti, 2022). Since 1950, the Colony has been abandoned, causing progressive deterioration (Fig. 5.09). The building is located along the coast, on the seashore, in a plot of approximately 60,000 sqm, occupied by a dense pinewood, that immerses the building. Symmetrical planimetric layout and monumentality characterizes the structure (Mulazzani, 2019), made of a reinforced concrete grid. Of particular interest is the ramps system for the access to the five-story dormitories, that allowed separated paths for boys and girls.

Construction period

Period 4: 1937 – 1938, abandoned in 1950.

Materials and construction techniques

The building is constructed using common techniques of Italian rationalist architecture, with a load-bearing frame structure made of reinforced concrete beams and pillars and hollow brick and concrete floors. The infill walls are made of brick, plastered. Former Colonia Varese building was subjected by later interventions, including the sealing of many windows with perforated bricks.

State of conservation

Since the building was abandoned in 1950, the state of neglect and lack of maintenance of any kind, led the building to in a critical state of conservation. Some parts of the building have suffered collapses over time, and in many pillars and beams reinforcing iron is exposed and oxidized. Parts of the plaster are missing or are detaching. Moreover, the context in which Former Colonia Varese is located determines specific conservation conditions. Indeed, several natural factors attacked the building, causing damage to both its structure and wall surfaces. First, the proximity to the sea has exposed the building to degrading actions in relation to the humidity and marine spry, containing salt and other elements, has damaged and still damages the surfaces, leading to the occurrence of phenomena such as chromatic alteration and its rapid development. Secondly, the extensive pine forest that now surrounds the site, while serving as an important green reserve, particularly valuable for birdlife and thus protected, also poses a threat to the building itself.

3D integrated survey

The integrated 3D survey was conducted in order to provide the Emilia-Romagna Region with a digital documentation of the former Colonia Varese, to let a comprehensive knowledge base, essential for address conservative issues to develop future preservation strategies (Masciotta et al., 2021). Integrated methodologies were applied: a topographic network for the definition of a local coordinate system, 3D laser scanning thorough a Leica Scan Station P50 for the acquisition of geometry for structural assessment (Li et al., 2025), and digital photogrammetry for surface analysis of decay (Tab. 5.02, Figg. 5.10, 5.11). Since the structural conditions did not internal accessibility, only external surfaces were surveyed, and the extensive acquisition resulted in a point cloud model. Acquired data served for the assessment of geometric distortions (both vertical and horizontal), and for the diagnostic survey and for the evaluation of the state of conservation, limiting onsite inspections to safe areas (De Fino et al. 2023). The methodology adopted was also based on preliminary research (bibliography, previous studies, original drawings, previous surveys, etc.) and led to the definition of an abacus of materials (and construction techniques) and one for the macroscopic morphologies of degradation, based on UNI 11182/2006. Then, CAD mapping was carried out on othomosaics extracted from point cloud model (Fig. 5.12) (Maietti et al., 2025).

Credits

The “Survey of the geometric-morphological features and analysis of the degradation and state of conservation of the former Colonia Varese in Milano Marittima” was funded by the Emilia-Romagna Region, Heritage, Logistics, Security and Procurement Sector, General Directorate of Resources, Europe, Innovation and Institutions. Responsible Manager: Elettra Malossi. Sole Project Manager: Elisa Tommasini. Working Group: Annalisa Loccioni, Irene Cavallari.

Partners: Emilia Romagna Region - Cultural Heritage Department, Department of Architecture of the University of Ferrara - DIAPReM/TekneHub Laboratory.

The survey and analyses were carried out by the Department of Architecture of the University of Ferrara, DIAPReM Centre. Scientific coordinators: Marcello Balzani, Luca Rossato, Guido Galvani.

Techincal coordinators: Guido Galvani (3D survey), Federica Maietti (diagnostic analyses), Ing. Andrea Giannantoni (structural analyses), Fabiana Raco (2D representation).

Working group: Martina Suppa (diagnostic analysis and representations), Gabriele Giau (three-dimensional survey support), Fabio Planu (CAD extraction support), Agnese Chianella, Luisa Pandolfi, Gabriele Giannantoni (structural analysis support).

The research activities on this case study were developed during the period spent by the PhD candidate at the Cultural Heritage Department of the Emilia-Romagna Region as Host Institution.

Fig. 5.04.

Project drawing of Colonia Varese, view from the sea (Source: Ravenna State Archives).

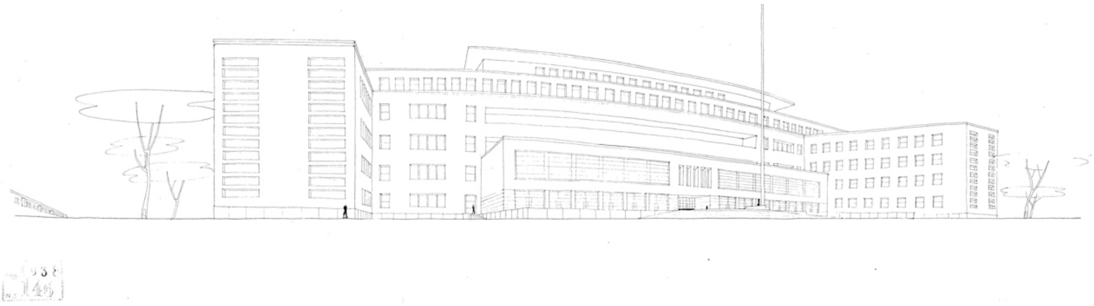


Fig. 5.05.

Project drawing of Colonia Varese, view from the entrance (Source: Ravenna State Archives).

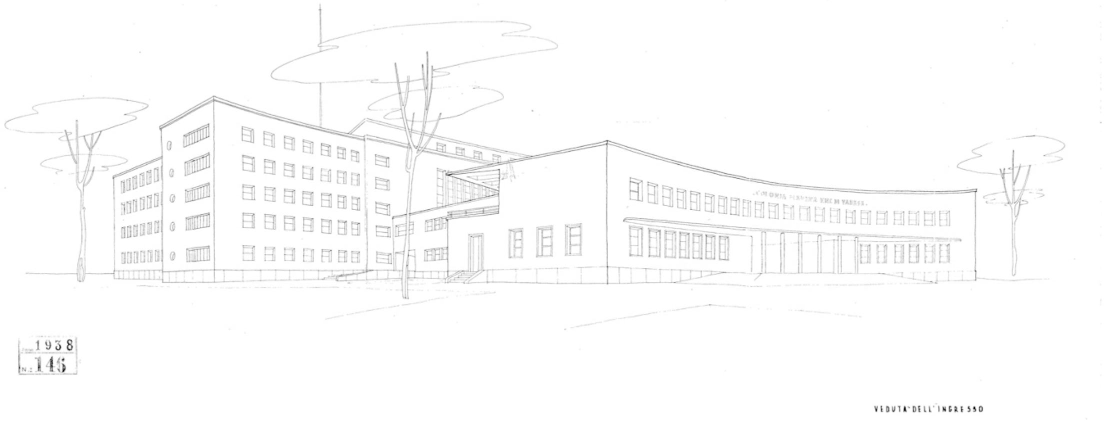


Fig. 5.06.

Historical photograph of Colonia Varese (Source: cerviaemilano marittima.org).

Fig. 5.07.

Project drawing of Colonia Varese, section showing the ramps system (Source: Ravenna State Archives).

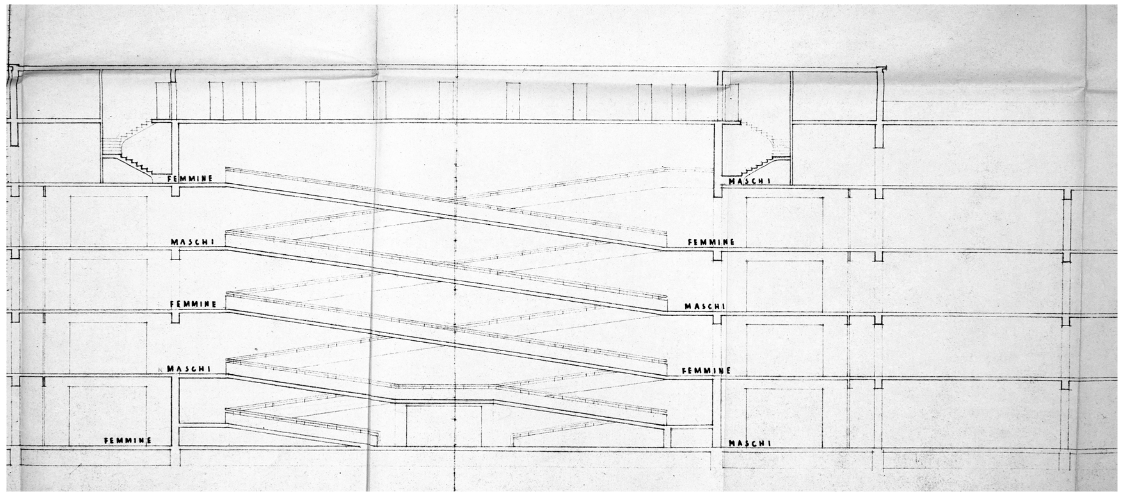


Fig. 5.08.

Project drawing of Colonia Varese, window detail (Source: Ravenna State Archives).

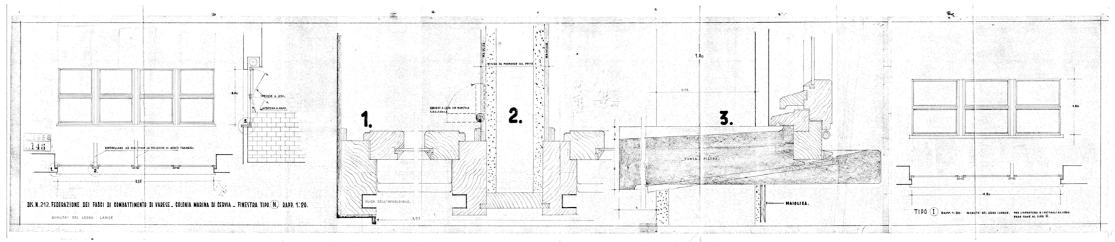


Fig. 5.09.

Former Colonia Varese nowadays, the state of conservation is critical.

Tab. 5.02.

Survey data of Former Colonia Varese in Milano Marittima.

Area	Surveying tool	Aim	Coordinates number
Exterior	Total Station Leica TPS 1202	Overall topographic network	-
Exterior	Laser scanner Leica P50	Geometric detail survey	19.000.000.000
Exterior	DJI mini 2 Drone	Geometric general survey	400.000.000
Exterior	DJI mini 2 Drone	Surface detail survey	4x 120 triangles mesh models

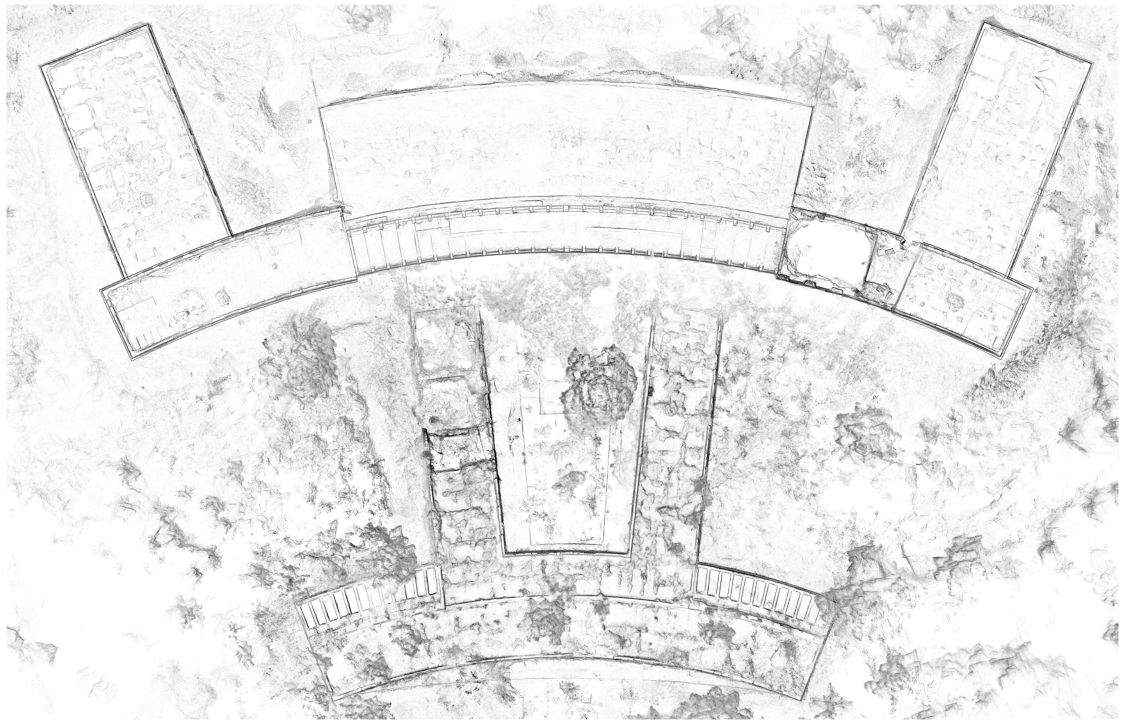


Fig. 5.10.

Plan view of Former Colonia Varese point cloud.

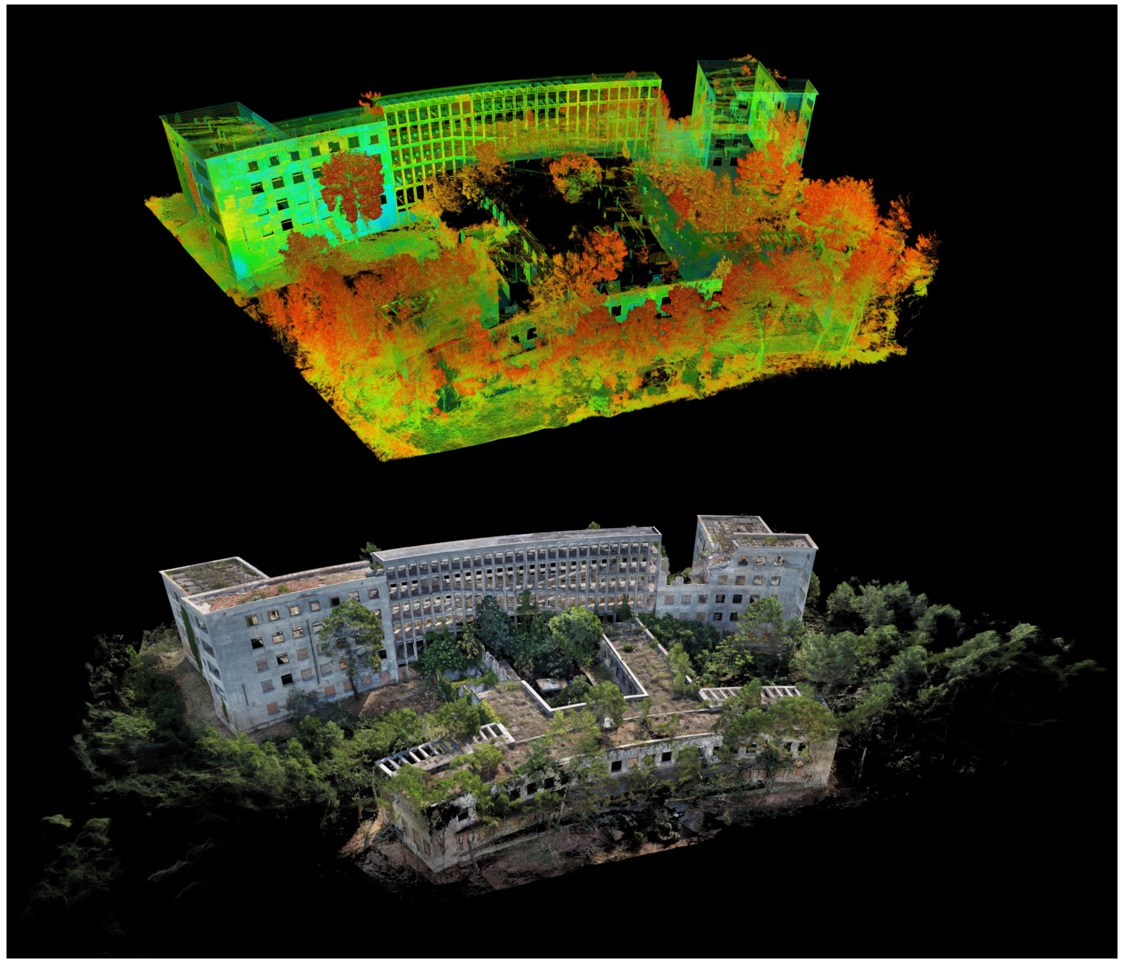


Fig. 5.11.

Laser scanner (top) and photogrammetric (bottom) point clouds of Former Colonia Varese.

Fig. 5.12.

2D drawings elaborated for state of conservation maps. Orthophoto (top), basic geometric CAD (middle), mapping of degradation morphologies (bottom).

5.4 Monitoring issues of Rocca Possente in Stellata di Bondeno

Environmental impact	●●●●○
Risk level	●●●●○
Level of surface degradation	●●○○○
Level of structural damage	●○○○○
Degree of accessibility	●●●●○
Hybridisation	●○○○○

The Rocca Possente, located in Stellata di Bondeno (Ferrara, Italy), is a significant example of military architecture strategically positioned along the Po River within a floodplain area recognized as a UNESCO World Heritage Site since 1999 (Fig. 5.13). Its unique form derives from its defensive function and its location establishes a peculiar relationship with the surrounding landscape, frequently inundated during river floods. The fortress has undergone numerous phases of destruction and reconstruction. The earliest construction dates to the late 13th century, commissioned by Nicolò II d'Este as part of a broader fortification system, which expanded upon a pre-existing structure from around the year 1000 (Fig. 5.14). The current configuration was established in 1629 by order of Pope Urban VIII (Maietti, 2004). Architecturally, the fortress features a star-shaped ground plan with four points and consists of three floors: a substantial buttressed basement, a central level, and a terraced upper floor designed to provide visual access to the surroundings. The building was damaged during the 2012 earthquake (Fig. 5.15). Restoration and structural consolidation were completed in 2021, ensuring the preservation of this historically layered monument (Libro & Letizia, 2023).

Construction period

Period 2: 1629. Restored in 2021

Materials and construction techniques

In terms of materials employed, the building is characterized by the homogeneity of the brickwork, with few stone inserts and metal structural reinforcements. Its four star-shaped plan represents an additional point of interest, as allows to study the laser scanning data response according to surface geometric variation. Specifically, this offered a meaningful context for evaluating how laser intensity values change according to scanning angles and positional configurations (Giau & Maietti, 2024).

State of conservation

Given the recent restoration and consolidation works, the Rocca does not present particular damages or aggressive decay pathologies. However, the frequent inundations of the surrounding landscape during river floods, stress the basement walls with damp. Moreover, a variation of the conservation conditions across different façades is observed, with North-exposed walls affected by typical phenomena such as biological patina, biological crusts and moss (Fig. 5.16). The homogeneity of surface material offered the possibility to assess the impact of these degradations on the intensity value.

3D integrated survey

The 3D survey of the Rocca Possente was conducted as part of FIRESPILL project, with multiple purposes (Maietti et al., 2022). On the one hand it was used to experiment a fast and low-impact acquisition protocol, possibly replicable in risk situations (Galvani et al., 2023). On the other hand, the point cloud model could serve to analyze the interventions carried out over the centuries and after the earthquake, and to contribute to the assessment of vulnerability in case of extreme events, such as floods, considering fortress peculiar location (Maietti et al., 2024). For these reasons, a territorial scale survey was firstly required, performed thorough a UAS DJI Matrice 300 drone, embedded with a DJI Zenmuse L1 scanner to ensure adequate coverage in short time. Second, the survey at architectural scale was conducted through a Leica Scan Station C10 for the exterior and a Leica BLK 360 for the interior (Fig. 5.17). Third, a topographic survey linked the three point clouds in a hierarchized numerical model. The same topographic network was also used to reference a photogrammetric point cloud model, derived from a subsequent survey carried out for the purposes of the present research, to the same coordinate system of the main morphometric model (Tab. 5.03).

Credits

The 3D survey was carried out in 2021 as part of the research project:
FIRESPILL - Fostering Improved Reaction of cross-border Emergency Services and Prevention Increasing safety Level
The project was financed in the framework of the Cross-border Cooperation Programme Interreg V-A Italy-Croatia 2014-20 and developed by Emilia-Romagna Region Reconstruction Agency, the Regions of Abruzzo, Friuli Venezia Giulia, Marche, Apulia and Veneto and the Croatian Counties of Split-Dalmatia (representing the Lead Partner, RERA S.D.), Istria, Ara, Sibenik-Knin and Dubrovnik.
Rocca Possente in Stellata is one of the case studies selected in cooperation with the Agency for Reconstruction of the Emilia-Romagna region in order to contribute to the improvement of risk prevention and management of mitigation actions (Libro & Letizia, 2023), improving digital documentation with data sources integration, experimenting acquisition protocols, and optimizing the use of technologies by territorial administrations fostering monitoring and security management (Maietti et al., 2022).
University of Ferrara (UNIFE) scientific coordinator: Marcello Balzani
UNIFE technical-scientific coordinators: Fabiana Raco, Manlio Montuori
UNIFE Research team: Guido Galvani, Dario Rizzi, Gabriele Giau, Fabio Planu, Martina Suppa, Francesco Viroli

Regional office involved: Agency for Reconstruction - Earthquake 2012

Tab. 5.03.

Survey data of Rocca Possente in Stellata.

Area	Surveying tool	Aim	Coordinates number
Exterior	Total Station Leica TPS 1202	Overall topographic network	-
Context	DJI Zenmuse L1 scanner	Territorial survey	120.000.000
Exterior	Laser scanner Leica C10	Geometric structure survey	200.000.000
Exterior	Laser scanner Leica BLK360	Geometric detail survey	400.000.000
Interior	Laser scanner Leica BLK360	Geometric detail survey	750.000.000
Exterior	DJI mini 2 Drone	Surface detail survey	30.000.000

Fig. 5.13.

Rocca Possente in Stellata.

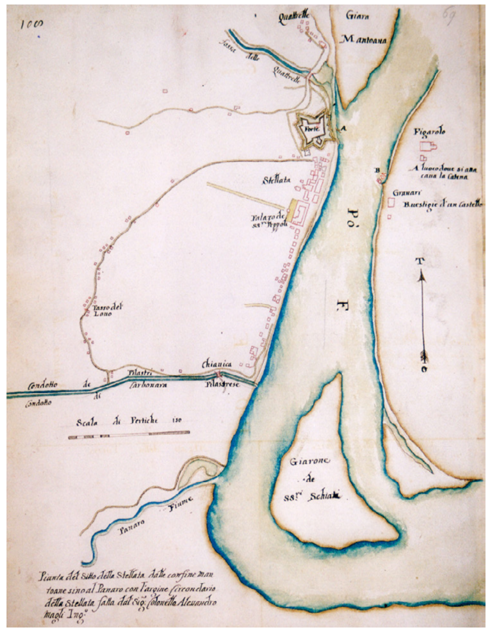


Fig. 5.14.

17th-century map showing the historic centre of Stellata along the banks of the River Po, including the Rocca Possente (Source: Maietti, 2004).

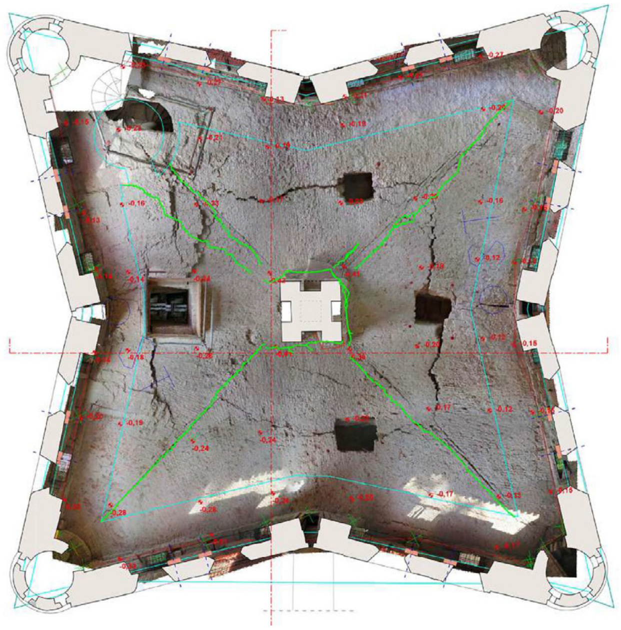


Fig. 5.15.

Orthophoto of the extrados of the "strong vault" after the 2012 earthquake, a widespread system of cracks is visible (Source: Libro & Letizia, 2023).

Fig. 5.17.

North façade of the Rocca, with degradation phenomena such as biological patina, biological encrustation and moss.

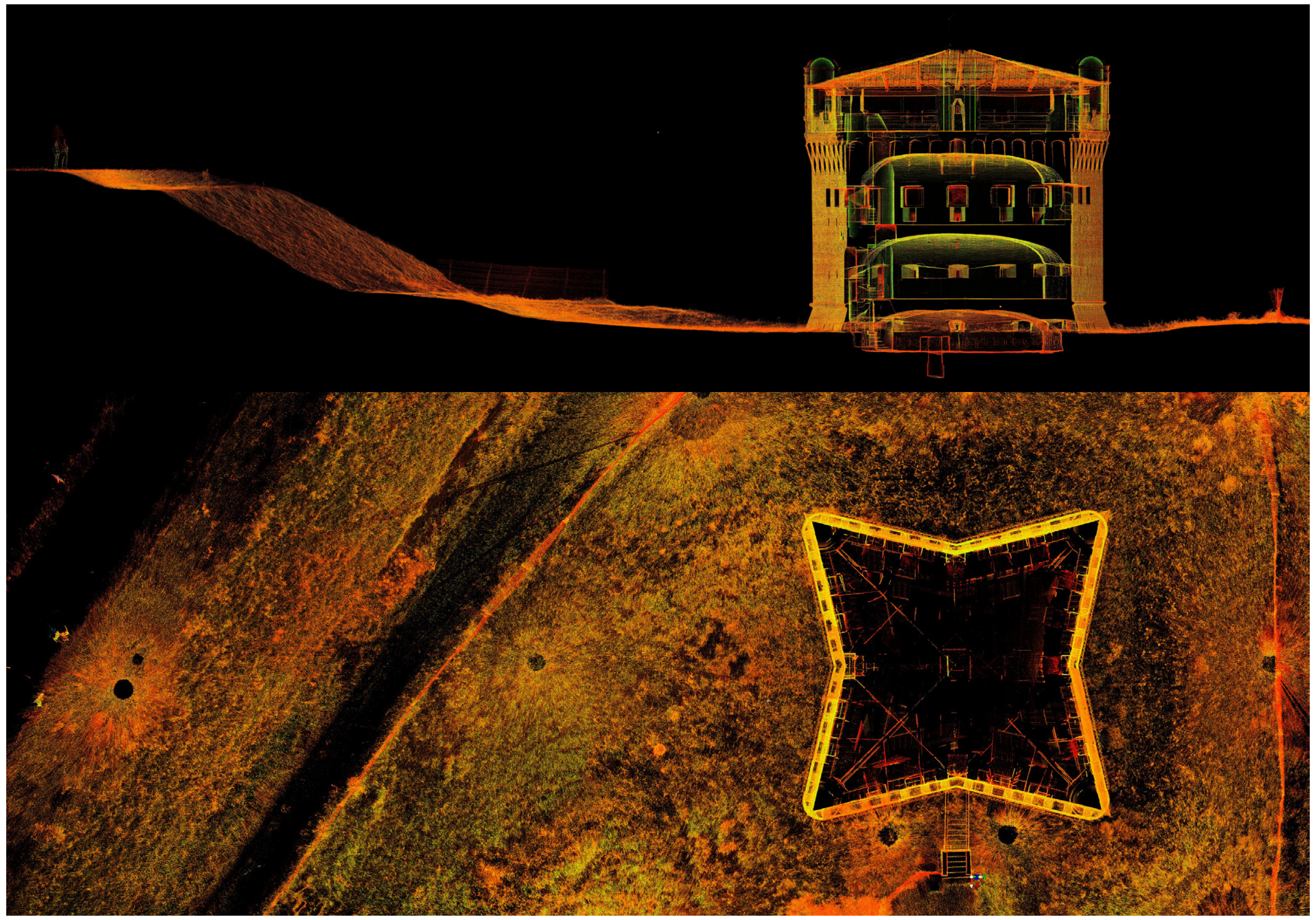


Fig. 5.17.

Laser scanner point cloud of Rocca Possente; the relationship between architecture and the river embankment emerges. Section (top), plan (bottom).

5.5 Brickwork and its state of conservation of Cristo Obrero Church in Atlantida

Environmental impact	●●○○○
Risk level	●●●○○
Level of surface degradation	●●●○○
Level of structural damage	●○○○○
Degree of accessibility	●●●●●
Hybridisation	●○○○○

Eladio Dieste (1917–2000) stands out as a pioneering figure in 20th-century Latin American architecture, known for integrating technological experimentation within a local industrial context. His work, particularly through the use of brick and traditional vaulting techniques, achieved a synthesis of simplicity, structural efficiency, and spatial elegance. Dieste's architectural sensitivity led to the development of reinforced ceramics, a construction system that enabled the creation of innovative lamellar vaults, such as gaussian and self-supporting structures. The Church of Cristo Obrero y Nuestra Señora de Lourdes in Atlántida, Uruguay is a seminal example of this approach, as it is Dieste's first major implementation of reinforced ceramic vaulting (Fig. 5.18). The church features a rectangular nave, integrating various liturgical spaces, and is distinguished by its continuous Gaussian vaults and lateral ruled surfaces (Melachos & Florio, 2018). In 2021, UNESCO recognized the church as a World Heritage Site, praising it as a world-class example of spatial and aesthetic expression due to technological innovation in construction (Fig. 5.19). The project reimagines traditional brickwork techniques, opening unprecedented possibilities in architectural design and construction (Melachos et al., 2023).

Construction period

Period 5: 1955 – 1960

Materials and construction techniques

The building is worldwide known for its 'reinforced ceramics' structure. It employs a foundation of beam-and-pile systems for the walls, while the lateral thrusts of the vaults are absorbed by buttress-shaped walls stabilized with steel turnbuckles. The design process combined traditional craftsmanship with technical ingenuity, including the use of transportable formwork for the construction of six-meter vault segments, and tensile elements for lateral stability (Sabalsagaray et al., 2017). In addition to structural purposes, brickwork is employed in the first floor wall of the main façade, where a combination of diagonal edge-laid non-structural walls, supported by transoms and by a moulded frame. On the back front, a portion of the wall gradually recedes from the main plane of the elevation to make space for a window that illuminates the sacristy. This sloping plane is achieved by laying the bricks in place in a stepped manner. All these different brickworks configures an interesting variety of construction techniques in building external surfaces, as declination of the same material. Some bricks of the roof have been replaced over time due to repair work.

State of conservation

The exterior surfaces of the building are affected by common decay morphologies mainly due to moisture, both rising and infiltration, which is associated with deposits, biological patina, and moss. The geometric characteristics of the building expose some parts of the wall and roof surfaces to atmospheric agents, favoring the formation of the mentioned decay morphologies in some areas. An interesting point concerns the main façade. It is clean and well preserved, except for some old wasp nests, which are used by birds as nesting sites. Given the recurring nature of this phenomenon, the property has decided not to remove them.

3D integrated survey

The integrated survey of the Church was developed with the objective of generating a point cloud in order to support multiple functions. Beyond its role in documentation, the survey aimed to produce a morphometric model to enable a comparative analysis between the original design drawings and the as-built geometry, with particular focus on the doubly curved surface of the roof (Melachos & Florio, 2024). Additionally, the point cloud serves as a geometric foundation for future informative modelling of the structure via the scan-to-BIM methodology and is intended to facilitate analyses concerning the conservation of the exterior wall surfaces. The survey was carried out thorough different methodologies: static laser scanning Leica Scan Station C10 and Leica BLK360, photogrammetry via DJI mini 4 drone and terrestrial integration, and SLAM Lixel K1 (Fig. 20, Tab. 5.04). The resulting models are referenced within a unique coordinate system and may be adapted for various applications depending on the quality of the collected data. The aim of the survey was also to assess point cloud obtained through this wide range of instruments/methodologies, in order to compare its data acquisition capabilities aligned with the specific objectives of the investigation (Rossato et al., 2025a).

Area	Surveying tool	Aim	Coordinates number
Exterior	Laser scanner Leica C10	Structure and detail survey	800.000.000
Exterior	Laser scanner Leica BLK360	Geometric detail survey	1.000.000.000
Exterior	SLAM Lixel K1	Geometric detail survey	19.000.000
Interior	Laser scanner Leica BLK360	Geometric detail survey	500.000.000
Exterior	DJI mini 4 + Canon EOS 90D	Surface detail survey	300.000.000

Tab. 5.04.
Survey data of Christo Obrero Church.

Credits

The 3D survey was carried out in 2024 as part of the research project:
Digital and parametric analysis of the Cristo Obrero y Nuestra Señora de Lourdes church. A modern architecture designed by Eladio Dieste UNESCO World Heritage Site.
Scientific Coordinator: Luca Rossato
Research team: Theo Zaffagnini, Gabriele Giau, Fabio Planu
International collaboration: State University UNICAMP, Campinas, SP, Brazil (Felipe Melachos), Mackenzie Presbyterian University, SP, Brazil (Wilson Florio), Eladio Dieste Foundation, Montevideo, Uruguay
The research project was financed by the 'FUND FOR THE INCENTIVATION OF DEPARTMENTAL RESEARCH'. FIRD - 2023 - Department of Architecture, University of Ferrara
The activity were carried out in cooperation with the international network I N S I D E Modern Heritage www.inside-mh.com

Fig. 5.18.

Christo Obrero Church.

Fig. 5.19.

Images of the construction site of the Church during the late fifties (Courtesy of Eladio Dieste Foundation, source: Rossato et al., 2025b).

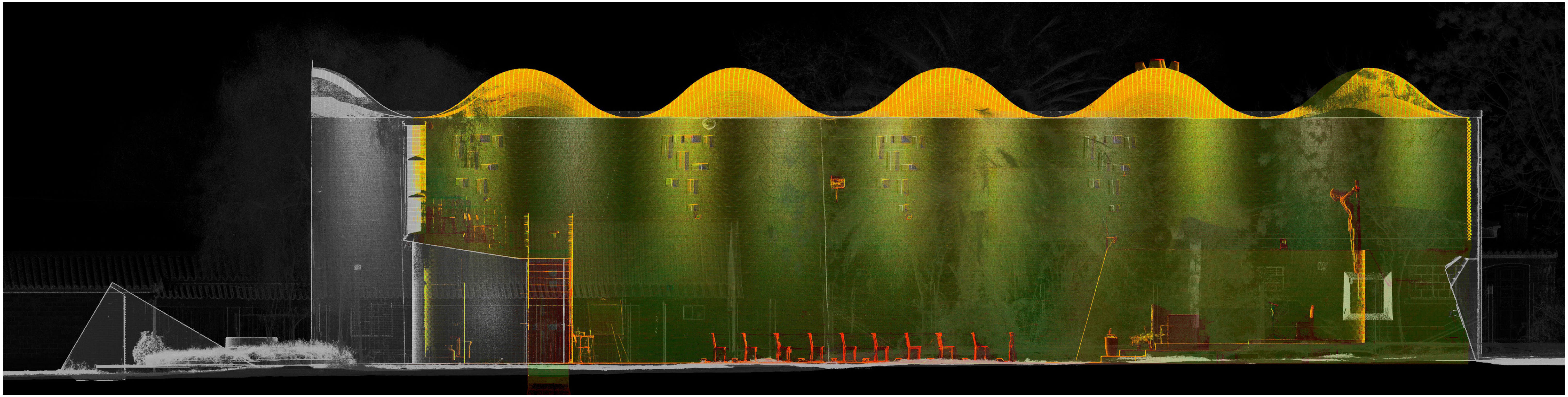


Fig. 5.20.

Christo Obrero Church, longitudinal section of the scanner point cloud.

5.6 The stone wall geometries and degradations of Sant Margaret’s Church in Braemar

Environmental impact	●○○○○
Risk level	●●●○○
Level of surface degradation	●●●○○
Level of structural damage	●●○○○
Degree of accessibility	●●●●○
Hybridisation	●○○○○

St Margaret’s Church il located in Braemar, a village on the banks of the River Dee, in Aberdeenshire county, in the northeast of Scotland (Fig. 5.21). The church was built between 1899 and 1907 for the Scottish Episcopal Church to cater for the many English visitors to Braemar and Deeside. The building is listed in category ‘A’, denoting “buildings of special architectural or historical interest which are outstanding examples of a particular period, style or building type” (Historic Environment Scotland, 2025) and it is considered of great significance within the UK Gothic Revival movement, as a major work by the prominent Aberdeen-born architect Sir John Ninian Comper (1864 –1960). His work almost entirely focused on the design, restoration and embellishment of churches (Symondson &, Bucknall, 2006).
The architectural scheme of St Margaret’s was conceived on a cruciform plan, although the north transept was never built. The interior, of exceptional quality, is visually dominated by an elaborately crafted rood screen dedicated to Eliza Schofield, the church’s principal patron. The stained-glass ensemble, entirely designed by Comper across a span of two decades, constitutes another distinguished feature (Scontland’s Churches Trust, 2025).
After falling out of liturgical use in 1997, the building was formally transferred to the custodianship of Historic Churches Scotland in 2013. In collaboration with a community-driven trust, the organization has initiated a restoration and adaptive reuse programme aimed at safeguarding the structure, currently listed as “at risk,” and reimagining it as a cultural venue.

Construction period
Period 3: 1899 – 1907

Materials and construction techniques
Prevalent material employed is locally caved granite, collected in the surrounding moorland. Construction technique consists of coursed squared rubble, with various sized stones. Ashlars display a notable spectrum of tonal variations. Smoothed and shaped blocks define the window openings and form the corner spurs. The roofing employs reclaimed slate from earlier structures, deliberately chosen to evoke an impression of antiquity while reinforcing Comper’s historicist design language.

State of conservation
Among the deterioration issues affecting the exterior surfaces, those related to dump and the disgregation of mortar joints are noteworthy, which in some cases has led to the detachment of some ashlars and their fall. Surfaces most exposed to rain, such as roofs and window sills, are subject to phenomena such as moss presence and biological crusts.

3D integrated survey
A three-dimensional survey campaign was carried out on the building in 2024, with the complete acquisition of both the exterior and interior spaces (Tab. 5.05). The phase-shift sensor Z+F IMAGER 5016 laser scanner was used to obtain the point cloud model (Fig. 5.22). RGB colour data was acquired using the integrated camera. The photogrammetric survey, conducted using a Nikon ZII full-frame terrestrial camera and a DJI Mavic 3 Multispectral drone, was aimed at generating a mesh model and for the possible export of high-resolution orthomosaics.

Fig. 5.21.
Sant Margaret's Church.

Credits

The 3D survey was carried out in 2024 by Douglas Pritchard and Daria Belkouri.
The research activities on this case study were developed during the period spent by the PhD candidate at the Scott Sutherland School of Architecture & Built Environment of the Robert Gordon University of Aberdeen, Scotland, as Host Institution.

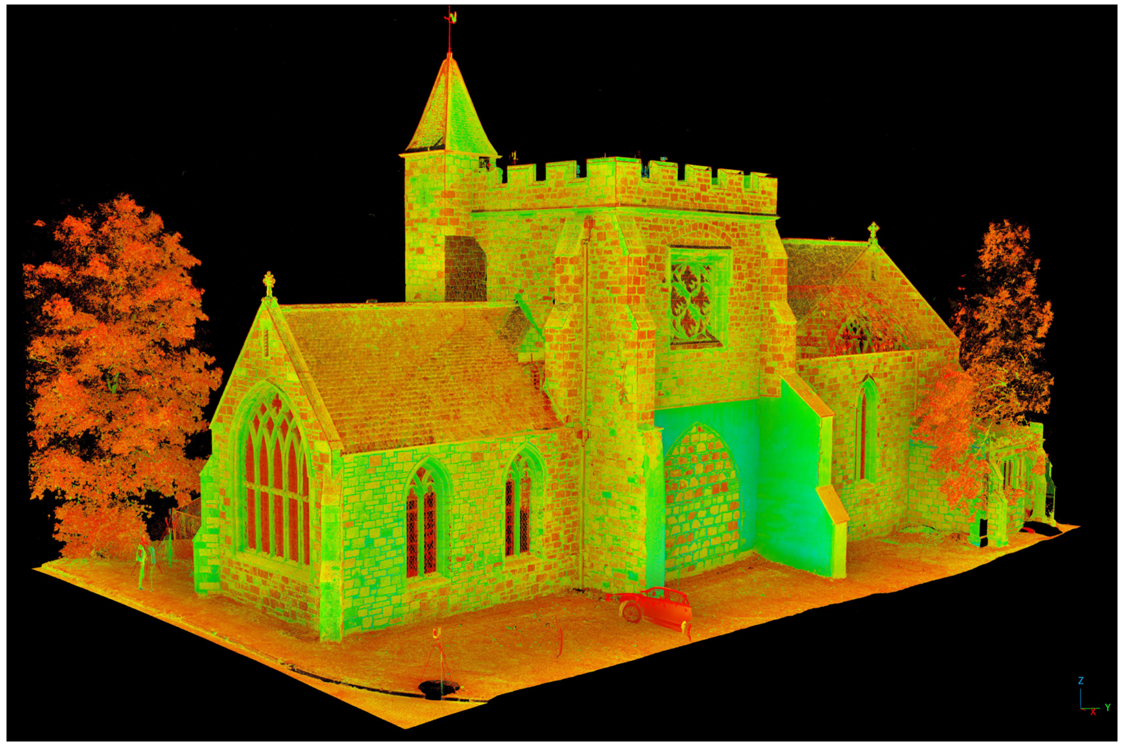
Tab. 5.05.

Survey data of Sant Margaret's Church.

Area	Surveying tool	Aim	Coordinates number
Exterior	Laser scanner Z+F 5016C	Geometric detail survey	2.300.000.000
Interior	Laser scanner Z+F 5016C	Geometric detail survey	2.000.000.000
Exterior	DJI Mavic + Nikon Z9 and Z7	Geometric and surface survey	-
Interior	DJI Mavic + Nikon Z9 and Z7	Geometric and surface survey	-

Fig. 5.22.

Sant Margaret's Church laser scanner point cloud.



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Summary

6. Experimentations on radiometric features for heritage surface documentation: intensity and colour data

Abstract

This chapter investigates the potential of laser scanner point clouds intensity value for the thematic documentation and interpretation of architectural heritage, in order to implement it into AI processes. As a prerequisite for an effective outcome, methods for associating accurate colour values to laser scanner datasets are examined. Three approaches are compared: onboard cameras, reprojection from photogrammetric models, and colourization through aligned images. Then, analyses focus on intensity values, exploring their correlation with surface features, specifically materials and states of conservation, across different sensors and environmental conditions. Tests were performed on existing databases, sampling intensity value in order to associate specific ranges to specific surface characteristics. Experimental campaigns on *ad hoc* datasets, using different laser scanner tools, demonstrate how reflectance varies with wavelength, distance, angle of incidence, humidity, and surface colour. Results confirm that intensity values, when critically interpreted and contextually calibrated, offer valuable indicators for identifying materials and degradation morphologies. The study establishes a foundation for integrating radiometric features as reliable descriptors in Machine Learning classification of heritage surfaces.

6.1 Radiometric features

Point cloud files are informatically presented as tabular data of the .csv (comma separated value) type, in which each row is a point and each column a different descriptor for each point (Fig. 6.01). There are values indicating location (x, y, z coordinates), colour (RGB values), reflectance (intensity, if the point cloud was obtained through laser scanning) and orientation (component of the normal vector with respect to the surface that the point forms with its neighbours). The components listed above describe the general point cloud characteristics, in other words they are considered “global features”. Among

these, RGB values and intensity are considered “radiometric features”, since the former refer to the visible colour of the surface, the latter to the quantity of energy reflected by the surface and recorded by the sensor of the laser scanner (Paragraph 4.1).
For surface analysis, RGB values give the most information and are easiest to interpret not only in automatic algorithmic processes but also by users (Cera & Campi, 2021). Similarly, as described in the paragraph 4.1, intensity value can, under certain conditions, provide indications about surface characteristics, revealing continuities and discontinuities in the surfaces, which can highlight material variations, different states of conservation and degradations. For instance, intensity can be used in the detection of moisture and bio-deterioration (Tan et al., 2016, Suchocki et al., 2017) or cracks and cavities (Nowak et al., 2020). In the present research, therefore, the objective was to use reflectance during algorithmic processing and evaluate its impact on its performance. To do this, two operations are required prior to machine learning processing:

a. Optimise the input data by ensuring that the point clouds used include both reflectance values and RGB colour information.
b. Test the relationship between intensity values and surface characteristics.

The methodologies and results for point (a) are presented in Section 6.2, while those for point (b) are discussed in Sections 6.3 and 6.4. The overall findings and considerations are summarised in Chapter 10 (Results).

Fig. 6.01.
Structure of the 3D point cloud matrix. n is the total number of points.

Point	X	Y	Z	R	G	B	i	Nx	Ny	Nz
1	X_1	Y_1	Z_1	R_1	G_1	B_1	I_1	Nx_1	Ny_1	Nz_1
2	X_2	Y_2	Z_2	R_2	G_2	B_2	i_2	Nx_2	Ny_2	Nz_2
3	X_3	Y_3	Z_3	R_3	G_3	B_3	i_3	Nx_3	Ny_3	Nz_3
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
n	X_n	Y_n	Z_n	R_n	G_n	B_n	i_n	Nx_n	Ny_n	Nz_n
		Position			Color		Reflectance		Orientation	

6.2 Colour data as a thematic “signifier”

6.2.1 Question and objectives for radiometric features processing

To set up an algorithm to process both RGB values and intensity, point clouds must include both. In order to use them effectively, it is therefore necessary to associate a “faithful” RGB data with the points of a laser scanner cloud. Conversely, the possibility of transferring the intensity value from reflected signal to the photogrammetric point cloud, although technically feasible, is considered a less advantageous option because it would lose the geometric accuracy associated with the coordinates measured through LIDAR sensors. Indeed, point clouds from laser scanners are, in general, metrically more accurate than photogrammetric ones, as they consist of coordinates that are statistical values associated with measurements, not derived from probabilistic calculations, as is the case with Structure-from-Motion processes (Mora et al., 2019; Peterson et al., 2019). Hence, in this research three methods of adding robust colour values to laser scanner point clouds are investigated, and the following results used in AI experimentations:

- Colour value derived from laser scanner onboard cameras,
- RGB reprojected from photogrammetric point clouds,
- Laser scanner point cloud colourized thorough aligned images.

Preliminary considerations can be stated concerning colour models. RGB is the most common one, but other models can be employed, such as the HSV (Hue-Saturation-Value). In fact, the former colour space is sometimes not suitable for a colour-based segmentation (Musicco et al. 2021), and the latter is considered more effective because it describes the colours taking into account both the human perception and the similarity among colours (Gonzalez & Woods, 2018). It is graphically represented by using a cylindrical coordinate system (Pepe et al., 2016), where:

- hue is the angle around the cylinder axis and it represents the colour perception (0° corresponds to the Red, 120° to the Green and 240° to the Blue);
- saturation is the distance from the axis of the cylinder and it represents the “purity” of the colour, it varies from 0% (grayscale) to 100% (full saturation);
- value (or brightness) is the distance along the axis of the cylinder and represents the difference between light and dark, its value varies from 0% to 100%.

For the way the HSV colour space is set up, the hue component tends to remain constant in areas with different illumination conditions, since the shadows are descripted by the value and the saturation components. For this reason, the primary colour should not change so much (Grilli & Remondino, 2019). It is possible to convert RGB values to HSV using the equations below:

$$Hue = H = \begin{cases} 60^\circ \times \left(\frac{G' - B'}{\Delta} mod6\right) & , C_{max} = R' \\ 60^\circ \times \left(\frac{B' - R'}{\Delta} + 2\right) & , C_{max} = G' \\ 60^\circ \times \left(\frac{R' - G'}{\Delta} + 4\right) & , C_{max} = B' \end{cases} \quad (1)$$

$$Saturation = S = \begin{cases} 0 & , C_{max} = 0 \\ \frac{\Delta}{C_{max}} & , C_{max} \neq 0 \end{cases} \quad (2)$$

$$Value = V = C_{max} \quad (3)$$

where the R, G, B values are divided by 255 to change the range from 0-255 to 0-1 ($R'=R/255$, $G'=G/255$, $B'=B/255$), $C_{max}=max(R',G',B')$, $C_{min}=min(R',G',B')$ and $\Delta = C_{max} - C_{min}$.

6.2.2 Colour captured from laser scanner onboard cameras

In a laser scanning survey, colour data may or may not be acquired, depending on the specific needs and purposes of the survey. When acquired, it is not necessarily reliable for the purposes of material and state of conservation analyses. In fact, the cameras associated with laser scanners have limitations, mainly due to the fact that the exposure cannot be fully controlled and the automatic 360° acquisition may unintentionally capture external moving objects interposed between the instruments and the object of the survey, and this can result in an improper colouring of the points.
A typical example of this issue is in surveying crowded spaces, which cannot be closed to the public, it can often happen that the passage of people is photographed by the instrument's onboard cameras, but not measured by the laser beam. The result is that points on the architectural surface that were occluded by bodies in the photos will have the RGB data of people. In professional practice, low-impact surveys, which do not involve closing or contingent areas, are increasingly needed to simplify overall logistics. To overcome this problem, it is necessary to organize the survey considering this possible issue and to adopt the necessary strategies to capture the colour data as correctly as possible. Scheduling acquisition at times of little or no crowding. Alternatively, if the tool is equipped with sufficient acquisition speed, redundant stations can be run and data cleaned in post-processing (Bianchini et al., 2022). Furthermore, not all the laser scanners are equipped with high resolution cameras that produce a sufficiently satisfactory result from a quality point of view, suffering from chromatic aberrations mainly due to the difficulty of handling overexposed and underexposed areas, backlighting, etc., although progress has been made with cameras capable of taking HDR (High Dynamic Range) photos (Fig. 6.02).

Fig. 6.02.
RGB data of laser scanner point cloud obtained through onboard camera in BLK360 in Former Monastery of St. Agostino Verucchio dataset. Colour difference between light and shadow areas are observed.

In this research, the described methodology was applied in the case of Former Monastery of St. Agostino in Verucchio (Rimini), where laser scanner Leica BLK360 was used, and in St Margaret's Church in Braemar (Scotland), surveyed with laser scanner Z+F 5016C. The integrated camera system in both tools is positioned at the nodal point of the scanning unit. In some scanners, however, the camera is positioned with a slight offset from the instrumental centre, so a little parallax can be observed (Pritchard et al., 2023).
Another methodology can be used to associate a more consistent colour data with the laser scanner point cloud, as an alternative to the onboard camera. This is the coaxial photogrammetry procedure, where an external camera is suitably calibrated, thanks to a stand that, through support rods, allows the camera lens entry point to be aligned to the instrumental centre of the laser scanner (White & Jones, 2008). Once the scan is performed and the instrument removed from the tripod, the camera is located on this support and the photographs manually taken. This procedure allows better control the exposure and, especially, avoiding moving people interposed between the instrument and the surface to be surveyed. It should be considered that this procedure extends the acquisition time *in situ*. Moreover, this method can be performed with scans standing on common topographic tripods, since it is not conceived for "lighter" laser scanners, such as Leica RTC360 or BLK360.

6.2.3 Colour reprojected from photogrammetric point clouds

In point clouds obtained from digital photogrammetry processes, RGB values are much more reliable and consistent, as they are derived from high-resolution photographs. When a building is surveyed both thorough laser scanning and photogrammetry, two point clouds are produced according to the two different methodologies. Through this strategy the colours of the photogrammetric point cloud are reprojected onto the laser scanner one. Prerequisite for the application of this process is that the two point clouds belong to the same reference system, either local or global, so that they overlap each other. Moreover, the densities of the two should be comparable, since low density photogrammetric point clouds will produce unsatisfactory results. Due to the different nature of the source data and processing methods, these two point

Fig. 6.03.
RGB data of laser scanner point cloud obtained through reprojection from photogrammetric point cloud in Rocca Possente in Stellata dataset. Original photogrammetric point cloud (right), colourized laser scanner point cloud (middle) and cloud-to cloud distances (left). Red areas show distances bigger than 2cm, note that shadow cones in façades and the roof, not acquired thorough terrestrial laser scanning, and noise surfaces, such as grass.

clouds will necessarily have deviations and dimensional variations between them. Reprojection produces a more satisfactory result the closer the two point clouds are. It is possible to reduce the deviations by correctly applying the surveying and data processing methodologies, by including an appropriate number of target points within the Structure-from-Motion calculation. However, it is necessary to establish a tolerance threshold within which these deviations can be considered acceptable, depending on the scale and purpose of analysis.

One issue to be considered in adopting this methodology is the fact that, often, the laser scanner point cloud has missing parts resulting from shadows quite typical in terrestrial acquisitions, while clouds from photogrammetry are more complete, often taking advantage from aerial acquisitions by drone. Since the geometric structure for reprojection is the laser scanner point cloud, missing areas also subsist in the final outcome. While these can be considered negligible for the overall analysis of the elevations, the described methodology produces overall a good result in terms of associating homogeneous and reliable colour data with accurate measurements.

Both the reprojection process and the assessment to cloud-to-cloud distances can be done thorough the open source software Cloudcompare. In this research, the presented methodology was applied in the case of:

- Rocca Possente in Stellata (Ferrara), where for the laser scanning a Leica HDS C10 was used, and for the digital photogrammetry, the camera integrated in the DJI Mini 2 drone (Fig. 6.03);
- Former Colonia Varese in Milano Marittima (Ravenna), where for the laser scanning a Leica P50 (Ultra-high speed time-of-flight enhanced by Waveform Digitizing technology - wavelength 1550 nm or 658 nm) was used, and for the digital photogrammetry the camera integrated in the DJI Mini 2 drone.

Fig. 6.04.

omparison of RGB data of laser scanner point cloud obtained through reprojection from photogrammetric point cloud (right) and from aligned images (left) in Christo Obrero Church in Atlantida dataset. With the first method some points were unreliable coloured, with the second the result improved.

6.2.4 Laser scanner point cloud colourised thorough aligned images

This methodology, as the previous one, exploits both laser scanner and photogrammetric surveys, belonging at the same reference system. In this case, the colour projection is not done via cloud-to-cloud, but using directly aligned images (Abdelhafiz et al., 2005; Crombez et al, 2015).

The results obtained through this process are generally satisfactory, due to the high number and resolution of source images typically available in photogrammetric projects. As with the previous method, areas missing in the laser scanner point cloud remain as such. However, unlike the previous approach, this method can yield improvements in areas where the photogrammetric point cloud is sparse. This sparsity often arises when the dense reconstruction process lacks a sufficient number of high-quality frames to confidently compute a dense set of points. Consequently, the photogrammetric point cloud may be incomplete, leading to unreliable colour assignments in the laser scanner cloud during colour transfer based on nearest-neighbour criteria. By directly colourizing the laser scanner point cloud using the aligned photographs, this issue is mitigated. Since only colour projection is required, rather than full spatial reconstruction, a smaller number of images is sufficient to achieve reliable results (Fig. 6.04).

6.2.5 Outcomes

The described methodologies led to different results and are strictly linked to the acquisition methodologies carried on during survey. Regarding the first one, on the one hand, it may produce point clouds with colours not homogeneous as the others. RGB values acquired by laser scanner onboard cameras may suffer more from changing surface light conditions than the colour data of a photogrammetric survey. In fact, in the former case the time between captures of two adjacent stations may also be substantial, since the instrument also has to acquire measurements. Therefore, a considerable amount of time may pass between the first and last scans of a façade, during which environmental lighting conditions may change. Changes in brightness are then captured by the scanners and it is therefore often necessary to process the images to balance image colour, saturation, or other operations (Pritchard et al., 2017). On the other hand, colour association to spatial coordinates is more automatic.

Regarding the second and the third methodologies, the acquisition by photogrammetric method is the same and colour is typically more homogeneous, since the capturing is

Tab. 6.01.

Comparison between Survey methodologies and colour value assignment methodology for used case studies.

Case Study	Survey Methodology		Colour Value Assignment Methodology		
	Laser Scanning	Photogrammetry	Embedded Cameras	Reprojection	Colourization
Archeol. Museum of Verucchio	x		x		
Former Colonia Varese	x	x		x	
Rocca Possente	x	x	x	x	
Christo Obrero Church	x	x			x
St Margaret's Church	x	x	x		

limited in time and changes in atmospheric condition can be better managed during on field survey. Colour association in post processing may be more demanding since two registration processes must be carried out in parallel.
As mentioned, in the first method, acquiring RGB data increases time required for each scan station, especially using an external camera, operation in which stationing becomes more time consuming. Photogrammetric surveys, instead, may be performed in parallel by another operator, reducing the overall acquisition time.
The different case studies selected for this research, were surveyed with different methodologies and, thus, RGB values can be obtained according to the source data types (Tab. 6.01).

6.3 The intensity value as an interpretative feature: sampling available point cloud databases[1]

6.3.1 Correlation of intensity value and surface specifications: objectives and methodology

The visual-comparative responses on intensity values analysis developed over years of experimentation (Maietti, 2023) demonstrate the need to target research towards comparative data. "Sampling" the intensity values on different materials, measured by different sensors and in environments with different boundary conditions, is the starting point to associate specific reflectivity ranges to specific materials. The methodology proposed in this section investigates point clouds achieved by different laser scanning tools, both time-of-flight and phase-shift, characterized by different outcomes in terms of intensity values, to set up comparative analysis between different sensors. The methodology was applied on some study cases chosen according to criteria mentioned in paragraph 5.1.
This section is a specific focus investigating possible in-depth uses of the intensity value as a benchmark for historical surfaces assessment. The aim is to explore the relationship between the intensity data and some characteristics of historical-architectural surfaces. The goal is to test the link between the intensity value and

1. Topics exposed in this chapter were published in two papers by the author:

Giau, G., Maietti, F. (2024) Comparative Analyses Between Sensors and Digital Data for the Characterization of Historical Surfaces. In: Giordano, A., Russo, M., Spallone, R. (eds.) *Advances in Representation. Digital Innovations in Architecture, Engineering and Construction*, pp. 707-725 Springer, Cham

Maietti, F., Giau, G., Galvani, G. (2024) 3D Heritage Data Fruition and Management. Point Cloud Processing for Thematic Interpretation. *Disegnarecon*, 17/ n. 32 - July 2024, DOI: https://doi.org/10.20365/disegnarecon.32.2024.8

materials, construction techniques, and decay pathologies, so that this descriptor can be incorporated as a feature in Supervised Machine Learning classification algorithms, in the following stages of the research (Dreier et al., 2025).
The experimentations reported in this section have been performed on a set of case studies, selected form “exisiting” point clouds, developed from some surveys carried on for different other purposes, generally for geometric and morphologic acquisition. Point clouds under analysis have been carried out by different acquisition techniques; this provided an opportunity to compare the results in terms of intensity value produced by different sensors.
The experiments were carried out “sampling” the intensity value on different materials, measured by different sensors and in environments with different boundary conditions, in order to identify characteristic intensity ranges associated with specific materials and states of conservation. The methodology involved manual segmentation of point clouds to isolate the relevant surface portions, intensity values distribution extraction for each, generation of comparative diagrams to visualize the results.
The specific aim of this phase of the research is to sample intensity values across different materials, recorded under diverse environmental conditions and with different devices, in order to identify characteristic intensity ranges associated with specific materials and conservation states. To this end, manual segmentation of the point clouds was performed to isolate the relevant surface portions, and comparative diagrams were generated to analyse the most frequent intensity values for each category under investigation.

6.3.2 Source data: from sensors to applied workflow

In the present research it is significant to add the applied tool among the variables to be considered since, as is well known, the reflectance depends both on the type of sensors and on the laser wavelength. Thus, it is essential to know what kind of results can be expected from a given sensor in order to be able to systematize the use of this value as a reliable indicator, especially as a feature for Machine Learning algorithms.
In the experiments described in this section surveys were performed with three different terrestrial laser scanners: Leica BLK360, Leica Scan Station C10 and Z+F 5016C. The sensor of the first one is a high speed time of flight enhanced by Waveform Digitizing (WFD) technology. The laser beam wavelength is 830 nm. Typically, it is an instrument used to servey small to medium environments or surfaces located at short distances, having a maximum range of 45m. The sensor of the second one is a time of flight, as well, but with a laser beam wavelength of 532 nm. The range is longer than the BLK one, reaching 300m. The latter has a phase-based measurement system. It has an approximate range of 360 meters with a laser beam wavelength of 1500 nm.
The input data used for the tests consist of unified and subsampled point clouds according to a minimum grid size of 5x5mm. Although the analyses performed focused on small samples, which would have allowed the use of denser and thus more detailed

clouds, it was still chosen to work on a "lightened" point cloud. This is to work on sections that are representative of a larger point cloud, such as a whole building. In fact, point clouds, once registered, are usually subsampled to reduce their computational weight and allow for better and more agile user management of the scan data, in the processes of navigation, querying, segmentation and classification, Scan-to-CAD and Scan-to-BIM. Therefore, sufficient resolution was chosen to discretize architectural detail but at the same time not overly dense. The choice to work on lightened portions did not compromise the critical-methodological aspects of the process. Actually, it allowed to work on more representative samples without triggering excessively time-consuming operations, at a stage of the research where the overriding goal is to define classes of superficial features.

In situ observations and detection on photographic documentation are in fact the primary step to reading the architectural surface, with which the classes of interest are identified and defined according to the purposes of analysis and based on the characteristics of the building under investigation. At an early stage, the different materials and conservation aspects visible on the exterior elevations were identified. The corresponding classes

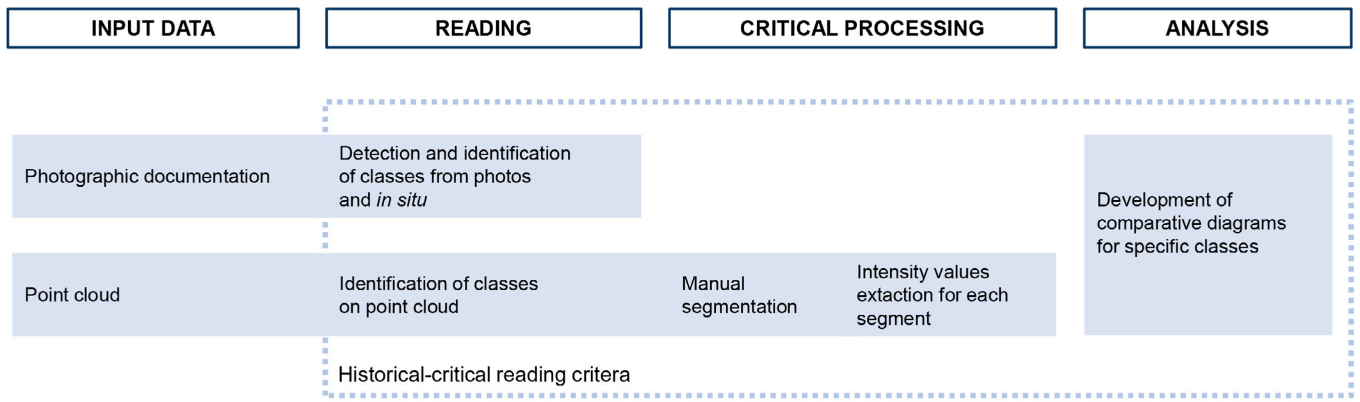


Fig. 6.05.

General workflow schema, highlighting the main research steps, the critical-interpretative process and the need for criteria.

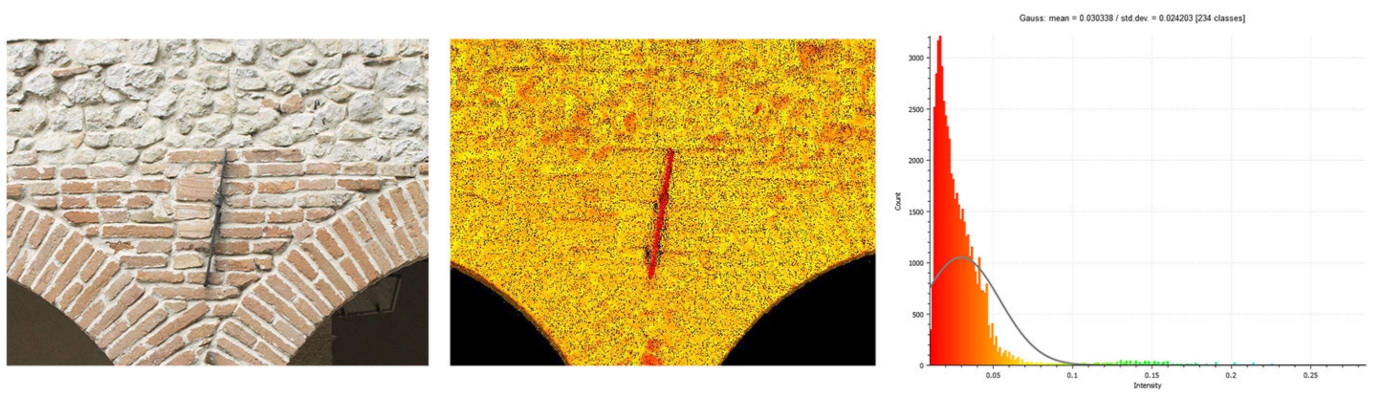


Fig. 6.06.

Comparative diagram for metal constraints of Former Monastery of St. Agostino in Verucchio dataset: photographic sample, point cloud extraction and intensity value distribution histogram.

were identified on the point cloud. Next, a manual segmentation of the various classes traceable on the point cloud was performed in order to generate multiple separate and homogeneous point clouds according to the different materials. Subsequently, the graph representing the intensity values of each segmented cloud was extracted. The graph is a histogram with the values of the reflectance data in the abscissa and the number of points in the ordinate. Superimposed on the histogram there is a Gaussian curve calculated on the histogram values (Fig. 6.05). Both segmentations and histogram extractions were executed thorough the open source software CloudCompare. As a result, comparative diagrams can be composed for each specific segmented class, consisting of the photographic sample of the investigated material, the corresponding portion of the point cloud, and the histogram of the distribution of intensity values for that class (Fig. 6.06). All these operations should be carried out taking into account the different factors that make each point cloud unique, such as the characteristics of the building under analysis, the instruments and methods used for the survey, the different boundary conditions, etc.

6.3.3 Interpretation process of comparative diagrams

The histogram showing the distribution of intensity values of a segmented sample is a useful tool for determining the reliability or unreliability of these values in describing a material or detecting decay pathologies that may be present. The following are some considerations on the interpretation of the graphs obtained, which may be valid in a general way.

Comparison of samples of different materials. A first indication can be gained by comparing histograms obtained from point clouds corresponding to different materials. If they display similar reflectivity ranges for different areas, then intensity values are not discriminating for these classes and cannot be used to perform additional analysis (e.g. algorithms application) to successfully detect materials or decay pathologies. On the contrary, if different reflectivity ranges for different areas are observed, then the intensity value is discriminating and reliable for these classes and it is possible to deepen the analysis.

Histogram distribution. Once it is established that different segmented homogeneous areas have different intensity ranges, the next step is the analysis of the intensity values distribution within the graph. If the reflectance values follow a normal distribution, it means, in general, that there is a valid correspondence between intensity and the segmented areas. In other words, the intensity values change according to materials. This, as demonstrated in the literature (Suchocki, 2020; Moyano et al., 2022), occurs in cases where the survey campaign was also carried out with the purpose of using the reflectance data as an indication for surface analysis purposes. In fact, as mentioned, the factors affecting the intensity of the laser beam on impact with the surveyed surface are many. Therefore, to obtain a homogeneous output data, the characteristics of each scan position in relation to the surveyed surface must be almost the same (incidence

angle of the laser beam, instrument-surface distance, etc.). Moreover, also the boundary conditions, such as atmospheric or general environmental conditions (temperature, humidity, etc.) should be as stable as possible during the survey activities.
In the case of reflectance values not following a normal distribution, there are two possible situations. The first one is that the point cloud under analysis is obtained by registration of scans with different characteristics, i.e., one or more factors determining the intensity value are changed among different scan positions. For example, among others: the boundary conditions changed during the survey, or the raw scans were not filtered in order to remove points on the surface hit at too sharp incidence angle. If, on the other hand, all these factors have been adequately controlled, then the trend of the graph is determined by discontinuities in the surface itself. For example, within the same sample, there may be additional material differences, not previously identified and therefore not segmented into two different clouds. Alternatively, some portions of the surface are affected by one or more degradation pathologies that change the laser response. In the case just described, intensity values can be considered valid, that is, they can provide insights into the surfaces under study, but they cannot be considered objective data in an absolute way. In fact, laser scanner reflectance is not a diagnostic data, consequently, it can be used as a valid support to visual investigation, but in case further study is needed, additional analysis with specific diagnostic instrumentation should be developed (Fig. 6.07).

6.3.4 Intensity value sampling for materials features

The surfaces of the exterior elevations of the Former Monastery of St. Agostino in Verucchio are in a good state of conservation, so the intensity value processing has been performed to highlight the material features. This allows to check whether there is a match between intensity and material and to compare samples of different materials to understand the significance of differences between graphs. A portion of the elevation characterized by material variety was then selected: curtain brick masonry, stone masonry, small stone elements (columns and keystone) plastered portions, metal ties, and wooden frames Fig. 6.08). Leica BLK360 was used in the survey.
Following the methodology previously described, a manual segmentation was performed in order to group points in clusters characterized by the same material. For each homogeneous area, the histogram of intensity values distribution was extracted. Observing the extracted histogram, it can be noted that different materials correspond to different intensity values responses. As expected, the trend of the metal graph differs more from the others. This has tendentially low reflectance values, while stone, stone masonry, and plaster have more similar curves. In addition, a non-normal Gaussian distribution can be observed in these three cases (Fig. 6.09).
According to the interpretation process, this irregularities may be due to scans with inhomogeneous characteristics or to physic characteristics of the surfaces. Isolating the sample referring to masonry wall, considering its good state of conservation, it is

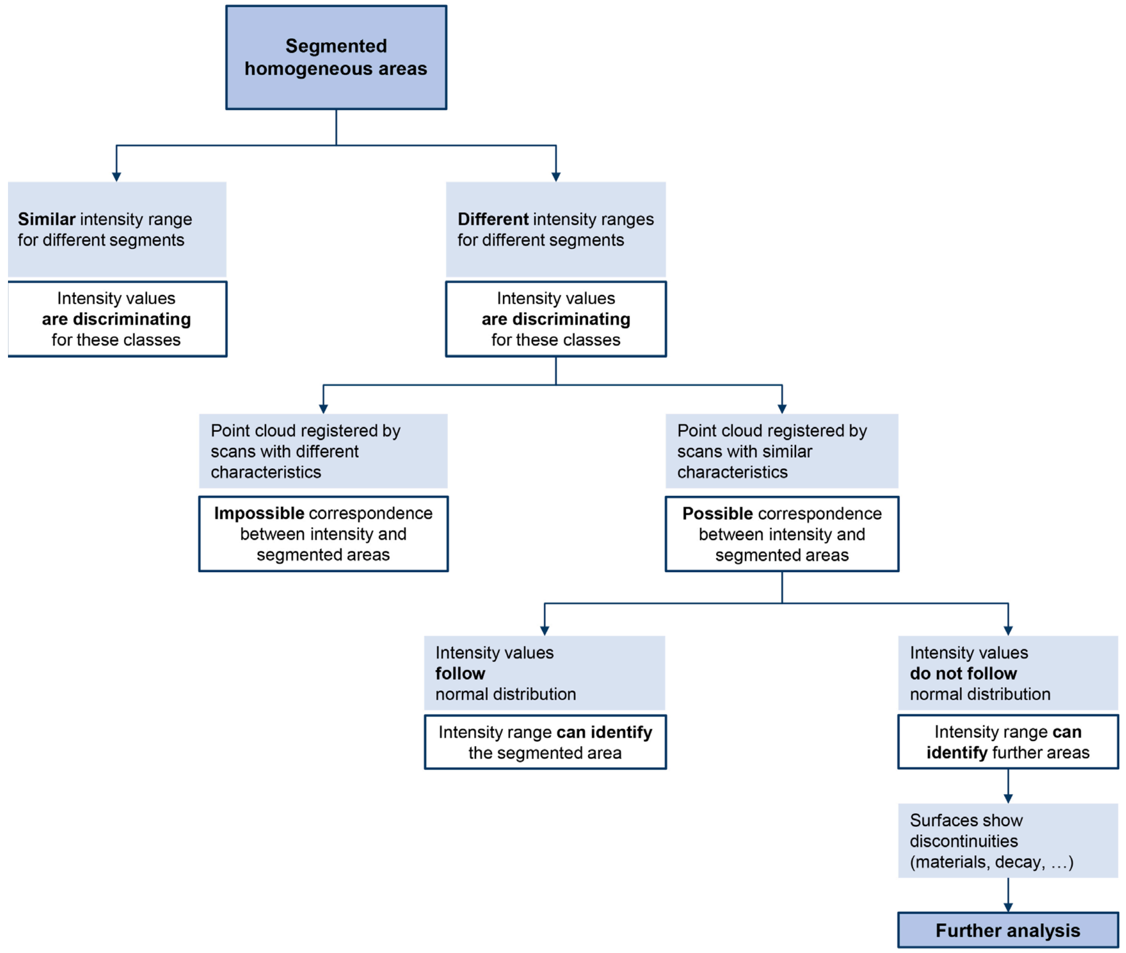


Fig. 6.07.
Interpretation process schema for the comparative diagrams elaborated.

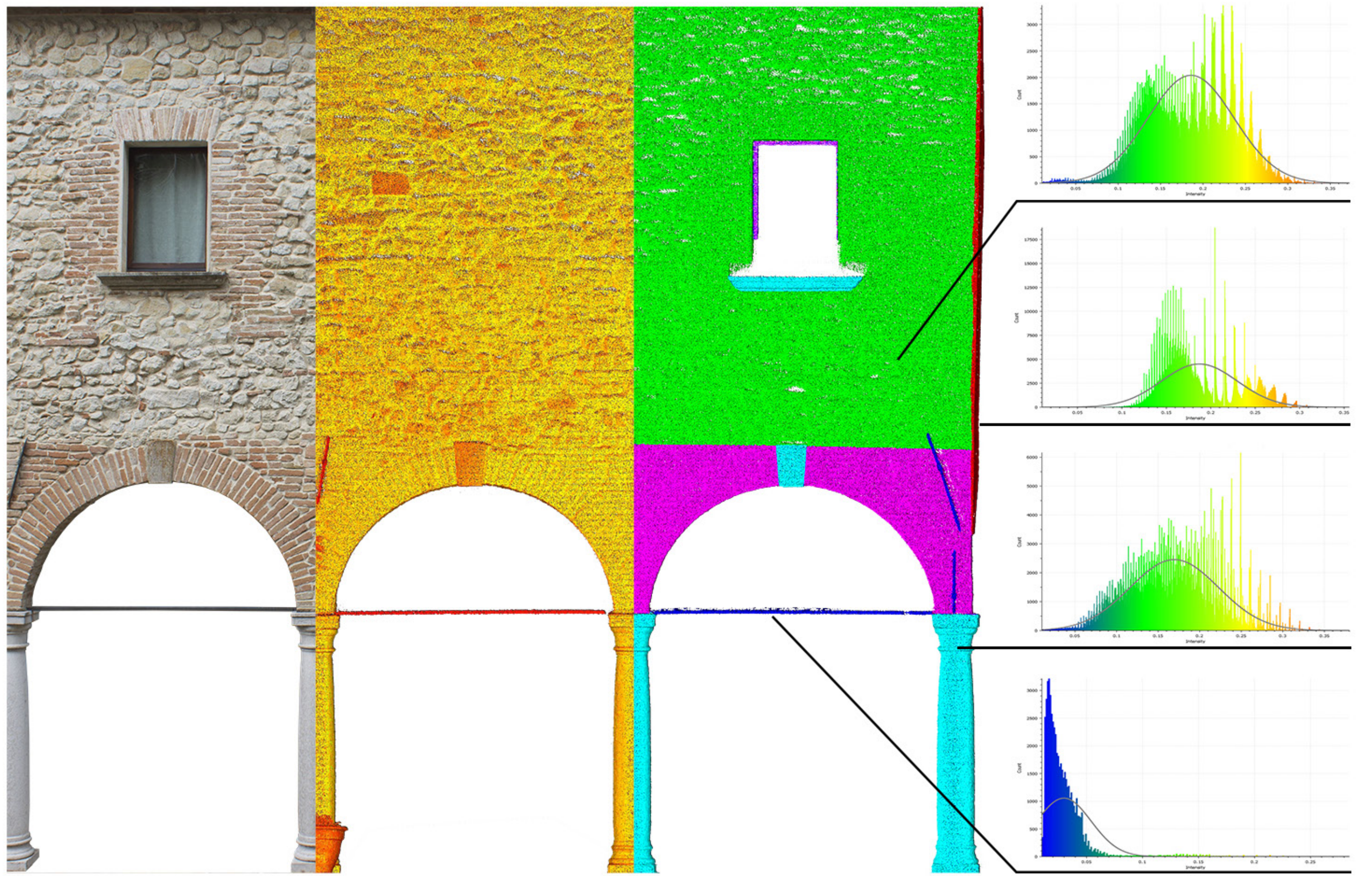
Fig. 6.08.
Detail of the materials of the external surfaces of the Former Monastery of St. Agostino in Verucchio.

reasonable to think that the non-normal distribution of the graph may be given by the material difference between bricks and mortar joints. The peaks of high values could correspond to the mortar, which is lighter than brick, and therefore more reflective (Fig. 6.10). Same consideration can be made for stone masonry. Both of these areas, indeed, are actually composed by a mixture of materials: brick-mortar and stone-mortar. The reasoning to be done regarding the “stone” class is different and takes into consideration the geometry of the elements themselves. The surface of the columns can be assimilated to a cylindrical volume in which the angles of incidence between the laser beam and the surface vary more than on a flat surface of the same area. Consequently, the intensity is less controllable and its variations, in this case, may result from this (Fig. 6.11).

The surfaces of the exterior elevations of St Margaret’s Church in Braemar, Scotland, although affected by some deterioration, mainly related to humidity, offered the opportunity to test the relevance of intensity data in the material analysis of masonry surfaces. The digital data from this case study provided the chance of analysing the reflectance data obtained from a phase-shift laser scanner, since a Z&F 5016C laser scanner was used in the survey. The construction technique employed in the building consists of local granite blocks and mortar joints. From an initial observation of the reflectance data displayed in false colours, a different response appears for the two components. In fact, sampling a portion of masonry, in the extracted histogram it can be observed a non-normal Gaussian distribution, suggesting two peaks, corresponding

Fig. 6.09.

Former Monastery of St. Agostino in Verucchio. From visual inspection to intensity value extraction, thorough manual segmentation. Homogeneous areas according to materials allow to analyse the reflectance response for these samples. Stone masonry (green), paster (red), stone (cyan) and metal (blue) are displayed.



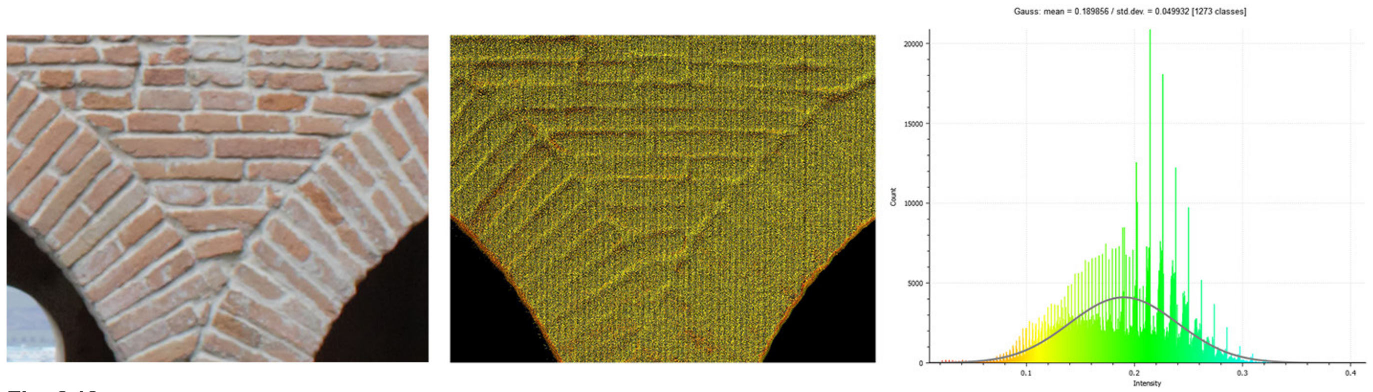


Fig. 6.10.

Former Monastery of St. Agostino in Verucchio. Comparative diagram for masonry wall. Histogram irregularities may be given by the different reflectance response between bricks and mortar joints.

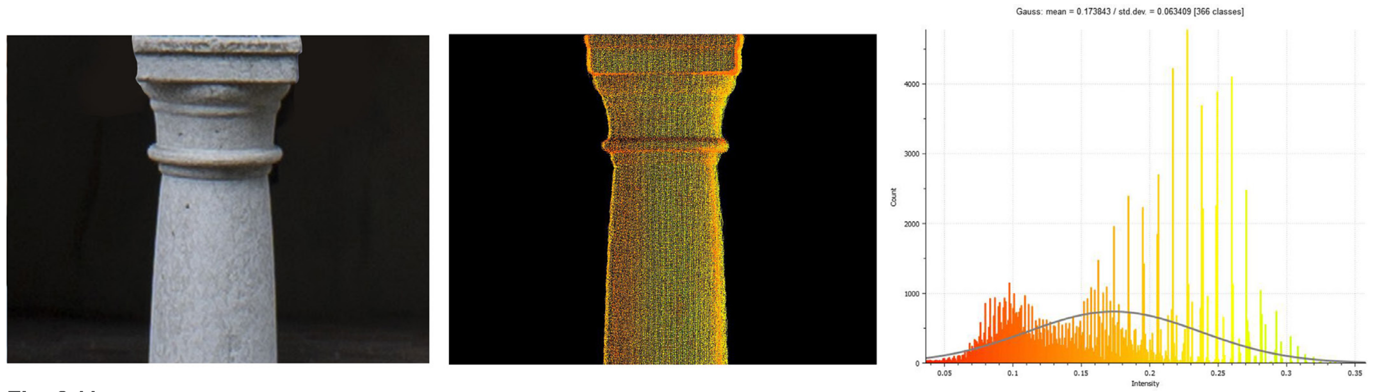


Fig. 6.11.

Former Monastery of St. Agostino in Verucchio. Comparative diagram for stone. Histogram irregularities may be given by the geometry of the surface surveyed.

Fig. 6.12.

St Margaret’s Church in Braemar. Comparative diagram for stone masonry. Histogram irregularities may be given by the different reflectance response between ashlars and mortar joints.

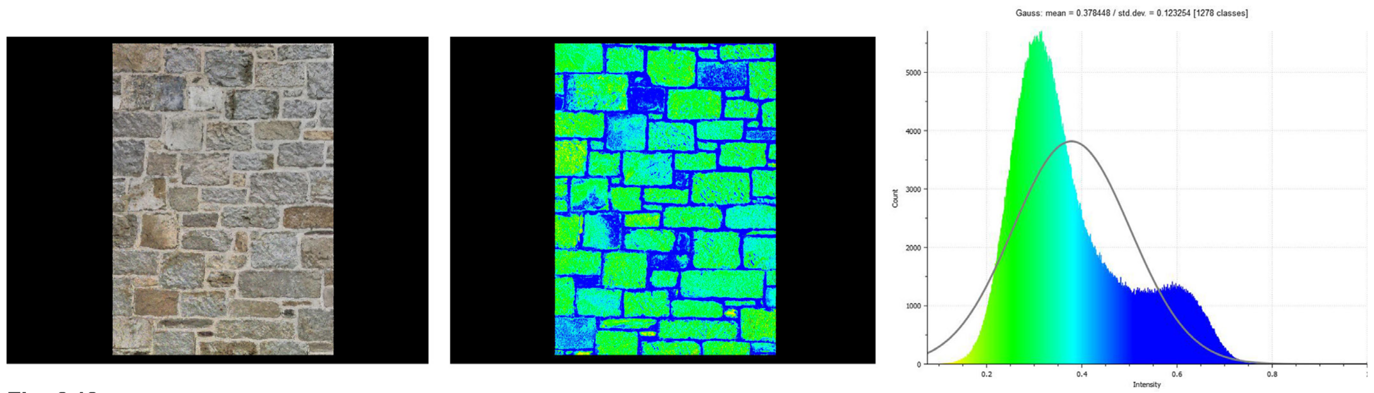


Fig. 6.13.

St Margaret’s Church in Braemar. Comparative diagram for stone masonry. Intensity display range between 0 and 0.51, highlighting mortar joints in blue.

to the two materials (Fig. 6.12). Once the minimum value between the two peaks has been identified, corresponding to an intensity of 0.51, it is possible to narrow the display range of the colour scale from 0 to that value. This clearly highlights the joints, and based on these intervals, for this sample, it is possible to segment the point cloud in order to separate stone ashlars from mortar joints (Fig. 6.13).

6.3.5 Intensity value sampling for state of conservation

In order to study how deterioration can affect reflectance data, several walls of the Rocca Possente in Stellata were taken into consideration. First, a portion corresponding to the north side of the staircase that gives access to the building was selected, characterized by a homogeneous brick masonry surface that, upon visual analysis was significantly affected by the presence of various degradation pathologies, such as patina and biological crusts, areas with efflorescence and different deposits. Therefore, the expected result is that intensity ranges are significantly affected by the state of surface conservation. The graphs, then, through anomalies in their distribution, make these surface alterations explicit. In this case study, since the same surface was surveyed with both laser scanners Leica BLK360 and Leica C10, it is possible to compare the results obtained with the two sensors and observe the difference in reflectance value is between the points of the two clouds. For the selected sample, comparing the results obtained by the two different instruments, a non-normal distribution is observed in both graphs (Fig. 6.14 and Fig. 6.15).

This indicates that the intensity data of both instruments are affected by surface discontinuities, in this case probably due to the degradations. The ranges both show an imbalance toward the lower values of the same. However, the graph of the point cloud obtained with C10, in addition to having higher numerical intensity values when compared with those of BLK360, shows more evident trends that can be decomposed into subintervals. By setting minimum and maximum reflectance values (based on the ranges identified in the graph) for the colour scale visualization, it becomes possible to highlight points within that interval (Balzani et al., 2017). This allows for a visual verification of correspondence with surface anomalies, specifically, as mentioned, degradations. (Fig. 6.16).

Another sample taken from a portion of the basement of the masonry, affected by different degradations of a biological nature, was examined. From the histogram analysis, it was possible to impose a viewing range that would highlight a specific degradation class, i.e. the biological patina (Fig. 6.17). In order to verify whether the points within this range belong significantly to that specific class or not, following steps are developed. First, leveraging the ranges imposed, the sample cloud was segmented into two: one part inside the interval and one outside (Wu et al., 2025). The former should include parts of the wall mainly affected by the searched decay, the latter should not. Second, a further segmentation of both clouds was performed on the basis of the RGB values, which could be considered sufficiently reliable because (I) they were obtained using the methodology described in paragraph 6.2.3 and (II) for the

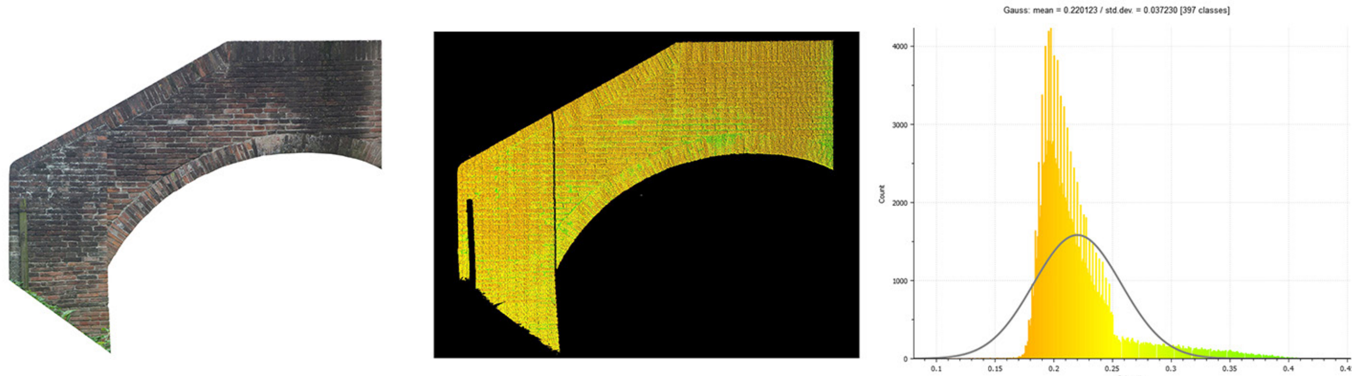


Fig. 6.14.

Comparative diagram for a masonry wall of Rocca Possente in Stellata, surveyed by a Leica Scan Station C10 laser scanner. The non-normal distribution of the graph may be given by decay pathologies of the surface.

Fig. 6.15.

Comparative diagram for a masonry wall of Rocca Possente in Stellata, surveyed by Leica BLK360 laser scanner. The non-normal distribution of the graph may be given by decay pathologies of the surface.

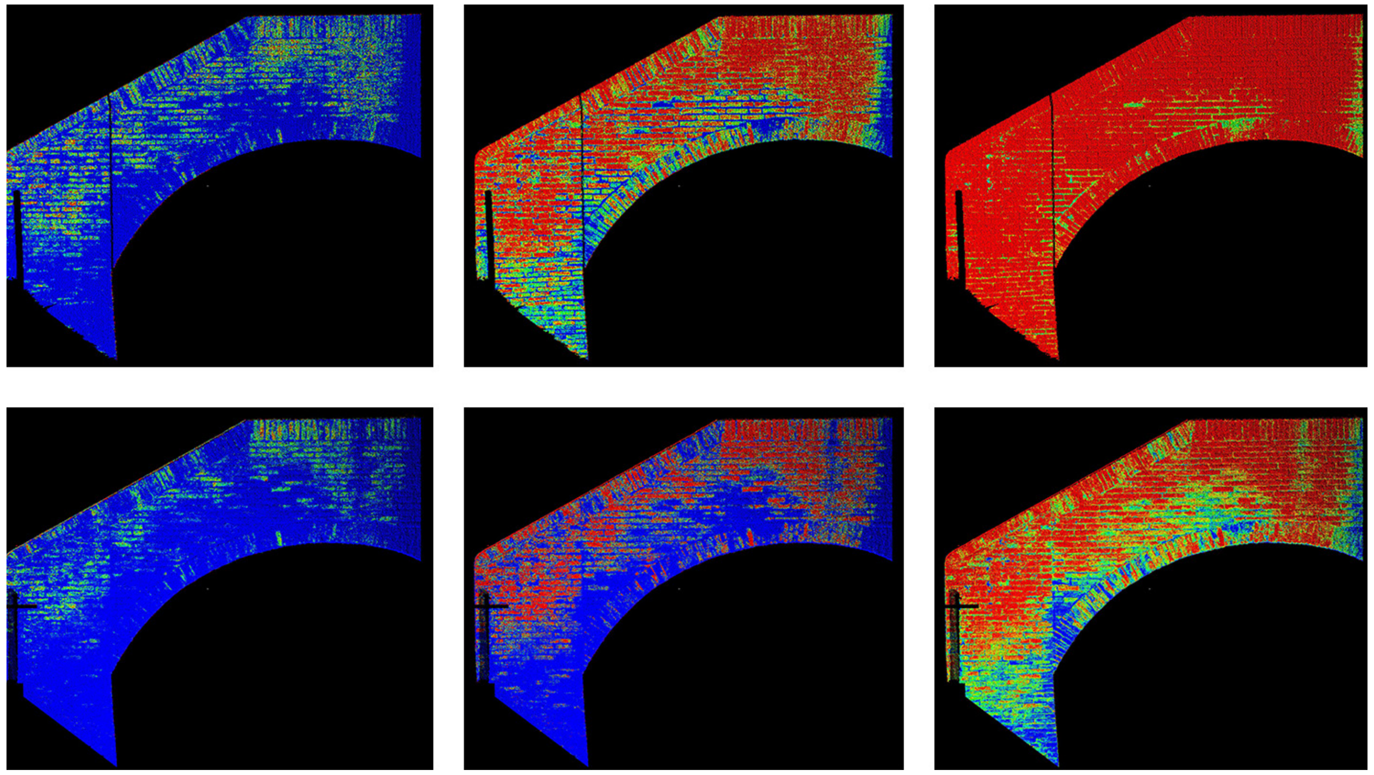


Fig. 6.16.

Visualizations of different intensity ranges. Leica C10 (above): ranges 0.18-0.20, 0.20-0.25, 0.25-0.45. Leica BLK360 (below): ranges 0.06-0.10, 0.10-0.12, 0.11-0.20.

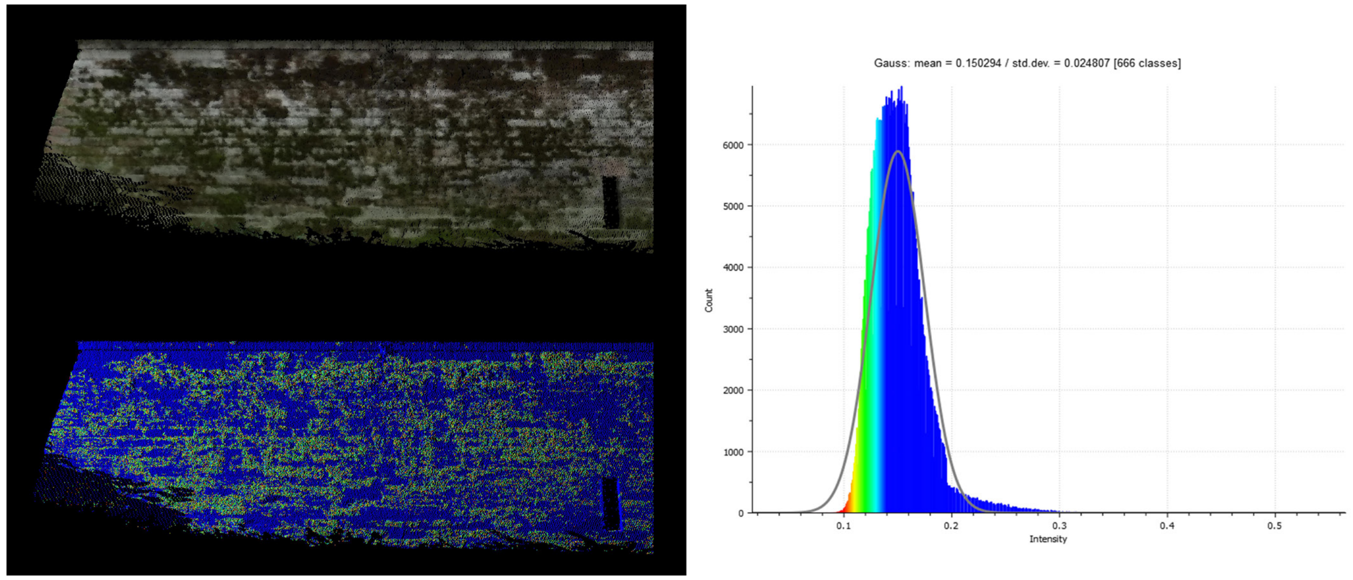


Fig. 6.17.

Comparative diagram for the masonry wall in the basement of the Rocca Possente. Visualization of intensity values range between 0.10 and 0.14, highlighting some decay pathologies, mainly biological crust.

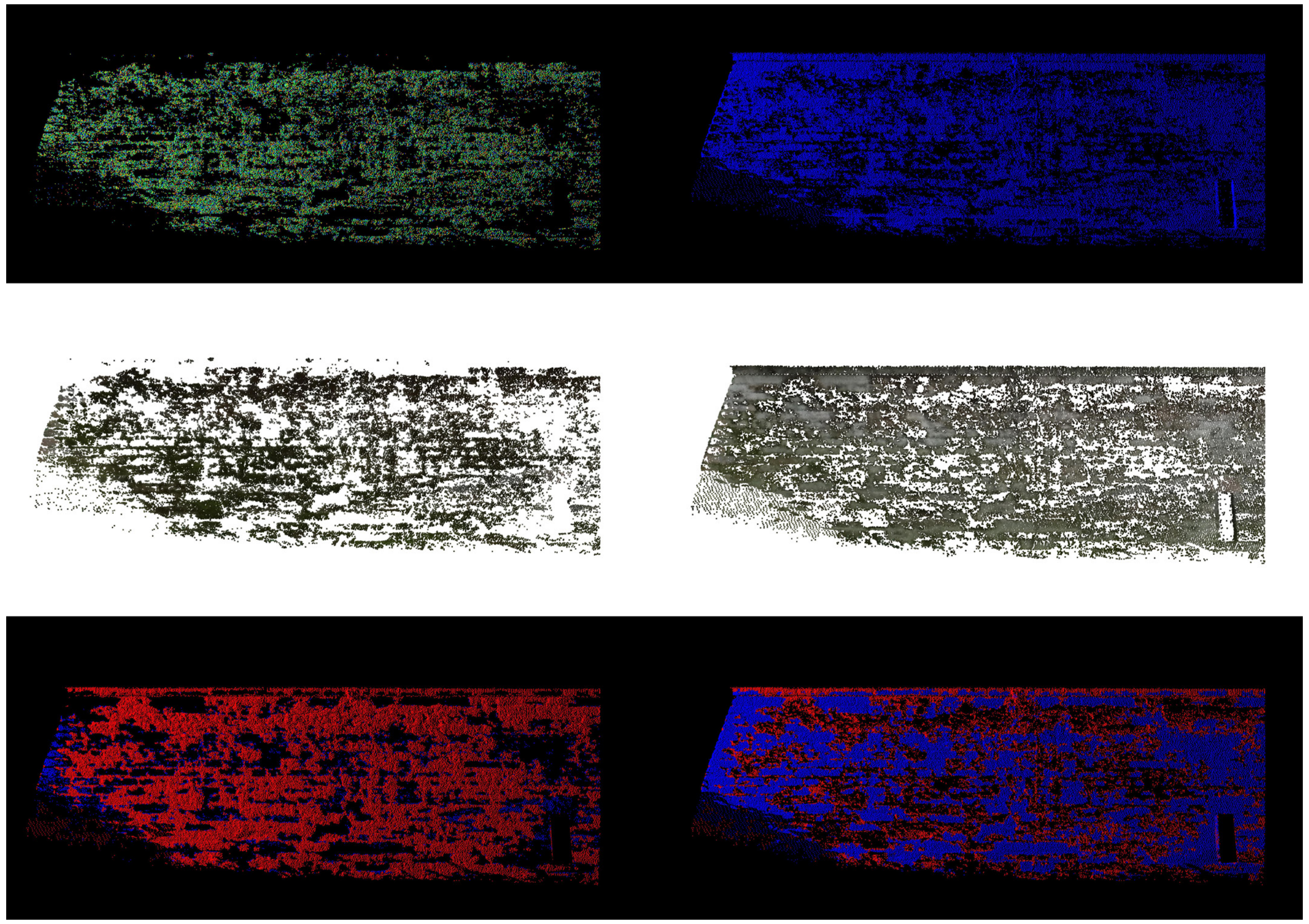


Fig. 6.18.

Point cloud segmentation according to intensity value ranges for surfaces with moss presence in the basement of Rocca Possente. Range between 0.10 and 0.14 (top-left) and outside 0.10 and 0.14 (top-right); RGB visualization of the two clouds (middle-left and middle-right); false colours visualization for moss presence in the point cloud with intensity range between 0.10 and 0.14 (bottom-left) and outside 0.10 and 0.14 (bottom-right), degraded areas are red, non-degraded in blue.

sample under examination they were easily associated with the searched class. On the clouds obtained it is thus possible to calculate the points with and without degradation, displaying them in “false” colours for immediate perception (Fig. 6.18). In numerical terms, the percentage of points with degradation present in the range (true positives) is 83.25%, the percentage of points with degradation excluded from the range (false negatives) is 36.66%, resulting in an overall reliability of 73.30%.

6.3.6 Outcomes

Experiments emonstrate that the link between intensity value and the characteristics of the surfaces can be considered reliable in many situations. Typically, intensity variations are liked to different materials. Depending on the sensors of the laser scanner tools, these differences can be more or less evident. In general, metal and darker materials have low intensity values, distinguishable quite clearly on point cloud. The same consideration about colour can be made for degradation morphologies. In these situations even a segmentation performed relying only in intensity value can lead to satisfactory results. This is not a generally valid principle, since other materials show slight differences in reflectance, and intensity value alone cannot be sufficient.

In general, followed methodology allowed accurate assessment of homogeneous samples per material. Extrapolating the histograms of the intensity values of the selected points, it is possible to interpret the data, verifying whether or not there are discontinuities or anomalies in the trend of the graph. Possible incongruities must be further investigated, as may be caused by degradations altering the value of the reflected signal.

In fact, working on avaiable databases, the critical-interpretative aspect involves not “only” the reading phase with regard to the condition of the analysis surfaces and context, as well as their history, but also the interpretation of the digital data themselves. It must be considered that most of the available data are the result of surveys carried out for purposes that did not include the analysis of surfaces supported by the intensity data, so many of the factors that can influence this radiometric feature were not taken into account during fieldwork. This is one of the several issues that are still open, hence extensive experimentation is not always possible. The intensity values of many areas can therefore be not consistent for the assessment purposes. If these analyses are required, altered data should be excluded from the sample before extracting the histogram. This general remark can be extended to other case studies; for this kind of analysis it might be more appropriate to work with single, non-unified scans, with data not “contaminated” by data from other scan-stations, since the intensity also depends on the angle of incidence of the laser beam and the distance of the instrument from the surface.

6.4 Grounding a methodological approach for intensity value analysis through *ad hoc* acquisitions

6.4.1 Analysing intensity variations: test materials and acquisition methodology

Having verified, also following the experiments described in the previous section, that the intensity value is determined by the different materials and state of conservation of the surfaces, the objective of the tests described in this section is to study the variation in relation to:

- geometric factors, such as the distance between the scan position and the surveyed surface and the angle of incidence of the laser beam,
- surface conditions, such as surface humidity and temperature,
- colour and type of painted coating.

Tests were performed on intensity value sampled on *ad hoc* surveyed database (Suchocki et al., 2020). By scanning surfaces with different time-of-flight laser scanning tools, each characterized by different wavelengths, it was also possible to compare the different responses of the same material through different instruments. The used scanners are:

- Scan Station Leica C10 - wavelength 532 nm (visible),
- Scan Station Leica P40 - wavelength 1550 nm (invisible),
- Leica BLK360 G1 - wavelength 830 nm (invisible).

The surface examined belongs to an external wall of the Department of Architecture at the University of Ferrara, characterized by a fair variety of materials concentrated in a limited space (Fig. 6.19). There are three types of surfaces: brickwork and mortar joints, plaster, and plaster with paint. A 50x50 cm mobile sample of cement mortar with white, black, red, green, and blue coloured strips was also added. The colouring was applied using primers and paints with varying degrees of dilution, in order to assess the extent to which a covering layer of paint can be perceived as a distinct material. and to assess how much the point cloud of the surface, attempting to replicate a coloured paste mortar. The pigments used are “Zenacolor” acrylics, selecting colours that most closely reflect the RGB reflectance value in order to facilitate the interpretation of the data acquired, and possible correlation (Fig. 6.20).

Although these were *ad hoc* tests, it should be noted that the measurements were not taken in a laboratory, i.e., in an isolated and controlled environment. It was not possible to eliminate the surrounding factors that, albeit to a minor extent, may affect the reflectance data. All in all, these conditions are also present in a standard survey campaign, so the test considered to measuring and recording certain values, such as the environmental temperature (around 30°C), to verify their homogeneity between the various scans.

To analyse any intensity variation in relation to the distance and angle of incidence of the laser beam with respect to the surface, a grid was set up on which the instruments were positioned. These were placed 6 m and 12 m from the wall in a perpendicular

Fig. 6.19.

Portion of external wall surveyed for reflectance testing, with indication of isolated sample areas for histogram analysis: masonry (1), plaster (2), and paint (3). Left: photographic image; right: point cloud obtained with Leica C10 Scan Station.

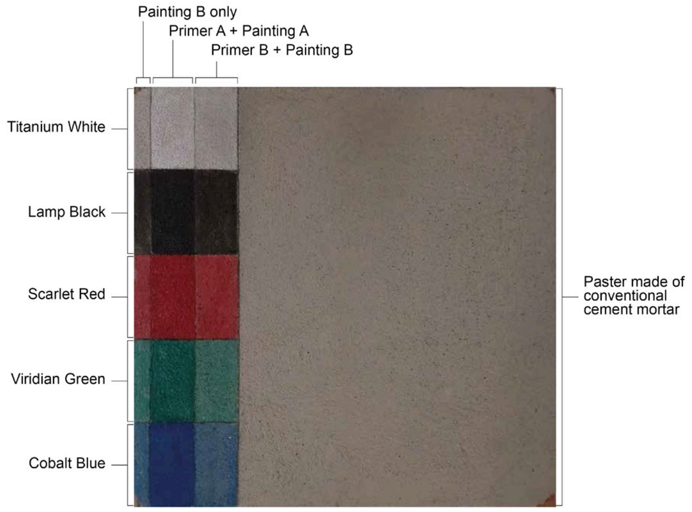


Fig. 6.20.

50x50cm plaster sample showing the techniques used for the painted strip. Base A: vinyl glue and water in a 1:1 ratio; base B: vinyl glue and water in a 1:4 ratio; paint A: pigment and water in a 1:1 ratio; paint B: pigment and water in a 1:4 ratio.

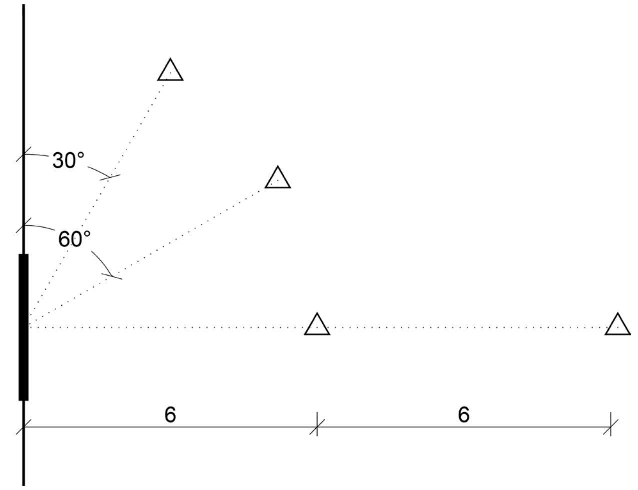


Fig. 6.21.

Layout of laser scan positions in relation to the surface area of the material samples analysed.

Surface	11:00-13:00	17:00	Dry	Wet
Brick Masonry	29,8°	44,7°	8,4%	28,1%
Plaster	28,4°	41,6°	15,7%	35,2%
Painting	28,0°	45,4°	17,1%	37,0%
Plaster – sample 50x50cm	28,4°	41,6°	15,0%	30,0%

Tab. 6.02.

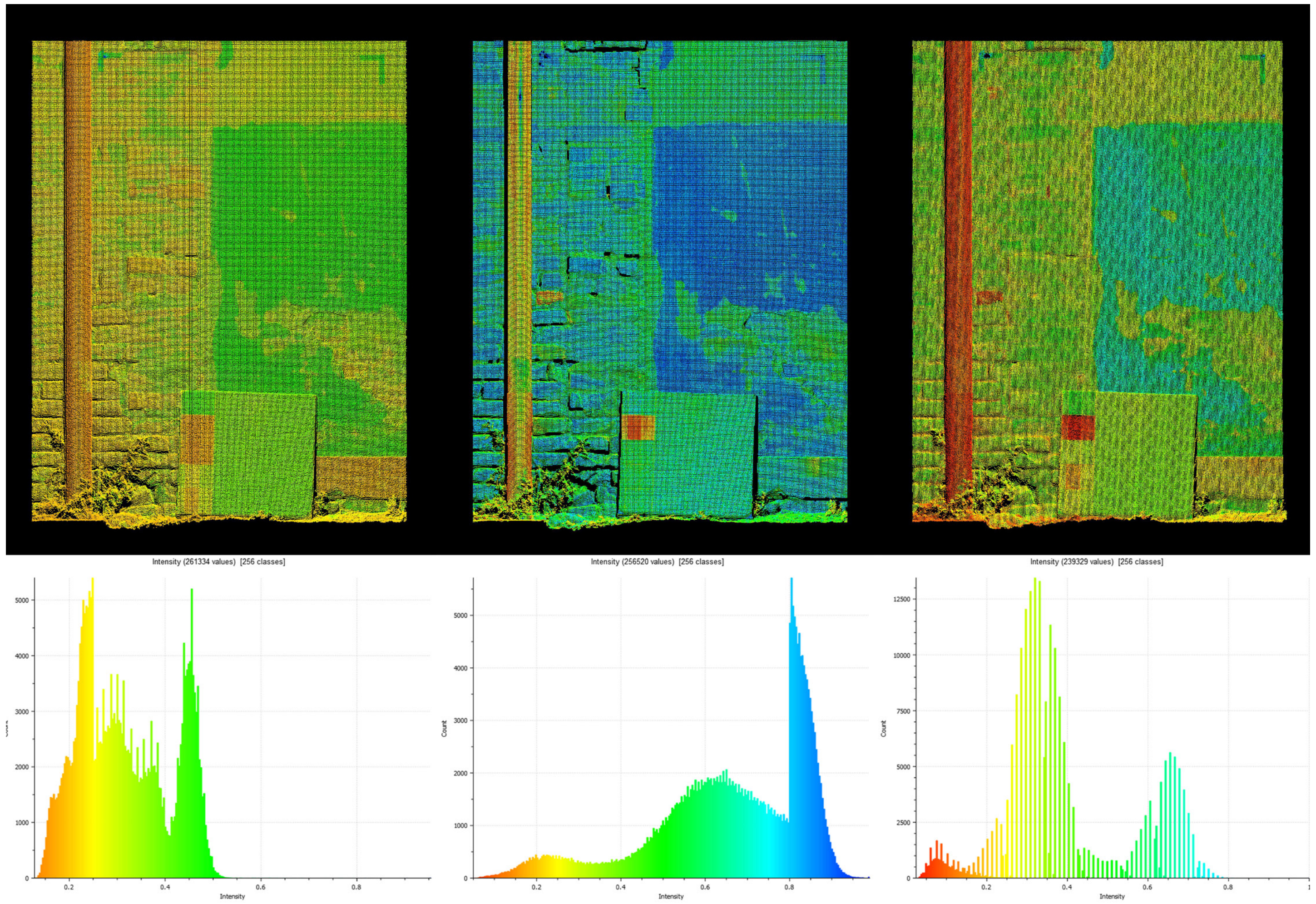
Temperature and relative humidity values measured for different materials: the former measured at two different times (11:00-13:00 and 17:00), the latter before and after wetting the surface by imbibition.

position, and 6 m away with an inclination of 60° and 30° (Fig. 6.21).
To analyse any intensity variation in relation to different surface temperatures, an initial cycle of acquisitions was performed between 11:00 a.m. and 1:00 p.m., and a further cycle of acquisitions was performed after 5:00 p.m. In this way, the surface temperature rose due to exposure to sunlight throughout the day. Between the morning and afternoon scans, an increase in environmental temperature of only 2°C was recorded, which was considered to have no influence on the data acquired.
Similarly, two acquisition cycles were performed to analyse any variation in intensity in relation to surface humidity: one with "dry" surfaces, and a second one after saturating the surfaces by wetting them with water and waiting a few minutes to avoid percolation and reflective areas. The relative humidity was measured at different points for each cycle and then the average for each material was calculated. As for the 50x50cm plaster sample, this was acquired both outdoors and indoors, and the humidity values taken into consideration are those from the indoor acquisitions. Tab. 6.02 shows the temperature and humidity values measured.

6.4.2 Data processing and elaboration of the comparison matrix

The scans acquired as described in the previous paragraph were recorded in a common local reference system using a cloud-to-cloud procedure, considering the substantial static nature of the surrounding scene. A preliminary consideration that can be made is that all instruments show trends in overall intensity values with different peaks, which correspond closely to the different materials. (Fig. 6.22). Subsequently, a significant sample was segmented for each material, subsampled in order to make them as uniform as possible, and a representative histogram of intensity values was extracted (Suchocki & Katzer, 2018). The histogram shows the intensity values on the x-axis and the number of observations on the y-axis.
Even if it is possible to standardize datasets even more, reducing the effect of the incidence angle and distance variations on the intensity value, in this investigation data were kept rough, since these corrections are not usually performed in a common workflow of survey data processing. However, two approaches for the correction of intensity data can be performed: data-driven and model-driven correction (Tan & Cheng, 2016).
Once the histograms had been extracted, comparison matrices were created for each material, showing the different scan stations on the x-axis with their respective characteristics of distance, angle of incidence, and sample humidity, and the different laser scanners on the y-axis (Fig. 6.23, 6.24, 6.25, 6.26). These matrices provide an overview of the behaviour of reflectance values in relation to the different characteristics of the scans. A first observation that can be made is that, as expected, longer wavelengths emitted by the instruments correspond to a higher intensity of the received signal. In general, for all materials and conditions tested, the trends in the graphs of the C10 and BLK360 laser scanners are similar to each other, while that of the P40 detects values distributed over a wider range. It is clear that very light surfaces, in this case white-painted plaster, reflect a lot and therefore the reflectance acquired by all instruments has higher values. Regular surfaces, such as plaster, have a fairly regular distribution of graphs. On the contrary, irregular surfaces, such as masonry, have more complex graphs. This is because masonry is actually composed of two distinct materials: brick and mortar joints. This distinction is most evident in data acquired with the Leica C10 laser scanner, whose point cloud allows the two materials to be visualised more clearly by narrowing the intensity-value colour scale, using the same methodology described in paragraph 6.3.7 (Fig. 6.27). Based on these preliminary observations, specific topics can be selected for investigation, and graphs can be generated by superimposing two or more scans.
It should be noted that the P40 graphs show a completely anomalous peak at values of 0.80. Given that this phenomenon is present in all scans and is not reflected in any anomalies in the surveyed surfaces, it was assumed to be an instrumental error and eliminated for processing. Similarly, and using the same criteria, the sudden jumps towards zero in some of the BLK360 graphs were considered instrumental errors and, for the processing of specific graphs, values were inserted by interpolating the adjacent ones.

Fig. 6.22.
Point cloud of the sample masonry surveyed with Leica C10 (left), P40 (centre), and BLK360 (right) laser scanners. First row: point clouds; second row: histograms of intensity values for the entire sample.



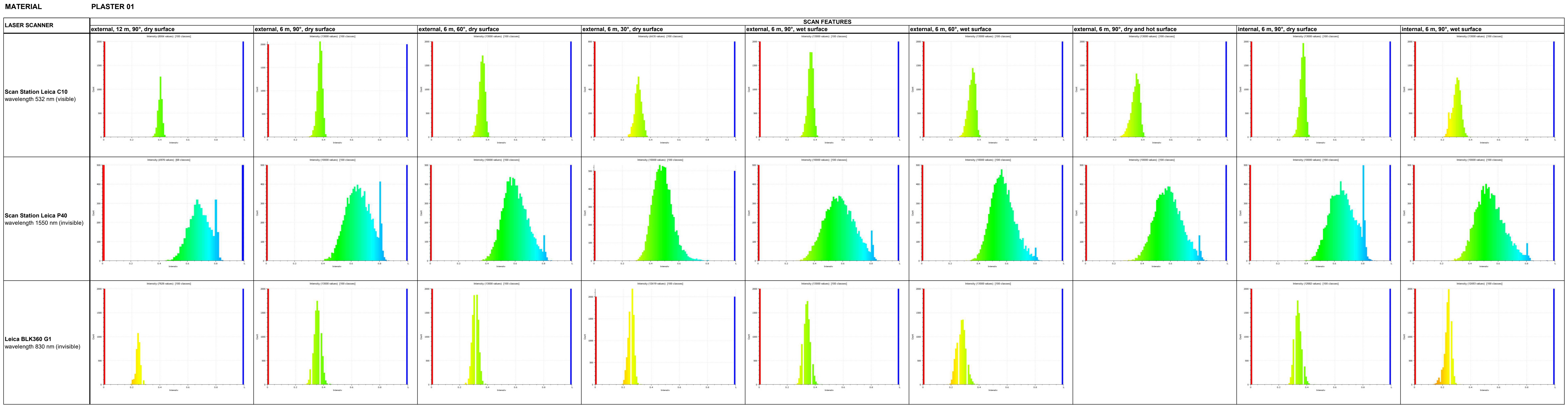


Fig. 6.23.

Comparison matrix for the 50x50cm plaster sample. The x-axis shows the different scan stations with their respective characteristics of distance, angle of incidence, and sample humidity; the y-axis shows the different laser scanner instruments (Leica C10, P40, and BLK360).

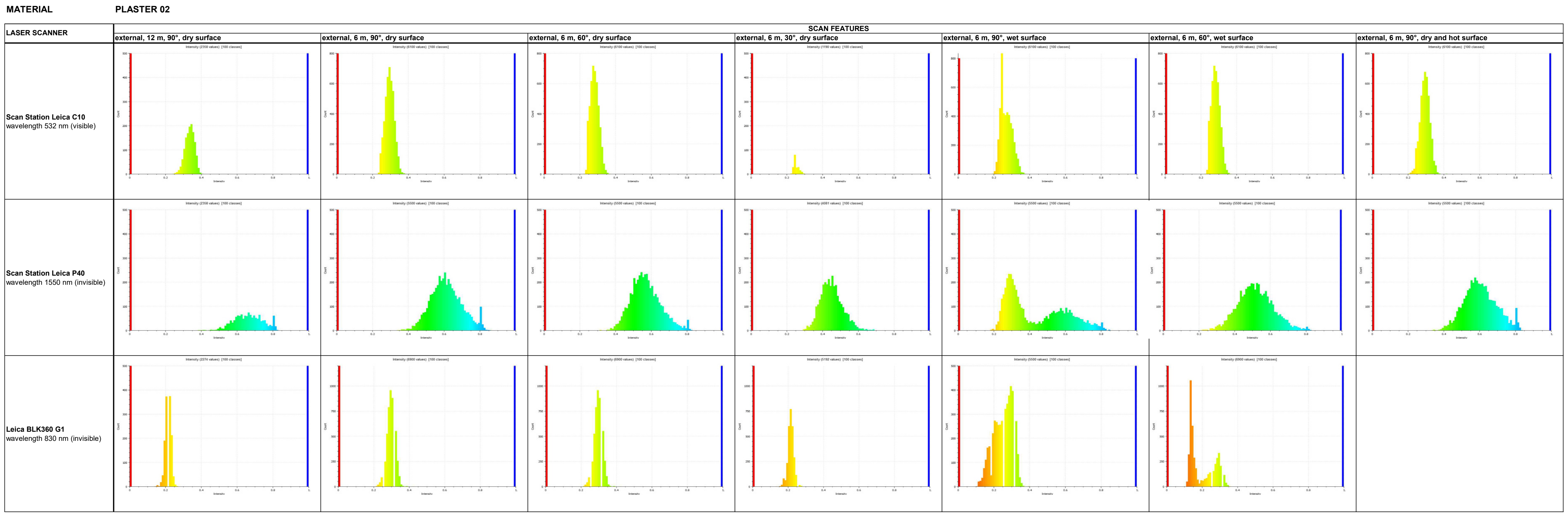


Fig. 6.24.

Comparison matrix for the exterior plaster sample. The x-axis shows the different scan stations with their respective characteristics of distance, angle of incidence, and sample humidity; the y-axis shows the different laser scanner instruments (Leica C10, P40, and BLK360).

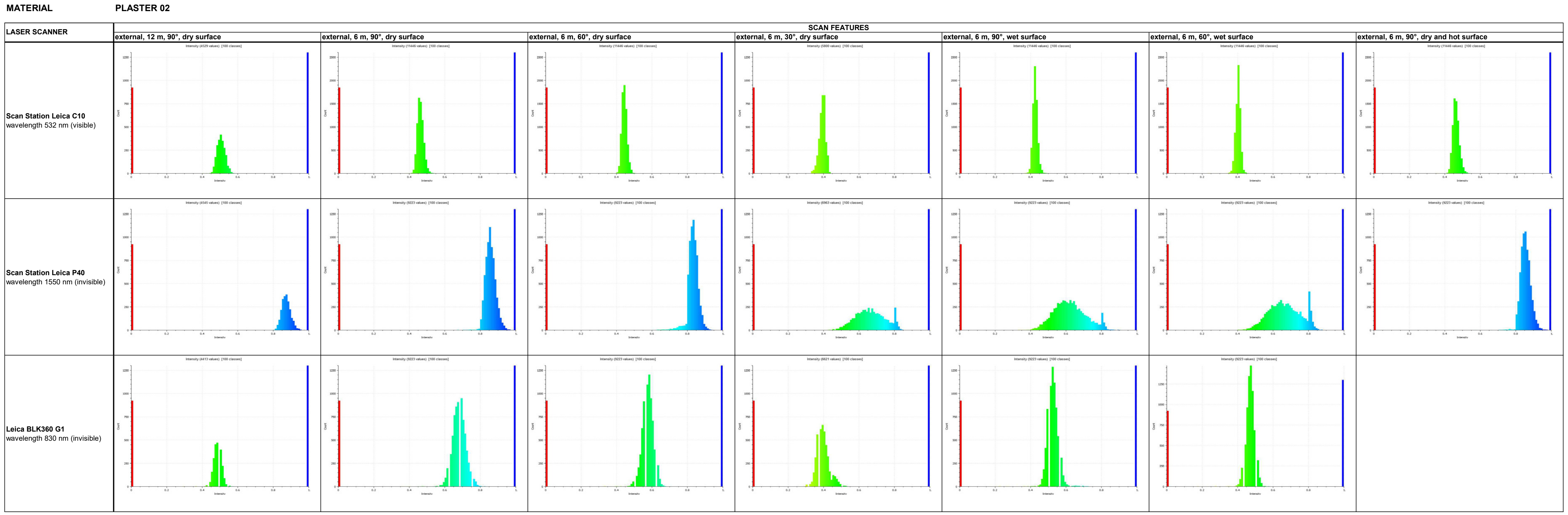


Fig. 6.25.

Comparison matrix for the painted exterior plaster sample. The x-axis shows the different scan stations with their respective characteristics of distance, angle of incidence, and sample humidity; the y-axis shows the different laser scanner instruments (Leica C10, P40, and BLK360).

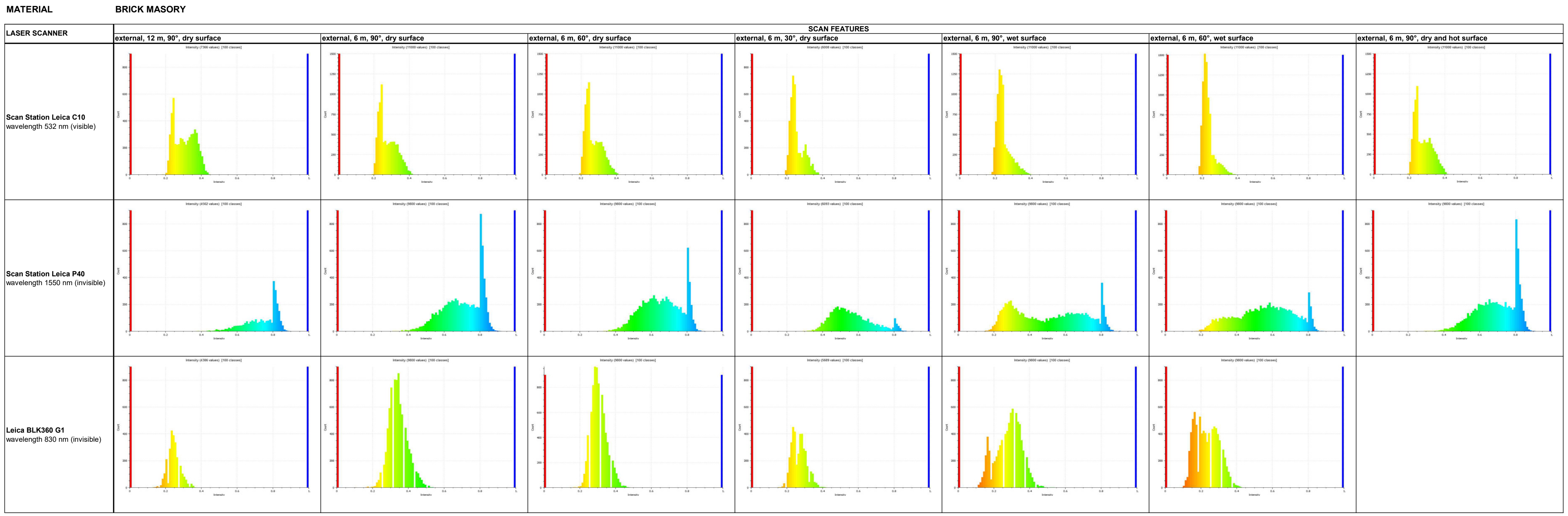
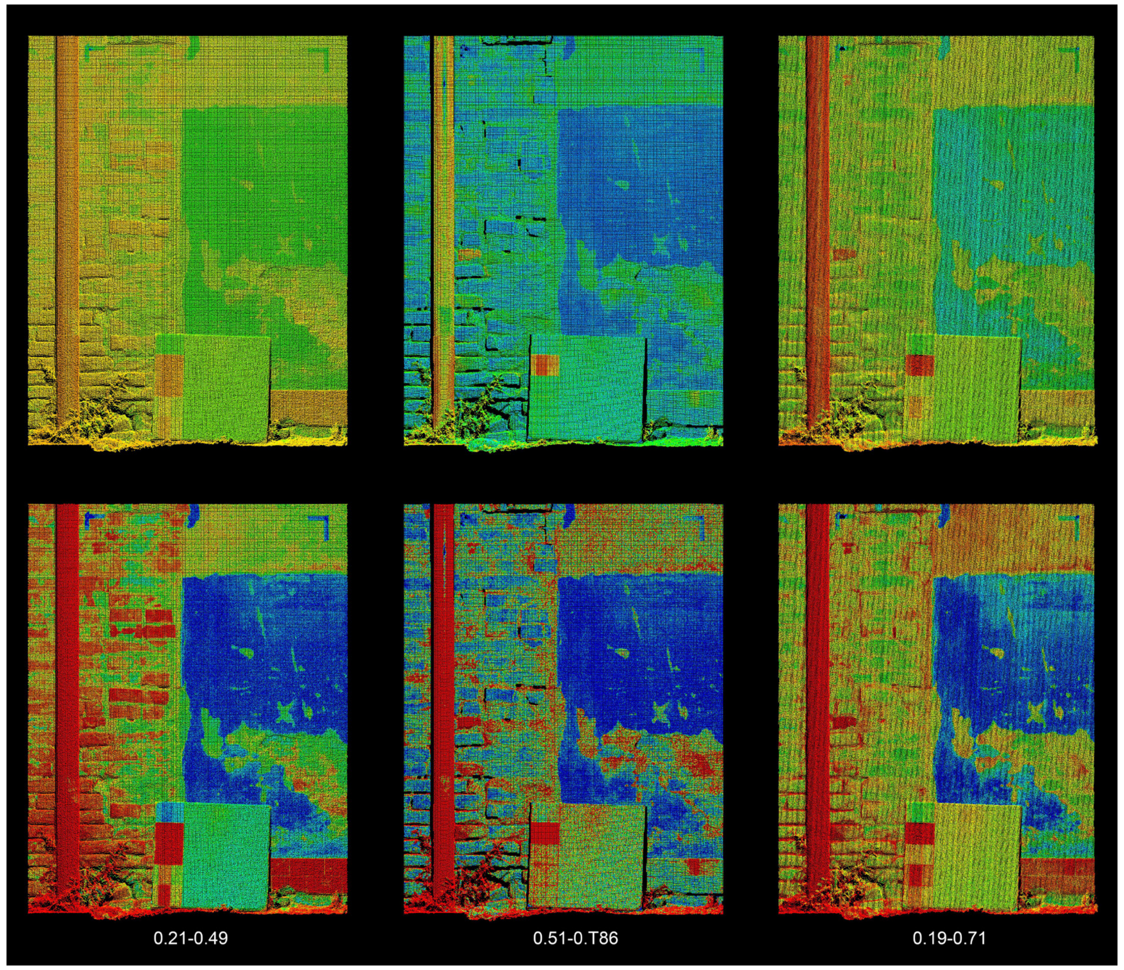


Fig. 6.26.

Comparison matrix for the brick masonry sample. The x-axis shows the different scan stations with their respective characteristics of distance, angle of incidence, and sample humidity; the y-axis shows the different laser scanner instruments (Leica C10, P40, and BLK360).

Fig. 6.27.

Point cloud of the sample wall surveyed with Leica C10 (left), P40 (middle) and BLK360 (right) laser scanners. First row original colour scale, second row visualization of intensity range between specific values highlighting the difference between different materials, such as bricks and mortar.



6.4.3 Geometric factors: distance and angle of incidence

To evaluate the variation in intensity values recorded by the different instruments as the angle of incidence between the laser beam and the detected surface varied, the graphs obtained from the frontal scan (90°) and the accidental scans (60° and 30°) were superimposed. This operation was performed for each material: 50x50cm plaster sample, exterior plaster, painted plaster, and brick masonry (Fig. 6.28, 6.29, 6.30, 6.31). In all cases, there is a decrease in values as the angle decreases, generally not with a linear but increasing trend, as shown by the delta variations between the peaks of the values (Tables 6.3, 6.4, 6.5, 6.6). The exception is brick masonry, where, probably due to the greater roughness of the surface and the difference in material between brick and mortar joint, the ratio between the displacement of the peaks for the BLK360 is the inverse of what usually occurs, while for the C10 there are no substantial differences between the different scan positions (Tab. 6.05).

In general, for positions with angles of 90° and 60°, given both the small size of the variation deltas and the large overlap area of the Gaussian bell curves of the values, the data from these scans can be considered comparable. This is more valid for the C10 and P40 laser scanners, while the BLK360 tends to be more affected by angular variation. These differences are accentuated with very light surfaces, such as painted plaster (Fig. 6.30).

Regarding the painted plaster sample surveyed by the P40 laser scanner, it should be noted that for the 90° and 60° scans, the reflectance values are very high (>0.80) and the bells are narrower than in other situations surveyed dy this instrument. Further investigation is needed to understand how to interpret this anomaly, whether it is caused by the instrumental error described in the previous paragraph or whether it is actually caused by the characteristics of the material. Therefore, the graphs have not been considered at this stage.

With regard to the variation in intensity values recorded by the different instruments based on the distance from the surface surveyed, there is substantial equivalence between the values obtained with the C10 and P40 laser scanners, while the BLK360 tends to be more affected by distance. An example is shown for the 50x50cm plaster sample, surveyed at a distance of 6m and 12m. Looking at the graphs, it can be seen that the BLK360 scan shows a significant decrease in the peak value (Fig. 6.32). This is probably related to the shorter range of the instrument, even though the distance is largely within the measurement range.

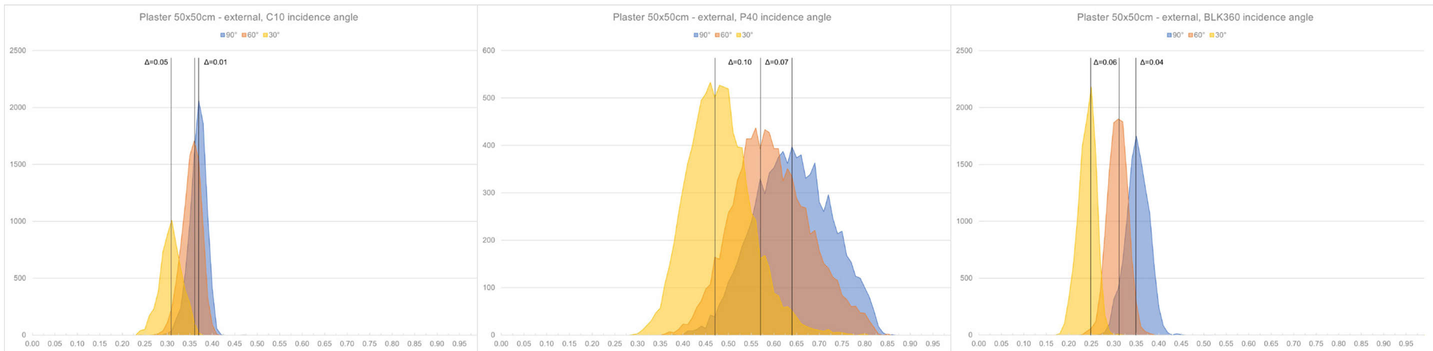


Fig. 6.28.

Sample of plaster 50x50cm; histograms for studying the variation in reflectance values in relation to the angle of incidence for the different laser scanner instruments: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those surveyed with a 90° angle, in orange 60° and in yellow 30°.

Tool	Δ 90° - 60°	Δ 60° - 30°	ratio
C10	0,01	0,04	1:4
P40	0,07	0,10	2:3
BLK360	0,04	0,06	2:3

Tab. 6.03.

Sample of plaster 50x50cm; delta variation between the peaks of the intensity values of the scans performed at 90° and 60° and between those performed at 60° and 30°, with indication of the ratio between the two deltas.

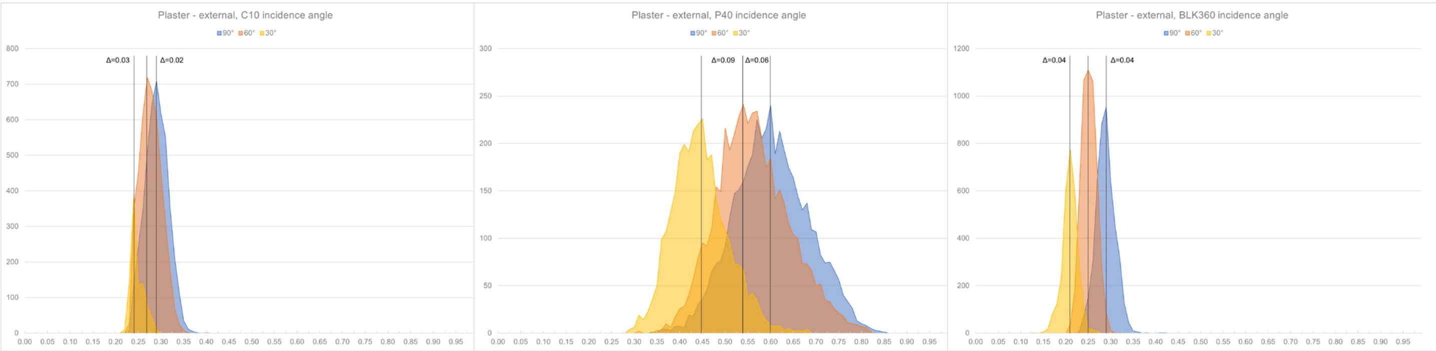


Fig. 6.29.

Sample of exterior plaster; histograms for studying the variation in reflectance values in relation to the angle of incidence for different laser scanner instruments: C10 (left), P40 (middle) and BLK360 (right). Values reported in blue are those surveyed with a 90° angle, in orange 60° and in yellow 30°.

Tool	Δ 90° - 60°	Δ 60° - 30°	ratio
C10	0,02	0,03	2:3
P40	0,06	0,09	2:3
BLK360	0,04	0,04	1:1

Tab. 6.04.

Sample of exterior plaster; delta variation between the peaks of the intensity values of the scans performed at 90° and 60° and between those performed at 60° and 30°, with indication of the ratio between the two deltas.

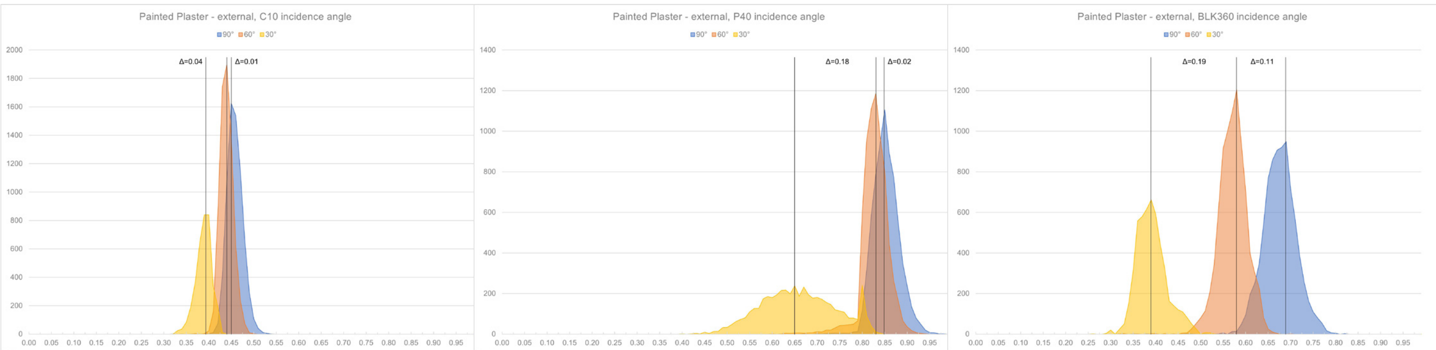


Fig. 6.30.

Sample of painted exterior plaster; histograms for studying the variation in reflectance values in relation to the angle of incidence for different laser scanner instruments: C10 (left), P40 (middle) and BLK360 (right). Values reported in blue are those surveyed with a 90° angle, in orange 60° and in yellow 30°.

Tool	Δ 90° - 60°	Δ 60° - 30°	ratio
C10	0,01	0,04	1:4
P40	0,02	0,18	1:9
BLK360	0,11	0,19	1:2

Tab. 6.05.

Sample of painted exterior plaster; delta variation between the peaks of the intensity values of the scans performed at 90° and 60° and between those performed at 60° and 30°, with indication of the ratio between the two deltas.

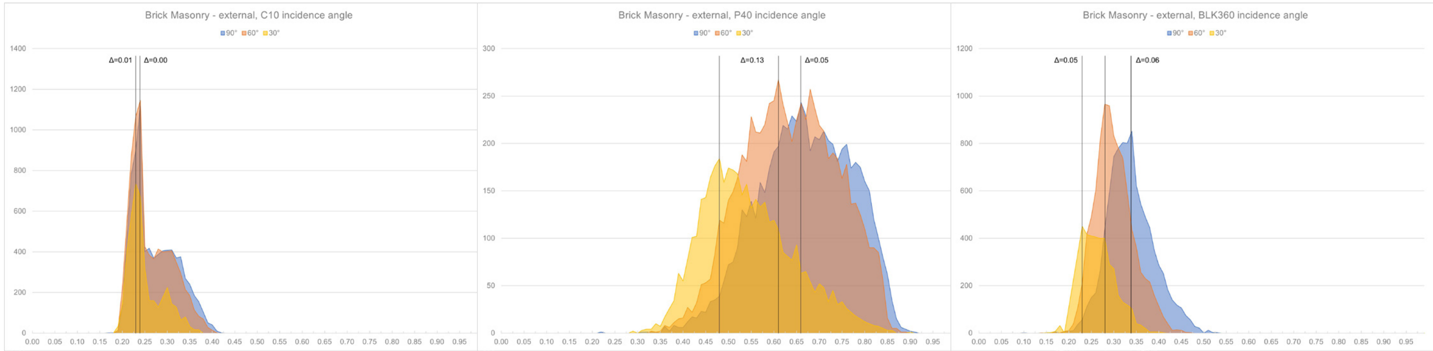


Fig. 6.31.

Sample of brick masonry; histograms for studying the variation in reflectance values in relation to the angle of incidence for different laser scanner instruments: C10 (left), P40 (middle) and BLK360 (right). Values reported in blue are those surveyed with a 90° angle, in orange 60° and in yellow 30°.

Tool	Δ 90° - 60°	Δ 60° - 30°	ratio
C10	0,00	0,01	-
P40	0,05	0,13	1:3
BLK360	0,06	0,04	3:2

Tab. 6.06.

Sample of brick masonry; delta variation between the peaks of the intensity values of the scans performed at 90° and 60° and between those performed at 60° and 30°, with indication of the ratio between the two deltas.

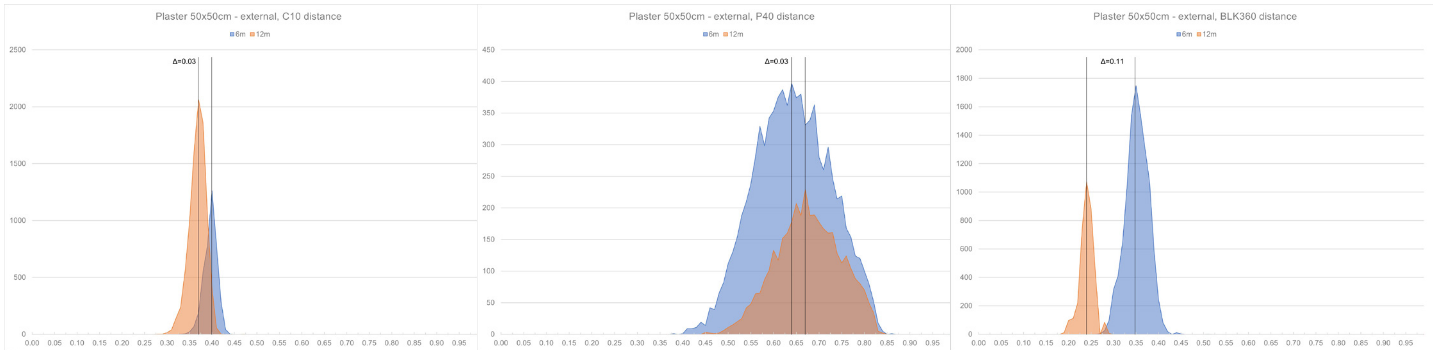


Fig. 6.32.

Sample of plaster 50x50cm; histograms for studying the variation in reflectance values in relation to distance for different laser scanner instruments: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those surveyed from a distance of 6 m, in orange 12 m.

6.4.4 Surface conditions: humidity and temperature

To evaluate the variation in intensity values recorded by the different instruments in relation to surface humidity, the graphs of the acquisitions of the two cycles (dry and wet) were superimposed. This operation was performed for each material. For the 50x50cm plaster samples, the scan performed indoors was considered (Figg. 6.33, 6.34, 6.35, 6.36). In all the cases analysed, a wet surface causes a decrease in reflectance values, but, compared to what was found with the angular variation, the data are generally more complex and less regular. In fact, different behaviours are found depending on the materials, both in terms of the trend of the graphs and the shift in peak values (Tab. 6.07).

As regards the 50x50cm plaster sample (Fig. 6.33), the graphs for all instruments show a negative shift in the Gaussian bell curve of intensity values, with a roughly similar peak delta. In the external plaster (Fig. 6.34), the wet acquisition curves are "deformed" compared to the dry ones, deviating from a normal distribution. This is more evident in the C10 and BLK360 scans and could be caused by differential water absorption by different areas of the same material. The peaks of the C10 and P40 scans always show a negative shift, while that of the BLK360 remains in the same position and the bell curve changes significantly towards lower values. In the painted exterior plaster (Fig. 6.35), behaviour similar to that of the 50x50cm plaster sample is observed, obviously with higher absolute values due to the lighter colour of the surface. The delta peak values differ between the various instruments. It should be noted, however, that the acquisition of the P40 with a dry surface presents the interpretation complexities explained in paragraphs 6.4.2 and 6.4.3, so at this stage it has not been taken into consideration for making overall deductions.

Finally, the sample graphs for brick masonry (Fig. 6.36), which already showed non-normal trends in dry conditions due to the presence of two materials (brick and mortar), appear much more irregular on the wet surface, showing, in the cases of P40 and BLK360, two bell curves with two distinct peaks. It is assumed that this dual behaviour is due precisely to the different behaviours of the two materials in relation to water absorption.

Analysis of the graphs to verify whether there were any differences in intensity values in relation to surface temperature did not reveal any noteworthy variations. Although an increase in surface temperatures was measured on all materials between the 11:00-13:00 and 17:00 scans (Tab. 6.07), this did not affect the intensity of the signal received.

Tab. 6.07.
Differences between reflectance value peaks in dry and wet scans, in relation to surface moisture variation for different materials.

Material	Δ Humidity	Δ Peak C10	Δ Peak P40	Δ Peak BLK360
Plaster 50x50cm	15,0%	0,07	0,13	0,09
External Plaster	29,5%	0,05	0,05	-
Painted Plaster	19,9%	0,03	0,25	0,17
Brick Masonry	19,7%	0,02	0,09	0,04

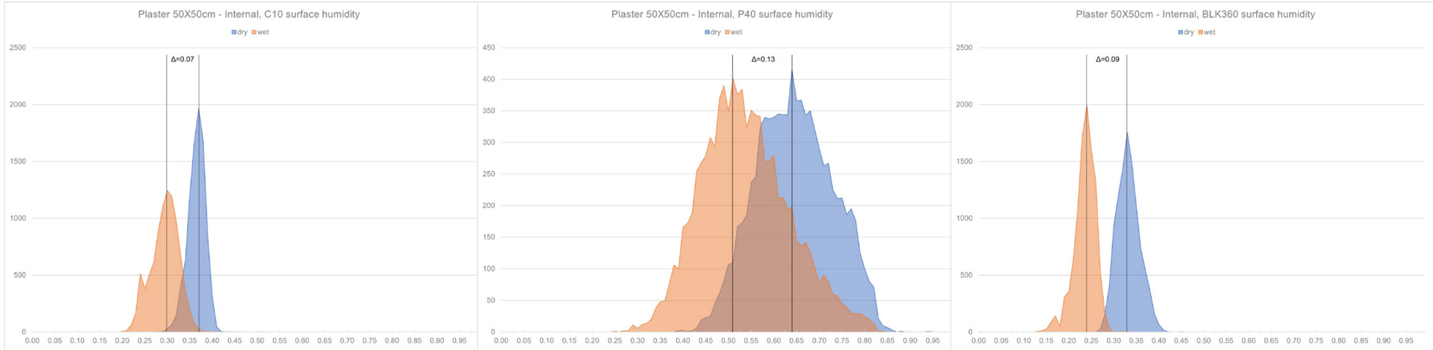


Fig. 6.33.
Sample of plaster 50x50cm; histograms for studying the variation in reflectance values in relation to surface moisture for different laser scanner instruments: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those surveyed on a dry surface, in orange wet.

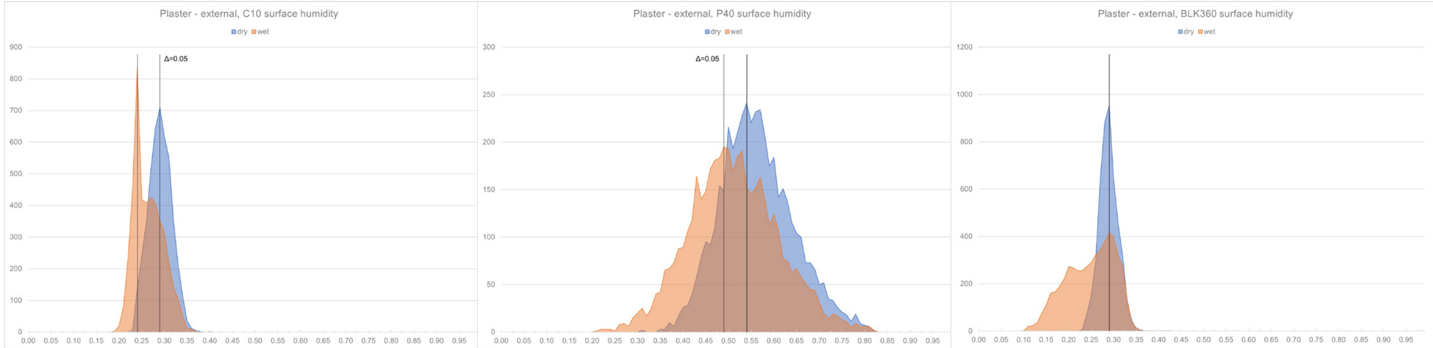


Fig. 6.34.
Sample of exterior plaster; histograms for studying the variation in reflectance values in relation to surface moisture for different laser scanner instruments: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those surveyed on a dry surface, in orange wet.

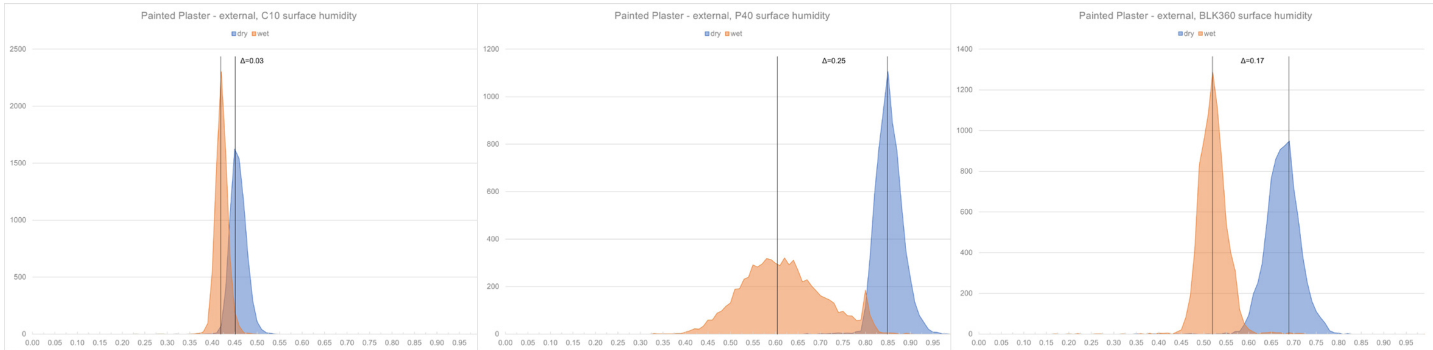


Fig. 6.35.
Sample of painted exterior plaster; histograms for studying the variation in reflectance values in relation to surface moisture for different laser scanner instruments: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those surveyed on a dry surface, in orange wet.

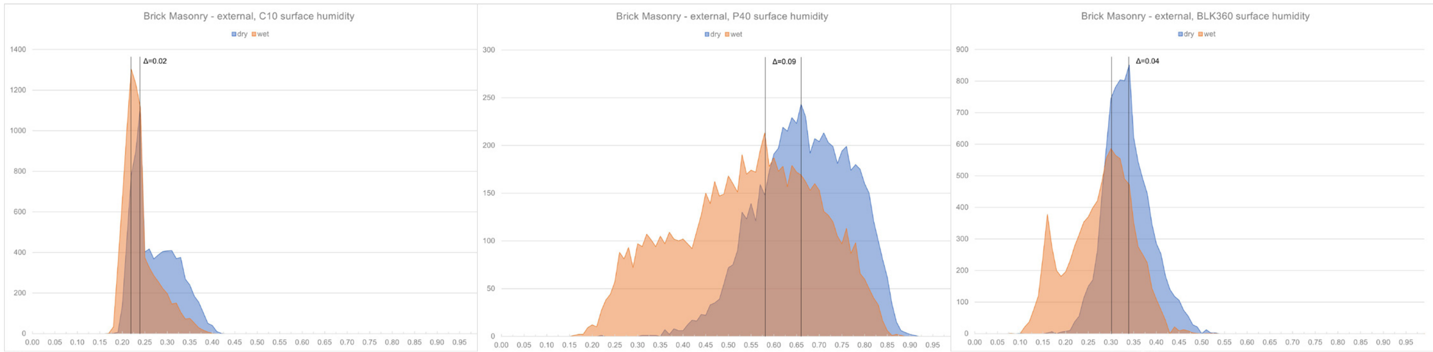


Fig. 6.36.
Sample of brick masonry; histograms for studying the variation in reflectance values in relation to surface moisture for different laser scanner instruments: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those surveyed on a dry surface, in orange wet.

6.4.5 Colour and painted coatings

To evaluate the variation in intensity values recorded by different instruments in relation to surface colour (Balaguer-Puig et al., 2017), data collected on a 50x50cm plaster sample was examined, where there is a strip painted with five colours: white, black, red, green, and blue. The acquisitions considered are those taken indoors, as these allow for better control of the surrounding environmental conditions.

By displaying the intensity data in false colours, similarities can be seen between the responses of the sensors of the three instruments, in particular the black portion stands out clearly compared to the others. C10 and BLK360 are confirmed to have similar behaviour, with differences between the colours being greater in the first case and less in the second. These differences become more noticeable when the colour scale range is narrowed to a range calibrated not on absolute values, but on the relative minimum and maximum values present in the clouds of each instrument. Overall, the C10 seems to be more sensitive to colour variations, with differences in the type of painting applied also being noticeable. In the P40 point cloud, on the other hand, no differences appear other than the one already mentioned for the colour black, even after changing the colour scale range (Fig. 6.37). Getting into more detail, some specific considerations can be made, such as the fact that for the C10, the colours red and black appear very similar and the differences between the types of paint stand out more than between the various colours.

To evaluate the variation according to the type of painting, the same methodology was followed as that adopted for evaluating the geometric factors and those relating to surface characteristics. As described in paragraph 6.4, the colouring was achieved by applying primer and paints with different dilutions (Fig. 6.20):

- Primer and painting A, respectively vinyl glue and water in a 1:1 ratio and pigment and water in a 1:1 ratio, simulate a coloured paste mortar;
- Primer and painting B, respectively vinyl glue and water in a ratio of 1:4 and pigment and water in a ratio of 1:4, simulate an opaque paint;
- exclusively with painting B, that is pigment and water in a 1:4 ratio, on a small portion of the sample.

This is done in order to evaluate and understand:

- the degree to which a paint layer behaves as an independent material;
- the degree to which the type of tint affects the resulting colour.

In this case too, a general comparison matrix was drawn up for each colour, showing the different types of paint, including the unpainted part, on the x-axis and the different types of laser scanners on the y-axis. It is immediately apparent, confirming the findings of the analyses reported in the previous paragraphs, that the graphs for the C10 and BLK360 show similar trends. Those for the P40 have higher values than the other two, both in absolute terms and in terms of range width. From this, the graphs were superimposed by instrument, thus highlighting the variations based on the type of paint applied.

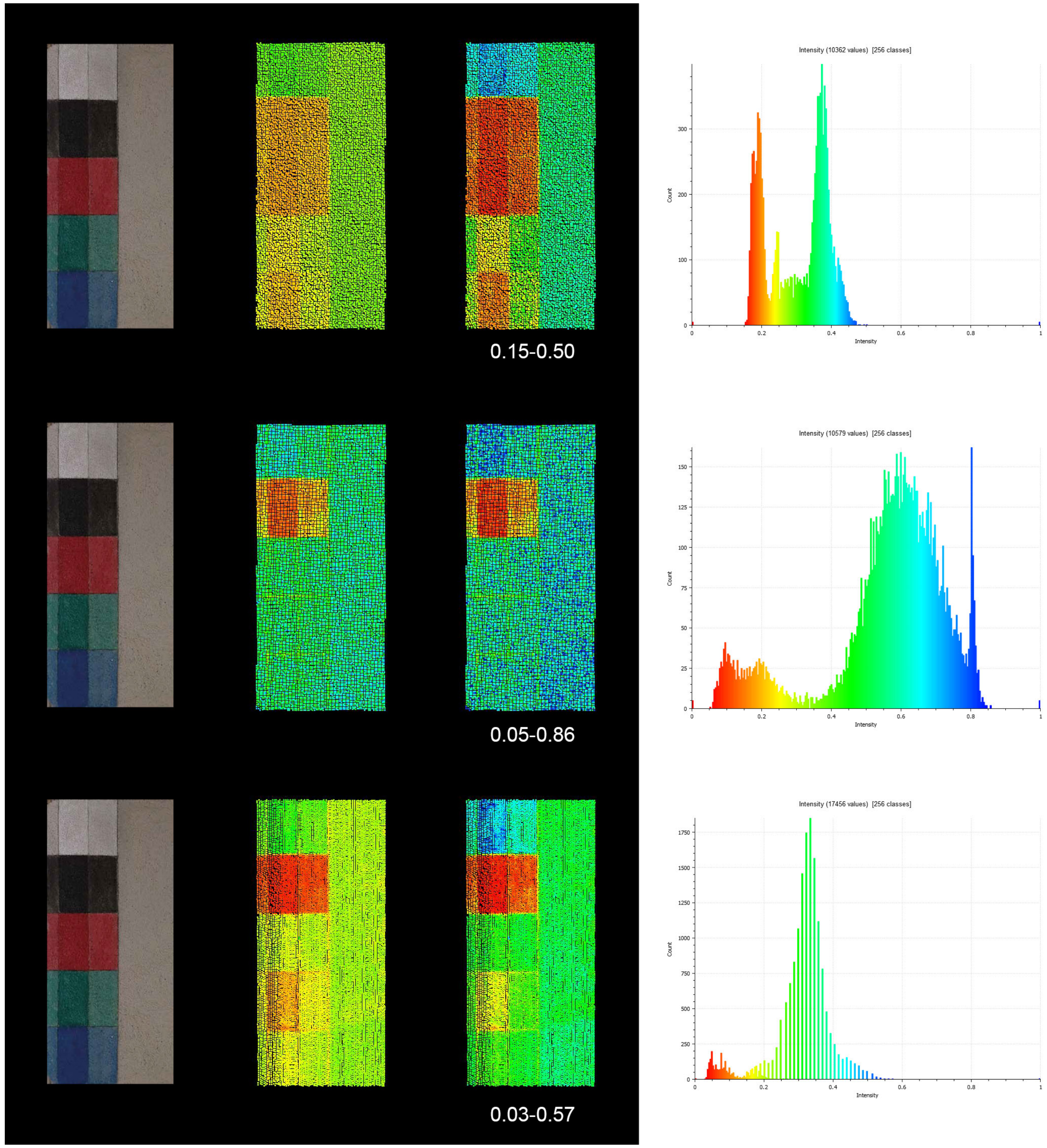


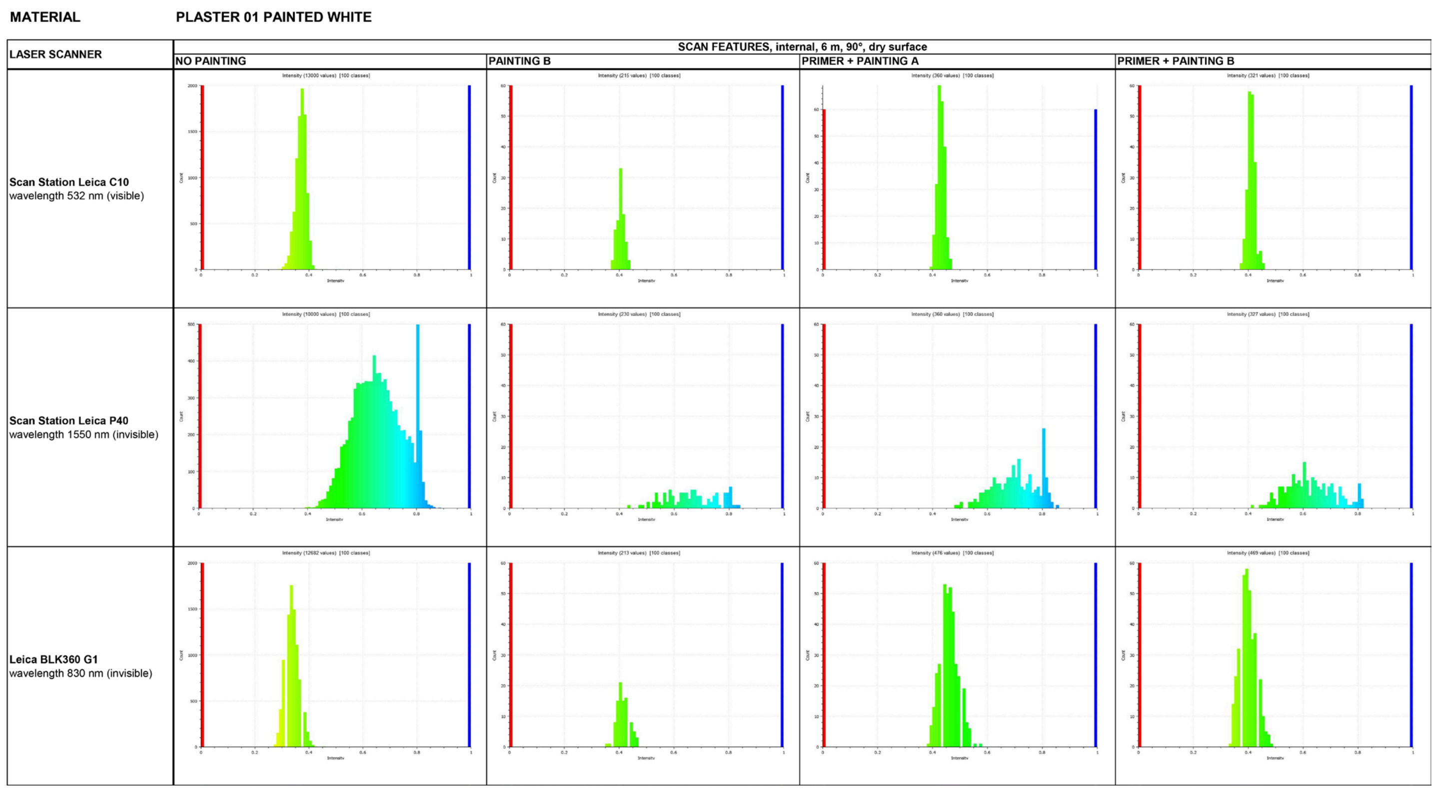
Fig. 6.37.

Point cloud of the coloured strip of the 50x50cm plaster sample detected with Leica C10 (top), P40 (middle) and BLK360 (bottom) laser scanners. First column photo, second point cloud intensity data displayed in “false colours”, third colour scale highlighting surface discontinuities and fourth intensity values histograms of the whole samples.

Fig. 6.38.

Comparison matrix for the white painted section, using different techniques, on the 50x50cm plaster sample. The x-axis shows the different types of painting, while the y-axis shows the different laser scanners (Leica C10, P40, and BLK360).

As regards the white data (Fig. 6.38, 6.39), comparing the graphs of the C10 and BLK360 with those of the P40, it emerges that the former have a clearer trend, over a narrow range of values, which "shifts" depending on the type of tint, while the latter have a "jagged" trend, set over a range of common values but with different peak values. Overall, the graphs of the C10 and BLK360 are easier to interpret, and for these tools, the part with only tint and the part with opaque tint have values with minimal or no peak differences, so they can be considered substantially equivalent. The unpainted part of the plaster, which is also darker in colour, has lower intensity values, while the part with a colour that attempts to simulate coloured mortar, which is also lighter in colour, returns higher values. On the contrary, the P40 graphs are more confusing and therefore more difficult to interpret. However, in this case, it emerges that the two most



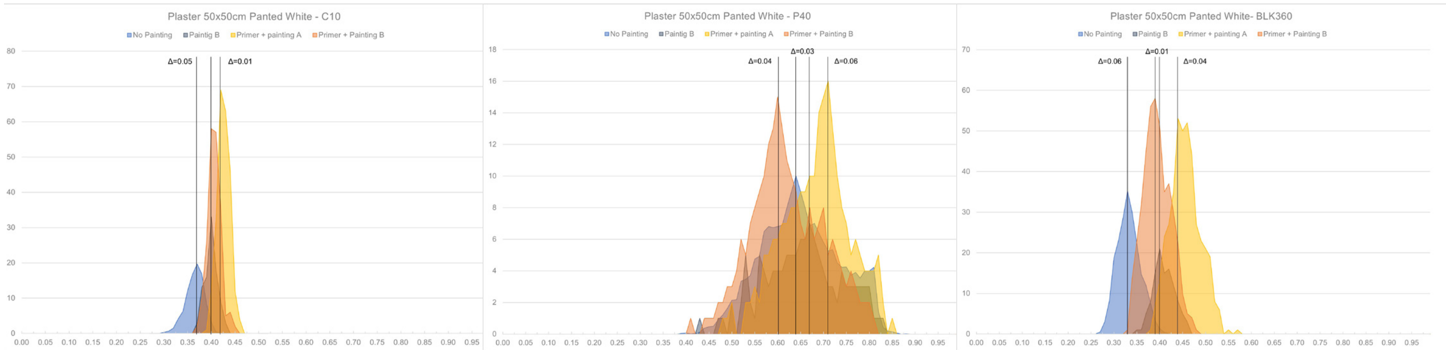


Fig. 6.39.

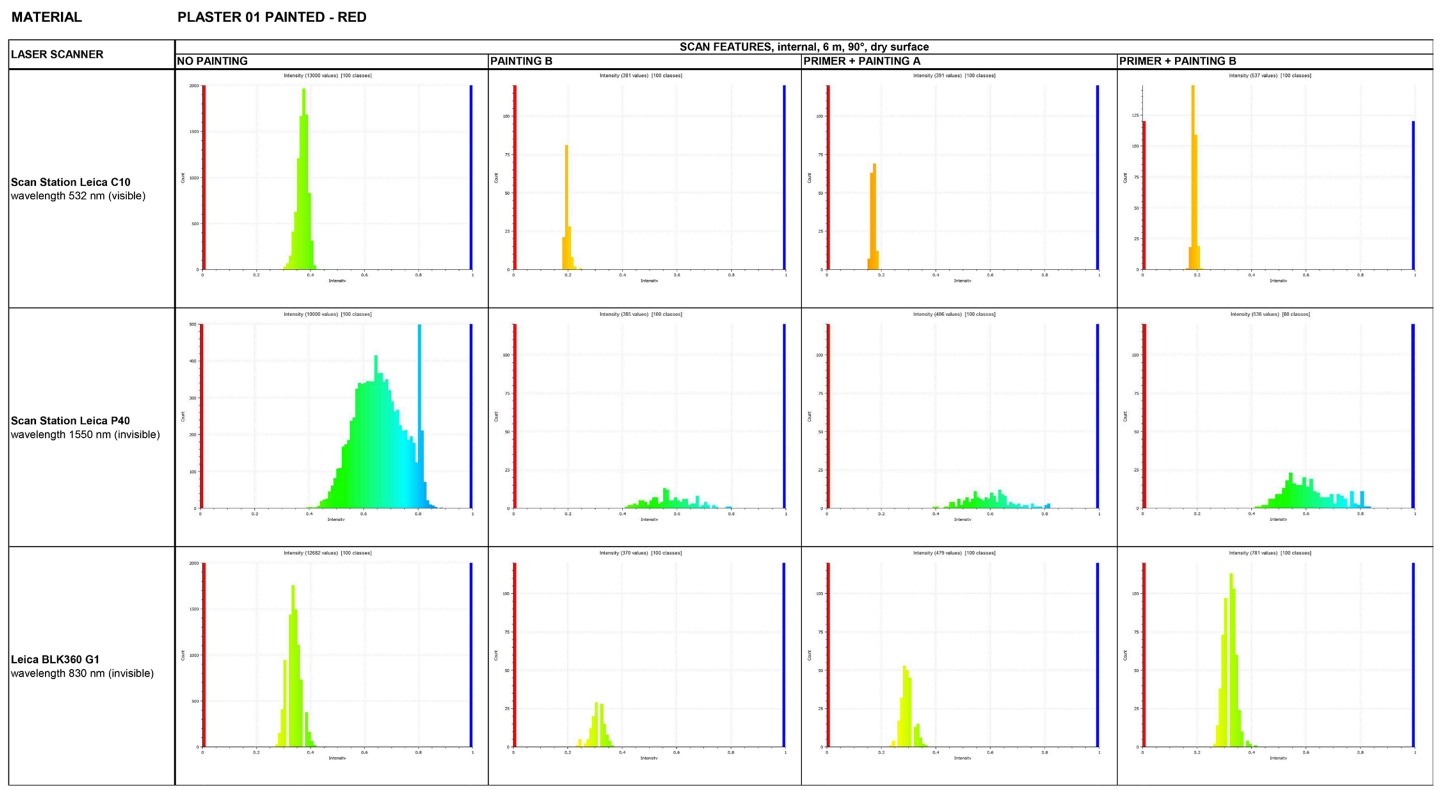
Sample of plaster 50x50cm; histograms for studying the variation in reflectance values in relation to types of white paint for different laser scanners: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those without paint, in gray paint B, in orange primer + paint B and in yellow primer + paint A.

similar types of surfaces are those without paint and those with only paint. On the other hand, the portion with opaque tint has the lowest values. As with the other instruments, the one with paint that attempts to simulate coloured mortar has higher values.

As regards the red data (Fig. 6.40, 6.41), observation of the C10 histograms clearly shows a significant shift in intensity values between the unpainted plaster (higher values) and the painted parts (lower values). However, there are no substantial differences between them. The BLK graphs, on the other hand, are all similar to each other. Those of the P40 show a behaviour similar to that observed for the white paint. Overall, the P40 and BLK360 graphs are difficult to interpret. For all these cases, it can be concluded that there are no particular differences between the three types of red paint applied.

Fig. 6.40.

Comparison matrix for the red-painted section, using different techniques, on the 50x50cm plaster sample. The x-axis shows the different types of painting, while the y-axis shows the different laser scanners (Leica C10, P40, and BLK360).



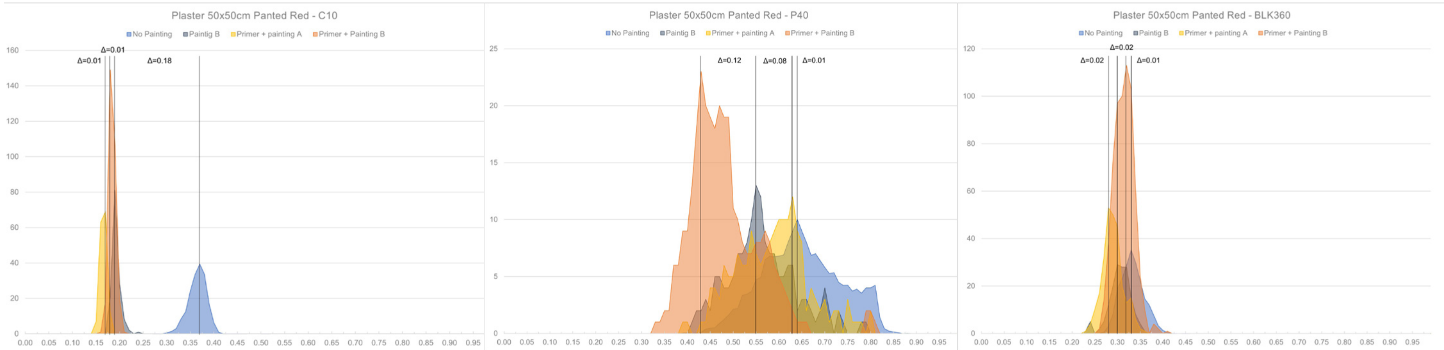


Fig. 6.41.

Sample of plaster 50x50cm; histograms for studying the variation in reflectance values in relation to types of red paint for different laser scanners: C10 (left), P40 (middle), and BLK360 (right). Values reported in blue are those without paint, in grey paint B, in orange primer + paint B and in yellow primer + paint A.

6.4.6 Outcomes

The systematic analysis developed on the laser scans of the various samples, highlighted a series of recurring trends that allow to draw some general conclusions about the influence of the different factors tested on the reflectance value. These include both instrumental characteristics (laser scanner wavelength) and geometric and surface conditions. First, it was confirmed that longer wavelengths correspond to higher average intensity values, with the Leica P40 (1550 nm) returning the highest intensities in absolute terms, albeit with greater dispersion. In contrast, the Leica C10 (532 nm) and BLK360 (830 nm) show clearer and more consistent distributions, with the C10 in particular capable of returning a more marked distinction between adjacent materials (e.g., brick and mortar joint). From a geometric point of view, a decrease in intensity values is observed as the angle of incidence of the laser beam with respect to the surface decreases. This phenomenon does not follow a linear trend and its extent varies depending on the instrument and the material being investigated. At angles of incidence between 90° and 60°, the variations are generally limited and the data comparable; more marked differences are found at 30°, especially for the BLK360, which proves to be the most sensitive to angular and distance variations. In the latter case, there is a reduction in intensity when the distance doubles (from 6 m to 12 m), while the data acquired by C10 and P40 remain substantially unchanged.

In relation to environmental conditions, surface humidity is one of the most significant factors affecting the variation of the reflected signal, causing a systematic decrease in intensity values. However, the extent and form of the variation are not uniform: regular surfaces (e.g., the 50x50 cm plaster sample) show a homogeneous shift in the curves, while heterogeneous surfaces (e.g., brick masonry) generate complex responses, in some cases characterized by double peaks, probably due to the different absorption capacities of the materials. Conversely, the increase in surface temperature did not show any significant effects on the intensity values, suggesting that within the tested ranges (between approximately 28° and 45°), temperature is not a determining factor.

With regard to the influence of colour and type of surface finish, there is a direct correlation between the reflectance value and the brightness of the applied paint: white surfaces reflect more, black surfaces less. The C10 proved to be the most sensitive sensor to colour variations and different painting techniques, allowing in some cases to distinguish even the differences between opaque paint and more diluted paint. Although the P40 showed high values, it had a lower capability to distinguish between finishes, with sometimes irregular results. The BLK360 offered responses consistent with the C10 but was more unstable in complex conditions. All these considerations are also confirmed from a graphical-visual point of view; in fact, the C10 makes it easier to read the differences between the different types of paint.

In summary, the data acquired demonstrate that the intensity value, if correctly interpreted, represents an effective indicator for the qualitative characterization of surfaces, in particular for the identification of material variations and humidity conditions. However, the analysis highlights the need to carefully consider the technical characteristics and limitations of the instrument used, as well as environmental parameters. Where appropriate and where the application context allows, standardization procedures can also be implemented to increase the reliability and comparability of the data.

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Summary

7. Point Cloud Segmentation and Classification thorough Machine Learning

Abstract
This chapter describes the methodological workflow for the semi-automatic classification of cultural heritage point clouds using supervised Machine Learning (ML), both directly on 3D data and via image-based segmentation. The process is developed thorough the three main phases: class definition, ML-based segmentation, and critical evaluation of the results. When dealing with point clouds, the second phase can be subdivided in data pre-processing, feature extraction, selection, manual annotation, and classification steps. Geometric features derived from covariance matrix describe the local characterization of architectural shapes, and serve as descriptors on which to base learning. Random Forest is applied as the primary classifier, trained and tested on a manually labelled dataset, and evaluated thorough accuracy, precision, recall, and f1-score. Regarding the 2D image-based segmentation as a complementary approach, Random Forest within the WeKa environment is described, exploring workflows that also enable back-projection of classified data to 3D models. These methods aim to enhance the semantic enrichment of point clouds, fostering more interpretable workflows for the digital documentation for conservation of built heritage.

7.1 Applied Workflow

The procedure for semi-automatic classification of cultural heritage point clouds (Fig. 7.01) can be divided into three macro-steps: definition of an abacus of classes to be segmented (I), Supervised ML procedure (II), critical analysis of results (III). The first phase is developed case-by-case through a critical examination of the building. It can be investigated both on-site and remotely, through the support of photographic documentation. In this step the categories of interest were defined, taking into account the purpose of the analysis and the final objectives. The criteria for abacus elaboration are discussed in detail in paragraph 2.4. The second phase follows the consolidated workflow for 3D classification applied to heritage buildings (Grilli & Remondino, 2020), summarized in these further five sub-steps: (i) neighbourhood selection, (ii) features extraction, (iii) features selection, (iv) manual annotation and (v) classification (Weinmann et al. 2014). The third phase is developed at first analysing evaluation metrics and statistics about the algorithm performance on test set, then visually inspecting the predicted result. This chapter focuses on the second phase.

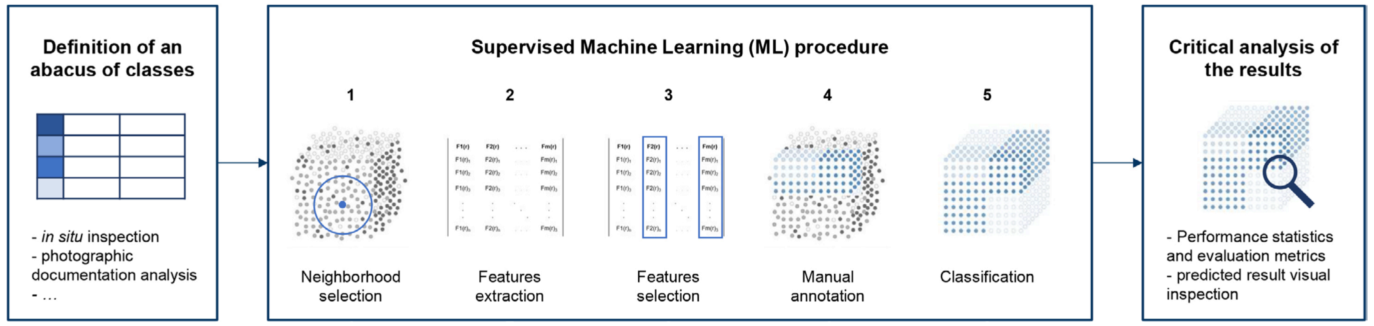


Fig. 7.01.

Methodological workflow diagram for cultural heritage point clouds data processing through Supervised Machine Learning.

7.2 A pipeline for point cloud input data processing

7.2.1 Noise filtering, subsampling and cleaning

Before applying any ML procedures, it is good practice to make "raw" input data suitable for algorithmic steps. Often pre-processing operations are required, such as filtering noise and subsampling point cloud.

Noise filtering helps in cleaning the surfaces from points not representative of the surveyed area. In literature, noise may be divided in two types: "outlier noise" and "random noise" (Uchida et al, 2020). Outlier noise is a point or group of points that are not related to the scanned surface, whereas random noise is the local fluctuation of points around their correct coordinates.

Subsampling aims at reducing file size, eliminating redundant points and regularizing the structure of the point cloud (Matrone et al., 2020). This simplifies all subsequent operations. In fact, ML does not need the high acquisition resolutions, performing even with "lightened" models, which however must always have sufficient resolution to support the scale of analysis. Very often, in a point cloud model of a building, there are also all those elements present on site at the survey time and which have therefore been acquired, such as furniture, cars, people, etc... All these unrelated entities can 'dirty' the input data, so it is recommended to remove them.

7.2.2 Point cloud covariance matrix

As described in paragraph 6.1, point cloud files are informatically presented as tabular data of the .csv (comma separated value) type, in which each row constitutes a point and each column a different descriptor for each point (Fig. 7.02). There are values indicating location (x, y, z coordinates), colour (RGB values), reflectance (intensity, if the point cloud was obtained through laser scanning) and orientation (component of the normal vector with respect to the surface that the point forms with its neighbours). The components listed above describe the general point cloud characteristics, in other words they are considered "global features". To these, other numerical attributes can be added, which describe the geometric characteristics of the local distribution of points, so are called "geometric features" (Weinmann et al., 2015). Most of them are derived from Principal Component Analysis (PCA) of a group of points. Basically, for each point a sphere centred in the point itself is created and the values of all 3D point coordinates inside this sphere are used to determine a covariance matrix (Oviedo de la Fuente et al., 2024). The covariance matrix is given by (Jutzi & Gross, 2009):

$$[Cov] = \begin{bmatrix} Var\,[A1] & Cov\,[A1,A2] & Cov\,[A1,A3] \\ Cov\,[A1,A2] & Var\,[A2] & Cov\,[A2,A3] \\ Cov\,[A1,A3] & Cov\,[A1,A2] & Var\,[A3] \end{bmatrix} \tag{1}$$

The elements of the matrix are:

$$Var[A_i] \;=\; \frac{1}{N} \sum\nolimits_{A_k\,\epsilon\, B(A;\varepsilon)} \left(A_{i_k} - \bar{A}_i\right)^2 \tag{2}$$

$$Cov[A_i, A_j] \;=\; \frac{1}{N} \sum\nolimits_{A_k\,\epsilon\, B(A;\varepsilon)} \left(A_{i_k} - \bar{A}_i\right)\left(A_{j_k} - \bar{A}_j\right) \tag{3}$$

where, A is a point, $B(A;\varepsilon)$ a neighbourhood of point A whose radius is ε, $A_k = (A_{1k}, A_{2k}, A_{3k})$ is a point belonging to $B(A;\varepsilon)$. The sum of $A_k\,\epsilon\, B(A;\varepsilon)$ is extended to the N points A_k of the cloud belonging to $B(A;\varepsilon)$. A_{jk} is the i-th component of A_k (in x, y and z dimensions), and $\bar{A}_i$ is the mean of all observations in the i dimension (Croce et al., 2021).

The covariance matrix (1) is symmetric, so its non-negative eigenvalues $\lambda_1 > \lambda_2 > \lambda_3$, correspond to an orthogonal system of eigenvectors $e1, e2, e3$ (Hackel et al., 2016a).

Point	X	Y	Z	R	G	B	i	Nx	Ny	Nz
1	X_1	Y_1	Z_1	R_1	G_1	B_1	I_1	Nx_1	Ny_1	Nz_1
2	X_2	Y_2	Z_2	R_2	G_2	B_2	i_2	Nx_2	Ny_2	Nz_2
3	X_3	Y_3	Z_3	R_3	G_3	B_3	i_3	Nx_3	Ny_3	Nz_3
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
n	X_n	Y_n	Z_n	R_n	G_n	B_n	i_n	Nx_n	Ny_n	Nz_n
	Position			Color			Reflectance	Orientation		

Fig. 7.02.

Structure of the 3D point cloud matrix. *n* is the total number of points.

7.2.3 Neighbourhood selection

Machine Learning classifiers are trained by providing them with a set of data that provides information related to the specific class, which constitutes the associated label (Grilli et al., 2019a). Features (global and local) set up this data. Each feature is a numerical value that serves, therefore, as a functional attribute for class discrimination. Consequently, the first consideration that can be made is that the size of the three-dimensional neighbourhood over which the covariance matrix is calculated is of particular interest. In practice, it is necessary to choose carefully the value to be assigned to the radius of the sphere, as it determines the results of feature computation, consequently affecting learning and algorithmic prediction (Hackel et al., 2017). It is clear that as the radius increases, the feature computation time also increases, as more points are contained. The same feature can be computed with different radii, thus at different scales. Different approaches are taken to optimize the selection of the surround: some experiments exploit algorithms for automatically estimating the optimal radius value (Weinmann et al., 2014), others are based on the size of the geometries of the features to be classified (Grilli et al. 2019b).

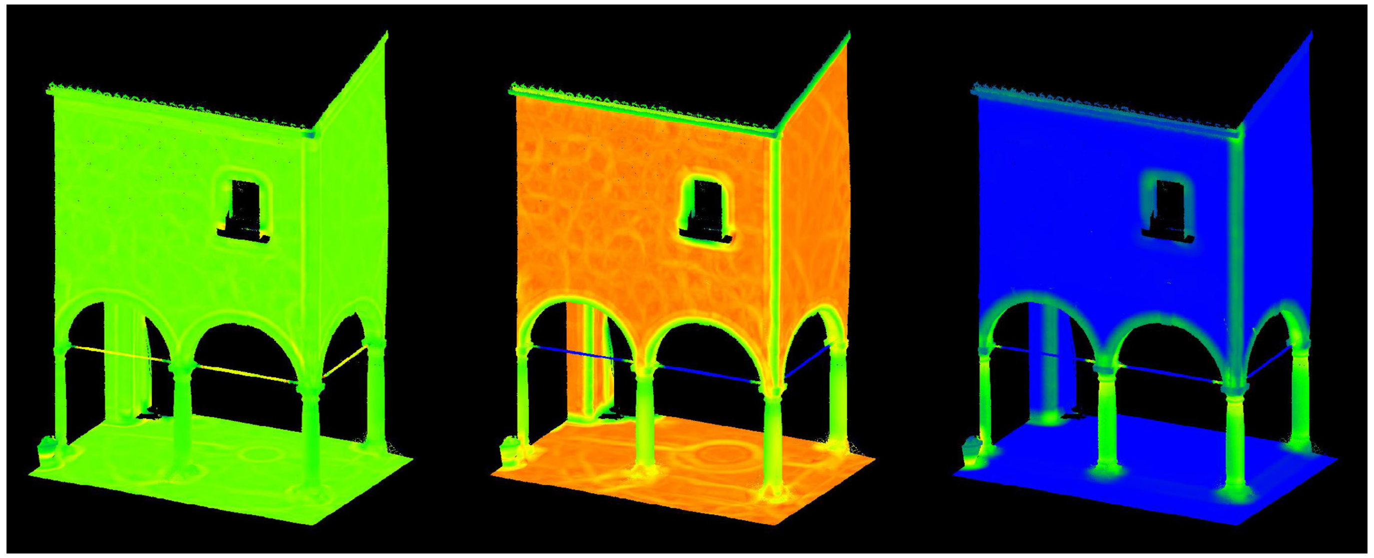
7.2.4 Geometric features extraction and selection

In this research, geometric features were calculated thorough the open source software Cloudcompare (Cloudcompare, 2024), in which these can be visualized as Scalar Field (SF) with associated colour scales. In general, values are normalized between 0 and 1. The fist, the second and the third eigenvalues (Fig. 7.03) of the covariance matrix are, respectively λ_1, λ_2 and λ_3 (Weinmann et al., 2013).

The eigenvalues themselves can be considered features, as each corresponds to one of the three main directions of the point distribution (eigendirections). The first (λ_1) represents the quantity of variation along the main axis of a point cloud, the second (λ_2) is associated with the second most important direction, and the third (λ_3) with the third direction. These values should be interpreted in relation to each other. For example, if the value of the first eigenvalue is significantly greater than the other two, it means that the surrounding points are distributed mainly along this direction, suggesting a linear shape or strong elongation. A low value might indicate a more compact or isotropic distribution. Or, if one of the eigenvalues is very small compared to the other two, the points are mainly arranged in a plane (two-dimensional distribution). From different arithmetic combinations of the eigenvalues, different geometric features are thus obtained (Tab. 7.01) (Hackel et al., 2016a).

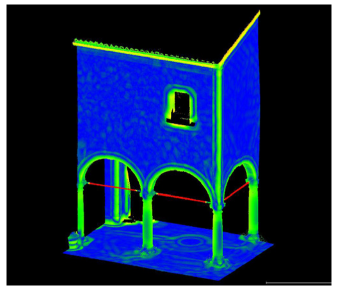
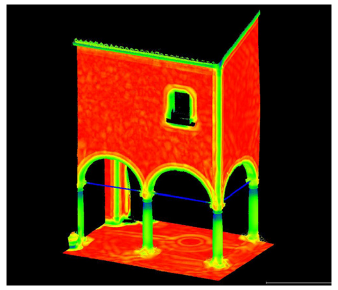
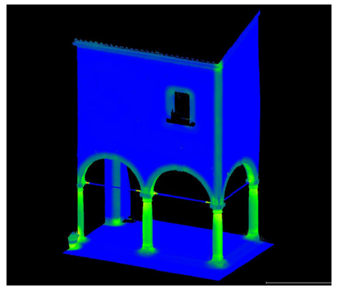
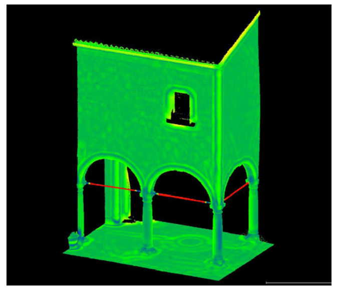
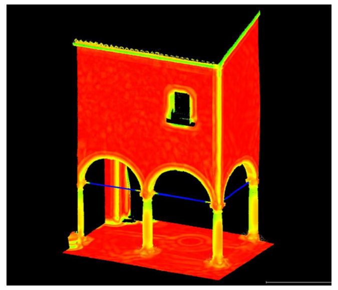
Fig. 7.03.

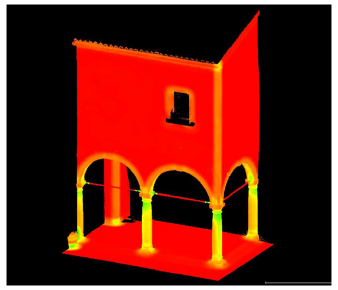
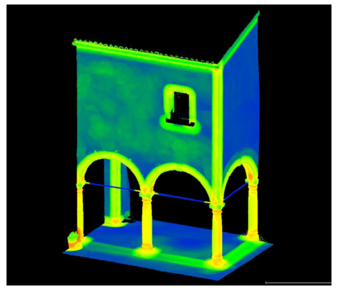
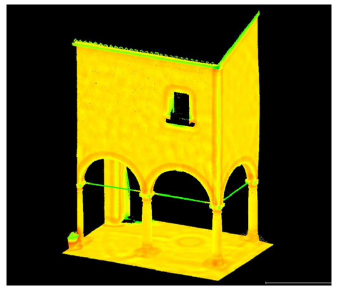
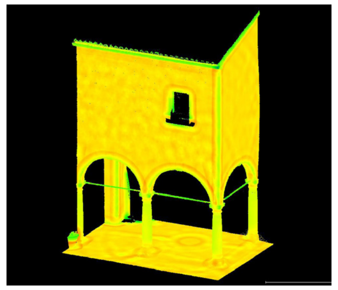
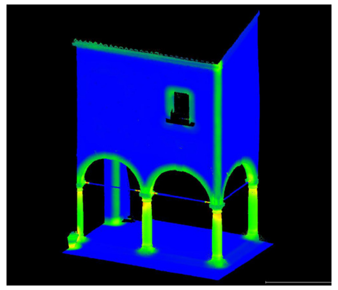
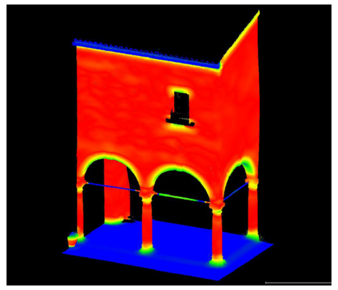
Colour scale visualization of first (right), second (centre) and third (right) eigenvalues.



Tab. 7.01.

Geometric features equations and graphic visualization thorough colour scales.

Visualization	Feature name	Equation	
	Linearity	$L_\lambda = \frac{\lambda_1 - \lambda_2}{\lambda_1}$	(4)
	Planarity	$P_\lambda = \frac{\lambda_2 - \lambda_3}{\lambda_1}$	(5)
	Sphericity	$S_\lambda = \frac{\lambda_3}{\lambda_1}$	(6)
	PCA1	$PCA_1 = \frac{\lambda_1}{\lambda_1 + \lambda_2 + \lambda_3}$	(7)
	PCA2	$PCA_2 = \frac{\lambda_2}{\lambda_1 + \lambda_2 + \lambda_3}$	(8)

Visualization	Feature name	Equation	
	Anisotropy	$A_\lambda = \frac{\lambda_1 - \lambda_3}{\lambda_1}$	(9)
	Omnivariance	$O_\lambda = \sqrt[3]{\lambda_1 \lambda_2 \lambda_3}$	(10)
	Eigenentropy	$E_\lambda = -\sum_{i=1}^{3} \lambda_i \, ln(\lambda_i)$	(11)
	Sum of eigenvalues	$\Sigma_\lambda = -\sum_{i=1}^{3} \lambda_i$	(12)
	Surface Variation	$C_\lambda = \frac{\lambda_3}{\lambda_1 + \lambda_2 + \lambda_3}$	(13)
	Verticality	$V_\lambda = 1 - \lvert\langle [0\ 0\ 1], e_3 \rangle\rvert$	(14)

Geometric features measure different characteristics (Hackel et al, 2016b) and are indicators that can be grouped according to what they help to discriminate.

a. Linear structures. PCA1, Linearity, and Anisotropy suggest whether points are aligned primarily along one direction (Weinmann et al., 2013). High values represent the probability that, in algorithmic prediction, points will be associated with linear structures[1].
b. Planar structures. PCA2 and Planarity suggest the points are distributed primarily along two orthogonal directions so whether the cloud is surface-like or plane-like[2].
c. Volumetric structures. Omnivariance, Eigenentropy, Sphericity and Sum of Eigenvalues describe the “three-dimensionality” of the distribution of points. Their values represent if the points extend uniformly (or not) in all three directions, therefore express the probability that the points, in algorithmic prediction, will be associated with volumetric structures[3].
d. Irregular structures. Surface Variation measures the variation in the geometry of a point cloud related to an estimated local surface that best approximates the point cloud. This characteristic quantifies the complexity of the surface, helping to understand how irregularly the points are distributed compared to the ideal surface. High values indicate greater surface irregularity or complexity, with significant scatter compared to the estimated surface. Conversely, low values indicate a more uniform and smooth surface.

1. PCA1 is an index that measures how significant the variance along the first principal direction is relating to the total variance, so when PCA1 approaches 1, it means that the variance along the first direction is dominant compared to the others. Linearity describes how closely aligned a distribution of points is along a principal direction, i.e., how similar a local region of the point cloud is to a one-dimensional structure. Anisotropy quantifies how much a point cloud is stretched or compressed along a direction, consequently high values of Anisotropy indicate that the variance along the main direction is much larger than the variance along the direction of least dispersion.

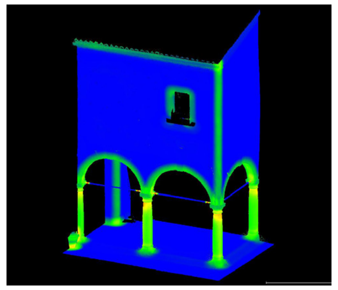
2. PCA2 is an index that measures how significant the variance along the second principal direction is compared to the total variance. Planarity quantifies how much a local region of the point cloud is pseudo two-dimensional.

3. Omnivariance describes the global spatial distribution of points in a local region of the cloud, measuring whether the variance along all three major directions is significant. Eigenentropy quantifies the related distribution of the variance of points in the three main directions, providing a measure of the "disorganization" or, conversely, the "uniform distribution" of variance in local space. Sphericity measures how close the distribution of local points is to a sphere, indicating the level of three-dimensional isotropy of the distribution of points. Sum of Eigenvalues indicates the overall dispersion of the points in the three-dimensional space of the local region, if the sum is high it means that the points are more dispersed in all directions, occupying a larger volume in space.

e. Vertical structures. Verticality measures how close the main direction of a local distribution of points is to the vertical, that is, the z axis. This feature is often used to determine the inclination of surfaces or elements in the point cloud. Verticality refers to the angle formed between the principal direction of a point distribution and the vertical z-axis of the coordinate system. Low values of Verticality indicate that the main direction of the point distribution is very close to the vertical (z axis). High values of Verticality indicate that the main direction of the point distribution is more inclined than the vertical, suggesting that the surface or structure is inclined or runs parallel to the horizontal plane. In practice, elements such as walls and columns will have low Verticality values because they are roughly aligned along the z axis. In contrast, horizontal surfaces, such as roads, floors, or flat roofs will have higher Verticality values, since they are distributed almost parallel to the horizontal plane.

Additional geometric descriptors that can be calculated are listed below.

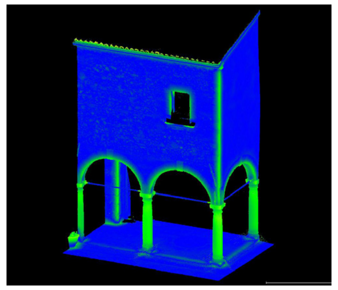
f. First Order Moment represents the weighted average of the distances of neighbouring points from the reference point. It is a measure of point dispersion. A low value means that the neighbouring points are concentrated close to the reference point, indicating a compact local distribution or a curved surface where the points are very close together. A high value indicates that neighbouring points are farther from the reference point, suggesting a wider distribution, such as flat surfaces where points are found distributed over a larger area.
g. Number of Neighbours estimates the density of a point cloud, calculated by counting for each point the number of points inside the sphere of the neighbourhood. Other options for density representation can be the “Surface density” (number of neighbours divided by the neighbourhood) or the “Volume density” (number of neighbours divided by the neighbourhood volume).
h. Curvature, divided in three types: “Mean”, “Gaussian” and “Normal change rate”. The curvature at each point is estimated using a tangent plane and a best fitting quadric around it. An attempt is made to approximate neighbouring points with a quadratic surface (ellipse or paraboloid), which is a good local representation of a curved surface (Dourios & Buxton, 2002). Next, the principal curvatures (maximum and minimum) are estimated, which correspond to the curvature values along the two main directions of the tangent plane. For the calculation of Gaussian curvature, the product of the principal curvatures is calculated; for that of the mean curvature, the arithmetic mean of the principal curvatures is calculated (Har'el, 1995). A positive mean curvature indicates a concave shape, a negative one indicates a convex shape. “Normal Change Rate” is a measure used to quantify how quickly the orientation of surface normal changes in a 3D point cloud (Tab. 7.02). It is an expression of curvature generally most useful in cultural heritage point clouds because it can help identify discontinuities, edges or other local geometric features on a surface. Basically, it describes how much the direction of the normal to a point changes with respect to its neighbours.

Visualization	Equation	
	$NCR = \frac{1}{N}\sum_{i=1}^{N}\theta_i$	(15)

Tab. 7.02.

Normal Change Rate equation and graphic visualization thorough colour scales, where, N is the number of neighbours considered and θ_i the angle between the normal of the central point and the normal of the neighbour i.

i. Roughness, like Surface Variation, measures the variation in the geometry of a point cloud related to an estimated local surface that best approximates the point cloud. In this case, its value is equal to the distance between the point and the best fitting plane computed on its nearest neighbours (Tab. 7.03). This feature quantifies the irregularity of the surface.

Visualization	Equation	
	$R = \sqrt{\frac{1}{n}\sum_{1}^{n}(d_n)^2}$	(15)

Tab. 7.03.

Roughness equation and graphic visualization thorough colour scales.

After the feature extraction process, the matrix of the point cloud file is enriched a new columns for each feature calculated (Fig. 7.04).

Point	X	Y	Z	R	G	B	i	F1(r)	F2(r)	. . .	Fm(r)	Nx	Ny	Nz
1	X_1	Y_1	Z_1	R_1	G_1	B_1	I_1	$F1(r)_1$	$F2(r)_1$	. . .	$Fm(r)_1$	Nx_1	Ny_1	Nz_1
2	X_2	Y_2	Z_2	R_2	G_2	B_2	i_2	$F1(r)_2$	$F2(r)_2$	. . .	$Fm(r)_2$	Nx_2	Ny_2	Nz_2
3	X_3	Y_3	Z_3	R_3	G_3	B_3	i_3	$F1(r)_3$	$F2(r)_3$	. . .	$Fm(r)_3$	Nx_3	Ny_3	Nz_3
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
n	X_n	Y_n	Z_n	R_n	G_n	B_n	i_n	$F1(r)_n$	$F2(r)_n$	. . .	$Fm(r)_3$	Nx_n	Ny_n	Nz_n
		Position			Color		Reflectance		Geometric features				Orientation	

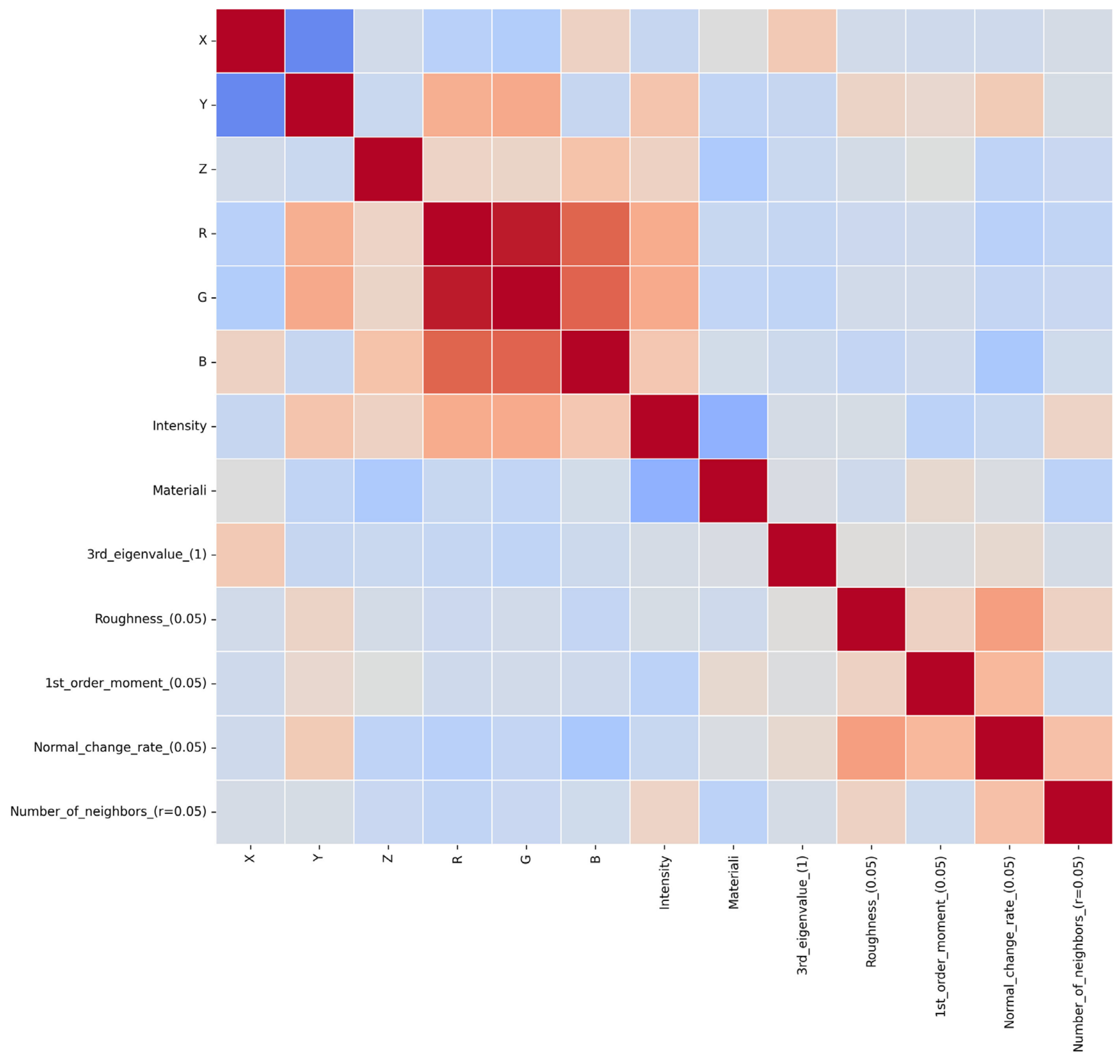
Fig. 7.04

Structure of the 3D point cloud matrix. *n* is the total number of points, *m* the total number of features, *r* the radius of the local neighbourhood.

In a training and prediction process, the choice of input data, and thus the choice of which features to use, is essential for obtaining a meaningful result: fewer features chosen *ad hoc*, rather than all features, is preferable (Grilli et al., 2019b). In addition, it is easy to see that a larger number of features, hence more columns in the .csv file, increases computational time, not only for the calculation of the features themselves but also in the algorithm training. Also not to be overlooked is the fact that files with many columns have a greater computational weight, thus generating management and storage issues.
In addition, as already mentioned, some geometric features are redundant, and their correlation can be expressed and displayed in a matrix that can help in choosing which ones to calculate (Fig. 7.05).

Fig. 7.05.

Example of correlation matrix between features of a point cloud. Intense colours indicate strong correlation, light colours low.



7.3 Manual annotation and classification

7.3.1 Manual annotation

As exposed in the state of the art (Paragraph 4.3), ML classifiers exploits mathematical algorithms to process a dataset with given features, and learn how to classify new and unseen observations from that data (Croce et al., 2021). In order to let the algorithm “learn” the correct label to associate with the various points, it is necessary to manually annotate a portion of the dataset. This operation is closely connected with the stage of drafting the abacus of the categories to be segmented. In fact, as can be easily guessed, a sample of points must be manually segmented on the point cloud for all the classes to be identified. These must be as well represented as possible in the annotated dataset.
The result of the annotated dataset is a point cloud matrix where the last column is the classification. Each numeric value each point is a label referring the abacus classes previously identified (Fig. 7.06).
The manually annotated dataset is the one on which the training and testing of the algorithm will be performed. Indeed, during the ML process, these data are divided in two parts. The first one (and the larger) is called “training set” and it is used by the algorithm to find the links between the features and the corresponding classification label and it is called “training set”. The second one is called “test set” and is used to evaluate the performance of the algorithm. This happen letting the ML model predict this part of the data, then comparing the predicted label with the “true” label assigned in the manual annotation. The evaluation metrics used are detailed in paragraphs 7.3.5 and 7.3.6.
The next step, is to choose the classification algorithm to be used. In the present research, Random Forest (Breinman, 2001) was used, as, based on literature (Matrone et al., 2020; Grilli & Remondino, 2019), it is the ML model that gives the best results in the application on point clouds of cultural heritage buildings.

Fig. 7.06.

Structure of the annotated 3D point cloud matrix. *n* is the total number of points, *m* the total number of features, *r* the radius of the local neighbourhood, L the label assigned.

Point	X	Y	Z	R	G	B	i	F1(r)	F2(r)	. . .	Fm(r)	Nx	Ny	Nz	L
1	X_1	Y_1	Z_1	R_1	G_1	B_1	I_1	$F1(r)_1$	$F2(r)_1$	. . .	$Fm(r)_1$	Nx_1	Ny_1	Nz_1	L_2
2	X_2	Y_2	Z_2	R_2	G_2	B_2	i_2	$F1(r)_2$	$F2(r)_2$	. . .	$Fm(r)_2$	Nx_2	Ny_2	Nz_2	L_1
3	X_3	Y_3	Z_3	R_3	G_3	B_3	i_3	$F1(r)_3$	$F2(r)_3$	. . .	$Fm(r)_3$	Nx_3	Ny_3	Nz_3	L_1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋱	⋮	⋮	⋮	⋮	
n	X_n	Y_n	Z_n	R_n	G_n	B_n	i_n	$F1(r)_n$	$F2(r)_n$	. . .	$Fm(r)_3$	Nx_n	Ny_n	Nz_n	L_L
	Position			Color			Reflectance	Geometric features				Orientation			Label

The manual annotation step is crucial to the success of a supervised ML process. It is the phase when the point cloud model is enriched with semantic levels derived from the specific knowledge of the expert. The accuracy and completeness of manual annotation is critical as it directly influences the performance of the algorithm.

7.3.2 Decision Trees and Random Forest

Random Forest (RF) is an ensemble of various Decision Trees (DTr). A DTr (Breinman et al., 1984) is a predictive modelling tool used, in general, for classification and regression. From the data characteristics (features), decision rules are inferred allowing the prediction of a target variable. Graphically, it looks like a tree, in which each internal node represents a "decision" based on an attribute, in which the data are divided according to its specific value. Each "branch" represents the outcome of that decision. A series of consecutive decisions leads to the final outcome, called "leaves", representing classes (Hastie el al., 2009). Decision trees are, in fact, constant approximations until the outcome is reached. DTrs are a widely used tool in machine learning, and much of their success is due to ease of understanding and interpretation, since they can be visualized graphically (Fig. 7.07). There are also other advantages derived from the use of decision trees, including minimal data preparation requirements when compared with other techniques (for example: they do not require normalizations and in some cases support missing values) and the ability to assess model reliability using statistical validation tests.

However, one of the main issues is that a DTr classifier can run into overfitting. This term describes the phenomenon whereby the predictive model overfits the training data, so overly complex trees are formed that do not generalize well to the data. It can also happen that DTr are unstable, because small variations in the source data could generate a tree with a completely different structure. Also, if some classes dominate over others, it is very likely that unbalanced trees will be generated. There are several strategies to try to avoid these problems. For example, "pruning" or setting the maximum tree depth can avoid overfitting. To get around the problem of tree instability, on the other hand, there is a tendency to use decision trees within an ensemble, such as, indeed, RF.

Random Forest (Breinman, 2001) seeks to improve accuracy and reduce overfitting by combining a sufficient number of DTrs (Hastie et al., 2009). It is one of the most widely used techniques for classification tasks, thanks to its effectiveness in building predictive models. The idea behind it is that by combining simple models with critical issues, these can be overcome and a stronger model can be obtained producing more accurate and robust predictions.

During the training phase, the algorithm builds a number of DTr, each built on a different subset of the original dataset. This method is called bootstrap aggregating (or bagging). This selection is done randomly. Also, even during the construction of each tree, at each node, not all features are considered. Again, a subset of features is randomly selected and the best split is chosen only within this subset. It is through this selection that overfitting is reduced, because an attempt is made to dissociate trees from each other. Once all trees have been constructed, the final prediction is obtained by aggregating the results of all trees. In the case of ranking, the mode of tree predictions is taken into account (Fig. 7.08). Guaranteeing greater robustness than single DTr, the success of RF is due to the fact that it generally provides good results in a variety of problems without the need for excessive parameter tuning. This point is particularly suitable in the context of building point clouds, that are very heterogeneous datasets.

RF also can provide a measure of the importance of different features in decision making, which is useful for making considerations about the dataset and the most or least effective attributes. This aspect is particularly useful in this research for the validation of the extracted features and the different selected neighbourhoods (Grilli et al., 2019b).

RF of the open source Skicit-learn library for Python (Python, 2025) was used in the present research (Scikit-learn, 2024).

Fig. 7.07.

Decision ree schematic visualization.

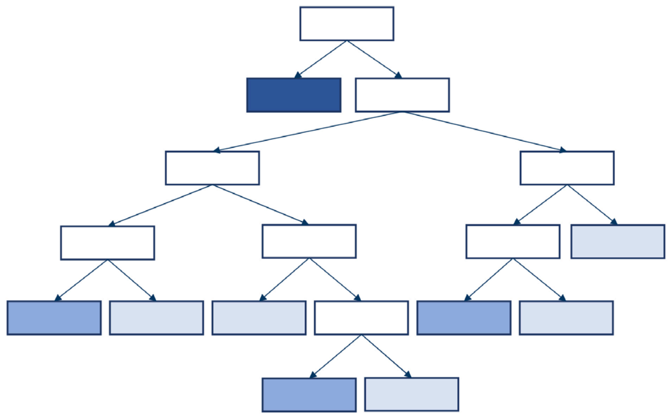
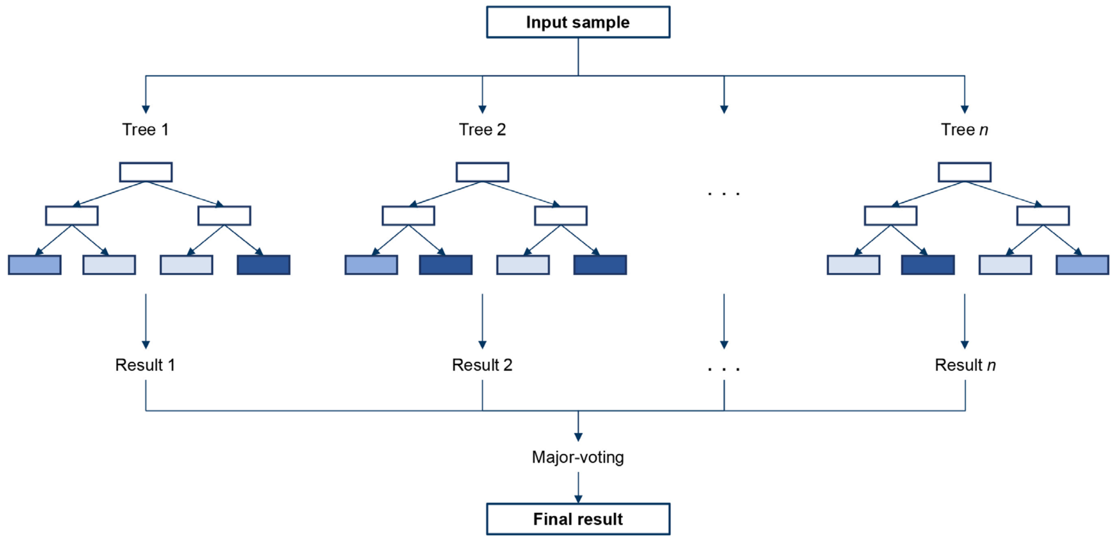


Fig. 7.08.

Random Forest function schematic visualization.



7.3.3 Hyperparameter optimization thorough Grid Search Cross Validation

In RF, parameters are values that the model learns automatically during the training process. They are determined directly from the input data and influence the model's predictions. For example, in a single DTr within a RF, one parameter is the split threshold for each node in the tree. These thresholds determine how the data are split at each level of the tree and are calculated from the training data. The values that must be set before the training process are called “hyperparameters”. These are, in both cases, configurations that rule the behaviour of the algorithm. Based on the settings assigned to the hyperparameters, therefore, the quality of the final model is determined. The main hyperparameters that can be configured in RF can be divided into two categories: those related to trees and those related to forest[4]. If not configured, the hyperparameters assume pre-set default values.

The hyperparameters allow to control how trees are constructed and how these trees interact with each other within the forest. Choosing the correct values can have a significant impact on model performance and the balance between underfitting and overfitting. The equilibrium between these two aspects affects both model performance and computational efficiency. However, it is difficult to choose the correct values for different hyperparameters a priori; empirical evaluation based on multiple attempts is often required. To do this as statistically correct as possible, Grid Search Cross Validation (GSCV) processes can be used to find the values that maximize model performance. This is the result of the integration of two techniques: Grid Search and Cross Validation.

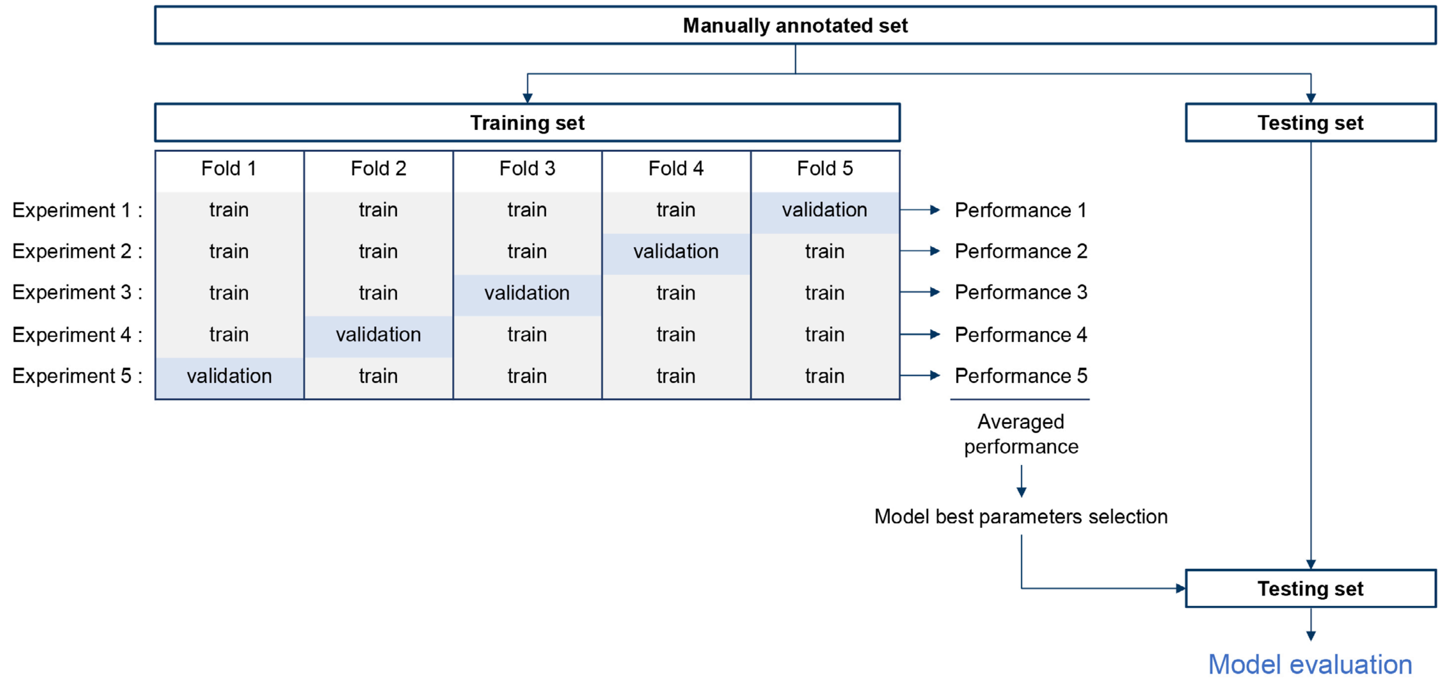
Grid Search is an exhaustive search method that systematically explores a predefined set of hyperparameter values to find the combination that produces the best performance for a machine learning model. The grid of possible values for each hyperparameter to be optimized is user-defined, then the algorithm runs through all possible combinations: for each of them the model is trained and evaluated. This is often done using techniques such as Cross Validation, to ensure that performance is not overestimated on a particular data set.

Cross Validation is a technique used to evaluate model effectiveness by dividing the data set into a number of subsets (or “folds”). The approach involves dividing the data set into k parts, training the model on k-1 parts and validating it on the remaining part. This process is repeated k times, each time changing the part used for validation. The final result is the average performance of the model over all iterations (Fig. 7.09).

At the end of GSCV, the combination of hyperparameters that produced the best performance is selected. Finally, the model is trained on the entire dataset using the optimal hyperparameter combination found. Although it can be computationally expensive in terms of time, especially with many possible parameters and values, it helps to build a more robust and accurate model. GSCV can also be used to select the best model among multiple ML models.

4. The key hyperparameters in Random Forests can be grouped into tree-related and forest-related parameters. Among the tree-related hyperparameters, the most frequently edited are: *max_depth* controls tree depth, deeper trees capture more detail but risk overfitting and higher computational cost, shallow trees generalize better but may underfit; *min_samples_split* defines the minimum samples to split a node, low values produce complex models, while higher values simplify and improve generalization; *min_samples_leaf* sets the minimum samples per leaf, larger values reduce sensitivity to noise and overfitting by preventing small, noisy leaves; *max_features* determines the number of features considered at each split, fewer features reduce variance and correlations among trees, while more features increase complexity and risk overfitting. Among the tree-related hyperparameters, the most frequently edited are: *n_estimators* specifies the number of trees, more trees usually improve accuracy but with diminishing returns and higher computation; *bootstrap* enables sampling with replacement, promoting diversity among trees and reducing overfitting; *random_state* ensures reproducibility by fixing the randomness in sampling and feature selection.

Fig. 7.09.
Diagram of K-fold Cross Validation applied on a training set in a ML process.



7.3.4 Validation metrics and confusion matrix

In previous paragraphs, “best performance” of the algorithm has been mentioned several times; this is evaluated by a specific metric to be set by the user. For each training and validation cycle in the Grid Search, a performance metric is measured on each validation fold. Once the model has been evaluated on all k folds for a particular combination of hyperparameters, the performance is aggregated. For example, the average of accuracy over all folds can be calculated, representing the effectiveness of the model with that specific combination of hyperparameters. After evaluating all combinations, GSCV chooses the one that produced the best aggregate performance

over all folds. This combination is considered the “best” one because it has been shown to generalize best on unseen data. Once the optimal combination of hyperparameters has been identified, the RF model is trained on the entire train dataset using these hyperparameters, and then predictions are made on the test set. Validation metrics are also used to evaluate performance on the test set. The most commonly used for classification problems are: Accuracy, Precision, Recall and F1-score. All these metrics have values from a minimum of 0 to a maximum of 1.
For all formulas for calculating the metrics below, it is considered:

- TP (True Positives): Number of positive samples correctly classified,
- TN (True Negatives): Number of negative samples correctly classified,
- FP (False Positives): Number of negative samples misclassified as positive,
- FN (False Negatives): Number of positive samples misclassified as negative.

Accuracy. It measures the proportion of correct predictions to the total number of predictions performed. It represents the percentage of observations correctly classified by the model. Accuracy is calculated as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

In the case of cultural heritage point clouds, which are unbalanced datasets where some classes may be much more frequent than others, accuracy is not the most appropriate metric. In fact, in a classification problem where 95 percent of the data belongs to the negative class, a model that classifies everything as negative will have an accuracy of 95 percent, but it will be practically useless, since it will not have discriminated any values belonging to the 5 percent of the positive class. Consequently, other metrics can provide a more appropriate assessment of the model's performance.

Precision. It measures the proportion of correctly identified positive samples (True Positives) to the total number of samples classified as positive (sum of True Positives and False Positives). It indicates how many of the positive predictions are actually correct. Precision is calculated as follows:

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

Precision is especially useful in cases where classes are unbalanced or when it is important to minimize false positives, in situations where this condition is critical. However, precision does not account for false negatives, so it may not be sufficient on its own in complex contexts where it is also relevant to identify all positives.

Recall. It measures the proportion of correctly identified positive examples (True Positives) to the total number of actual positive examples (sum of True Positives and False Negatives). Then, it indicates how many of the positive examples in the data were correctly identified by the model. Recall is calculated as follows:

$$Recall = \frac{TP}{TP + FN} \tag{19}$$

Recall is particularly relevant when the goal is to correctly identify as many positive examples as possible, even at the cost of generating some false positives. Conversely, high recall may be associated with low precision, that is, the model may classify many examples as positive, but increases the number of false positives (FP). Precision focuses on the quality of positive predictions: how many of the examples classified as positive are actually correct. Recall focuses on quantity: how many of the positive examples were correctly identified.

F1-score. It is a particularly useful metric when precision and recall need to be balanced, to have a more equilibrated assessment of model performance. It is the harmonic mean between the two, providing a single value that reflects both aspects. The F1-score takes into account both the model's ability to correctly identify true positives (recall) and the precision with which it classifies examples as positive (precision). The F1-score is calculated as:

$$F1 - score = 2\,\frac{Recall \times Precision}{Recall + Precision} \tag{20}$$

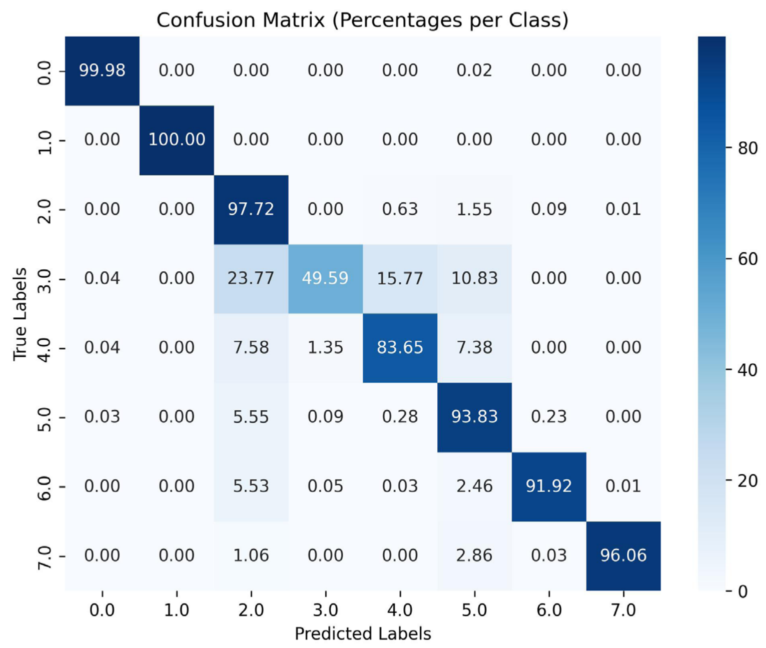
or:

$$F1 - score = \frac{2TP}{2TP + FP + FN} \tag{21}$$

is particularly useful when you have an unbalanced dataset, where, as mentioned, accuracy could be misleading. Since the F1-score is a harmonic mean, it strongly penalizes extremely low values of precision or recall. If one of these two metrics is very low, the F1-score will be low, even if the other is high.
By applying the trained algorithm to the test set, it is also possible to obtain a confusion matrix, which is an excellent tool for analysing the algorithm's performance, class by class (Croce et al. 2021). The rows of the confusion matrix display the manually annotated classes, while the columns display the predicted ones. In this way, a measure of the number of correct and incorrect predictions is provided for each class. The values can be displayed in absolute numbers or in percentage (Fig. 7.10), which is recommended for point cloud datasets, given the high number of observations.

Fig. 7.10.

Example of a confusion matrix for algorithm performance evaluation.



7.3.5 Prediction and final result

Once the algorithm has been trained, tested, and validated on the manually annotated dataset, it is applied to the remaining part of the dataset, that is, the unannotated part. The goal is to extend the classification to the entire dataset under analysis (Grilli et al., 2017). Degree of success depends on multiple factors: the computational parameters seen above, the quality and completeness of the manual annotation, the characteristics of the input data, and the effectiveness of the extracted features. To define whether a prediction can be considered acceptable or not, at first, it is possible rely on the performance evaluation metrics on the test set, general and divided for each class, and the confusion matrix. However, in the final analysis, it is always necessary to check the resulted point cloud, in order to identify areas where critical issues, if any, exist.

After semiautomatic ML classification, there is, therefore, always a percentage of coordinates that are misclassified. In each case then, for the preparation of the actually valid and usable final point cloud model, it is necessary to move the mis-predicted parts to the correct class. In addition, there may be cases where multiple classification categories are required in the final model, for example: one for materials, one for construction techniques, and one or more for state of conservation. In these cases, an additional post-processing step is required, transfer all these categories to a single point cloud. This is done by interpolating the Scalar Fields (SF) representing the various categories of analysis, from the different clouds, produced by the semi-automatic procedure, to the final cloud.

The whole process of point cloud classification through supervised ML algorithms described in the previous paragraphs is shown schematically in Fig. 7.11.

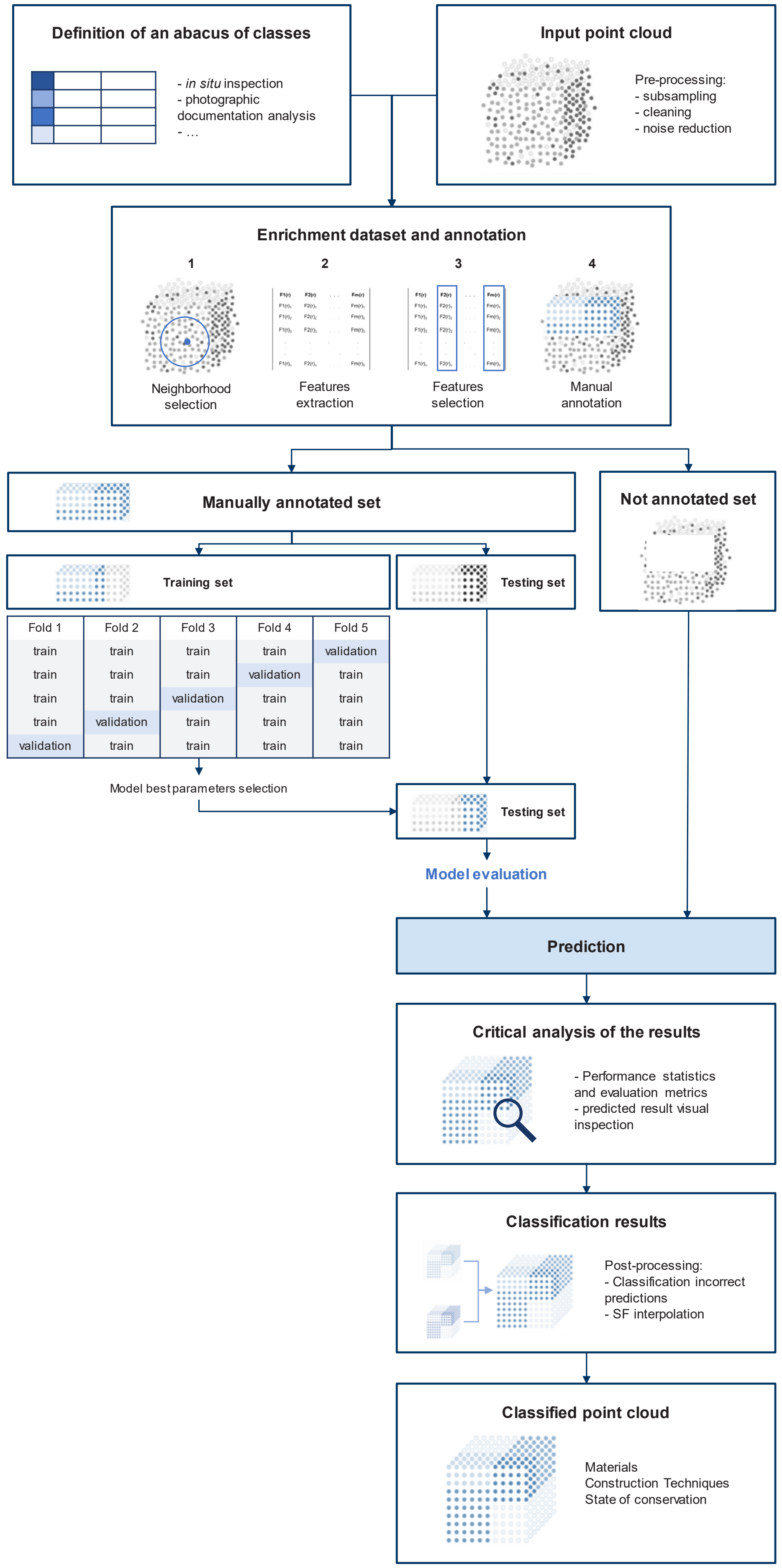


Fig. 7.11.

Schematization of the point cloud classification process with supervised ML algorithms.

7.4 Classification via images

7.4.1 Supervised 2D segmentation for 3D classification

An alternative way to classify point cloud is using 2D images and back-projecting the result to the 3D model, exploiting photogrammetric procedure and collinearity equations between aligned images and models. The shift from three-dimensional to two-dimensional has its main reason in the possibility of exploiting more mature and tested AI algorithms, given the larger domains of use of image segmentation (biology, medicine, etc...). The development of hardware components such as GPUs have given further impulse to research with these methods, leading to reliable results and greater availability of ML models (Grilli et al., 2018).

Although most applications on images exploit Deep Learning algorithms (Garcia-Garcia et l., 207), such as Convolutional Neural Networks (CNNs), Supervised Machine Learning algorithms are used in the present research as they can offer the specialist the opportunity not only to train, but also to correct, the algorithm during the process. In literature this procedure is called “interactive approach” (Grilli & Remondino, 2019) as feedback from the user guides and improves ML segmentation. This iterative process is undoubtedly more intensive in terms of the effort and skills that the specialist must bring to bear, but the obtained results are better. In fact, in the domain of architectural cultural heritage, the number of already annotated images that can train neural networks is not sufficient to guarantee satisfactory results (Grilli & Remondino, 2019), especially in relation to detailed and highly building-specific categories of analysis such as materials and state of conservation. Regarding images, “segmentation” refers to labelling each pixel, while “classification” means label the whole image (Stathopoulou & Remondino, 2019).

7.4.2 Random Forest application on images

This research exploits WeKa plug-in for Fiji/ImajeJ open source software, to perform pixel-based segmentation (Schindelin et al., 2012). It offers a set of ML algorithms based on ensembles of decision trees, that can be applied to one or more images (Witten et al., 2016). Specifically, Random Forest is explored, given the good results achieved in previous research (Grilli & Remondino, 2019; Croce et al., 2022). The input image is a RGB image, where each pixel includes information about its colour.

Manual annotation consists in drawing regions corresponding to each class directly on the image, and assigning them the proper label. Once this is done on a representative part of the image, the algorithm can be launched to perform the training and testing operations on annotated pixels. WeKa gives not many options in hyperparameter selection, leaving the user the possibility to choose only the number of trees of the forest. However, this aspect is not limiting, as this tool is intended as an interface to facilitate the application of ML algorithms even for non-highly experienced computer users, such as presumably those involved in the cultural heritage preservation chain, and the embedded RF model is sufficiently optimized to be generally effective.

Feature extraction involves the extrapolation of HSV values and other values that refer to visual properties such as, among others, shape, patterns, textures and contours. In order to apply RF, all these features configure a set of vectors. Feature computation is the step that requires most time in the entire process. When the training is completed, the algorithm immediately extends the prediction to the entire image, visualizing it in a transparent overlay. This facilitates the visual inspection by the user and, especially, gives the opportunity to correct areas incorrectly segmented, and launch again the algorithm. If no new features are required to be extracted, the prediction update does not need to repeat this step, so the computation time is less than that of the first training cycle. This reiterative process can be replied as soon as a satisfactory prediction is reached, then a predicted image can be saved as a copy of the original one, where same pixels dimensions and with RGB corresponding to the colour of the class.

The evaluation metric available in WeKa is Out-of-bag (OOB) error. This is considered an internal validation method to estimate model performance without needing a separate validation set or cross-validation. Indeed, each tree in the RF is trained on a random subset of the training data, called bootstrap, and obtained by subsampling with replacement. On average, about 63% of the original dataset ends up in this sample. The remaining data, are called the “out-of-bag data” for that tree, and can be used to test the related tree. By aggregating the predictions for all OOB trees, the model computes the OOB error. This method is reliable whit large number of trees, gives a good approximation of test error and requires less computation, compared to Cross Validation.

Trained model can be applied to other images. In architectural surface analysis, these new images should have not only the same classes to be identified, but also similar characteristics in terms of surface. For example, a model trained to recognize rising damp on an image of a plastered wall is unlikely to be able to do so on one of a brick wall.

While RF applied on images can lead to convincing results for surface analysis, it is also requires large computational capabilities, although still smaller than those required by neural network training. Factors affecting timing are: the number of features extracted, trees and classes, as well as the size of the image to be segmented.

Considering the digital photogrammetry method, which allows to create spatial correspondence between 2D images and 3D models (Remondino & Campana, 2014), three different methodological workflows can be followed for image segmentation for building classification, based on the input/output image. These can be:

- on the images of the photo dataset,
- on the texture,
- on the orthomosaic.

7.4.3 Procedure through aligned images

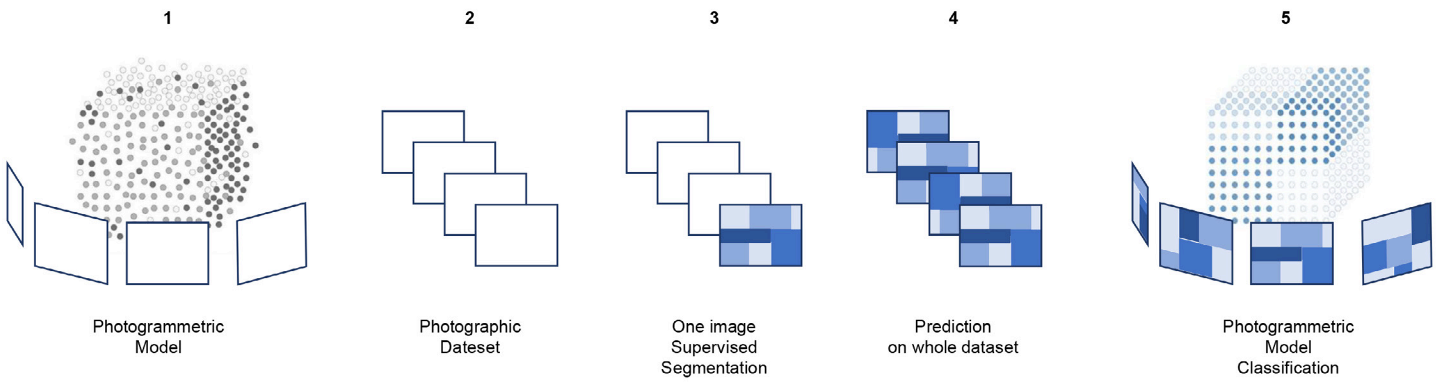
This methodology aims to exploit a ML model trained on an image and apply it on a dataset of a photogrammetric survey (Stathopoulou & Remondino, 2019). This application can be successful if the building being analysed is fairly homogeneous in terms of surface characteristics, and thus the same ML model can be applicable for multiple input images. Further preliminary consideration is that the photos should be as homogeneous as possible with each other in terms of brightness, contrast, exposure, etc. This second point, usually turns out to be satisfied, since radiometric aspects are usually also taken into account in the photogrammetric process itself, in order to obtain a point cloud, a textured mesh model or a uniform orthomosaic.

The idea behind this method is to use the spatially aligned and oriented cameras in the photogrammetric model to place the segmented images and, by exploiting the collinearity between the pixels in the photos and the coordinates, assign class colours to the point cloud, thus classifying it (Fig. 7.12).

Given the size of datasets of cultural heritage objects or buildings, which often consist of many photos, this methodology is not always sustainable: computation times can increase greatly, so it is convenient to adopt it on limited portions or small datasets. A possible strategy to fasten the procedure, without lose too much accuracy and precision in the classified model, is to segment only some pictures, located in specific and strategic positions, and use them to mask the original photos in the photogrammetric project. In this way, computational times for algorithmic processing are reduced. Moreover, performing segmentation on source images rather than on a output of photogrammetric process such as texture (paragraph 7.4.4) or orthomosaic (paragraph 7.4.5), allows to carry on the two tasks (photomodelling and image segmentation) in parallel, not one after the other: this is an approach to reduce the overall time required.

Fig. 7.12.

Schematization of supervised ML algorithms methodology applied on source images of a digital photogrammetric survey.



7.4.4 Texture segmentation

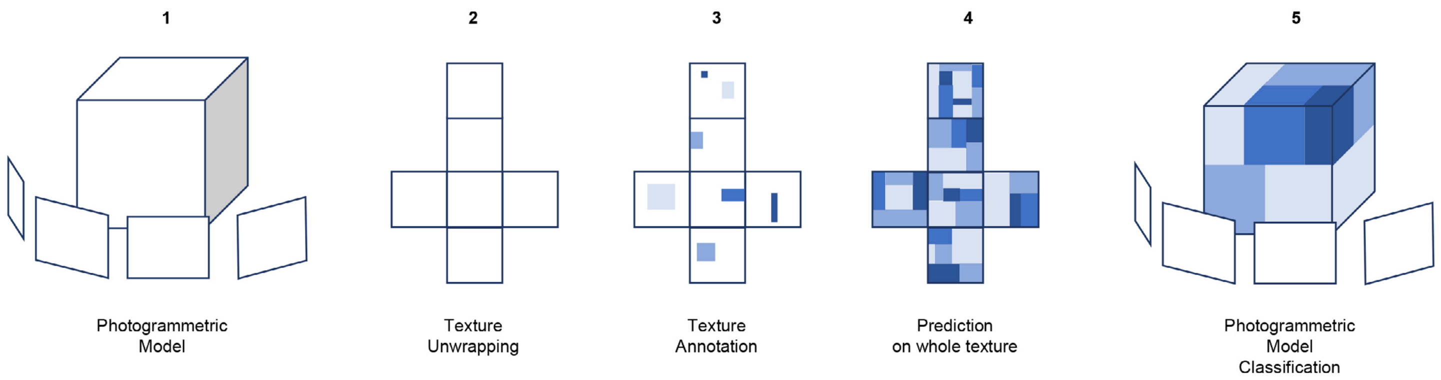
This methodology aims to exploit high resolution texture generation during the photogrammetric process, to apply supervised ML segmentation on it, training the model on a reduced part and extending the prediction to the entire image (Grilli et al., 2018). Indeed, texture represents the whole external surface of an object/building in a single image, that is wrapped on a mesh model thanks to its UV mapping[5]. According to this principle, by replacing the mesh with the segmented texture, it is possible to back-projecting class colours to the 3D model, thus classifying it (Fig. 7.13).

Textures are well suited to representing in a two-dimensional environment three-dimensional surfaces, even complex ones. However, the distortion that necessarily generates can make the image difficult to interpret. Operations can therefore be performed to choose lines and borders along which develop the texture unwrapping, preferring the greatest possible regularity of the main surfaces in the result (Grilli & Remondino, 2019). This further step in texture preparation is convenient when the building (or the object) under analysis is morphologically referable to a geometric solid which can be decomposed along the edges quite clearly.

Compared to the segmentation on multiple aligned images, it requires less time for computation, since it works on a single image, but its size can be an obstacle. This cannot be excessively reduced, without incurring a loss of detail that would not be advantageous for the purpose and scale of analysis especially for the state of conservation.

Fig. 7.13.

Schematization of supervised ML algorithms methodology applied on texture of a mesh model obtained from a digital photogrammetric survey.



5. UV mapping refers to the process of translating a 3D model’s surface into a 2D parametric space, defined by U and V coordinates, to enable the application of texture data. By unwrapping the geometry into a flattened representation, each vertex of the 3D object is assigned a corresponding pair of 2D coordinates. These coordinates are shared with the texture image, which can then be accurately mapped onto the model’s faces.

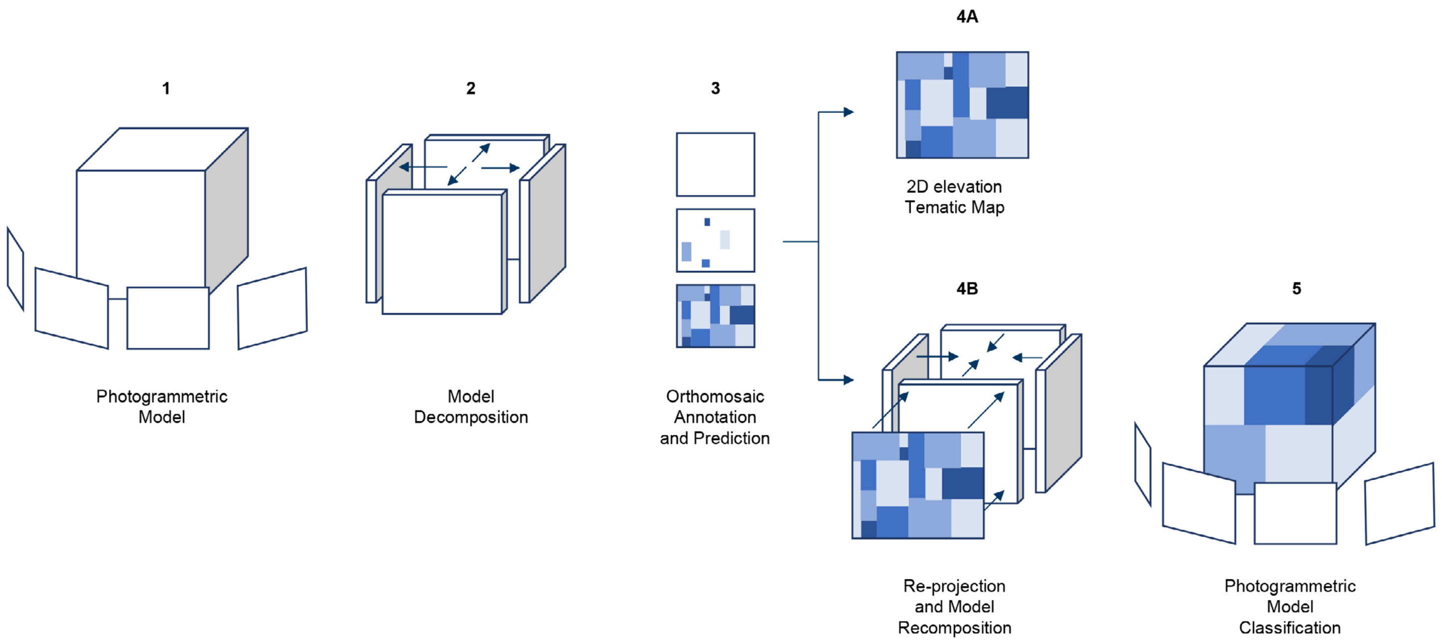
7.4.5 Orthomosaics method

This methodology consists of segmenting the orthomosaics obtained by digital photogrammetry processes (Fig. 7.14) (Croce, 2022). The advantage of this approach over the previous method is twofold. First, the annotation takes place on images that are easily interpreted, because they are obtained from the projection of the three-dimensional model onto a plane representing a building elevation, thus without undergoing deformation generated by UV maps. Second, the predicted image is itself already a mapping of the topic under analysis related to that specific elevation. This aspect may have a more immediate impact in conservation practice, where the mapping of materials, construction techniques, and state of conservation still takes place, on many occasions, in a two-dimensional environment. A product is thus obtained in a semi-automatic way that can facilitate interpretation and reduce the time required to produce descriptive drawings of the different features.

However, the main drawback of this methodology is the difficulty of transferring the two-dimensional information to the three-dimensional model. This can be done by dividing the overall three-dimensional model into sub-elements, such as one for each elevation, and projecting the segmented image onto it (Campanaro et al., 2016). This procedure can be intensive, especially working on complex buildings, both volumetrically and in terms of decoration. In fact, in orthomosaics the depth surfaces of cantilevered elements, whether large or small, is lost, consequently generating a back-projection with missing data in those areas.

Fig. 7.12.

Schematization of supervised ML algorithms methodology applied on source images of a digital photogrammetric survey.



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Summary

8. Thematic segmentation of surface features: application processes on case studies

Abstract

This chapter presents the application of the methodological workflow for the thematic documentation of architectural heritage through digital data classification, explained in chapter 7, on four case studies among those described in chapter 5, selected according to their different characteristics. The research thus explores the use of supervised Machine Learning (ML) for materials, construction techniques and degradation morphologies recognition. Depending on the purposes and on the features of the case study buildings, two main strategies were tested: the employment of Random Forest on point cloud datasets and of image-based segmentation techniques. Algorithmic predictive performance was evaluated thorough statistical metrics, confusion matrix, and visual inspection of the results. The outcomes lead to the definition of a combined methodology, in order to obtain a thematic model according to different levels of knowledge needed. The integration of 2D image segmentation is demonstrated as a complementary approach to overcome limitations of 3D point cloud classification, supporting more effective and comprehensive digital heritage documentation. Results highlight also the relevance of intensity value as a feature to support the optimization of classification accuracy.

The processes of applying supervised ML procedure on case studies detailed in Chapter 5 is described. Different experiments were carried out on the case studies, based on their characteristics and specificites, such as:

- the features of the buildings and their context,
- categories to be analysed,
- the level of detail required (scale of analysis and representation),
- classes to be identified,
- characteristics of the source data.

Since the primary objective of the research is to define a methodology for data classification to be experimentally verified, limited datasets or portions of datasets have been considered at this stage, to keep processes and results under control. Using point

cloud models of buildings with relevant analysis categories and classes to map, but at the same time limited in size, simplifies management and keeps computation time acceptable.
The case studies described in detail are:

- Former Monastery of St. Agostino (Italy),
- Former Colonia Varese in Milano Marittima (Italy),
- Cristo Obrero Church in Atlantida (Uruguay),
- St Margaret's Church in Braemar (Scotland).

Regarding Rocca Possente in Stellata di Bondeno (Ferrara), the experiments, from a methodological point of view and in terms of the results obtained, were similar to those carried out at the Former Monastery of St. Agostino, and therefore have not been extensively reported in this thesis. However, they contributed to providing comparative data, especially with regard to geometric features (Paragraph 7.2), which were useful for optimizing extraction for testing on subsequent case studies.
For each case study, the outcomes obtained are described; the overall results are exposed in Chapter 10 (Results).

Fig. 8.01.

Former Monastery of St. Agostino in Verucchio.

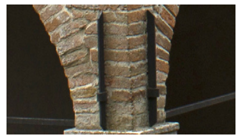
8.1 Former Monastery of St. Agostino in Verucchio

8.1.1 Facing materials recognition

The 33D point cloud of the municipal Former Monastery of St. Agostino in Verucchio (Rimini) (Fig. 8.1) is a case study suitable for tests focused in materials recognition, as its external surfaces are made of a variety of materials (Paragraph 5.02). The aim of this experimentation was to classify the exterior of the building according to materials and construction techniques. In the elaboration of abacuses, developed thorough *in situ* inspections and photographic documentation analysis, two main issues emerged: one regarding mixed materials and one related to different geometric characteristics of elements made of the same material.

Tab. 8.01.

Abacus of materials of the external surfaces of the Former Monastery of St. Agostino in Verucchio.

Material	Image	ID	Colour
Vegetation		00	
Stone Masonry		01	
Brick Masonry		02	
Brick Molding		03	
Plaster		04	
Shaper Stone		05	
Metal		06	
Wood		07	

Material	Image	ID	Colour
Roofing Tiles		08	
Downspouts		09	
Window Frames		10	
Stairs		11	
Sanpietrini Paving		12	
Terracotta Paving		13	
Cobblestone Paving		14	
Modern Materials	-	15	

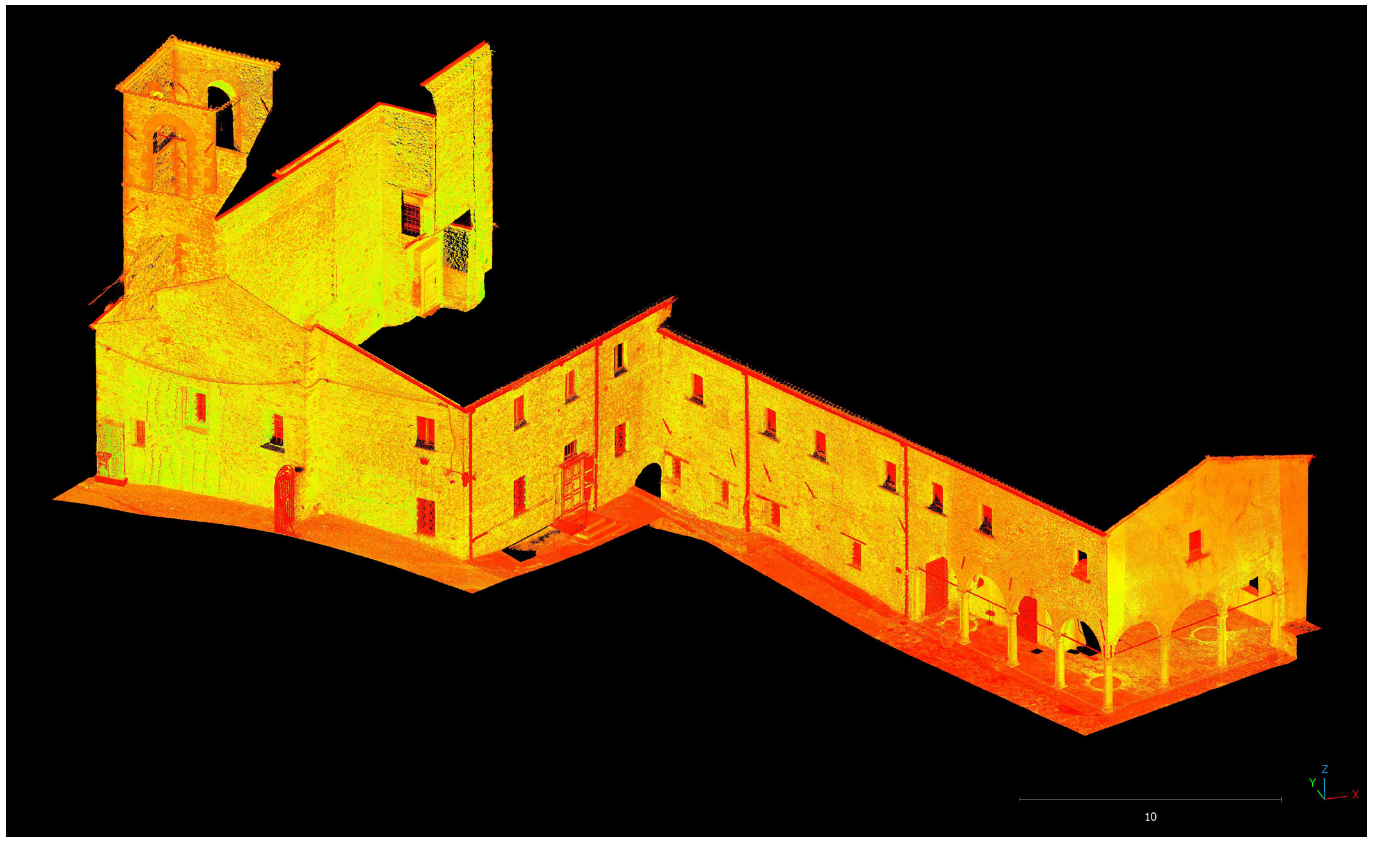


Fig. 8.02.
Former Monastery of St. Agostino point cloud, BLK intensity data visualization.

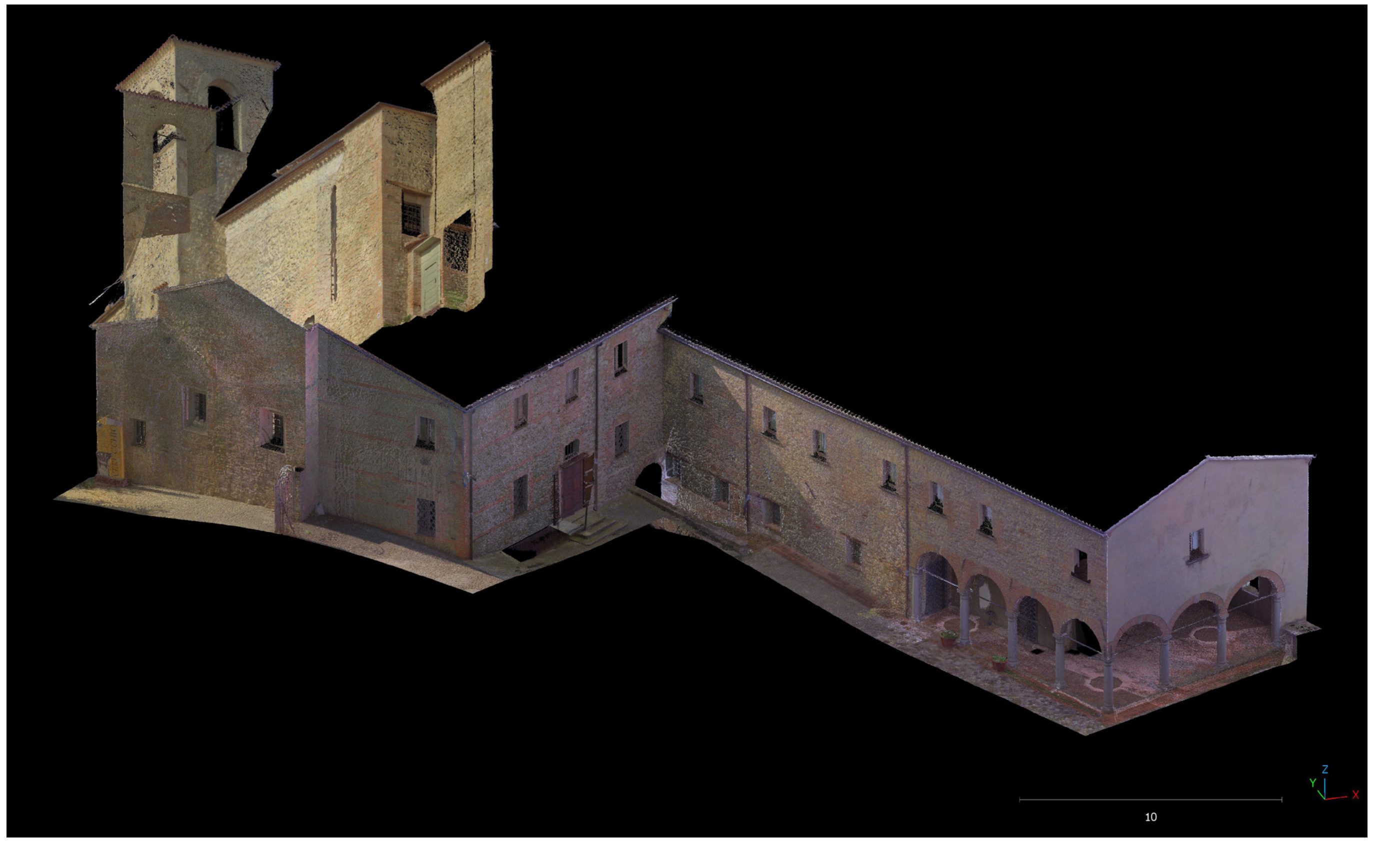


Fig. 8.03.
Former Monastery of St. Agostino point cloud, BLK RGB colour data visualization.

Regarding mixed materials, both stone and brick walls are, from a construction point of view, jopined with mortar, which in turn is made from a heterogeneous mixture of components. For classification, it was chosen to focus on their use in the construction process and the logic of the prevailing material. For this reason, brick class also includes mortar joints. The same reasoning applies to the techniques used in pavements: cobblestone, terracotta and *sanpietrini*.
Regarding geometric features, brick moulding on the upper part of the façades has been considered a separated class, due to its ornamental purpose and its articulated geometry. Indeed, geometric features characterize this element with different values than the ones associated to brick masonry, whose geometry is more "planar", leading a conflict in classification, even though the material of both is brick.
For these reasons, the resulting mapping criteria adopted for the automatic classification of Former Monastery of St. Agostino surfaces can be considered a hybrid between materials and construction techniques (Tab. 8.01). The subdivision into two distinct categories, that is, into two scalar fields, one for materials and one for construction techniques, have been done in post-processing, aggregating the classes of construction techniques that are made of the same material.
Further specific objectives of the experimentation on this case study are:

- verify whether, for classification tasks of this kind, Random Forest is the best performing Machine Learninn model, compared with k-Nnearest Neighbors (KNN), GradientBoosting, and Xtreme Gradient Boosting (XBoost);
- analysis of geometric features calculated in neighbourhoods of different dimensions, to evaluate their impact on the algorithmic prediction and the correlation with the classes to be searched, in order to optimize the extraction phase in following experiments;
- evaluation of the impact of the intensity data on the ML process,
- evaluation of RGB data acquired by scanner built-in cameras in algorithmic procedure.

All these specific objectives contribute to set up an algorithm and a methodological workflow in order to improve the prediction effectiveness.

8.1.2 Input dataset, features extraction and manual annotation

The former monastery has been surveyed by applying integrated procedures (paragraph 5.2), resulted in a laser scanner point cloud (Fig. 8.02). Colour data was acquired thorough built-in cameras in the BLK (Fig. 8.03). Non accessible surfaces, like north façade and roofs, were acquired thorough aerial photogrammetry, using a UAS drone DJI mini 2. However, for the experimentation described in this section, only external surfaces surveyed with BLK were considered, in order to assess the contribution of BLK RGB data in algorithmic procedure. The input point cloud is thus structured with: coordinates (x, y, z), radiometric features (R, G, B, intensity), normal (Nx, Ny, Nz).
Pre-processing operations (cleaning incoherent points, outlier removal) as well

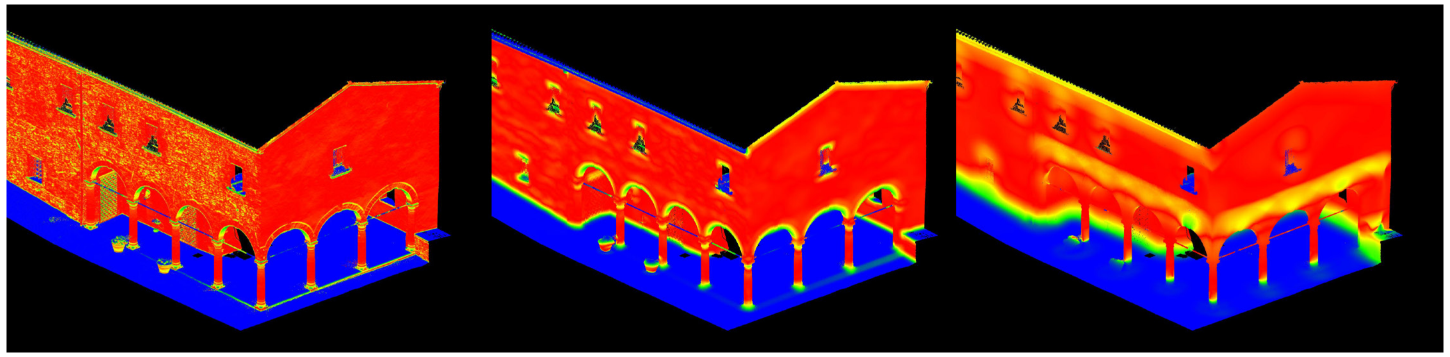


Fig. 8.04.

Verticality feature visualization, extracted with three different radii: 0,05m (left), 0,30m (centre), 1,00m (right).

as subsampling were performed. The resolution grid chosen is 5mm, considered appropriated for the scale of analysis.

In order to find the proper features associated to the proper neighbourhood dimension, all geometric features were extracted with three different radii: 0,05 m, 0,30 m and 1,00 m (Fig. 8.04). For the first and the second value, the choice was driven by considerations on the relation between the geometric dimensions of the building elements and their materials. The higher value was chosen to detect principal surfaces as it applies a sort of smoothing filter (Croce et al., 2021). The basic structure of the input point cloud is thus enriched with the columns representing the geometric features. For a preliminary analysis of the features, a correlation matrix was developed to show whether they express associated values, in the darker cells, or complementary values, in the lighter cells (Fig. 8.05).

Regarding the manual annotation phase, all abacus categories were individuated on the point cloud, segmented and properly labelled. About 15% of the entire dataset was annotated, since this reduced portion was considered to exhaustively describe all materials (Fig. 8.06). In this way, the dataset for training and test the ML algorithms was set: in the point cloud structure, for the annotated points, it is now present also de value of the label associated to each class. The non-annotated dataset, consisting in the remaining points, constitute the dataset that has to be predicted.

8.1.3 Classification and validation results

Preliminarily, ffour different algorithms were tested: Random Forest (RF), k-Nnearest Neighbours (KNN), GradientBoosting, and Xtreme Gradient Boosting (XBoost). The goal was to understand, as expected, whether RF can be considered the best performing ML model for point cloud classification. A portion of the annotated dataset was used for training (75%), the remaining for validation (25%). Evaluation metrics compared confirmed RF as the best model (Tab. 8.02).

RF was chosen to carry on the process: a grid search cross validation was performed in order to tune parameters and optimize the training. Evaluation metrics related to the test set show generally high values, suggesting a good algorithm performance (Tab. 8.03). However, from the values displayed in the confusion matrix (Fig. 8.07), emerges

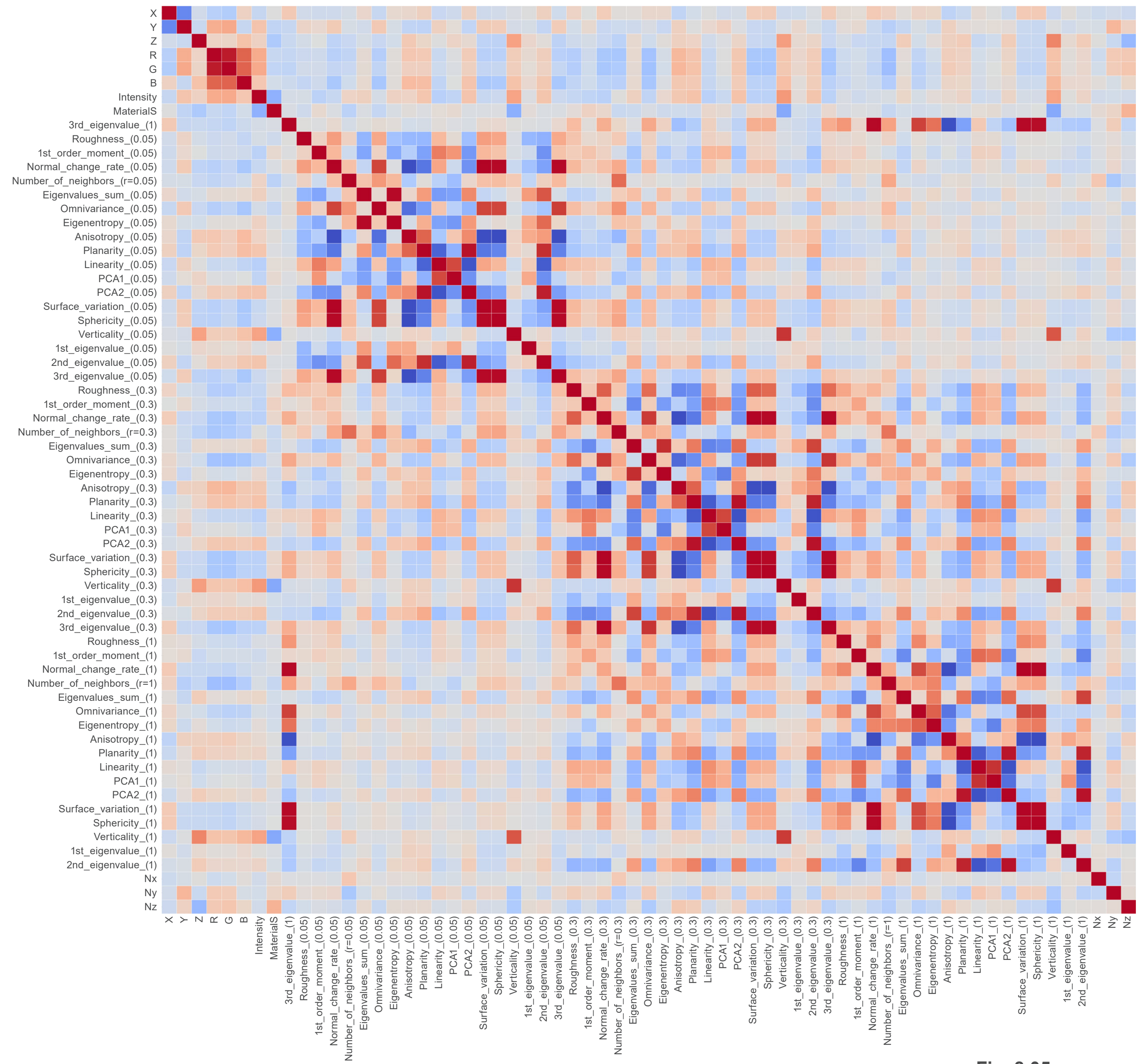


Fig. 8.05.

Correlation matrix for all the features of the Former Monastery of St. Agostino dataset.

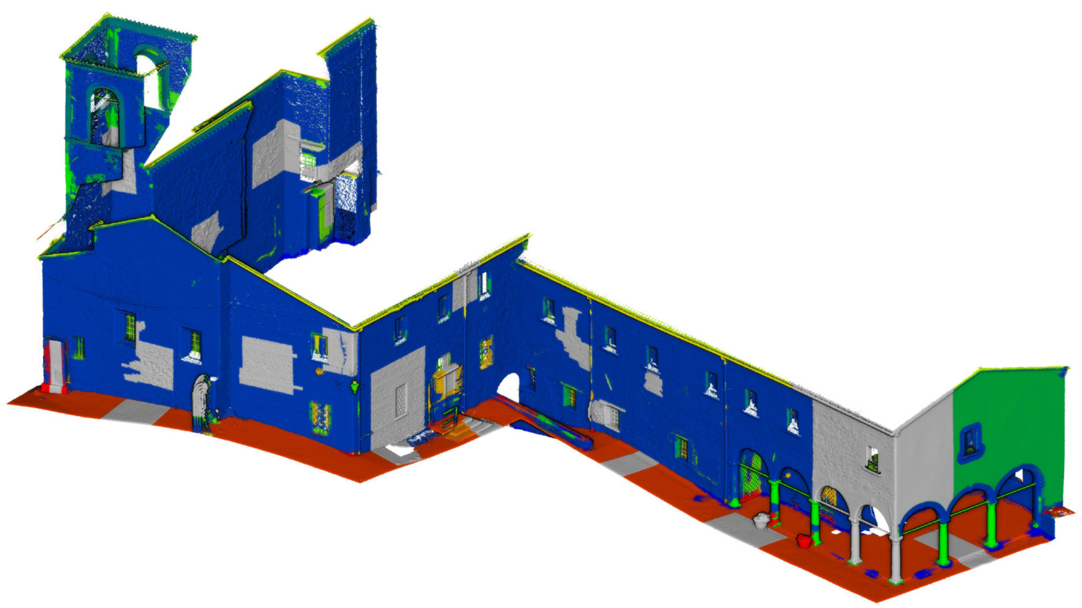


Fig. 8.06.

Former Monastery of St. Agostino point cloud, classes manually annotated are displayed with colours, grey areas correspond to the not annotated part of the dataset.

Tab. 8.02

Evaluation metrics the four ML models tested.

ML model	Accuracy	Precision	Recall	F1 score	Training time
Random Forest	0.9979	0.9979	0.9978	0.9979	1 h
KNN	0.9103	0.9272	0.9122	0.9196	2h 30m
GBoosting	0.8367	0.8320	0.7623	0.7957	8h
XGBoosting	0.5642	0.5455	0.6068	0.5742	7m

Tab. 8.03

Evaluation metrics on test set.

Class	Precision	Recall	F1-score	Points number
Vegetation	0.96	0.98	0.97	74869
Stone Masonry	0.66	0.63	0.64	245371
Brick Mouding	0.88	0.89	0.88	27167
Brick Masonry	0.83	0.95	0.88	566682
Plaster	0.99	0.81	0.90	185463
Shaped Stone	0.96	0.74	0.84	76110
Metal	0.91	0.88	0.89	30009
Wood	0.93	0.89	0.91	132828
Roofing Tiles	0.98	0.84	0.90	5112
Downspouts	0.95	0.88	0.92	32292
Window Frames	0.85	0.73	0.79	29445
Staircase Flooring	0.97	0.96	0.97	12146
Sanpietrini Paving	0.95	0.96	0.95	37029
Terracotta Paving	0.97	0.92	0.94	60666
Cobblestone Paving	0.97	0.99	0.98	72554
Modern Materials	0.97	0.63	0.77	29500
Accuracy			0.86	1617243
Macro avg	0.92	0.86	0.88	1617243
Weighted avg	0.87	0.86	0.86	1617243

that the class “Stone Masonry” is the less well predicted. A consistent number of points were wrongly labelled in “Brick Masonry” class. Other classes with a minor level of corrected predictions are “plaster”, “shaped stone”, “window frames” and “modern materials”, a class representing the contemporary, often temporary elements, composed of multiple materials that were chosen to be grouped into a common category. Most of the misclassified points for these classes were labelled in “Stone Masonry” or “Brick Masonry”.
Extrapolating feature importance histogram (fig. 8.08) it is possible to identify which features were most involved in class discrimination and which less. Features with high and medium relevance are 14 out of 62 (about 20%). Ranking the features in descending order, the graph trend decreases linearly in these first features, then shows a plateau with low values decreasing to zero in the last 15 features. About global features, the graph shows a high value of Z coordinate (Tang et al., 2023), and a medium-low importance of normals and radiometric features. Among these, however, intensity has a higher value, confirming that this attribute can contribute in labelling points. About geometric features, Verticality is highly relevant, even if calculated with

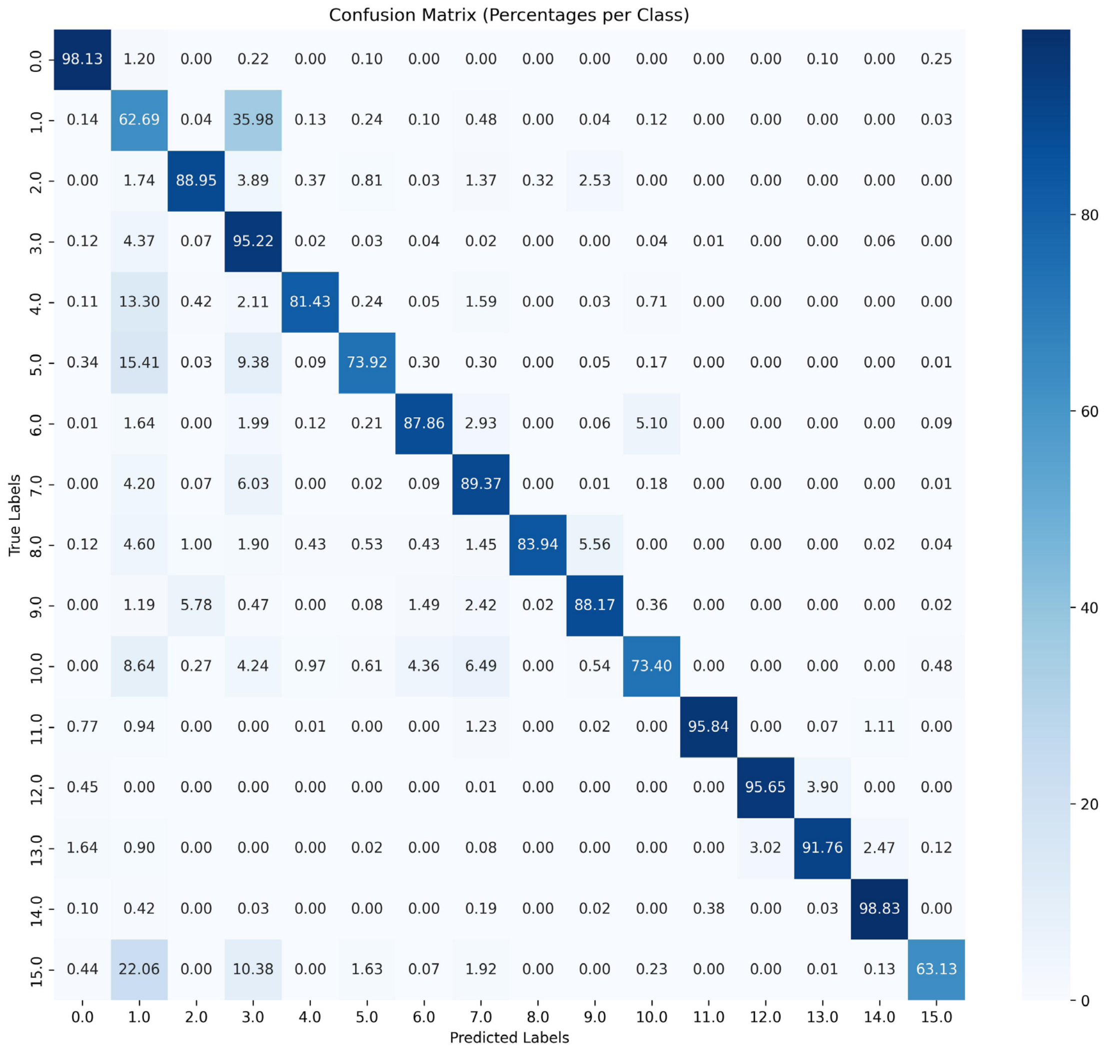


Fig. 8.07.

Confusion matrix on test set for the Former Monastery of St. Agostino point cloud. Values in percentage.

different neighbourhood radii (Grilli et al., 2019). Features extracted with r = 0,30m are generally relevant and, surprisingly, most of r = 0,05m features are irrelevant.
Thereafter, it was chosen to run train again the algorithm, considering only global feature and 17 most important geometric features. Computing time, obviously, decreases and the resulting confusion matrix shows improvement in all classes, even if nearly 20% of points expected to be labelled as “Stone Masonry”, are still labelled as “Brick Masonry” (Fig. 8.09). This improvement confirms that algorithm performance both in speed and accuracy is enhanced by high quality features, rather than high quantity. However, the trained RF classifier has been run on the not annotated dataset and the predicted result visualized. From the critical visual inspection of the final classified model, it is evident that some classes are not well classified. In particular, according to the confusion matrix, large areas of brick masonry and stone masonry are very confused with each other. Moreover, the same issue was also found for pavement surfaces, although statistical values do not report it (Fig. 8.10). These areas, correspond to extremely variable surfaces, mixed materials that, probably, geometrically are similar. This may be confirmed by the low relevance in classification of features derived from 0,05 m

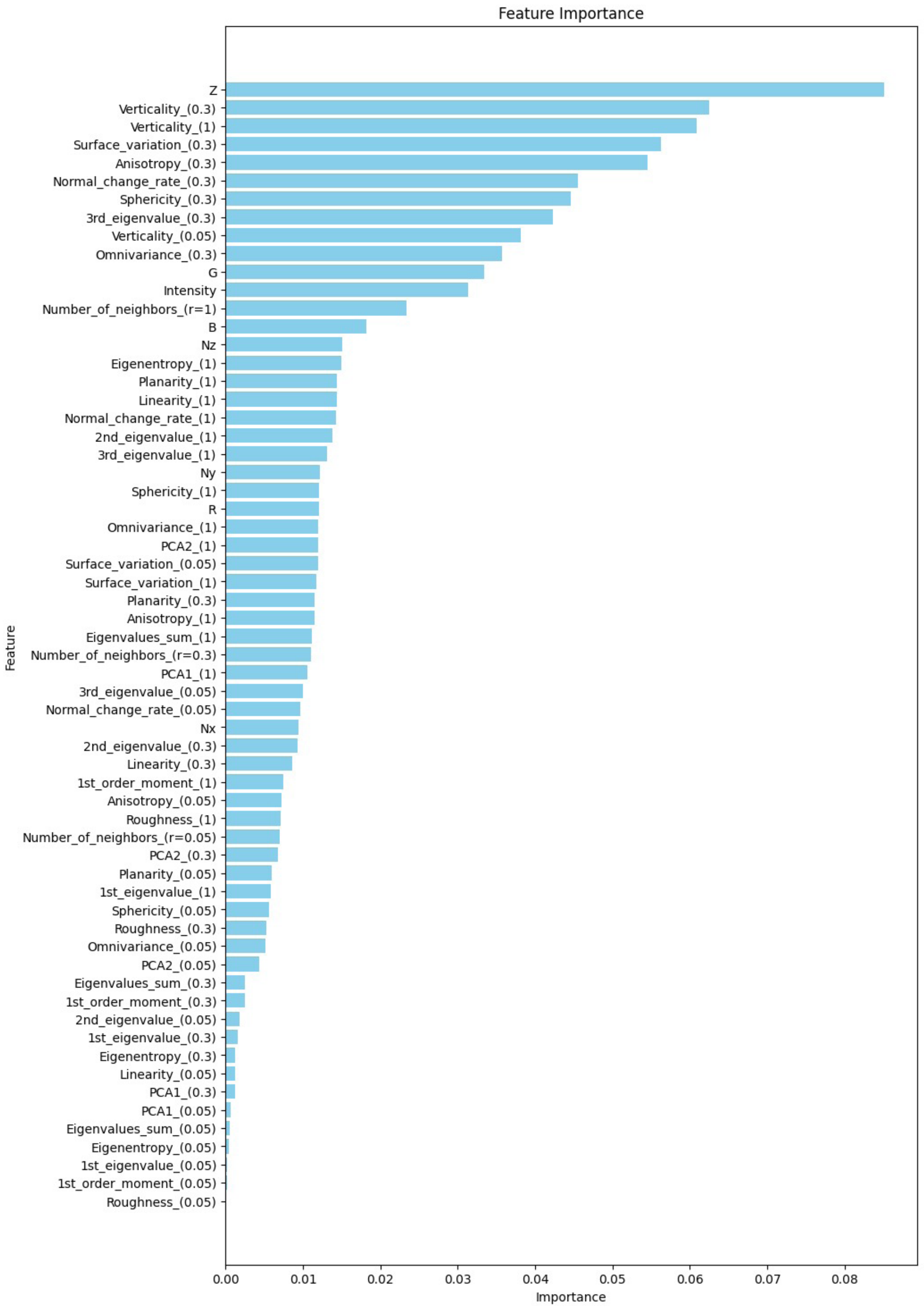


Fig. 8.08.

Feature importance histogram for the Former Monastery of St. Agostino point cloud.

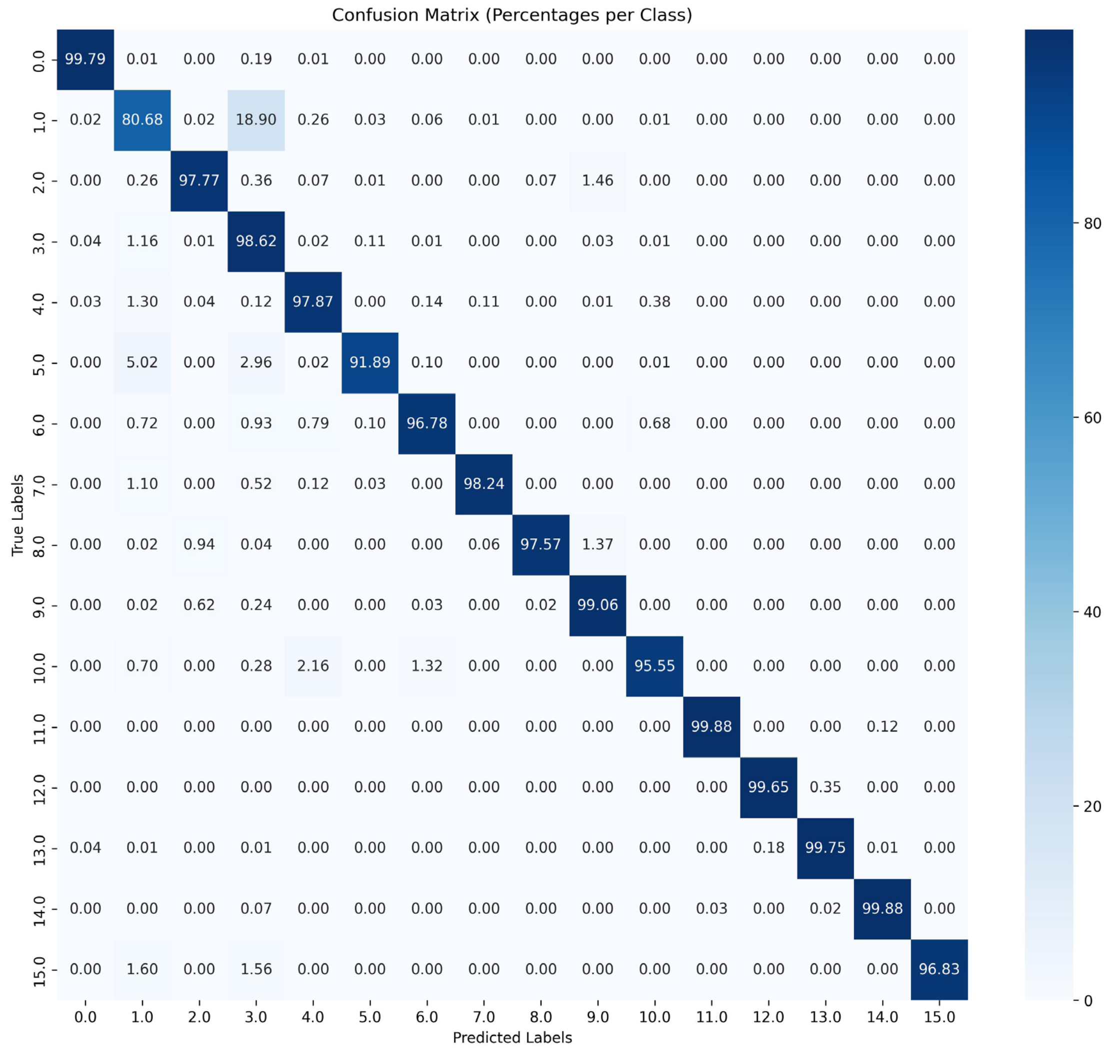


Fig. 8.09.

Confusion matrix on test set for the Former Monastery of St. Agostino point cloud after feature selection. Values in percentage.

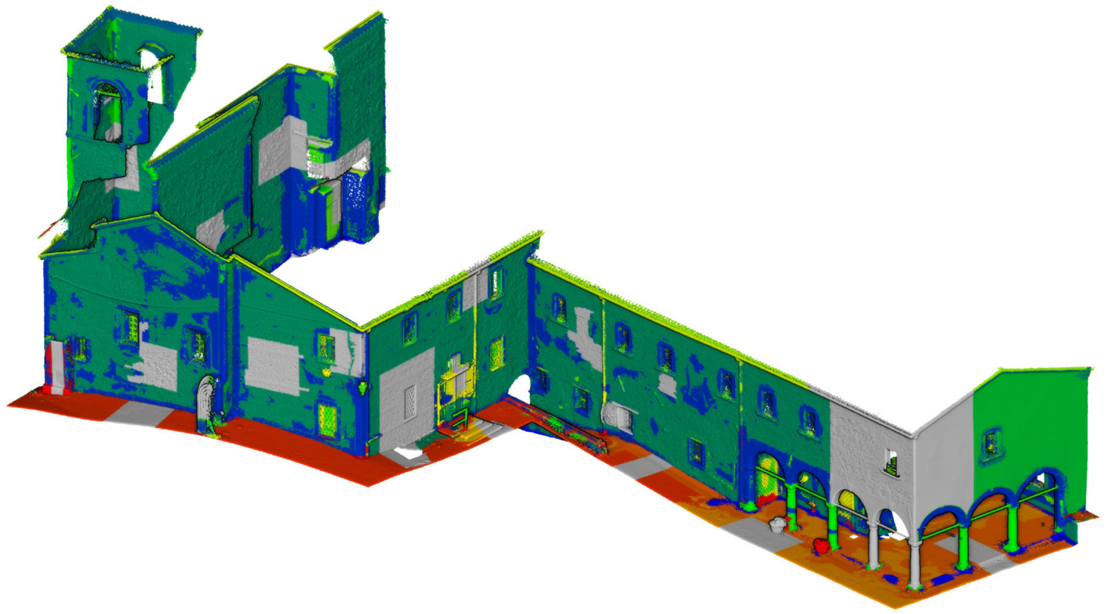


Fig. 8.10.

Former Monastery of St. Agostino predicted point cloud using FR classifier. Classes automatically labelled are displayed with colours, grey areas correspond to the manually annotated dataset used for training and testing.

radius. It is expected that lower values of the neighbourhood radius provide better performance in describing finer details (Croce et al, 2021), but in this case the value is not significant.

8.1.4 Multi-Level methodology

To improve the result, a Multi-Level, Multi-Resolution procedure (MLMR) was followed (Teruggi et al., 2020). Classes with critical predictions were merged into two macro-classes ("Masonry Wall" and "Floor Paving") for a new cycle of training and prediction. Results of the first level of classification are further segmented into the final classes, to address the heterogeneity in point cloud (Fig 8.11).

Inthis way, misclassification issues due to the number of classes to be identified might be overcame, since the number of analysed classes decreases for each level. Typically, MLMR methodology involves various subsampling of the original point cloud, so that each level of analysis corresponds to a different resolution of the point cloud: lower for a general scale, higher for a detailed scale. This is done to optimize computation time and due to the fact that general classification levels do not need very detailed point clouds. The result of each level is back interpolated to the higher resolution cloud, using nearest neighbour formula, in order to proceed to the next steps, until the final result is obtained. In the Former Monastery of St. Agostino dataset, given the still manageable point cloud dimension, the resolution was the same in both level of analysis. Moreover, subsampling too much the dataset for the first level would have made it more difficult to recognize small elements like metal chains and downspouts. The ML application steps followed are the same described above, with the same criteria for feature selection. The evaluation metrics shows extremely high values (Tab. 8.04) and the predicted model confirms a satisfactory result (Fig. 8.12), even if some minor parts are not correctly assigned, despite the metrics. This may occur in materials of elements with similar geometry, or due to the lack of a sample of this kind in the manually annotated dataset, as in the case of the bell tower arches whose were classified as "Brick Moulding" instead of "Stone". The same happened in the walls under the portico: they are plastered, but the actual missing of this part in the training set led to a completely misclassified surface. However, given the simple geometry of this part, points were rapidly manually corrected

From point cloud model thus obtained, classes of "Stone/Brick Masonry" and "Paving" were isolated and some misclassification errors were manually adjusted, to not affect prediction at the following step (Teruggi et al., 2020). The two main surfaces were processed separately for the second level of analysis. First training involved all features, to investigate if different features, at this scale, are able to highlight the discontinuities between the materials. For the wall classification, in addition to "Stone Masonry" and "Brick Masonry" classes, also "Shaped Stone" was included, because many angular stones were not identified in the previous level. In this way, Multi-Level methodology is tried to be exploited also to correct the classification itself. The results achieved are

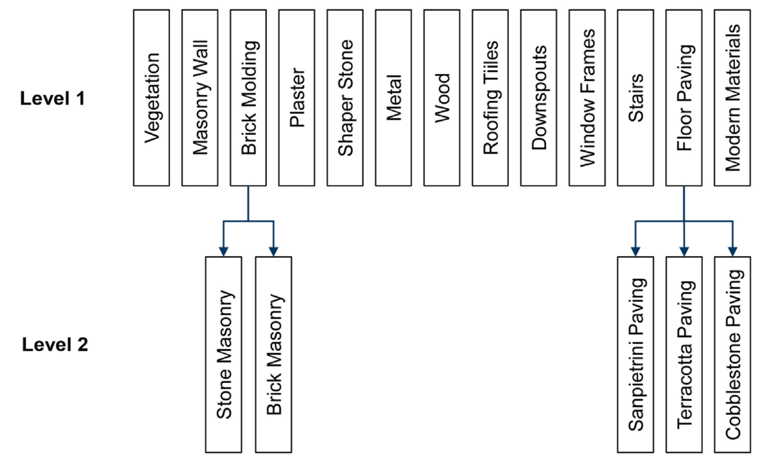


Fig. 8.11.
Diagram of Multi-Level approach adopted in Former Monastery of St. Agostino classification.

Tab. 8.04.
Evaluation metrics on test set, first level of analysis.

Class	Precision	Recall	F1-score	Points number
Vegetation	1.00	1.00	1.00	74869
Stone/Brick Masonry	0.99	1.00	0.99	812053
Brick Moulding	0.99	0.98	0.99	27167
Plaster	0.99	0.98	0.99	185464
Shaped Stone	0.99	0.94	0.96	76110
Metal	0.98	0.97	0.98	30009
Wood	1.00	0.99	0.99	132828
Roofing Tiles	1.00	0.99	0.99	5112
Downspouts	0.99	1.00	0.99	32292
Window Frames	0.98	0.97	0.97	29445
Staircase Flooring	1.00	1.00	1.00	12146
Paving	1.00	1.00	1.00	170248
Modern Materials	1.00	0.96	0.98	29500
Accuracy			0.99	1617243
Macro avg	0.99	0.98	0.99	1617243
Weighted avg	0.99	0.99	0.99	1617243

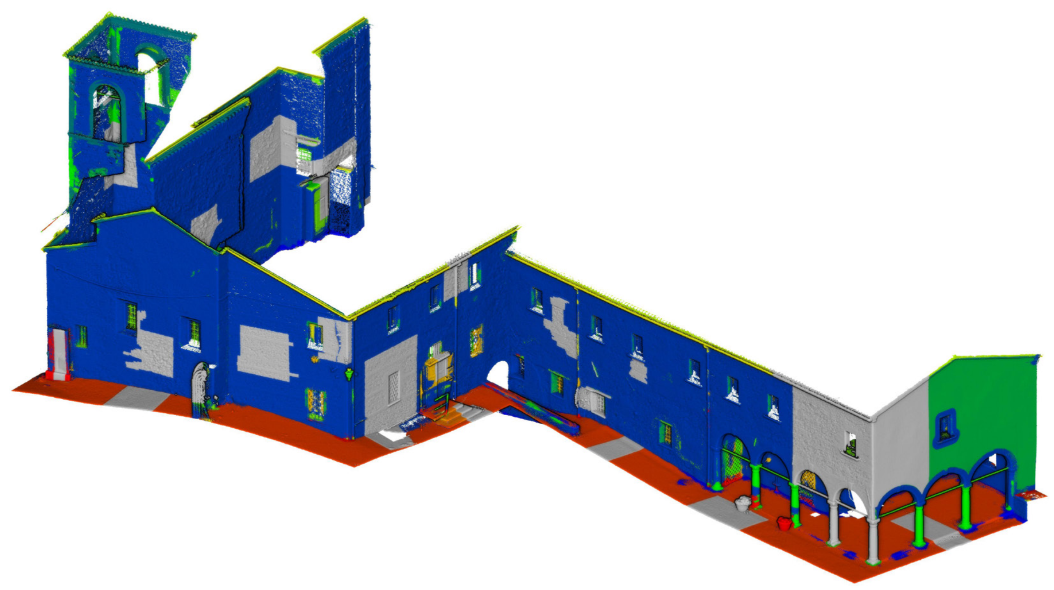
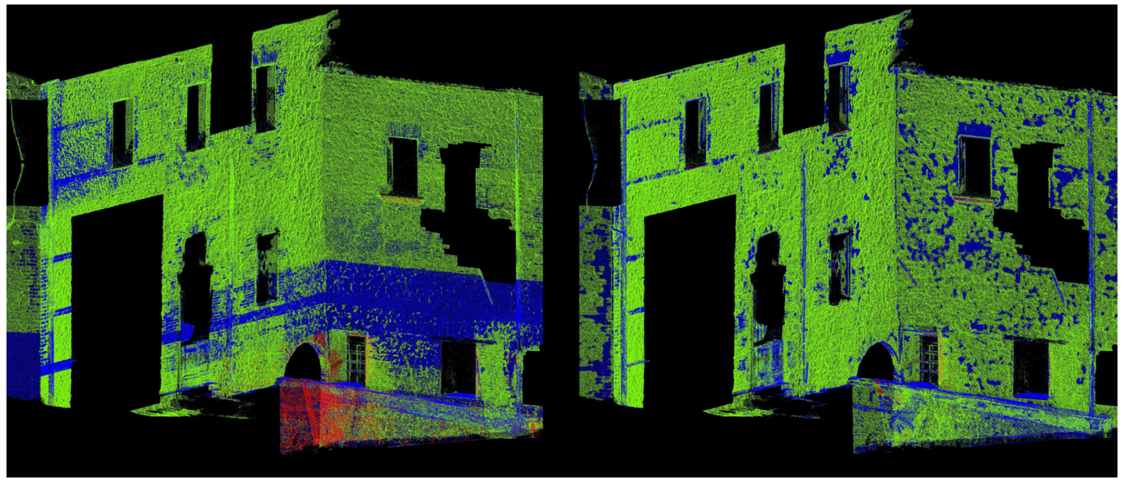


Fig. 8.12.
Predicted model from the first Level classification of the Former Monastery of St. Agostino. Classes automatically labelled are displayed with colours, grey areas correspond to the manually annotated dataset used for training and testing.

Fig. 8.13.

Detail of segmented masonry considering features calculated with radius 0.05 m (left) and 0.02 m (right). In both cases the results are not acceptable.



different for the two macro-classes. While the pavement was all in all correctly divided and the misclassified points can be easily corrected manually, the same cannot be said for the masonry. This did not return an acceptable result, even considering only the geometric features computed with the smallest radius (0.05 m) or with the addition of others drawn from an even smaller surrounding (0.02 m) (Fig. 8.13).

At this stage, a remark can be made regarding the defined categories of the materials abacus. Perhaps, ML procedure aimed at separating such morphologically interconnected materials is not feasible using the point cloud as a medium, unless distinguishing the parts of brick masonry from those of stone, considering them as a single entity under the class "mixed masonry." The choice to be taken should be guided by the purpose. To segment the two different classes anyway, the procedure to be adopted can be segmentation via images).

8.1.5 Classification via image segmentation

Since a complete photogrammetric survey is not available for this building, the meshes and textures were developed from the point cloud by laser scanner, using the RGB data of the cloud itself for texturing. The methodology adopted is that of texture segmentation and back projection on 3D model (Paragraph 7.4.4). To facilitate both the reading of the façade surfaces in manual annotation step and the algorithm training, the building was decomposed according to its main elevations, and meshes and textures were produced for each of them (Fig. 8.14). To optimize the whole process, the annotation, training and testing of the algorithm were performed on a representative elevation, then the trained ML model was applied on the other elevations. In Weka Trainable Segmentation, model used was Fast Random Forest classifier of 200 trees, considering 2 random features each, using a 32-thread workstation (Tab. 8.05). This procedure necessarily produces more prediction errors than a specific annotation for each elevation. Using the same procedure as described above, a coloured texture was also produced with the intensity datum displayed with a blue-green-yellow-red colour grading, scaled to a range of more significant reflectance values (Paragraph 6.2), so that material discontinuities

Step	Time	Out of bag error
Feature stack	2 min	-
balancing classes distribution and training	3 min	13.08%
Segmentation whole image	2 min	-

Tab. 8.05.

Fast Random Forest performance on an elevation of Former Monastery of St. Agostino. Time in training and segmentation considers the sum of all re-labelling steps conducted to refine the prediction to reach de final result.

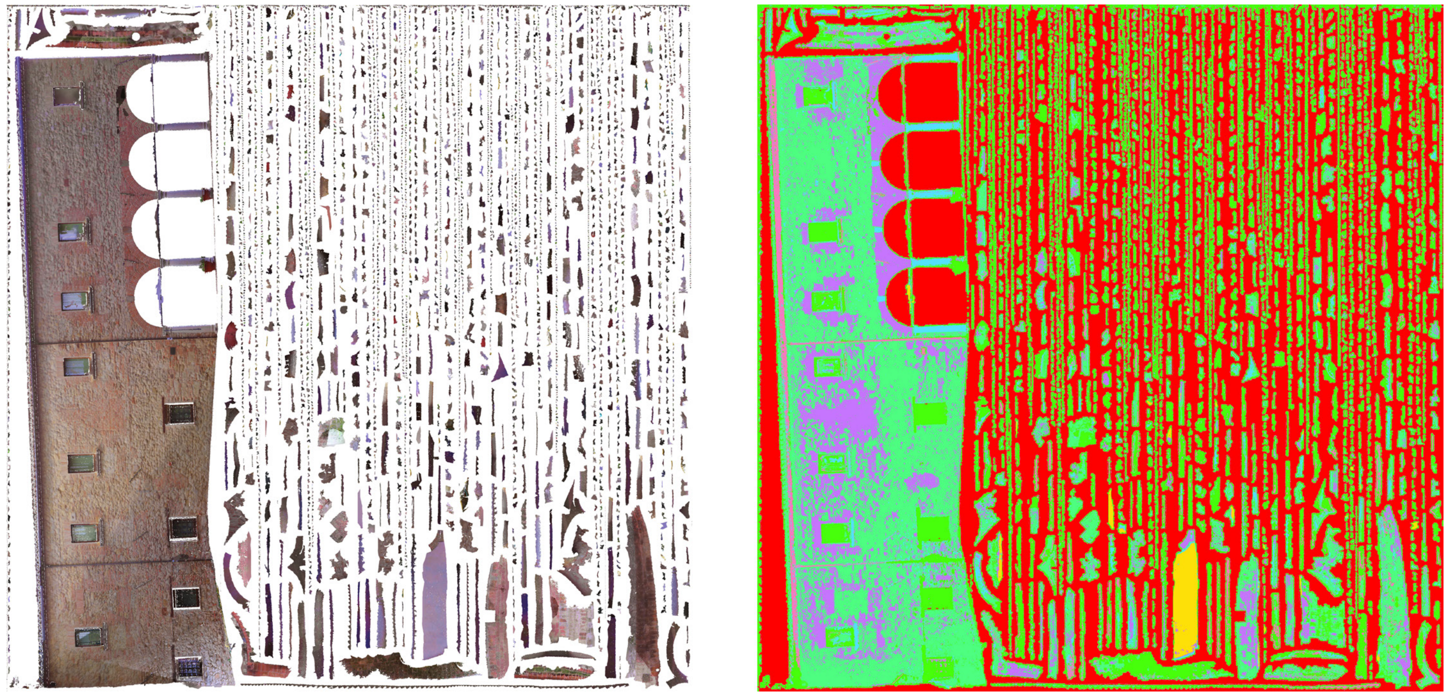


Fig. 8.14

Texture produced by the point cloud colour data (left) and segmentation with RF (right) of a Former Monastery of St. Agostino elevation.

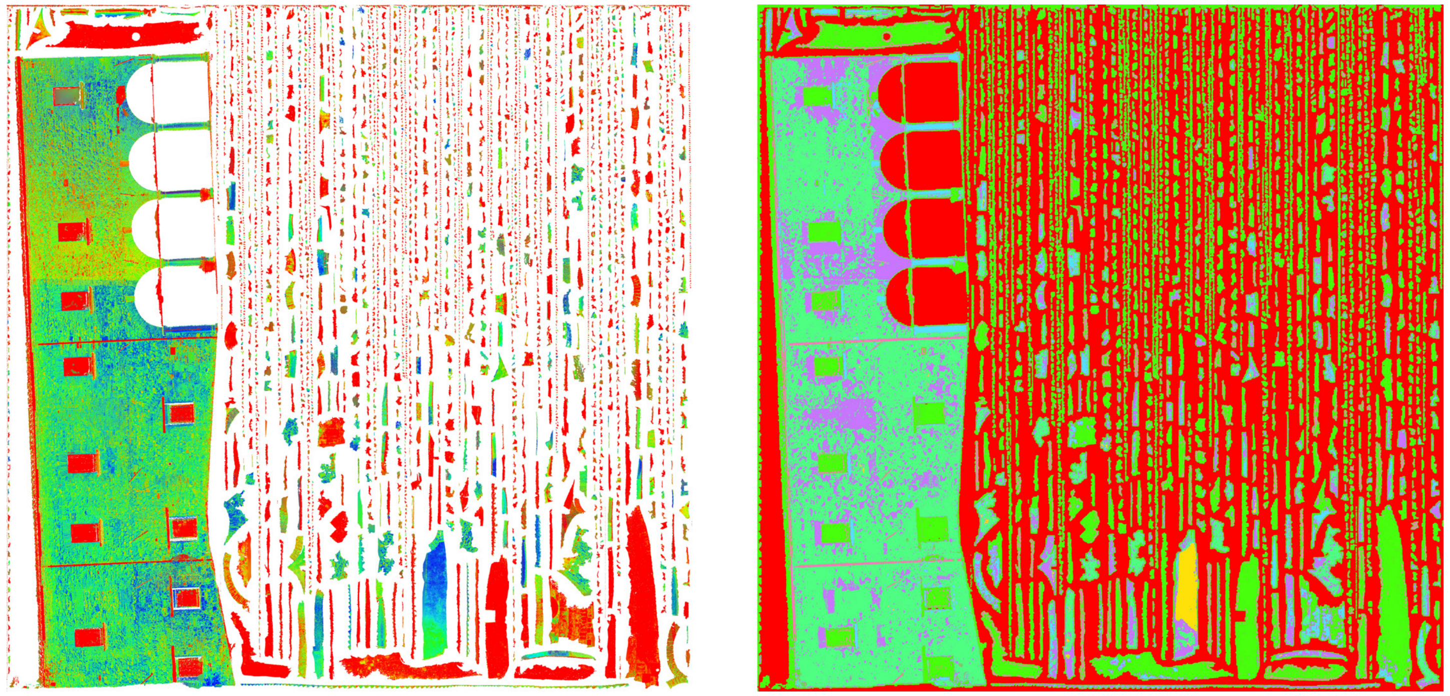


Fig. 8.15

Texture produced from the point cloud intensity data visualized with a blue-green-yellow-red colour scale appropriately restricted on a specific range (left) and segmentation with RF (right) of a museum elevation.

were made explicit. On this, the algorithm was again trained with the aim of testing whether, and how effectively, this radiometric feature could be used to segment an image as an alternative to the colour data. In a comparison of the two, as expected, this second segmentation is overall less accurate than the first, but there are some local improvements. For instance, class “metal” was better detected on the reflectance image than on the colour one, probably because of the very low values it assumes for this material, displayed with red colour in the adopted colour scale (Fig. 8.15).

8.1.6 Outcomes

The outcomes of experiments on the Verucchio Archaeological Museum dataset show that the use of RF on point clouds leads to good results for the recognition of classes of materials strongly characterized by different geometries. These are predominantly those identified in the first step of the multi-level methodology, while deepening the analysis, the results are more uncertain. Geometric features fail to be representative for these classes of detail. While it is necessary to reduce the radius of the surroundings to describe finer details, doing so generates too many prediction errors of the less detailed classes, which cannot be accepted. RGB colour data alone is not sufficiently representative to correct any errors induced by geometric features with inappropriate values. Consequently, image segmentation seems to be a viable way to overcome this gap. In fact, the radiometric features that Weka Trainable Segmentation allows to calculate, first of all the HSV values of the image, reinforce the effectiveness of the radiometric data and, working in 2D, the geometric ones are not considered. The results obtained demonstrate greater detail achieved.
Regarding the importance of geometric features in point cloud classification, this experimentation has provided initial insights that can be read in light of those developed on the other case studies to trace recurring patterns that can guide future choices, especially the selection of features upstream of extraction to save computation time and files weight.
Intensity has been shown to be a mean significant feature for three-dimensional classification and quite good for two-dimensional segmentation. In the latter, comparing the results with those obtained on the colour datum image, a lower overall accuracy was reached. This highlights the need to consider the segmentation of the reflectance image in relation to whether colourimetric data are included in the dataset. When colour data are available, reflectance serves a complementary interpretative role; when they are absent, it becomes the primary source of information.

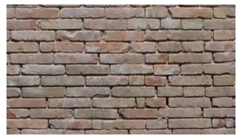
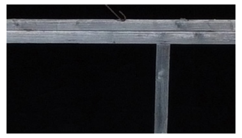
8.2 Former Colonia Varese in Milano Marittima

8.2.1 Overlapping issues: from construction techniques to state of conservation

The 3D point cloud of the Former Colona Varese in Milano Marittima (Fig. 8.16), is a case study suitable for tests focused in materials and, especially, in decays recognition. Indeed, this building is significant in terms of mapping and interpretation requirements in relation to state of conservation, of both structures and surfaces, since it has been abandoned for a long time (Paragraph 5.3).
Given the building dimensions and consequently those of the surveyed point cloud, considering that vegetation often makes data “dirty” and incomplete, and taking into account that the aim of the research is to assess the ML algorithms in a detail scale, the experimentation focused on the North wing of the building, which is an area with a challenging state of conservation and, at the same time, the best quality of input data.
To classify the exterior of the building according to materials and states of conservation, an abacus for each category was elaborated, after an *in situ* inspection and with support of photographic documentation (Fig. 8.17) and photogrammetric point cloud, especially for the analysis of those areas that, due to the precarious state of preservation of the structures, were not accessible or approachable. Regarding materials, an abacus of 7 categories was elaborated (Tab. 8.06), reporting the distinction between solid bricks and perforated bricks, taking into account the difference between original walls and

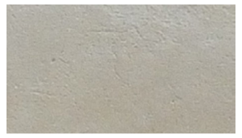
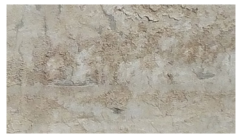
Fig. 8.16.
Aerial view of Former Colona Varese in Milano Marittima.

Fig. 8.17.
State of conservation of the external surfaces of Former Colona Varese.

Material	Image	ID	Colour
Vegetation		00	
Terrain		01	
Plaster		02	
Reinforced Concrete		03	
Solid Brick		04	
Hollow Brick		05	
Concrete Windowsill		06	
Wood frames		07	

Tab. 8.06.

Abacus of materials of the external surfaces of the Former Colonia Varese.

Degradation	Image	ID	Colour
Vegetation		00	
Terrain		01	
No Degradation		02	
Chromatic Alteration		03	
Lacuna		04	
Disgregation		05	
Lack		06	
Incongruous Interventions		07	
Rising Damp		08	
Seepage Moisture		09	

Tab. 8.07.

Abacus of state of conservation of the external surfaces of the Former Colonia Varese.

later window sealings, configuring a mixed-material-building-technique abacus. Among materials, also vegetation was included, as its massive presence. Regarding state of conservation, the abacus was drafted on the basis of the UNI 11182:2006 document, former UNI NORMAL 1/88 (Tab. 8.07). The methodology for categorizing decay pathologies involves the identification of five categories of degradation morphologies: physical-chemical (environmental conditions), physical-mechanical, biological, anthropogenic, and structural. Among many, the experimentations considered the overall state of degradation by macro areas, focusing on the most significant pathologies, that are more widespread, representative degradations of potential interest for intervention. Further specific objectives of the experimentation on this case study are:

- analysis of geometric features calculated in neighbourhoods of different dimensions, to evaluate their impact on the algorithmic prediction and the correlation with the classes to be searched, in order to optimize the extraction phase in following experiments;
- evaluation of the impact of the intensity data on the ML process,
- evaluation of RGB projected from photogrammetric point cloud to laser scanner point clouds in algorithmic procedure.

As for the experimentations on Former Monastery of St Agostino dataset, all these specific objectives contribute to set up an algorithm and a methodological workflow in order to improve the prediction effectiveness.

8.2.2 Input dataset

Methodological integration in the survey of Former Colonia Varese (Paragraph 5.3) resulted in the formulation of two models (from laser scanning and photogrammetry) consistent to a single local reference system. In the former, each point is characterized by the x, y, z, i (intensity) components, in the latter by x, y, z, r, g, b. (Fig. 8.18). The experimentations described in this section involve laser scanner point cloud with colour data transferred from the photogrammetric one, in order to exploit consistent RGB

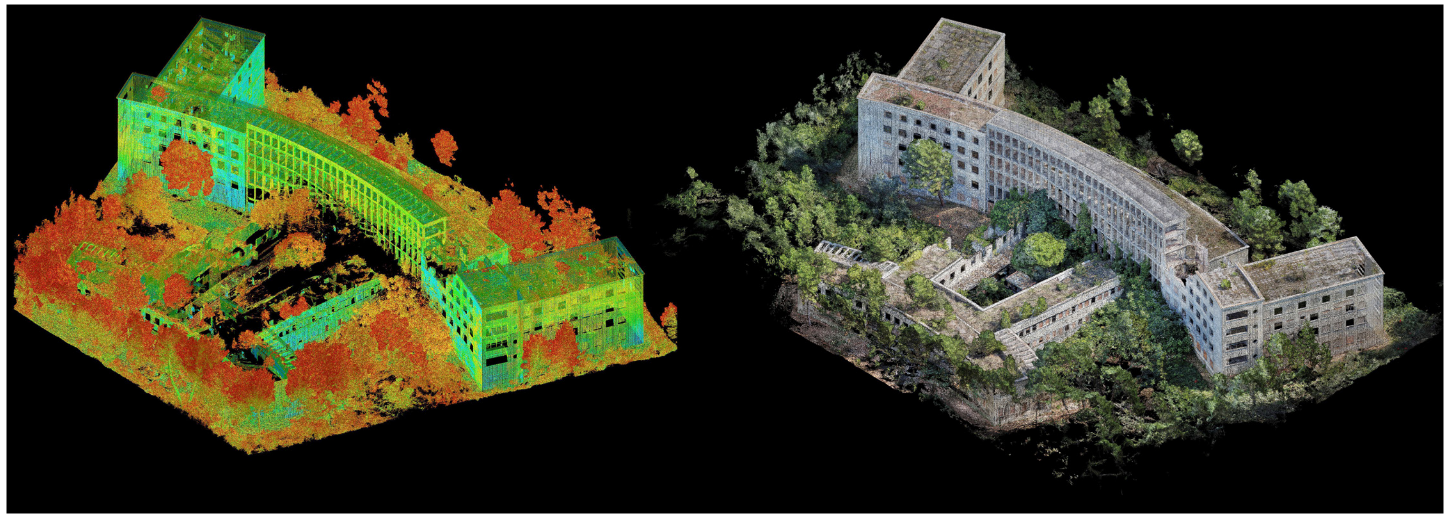
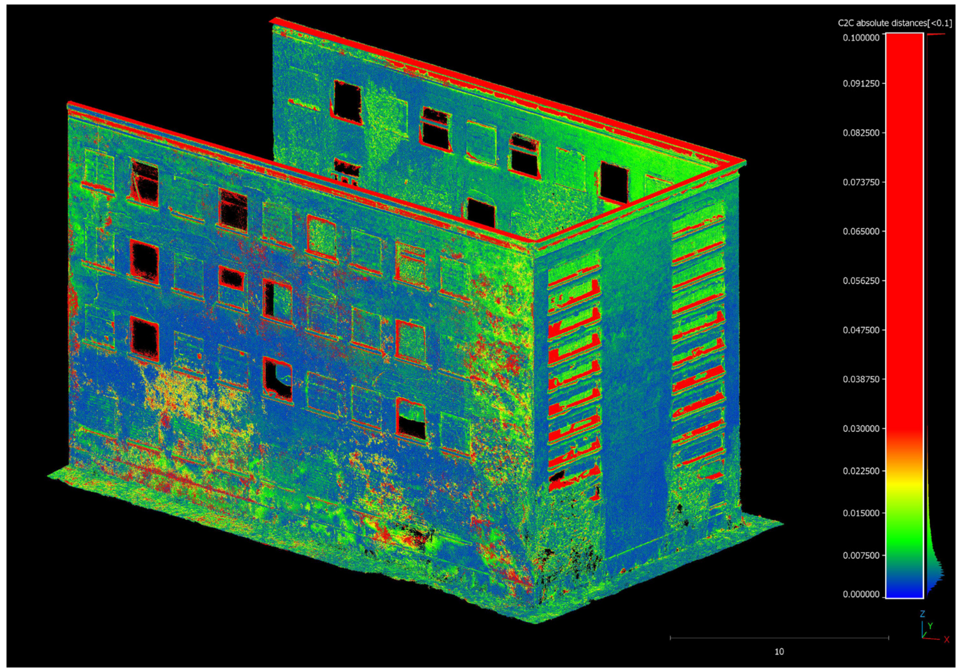


Fig. 8.18.

Point cloud models of Former Colona Varese, from laser scanning (left) and from digital photogrammetry (right).

Fig. 8.19.

Cloud to cloud distances between laser scanner and photogrammetric models red areas represent a value bigger than 3cm.



data in algorithmic procedure and, at the same time, asses contribution of intensity value. The reprojection of colour data was possible because of the common reference system between these point cloud models, and after verifying that the distances of the coordinates of the measured (laser scanner) and derived (photogrammetric) clouds were within acceptable tolerances for the scale of analysis (Fig. 8.19). The input point cloud is thus structured with: position coordinates (x, y, z), radiometric features (R, G, B, intensity), normal (Nx, Ny, Nz). Usual pre-processing operations such as cleaning incoherent points and outlier removal were performed, as well as subsampling at 5mm space grid.

Tab. 8.08.

Evaluation metrics on test set.

Class	Precision	Recall	F1-score	Points number
Vegetation	1.00	1.00	1.00	718292
Terrain	1.00	1.00	1.00	396770
Plaster	0.93	0.98	0.95	265741
Reinforced Concrete	0.95	0.37	0.53	17954
Solid Brick	0.82	0.77	0.80	27780
Hollow Brick	0.89	0.90	0.90	100788
Concrete Windowsill	0.99	0.75	0.86	12500
Wood frames	0.99	0.96	0.98	7105
Accuracy			0.98	1546930
Macro avg	0.95	0.84	0.88	1546930
Weighted avg	0.98	0.98	0.97	1546930

8.2.3 Point cloud classification

The cclassification of Former Colonia Varese dataset was developed in two phases: first for materials, second for decay morphologies. Supervised ML methodology followed the same steps described for Former Monastery of St. Agostino case study. Geometric features were extracted with three different radii: 0,05 m, 0,30 m and 0,60 m to enrich the input dataset. All categories of materials were identified on the point cloud, segmented and properly labelled for training and test sets. The ML algorithm used is RF, and also in this case evaluation metrics related to the test set show generally high values, suggesting a good algorithm performance (Tab. 8.08).

However, “Reinforced Concrete” class, shows a very low recall metric, meaning that many of its points were not correctly identified by the model, being classified as other materials, especially “Plaster,” which includes many points from other adjacent materials, being the most prevalent strictly architectural category (excluding ‘Vegetation’ and “Terrain”). Being “Reinforced Concrete” constituted of few points, it is not so demanding to manually correct the final result. However, other tests were done, selecting one group of features at a time, first those calculated with radius 0,05 m, then 0,30 m, and 0,60 m. As expected, none of the three solutions involving a single radius for all features turns out better than the one with mixed features, as made explicit by the confusion matrix (Fig. 8.20) and from the visual inspection of predicted models (Fig. 8.21). Improvements in classification occur only when a number of features is selected among the most relevant, according to feature importance histogram, whose graph (as far as this experiment is concerned) can be assimilated to a negative exponential function (Fig. 8.22 and Fig. 8.23). Feature importance computation confirms, on the one hand, high relevance of Z coordinate and Verticality, followed in this case by “Normal Change Rate” and “Surface Variation”. On the other hand, “Intensity” is less used, showing low values. This could be due to two factors. Firstly, the reflectance datum may be inhomogeneous over the surfaces. Former Colonia Varese laser scanner survey, in fact, had to take into account the strong limitations that the context around the building imposed, particularly of accessibility. The vegetation forced the positioning of the instrument at strategic points in order to acquire as best and as complete as possible the volumes, with the purpose of supporting evaluations on distortions and structural deformations. In this way, in many situations the regularity of the scan positions in relation to the surfaces has been necessarily left out. This has affected the quality of the reflectance data, which is heterogeneous and thus, not very meaningful to be systematically associated with material classes. Secondly, among radiometric features, RGB quality is sufficiently good and homogeneous, reliably describes the colours of the building surfaces, being derived from a photogrammetric process, thus with photographic quality. Indeed, even if not extremely high, their importance is meaningful.

The classification of the Former Colonia Varese according to its state of conservation required preliminary conceptual considerations. Many decay pathologies overlap in several areas, so the same degradation morphology may have diverse radiometric

Fig. 8.20.

Confusion matrix comparison between models trained with different groups of geometric features. 0,05, 0,30 and 0,60 m radii (top left), 0,05 m radius (top right), 0,30 m radius (bottom left), 0,60 m radius (bottom right).

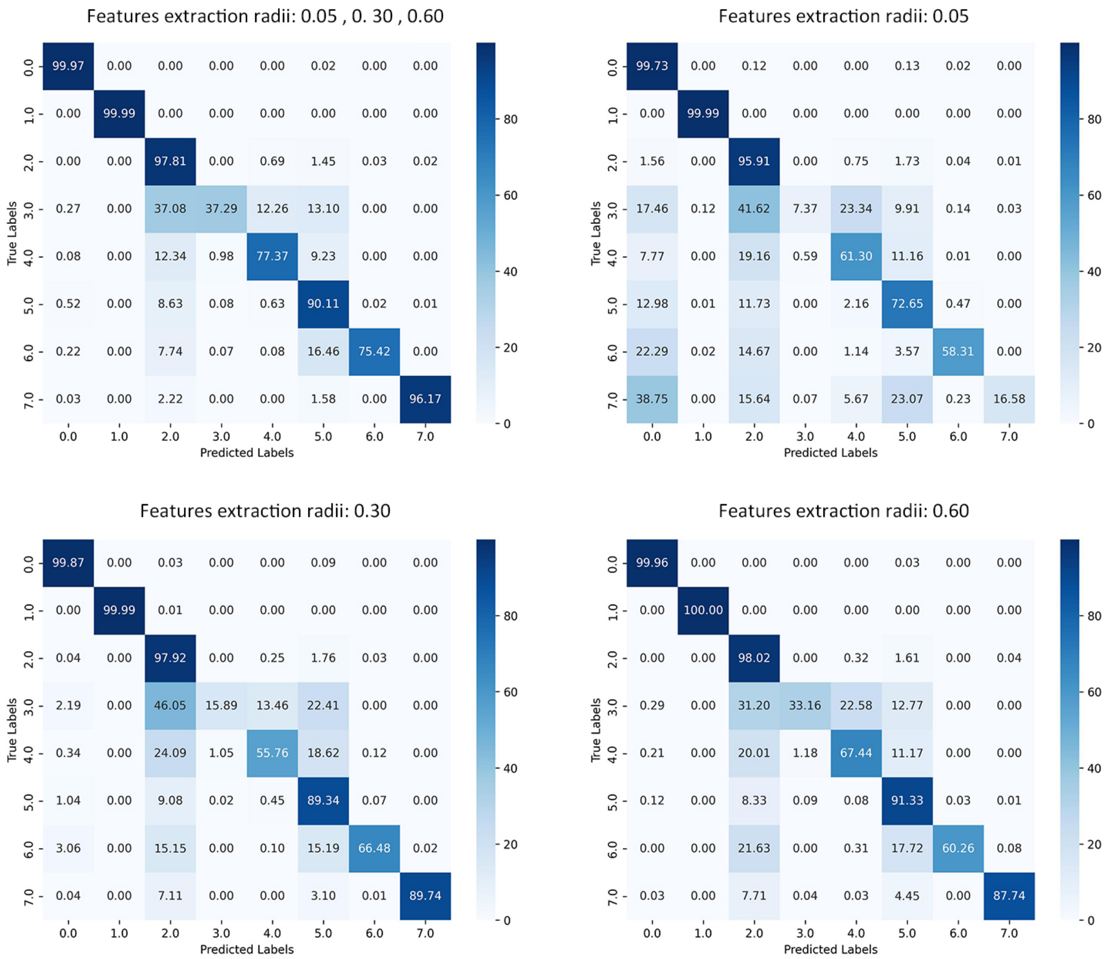
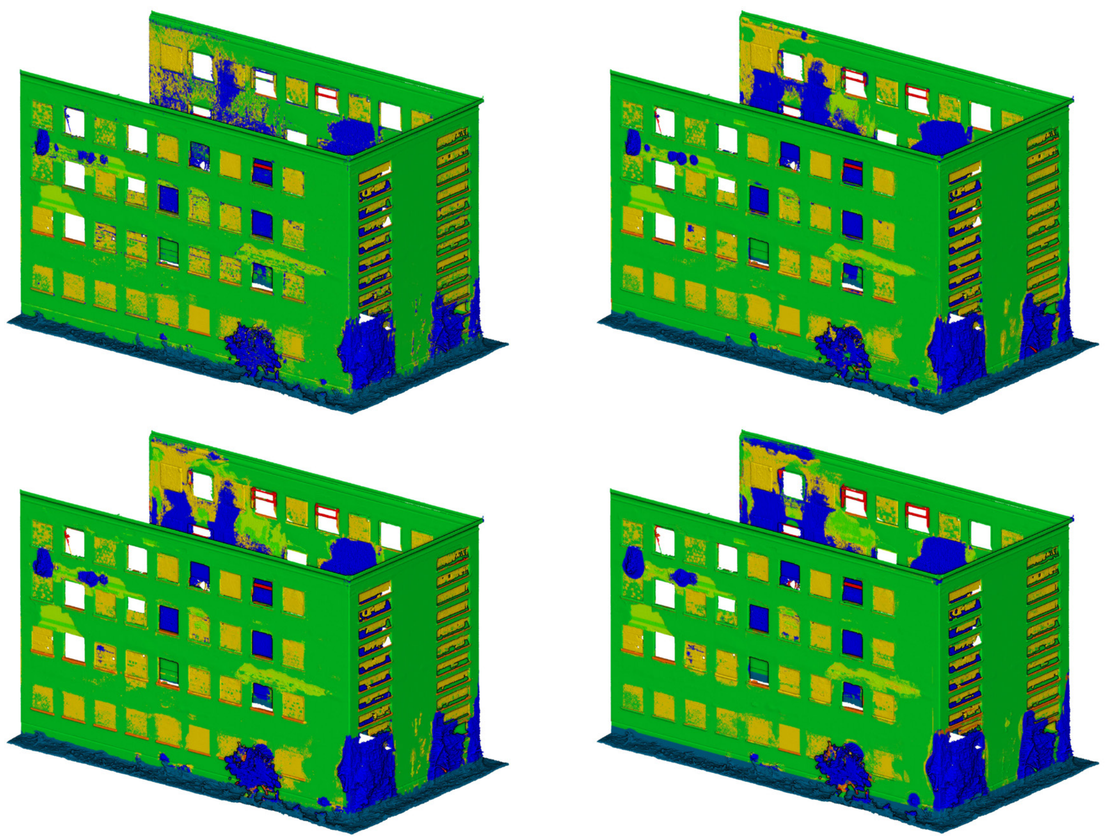


Fig. 8.21.

Predicted models comparison between models trained with different groups of geometric features. 0,05, 0,30 and 0,60 m radii (top left), 0,05 m radius (top right), 0,30 m radius (bottom left), 0,60 m radius (bottom right).



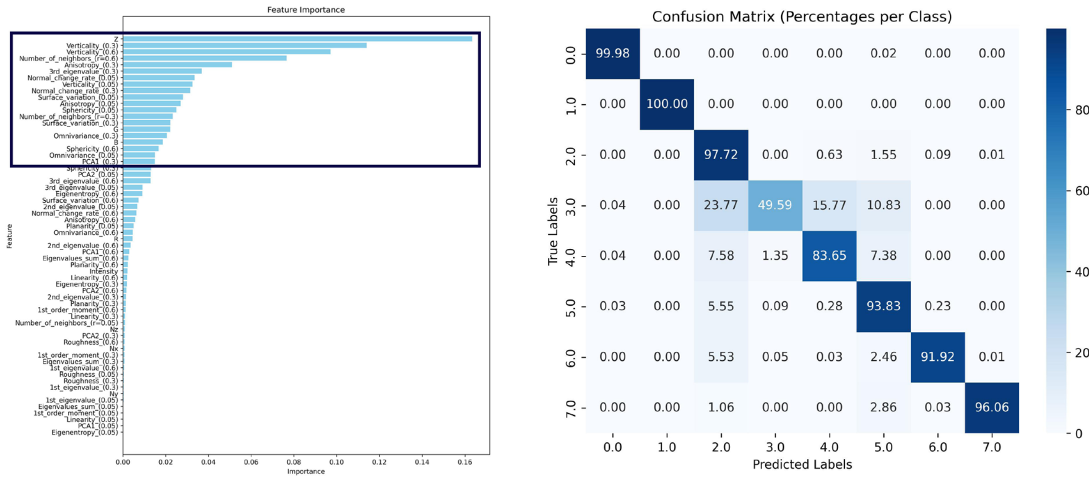


Fig. 8.22.

Confusion matrix of RF model trained after most relevant feature selection.

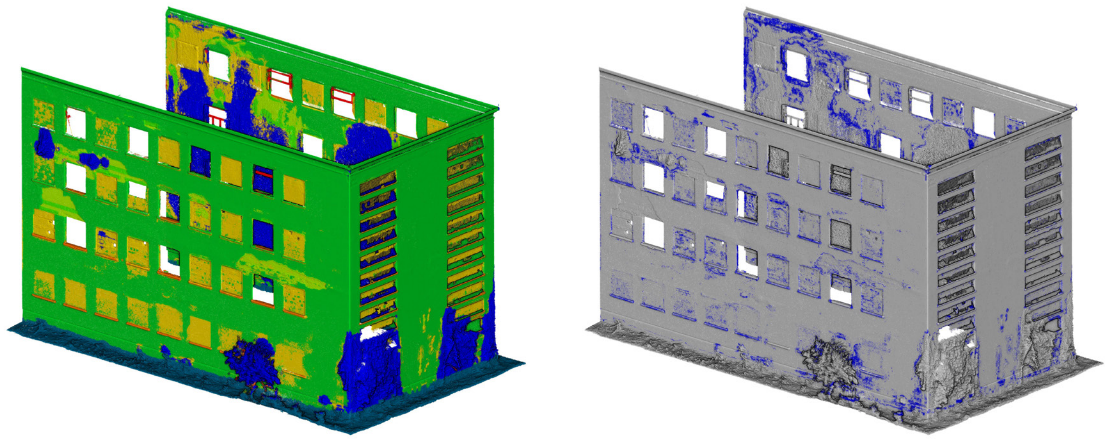


Fig. 8.23.

Final prediction on point cloud model (left), and visualization of points assigned to other classes after feature selection, displayed in blue (right).

connotations as a result of the sum of different components. This makes recognition by automatic procedures more complicated, and forces to choose between increasing the number of classes, generating new categories for each overlap, or increasing the levels of analysis, introducing a binary layer (degradation / no degradation) for each degradation morphology. Considering both procedures to be time-consuming and expensive in terms of generating duplicate files for calculations and complementary operations, a third method was pursued. Basically, degradations that do not overlap were merged, and each of them is a different layer. This strategy is functional only for processing, because for the formulation of the final queryable model, it is more suitable to provide a specific layer for each degradation morphology, being more manageable and understandable. (See paragraph 4.6. The thematic point cloud model of the Colosseum). In addition, analysing the output of material segmentation, it is observed that some degradation morphologies can be derived directly from this classification. For example, "Vegetation" remains "Vegetation" in both classifications; solid brick and reinforced concrete areas are those where the plaster is missing, so both of these materials converge into the "Lack" degradation class. Moreover, most of decays affect plaster surface. So, it is possible to adopt a Multi-Level methodology (Teruggi et al., 2020) in the transition between materials analysis and state of conservation one (Fig. 8.24). As follows, dataset to be analysed has less points, resulting in a lighter file and, consequently, processing time decreases.

Since this is a new classification category, the algorithmic processing again involved all features, calculated with the three different radii (0,05 m, 0,30 m and 0,60 m) in order to evaluate the most significant. After the previously discussed steps of manual annotation, training and testing, the feature importance computation returns (in addition to the Z coordinate and verticality) high values generally for the 0,05 m features, confirming, their probability to detect fine details, as differences between degradation morphologies are (Fig. 8.25).

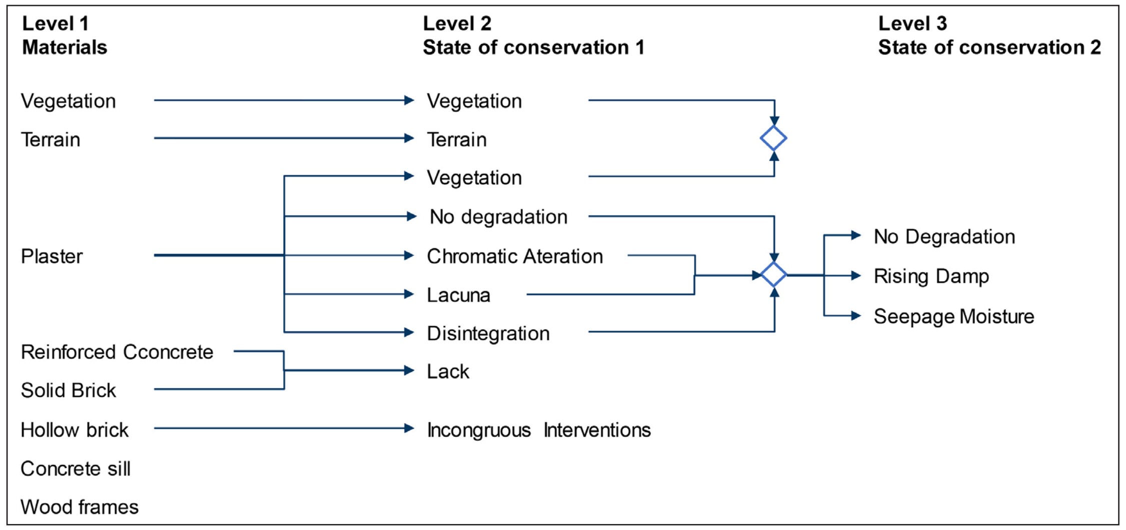
Nevertheless, the output of the first level of degradation analysis on point cloud produced a very heterogeneous result. Despite good performance metrics (weighted average f1-score 0.95%), at a visual inspection some areas turn out to be identified quite well, others are confusing, and most importantly, the contours of the degradation morphologies are very irregular and not faithful to the real conditions (Fig. 8.26). Therefore, semiautomatic segmentation procedure on images was applied (Grilli & Remondino, 2018).

8.2.4 Image segmentation to improve state of conservation mapping

From photogrammetric survey of the Former Colonia Varese, a textured mesh model and orthomoisaics of the elevations of the selected building whing were obtained. These two high-resolution images, together with the source photos, constitute two-dimensional materials on which supervised ML procedures can be applied to explore whether semi-automatic analysis of the state of conservation can be improved. Therefore, all three methodologies described in the paragraph 7.4 were tested, divided

Fig. 8.24.

Diagram of Multi-Level approach adopted for state of conservation classification in Former Colonia Varese point cloud.



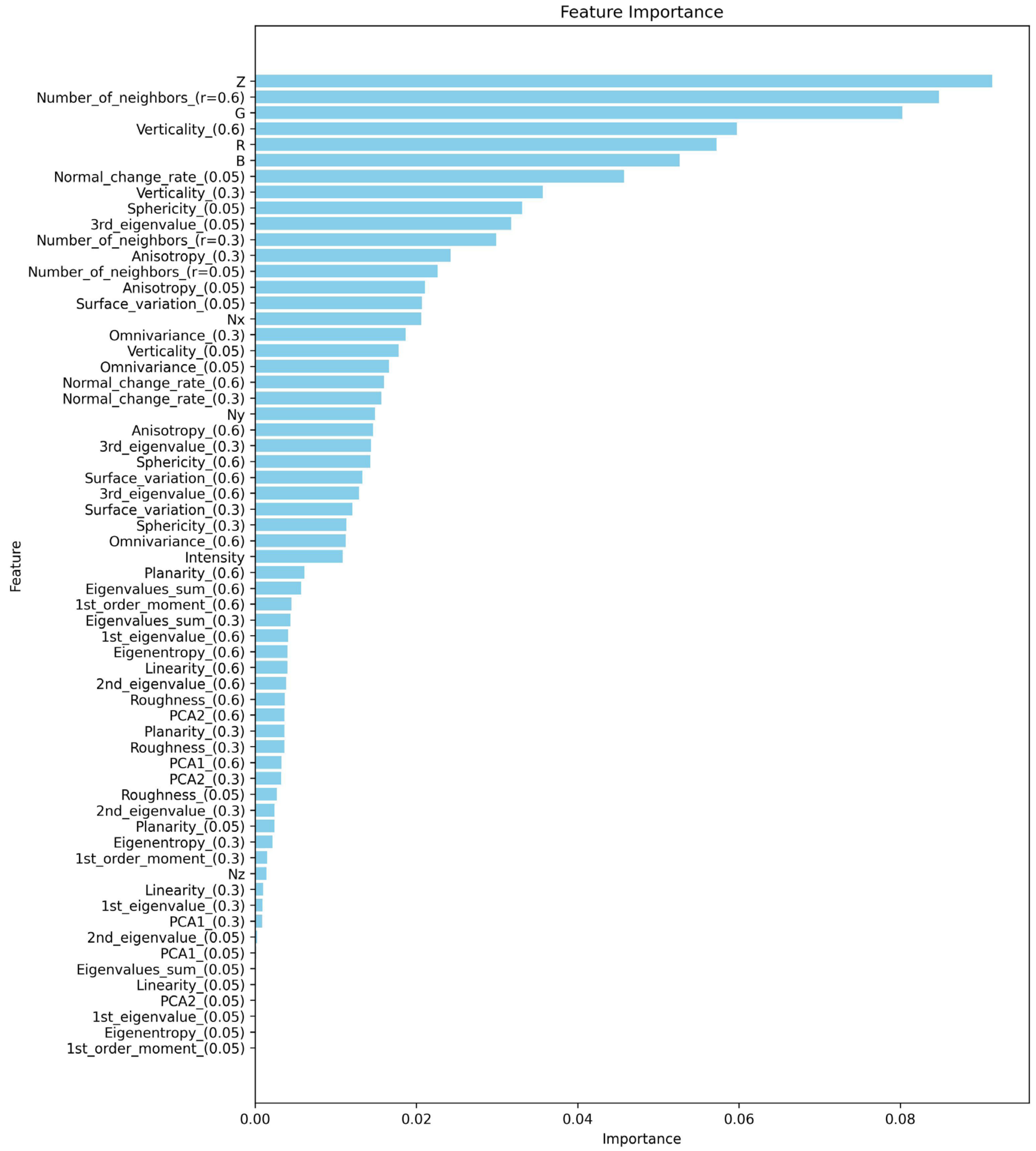
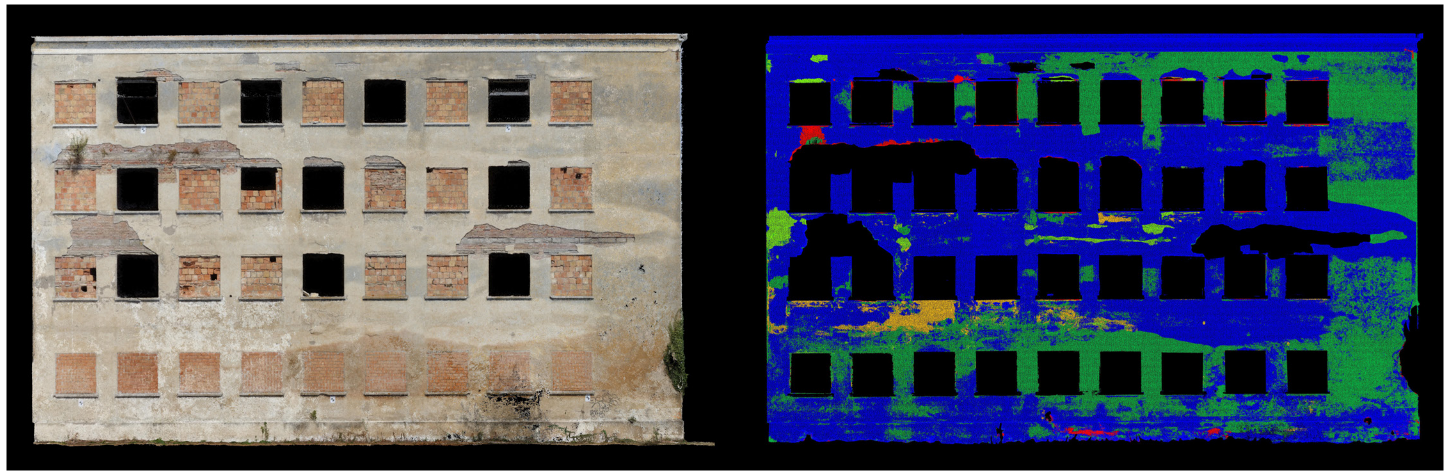


Fig. 8.25.

Feature importance histogram for decay morphologies on plaster, first level.

Fig. 8.26.

Point cloud of decay morphologies on plaster, first level. The image shows both parts manually annotated and automatically predicted.



according to the input data into:

- orthomosaic,
- texture,
- images of the photo dataset.

The methodology of orthomosaic segmentation was applied, at first, on one elevation of the whing investigated, considering the first level of the degradation analysis. The workflow exploited the possibility to re-label pixels not correctly predicted, directly in WeKa software interface. This operation was repeated three times since the achievement of a satisfactory result (Fig. 8.27). Model used was Fast Random Forest classifier of 200 trees, considering 2 random features each, using a 32-thread workstation (Tab. 8.9). The trained RF model can be applied to the orthomosaics of the other elevations.
For texture segmentation, the entire volume of the north wing of Former Colonia Varese was considered. The overall result is good (Out of bag error 10.56%), but less accurate than that obtained on the orthomosaic of the single elevation. However, segmentation transfer from 2D to 3D is feasible (Fig. 8.28).
Regarding the segmentation of source images, the same elevation analysed through the orthomosaic was considered for an initial test. Segmentation on a complete set of about 300 images required a not feasible tame frame for practical applications. In addition, the result obtained has a higher error value (Out of bag error 24.25%), and showed “confused” areas. Since the photogrammetric reconstruction method requires extensive overlap between frames, many areas appear in multiple images; these pixels may be classified differently in different photos, producing ambiguity in the point cloud (Fig. 8.29). Consequently, it is best to classify not the whole dataset, but only a part, preferably photos framing the surfaces strategically, ensuring the overall description with little overlap between them.

Tab. 8.09.

Fast Random Forest performance on an elevation of Former Colonia Varese. Time in training and segmentation considers the sum of all three passages to reach de final result.

Step	Time	Out of bag error
Feature stack	7 min	-
balancing classes distribution and training	20 min	1.07%
Segmentation whole image	9 min	-

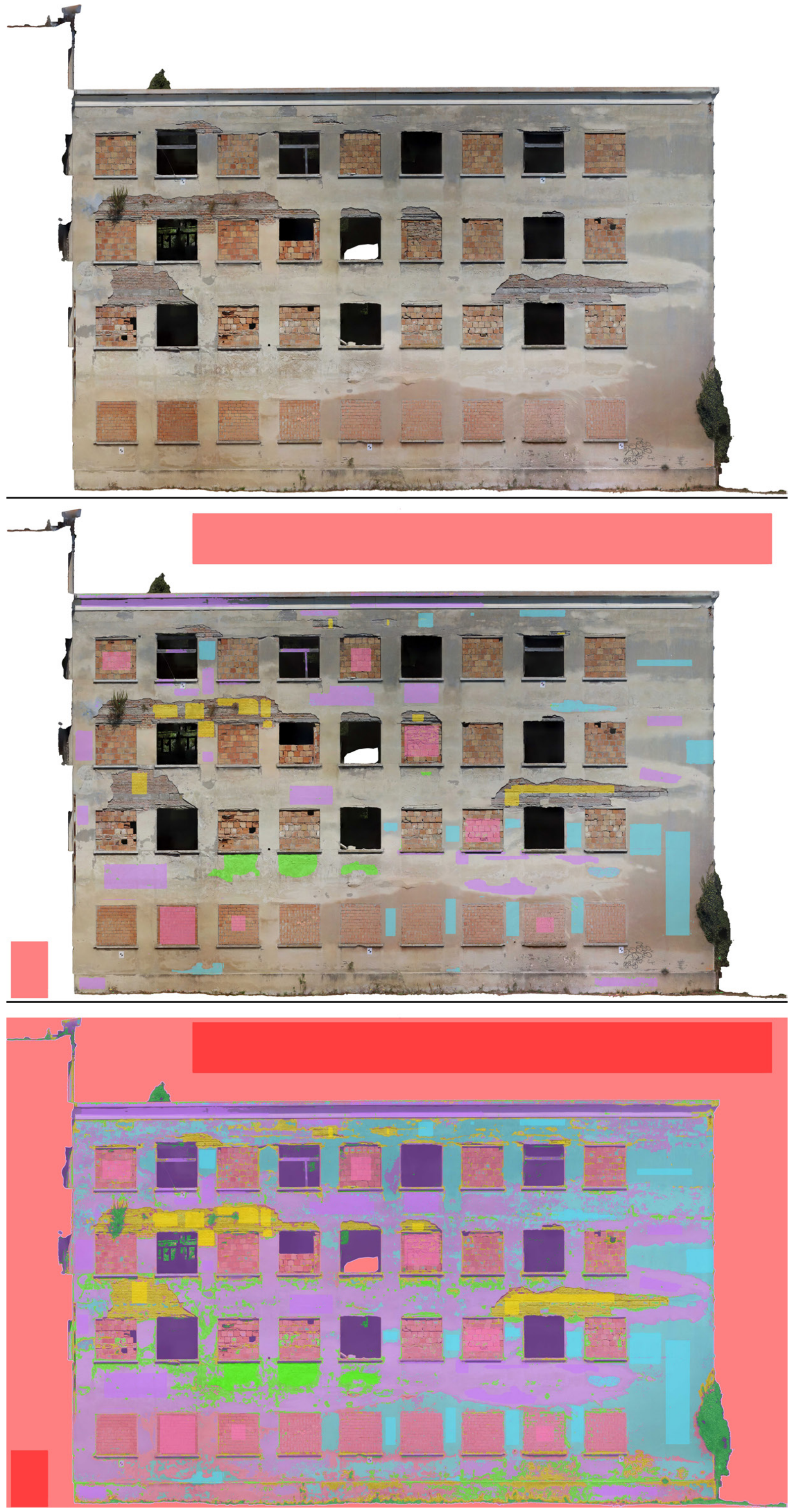


Fig. 8.27.

Classification of an elevation of Former Colonia Varese performed segmenting the orthomosaic. Original image (top), manual annotation (centre), segmentation (bottom).

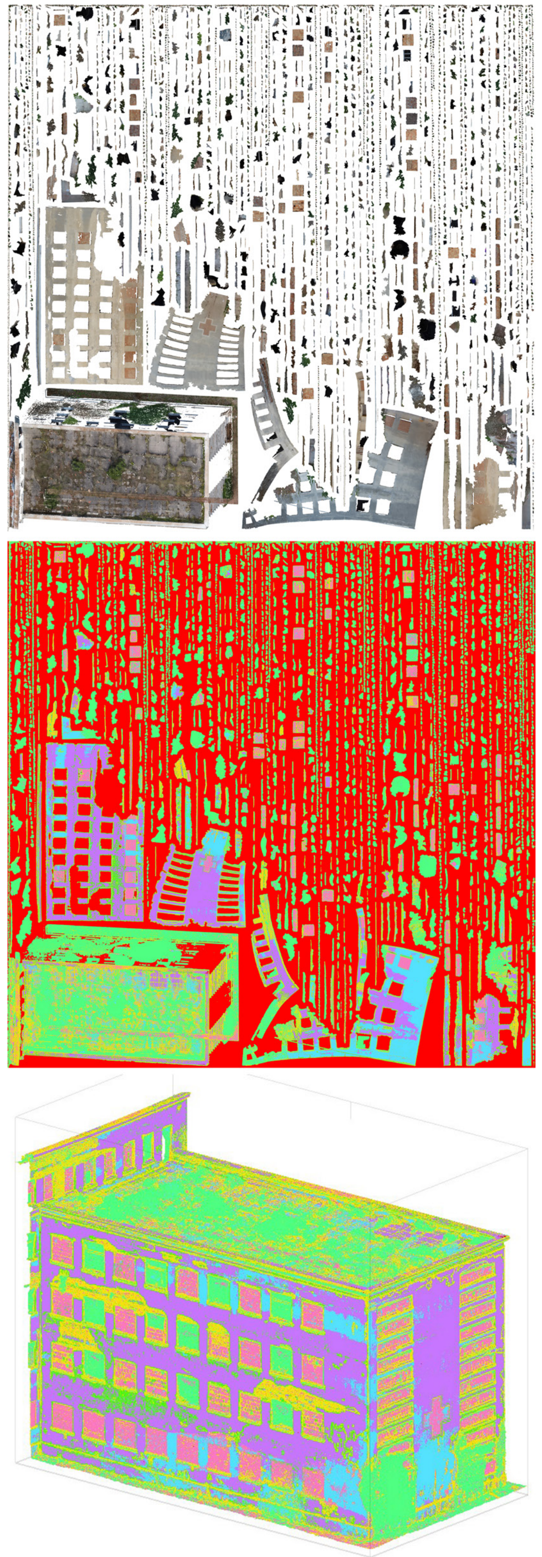
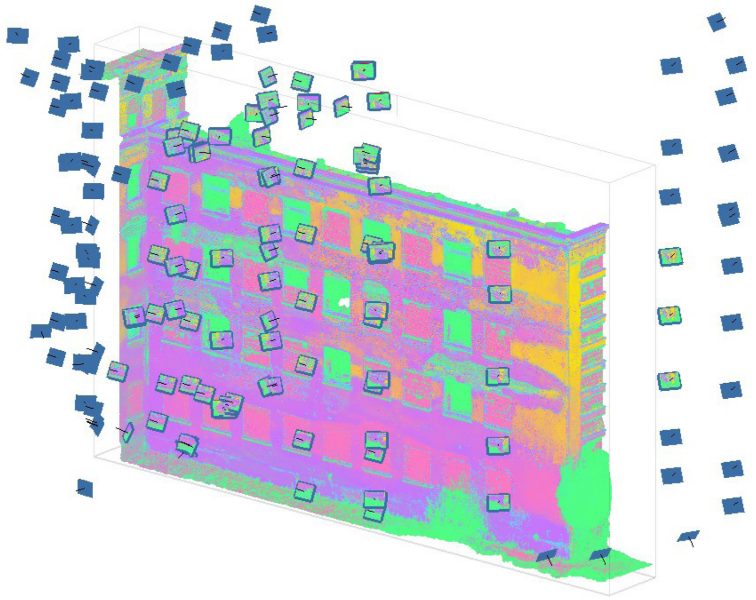


Fig. 8.28.

Texture classification of North Wing of the Former Colonia Varese: original image (top), segmentation (middle), and final 3D model classified (right).

Fig. 8.29.

Point cloud segmentation via source images segmentation. Misclassified points are observed.



8.2.5 Outcomes

Experiments on this point cloud case study led to good results for material identification, while for degradation, semi-automatic recognition was not considered satisfactory, for several reasons. The first concerns decay morphologies readability on point cloud, affected by the difficulty of recognizing some degradations. Moreover, technical-operational difficulties related to the manual segmentation task of complex areas occurred. In addition, geometric components are useless in relation to radiometric features, especially with regard to plaster decay morphologies. For all that, classification according to state of conservation is more advantageous when developed via image segmentation. The three methodologies described in paragraph 7.2 were pursued. For the specific case study, those on orthomosaic and texture proved to be more convenient, compared to the one on source images. With the former, greater detail is achieved but remains constrained to the two-dimensional descriptive and representational medium; with the latter, the two- and three-dimensional correspondence is maintained.

Regarding the importance of geometric features in point cloud classification, this experimentation provided additional insights to the data collected with the ones on the Former Monastery of St. Agostino (Paragraph 8.1) and will contribute to the definition of an optimized extraction procedure.

As detailed in paragraph 8.2.3, in this case study, intensity value did not prove to be a significant feature for three-dimensional classification because of the boundary conditions under which the survey was performed and its original purpose.

8.3 Cristo Obrero Church in Atlantida

8.3.1 Brickwork and state of conservation detection

Eladio Dieste's Cristo Obrero Church in Atlantida (Fig. 8.30) allowed multiple experimentation possibilities, related to the variety of brickwork or different construction techniques and the degradation morphologies affecting surfaces (Paragraph 5.5). The combined materials and construction techniques abacus has a total of 12 classes (Tab. 8.10). All kinds of brick classes also includes mortar joints, for the reason described in paragraph 8.1.1. The abacus of the state of preservation also takes into account, for the roof, the distinction between original and replaced bricks (Tab. 8.11).

Since this building was surveyed both through static laser scanner, specifically Leica

Fig. 8.30.

Picture of Eladio Dieste's Cristo Obrero Church in Atlantida, showing buildings' brickwork variety.

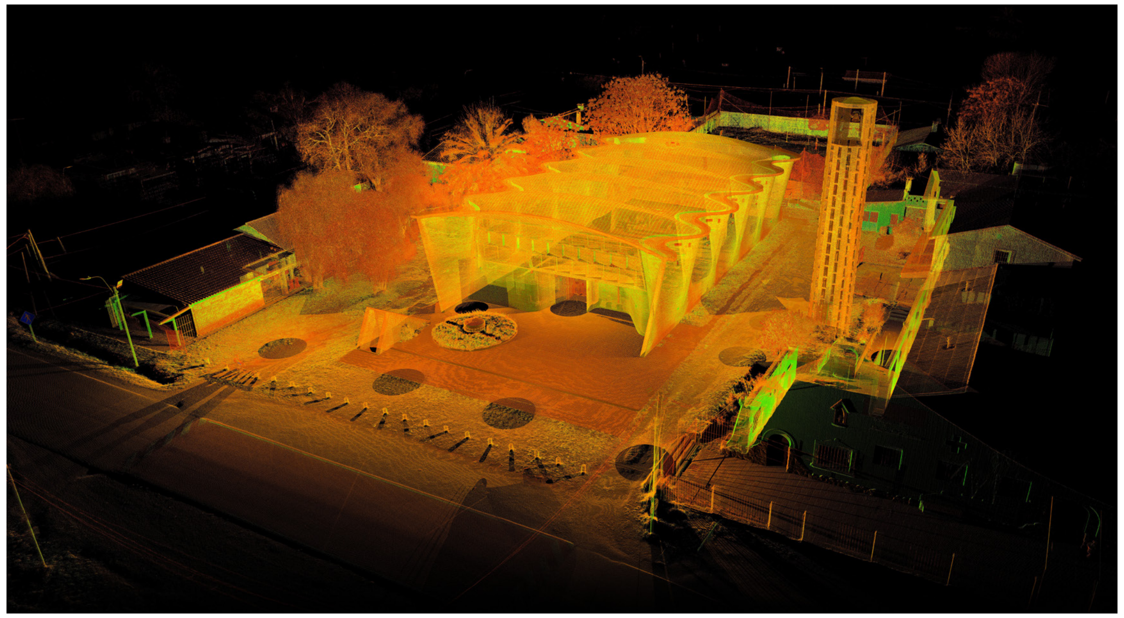
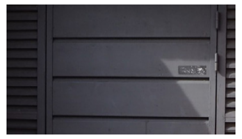


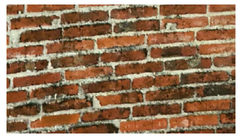
Fig. 8.31.

General view of Cristo Obrero Church Leica Scan Statio C10 laser scanner point cloud.

Mat./Constr.Tech.	Image	ID	Colour
Grass		00	
Brick Paving		01	
Brick Wall		02	
Brick Molding		03	
Brick Infill		04	
Brick Transom		05	
Brick Molded Back		06	
Brick Roof		07	
Alabaster		08	
Metal		09	
Wood		10	
VConcrete		11	

Tab. 8.18.

Abacus of Materials-Construction Techniques of the external surfaces of the Cristo Obrero Church.

Degradation	Image	ID	Colour
No Degradation		00	
Old Bricks (Roof)		01	
New Bricks (Roof)		02	
Solid Deposit + Biological Patina		03	
Deposit		04	
Moisture		05	
Moss		06	
Grass		07	

Tab. 8.11.

Abacus of State of Conservation of the external surfaces of the Cristo Obrero Church.

Scan Station C10 (Fig. 8.31), and SLAM technology (Lixel K1), this case study is also an opportunity to test and compare results of semi-automatic classification on point clouds acquired with different sensors that produce data with different geometric accuracies.
To resume, the objectives of the tests on this case study are:

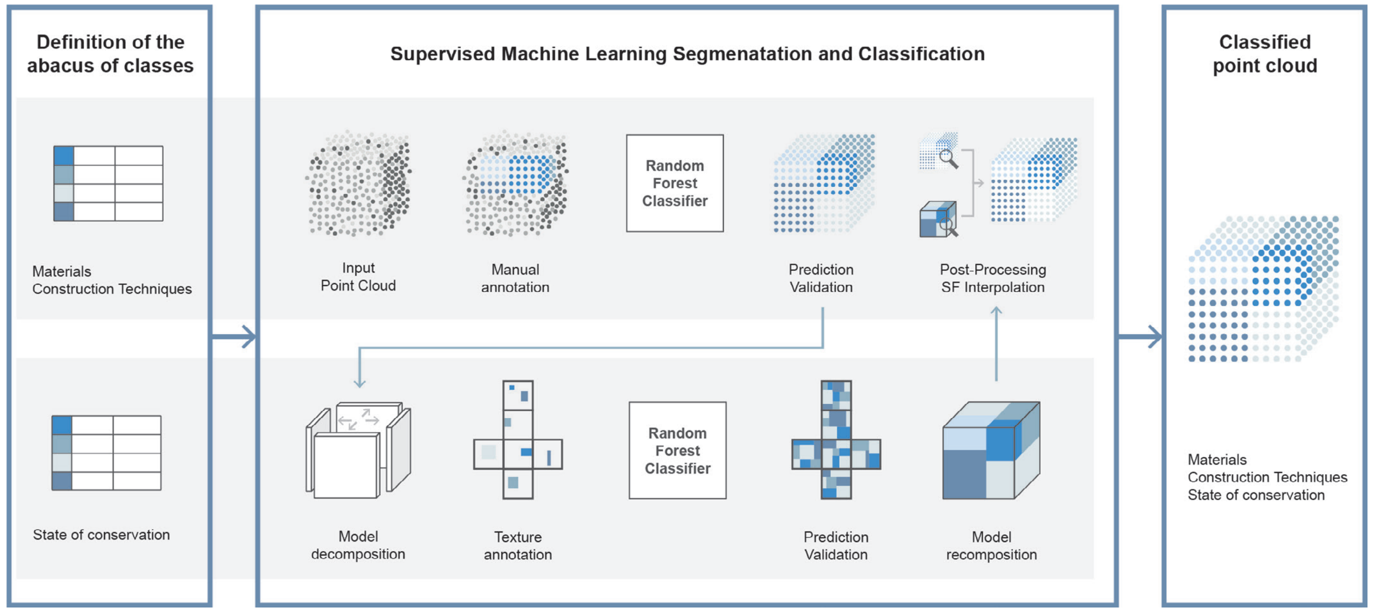
- to classify the exterior of the building according to materials-construction techniques,
- to classify the exterior of the building according to state of conservation,
- compare semi-automatic classification on different source data.

8.3.2 Combined workflows: point cloud and image segmentation

Based on the outcomes and considerations resulted from the experiments on the case studies previously described, to classify the point cloud model of Eladio Dieste's Cristo Obrero Church, a workflow was developed and fine-tuned, incorporating the application of supervised machine learning algorithms to both point cloud data and images. In this way, the strengths of the two respective methodologies are leveraged (Fig. 8.32).
The methodology adopted for materials-construction techniques classification involves point cloud segmentation (Paragraph 7.1). This is because the construction techniques have a strong association with building geometry, so geometric features are likely to provide effective discrimination between classes. Procedure followed, furthermore, a multi-level methodology where detail classes are required, such as for the decomposition of the first floor wall of the main façade.
The methodology adopted for state of conservation classification involves image segmentation, to obtain a more reliable algorithmic prediction. Since the final outcome must be a 3D model, it has been decided to segment the texture, to move from the two-dimensional to the three-dimensional domain more automatically (Paragraph 7.4.4).

Fig. 8.32.

General workflow adopted for point cloud classification according to materials-construction techniques and state of conservation.



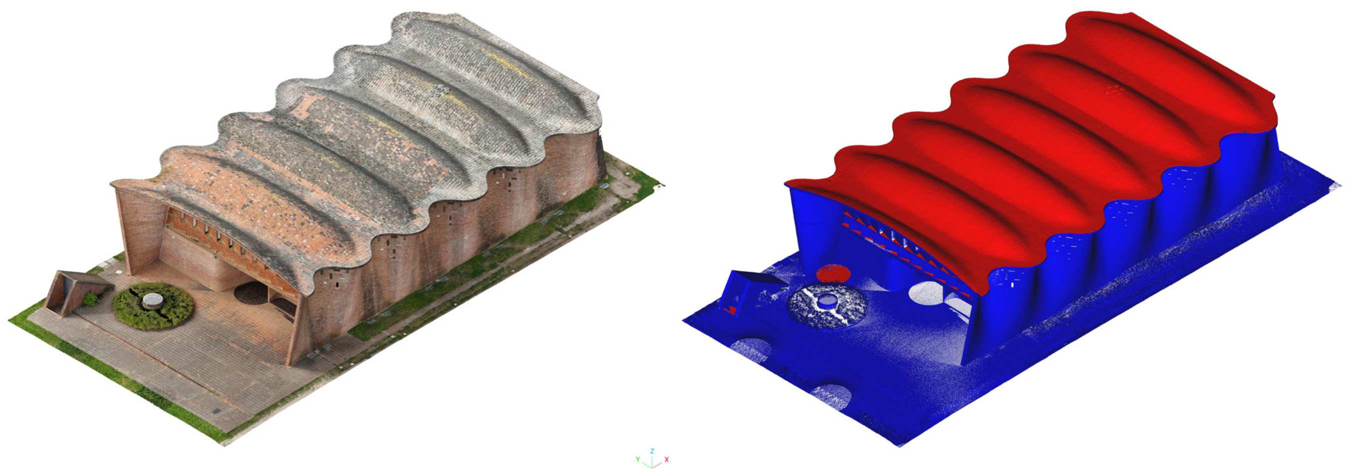


Fig. 8.33.

Point cloud integrated model. RGB colour data visualization (left), source visualization (right): blue surfaces were surveyed by laser scanning, red surfaces by photogrammetry.

This classification step exploits the results of segmentation according to construction techniques. In fact, from this model, the surfaces characterized by degradation phenomena were isolated, i.e. the roof and the South, East and West elevations (the North one, corresponding to the main façade, was recently restored and does not show degradation pathologies). Then, each of these surfaces were separately processed to derive meshes and textures. This decomposition made it easier to read the surfaces for the manual annotation phase. In fact, the UV mapping of the textures was carried out considering the elevation as the primary surface, reducing its deformations. The results were back-projected to the respective three-dimensional models, then transferred to a single point cloud, which is thus classified according to both thematic categories.
The experimentation exploits both laser scanning and photogrammetric surveys. Specifically, the morphometric model was built integrating the two point clouds as follows. The primary geometric structure was taken from the Leica Scan Station C10 laser scanner survey, with colour information mapped using photogrammetric images. To evaluate the geometric reliability of photogrammetric survey and to determine whether the colouring process would led to good results, cloud-to-cloud distances were calculated between laser scanning and photogrammetric point clouds. Results showed a mean difference of about 0,2 cm, with few points over 1 cm. To achieve comprehensive geometric coverage, areas not captured by the laser scanner, such as the roof extrados and any occlusions, were integrated with data from the photogrammetric survey. Selection of these surfaces was performed semi-automatically, segmenting the cloud according to cloud-to-cloud distances, keeping point with a distance major than 1cm from the laser scanner point cloud. Outliers, noise or incoherent points belonging to this group were manually erased in short time (Fig. 8.33).
Materials - construction techniques classification through point cloud segmentation was supported, at a first stage, from the two different acquisition methodologies used for the integrated survey. In fact, in the model as described in paragraph 8.3.2, the

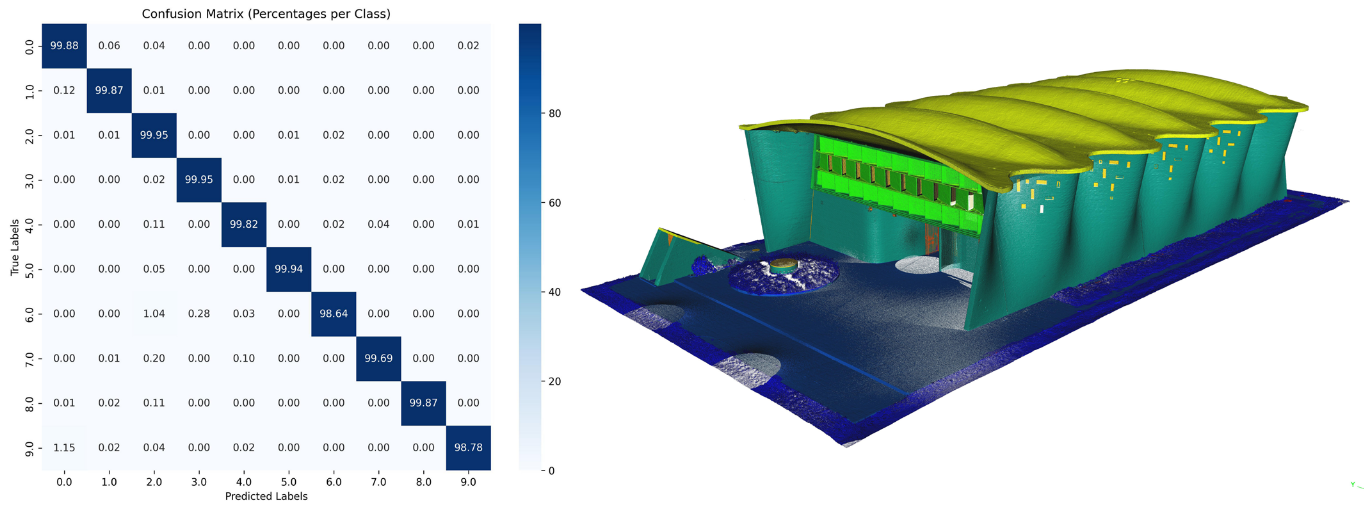


Fig. 8.34.

Point cloud classified model according to materials-construction techniques: confusion matrix (left) and visualization (left).

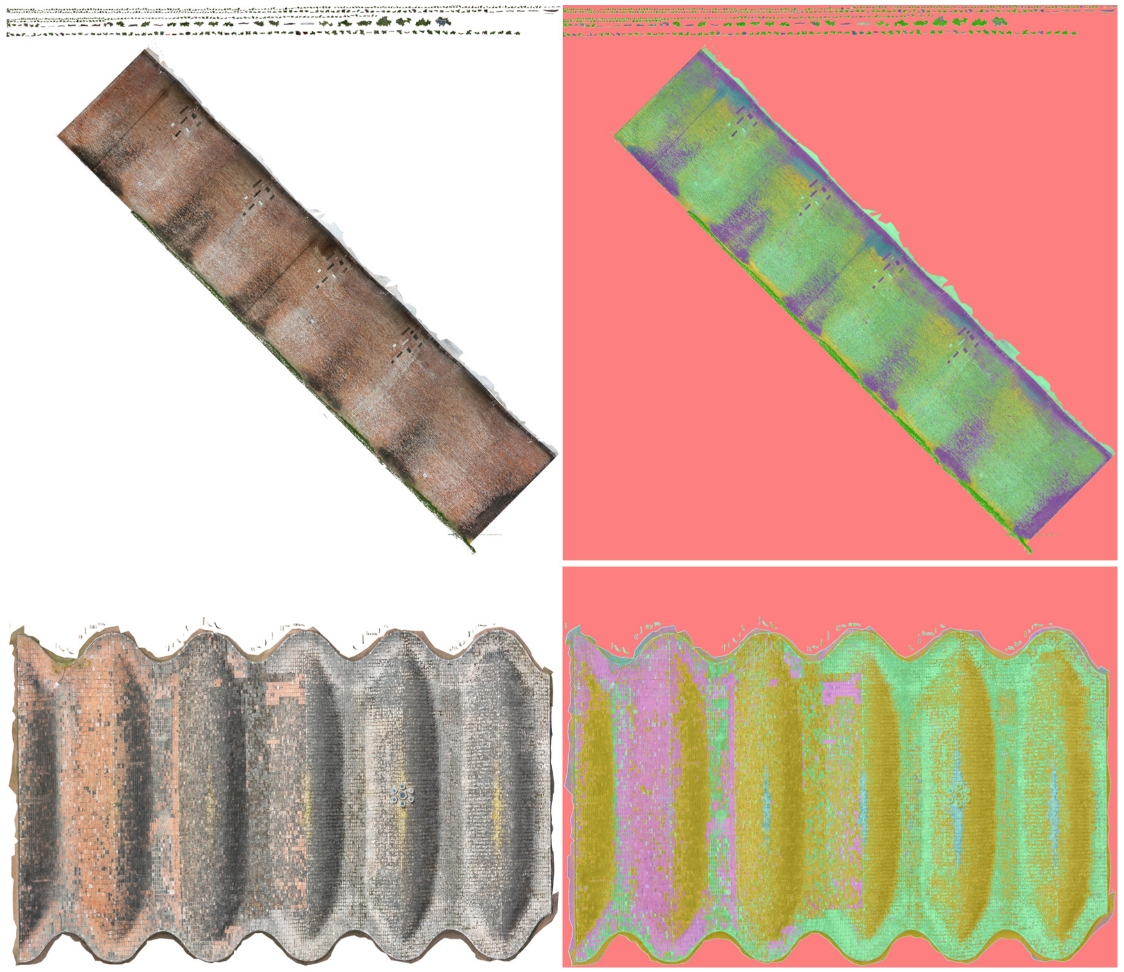


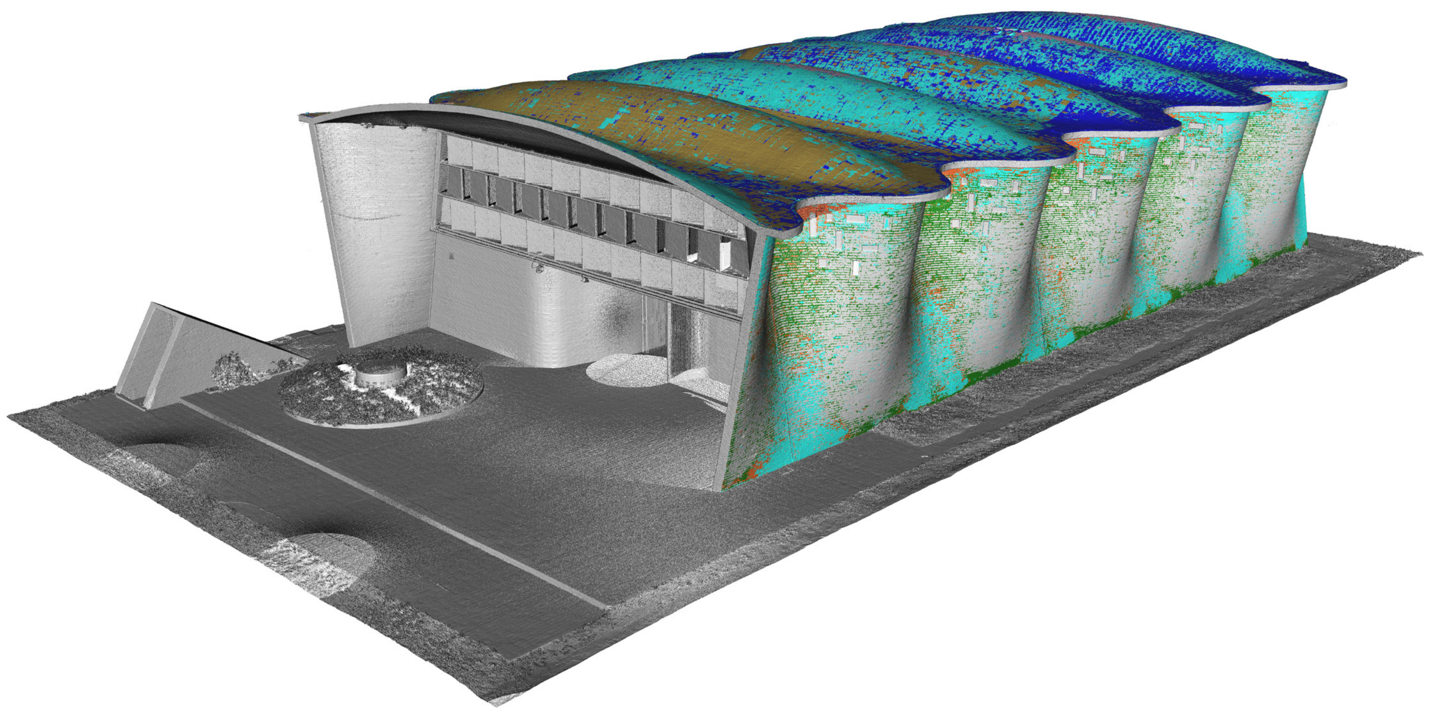
Fig. 8.35.

Texture classification according to state of conservation: West elevation (top) and roof (bottom): original textures (left) and segmented ones (right).

surfaces taken from the photogrammetric point cloud are quite isolated each other. This allows an easy manual classification for these parts. For the laser scanner point cloud, classification was done through RF, taking advantage of two levels of analysis to further divide the elements of the main facade. The steps are the ones described in chapter 7 and tested on case studies previously developed. Neighbourhood selection was made referring to some recurring dimensions in the analysed architecture, such as brick sizes (0.05 m and 0.30 m), plus a wider one to discriminate macro classes (0.80m). Geometric features selection in this case was made before their extraction, in order to optimize this step saving computing time. According to previous experimentations and literature references (Grilli et al., 2019), features with medium-high or high relevance were considered in at least two out of three case studies. Manual annotation involved *circa* 25% of the dataset. Evaluation metrics and confusion matrix shows good algorithm performance (weighted average f1-score 0,98), confirmed by final visual inspection. Few misclassified areas were manually re-labelled to obtain a point cloud correctly classified (Fig. 8.34).
From the model classified according to materials-construction techniques, the surfaces to be analysed for state of conservation detection were isolated, meshes and textures calculated and processed in Trainable Weka Segmentation (Out of bag error: 1.422%). Presenting similar features, the model was trained on one elevation and applied on the others. As for the roof, since the decay morphologies are different, RF was again trained (Out of bag error: 1.964%) (Fig. 8.35). The results obtained from image segmentation were transferred from 2D to 3D by exploiting the properties of UV mapping of textures. The resulting classification of the three-dimensional model was organized into a model

Fig. 8.36.

Point cloud classified model according to state of conservation.



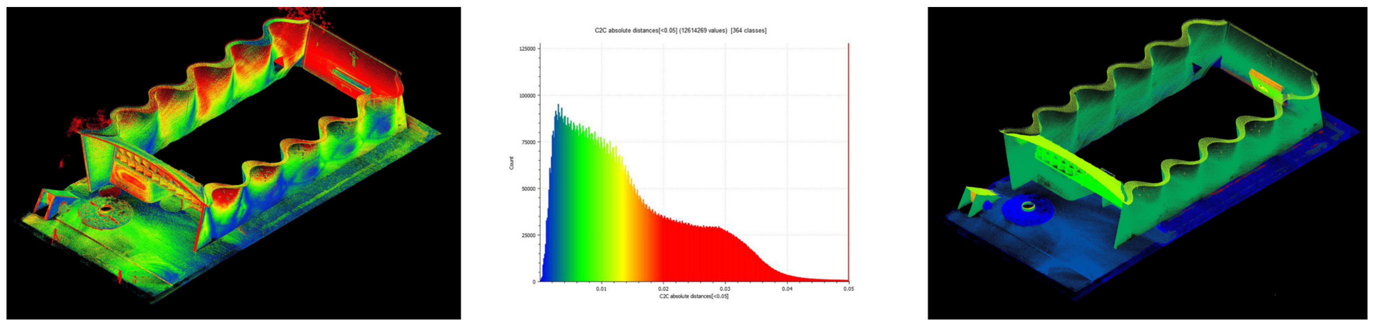
queryable on multiple levels of knowledge. Summarizing, final point cloud consist in a morphometric model with colour information and four scalar fields: intensity (for parts of the model derived from laser scanner point cloud only), source (to immediately distinguish parts taken from laser scanning or from photogrammetry), materials - construction techniques, and state of conservation (Fig. 8.36).

8.3.3 Outcomes

The proposed methodology tests the adaptability of ML procedures to specific needs and different descriptive media to be segmented. The application described in this case study can be adapted to others, declining it in relation to morphological and material identity of each heritage site.
The final outcome on a point cloud model that represents the building not only through geometric-morphological and colorimetric features, but also through thematic categories. The points, semantized in this way, can be used as support documentation for surface interpretation also facilitating BIM modelling, possibly laying the basis for a semi-automated informative implementation, directly derived from the survey metric model.
However, to achieve a reliable level of accuracy, the methodology required numerous steps, having to integrate two ML procedures carried on different media, managing a transition from three-dimensional to two-dimensional and vice-versa. This complexity determines that the entire workflow becomes advantageous only if the data analysis process is carefully designed, taking into consideration the purpose of the analysis, the type of data to be acquired in the survey phase, the level of accuracy that can be expected from the different algorithmic predictions, and the characteristics of the building to be analysed.
To compare semi-automatic classification on different laser scanner source data, thus associated to different levels of accuracy, classification according to materials-construction techniques was considered. The same methodology described earlier was applied to point cloud model surveyed with Lixel K1 SLAM. Previous research by the author (Rossato et al., 2025) assessed metric consistency of this point cloud, compared to Leica C10 one, chosen as reference because of the lowest instrumental

Fig. 8.37.

Lixel K1 SLAM point cloud classification assessment: evaluation of geometric accuracy thorough cloud-to-cloud distances (left), deviations histogram (middle), and classified model according to materials - construction techniques (right).



error (Suchocki, 2020). K1 cloud is noisier and, as expected, the areas with significant deviations are several, and having a lower density of points (Campi, 2024). The modal value observed is of around 1.8cm, but with a considerable number of points with deviations as high as 2.5cm. From a colorimetric point of view, the SLAM point cloud has a RGB data quality comparable to the photogrammetric point cloud. Despite this minor geometric accuracy, the algorithmic performance, although lower than the one on the C10 laser scanner cloud, is still good, as confirmed by evaluation metrics and confusion matrix elaborated on test set (Fig. 8.37).

8.4 St Margaret's Church in Braemar

8.4.1 The stone wall geometries and degratations

The interest for testing segmentation procedures focused in masonry analysis, lies in the fact that this kind of construction technique is widely diffused in historical architecture. Having been typically employed for the construction of typical structural elements, its analysis is thus extremely relevant in architectural conservation, both for static reasons and for the historical and cultural significance (Forster et al., 2023). Many crucial factors can be read and interpreted from the masonry to guide interventions, such as repairs, maintenances, and conservation in general. For this reason, research has been performed into automating the segmentation of masonry using ML and DL algorithms, with the aim of supporting its interpretation (Valero et al., 2019; Ibrahim et al., 2020)

In this research, the analysis of traditional stone masonry was performed on the dataset of St Margaret's Church in Braemar. The building, constructed of coursed squared rubble granite blocks, is particularly suitable for testing procedures to effectively separate the ashlars from the mortar joints. Considering that one of the conservation issues of this building concerns the disgregation of the mortar joints, automatic segmentation can be useful for assessments aimed at possible intervention (Fig. 8.38).

Although the building was surveyed using both laser scanning and digital photogrammetry, the experiment reported here was developed using only the point cloud obtained with the former as input data, to test the impact of the reflectance data of the instrument used (Z&F 5016C), also replicating the procedure on other existing datasets of buildings surveyed using this procedure. For this specific case study, the colour data associated with the tool's built-in camera was considered to be of sufficient quality and reliability compared to what could be observed on the field. Furthermore, the laser scanner point cloud is complete with all the external wall surfaces and, given the church's modest height, there are no particular shadows or missing data.

8.4.2 A benchmark for the use of intensity value in segmentation

First, the laser scanner point cloud was subsampled with a 5x5mm grid, and a filter was applied to reduce noise and remove outliers. Neighbourhood selection and geometric feature selection were performed according to criteria adopted for the Cristo Obrero Church case study (Paragraph 8.3.4). Then, to achieve the specific objective, a two-stage multi-level segmentation and classification procedure was applied.

The first consists of identifying the macro material elements of the building and the components, such as masonry, windows (including carved stone frames and window frames), roof, metal elements, ground (including natural and paved surfaces), vegetation, and 'discarded elements'. The latter class collected all the external elements, such as cars, silhouettes of people, reflections from glass surfaces, and more generally all those elements that are not part of the architecture or fixed equipment, which are usually removed from the dataset through manual operations. In this way, an automated ML procedure was also used to clean up the dataset. At the end of the automatic classification, misclassified points and underrepresented classes were corrected manually (Fig. 8.39).

Fig. 8.38.

Picture of St Margaret's Church in Braemar, showing exterior surfaces in granite masonry.

The second step considered the masonry class, isolated from the others. The subclasses to be identified are ashlar and mortar joints. To create the training and test dataset, a sample portion of the wall surface was considered, where the two classes were automatically segmented by selecting appropriate reflectance data ranges (Paragraph 6.3.4). To achieve effective segmentation, the selected portion of the wall was divided into three different areas, and three different intensity ranges were used for each: 0.45-1; 0.35-0.45 and 0.25-0.35. This automatic segmentation made it possible to separate ashlars and joints for most of the surface. For the remaining, the process was carried out manually, correcting the stones identified as mortar and extracting the unidentified joints (Fig. 8.40).

8.4.3 Outcomes

First-level classification of the exterior surfaces of the building showed satisfactory statistical results (weighted average f1-score 0,99). However, visual inspection revealed that the 'discarded elements' class contains a relatively high number of false negatives, with many points that should have been identified in this class instead being assigned to other categories. Even so, correcting these errors manually is not overly demanding and requires significantly less effort than performing a fully manual cleaning. Overall, the outcome represents a solid starting point for further analysis.

The separation of ashlars and joints worked for most of the surfaces (weighted average f1-score 0,99). The critical issues observed concern, for example, the upper part of the masonry, probably due to the lower resolution of the point cloud model in those areas. From this classified point cloud, it is possible to extract orthoimages that can

Fig. 8.39.

St Margaret's Church point cloud model, RGB (left) and first-level classification (right) visualization.

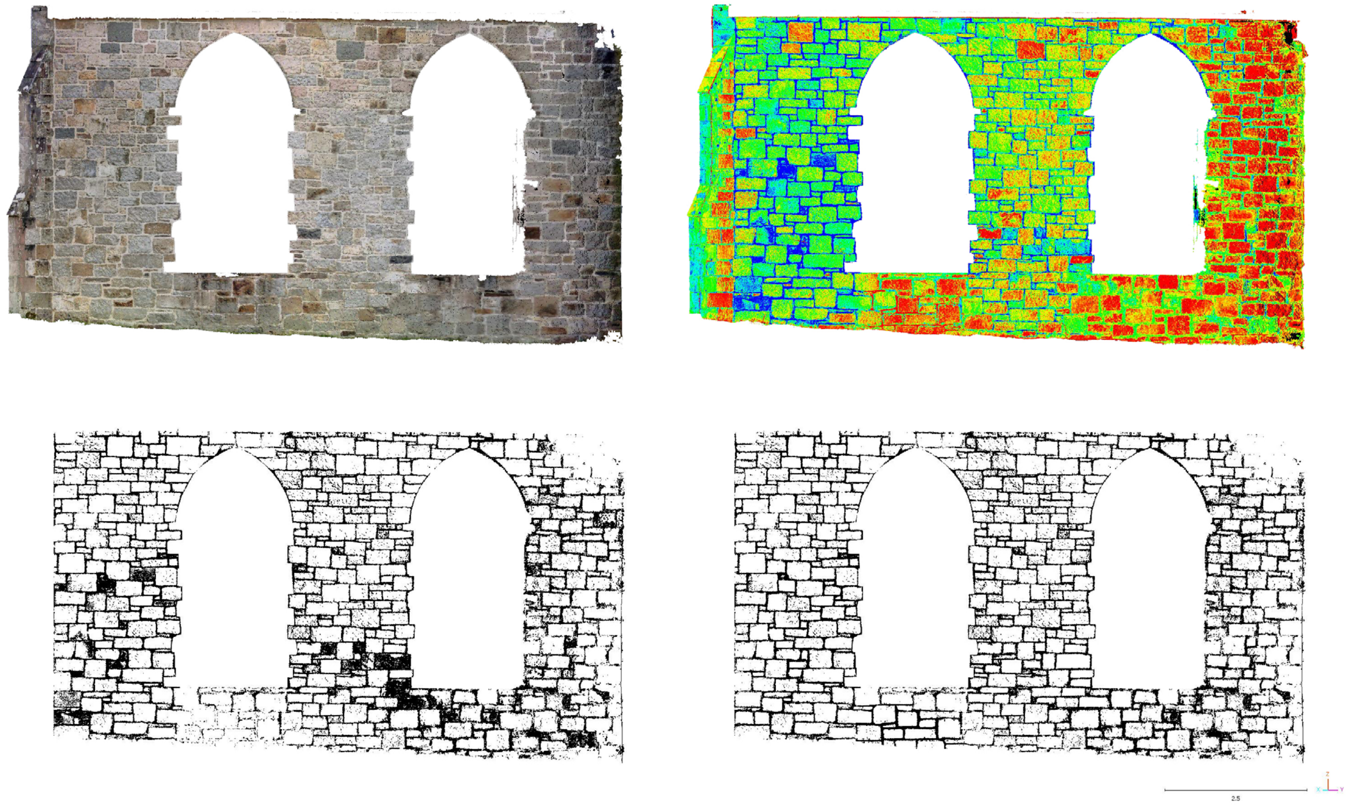


Fig. 8.40.

Annotated dataset for second-level classification of St Margaret's Church walls. Point cloud visualization according to: RGB data (top left), intensity value (top right), mortar joints automatically detected (bottom left) and mortar joints after manual correction (bottom right).

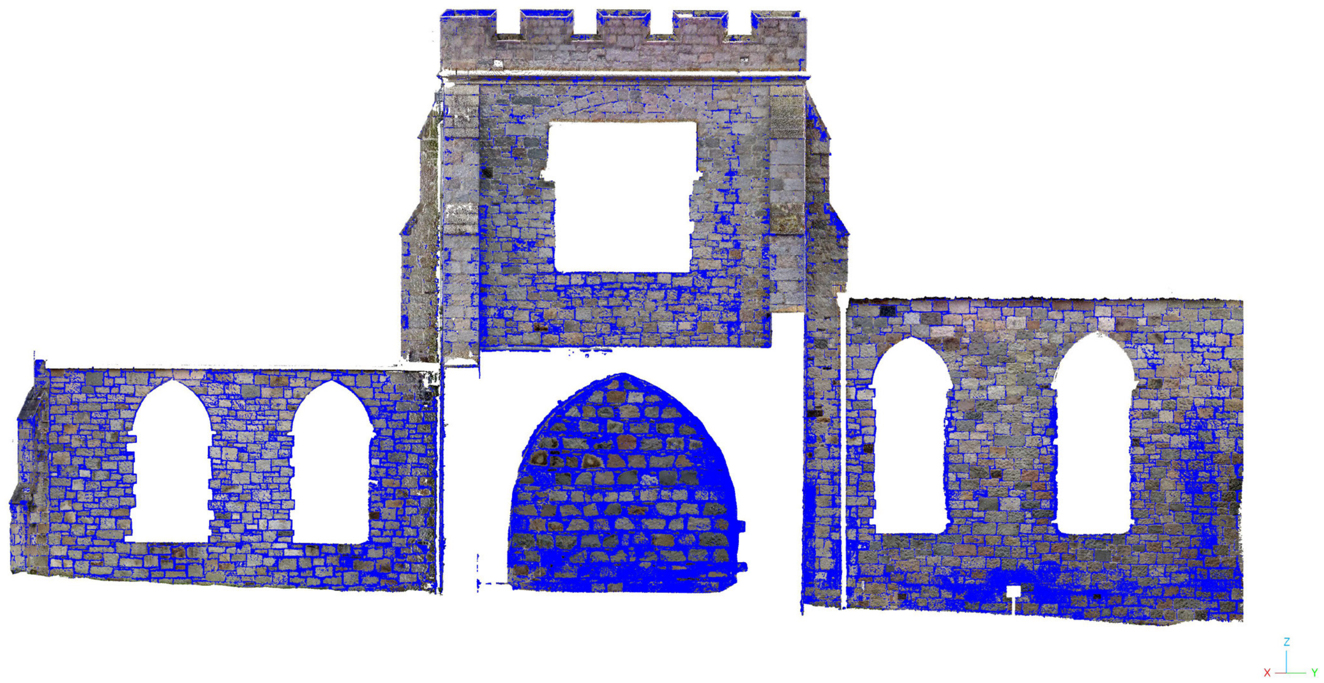


Fig. 8.41.

St Margaret's Church elevation showing a segmented point cloud wall. Mortar joints are highlighted in blue. Misclassified points are visible in top of the tower. The different geometric characteristics of mortar joints highlight different types of masonry.

facilitate interpretation and evaluation, such as the different geometric characteristics of mortar joints or the block shape, which may highlight different types of masonry (Fig. 8.41). These considerations can be replicated for other buildings, even larger and more complex ones, and facilitate and accelerate extensive interpretations of the masonry wall (Vandenabeele et al., 2024). Among others, important aspects to consider when assessing masonry are its form (for example, whether the units are squared or rounded), the dimensions of the blocks, and the pattern of bonding and coursing. Consistent stylistic features typically indicate a single construction phase, whereas differences usually suggest later modifications or changes (Forster et al., 2023).

As regards the incidence of intensity value in algorithmic segmentation, this has little relevance in first-level classification, whereas it is extremely important for second-level classification (Fig. 8.42).

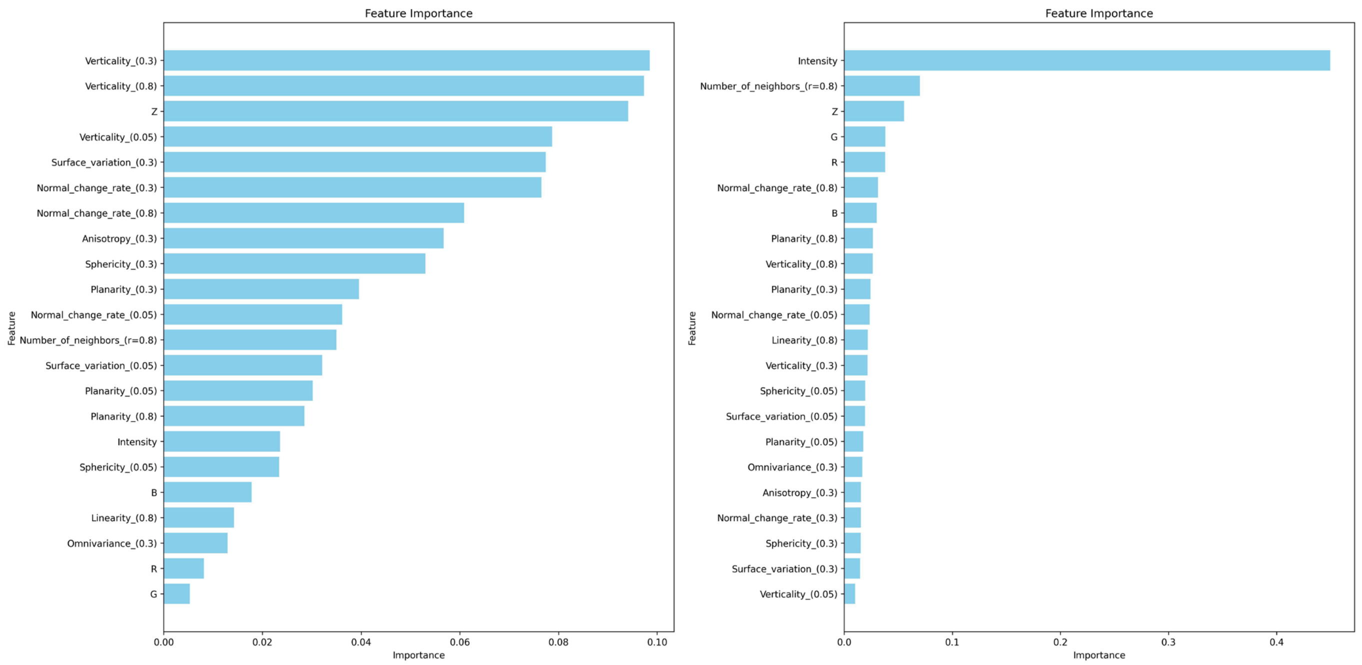


Fig. 8.42.

Feature importance of first-level (left) and second-level (right) classification of St Margaret's Church laser scanner point cloud. Intensity value appear to be the most important feature for ashlar-joint segmentation, far outperforming the others.

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Summary

9. Grafting critical-interpretative classified outcomes into Scan-to-BIM process

Abstract

This chapter explores the integration of semantically classified point clouds within Scan-to-BIM workflows for the digital documentation of architectural heritage. It discusses adaptive BIM modelling strategies that align data acquisition and analysis with modelling objectives. The research takes into consideration interoperability issues and challenges between classified point clouds and authoring software, proposing procedures that enhance semantic transfer and streamline modelling. Different strategies for representing complex materials and surface conditions through object or surface decomposition are examined. Different methods for modelling the state of conservation are compared, from segmented clouds directly imported in BIM software, meshes generation, adaptive components, to simplified “patches”. Each of them reaches different degrees of geometric accuracy, semantic depth, and modelling efficiency. The chapter also examines the role of collaborative digital twin platforms and the use of standardized ontologies to ensure interoperability andaccessibility.

9.1 The concept of “adaptive” BIM modelling

Parametric modelling of existing heritage through BIM is becoming as pervasive as necessary, considering potential advantages it brings, and regulatory trends increasingly stringent. However, these tools can be still ineffective from the point of view of users, such as professionals, site managers and companies, who must deal with such complexity. Actual research challenge is to bring discretization and simplification processes on source data toward an easier informative integration into BIM models, by facilitating and enhancing interpretation needs (Maietti et al., 2026). The idea is that, in order to be truly effective, data acquisition and analysis should prioritise modelling requirements and, above all, the informative content in the BIM model, in relation to the purpose (Li et al., 2025). For this reason, strategies are being developed to optimise

3D data acquisition starting from BIM purposes, reversing the usual workflow. This thesis fits into this context, given that the segmentation and classification of point cloud models are functional to facilitating the interpretation and hierarchisation of information in the Scan-to-BIM process. In the definition of digital data segmentation criteria, specific BIM population requirements and strategies are taken into account. This overall methodology is aimed at a streamlining of existing heritage digitization pursuing the adaptive informative population to specific objectives.

Hence, the purpose of BIM modelling, as tested within the case studies presented, is to integrate point clouds geometric and radiometric data with information related to materials, construction techniques, and state of conservation, through a Scan-to-BIM approach. The point cloud classification processes allow the extraction of detailed information to be integrated into BIM models to optimise the knowledge and critical decision-making process for the management and preservation of architectural heritage (Croce et al., 2021). The potential relevance in embed these information in BIM environments, is to provide a more complete and accurate assessment, ensuring that any restoration or redevelopment work is based on accurate data. Each case study modelling started with the definition of informational needs, considering the model not only as a documentary tool or data repository, but also as an assessment tool throughout the entire building lifecycle, including the design phase. Key topics mainly concerned representation, considering different needs, and methodological approaches for material and degradation mapping, in order to define the most suitable methods for an adaptive solution.

The representation process followed in this research was based on modelling the architectural components directly onto the point cloud imported into the BIM software, keeping the coordinates of the local system defined in the point cloud. Each construction element was broken down to identify subcategories. For instance, floors were divided into structural parts, upper and lower finishes (where applicable); openings were separated from frames and the compositional or finishing elements. This procedure allows not only a specific identification but also facilitates the association of targeted information and, above all, uniquely queryable data.

Clearly, during the three-dimensional parametric modelling, all the issues related to H-BIM were encountered, both those of an interpretative nature and practical limitations, which have been widely discussed in the literature (Dore & Murphy, 2017; Bianchini et al., 2021). As is well known, the modelling of historic features often requires a degree of discretisation in their geometric accuracy due to the constraints of commercial BIM software, which are typically designed for new, standardized construction. Consequently, levels of abstraction must be introduced. For example, one of the most common simplifications is assuming verticality in non-plumb walls. While acceptable for restoration goals, the geometry of the model may not reveal subtle but important indicators of degradation, that must be indicated thorough informative notes. The specific characteristics that make it difficult to model the morphology of existing built

environment become even more challenging when surfaces affected by conservation issues need to be represented. As historic buildings often present heterogeneous material compositions and complex decay pathologies, documenting their surface degradation requires tailored digital workflows that can both support semantic richness and ensure interoperability. For this reason, especially for the state of conservation, different applicative simulations of thematic data integration on BIM models were developed. Results and method comparison are explained in Chapter 10 (Results).

Just the point cloud model is the input data in geometric BIM modelling in the scan-to-BIM process, the classified point cloud model, whether according to material or macro decay pathologies, is the main source for modelling surface characteristics. As described in the previous chapters, 3D point clouds, while proven in terms of metric accuracy, are inherently descriptive rather than interpretive. As such, the traditional transition from point cloud to H-BIM model demands a critical transformation: the encoding of meaning, specifically, the classification and localization of materials, construction techniques or decay phenomena. This issue is resolved during the modelling phase, when using input data that has already been semantically analysed, thanks to the use of point clouds classified according to these three specific categories. It should be noted that the critical interpretation phase of the source data is not skipped, but moved to an earlier stage in the workflow, so that it can also support other phases of the historical architectural asset documentation process. With regard to the BIM modelling phase alone, this is streamlined and optimised in terms of time.

From an operational point of view, the segmented and classified point cloud can be attached and integrated into the BIM modelling environment. The authoring software used is Autodesk Revit, given its widespread use, including for H-BIM applications. However, limitations immediately arise in assigning colours to the point cloud. In fact, the intensity channel, or other scalar fields, cannot be displayed in Revit using colour

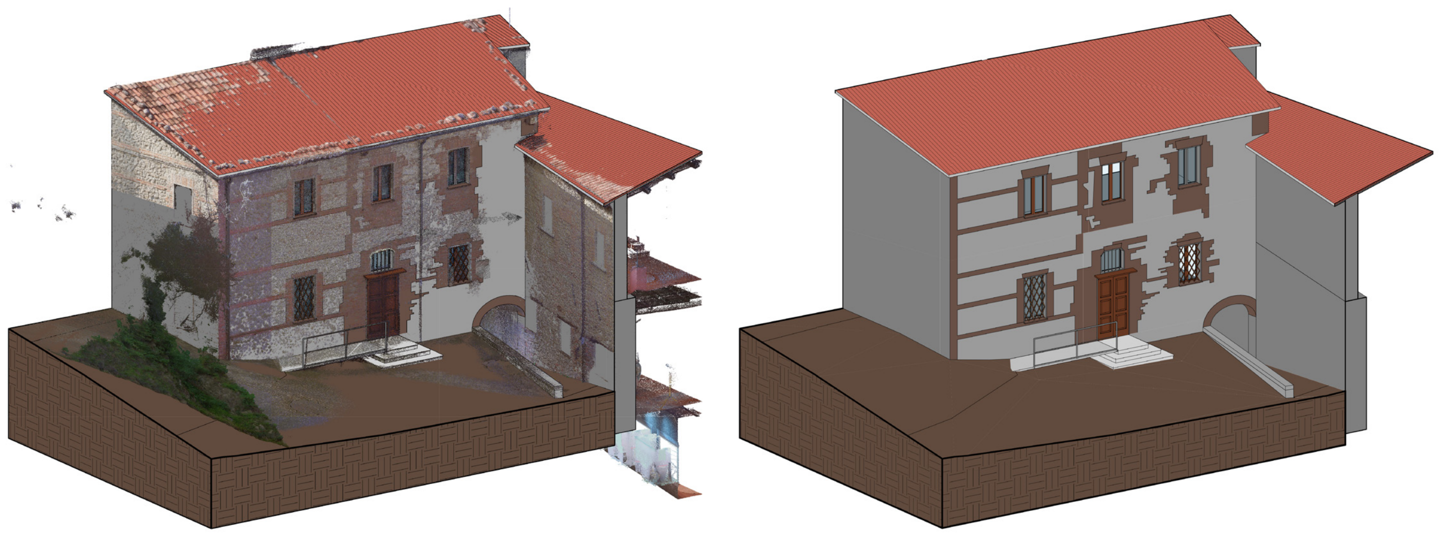


Fig. 9.01.
Axonometric view of the BIM model of the Former Monastery of St Agostino in Verucchio, modelled on the surveyed point cloud (top).

scales with multiple values suitable for discretising the different homogeneous areas assigned. On the contrary, only RGB colour data is sufficiently supported for reading the point cloud (Fig. 9.01). For this reason, to link a classified point cloud within Revit, with homogeneous areas displayed by a single false colour representative of that particular characteristic, it is necessary to carry out preliminary operations, which essentially consist of transferring the classification colour scale to the RGB channel. It is clear that, in doing so, the colour information of the visible spectrum is lost, which, especially in photogrammetric surveys, is both of fundamental importance for understanding the point cloud model and of considerable interest for reading surfaces. This currently unresolved critical issue complicates the complete transfer of information from a classified cloud within Revit and makes the workflow less fluid. A viable alternative is to import the segmented cloud, i.e. with each homogeneous area belonging to a single sub-cloud referring to that specific category. Within Revit, it is thus possible to turn the different segments on and off as required, preserving the RGB colorimetric data and the classification, the latter maintained through segmentation. However, this makes it more complicated to visualize all the classified categories at a glance. When the cloud is used as a modelling aid, two separate copies are often used, one with the original colour data and one with the classified areas, which can be turned on and off as required.

9.2 Modelling complex materials

The case study of the Former Monastery of St Agostino in Verucchio is an example of a very common material condition in historical architectural surfaces. In fact, when associating materials in BIM modelling operations, it is possible to group the issues encountered into two categories, each with different methodological and operational implications. On the one hand, there are clearly distinguishable elements that can be associated with a single material, sometimes with a simple stratigraphy, which are easy to manage. On the other hand, there are much more complex cases, such as those related to stone or brick masonry, where the variety of materials used and their close interconnection require additional assessments. This is the case, for example, with the perimeter walls of the building, where the mixed masonry, composed of stone and brick sections, makes it difficult to identify homogeneous blocks and therefore requires more complex modelling (Fig. 9.02). The distinction between materials becomes particularly useful here in defining any restoration or conservation work related to deterioration. In this context, associating the correct material with each area of the surface is crucial, as it allows for accurate and effective queries within the model.
However, this accuracy also entails a number of significant disadvantages. First of all, there is a significant increase in modelling times due to greater operational complexity.

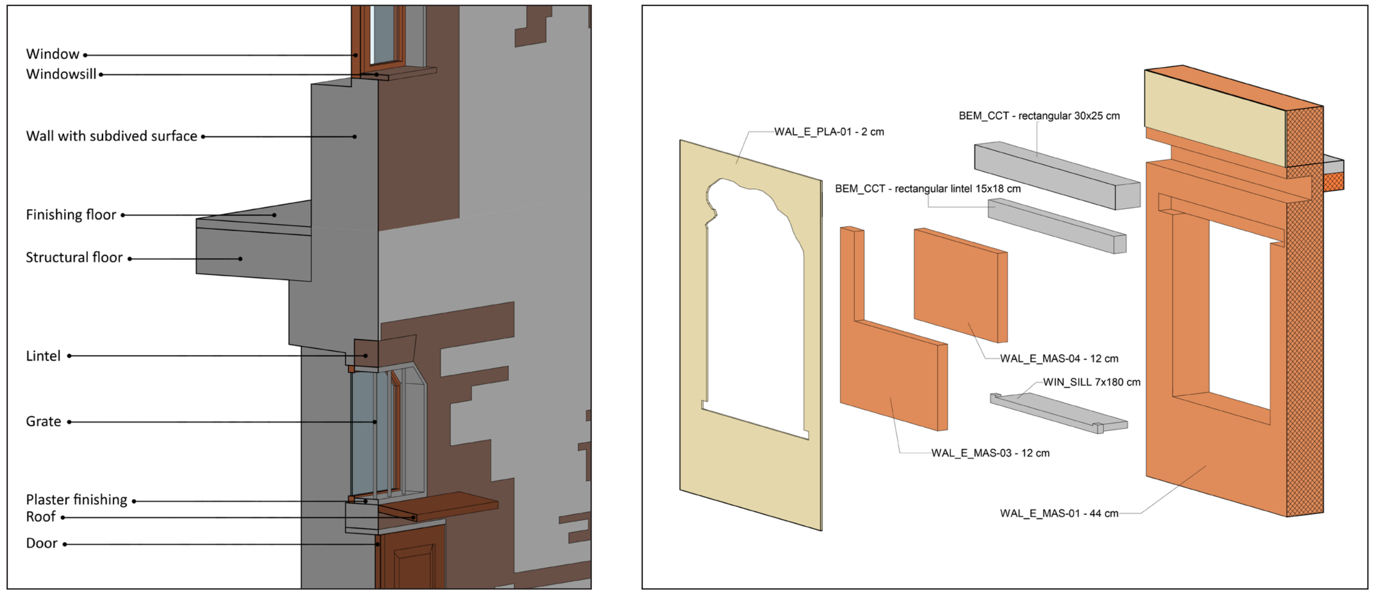
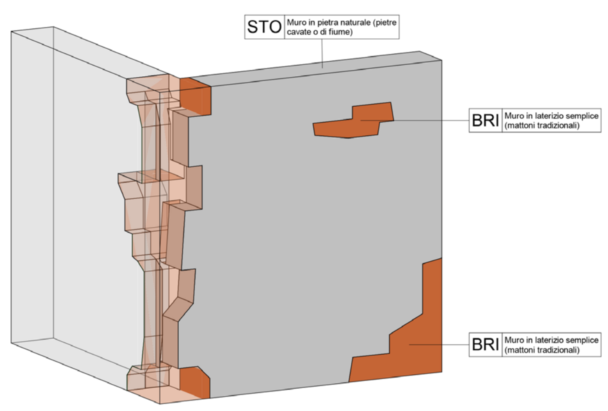


Fig. 9.02.
BIM modelling according to materials: axonometric cross-section of the Former Monastery of St Agostino (Left) and exploded axonometric view of Former Colona Varese (Right). Some materials can be associated with a single element, others require further surface subdivisions (See also Fig. 9.03).

It is also necessary to carefully understand and model the volumetric development of the different material areas, which can be difficult to interpret, especially in cases of uneven masonry. The management of masonry joints is another critical issue, as the decomposition into complex geometries can generate inconsistencies and computational difficulties for the software itself. Added to this, is the proliferation of locally modelled elements necessary for defining Boolean operations for shaping and cutting architectural components, which, while allowing for detailed representation, generate redundancies and weigh down the model, complicating both data management and the possibility of automating computerisation. Finally, the *ad hoc* modelling of certain portions using local objects further limits their compatibility with other parameters and analysis tools.
According to these considerations, this method proves to be particularly suitable only in limited contexts, such as in the case of small buildings or in archaeological sites of particular value, where the distinction between materials often corresponds to very precise stratigraphic masonry units with related information. In more extensive or complex situations, this strategy risks producing errors that are difficult to resolve, compromising the overall effectiveness of the modelling.
A more sustainable alternative is to work at the surface level. Once the volumetric representation of the architectural components, particularly the masonry, has been completed, the surfaces can be subdivided by tracing the perimeters of the areas characterised by different materials. It is essential that this subdivision only takes place after the reference solid has been defined, as any changes to the volume may affect the geometry of the derived surfaces. Unlike objects, surfaces cannot be directly enriched with specific parameters, but they can be associated with materials, allowing for indirect attribution of informative value. To ensure the uniqueness of the query, it is possible to

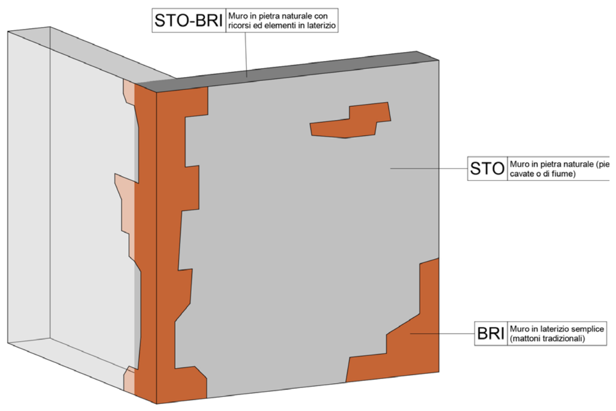
choose between using category-specific design parameters or adopting keynotes. In the case, the latter option was tested, creating an external reference file, which can be extended if necessary, structured as a dictionary of materials, organised hierarchically and with detailed definitions. The use of keynotes also allows to operate on two levels: the value can be assigned to both the object and the material, allowing for more flexible and layered modelling. In this way, the wall element takes on a value for the entire material, while the subdivided surface retains the reference to both the specific material and the corresponding keynote (Fig. 9.03). This approach has the advantage of preserving the overall characteristics of the element while facilitating multiple readings of the model. To facilitate compilation and adapt to different operational scenarios, the keynotes have been indexed according to material composition and grouped by element category. In the case study of the Former Monastery of St Agostino in Verucchio, for example, a set of compositional variables has been set for brick, stone and mixed masonry, including different configurations of masonry textures.
Although execution times are shorter than with the volumetric approach, and although mapping allows for a fairly detailed material representation, some limitations remain. Informative implementation is still limited to the material assigned to the surface, without involving the object as a whole. Furthermore, the surfaces defined in this way are not volumetric entities, but areas or regions belonging to an existing support surface. The information assigned directly to the surface is limited to keynotes or materials and refers to an external database for further details. Overall, therefore, the objects have a limited level of informative implementation, which is not always sufficient for more advanced processes.

Fig. 9.03.
Sample of architectural elements of the wall, modelled by composing parts, shaping and operating with Boolean subtractions (Left), and modelled by surface subdivision for the specific attribution of keynotes (Right).



Muro composto			
Muro	**N.**	**Nota chiave**	Materiale
BRI - 30cm	2	BRI	BRI_Laterizio
STO - 30cm	2	STO	STO_Pietra

Restituzione degli elementi architettonici del paramento murario per composizione di parti, sagomando e operando con sottrazioni booleane.



Muro suddiviso			
Muro	**N.**	**Nota chiave**	Materiale
STO-BRI - 30cm	2	STO-BRI	Misto lapideo laterizio

Restituzione degli elementi architettonici del paramento murario per composizione di parti, sagomando e operando con sottrazioni booleane.

9.3 State of conservation in parametric environment: methodologies and open issues

The issue of mapping surface degradations is particularly critical, both from an interpretative point of view and in terms of its implications for the definition of future intervention strategies. In the case study of the former Colonia Varese, it was decided to represent only the actual condition as a starting point for the design, seeking to make the mapping as adaptable as possible to the needs of any future interventions.
The modelling of degradation in historic buildings within H-BIM environments has emerged as a critical research frontier, particularly considering the increasing demand for integrated conservation tools. Strategies described in this research field converge on a main shared goal: to develop methods capable of accurately representing surface decay while also supporting intervention planning and long-term management. The aim is to bridge the gap between the acquisition of diagnostic data and its semantic representation within HBIM environments. However, the methodologies adopted, while conceptually aligned, diverge significantly in execution. This divergence reflects broader disciplinary tensions between fidelity and feasibility, automation and interpretation, as well as geometric accuracy and semantic richness. The balance should be found in relation to the aims of the model and the specific objectives. With this perspective, various methods were tested for transferring point cloud information, classified according to state of conservation, within a H-BIM modelling process.
An initial approach was to extend the same modelling logic used for material association (paragraph 9.2) to degradation. However, the results obtained showed that this procedure was not feasible. The need to subdivide an excessive number of elements made this strategy unsustainable for several reasons: firstly, due to the high margin of error, but also due to the impact on modelling times and costs and the limited adaptability of the model to any subsequent changes.

9.3.1 Attached segmented point cloud

Based on what described in paragraph 9.1.1 (Issues concerning interoperability between classified point cloud models and authoring software), an initial operational strategy involved the direct use of the segmented and classified point cloud to represent degradation within Revit (Figg. 9.04 and 9.08). In this procedure, the overall point cloud was imported divided into instances corresponding to the different types of degradation. Each homogeneous area was therefore represented by its own cloud, while leaving areas without degradation blank. In this configuration, the colour value assigned to the cloud is derived from the classification, not from the original RGB information of the surface. In fact, it was decided to forego the RGB data of the cloud in favour of the visual clarity of the degradation mapping, which was considered a priority. This method has led to satisfactory results in terms of consistency in the reading of the decays. Furthermore, degradation modelling is not necessary, as there is already a portion of the point cloud that allows for the rapid visual identification of segmented pathologies. However, several critical issues have also emerged: it is often necessary to link multiple instances to obtain a complete representation, and if the RGB value of the classification has not been assigned during pre-processing, it must be assigned manually. A further limitation is that the model can easily become overloaded, especially with high-density clouds, which must be sub-sampled to avoid unsatisfactory performance. The most significant issue, however, is the inability to associate parameters to the point cloud, which in Revit remains a simple attached link and not an internal information object. This means that the classified cloud is only a visual overlay on the BIM model, useful for qualitative assessments or to guide manual tracing, but lacking any structured information value. Furthermore, it is not possible to export these links to IFC, so interoperability is not guaranteed and the workflow is incomplete. The model thus functions primarily as a visual and descriptive tool, supporting restoration planning at a preliminary level.

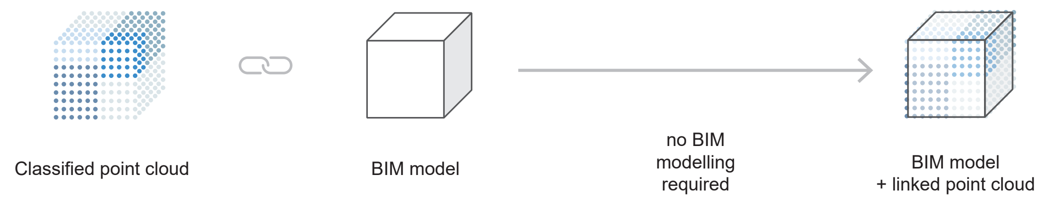


Fig. 9.04.

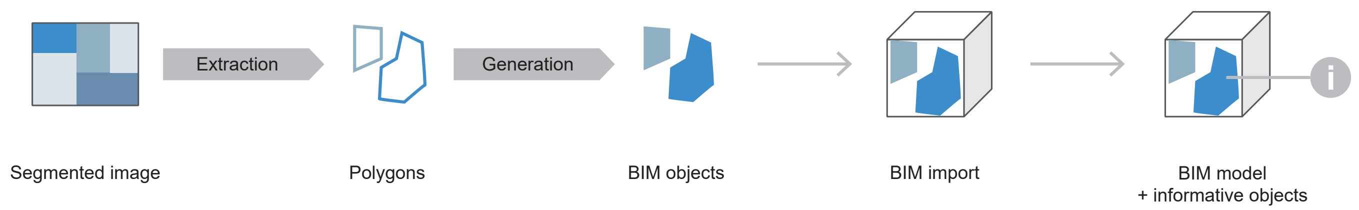
Process of representing degradation in a BIM environment using attached segmented point clouds.

9.3.2 Imagery

An alternative approach is to use orthoimages of the segmented point cloud elevations to read the classification colour index within Revit, thus avoiding the import of multiple instances. This method allows to work surface by surface tracing the areas according to projection views, but it also presents significant technical issues. The images are often difficult to scale accurately, introducing stitching errors between surfaces. Furthermore, the file size increase during the modelling phases, since the images can only be viewed in rendering mode, which requires greater memory and graphics processing power. In this case, too, the images cannot be integrated at an informational level or directly associated with three-dimensional objects, making the strategy ineffective and, indeed, inadvisable. Experiments in photorealistic texturing of BIM objects using calibrated and aligned images, or through orthoimages, are described in the literature and allow, through the use of AI-segmented images, the texturing of surfaces according to different topics, such as materials, and state of conservation (Alshawabkeh et al., 2024). In this case too, it remains a mere visual mapping, certainly useful for interpretation and assessment but not directly queryable to obtain quantities or contain metadata.
Through more advanced Visual Programming Language (VPL) techniques, possibly combined with edge detection and clustering algorithms, it is possible to model from images to BIM objects that can be parameterised, using procedures that increasingly seek automation and fewer manual processes (Fig. 9.05). For example, a possible workflow focuses on the use of false-colour orthophotos and thermograms to facilitate the detection and mapping of decay phenomena (Lanzara et al., 2022). The core of the methodology is a VPL algorithm developed in Grasshopper, which processes raster images via RGB pixel clustering. These clustered pixels are then vectorised into polygons that can be imported into HBIM environments as 3D block elements. The use of orthophotos solves the correct scale issue. Thus, it accelerates the generation of decay maps in BIM environments. One of the key strengths of this approach is that it operates directly on imagery, and this makes it particularly well-suited for early-stage assessments or scenarios where thermographic and reflectance-based data are readily available. However, limitations connected to the two-dimensionality of the images persist. For instance, curved or complex surfaces need special handling, such as multiple projections.

Fig. 9.05.

Process of representing degradation in a BIM environment using segmented images as input data and the generation of parametric objects using VPL techniques.



9.3.3 Mesh generation

To overcome some of the limitations of importing the segmented point cloud directly into the BIM environment, a more structured solution is to convert homogeneous groups of points into meshes (Figg. 9.06 and 9.08). Through this procedure, the surfaces generated by the cloud, while maintaining the division into instances, are imported into the model and can be enriched with design parameters and keynotes. Weight, surface consistency, and import format compatibility should be carefully evaluated to avoid parametric limitations, but the combined assessment of the point cloud and imported surfaces enables a multi-thematic use of the model (Martín-Lerones et al., 2021). Although this is a more complex strategy, it allows for a consistent and fairly accurate reading of the modelled elements, as well as enabling the visual identification of different decays without the need to model the degradation from scratch. The effectiveness of this approach depends on the possibility of generating simplified meshes from the segmented data: in this way, the surfaces can be managed in the model without compromising performance. However, importing requires the use of compatible formats such as .sat files in order to transform them into computerisable "massing" objects. Alternatively, it is necessary to model the surfaces as masses, which leads to a significant increase in rendering times. It may also be necessary to redefine the surfaces based on the reference material on which the degradation morphologies are located, with further subdivisions. This is unless it is chosen to interpolate them with the underlying objects, an operation that introduces a significant margin of error from a software point of view. Even with this strategy, it is necessary to deal with a possible increase in the weight of the model, in the case of overly dense meshes, which must be mitigated through targeted operations of sub-sampling the source cloud or reducing the number of triangles.

The transition from point cloud to mesh is a fairly common operation in three-dimensional modelling, as it is suitable for the integration of automatic functions. Similarly, it is possible to enable the semi-automated translation of complex surface degradation point cloud data into structured, analysable, and updateable HBIM components. This can be achieved integrating Python scripting within a VPL environment (for example Dynamo for Revit) to automate the mesh generation derived from segmented point clouds (Avena et al., 2024). Specifically, this reduces reliance on manual node-based programming and, by embedding RGB and classification data directly into the mesh vertices, the workflow allows for a detailed, object-oriented representation of surface degradation. It is relevant to highlight that this strategy is scalable, suitable for a broad range of heritage contexts. Even if through node-based visual programming or integrated scripting, VPLs offer a flexible and extensible means of structuring workflows, enabling users to adapt the process to the specific requirements of different heritage assets, the implementation of this strategy requires a higher level of technical proficiency, particularly in scripting and data pre-processing.

The entire workflow is particularly effective in fully exploiting the potential of the segmented point cloud. Indeed, the major advantage of this approach is its capacity to retain both geometric accuracy and semantics. The pipeline begins with machine learning-based classification of the input data, followed by segmentation, mesh generation and retexturing. Each mesh segment is then imported into Revit as a parametric object, complete with categorization and metadata.

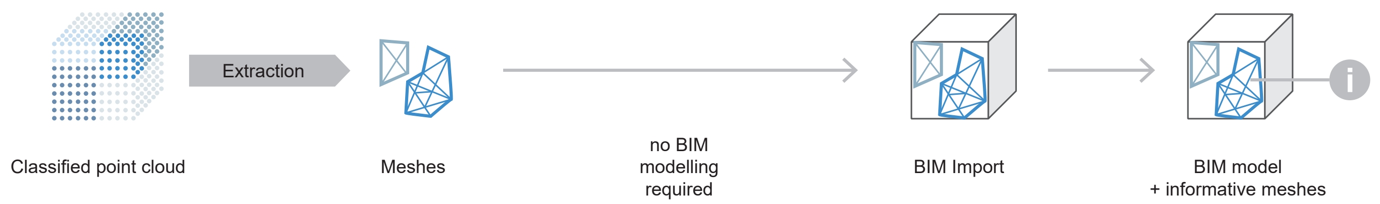


Fig. 9.06.

Process of representing degradation in a BIM environment using mesh generation, then imported. VPL techniques can automate more mesh extraction, enhancing the workflow.

9.3.4 Adaptive components

Another approach explored for mapping degradation is through the use of adaptive components (Figg. 9.07 and 9.08). In this strategy, surfaces are defined manually by tracing their perimeters using an *ad hoc* family. This method allows for high precision in terms of the geometry of the survey, avoiding overlaps or occlusions between elements. Also, the flexible geometry of these objects allows them, (albeit with some limitations) to be modelled to conform to curved or irregular surfaces, thereby enabling decay mapping on non-standard geometries. A further strength is that full informative implementation of the components is possible, which can be enriched with customised parameters (Lo Turco et al., 2017). Thus, it allows degradation data to be linked directly to restoration actions, creating a closed-loop information system. So, decays described through adaptive components can be effectively integrated into H-BIM, leveraging a hierarchical taxonomy of building components and material conditions, which can lead to the generation of thematic mapping (Malinverni et al., 2019). However, adaptive components can be difficult to read as they are often coplanar with the reference surfaces. Furthermore, since the number of vertices in adaptive components is fixed, there is a need for advance and rigid management of the available models. It is necessary to define in advance a set of components distinguished by the number of vertices, and to use the one that best discretizes the specific morphology of degradation with an appropriate level of approximation. It is not possible to change the number of vertices retrospectively, and any variation in the reference surfaces or objects requires the components and the position of their vertices to be reviewed. Finally, this method can also significantly increase the weight of the model, as each component requires the position of its vertices to be recalculated.

It is therefore clear that adaptive components, given their ability to include information parameters, led to the achievement of a semantically enriched and diagnostically oriented model capable of supporting complex conservation decisions. This approach aims at evolving the role of HBIM not only as a documentation tool, but also as an integrative platform for the analysis, interpretation, and management of historic built environments. The main disadvantage is that thematic consistency, both geometric and informative, is achieved through the manual generation of BIM object families (Aricò et al., 2024). This procedure is time-consuming, consequently costly, and for this reason not sustainable in many cases, such as for large buildings or for professional assignments characterized by tight deadlines.

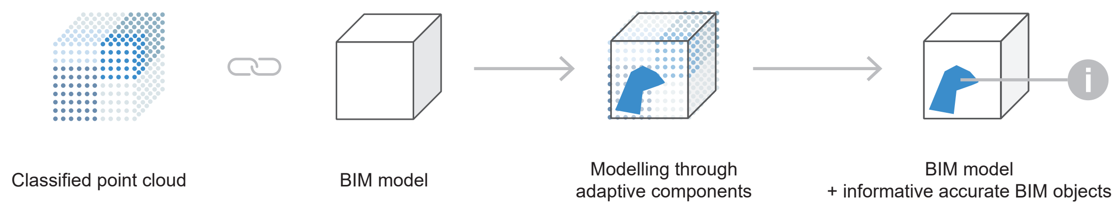


Fig. 9.07.

Process of representing degradation in a BIM environment using adaptive components.

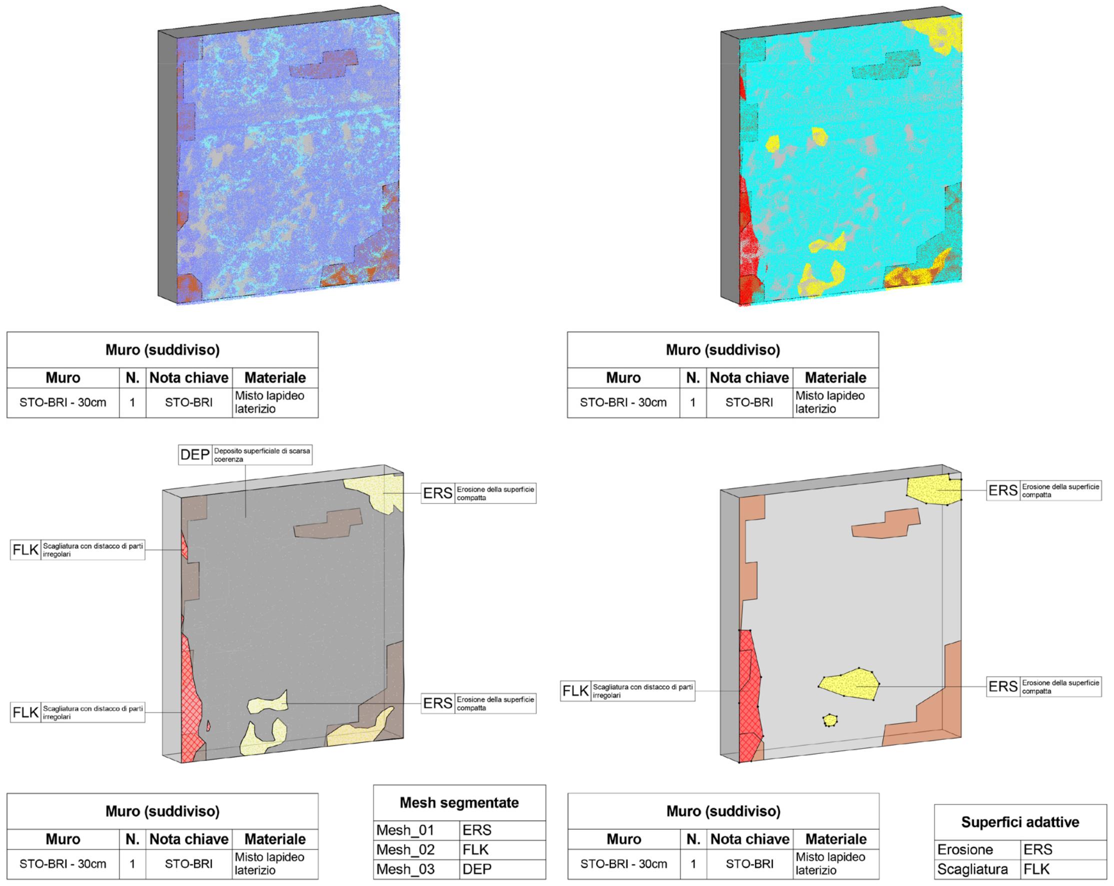


Fig. 9.08.

Top: processed point cloud linked into the model without (left) and with (right) RGB values according to classification. Bottom: adaptive generic model for decay mapping through the adaptive components (left) and imported meshes (right) filled in with decay information.

Fig. 9.09.

Former Colonia Varese BIM model with degradation morphologies visualized thorough segmented and classified point cloud.

9.3.5 Simplified patches

A large part of the critical issues associated with the adaptive components method is therefore due to the difficulty of geometrically reproducing the morphological complexity of degraded areas in most authoring software. An alternative approach consists in addressing the modelling of surface degradation in historic buildings shifting from geometric accuracy toward a more strategic balance between graphical representation, semantic richness, and long-term information management. This approach highlights the urgent need for simplified yet semantically robust HBIM strategies applicable across different heritage contexts. For this reason, the priority is to model decay through efficient representations, interoperable, and sustainable over time. This is achieved following a hierarchical model-level approach, supported by ontologies, where BIM objects act more as information containers than detailed visual replicas of architectural surfaces (Li et al., 2025). Geometrically, damage can be mapped, tracked, and visualized using simple parametric elements: symbolic “patches” superimposed on the surfaces of BIM objects (Barontini et al., 2021). These patches represent decay phenomena using standardized colours and metadata, and can be easily added, modified, and classified (Fig. 9.10). Such a strategy drastically reduces modelling time and complexity, in favour of enhanced cost-efficiency. Therefore, to save time and optimise modelling, compared to adaptive components, with the use of simplified patches the informational potential that BIM allows is maximised, renouncing accurate geometric description. In doing so, while useful for locating and categorizing decay, such patches do not capture changes in decay morphology of the affected material. In many cases, especially in ornamented parts, oversimplification may be a evident limitation in decay representation, producing ambiguity and lack of clarity. Moreover, the geometry of some degradation patterns helps proper interpretation, for example aiding to determine the causes or the origin of the phenomena. This reduces the possibilities of using the BIM model as a support for detailed diagnosis.

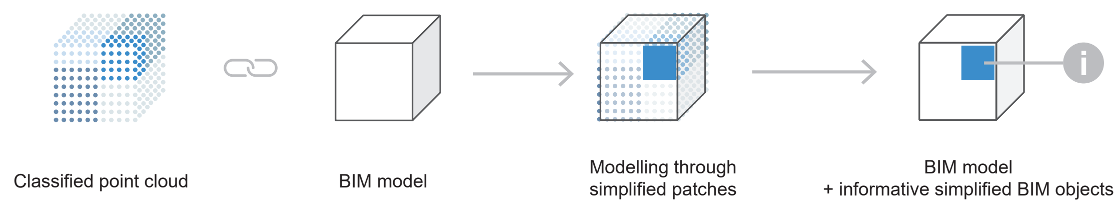


Fig. 9.10.

Process of representing degradation in a BIM environment using simplified patches.

9.3.6 Specifically developed tools in BIM software

Traditional BIM software limitations in dealing with the representation of the complexity and uniqueness of historical buildings raise questions about the need to develop tools for the creation of parametric H-BIM objects for degradation modelling directly within the 3D environment. This approach, as implemented in the ACCA Edificius software, introduces specialized tools such as decay area and crack objects (Lanzara et al., 2021). These tools allow users to map degradation by "drawing" directly onto the surfaces of the digital model, adjusting parameters such as geometry, pattern, depth, and typology (Fig. 9.11). The strength of this method lies in its intuitive interface and its ability to reflect complex degradation morphologies without forcing simplification into pre-existing geometric primitives. Additionally, the tools support the input of textual, numerical, and graphical attributes, thereby enriching the model with both qualitative and quantitative data. Such capabilities significantly enhance the potential of BIM to serve as a platform not only for design but also for condition assessment and conservation planning. However, the main operational drawback of this strategy is the large manual effort needed during the painting-based modelling. It remains thus a time-demanding task, especially for large or highly articulated surfaces.

This approach is strictly linked to the need of extending BIM concept to include semantic layers describing the degradation of materials and structures. A pivotal contribution in this regard is the adoption of the buildingSMART Data Dictionary (bSDD), which facilitates the formalization of degradation phenomena in a semantically consistent format compatible with the IFC (Industry Foundation Classes) open standard (BuildingSMART International, 2025). The bSDD-based approach enables the integration of decay-related information through uniquely identified terms, overcoming the ambiguity often caused by heterogeneous terminologies and languages. It allows for the codification of degradation and alteration processes according to a structured ontology, thus supporting interoperability across different BIM authoring tools and Common Data Environments (Scandurra et al., 2023). In this framework, decay may be classified in relation to the material affected and further broken down into typologies of phenomena, each described through standardized property sets. In this way, the preliminary semantic decomposition of the architectural system into meaningful units, organized by material, typology, and function, is extended to the state of conservation domain, moving toward integrated, semantically rich, and interoperable systems. The approach is scalable, as it can be applied to assets of different sizes, including artworks (Scandurra et al., 2024).

The aim of this methodology, despite still faces practical challenges due to manual operations, aims to enable a robust documentation framework capable of supporting complex heritage scenarios, enhancing both the modelling and semantic representation of degradation, through the coupling of custom parametric objects with bSDD-based ontologies and collaborative environments.

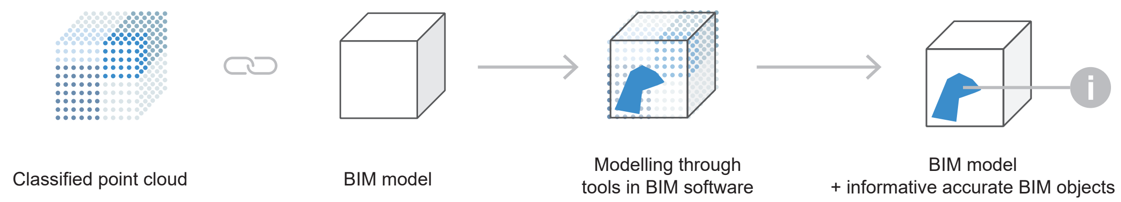


Fig. 9.11.
Process of representing degradation in a BIM environment using specifically developed tools in BIM software.

9.3.7 Digital twin collaborative web platforms

Every method described, to be effectively useful for heritage conservation, should provide a model that can be updated regularly and by diverse actors. Generally, the approach followed to structure the flow of information is through the use of spreadsheet forms. Each BIM object, including decay objects, has a unique identifier, and inspection data is recorded directly into spreadsheets. These sheets can then be imported into the BIM environment, streamlining the update process and minimizing transcription errors. This strategy reflects a pragmatic stance: rather than requiring that all stakeholders understand or use BIM software, the framework aligns with their current practices by operating through familiar tools like Excel (Barontini et al., 2021). By allowing them to work with spreadsheet forms instead of proprietary software, this approach opens H-BIM to a wider number of stakeholders.

To solve this issue, modelling strategies involves the integration of documentation workflows with collaborative, cloud-based platforms. These platforms serve as Common Data Environment (CDE), enabling multidisciplinary teams to access, update, and validate data within a centralized, version-controlled environment. In this way, the aim is to make the BIM model as interoperable and accessible as possible, even without the need for PCs with high computing capabilities and proprietary software installed, through an intuitive and user-friendly interface. These platforms allow data from different sources to be linked, so this integration, in some ways, bridges the gap between traditional 2D documentation (e.g., CAD drawings, degradation maps) and the demands of modern digital workflows. Finally, digital twin platforms extend the querying capabilities, otherwise limited by the constraints of the BIM software environment.

Considering the potential offered by these systems, an assessment was also developed on the direct use of digital twins for managing geometries and the state of conservation information (Figg. 9.12 and 9.13). The use of increasingly widespread web platforms offers great potential, especially as it allows for continuous updating of the model and organisation of data according to semantic structures independent from the modelling software (Themistocleous et al., 2022). The use of a platform capable of hosting a digital twin of the building allows reference categories to be reorganised and redefined, introducing information elements not originally planned and linking them to external resources, As if a new layer were superimposed on the model, making specific information visible at a precise moment in time. This approach allows to work on the current state of the art while maintaining an indirect relationship with the design phase or other disciplines, thus opening up the model to multidisciplinary, broader and more flexible use. However, for this to be possible, the model elements must be compatible with the IFC exchange format, and the meshes must remain distinct according to the segmentation performed. It should also be noted that surface subdivisions created in the authoring software (as the ones used for complex materials modelling – paragraph 9.2) are not guaranteed to be transposed to the platform, which may invalidate some of the previous operations.

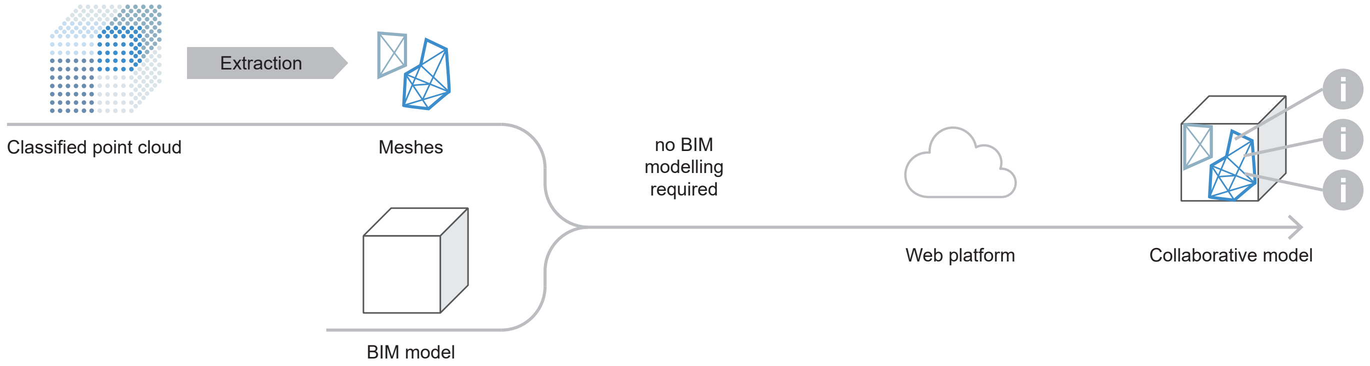


Fig. 9.12.
Process of representing degradation in a collaborative web platform.

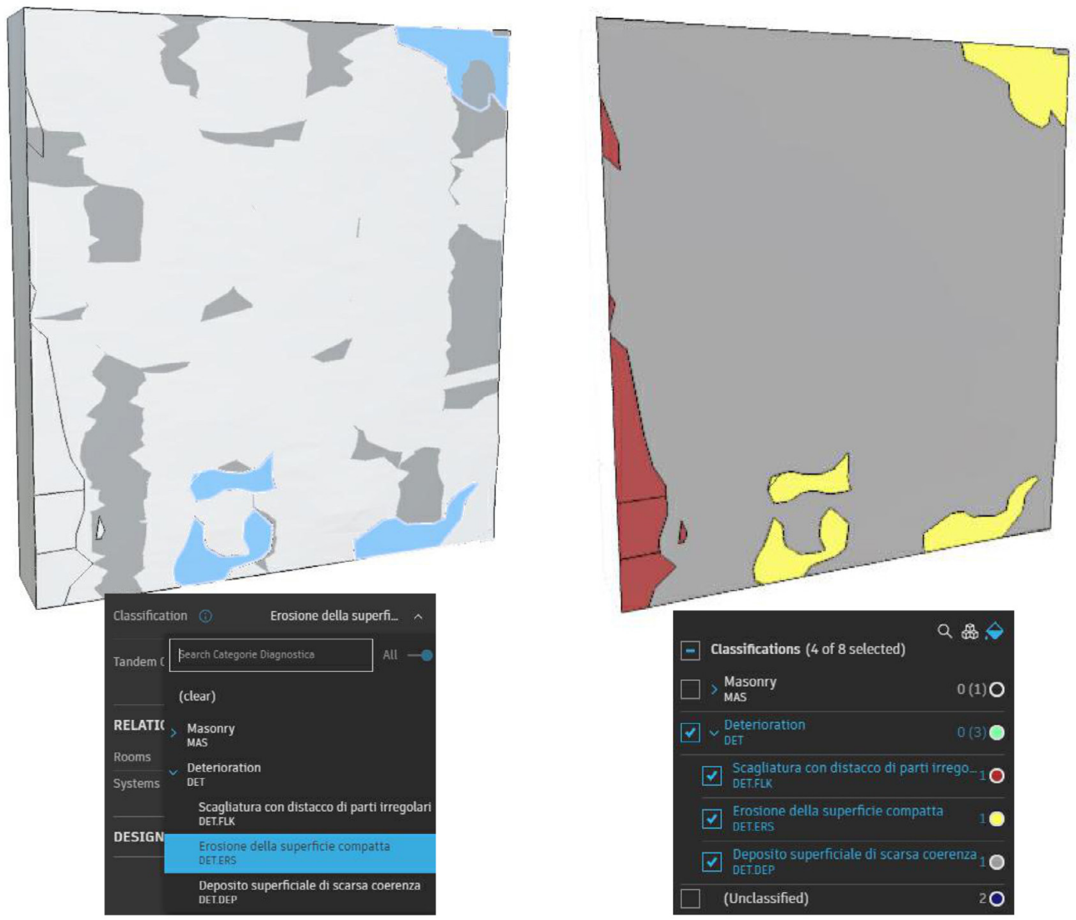


Fig. 9.13.
Digital Twin management of BIM model and imported meshes.

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10. Achieved results and assessment

Abstract
This chapter presents the final outcomes of the research, evaluating the application of supervised Machine Learning for the thematic segmentation and classification of architectural surfaces and its integration within the Scan-to-BIM workflow. Results obtained from multiple case studies (Chapter 8) confirm the effectiveness of this procedure in generating structured and queryable documentation of materials, construction techniques, and states of conservation, while emphasizing the need for case-specific calibration due to the heterogeneity of historic architecture. Point cloud data proved more suitable for identifying material and constructive features, whereas image-based segmentation achieved higher accuracy in detecting decay morphologies. The research proposes an integrated methodological model combining both approaches, enhancing robustness and interpretability. A critical assessment of laser scanner intensity data (Chapter 6) demonstrated its contextual significance in distinguishing materials and degradation patterns, given that its use must be evaluated case-by-case according to the characteristics of the survey. Finally, several Scan-to-BIM strategies aimed at include the information of the classified point cloud into a parametric model were compared (Chapter 9), highlighting the balance required between geometric accuracy, modelling effort, automation, and interoperability, in the choice of the most suitable H-BIM process in relation to the different purposes needed in supporting conservation practice.

10.1 Evaluation of surface features' thematic segmentation outcomes

The experiments carried out on the selected case studies described in chapter 8 have made it possible to verify the effectiveness and limitations of supervised ML methodologies applied to the segmentation and classification of architectural surfaces. The results obtained demonstrate that the proposed workflows are capable of producing a structured and queryable documentation of building materials, construction techniques, and states of conservation. At the same time, they highlight that the inherent heterogeneity of historic architecture, whether in terms of morphology, materiality, or conservation conditions, inevitably requires a case-specific calibration of both datasets and methodological choices, rather than the adoption of a single, standardized pipeline.

To summarise the experiments developed on the various case studies a synoptic table was drawn up correlating the categories of investigation, the type of digital data used for the experiments (point clouds or images), each reporting the methods followed and the results obtained, and the relevance of intensity value found in surface analysis

Tab. 10.01.

Supervised Machine Learning classification experimentations synoptic table, summarizing the categories of investigation, the type of digital data used (point clouds or images), each reporting the methods followed and the results obtained, and the relevance of intensity value for each case study building.

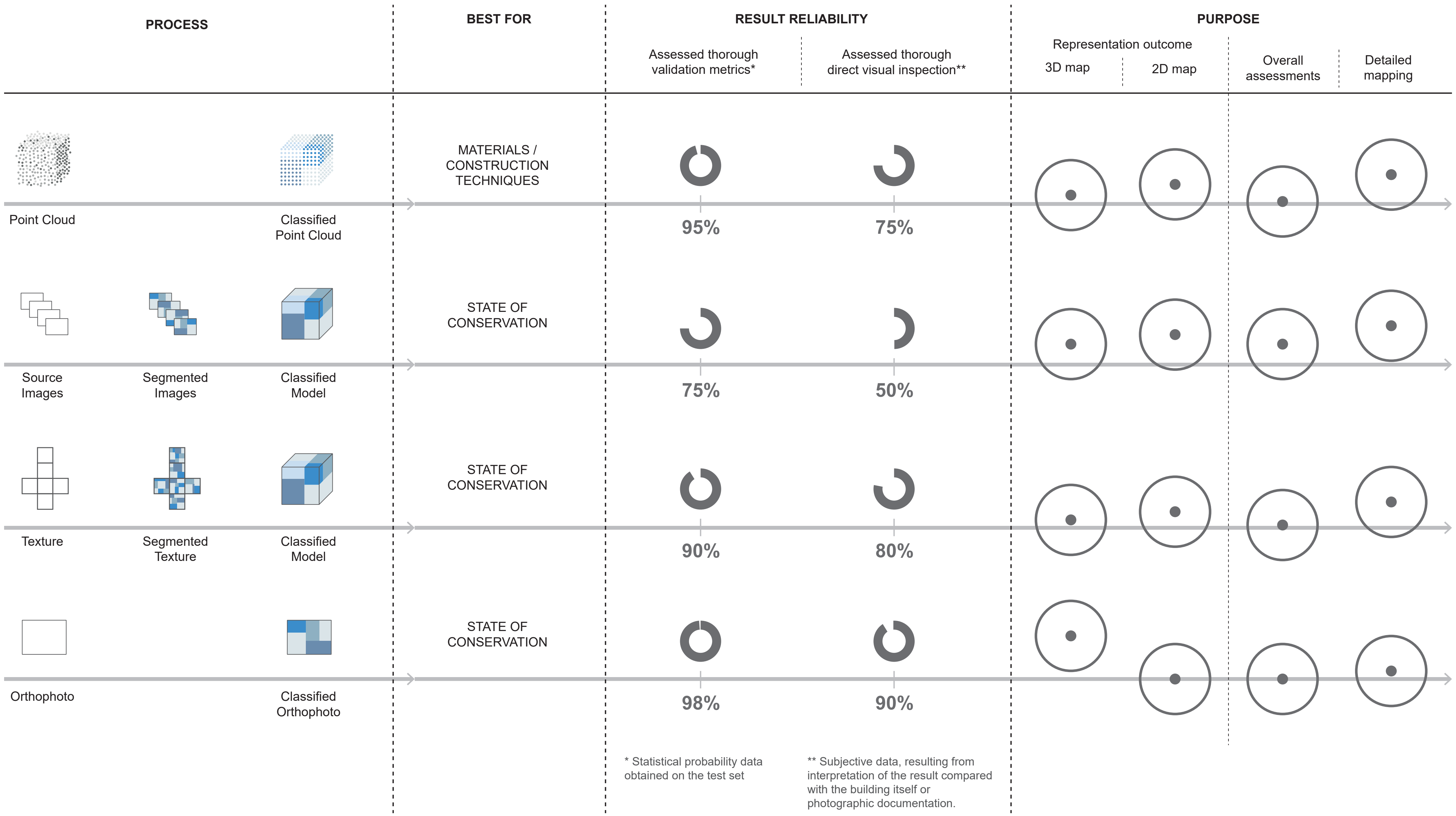
CASE STUDY BUILDING	INVESTIGATION CATEGORY	INPUT DATA: POINT CLOUD		INPUT DATA: IMAGES				INTENSITY VALUE	
		Method	Result	Type: Source photos	Type: Texture	Type: Orthophoto	Result	Importance in relation to other point cloud features	Result obtained on false colour image
Archaeological Museum of Verucchio	Materials / Construction Techniques	High number of classes ↓ Multi-Level Methodology	✓ (First level) ✗ (Second level) due to the geometric characteristics being too similar between the different classes	—	■	—	✓ Greater level of detail achieved compared to that on the point cloud	●●●●○	✓ but < RGB image
Former Colonia Varese	Materials	Low number of classes ↓ Single-Level Methodology	✓					●○○○○	—
	State of Conservation	Overlap of degradation morphologies ↓ Multi-Level Methodology	✗ due to the geometric characteristics being too similar between the different classes	■ Greater uncertainty (Oob error ca 25%) Feasible transfer 2D-3D	■ Medium uncertainty (Oob error ca 10%) Feasible transfer 2D-3D	■ Minor uncertainty (Oob error ca 1%) Difficult transfer 2D-3D	✓	●○○○○	✓ but < RGB image
Cristo Obrero Church	Materials / Construction Techniques	Variety of construction techniques ↓ Multi-Level Methodology	✓					●●●○○	—
	State of Conservation	—		—	■	—	✓	—	✓ but < RGB image
Sant Margaret's Church	Materials	Need to isolate specific components to perform detailed analyses ↓ Multi-Level Methodology	✓					●●●●●	—
Observations		Effective* for identifying elements discriminated by specific geometric characteristics or with clear intensity values * Assessed thorough high evaluation metrics (Weighted average f1-score higher than 0,97) and visual inspection of the classified point cloud model.		Effective** for identifying elements discriminated by colourimetric or pattern characteristics ** Assessed thorough high evaluation metrics (Out of bag error less than 25%) and visual inspection of the segmented image.				Valid as a support value*** *** Use must be critical, assessing reliability on a case-by-case basis according to the characteristics of the survey.	Valid as an alternative to the colour data, if absent***

(Tab. 10.01).

From the synoptic table it is possible to summarize the result concerning the first specific objective of the research, that is to test and evaluate current procedures for automatic and semi-automatic segmentation and classification operations, leveraging AI algorithms applied on different data sources. This, in order to identify case-specific best strategies for the description of the characteristics of historic surfaces. It emerged that, in general, point cloud source data is particularly suitable for identifying materials and construction techniques, as Supervised Machine Learning can leverage the strengths of three-dimensional features, more effective in identifying macro-classes strongly linked to geometry. Instead, for the detection of fine surface details and decay morphologies, more assimilable to two-dimensional surfaces, better results are achieved by working on the images, using pattern and radiometric descriptors.

Therefore, the processes examined exhibit varying degrees of variability, which result in different levels of element identification across the respective workflows. Table 10.2 summarises the different workflows for the segmentation and classification of materials, construction techniques and state of conservation, showing the percentages of reliability of the results obtained and consistency with certain types of objectives.

The reliability of the result was assessed using two criteria. The first data is obtained during algorithmic processing and, while it is the result of statistical values returned on the basis of well-defined metrics, it suffers from discrepancies with respect to the final result, as it is calculated on the test set. In fact, although manual annotation attempts to be representative of the entire point cloud, it always leaves something



Tab. 10.02.

Supervised Machine Learning classification experimented processes with indication, for each, of the category of analysis for which they are most suitable, the percentage reliability of the result obtained and consistency with certain types of purposes.

indeterminate, so it can only provide a partial indication. The second data is obtained through a visual comparison between the final classified model and the surfaces of the building itself, including through photographic documentation, or thorough detailed mapping drafted by experts where available (Former Colonia Varese). This criterion is undoubtedly very subjective and can be effectively carried out by professionals in the field of conservation, such as architects or restorers, introducing a very strong critical-interpretative component into this process. This second assessment also takes into account the discrepancies that occur in the various stages and accumulate during the steps, especially those involving a transition from three-dimensional to two-dimensional and vice versa. Furthermore, these assessments, as well as the conclusion that, in general, processes applied on point clouds are best for materials and construction techniques identification, while those on images are best for state of conservation, are derived from the specific applications carried on in this thesis. The operations were carried out with a view to achieving the result, not with the aim of obtaining a sufficiently large sample for statistical evaluation, as this would have involved repetitive operations that were not sustainable within the overall scope of the research.

In any case, beyond the reliability of the results, the underlying purpose remains crucial, as each process is more or less suited to specific objectives and meets those needs to varying extents. Obviously, it also emerges that some procedures, as developed in this research, are not suitable for meeting certain expectations regarding certain purposes. For example, those that generally produce three-dimensional mappings, which are more or less accurate, can lead to the creation of two-dimensional drawings, but it is difficult to achieve the scale of representation suitable for detailed mapping (1:50 or 1:20) without requiring manual intervention, which can be more or less extensive, as is the case with processes that work exclusively on two-dimensional extraction data (orthophotos).

Board 1 shows how these processes fit into the overall Scan-to-BIM methodological workflow, illustrating the current research scenario in this field. The overall process ranges from surveying to parametric modelling, through the thematisation of architectural surface characteristics on point cloud models with the support of artificial intelligence algorithms.

The synoptic table (Tab. 10.01) shows also considerations regarding role of intensity data. Generally, it has emerged as significant[1], as its contribution proved valuable in several contexts, especially for distinguishing classes with distinct radiometric behaviour (e.g., metals or mortar joints). In other cases, however, its effectiveness was undermined by acquisition constraints and inhomogeneities, confirming that the utility of this feature cannot be generalized but must be critically assessed in relation to survey project. Similarly, geometric features have shown high predictive capacity at macro-scale segmentation, whereas their descriptive power diminishes when attempting to discriminate materials or decay pathologies with subtle morphological differences, often generating misclassifications that propagate through the workflow. This evidences the structural limitation in relying solely on 3D-derived features and reinforces the necessity of integrating complementary strategies, based on radiometric features, such as the intensity value.

With regard to image segmentation, experiments carried out on images with reflectance data displayed in false colours produced good results, as assessed through visual comparison with the surface under analysis. When compared with those obtained from the image-segmentation of the same surfaces displayed with photographic colour data, the latter showed greater accuracy in all experiments. In any case, the intensity value used must be critical, assessing its reliability on a case-by-case basis according to the characteristics of the survey.

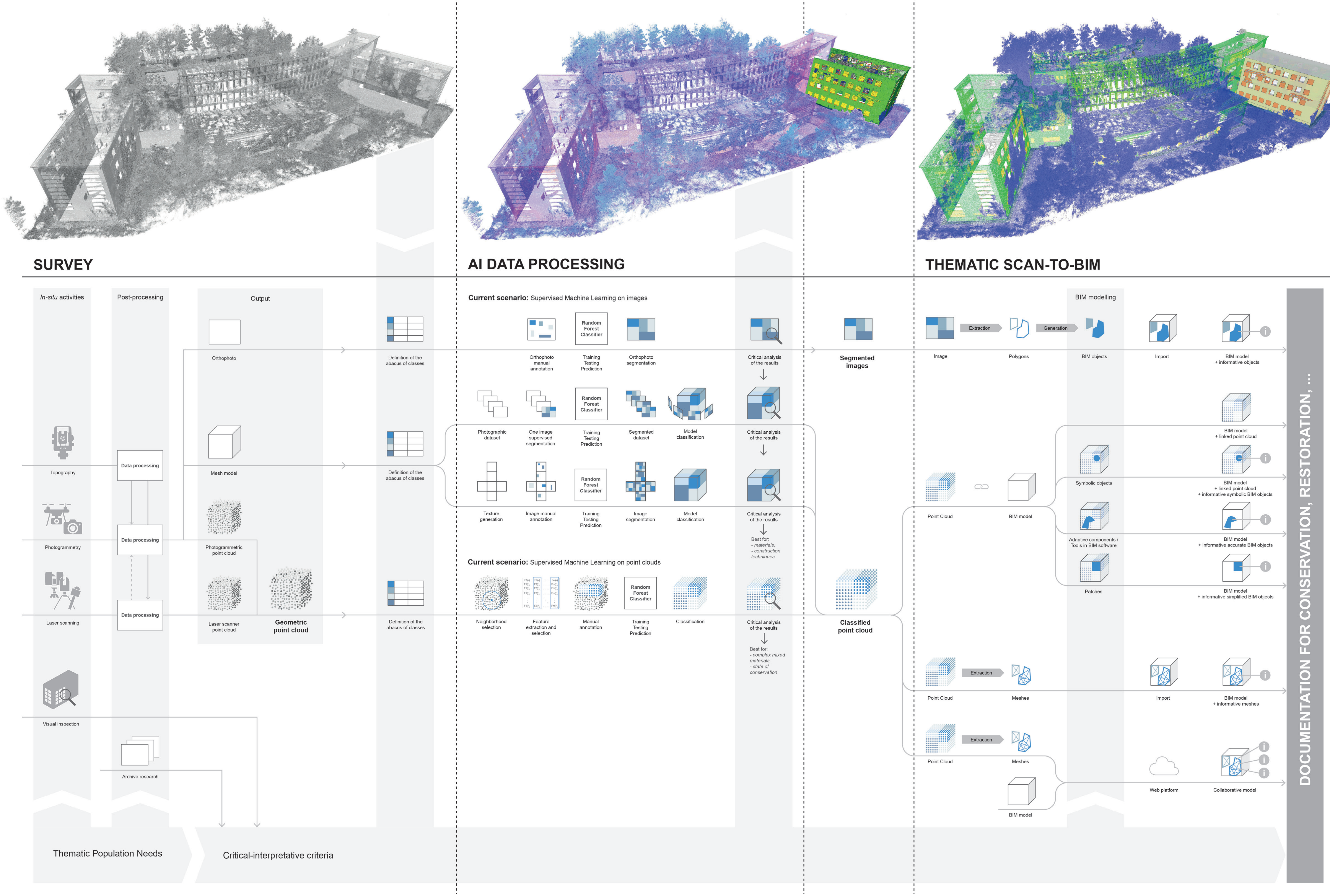
Critical issues encountered across the tests on the case studies bring out broader methodological considerations. On the one hand, the definition of classification abacuses strongly influences algorithmic performance: some categories that are necessary needed from a conservation perspective may not always correspond to classes distinguishable by ML, and this misalignment produces systematic ambiguities, that must be manually corrected in order to deliver an useful and usable classified model. On the other hand, the transferability of trained models remains limited: what works effectively for one building may fail when applied to another, underscoring the necessity of carefully balancing generalization and specificity in experimental practice. This issue fits perfectly between these two opposing but equally important requirements, which do not only concern the specific phase of semantic classification but extend to the operations of surveying and representation and, more generally, to the overall documentation process. This consideration leads to the conclusion that, where there is a sufficient level of generalisation and standardisation within the same case study (or, more rarely, a group of case studies with similar characteristics with a sufficient degree of approximation), the application of supervised ML procedures becomes advantageous. Logically, this is easier to achieve with buildings of a certain size.

Board 01.

Next page. Overall Scan-to-BIM methodological workflow, ranging from surveying to parametric modelling, through the thematisation of architectural surface characteristics on point cloud models with the support of artificial intelligence algorithms - current scenario.

1. The level of feature importance is assessed in relation to the other features of the point cloud.

METHODOLOGICAL PROCEDURAL MODEL - current scenario



10.2 A procedural model supporting documentation and conservation practices

The second specific objective of this thesis is the development of a methodological-operational workflow for the effective employment of digital tools in architectural surface documentation for conservation purposes.

The study and the experimentations conducted have led to the development of a strategy emerged as a relevant outcome of the ML applications developed on the different case studies. It concerns the effectiveness of a combined methodology, which integrates point cloud–based classification with image segmentation procedures. This hybrid approach has proven particularly advantageous in dealing with the multi-category nature of the needs, where the coexistence of different layers (materials, construction techniques, and degradation morphologies) often exceeds the descriptive capacity of a single kind of source data. By leveraging the complementary strengths of the two methods, the combined workflow allows a more robust segmentation of complex surfaces. In this way, the methodological framework not only improves the accuracy of predictions but also enables the construction of layered classifications, in which different thematic dimensions can be coherently integrated. Such an outcome is significant in the perspective of conservation, where the possibility to cross-reference multiple categories of information within a single, queryable model represents a decisive step toward more informed, data-driven interpretation and decision-making.

Therefore, in order to classify a point cloud model according to different levels of knowledge of architectural surfaces, with the support of effective artificial intelligence methods, it currently seems necessary to proceed by combining cloud-based approaches with image-based ones, in a methodological affinity with integrated surveying, in which different methodologies are adopted to leverage their respective qualities, compensating for the weaknesses of the other methods. Board 2 outlines the proposed integrated workflow within the overall methodological model.

The thesis explored various approaches and methods in an attempt not to pursue an universal solution, but to propose a methodological model that can be applied on a case-by-case basis and adapted to the specific characteristics of the buildings under investigation. Respecting the singularity of each architectural case ensure that the resulting documentation remains a robust and meaningful support for conservation practice. It should be noted that it is not always necessary to apply the integrated method, but only in cases where more streamlined procedures, which operate on a single type of source data, are not sufficient to meet all requirements and identify all the necessary characteristics. In summary, the most effective method should be used in relation to the final purpose, the characteristics of the buildings, the source data and the categories to be analysed.

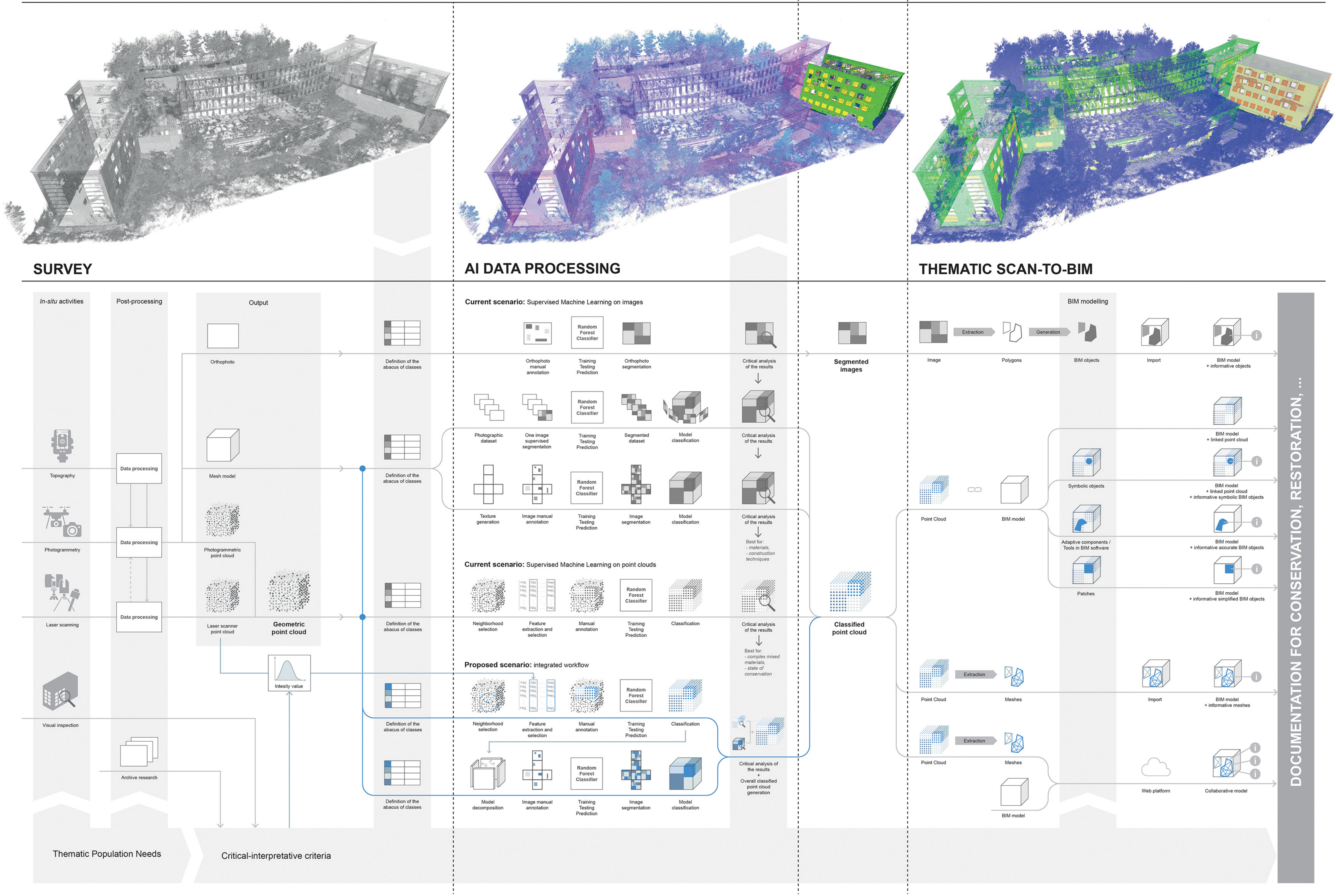
The proposed methodology, like integrated digital surveying, can be applied at different scales, from large buildings to heritage objects, with good scalability across various cultural heritage assets.

This process is, of course, always subject to future implementations, simplifications and optimisations. It is clear that combining different operations results in a more complex workflow that requires more steps, which can currently only be managed by operators who are experts in the field of surveying and data management.

Board 02.

Next page. Overall Scan-to-BIM methodological workflow, ranging from surveying to parametric modelling, through the thematisation of architectural surface characteristics on point cloud models with the support of artificial intelligence algorithms - proposed scenario.

METHODOLOGICAL PROCEDURAL MODEL - proposed scenario



10.3 Intensity value applicability for surface characterization

The third specific objective set, is to take into account, in point cloud AI processing, the intensity value feature in a meaningful and effective way. To achieve this, two types of test were executed. The first one evaluates the intensity value itself, thorough experimentations developed to assess the link between reflectance and the characteristics of the surfaces (Chapter 6). The second one consisted in the assessment of the intensity value feature importance in Supervised Machine Learning, using insights extracted during the training and test steps (Chapter 8).

Preliminarily, in order to avail of the reflectance value in point cloud processing without renouncing the descriptive effectiveness provided by colour data, it was necessary to associate robust RGB values with point clouds from laser scanners (Paragraph 6.2). Therefore, techniques based on re-projection from photogrammetric models or colourization from aligned images have been explored, which have proven effective in overcoming the limitations of onboard cameras, offering a better balance between colour fidelity and geometric accuracy.

Afterwards, investigations focused on the correlation between the intensity value and the characteristics of the surfaces. To summarise the experiments conducted on the various case studies, a synoptic table was drawn up correlating the categories of investigation, the objectives of the experiments, the methods used and the results obtained (Tab. 10.03).

These were developed using both avaiable databases, with the objective to associate specific intensity value ranges to specific materials and specific states of conservation (Paragraph 6.3), and *ad hoc* acquisitions, with the objective to study the intensity value variation in relation to geometric factors, surface conditions and colour (Paragraph 6.4).

To explore the relationship between the reflectance and the surface characteristics in a more comprehensive way, the sampling of the intensity values was performed on point clouds measured by different sensors, in environments with different boundary conditions. Results obtained show that intensity value can correlate significantly with materials and degradation morphologies, but under controlled acquisition conditions.

Tab. 10.03.

Intensity value experimentations synoptic table, summarizing the categories of investigation, the objectives set, the methods used and the results obtained for each case study building.

CASE STUDY BUILDING	INVESTIGATION CATEGORY	METHOD AND OBJECTIVE	RESULT
Archaeological Museum of Verucchio	Materials	Manual segmentation ↓ Association of intensity ranges with different materials	Reliability dependent on various factors ↓ Responses of varying intensity ↓ Usability subordinated to critical analysis of data
Sant Margaret's Church	Materials	Identification of different intensity ranges for homogeneous material ↓ automatic segmentation of ashlars-joints	Good* reliability in identifying areas of interest ↓ Possible support in AI processes
Rocca Possente in Stellata	State of Conservation	Identification of different intensity ranges for homogeneous material ↓ automatic segmentation of degradation morphologies	Identification of different intensity ranges for homogeneous material ↓ Possible support in AI processes
Palazzo Tassoni	Materials	Study of the variation in intensity values for homogeneous material according to:	
		- angular variation	decreasing intensity as the angle decreases
		- distance	irrelevant in architecture
		- surface temperature	irrelevant in architecture
		- surface humidity	decreasing intensity as humidity increases
		- colour	different responses depending on the wavelength of the different tools

Specifically, experiments on existing databases have highlighted the importance of survey context and consistency of scanning parameters. *Ad hoc* tests, on the other hand, allowed to individually isolate the factors affecting intensity (angle of incidence, surface humidity, colour, type of tint, etc.), trying to highlight specific trends for each. These observations suggest that intensity data, while not diagnostic in an absolute sense, can be useful to support the characterization and mapping of the state of conservation or materials for computational and diagnostic purposes, and, consequently, an effective discriminating feature when contextualized, calibrated and integrated into supervised machine learning pipelines.
Regarding the assessment of the intensity value feature importance in Supervised ML procedures, the results varied depending on the case. These were summarized in the synoptic table shown in paragraph 10.1 (Tab. 10.01). Using insights extracted during the training and test steps, its contribution was evaluated. In some cases it has emerged as very significant for distinguishing classes with distinct radiometric behaviour (e.g., metals or mortar joints), while for other classes its effectiveness resulted in an medium or medium-high value if compared to other features. Instead, in cases where the boundary conditions during the survey phase determined acquisition constraints and, consequently, produced a point cloud characterised by uneven intensity data, its effectiveness was low. Here, the algorithm did not find significant correlations between the intensity value and the classes to be identified, discarding this feature in the calculations. This proves, once again, that the utility of this feature cannot be generalised but, depending on the case, it is necessary to assess whether it can be successfully used or not.
In summary, variation in intensity can be used to derive information about the materials and degradation of the investigated surface, not only in a "traditional" way but also within algorithmic procedures. Board 2 shows the contribution of reflectance within the proposed integrated workflow. In any case, it remains a supporting factor, that become consistent and interesting if critically interpreted, through a comparison with different analysis. It can determine surface qualities once it has been established that the survey has been conducted by controlling, as far as possible or within a certain degree of tolerance, the factors that may modify or alter the responses of the intensity data.
Wider considerations emerge from the experiments carried out in chapter 6. These demonstrate that in the "informational" potential included in the digital data obtained from the 3D survey, the intensity value is a (potentially) powerful information concerning the interpretation of surfaces. The range of reflectance divided into different levels highlighting inhomogeneous (and homogeneous) areas on which to investigate further, makes the use of the intensity value an interesting parameter. Variation in intensity can be used to derive information about the materials and degradation of the investigated surface, but surface qualities are not uniquely determined. They become consistent and interesting features only if they are critically interpreted, through a comparison with different analysis.

The processing of digital data and associated radiometric features can open up many levels of investigation, the methodology requires further steps, as well as massive training data and dense cloud samples. In fact, the visual-comparative analysis developed over years of experimentations demonstrate the need to target research towards comparative data, "sampling" the reflectance of different materials, measured with different sensors and in environments with different boundary conditions. Paragraph 6.3 aims to trace some possible methodologies repeatable both for avaiable point cloud model and for *ad hoc* surveys.
Probably, if until recently, the process already showed promising research directions in terms of calibrating or controlling results on specific materials, though it remained challenging at a comparative level. Given and considering the large number of factors that determine and influence intensity data, it is probably an ambitious and uncontrollable task to define libraries of materials and surface conditions with predefined classes associated with absolute intensity ranges, to be used to interpret intensity values or as training sets for automatic classifiers. Today, however, thanks to new data segmentation techniques and algorithmic procedures, advancements and broader comparisons are now possible, allowing for more "manageable" and "monitorable" meanings. These developments open the door to working on interpretative hypotheses that must be verified through other investigative methods, aiming to integrate surface features into a broader framework of heritage knowledge that also includes intangible information linked to physical conditions.
In this context, automatic segmentation leads to degrees of uncertainty to be fixed thorough further testing and samples. Future developments should aim at the identification of intensity value "standard" ranges according to a set of criteria based on historical-critical knowledge. This needs a greater level of deepening, e.g., combining outcomes from diagnostic analysis, identifying additional classes, and the normalization of intensity data using data-driven or model-driven algorithms to correct for distance and angle effects, making datasets more comparable and reusable.

10.4 Correlation, description and usability of segmented surface features in BIM environment

The fourth specific objective of the thesis is to assess different Scan-to-BIM strategies and methodological processes for transferring data obtained from classified point cloud to the semantic H-BIM model. The evaluation has been carried on thorough the point of view of geometric coherence, modelling simplicity and speed, level of automation and informative, as well as IFC compatibility. Each criterion is evaluated on a scale from 1 to 5, with values assigned through a comparative assessment of the methods. The highest score is attributed to the best-performing method (among those examined) for a given indicator, while the remaining scores are determined accordingly. Consequently, the lowest value corresponds to the least effective method in relation to the best one (Tab. 10.04). This, to consider the overall data usability and availability. In fact, BIM models can be viewed and queried through open formats, in dedicated software or through web platforms. This promotes multidisciplinary interaction, as well as making the management of cultural heritage not only more meaningful, but also faster, more productive, efficient, and sustainable. The research direction is also tailored toward a more and more effective link among digital databases and H-BIM models conceived to support heritage assessment and to be basis for restoration projects, connecting interpreted information to parametric objects in the 3D models.

Of course, each tested method presents its own strengths and limitations, and no single solution can be universally applied. Considering the most challenging category to be modelled, that is the state of conservation, the key of the different approaches lies in finding the method that best responds to the specific needs, depending on the objectives, the level of detail required and the methods of information management. The balance between accuracy, readability, level of automation, interoperability and computational load remains the central issue to be addressed in modelling degradation within digital information models. Methods that aim to use parameterisable objects characterised by good geometric accuracy tend to require longer modelling times and greater technical expertise, and often involve a significant computational load. Conversely, strategies that simplify geometry aim for more efficient data management, but risk losing elements that are fundamental to the use of the model itself as a support for diagnostic interpretation. Promising strategies to meet the need for greater process automation, with a good balance between geometric representation and the possibility of populating information, tend to follow more complex pipelines, such as the method of generating meshes from segmented clouds using visual programming tools (Paragraph 9.3.3).

In several cases, effective modelling strategies could require the integration of multiple methods. For example, the methods of modelling the state of conservation by importing the segmented point cloud (Paragraph 9.3.1) and that using simplified patches (Paragraph 9.3.5) can be combined to exploit their respective strengths. The former provides a consistent graphic representation that is faithful to the geometries of the areas affected by the mapped phenomena, while the latter supports the population of information. In this case, even simplified patches are no longer necessary; a symbolic object with an abstract geometry such as a Euclidean solid, superimposed on the cloud of the respective degraded area, is sufficient to serve as a support for the qualitative parameters. Clearly, some critical issues remain, such as the inability to export point clouds in IFC exchange format, but only symbolic reference elements.

The aforementioned methodological workflow boards (Board 1 and 2) show the Scan-to-BIM processes tested into the general procedural model. The various strategies are considered as different alternative possibilities for the informative modelling of the characteristics of the surfaces. The choice of the path to follow depends on many factors such as specific goals, required detail, and information management approaches. Ultimately, ensuring interoperability remains a priority, making collaborative platform-based workflows increasingly advantageous. Moreover, the integration of ontologies is guiding these procedures toward a fully semantic representation of semantic categories related to conservation and restoration, such as the degradation morphologies. In this way, thematic analysis of the segmented point cloud will enable a more direct hierarchization, extraction, and management of different levels of knowledge within the BIM process, allowing to foster accessibility and querying of complex information content.

Tab. 10.04.

Next page. Comparative overview of the methods described for the informative modelling of the state of conservation, evaluated on the basis of six qualitative indicators.

Workflow	Geometric consistency	Modelling simplicity	Modelling speed	Automation degree	Informative level	IFC compatibility
Images	●○○○○	●●●○○	●●○○○	●●○○○	●●●●○	●●●●○
Segmented point cloud	●●●●●	●●●●●	●●●●○	●●●●○	○○○○○	○○○○○
Segmented point cloud + symbolic objects	●●●●●	●●●●○	●●●○○	●●○○○	●●●●●	●●●○○
Adaptive components	●●●○○	●●●○○	●○○○○	●○○○○	●●●●●	●●●●○
Dedicated tools in BIM softwares	●●●○○	●●●○○	●●○○○	●○○○○	●●●●●	●●●●●
Simplified patches	●○○○○	●●●●○	●●●○○	●○○○○	●●●●●	●●●●●
Meshes	●●●●○	●●●○○	●●●●○	●●●●○	●●●●●	●●●●○
Meshes (via VPL)	●●●●○	●●○○○	●●●●●	●●●●●	●●●●●	●●●●○
DT platform	●●●●○	●●●○○	●●●○○	●●●○○	●●●●●	●●●●●

Summary

11. Conclusion and future developments

Abstract

This final chapter examines the main impacts, considerations, limitations, and future developments arising from the research, highlighting its contribution to digital heritage documentation and AI-assisted analysis of architectural surfaces. The study advances the scientific domain of point-cloud classification through AI methodologies, oriented toward Scan-to-BIM integration, by defining a procedural model whose effects can be observed in supporting the acceleration of digital transformation within architectural heritage documentation and conservation. The chapter also reflects on broader issues, including the importance of a reliable and integrated survey as a foundational dataset for classification, the potential and diverse uses of thematic point clouds, the rapid development of the digital transition, and emerging skills gaps, emphasizing that AI should serve as a support to, rather than a replacement for, expert interpretation. The limitations identified, such as the inherent complexity of automatically classifying surfaces, which relies on critical-interpretative readings, and the challenges of transferring thematic mappings into BIM environments, open opportunities for future research. These include exploring scenarios in which surface analysis may progressively shift from supervised to unsupervised learning. The research emphasizes the stages and aspects in which critical, domain-specific expertise must remain central.

11.1 Impacts

The most immediate impact of the thesis lies in contributing to advances in the scientific domain of digital heritage documentation, architectural surface analysis, and Scan-to-BIM integration, which is articulated in different aspects.

First, the research demonstrates, through applicative tests on case studies, that supervised Machine Learning can effectively support the classification of architectural surfaces. It clarifies where and why specific types of digital data and related segmentation

processes perform better: 3D point clouds for materials and construction techniques, image-based segmentation for fine-scale deterioration patterns. For this reason, the research proposes an integrated methodological workflow that combines point-cloud-based and image-based approaches. This hybrid model reflects the complexity of historic architecture and acknowledges the limitations of relying on a single data source.
Second, an assessment of laser scanner intensity value reliability is produced, clarifying its potential and limitations in supporting surface analysis. It shows that intensity can be a powerful discriminating feature when contextualized, calibrated, and critically interpreted. By combining cloud sampling, multi-sensor acquisitions, and ML feature-importance analyses, the work contributes further knowledge about:

- the external factors affecting reflectance values (geometry, colour, humidity, etc..),
- the non-linear relationship between intensity and surface characteristics,
- the challenges of building generalizable intensity libraries.

Third, the research applies a comparative framework to evaluate several strategies for transferring classified point-cloud data, according to surface characteristics, into H-BIM models. The different pipelines are analysed according to the geometric and informative qualities of the output, as well as the modelling effort required. This contributes to the refinement of semantic modelling pipelines and supports the ongoing shift toward more automated, effective and interoperable H-BIM processes oriented to store information aimed at the conservation of surfaces.
Overall, the research contributes to identify key points for bridging gaps between digital surveying, ML-based classification, and H-BIM workflows, recalling the necessity of case-specific considerations for applications on historic architecture, in order to raise greater awareness among future users of AI-supported processes, emphasising that a critical approach must remain central, identifying at which stages.
Indeed, beyond the more technological aspects, it is essential, in the present research, the discussion about the gap that is being created between the massiveness of the data and its actual usability. Huge amounts of data are acquired, but the ones required to address specific analytical questions are sometimes missing, or the relevant information is not associated with the geometric data collected. In the context of digital surface surveys, the quantity of the data does not (or may not) correspond to its quality. The need for an informed and structured representation, also based on semantic classification, and thus not only on the identification of architectural elements but enriched with non-geometrical information relating to surface features, is a line of significant room for investigation. The present research aims to contribute to the efficiency and optimization of digital resources.

The research presented in this thesis was developed under a position financed by the Italian PNRR (P*iano Nazionale di Ripresa e Resilienza*), D.M. 351/2022, M4C1 I. 4.1 (*Missione 4, Componente 1, Investimento 4.1*), measure aimed at increasing the number of innovative PhDs for the Cultural Heritage. The objectives of the research project therefore considered the digitisation of cultural heritage in the terms set out by the PNRR and the PND, aiming at an acceleration of digitization for the restoration and renovation of physical cultural heritage.
The main medium- to long-term impact of the research therefore lies in analysing the consequences of the acceleration of digital transformation processes in the field of documentation and conservation of architectural heritage. The disciplines of surveying, representation, diagnostics, restoration and information technology converge in an interdisciplinary approach that promotes substantial progress in the critical management of digital data. The main stakeholders involved include professionals in the sector, in particular architects, conservators and heritage experts, who will benefit from the positive impact of the research on the process of documenting and managing cultural heritage. The use of applications that implement classification algorithms will optimise the processing time of large amounts of data, constantly improving the accuracy of their interpretation and speeding up processes.
Hardware and software technologies, from three-dimensional surveying tools to BIM platforms, are an integral part of this sector, whereby the industrial sector can also benefit from the constant improvement of digital workflows. Some point cloud management or Structure from Motion modelling software has already integrated automatic segmentation functions, mainly identifying classes on an urban scale, in response to demand from the academic community and professionals. Thus, the AI sector itself can also explore new directions through segmentation algorithms applied to heritage surfaces, also using existing 3D databases and already digitised collections.
A further impact concerns the new skills required. The introduction of processes based on artificial intelligence and information modelling requires the acquisition of new professional and technical skills. Although in the initial phase this complexity may represent a significant obstacle to the widespread application of the proposed methodologies (Paragraph 11.3.4), in the medium to long term it will be a driving force for the creation of new hybrid professional profiles, capable of operating between digital technology and critical knowledge of the built environment.
Positive impacts are also foreseen in cultural institutions, such as museums and conservation bodies, or for public administrations engaged in heritage management and conservation, as well as responding to progressive obligations to adopt BIM also in public restoration tenders[1]. As emerged from the discussion with the Cultural Heritage Department of the Emilia Romagna Region (Paragraph 11.2.4), a tool such as classified point clouds can be a technical support for decision-makers to make more informed and

1. Mention is made to Legislative Decree 36/2023, Article 43 (D.Lgs. 36/2023, art. 43), which is the main updated regulatory reference for the adoption of BIM in Italian public administration. The legislation implements a gradual transition by progressively lowering the economic threshold above which BIM design must be used for public contracts. However, for interventions on cultural heritage, the obligation only applies to values above the EU threshold of €5,538,000.

effective choices. These models allow to understand priorities and values more clearly, allowing, for example, at an operational level, the pursuit of the principle of minimum intervention, guiding, from a broader perspective, more sustainable conservation actions from an economic and environmental point of view.

The improvement in environmental sustainability also stems from the transfer of many knowledge and asset management operations to collaborative virtual models, reducing the need for direct physical intervention and optimising scheduled maintenance cycles. A further impact concerns the promotion of social inclusion given the possibility to use digital models to extend knowledge and enjoyment of sites and collections to different categories of users.

Ultimately, the methodological process developed in this research, from surveying to the H-BIM model, through automatic recognition workflows, can enable progress in thematic management and digital data sharing at various scales: from historical, architectural and archaeological heritage to widespread heritage, to assets preserved in museums and cultural sites. In this perspective, the research is fully aligned with European and national strategic objectives to accelerate the digitisation of cultural heritage, helping to make knowledge more accessible, sustainable and interoperable.

11.2 Discussion

The relevance and multidisciplinary nature of the topic addressed by the research leads to reflections on a number of issues related to the discipline of surveying and representation for documentation aimed at the conservation and restoration of architectural cultural heritage. It concerns a series of aspects, some methodological, others theoretical-critical, and still others practical-operational. In order to address these issues, during the course of the thesis, there was continuous dialogue with functionaries of the Cultural Heritage Department of the Emilia Romagna Region, a public body that manages historical and architectural buildings in the area, including the widespread heritage. Since the research aims to improve the efficiency of the management of the extensive and complex cultural heritage, contributing to the acceleration of digitisation for its documentation, knowledge, conservation and enhancement, the objectives of these meetings were therefore to understand the critical questions that conservation operators may encounter in their daily activities in relation to the introduction of digital procedures and the state of the art of this process. This, in order to subsequently conceive how the proposed data management workflow could potentially support such activities.

11.2.1 The centrality of 3D surveying

A first basic consideration concerns the source data, i.e. the metric-morphological survey. Heritage conservation is a complex field, and there are many digital data management processes involved, including diagnostic and specialist investigations to map the state of conservation. For many of these, the essential starting point is metric survey, that form the knowledge basis on which to draft the different assessments.

It is fairly intuitive to affirm that the quality of the survey determines the quality of the analyses developed on it, or linked to it. As described in the survey protocols and guidelines section (paragraph 3.5), surveying with advanced technologies is not in itself sufficient to obtain a consistent result, and the correct application of acquisition methodologies makes a difference to the output obtained. With the widespread availability of increasingly competitively priced tools and user-friendly software (or even with the possibility to resort to in-cloud data registration, thus without the possibility of control at all stages), more and more operators are producing digital data, which are not always of the needed quality. The main problem arises when it is taken for granted that integrated three-dimensional surveying processes necessarily produce reliable results, in other words when too much trust is placed in the instrumental data, neglecting the control of operational systematic errors, in an uncritical application of the methods. Cases such as this, apparently avoidable in a scientific-experimental discipline such as surveying (Migliari, 1999), are rare in research but increasingly frequent in professional practice (Teppati Losè & Rinaudo, 2025). At best, they prove useless; at worst, they risk becoming counterproductive. For instance, when a metric survey containing undetected errors is assumed to be entirely reliable and used uncritically, inaccuracies in measurements and quantities may arise, potentially leading to serious consequences during operational and construction phases.

Considering artificial intelligence as advanced statistical models that solve problems given the circumstances, it is clear that as circumstances improve, the problem will be solved more effectively. So, data analysis processes using automatic or semi-automatic methods, such as those explored in this research, clearly confirm the causal relationship between survey quality and correct analysis. In fact, although AI processes have internal strategies for optimising and cleaning data, these strategies, acting at the IT level, certainly bring improvements but do not compensate for any geometric-morphological inaccuracies or shortcomings in the original survey. Furthermore, photogrammetric surveys carried out in suboptimal or uneven lighting conditions return inconsistent colour data which, during algorithmic processing, either becomes unusable (negating one of the main potentialities of photogrammetric surveying, namely the ability to acquire surface colour), or produces an incorrect prediction (providing conflicting colorimetric information).

All these factors demonstrate the centrality of a reliable integrated 3D metric survey on which to base the semantic process, and the critical-interpretative aspect is always essential, from the initial stages of surveying.

11.2.2 The potential of the thematic point cloud

The experiments carried out confirm that the most efficient and versatile medium for reporting thematic analyses is the point cloud model, as it is the product of measurement procedures that can be certified with a certain level of accuracy in relation to the methodology adopted. It is, moreover, a tool directly queryable and fundamental for the development of multi-scale products: from various forms of extraction characterised by a high level of morphometric description to H-BIM models. The latter, due to the intrinsic characteristics of the processes undertaken for their elaboration, entail greater degrees of geometric simplification while offering substantial potential for integrating multidisciplinary information. H-BIM processes aim to manage the complexity of digital models through discretisation. A semantic point cloud, enriched with different levels of analysis, constitutes an intermediate step between a purely geometric model and an informative one, also allowing for annotation support even on two-dimensional drawings. Although these are still the most widely used type of representation in restoration practice, and the most reliable in ensuring control over the operations to be carried out onsite, the trend seems to be that traditional drawings will disappear over time. This horizon still seems a long-term scenario, while in the short and medium term BIM is unlikely to achieve, or does so in research contexts (Bacci et al., 2019), the levels of detail required for restoration projects, nor are all professionals involved in the construction field able to manage advanced parametric modelling.

If the point cloud survey constitutes a 'geometric memory' of the building at the time of the measurement, the thematic point cloud adds a 'surface memory'. As with the geometric description of the surveyed "object", it is possible to extract dimensional drawings containing thematic annotations of any surveyed space, according to section plans that can be set as needed on the digital model.

From a strictly operational point of view, the classified point cloud model introduces advantages in the process of digitisation of historical heritage. It is a very powerful working tool because, for example, it helps BIM specialists in modelling (Croce et al, 2021). Assuming that archaeological modelling requires objects to be distinguished according to construction techniques, perhaps because information is needed to indicate stratigraphic units, the BIM specialist will have access to a point cloud that not only provides the geometric basis but also offers clear indications of the different parts to be modelled. This speeds up the process and reduces errors. Indeed, the BIM specialists will not be required to address interpretative questions that fall outside their specific expertise, nor will they engage in decision-making processes that may lead to inaccurate outcomes.

In addition to supporting BIM modelling, the thematic point cloud is a tool that facilitates the interpretation of historic buildings and serves as a model for directly studying some characteristics. Open formats and open source software make it possible to share and transfer these models. However, even with the most widely used and powerful software, Cloudcompare, there are still limitations, ranging from a rather unfriendly interface to the impossibility to perform queries, which weakens the interrogation process. Ontologies can also contribute in this direction, enabling a further step towards greater usability and interoperability (Codiglione et al., 2024). In any case, one of the operations that can be performed even at present is to isolate parts according to certain homogeneous characteristics in a measurable three-dimensional spatial visualisation, which can help in the study of the monument from a historical point of view, leading to advances in knowledge of the monument, such as in the thematic point cloud model of the Colosseum (Paragraph 4.6). Another example of operations that can be carried out concerns possible assessments of the relative relationship between areas with different surface characteristics. Assuming, as is standard practice, an subsampled cloud with a constant grid, i.e. with uniform resolution in all its parts (excluding inevitable and unresolvable occlusions) it is possible to compute the number of points in the two (or more) areas and compare them with each other. In practice, this means calculating the percentage of a surface affected by a given type of degradation.

11.2.3 Reading and critical interpretation of supervised segmentation procedures

In operational terms, semantic segmentation is part of the critical-selective-interpretative phase that follows the surveying phase. Whereas in the past, discretisation operations for model formulation (of any type) were contextual to the measurement phases, today the two activities are largely separate, with the latter focusing mainly on the massive and optimised acquisition of geometries. The risk may be that, especially in the field of surface analysis, the data collected might not be finalised and ultimately useful, neglecting information that is actually significant for supporting analysis from a historical, material or conservative point of view. "Support", because attributing meaning to an element implies a component of critical knowledge of the artefact that remains, at present and probably for a long time to come, undetectable in a massive and automated way. Surveying is a scientific measurement process based on codified rules that allow for the definition of a rigorous, repeatable and verifiable method (Migliari, 1999); on the contrary, surface analysis requires a strong component of critical, even subjective, interpretation. A phase of "human" interpretation is necessary, based on, and beginning with, the observation of the physical artefact. Automation in this context can take place at a later stage, with the aim of quantitatively extending the semantic attributions previously made. It is precisely in this context that Artificial Intelligence algorithms can be used: to automatically assign the meanings identified and to facilitate more structured subsequent interpretations.

Thereafter, if the goal of AI processes is restoration and conservation, at the moment, the best results are achieved with supervised procedures, so, the model is trained on a sample given by the user, and can provide a prediction consistent with the required accuracy and with the level of detail expected. As a consequence, the need for critical-interpretative intervention by the specialist is particularly required in the preparation of

training data and in the validation of automatic results.
Consequently, the specific integrated approach for the surface classification using Supervised ML proposed by this research is to be understood as integrated not only from a technical-operational point of view, for the segmentation itself, but also from a critical-interpretative point of view. In fact, in this intermediate phase in which AI-based processes are becoming widespread but are not yet autonomous, especially in the field of complex architectural surface classification, the direction seems to be towards a hybrid analysis, combining "analogic" and "automated" approaches. The former remain fundamental and essential for critical interpretative reading, based on in-depth knowledge of surfaces and the degradation phenomena that affect them, while the latter aim to represent them semantically on a metric support. The product of the two allows to overcome the current interpretative limitations of automatic procedures and, at the same time, to streamline the extensive annotation phases. In this way, specialists can be provided with semantic data, which may only need to be verified and not analysed.

11.2.4 Heritage digitisation as a pervasive process: potentials and shortcomings

The procedural and critical-interpretative model developed is part of the broader scenario of the digital transition of cultural heritage documentation processes promoted at national and international level. In this context, it should be emphasised that this is no longer just a requirement linked to documentation and conservation, but also a strategic tool for extending its reuse in other areas, such as education and tourism. European guidelines encourage and finance integrated projects that combine the collection, management and reuse of digital data. This drive to accelerate the innovation process has led to the definition of the various aforementioned protocols, aimed at standardising procedures and ensuring qualitatively consistent results. The next step is to develop digital data management models that take into account the new phases that have arisen with the implementation of automated processes and that are transparent, accessible and capable of adapting to the growing complexity of the information acquired. The present research aims to extent the systematisation of processes from those related to surveying to those related to diagnostics (or pre-diagnostics), in order to make not only data collection more efficient and target-oriented, but also its classification, minimising the dispersion of information.
These guidelines for data use must question how useful and interoperable the collected data really are, in order to ensure greater accessibility and usability of the models. Often, in fact, they are not fully exploited, or acquisitions and analyses are repeated due to the inability to access databases that are already achieved but unavailable. These are just some of the aspects that lead to a significant gap between the theoretical guidelines and operational practices. Therefore, from the discussion with the Cultural Heritage Department of the Emilia-Romagna region, the question concerning the actual applicability of these advanced tools was addressed and some specific topics emerged. On the one hand, it was recalled a clear and great awareness of the potential of 3D surveying and the usefulness of digital models. On the other hand, numerous issues have been highlighted, ranging from managing and infrastructural problems to those relating to competencies and economic resources.
Specifically, there is a lack of shared methods and processes among the figures involved in cultural heritage conservation, such as institutions, professionals and technicians. There is a clear need for a unified regional platform capable of receiving, archiving and using complex digital models, in which data can be used for both technical purposes and public accessibility for enhancement and conservation activities. Among other aspects, this lack results in some of the 3D surveys already produced (e.g. those following the 2012 earthquake), scattered across different archives and not retrieved or standardised. The biggest structural problem concerns the lack of economic resources to systematically manage the historical built heritage, which is widespread and extensive. This has a strong impact on municipalities, especially smaller ones, which also have limited human resources. There is also a gap in adequate technical and scientific skills within public bodies: many technicians are not trained to manage 3D or BIM models, so work is still mainly carried out on 2D drawings. All these factors make the effective adoption of BIM difficult, despite increasingly clear and stringent regulations, and it often remains a requirement on paper, with no real operational impact on local authorities, who often still use traditional CAD design.
From this discussion it emerged also that some needs can be covered by strategic actions. Since one of the main critical issues highlighted is long-term sustainability (evidently, municipalities cannot maintain stable internal consultancy or expertise that would enable them to use digital data), it is important to encourage policy makers to recognise that some skills cannot be internal to each public entity, but must be centralised or outsourced. There is a need to establish a shared management system among municipalities, possibly with the support of universities or *consortia*, in order to optimise resources. Looking ahead, for a management body such as the Cultural Heritage Department, the use of three-dimensional models, including classified ones, can be an effective decision-making and strategic support tool: a way to decide on the priority of interventions, assess the sustainability of certain actions in the project and, ultimately, contribute to decisions on the distribution of funds.

11.3 Limitations

11.3.1 The multiple dimensions of surfaces in classification and interpretation

While documented research in the literature shows that a certain degree of generalisation can be achieved, in the fairly near future, with regard to the semantic classification of the elements that compose architectural artefacts, the horizon seems to be further away when dealing with surface analysis. There are various reasons for this, both interpretative and technical. Firstly, regarding the compositional elements of architecture, there is a theoretical approach, rooted in the tradition of classical and Renaissance treatises, which allows for an analytical decomposition of buildings that can be used as a reference for the discretisation of Scan-to-BIM (Dore & Murphy, 2017; Barni & Inglese, 2024). At the same time, a reference consists of the classes of technological components of the UNI 8290 standard (Daniotti et al., 2017), which in a certain way can be considered the basis of the components and families available in authoring software. Although not entirely resolutive, these references help in the semantic classification of buildings and, therefore, in the segmentation of point cloud models. As regards surface analysis, however, interpretation is more complex and varies depending on the category. Regarding materials and construction techniques, there may be historical and archaeological components specific on a case-by-case basis or limited to certain periods or geographical areas that guide segmentation. The level of uncertainty increases when dealing with the state of conservation because, despite established reference documents such as UNI 11182 (former NorMaL 1/88), degradation phenomena often manifest themselves case-specific features. Overall, the surfaces of a building, composed of different materials, assembled using different construction techniques and potentially subject to various types of deterioration, produce a pattern that is almost unique for each building.

In addition, segmenting and classifying point clouds according to construction elements leverages primarily the three-dimensionality of the model, exploiting the different geometric features to identify them. For material and construction techniques analyses, the same principle may be applied in some cases, where the association of a specific material with a specific morphology is effective for class discrimination. However, in other cases, especially for state of conservation, pseudo-planar morphologies are not related to geometric differences that can be represented on the point cloud. In these situations, as described, image-based segmentation working on colours and patterns is therefore more successful. While this specific step can lead to interpretative and operational advantages, it also implies a more complex workflow, involving steps to shift from three-dimensional to two-dimensional and vice versa, leading to a greater risk of information loss.

11.3.2 Open issues in Scan-to-BIM surface representation

This research shows that the formulation of classified point cloud models can effectively be used functionally if aimed at the informative implementation of relational 3D models. However, one aspect of the process that still needs to be resolved is the automation of the transfer of semantic classifications within the BIM model. Currently, the simple creation of generic links, which allow for a visual overlay of the elements of the segmented point cloud, is sometimes considered an informative implementation. These tools can be useful in the modelling phase, as described, as they provide a reference that has already been interpreted according to different categories, thus facilitating the work of the BIM specialist and relieving them of the task of having to interpret or make decisions in areas that are outside their specific expertise and are thus not always immediately understandable. Automated solutions for transferring this information to the BIM model are currently partial, relating to primitive geometric elements (Macher et al., 2017) or using visual programming languages (Pepe et al., 2020), and manual interventions, especially for the representation of degradation, are still widespread (Angilieri et al., 2025).

When addressing the topic of degradation, the critical issues increase, as it is not only a matter of information transfer, but also a lack of adequate modelling tools. The literature reports experiments aimed at automating the geometric representation of mappings (Avena et al., 2024). Alternative strategies can also be hypothesised, some of which have been tested in this research, each with its own limitations, so that none can currently be considered definitive. This is despite the introduction, in some authoring software, of specific, parametric and measurable objects capable of representing areas of degradation in a simpler and more functional way (Lanzara et al., 2021).

In consideration of the current requirements for conservation and restoration projects, it is still advantageous to work in 2D, despite the limited information capabilities: viewing the morphology of the deterioration more accurately and selecting a polyline to quickly understand the area.

While waiting for the tools to evolve, it may be useful to consider a possible change of perspective: perhaps BIM, at least for now, is not the most suitable tool for developing degradation maps that replace the functions of those developed using traditional two-dimensional methods, but it can still offer an innovative contribution through other types of representation and information links, such as textual data, quantity calculations (including through external systems) or references to additional materials.

11.3.3 Changing scenarios in laser scanner sensors

The definition of a clear methodological process for the classification of survey data cannot ignore the evolution that acquisition tools and techniques continue to undergo over time. Laser scanner sensors are evolving towards less static and more dynamic systems (SLAM), in which the radiometric response of the reflectance data, being subject to continuous changes in position and angle of incidence in relation to surfaces, is less controllable and therefore less significant for surface analysis. Even regarding static laser scanners, beyond the technological developments of the sensors, there has been a change in surveying methods. Approaches based on cloud-to-cloud registration are increasingly being used, as they are considered advantageous in terms of overall time, cost and reduced complexity of on-site operations. However, they imply an increasing number of scan positions and a consequent multiplication of factors to be monitored. This makes it more difficult to calibrate and correctly interpret the intensity value obtained. In this scenario, colour data, especially that derived from photomodelling processes, becomes more important. Considering the IT developments in Structure from Motion software, which essentially consist of ever-increasing advances in terms of the robustness of reconstruction algorithms and the reduction in processing times, it cannot be excluded that, for surface analysis purposes, the practice will move towards completely photogrammetric surveys, obviously with adequate topographical support for orientation and dimensional control. This does not only have negative aspects: RGB data is easier to interpret, consistent with what can be seen visually on the surfaces of the historic buildings.

11.3.4 Need for specific trainings and advanced skills

A common limitation affecting advanced digital processes for diagnostics and conservation, including the one proposed in this research, concerns the new skills required to effectively manage the emerging tools. This challenge is evident not only at the level of management and public administration (Paragraph 11.2.4), but also within the operational practices of professionals.

At present, the main advantage that automated classification brings in terms of saving time and resources in the process of understanding a historical building concerns extensive annotation operations, which are optimised. However, the actions required to manage the entire process are increasing, not only upstream for data preparation and algorithmic training, but also downstream for the validation of results and the composition of the general final model through the interpolation of the various levels of thematization. These tasks are generally more complex and require a higher level of digital competence, basically because it is no longer required to work in two dimensions but in three. Within the process, as a result, there is a shift in operations, and costs, from a defined and somewhat traditionally codified phase to a new, uncodified phase, lacking precise guidelines because it is still experimental. Undoubtedly, therefore, these methods can initially only be managed with effectiveness by a small number of experts who are already involved in the digitisation of heritage and have in-depth knowledge of digital surveying and data management.

In the future, the progressive automation of some steps that are currently too cumbersome on the one hand, and the growing basic IT and digital skills of every professional joining the working world on the other, will make this transition feasible. In this transitional phase, beyond training new qualified professionals, it is essential to update the skills of those already in the field, or at least to support them with ones capable of effectively managing digital databases. The adoption of multi-level BIM systems, driven by legislation, is a first step in this direction, and many efforts are also being made by public administrations. In order to develop these skills, it is first necessary to identify the needs and obstacles that prevent or hinder the usability of data, and what the actual applicability of these systems could be, as well as the benefits they bring in practice, in a coherent way that is useful for decision-making.

11.4 Future developments

The thesis led to the definition of a procedural model for the thematization of point cloud models according to surface characteristics such as materials, construction techniques and states of conservation. In doing so, various sub-processes and operational phases were addressed, including the study of intensity value and its relation to surface characteristics, and algorithmic processing through Supervised Machine Learning. Each of these processes has room for future development and implementation. Furthermore, within them, issues such as the type and characteristics of the case studies chosen, the software infrastructure available, and the critical interpretation required in many steps of the workflow played a significant role in the experimentations. All these aspects can also be addressed in future research.

The section of the thesis concerning the study of reflectance data shows an example of how to proceed and, above all, the sampling operation would need to be conducted extensively on a larger number of databases, analysing more and more materials and considering further variations in boundary conditions. Consequently, further developments of that field of research include a larger number of tests, in order to identify intensity value standard ranges according to parameters and criteria outlining more controlled boundary conditions, to understand the direction in which the sensors are going in the industrial context of the production of surveying instruments.

With regard to the algorithmic processing itself, in order to develop the research and the proposed procedural model, certain limitations of a practical and operational nature (Paragraph 1.3) were taken into consideration, which can nevertheless be addressed through future developments in the research. A first issue concerns the limitations imposed by the considerable hardware capacity required: by increasing the computational capabilities available, it is possible to extend the size of the datasets being analysed and, at the same time, reduce calculation times, speeding up the entire process. A second issue relates to the preference for Machine Learning (ML) algorithms rather than Deep Learning (DL), based on the greater performance of the former compared to the latter, depending on the categories of analysis sought and the input data available. This issue may be addressed in the future through the generalisation of the same ML algorithm to other datasets with different characteristics, as well as the creation of larger annotated datasets to train deep neural networks. Indeed, the 3D thematic point cloud models produced in this research could be used to contribute to the construction of a significant amount of annotated 3D data, that can be leveraged as available training information for the improvement of the application of DL algorithms to the cultural heritage domain.

Given the scalability of the proposed model, it would be worthwhile testing it not only on more diverse buildings, but also on other types of cultural heritage and at different scales, such as sculptural objects (Grilli & Remondino, 2019) or archaeological remainings (Barba et al., 2022). This could give rise to other types of problems, and addressing them would certainly constitute a possible development of the workflow presented.

At present, both the entire process from surveying to BIM modelling and the specific thematisation phase supported by artificial intelligence applications require several software programmes and tools to be combined. This is also reflected in the proposed integrated workflow, since each software is specialised to perform a specific task. In fact, to achieve the set objectives, existing and already available software tools were tested and applied to produce a semantic point cloud model capable of fulfilling the needs of describing the architectural surfaces that different circumstances may require. The use of multiple software programmes produces an inevitable complication and restricts the category of users to those with fairly advanced IT skills. Therefore, a forthcoming progress of the research could be the development of a dedicated platform in which some of the different phases of the proposed methodological workflow could be joined and made available to a broader range of users, reducing the use of different software programmes. This would make the procedure more fluid, and could also occur when the automatic segmentation and classification tools integrated into point cloud management software become more efficient, partly as a result of the progressive maturation of DL procedures.

In addition to technical and operational developments, future research may focus on improving the proposed procedural model. Considering that it will always be necessary to integrate innovative and traditional approaches to overcome the current interpretative gaps in digital data, research must first be directed towards the interdisciplinary systematisation not only of the survey processes but also of the analysis processes, with protocols that can be replicated and calibrated to specific objectives. To do this, it is necessary to understand how to adopt multiscale reading models to interpret surfaces in greater depth. The segmentation and classification presented in this research can be tools for thematising quantitative data in a qualitative and descriptive direction. Artificial intelligence represents a promising way to accelerate this process on complex data, but it must be supported by an operational model to follow and accompanied by critical and theoretical analysis.

The critical interpretation of the data under analysis can take place either before or after automatic processing, depending on the degree of maturity of the technology. In fact, envisaging a future scenario in which automatic classification for surface categories has been successfully generalised, allowing a transition from supervised to unsupervised learning, the interpretation of the result produced by AI must always be reviewed by a specialist in order to attribute the correct meaning to the clusters identified (Board 3). At the moment, in the field of architectural surface analysis, it seems that this more autonomous scenario is still a long way from being achieved. However, the process of digitising cultural heritage documentation can be seen as an integral part of the more general digitisation of our world, which is leading to the growing accumulation of unimaginable amounts of data that enable AI models to function (Bin Rashid & Kausik, 2024). So, we are building our world in an AI-friendly way, setting it up in such a way that it becomes increasingly successful. This revolution in the field of cultural heritage analysis may not be as fast as in other fields, but it is more gradual, with long-term impacts that are nonetheless deep and pervasive. It therefore seems that a shift in the critical phase of surface analysis may occur, as was the case with geometric surveying. Just as the possibility of applying tools for the automatic and massive acquisition of measurements has shifted the phase of the selection of the information to be discretised from the preliminary phase of survey design to that of post-processing, so the development of artificial intelligence algorithms will shift the critical reading phase from the data pre-processing to the classified output. In both cases, the critical component does not disappear but moves on to a subsequent phase. In this sense, it will be essential to know how to query and hierarchise data according to interpretation keys oriented towards different purposes: documentation, conservation and intervention on heritage. Therefore, the training of adequate professionals prepared to understand and manage the phenomenon is another challenge to be faced. (Paragraph 11.3.4).

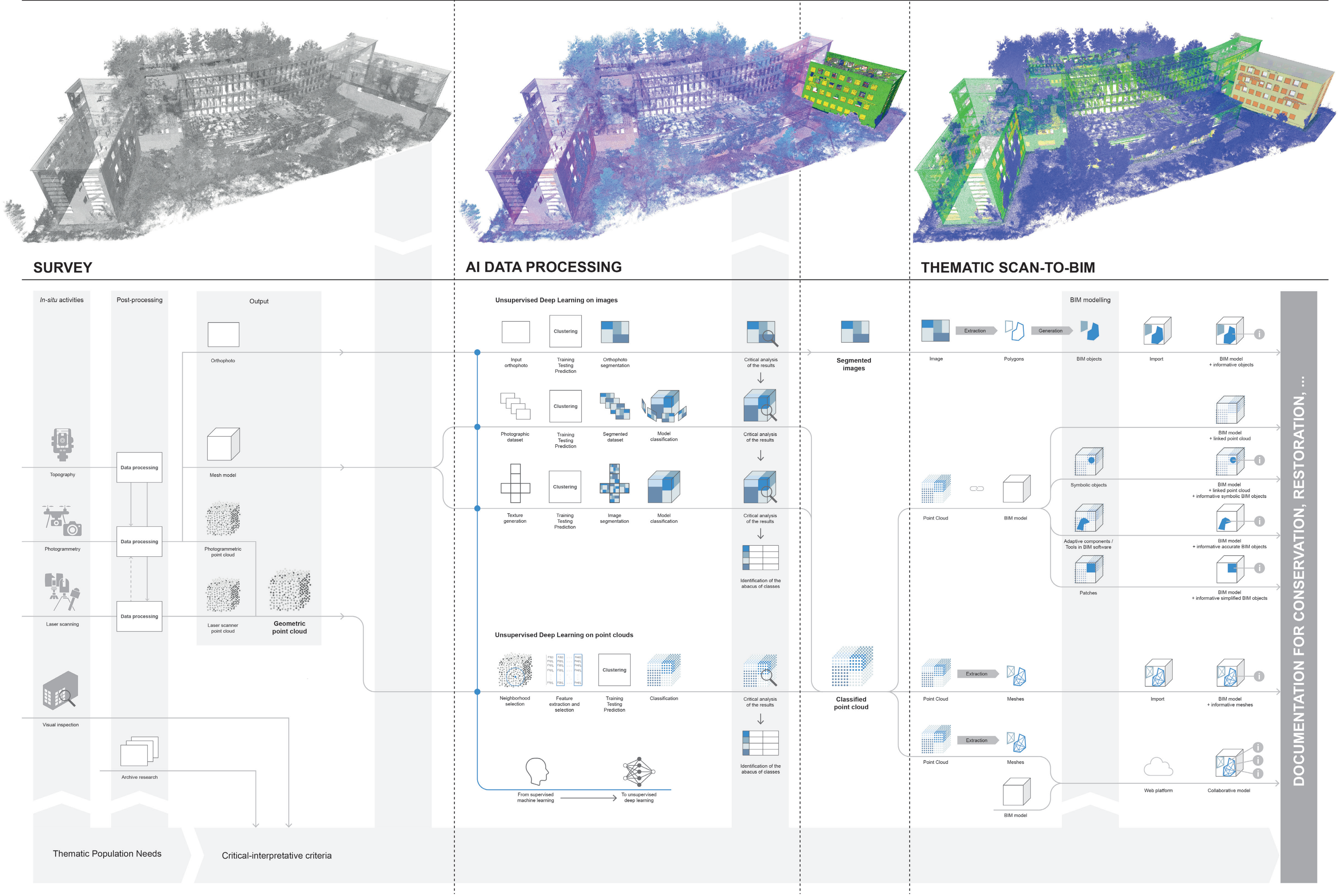
Board 03.

Next page. Overall Scan-to-BIM methodological workflow, ranging from surveying to parametric modelling, through the thematisation of architectural surface characteristics on point cloud models with the support of artificial intelligence algorithms - future scenario: from supervised to unsupervised learning.

The employment of Artificial Intelligence in this research is intended exclusively as a process of analysing data from 3D surveys of historical architecture, through quantitative and qualitative operations for the identification of cultural heritage surface characteristics. Consequently, the application of these AI-based techniques does not interact, replace, or influence human decision-making processes, and therefore has no repercussions on the ethical dimension. Furthermore, according to the EU AI Act, the activities of the thesis fall within the “Minimal risk” class (European Commission, 2021). However, there are still some practical operational risks, which requires caution when using artificial intelligence for surface analysis and interpretation. It should not be adopted simply because of its technological appeal, but only when it brings effective improvements to the overall documentation process. This improvement can be expressed in terms of reduced time and costs, as well as expanded interpretative potential. In other words, artificial intelligence should be considered a tool to support human intelligence, aimed at promoting a deeper understanding of cultural heritage for the purposes of its conservation and enhancement.

METHODOLOGICAL PROCEDURAL MODEL - Future scenario

Toward a thematic documentation of heritage features
Digital data segmentation for comparative, critical-interpretative analysis within the Scan-to-BIM process



The main interpretative risk associated with its use in this field is that it leads to analysing only what this technology is capable of detecting, structuring processes aimed more at the functioning of the algorithm itself than at a real understanding of the building being studied. This is determined primarily by the definition of classes of analysis based exclusively on what can be automatically distinguished, relegating the actual objective of the investigation, and its authentic knowledge interest, to the background.
For this reason, and considering that the current enthusiasm for artificial intelligence, the so-called AI hype, can be interpreted as a possible "technology bubble" (Floridi, 2024), it is essential to clearly identify which problems AI is actually capable of addressing and how it can do so in a meaningful and sustainable way.

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