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Digitization in conservation process: An integrated approach in Scan-to-BIM modelling using 3D semi-automated and AI-based strategies

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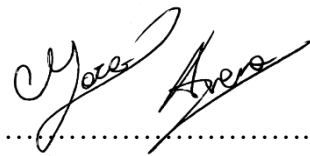
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A handwritten signature in black ink, appearing to read 'Marco Avena', written over a horizontal dotted line.

Marco Avena
Turin, May 12, 2025

Abstract

The documentation of Cultural Heritage (CH) through 3D metric surveys and digitization processes is essential for the conservation, management, and enhancement of these valuable assets. Utilizing 3D surveying technologies, heritage conservation efforts increasingly rely on reality-based methods, incorporating both image- and range-based techniques to produce accurate and detailed models of CH environments. Due to the diversity and complexity of data associated with CH, it is vital to structure this information effectively. This enables the creation of workflows that can efficiently analyze and extract all necessary features for developing informative 3D models with multidisciplinary content, supporting experts in heritage conservation.

A major challenge in CH documentation is the digital 3D modelling of complex shapes, which is traditionally a manual and time-consuming task. Addressing this, the research proposes an innovative methodology to automate and enhance Historic Building Information Modelling (HBIM) processes, using 3D metric survey data to generate reality-based models enriched with both semantic and geometric information. This approach bridges the gap between efficient data acquisition and labor-intensive modelling processes. The methodology leverages Visual Programming Languages (VPL), Artificial Intelligence (AI), and Generative AI (GenAI) techniques to automate repetitive tasks, minimizing manual effort and expediting the generation of enriched HBIM models. This type of approach allows the investigation of leveraging such a workflow to integrate 3D models classified – through established ML or DL techniques – or predicted – using GenAI techniques – into the parametric environment as appropriately categorized BIM elements. This approach facilitates the creation of comprehensive 3D databases, significantly enhancing heritage asset study, conservation and management. The proposed semi-automated workflow allows for integrating and categorizing 3D models directly within the parametric environment as structured HBIM elements. This method not only optimizes the modelling process but also facilitates semantic enrichment, enhancing the informational value of CH models. By harnessing the power of VPL, AI, and GenAI, the approach aims to overcome documentation challenges in CH, fostering sustainable digital preservation practices and improving the interdisciplinary management of heritage assets. This research establishes best practices in CH digitization, supporting the ongoing maintenance and appreciation of cultural assets.

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Chapter 1

Introduction

1.1 Research topics

The complexity associated with the heterogeneity of Cultural Heritage (CH) implies the need to adopt appropriate documentation strategies aimed at the preservation, management and enhancement of these specific assets. Architectural heritage, with its historical and social significance, plays a vital role in cultural development and outreach. This is strongly supported by the European Horizon 2020 agenda (EU Commission, 2023) and the broader digital transition mission at both national and international levels. In this context, 3D surveying technologies have become essential tools in heritage conservation efforts, focusing on reality-based methods that employ both image- and range-based techniques to generate highly accurate and detailed models of the investigated environments. These technologies are also increasingly integrated into information management systems, enabling the development of tailored platforms for sharing heritage knowledge (Soler et al. 2017).

In this context, the digitization of CH now brings together research communities that previously had limited interaction, fostering collaborations between scientific-technological fields and the humanities through a more holistic approach. By integrating 3D sensing technologies with reality-based modelling, this method lays the groundwork for advanced generative processes. The fusion of complex geometries and enriched information within the modelling process can lead to the creation of valuable, user-focused cognitive models. In this framework, the enriched 3D models, characterized by heterogeneous and structured information content, promote collaboration and knowledge exchange across various research sectors. Building Information Modelling (BIM) and Heritage Building Information Modelling (HBIM) approaches offer significant potential for enhancing interdisciplinary analyses by increasing efficiency (Lovell et al. 2023). This makes capturing a complete and detailed view of architectural heritage possible, addressing the complexity and granularity through space, time, and multi-scale, multi-content models. To facilitate at the same time the generation, fruition and sharing of these enriched models, it is necessary to use appropriate processes. In particular, approaches such as Scan to BIM allow the generation of 3D reality-based models with high metric accuracy and offer the possibility of semantically enriching these models by structuring information in a flexible but rigorous manner.

Additionally, having access to 3D data from multisensor surveys – LiDAR (Light Detection and Ranging), UAV (Unmanned Aerial Vehicle) and terrestrial digital photogrammetry, TLS (Terrestrial Laser Scanning) and MMS (Mobile mapping Systems) technologies – offer the possibility of generating multiscale BIM models, from urban to architectural scale (Błaszczak-Bak et al. 2024). In this way, it is not only possible to represent the morphological complexity of the built heritage but also to use these information models in relation to the territory in which they are embedded. In fact, in recent years, the research on geospatial data has

evolved, leading to recent approaches for managing vocabularies, object libraries, and semantics aimed at fostering mutual enrichment between the BIM approach and Geographic Information Systems (GIS) (Brumana et al. 2019). In this way, the BIM-GIS integration facilitates the Information Management (IM) phase (Floros & Ellul 2021) and improves the decision-making process regarding the conservation and enhancement of CH.

It is evident from what has just been described that it is essential to structure information accurately regarding the documentation of Cultural Heritage. Given the heterogeneity of the available data, there is a need for appropriate workflows capable of analyzing and extrapolating in an optimized way all the features useful for generating informative 3D models with multi-disciplinary content. In this scenario, a key aspect that needs to be emphasized and on which numerous researches have been conducted in recent years, concerns the low level of automatism associated with the processes of geometry extrapolation from 3D survey data. In the field of Scan to BIM, the extrapolation of geometric features is highly dependent on the complexity of the 3D survey dataset and the experience of the BIM operator, who is required to precisely interpret the data. These modeling activities turn out to be laborious and time-consuming. With the aim of streamlining and making such procedures more sustainable, in recent years there has been a focus on identifying workflows capable of automating such processes, placing alongside traditional modeling approaches capable of exploiting the potential related on the one hand to Visual Programming Language (VPL) and on the other hand to the implementation of algorithms that exploit Artificial Intelligence (AI). These two complementary strategies represent a viable and promising solution for structuring and automating processes related to 3D metric documentation. On the one hand, in fact, AI makes it possible to investigate new semi-automatic or automatic strategies capable of semantically classifying 2D (image) or 3D (point cloud) data by defining a specific semantic hierarchy among the information extracted from the input datasets. In recent years, manual labeling operations of 2D or 3D data, capable of dividing elements possessing similar characteristics into specific clusters, have now been almost entirely replaced by approaches using ML (Machine Learning) or DL (Deep Learning) algorithms, which represent nowadays the state of the art in the context of 3D data segmentation and classification (Grilli & Remondino 2020; Pierdicca et al. 2020). In parallel, recent research is shifting attention to architectures capable of training generative AI (GenAI) models. Such algorithms are able to predict and generate new 3D geometries from a set of input datasets from which they automatically learn useful information to generate new data having the same distribution as the data used in the training phase (Gao et al. 2022). However, these approaches can face obstacles when applied to the CH field, where the inherent complexity and diversity of information make numerous tasks particularly challenging. For instance, deep learning algorithms require extensive training datasets to function properly, but these are often unavailable. Similarly, GenAI approaches can be hindered by insufficient training data, leading to overly

generalized workflows that fail to provide the documentation needed to ensure the authenticity of cultural assets. This is further complicated by the fact that this particular field is traditionally marked by underfunding and limited resources, making the generation of these datasets an even greater challenge.

1.2 Context of the research and methodological framework

1.2.1 Transition and Digital Management of Cultural Heritage

The concepts of Heritage management and strategies for its monitoring are of fundamental importance and extremely relevant today. If we think, for example, of the inclusion of a site, a landscape, or a monument on the World Heritage List (UNESCO, n.d.), such a process not only represents an important occasion of objective recognition of the value of that specific asset but also brings with it beneficial effects that inevitably impact the surrounding territory. However, in order to benefit from these effects, it is necessary to adopt specific management policies for the assets, accompanied by careful and continuous documentation, thereby contributing to their protection, conservation, and enhancement.

In general, it can be said that cultural heritage is difficult to manage, as on the one hand, it presents such vastness and complexity that it complicates any attempt at coordination and protection policies, and on the other hand, it is exposed to continuous risks that undermine its existence. In particular, in recent years, we have witnessed numerous catastrophic events that have seriously endangered (and in some cases completely destroyed) both individual architectural assets and entire cultural landscapes. In Italy, but more broadly around the world, we have seen dramatic seismic events in recent years, such as those that occurred in Central Italy during the 2016-2017 period; or the occurrence of high storm surges in the Adriatic Sea coinciding with the rising sea levels; or the advent of catastrophic flooding effects that specifically threaten the integrity of entire UNESCO Sites. In addition to the extraordinary events mentioned above, further risk factors are represented by the assets' natural deterioration and wear and tear. It is, therefore, of fundamental importance to adopt strategic policies for planned management, which inevitably rely on consistent and ongoing documentation activities.

As part of the process of heritage preservation and enhancement, Alois Riegl defines monuments as *performances*, i.e., documents whose temporality is socially recognized, and “in this sense preservation is an archive of time” (Riegl 1903). In order to contribute to the continuous nourishment of this archive, it seems clear that it is essential to manage the large amount of heritage-related information (both semantic and geometric information) in our possession in an efficient and programmed manner. The process of documentation thus assumes in this context the condition that makes possible and effective the preservation of memory. In this regard, Andrew Jones, making use of a metaphor drawn from the novel *The*

Mysterious Flame of Queen Loana by Umberto Eco (Jones 2007), very effectively expounds the concept that memory represents a “container of information,” understood as a repository of knowledge. However, in order for this repository to contribute to the preservation of memory, it needs to be organized in an encyclopedic manner, where information is stored according to predetermined rules (classification codes, historical information, 3D maps, 3D models etc.). Therefore, in order to effectively document Heritage and thus promote its digitization, it is necessary to structure information according to intelligent logic and capable of generating appropriate databases useful for the management and protection of these assets through, for example, BI (Business Intelligence) processes (Meschini et al. 2022a; Sammartano et al. 2023).

Therefore, if on the one hand in recent years we have witnessed a rapid evolution in the field of technology with increasingly cutting-edge and effective tools for acquiring and processing heterogeneous data, on the other hand, it must be emphasized that this amount of information cannot always be efficiently managed and decoded by the various actors working in the field of Heritage protection and conservation.

1.2.2 3D information models: documentation and digitization strategies for cultural heritage preservation and enhancement

In such a complex scenario as that of CH, the importance and necessity of developing processes and employing appropriate tools/platforms capable of promoting the documentation and digitization of this Heritage, along with the numerous pieces of information associated with it, appears evident nowadays. A similar attempt had already been foreshadowed in 1974, albeit in an embryonic manner and with the tools in place at the time, by the Emilia-Romagna Region, which founded the *Institute for Artistic, Cultural and Natural Heritage* (Emiliani 1974). It has operated for more than forty years as a technical-scientific body for the management and documentation of the artistic, cultural, historical and natural heritage of the Region, promoting activities of cataloging, coding, processing and analysis of the surveyed heritage data by means of automated and programmable tools (computers). In this regard, Lucio Gambi also states that, in order to achieve complete and comprehensive documentation, the Institute would have to connect the data in the files of the regionally identified assets (semantic information) to cartographic data (spatial information) (Emiliani 1974).

As mentioned earlier, within the slow process of information digitization that is occurring in our cities, fields such as Geomatics and Computer Engineering have made great strides. Certainly, in recent years, great importance has also been given to the potential of using BIM and HBIM approaches. In particular, in dealing with Cultural Heritage, starting from 3D metric surveys and point clouds, it is possible to generate accurate HBIM models of the existing Built Heritage, i.e., advanced information-management models capable of producing prevention and conscious

management modes of buildings. However, the production of 3D informative models from reality-based data, enriched with both geometric and semantic information, is a laborious, time-consuming, and mostly manual process (Tommasi et al. 2016; Xu and Stilla 2021). There is a gap between reducing surveying times and 3D data acquisition (point clouds) and manual modelling activities. For this reason, improving Scan-to-BIM processes to automatically derive BIM/HBIM objects, such as walls and slabs, from 3D surveying datasets (Rashdi et al. 2022) is an increasingly attractive research investigation area.

In recent years, in this scenario related to process automation, a key role has been assumed by VPL. The approaches grounded in VPL strategies stand as a continuously advancing domain within the Scan-to-BIM field, presenting the opportunity to automate various operations concerning the interpretation and modelling of 3D metric data surveys. The use of the VPL strategy represents an innovative and flexible methodology that can semi-automatically model also complex 3D shapes related to CH. Among its many benefits, VPL offers the flexibility of visual coding, making it highly adaptable to diverse and heterogeneous case studies (Lanzara et al. 2022; La Russa et al. 2023).

In parallel, in recent years, Artificial Intelligence (AI) has emerged as a transformative catalyst in the digitization processes of Cultural Heritage, assuming a pivotal role in boosting the processes associated with CH documentation, preservation, and valorization (Llamas et al. 2017). The potential is huge, and applications are multiple as AI algorithms represent a powerful solution to enhance the automation level in the digitization and understanding processes. High-quality 3D reconstructions are feasible with NeRF methods, becoming emerging and viable alternatives to photogrammetry and computer vision (Remondino et al. 2023). Abate et al. (2023) used Convolutional Neural Networks (CNNs) to identify illicit traffic of CH goods based on classified images. The surveyed point clouds can be semantically enriched using ontology-based methods (Poux et al. 2017) or adopting an ontology-based semantic conceptualization to support a machine learning-based segmentation (Colucci et al. 2021). The semantic classification of spatial data is of fundamental importance, facilitating the generation, understanding, access and analysis of heritage digital assets (Croce et al. 2021; Murtiyoso & Grussenmeyer 2019; Teruggi et al. 2021). Nowadays, machine learning (ML) and deep learning (DL) algorithms supporting the 3D semantic segmentation of point clouds have notably increased (Matrone et al. 2020a; Grilli et al. 2023). AI has unquestionably solidified its position as a robust and highly effective solution for substantially elevating the automation capabilities within the domain of heritage dataset processing, with a particular emphasis on tasks such as classification and semantic segmentation (Grilli & Remondino 2019; Patrucco & Setragno 2023b). The remarkable achievements obtained through these algorithms have subsequently stimulated their application in semantic modelling for CH using Scan-to-BIM approaches.

Ultimately, another promising documentation strategy is Generative AI. Point clouds are generated through 3D laser scanners, depth cameras, and LiDAR (Light Detection and Ranging) systems. However, these sensors face challenges such as limited resolution, restricted viewpoints, occlusion, and issues with light reflections during scanning. Consequently, the resulting point clouds are often sparse, incomplete, and affected by noise, leading to missing geometric and semantic details (Zhuang et al. 2023). In this scenario, significant progress has been made in the field of 3D computer vision in recent years, and today, thanks to special architectures and predictive models, it's possible to reconstruct and restore damaged or incompleated point cloud derived from a 3D metric survey. In the specific case benefiting from large-scale point cloud datasets, deep learning-based point cloud completion methods fill such gaps by adding points where necessary. In this way, it is possible to semi-automatically generate a part of an object that was lost in the survey phase or missing from the beginning, a factor that assumes importance when it comes to digitization and enhancement of cultural heritage.

At the state of the art, AI, GenAI, and, more generally, Machine/Deep Learning techniques do not - and never will - claim to replace the interpretation of an expert. At the moment, however, they represent a promising tool for automatically - or semi-automatically - performing a number of repetitive and routine operations (especially in modeling from point clouds) that do not require particular interpretation by the operator, whose role becomes that of supervising - in an “intelligent” manner, making use of his or her own experience and sensitivity, which cannot be replicated by artificial intelligence - these basic and “time-consuming” operations.

Although in different ways, all of the above strategies make an important contribution in promoting innovative workflows to support the documentation, management, preservation, and enhancement of Cultural Heritage. The multidisciplinary associated with these strategies is also a great strength in achieving these goals. An integrated and synergistic use of these strategies will make it possible to contribute effectively to the digitization of Heritage. The fruition of informative 3D models enriched with both geometric and semantic information from reality-based data, therefore, contributes to the possibility of maintaining unchanged and, at the same time, promoting the value of authenticity attributed to Cultural Heritage (Maietti et al. 2018).

1.2.3 Specific research questions

Drawing from the discussions and insights presented in the previous sections, this dissertation has been structured around a set of key research questions. These questions have been carefully considered to address the core themes and challenges identified throughout the analysis, guiding the direction and scope of the research:

- The Scan-to-BIM approach represents a much-investigated field of research in recent years (Barazzetti 2016; Banfi et al. 2019; Previtali et al. 2019; Avena et al. 2021). In particular, in recent years, the AEC (Architecture, Engineering and Construction) field has shown an exponential increase in the use of BIM and HBIM methodology in various application fields, such as renovation and restoration planning, building maintenance, cost management, and energy-structural retrofit projects. However, obtaining complete and comprehensive As-Built BIM models is a process that nowadays is, in most cases, manual, laborious, and time-consuming (Tucci et al. 2019; Croce et al. 2023). In particular, taking into consideration the context of CH, this issue becomes immediately apparent. In most cases, complex architectural elements belonging to historical factories require ad hoc manual modeling by the BIM operator and specialist (Santos et al. 2022). Thus, it turns out that the gap between the reduction of survey time and acquisition of 3D data (point clouds), on the one hand, and the aforementioned manual modeling activities related to the existing built heritage, on the other hand, is constantly increasing. In this scenario, the first question that guided the development of this work of thesis was: How can this gap be reduced and the Scan-to-BIM processes made as automatic as possible?
- In recent years, the increasing demand for more adaptable and sustainable strategies in digitization processes has introduced significant challenges for the heritage documentation research community (Lanzara et al. 2022; Tucci et al. 2023). One of the most pressing issues lies in the execution of tasks such as parametric modeling (Abbate et al. 2022; Spanò et al. 2023) and AI-driven semantic enrichment (Yang et al. 2020; Buldo et al. 2023). While these operations are essential for enhancing the accuracy and depth of documentation, they have traditionally been time-consuming and labor-intensive. In this specific context, the second research question of this work of thesis was : From a Scan-to-BIM perspective, is it possible to propose a methodology that can use AI approaches and, more generally, programming languages in shared and interoperable BIM environments, in order to facilitate both modeling and AI-driven semantic enrichment of CH-related elements?

- In the domain of 3D Cultural Heritage documentation, raw point clouds captured by different 3D sensors and depth cameras often exhibit sparsity and incompleteness due to occlusion and limited sensor resolution (Vetrivel et al. 2015; Adamopoulos et al. 2021; Yang et al. 2022). Consequently, hole filling, alongside point cloud and polygonal mesh completion (Guo et al. 2018; He et al. 2023), emerges as a critical endeavor aimed at rectifying missing or occluded regions within the point cloud representation. The completion approach, also known as GenAI (Qi et al. 2017; Xiang et al. 2021; Xiao et al. 2024), can assume paramount importance for CH documentation, including visualization, object monitoring, and virtual environment construction. These preliminary considerations led to the formulation of the final research question of this work of thesis: How can generative AI-based completion techniques be effectively employed to address sparsity and incompleteness in 3D point clouds, thereby supporting and enhancing Scan-to-BIM processes?

Finally, it is crucial to emphasize the actual added value that semantically enriched parametric models can bring to documentation and digitalization processes in the field of Cultural Heritage (CH). In fact, as demonstrated by previous studies (Meschini et al. 2022a), the proper use of semantically enriched information models can play a key role in addressing CH management needs over time. However, it is evident that these strategies must be supported by well-structured and coordinated activities aimed at organizing both geometric and semantic information. One possible strategy to fully leverage the integration of these heterogeneous parametric models can be found in the adoption of dedicated Asset Management Systems (AMSs) (Meschini et al. 2022b). These platforms, indeed, enable the integration of BIM models within GIS environments, enhancing interoperability and facilitating the exchange of heterogeneous data. This, in turn, significantly contributes to improving decision-making processes and facilitates the management of complex systems.

1.3 Objectives and goals

The processes and strategies briefly described in the preceding paragraphs represent only some of the many initiatives undertaken and research topics concerning CH management and documentation. It seems clear, however, that it is essential that at the basis of these strategies, activities for organizing information are studied and coordinated, themes that have been the subject of continuing research in recent years. Suffice it to say that the concept of planning activities to conserve and enhance the Heritage is the basis of the *Conservazione Preventiva e Programmata* (Della Torre 2003) methodology, according to which, through appropriate Conservation Plans, it is possible to coordinate this process and respond to the management needs of the Cultural Heritage over time.

Based on what has been emphasized in the previous rows, the aims of this work of thesis are as follow:

- The first objective of this research has been identified in the attempt to propose an innovative methodology capable of - starting from 3D metric survey data - automating and optimizing HBIM modeling processes, facilitating the generation of 3D models enriched with both semantic and geometric information, and thus contributing to the documentation and digitization of Cultural Heritage. For these reasons, this research will focus not only on the traditional modelling techniques related to Scan-to-BIM but also and especially on the possibility of leveraging visual programming languages (VPL) to make routine modeling and usually time-consuming operations semi-automatic or automatic. The contribution of this research and the workflow proposed to pursue this first objective will be analysed in Chapter 2.
- The second objective, in continuity with the first one, investigates the possibility of enhancing the previous workflow by integrating classified 3D models – through established ML or DL techniques – into the parametric environment as appropriately categorized BIM elements. The precise pursuit of Scan-to-BIM process automation has enabled a focus on the need to devise innovative methods and management strategies for generating complex historical elements. The challenge, therefore, is centered around the need to steer clear of Scan-to-BIM approaches that tend to oversimplify reality-based models. It is crucial to take full advantage of the detailed information gathered from 3D metric surveys and ensure that the resulting models achieve the necessary LOA (Level of Accuracy). This should be done in alignment with the specific goals and technical requirements of the survey, so that the models not only capture the complexity of the existing conditions but also maintain the precision needed for the intended purpose. From

this perspective, the integrated use of strategies adopted within VPL environments with appropriate Python scripts was proposed. This approach facilitates the creation of comprehensive 3D databases, significantly enhancing heritage asset study, conservation, and management. By leveraging these enriched digital models, researchers and all experts working in the heritage field can gain deeper insights into the historical heritage and ensure more effective stewardship. In this way, the proposed methodology explored the possibility of implementing some innovative tools capable of automating modeling and semantic enrichment processes without compromising accuracy criteria in traditional pipelines. This methodology implements the workflow proposed in Chapter 2 and it will be analyzed in detail in Chapter 3.

- The third and final objective represents the last phase of this research in chronological terms. However, it is important to clarify that the methodology proposed in this section of the thesis actually belongs to the initial stage of the Scan-to-BIM process automation workflow outlined in the previous points. In particular, in line with the objectives described in the previous points, GenAI strategies were explored to integrate into the proposed methodology, particularly when the need arises to complete an incomplete or sparse point cloud. The aim here is twofold: first, to address gaps resulting from issues in the data acquisition phase (such as occlusions or 3D sensor limitations), and second, to manage inherent gaps in the surveyed object itself (caused by deterioration or degradation due to natural factors). In both cases, completion techniques can take on paramount importance for a plethora of downstream applications, including visualization, object recognition, and virtual environment re-construction. Therefore, the models thus created are not 3D models for their own sake but information models that can ensure informed asset management and facilitate strategic planning actions at different scales. The proposed workflow to achieve the final objective of the thesis, will be analyzed in Chapter 4.

Finally, it is worth highlighting that this research focused on the development of an innovative methodology aimed at promoting the automation of a specific phase within the broader framework of CH documentation and digitization, the Scan-to-BIM process. In this regard, Figure 1_1 shows the outline of the digitization process proposed in this thesis work.

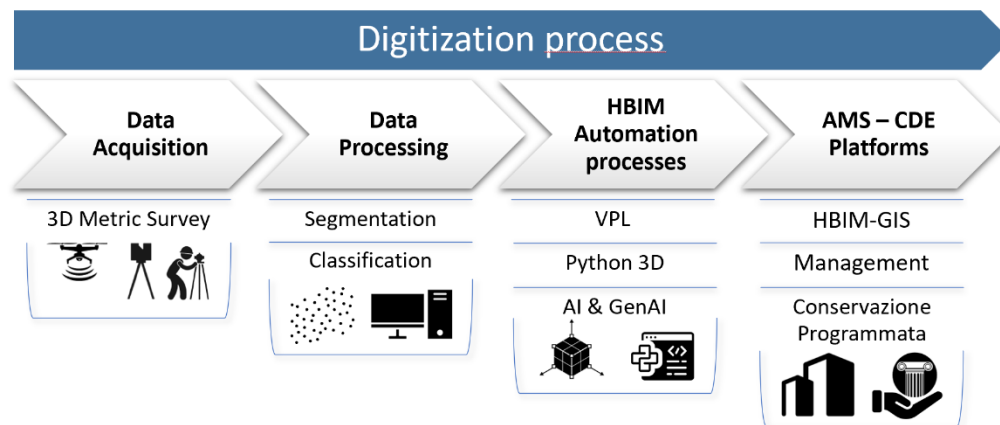


Figure 1_1: Schema of the Digitization process implemented in this thesis work.

Nonetheless, throughout each step leading to the formulation of this methodology, particular attention was consistently paid to ensuring that the parametric models generated could be effectively utilized by various domain experts without any loss of information, whether geometric or semantic. Although these considerations might appear tangential to the primary objectives of this thesis, significant emphasis was placed on data management, with the overarching goal of fostering interoperability and ensuring the seamless use of these models across different platforms and environments. In this scenario, for example, implementing these HBIM models in a GIS environment promotes the creation of innovative Asset Management Systems called AMS platforms. Concretely, these systems aim to create interoperable BIM-GIS platforms that provide real-time visualization of specific assets in an interactive and queryable 3D environment. A GIS-BIM information protocol is thus generated to promote the informative digitization of CH.

The goals and objectives previously discussed have been partially fulfilled through a series of peer-reviewed articles that were published during the course of the PhD program in which this dissertation was undertaken. These publications have contributed to advancing the research and providing initial insights into the topics explored in this dissertation.

1.4 Structure of the dissertation

This thesis is structured into five chapters. Chapter 1 serves as the introductory section, outlining the research theme, context, and the key questions that guided the study. Chapters 2, 3, and 4 constitute the core of the work and present an innovative methodology articulated in three distinct phases, each corresponding to a specific stage within the broader process of cultural heritage (CH) documentation and digitization.

In particular, each of these three chapters is conceived as a self-contained section, including an introduction to related works, a central part dedicated to the proposed methodology, and a final section where results are presented and discussed.

It's important to underline that the sequence of these chapters follows the chronological evolution of the PhD research, reflecting a progressive deepening of the study, from initial explorations to increasingly advanced techniques, culminating in the use of Generative AI. Considering this perspective, it's also important to note that, from a strictly operational perspective, Chapter 4 would ideally represent the initial step within the proposed Scan-to-BIM workflow. The structure was thus deliberately designed to showcase the evolution of the research while maintaining coherence with the timeline of its development.

The integration of these three core chapters ultimately leads to the formulation of the comprehensive methodology and workflow proposed in this thesis.

The structure of the dissertation is as follow:

- In the first section, developed in Chapter 1 (Introduction), the groundwork for the research is established by addressing several key topics. Specifically, this chapter outlines the research themes and contextual framework, providing an overview of the transition and digital management of Cultural Heritage (paragraph 1.2.1). It further examines the role of 3D information models as essential tools in the documentation and digitization strategies aimed at the preservation and enhancement of CH (paragraph 1.2.2). Additionally, the chapter presents the specific research questions that guided the study, alongside the objectives and goals that shaped the overall methodological approach (paragraph 1.3).
- In the second section, developed in Chapter 2 (HBIM approach and automation processes) the advancements in digitalization within the fields of geomatics and computer engineering are examined, with a particular focus on their impact on Cultural Heritage conservation. Following an overview of the primary geomatic techniques employed for 3D metric documentation (paragraph 2.1), the discussion centers on the significance of HBIM methodologies in this domain. Specifically, the chapter outlines the key Scan-to-BIM modeling techniques, ranging from traditional, labor-

intensive approaches to more innovative and semi-automated solutions (paragraphs 2.1.1, 2.1.2, 2.1.3). The core objective of this chapter is to propose a methodology that enhances HBIM modeling processes through the application of Visual Programming Languages (VPL). This approach facilitates the automated extraction of fundamental geometric features from point clouds derived from 3D metric surveys, significantly optimizing the modeling workflow (paragraphs 2.2, 2.3). A portion of the work presented in this section of the dissertation was conducted and published partly prior to the writing of this thesis (Avena et al., 2021; Spanò et al., 2023), and partly during its development (Roman et al., 2023).

- In the third section, developed in Chapter 3 (Scan-to-BIM process optimization using AI-based semantic enrichment strategy) a possible advanced application of 3D data is explored, focusing on the automatic generation of complex historical elements and the semantic enrichment of HBIM models. In this context, the study examines the possibilities of leveraging classified and segmented point cloud data to enhance Scan-to-BIM processes (paragraph 3.1). This approach not only aims to further automate modeling workflows but also seeks to promote a methodology capable of semantically enriching parametric objects within the HBIM environment. In alignment with the methodology proposed in the previous chapter, this section introduces a strategy that integrates the capabilities of VPL with Python 3D libraries to optimize the proposed workflow (paragraph 3.2). This implementation enhances the efficiency and effectiveness of semantic enrichment processes, fostering a more intelligent and structured use of 3D metric data. A portion of the work outlined in this section of the dissertation was published in Avena et al. (2024) while the thesis was in progress.
- In the fourth section, developed in Chapter 4 (GenAI approach for 3D survey data completing and optimization) the application of Generative AI to optimize reconstruction processes—particularly to refine and complete the previously described Scan-to-BIM pipeline—is proposed. Given that 3D metric survey data often exhibit gaps or missing information, leading to challenges in the modeling phase, the chapter first examines existing completion techniques for both point clouds and meshes (paragraph 4.1). Subsequently, the focus shifts to innovative Generative AI techniques, which leverage neural networks to efficiently generate new content based on diverse training inputs (paragraph 4.2). The paragraph 4.3 offers a detailed account of the proposed pipeline. In general, this chapter explores the potential of employing these generative methods to reconstruct incomplete architectural datasets, enabling their integration within the workflow proposed in the preceding chapters. By doing so, this research proposes and presents a comprehensive methodology that not only enhances traditional documentation techniques but also provides an innovative tool for the preservation and safeguarding of Cultural Heritage.

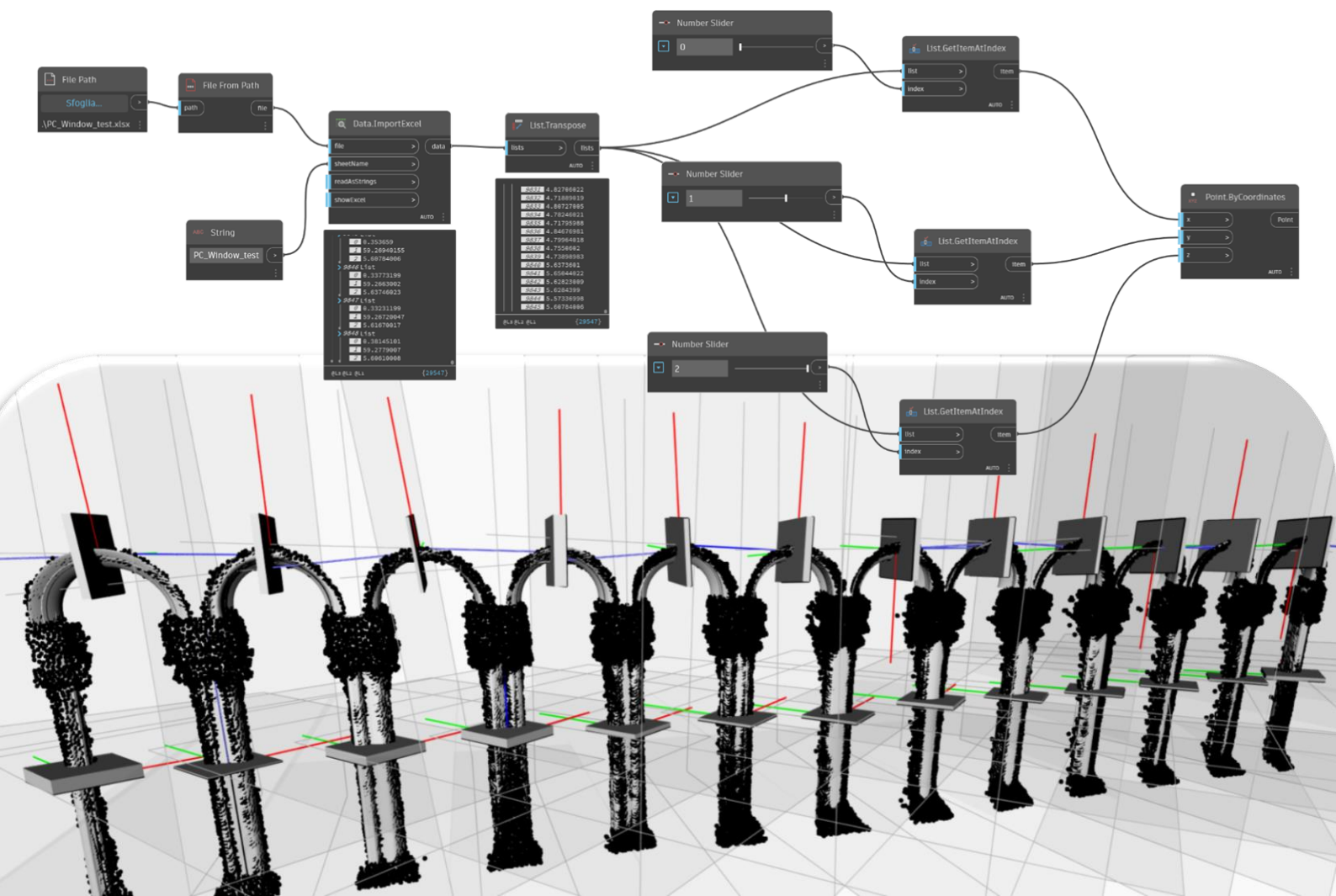
- In the fifth section, developed in Chapter 5 (Conclusion and future perspectives) is framed as a comprehensive overview of the research outcomes and the broader implications of the methodology. This section reiterates the primary objective of the study: to explore and validate innovative strategies aimed at optimizing and automating the Scan-to-BIM workflow for architectural heritage. It summarizes how the research addressed three fundamental aspects – semi-automatic modeling using Visual Programming Languages (VPL), semantic enrichment of HBIM models through classified data integration, and data optimization using Generative AI techniques. Additionally, the chapter critically discusses the challenges encountered, particularly focusing on the scarcity of high-quality training datasets and the multidisciplinary expertise required to implement AI-driven workflows effectively. These challenges are framed as key areas for further investigation. Finally, the chapter outlines future research directions, emphasizing the need for expanding labeled datasets, refining AI algorithms tailored to heritage-specific complexities, and promoting the integration of AI tools into practical heritage management workflows. By addressing these avenues, the research aspires to contribute to the advancement of more efficient, accurate, and sustainable digital documentation processes for cultural heritage.
- In the sixth section, developed in Appendix A (Complementary application case: The Standard of Ur), the methodology proposed in Chapter 3 is further evaluated through its application to an additional dataset, with the aim of assessing its scalability and adaptability across different Cultural Heritage scenarios. This section investigates the potential of the workflow when applied to models derived from alternative data sources and characterized by different geometric resolutions and representation needs. Following the same semantic enrichment principles described in Chapter 3, the implementation relies on a material-based classification strategy using supervised machine learning techniques. The resulting semantic information is integrated into a BIM environment, enabling the assignment of parametric attributes to each classified component. In line with the workflow developed in the third section, the process leverages the combined use of VPL and Python 3D libraries to manage the transfer and segmentation of semantic data. This complementary application validates the versatility and robustness of the proposed approach, demonstrating its relevance beyond traditional architectural-scale use cases. A portion of the work presented in this section was also published in Avena et al. (2024) during the development of this thesis work.

1.5 Keywords

- Cultural Heritage
- Geomatics
- 3D metric survey
- Cultural Heritage documentation
- Multi-sensor
- Multi-scale
- Building Information Modelling
- Historic Building Information Modelling
- Informative models
- Scan-to-BIM
- Level of Detail
- Level of Information
- Level of Accuracy
- Automation processes
- Asset Management System
- Visual Programming Language
- 3D Python Libraries
- Artificial Intelligence
- Machine Learning
- Deep Learning
- Data Segmentation
- Data classification
- Data integration
- Generative AI
- Completion
- Synthetic Dataset

Chapter 2

HBIM approach and automation processes



As mentioned earlier, within the slow process of information digitization that is taking place in our cities, fields such as Geomatics and Computer Engineering have made great strides, playing a key role in the framework of heritage conservation and safeguard strategies.

In particular, the BIM approach emerged as a methodological framework designed to oversee the entire lifecycle of a building through the use of parametric models embedded with semantically rich information (Eastman et al. 2011). Enriched 3D models, meticulously structured through the incorporation of comprehensive metadata and systematically organized within robust data management platforms, greatly enhance the efficiency of information sharing and foster stronger collaboration across a wide range of research disciplines (Addison et al. 2008) while also contributing to increased efficiency and productivity within the construction sector (Bryde, 2013). These models streamline communication between different sectors and ensure that data is accessible, well-structured, and easily interpretable, allowing researchers from various fields to work together more effectively and innovate more seamlessly (Figure 2_1).



Figure 2_1: Information sharing scheme in the BIM process (www.bimportale.com 2020)

In this framework the HBIM approach represents a cutting-edge technique for digitally reconstructing historic structures by developing comprehensive BIMs from data captured through remote sensing (Dore & Murphy 2019). More in detail, the HBIM approach could be described as “a novel solution whereby interactive parametric objects representing architectural elements are constructed from historic data, these elements (including detail behind the scan surface) are accurately mapped onto a point cloud or image-based survey” (Murphy et al. 2013) (Figure 2_2). The HBIM framework includes an innovative library of customizable parametric components, grounded in historical architectural records, and a method

for aligning these components with data gathered from building surveys. In this scenario, the production of a 3D BIM model from reality-based data is known as Scan-to-BIM process.

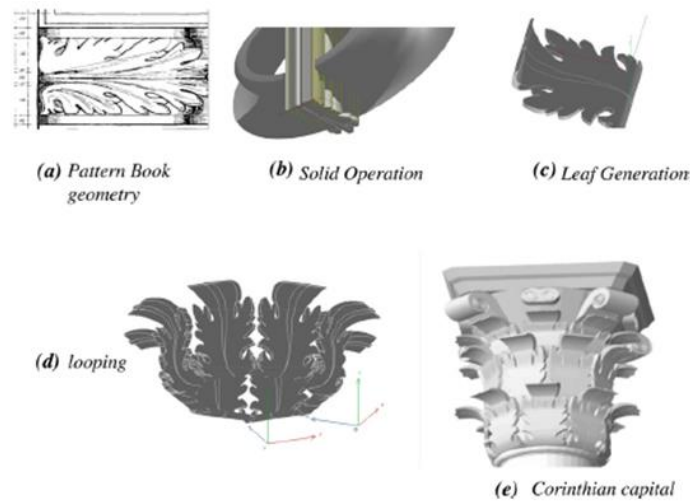


Figure 2_2: Examples of HBIM models (Murphy et al. 2013).

2.1 3D metric surveying techniques and HBIM modeling for heritage documentation: related works

The Scan-to-BIM approach is widely recognized by the possibility of incorporating procedures and parameterization rules into the creation of intelligent 3D objects (Sammartano et al. 2021a), allowing for greater accuracy and efficiency in the modeling process. Integrating BIM techniques within the cultural heritage (CH) sector continues to pose considerable challenges, primarily due to the complexity of geometric data and the intricate processes required to interpret and manage this data within a BIM environment (Murphy et al. 2013; Barazzetti 2016). The irregular and unique shapes of historical structures, along with their often-degraded conditions, further complicate the modeling process. Nevertheless, recent technological advancements in 3D data acquisition have greatly expanded the capabilities for collecting detailed information. These advancements allow for the gathering of vast and highly accurate datasets that capture both the geometric configurations and radiometric characteristics of heritage structures (Roman et al. 2023). Such data not only enhance documentation and preservation practices, but also support multi-scale decision-making processes (Avena et al. 2021) (Figure 2_3, Figure 2_4).



Figure 2_3: Example of using an Urban-BIM approach to documenting the CH, the case study of Norcia (PG) hit by earthquake in 2016-17. (Avena et al. 2021).

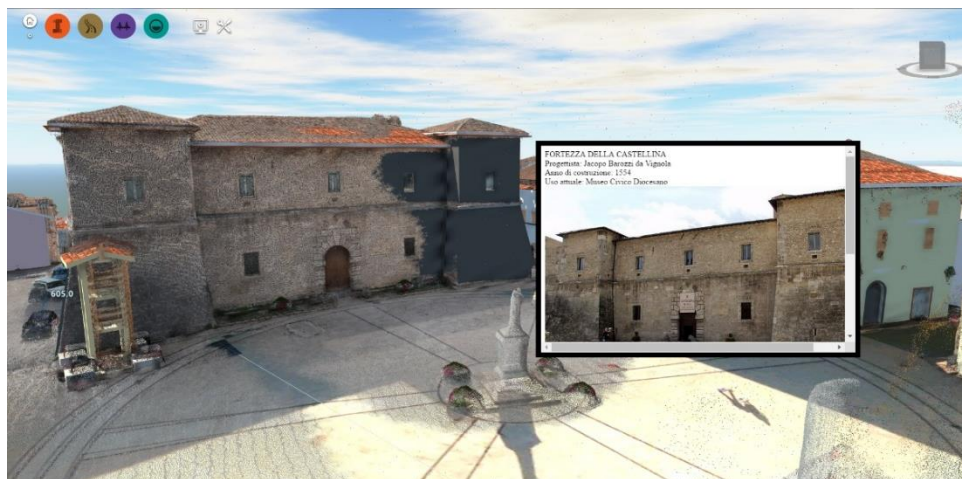


Figure 2_4: An Urban-BIM model to promote the enhancement of architectural assets using AMS platforms, the case study of Castellina di Norcia (PG) (Avena et al. 2021).

Survey data can now be acquired through a variety of techniques (Spanò et al. 2017), including terrestrial and UAV-based photogrammetry, as well as different types of laser scanning systems (terrestrial, mobile, handheld, and backpack-mounted) (Figure 2_5a-b). Among these, the integration of range-based methods (such as Terrestrial Laser Scanning, TLS) with image-based approaches (including UAV and close-range photogrammetry), typically employing Structure-from-Motion (SfM) techniques, has long been recognised as a particularly effective strategy for heritage digitization (Munumer & Lerma, 2015; Sammartano et al. 2021). These innovative technologies enable the efficient collection of large amounts of data, which are essential for constructing comprehensive HBIM models that faithfully represent the original architectural and material properties of cultural heritage assets, providing advantages in preservation practices (Banfi et al. 2022; Stanga et al. 2023).

In this scenario, a typical Scan-to-BIM process generally involves four primary steps (Bassier et al. 2019):

- **Point Cloud generating**, which involves the creation of a dense 3D point cloud, either from photogrammetric image datasets or by utilizing laser scanning techniques, depending on the project's requirements;
- **Point Cloud segmenting**, where the point cloud is divided into distinct clusters or regions that share similar geometric or surface properties, facilitating the organization and analysis of the data;
- **Point Cloud classifying**, in which the previously individual 3D point is systematically classified and labeled according to predefined categories – in our case architectural elements – allowing for a clearer understanding of the structure and its elements;
- **From classified point cloud to parametric modeling**, where the actual 3D model is constructed. This involves converting the classified point cloud into a detailed 3D representation, incorporating both geometric and semantic data to provide a comprehensive model. In this way, the parametric model is structured based on the semantic enrichments resulting from the previous segmentation and classification processes.

Additionally in a typical Scan to BIM workflow, prior to the steps listed above, pre-processing of the data is often undertaken to reduce file sizes and improve the overall efficiency of the workflow (Shi et al. 2018). This pre-processing aims to optimize the handling and management of large datasets, particularly when working with highly detailed scans. However, these operations can sometimes lead to a reduction in the quality or accuracy of the data, which can influence the final model. The quality of the results is often affected by the specific software tools chosen for the task, as well as the subjective choices made by the operator throughout the process, including decisions related to data filtering, simplification, and modeling techniques (Zhang et al. 2022).

The workflow previously described represents a conventional approach to the Scan-to-BIM process and served as the foundational framework for this work of thesis. It provided the initial basis for addressing the first research question, namely the development and integration of an innovative pipeline within the standard workflow, with the objective of automating the modelling process, as detailed in Section 2.2.

The following paragraphs provide a brief overview of the main steps comprising the workflow proposed by Bassier et al. (2019), with the exception of the initial point concerning established 3D metric data acquisition techniques. This aspect is excluded, as it has been extensively addressed in existing literature and falls outside the main investigations of the present doctoral research.



Figure 2_5: (a) Image depicting the point cloud of Piazza S. Benedetto in Norcia acquired by the integration of TLS and UAV techniques (Avena 2020); (b) Example of integrated 3D metric survey (TLS, UAV and terrestrial cameras techniques) of Villino Caprifoglio, Turin (Sammartano & Avena 2024).

Point Cloud segmenting

Typically, in the HBIM domain and, more broadly, in the Heritage field, once the architectural elements comprising the surveyed object have been identified, the segmentation process represents the first and fundamental step. During the point cloud segmentation phase, local features are analyzed to determine similarities among different elements, enabling the extraction of point clusters, commonly known as segments, from the 3D data. These segments represent groups of points that share specific characteristics, such as geometric or surface properties, which help in organizing and interpreting the data more effectively. In this way, similar surfaces or those with shared features facilitate the identification of architectural elements, promoting intelligent processes of automation. Over time, a wide range of techniques and algorithms have been developed to optimize this process, ensuring accurate segmentation and facilitating the subsequent stages of 3D modeling and analysis. The strategy proposed by Rabbani et al. (2006) focused *on the edge-based segmentation method*, with the aim of defining the edges of the various regions and then grouping the points inside the detected boundaries. Another strategy is based on the *region-growing algorithms*, in which one or more points, called seed points, characterized by specific features are used to create groups of points with shared features (Rabbani et al. 2006; Grilli et al. 2017). The objects can also be decomposed into basic geometric primitives, such as cubes, cylinders, and planes based on mathematical functions, using *model-fitting algorithms*. Finally, machine learning segmentation algorithms (including neural network or deep learning approaches) use artificial intelligence to train models and make computers able to make decisions. Machine learning approaches are K-means, hierarchical clustering or mean shift (Wang et al. 2023).

Generally, in the scan-to-BIM processes, a region growing-based approach, coupled with bottom-up methods, are the most used (Vo et al. 2015). The features employed for the seed points could be efficiently combined to achieve better performances: Tang et al. (2019) employ planar features, local relationships, and geometric constraints to segment an indoor model. A similar approach is used by (Shi et al., 2018).

Point Cloud classifying

The classification phase aims to label the previously detected segments, and it is performed both on clusters of points and on meshes. The approaches can be categorized as supervised (semantic classes are assigned based on a training model created from annotated data), unsupervised (no annotations are required, and data are automatically classified based on the user parameters definition), and interactive (the user has to give inputs and feedback to lead the classification). In the Scan-to-BIM process, classification is generally achieved by a supervised approach, defining topological features and spatial relations. Some works (Shi et al. 2018; Bassier et al. 2019) proposed methods to classify meshes. Macher et al. (2017) delineated a semi-automatic approach to detect primitive-based elements. About point cloud datasets and automatic or semi-automatic techniques, Deep and Machine Learning (DL/ML) algorithms are more and more exploited for classifying building heritage elements (Grilli & Remondino 2020; Matrone et al. 2020a; Croce et al. 2021).

From classified point cloud to parametric modeling

In general, the process of generating parametric models from point clouds refers to the creation of 3D shapes from labeled primitives—such as walls, slabs, and ceilings—extracted from classified points. In the literature, there are many attempts to generate an effective and broadly applicable automated workflow. Following Xu and Stilla (2021), a general classification for the BIM modelling phase includes:

- **parametric modelling** (e.g., model matching or fitting): it uses standard mathematical expressions, such as cubes, planes and cylinders (Kyriakaki-Grammatikaki et al. 2022) in order to fit shapes into clusters (model fitting method). The estimation of these shapes allows the user to recognise the main architectural elements of an existing building, such as floors and ceilings (Leoni et al., 2019), wall surfaces (Hossein Pouraghdam et al. 2019), and primitive geometries -masses - describing indoor spaces (Jenke et al. 2009). Representative algorithms are HT algorithm (Hough-Transform), sample consensus (RANSAC) (Schnabel et al. 2007) and maximum likelihood estimation SAC (e.g., MLESACT).

- **surface modelling** (e.g., boundary representation, B-Rep model and Isogeometric Analysis (IGA) method for CAD representation): it's a non-parametric modelling method. It suits complex shapes and doesn't require mathematical formulas to describe the surface. The surface modelling strategy is the most common approach in literature. Thanks to several adaptable software and plug-ins, such as Grasshopper, it is possible to associate geometric and semantic information to the relative volumes (Costantino et al. 2021), both for constructive elements, such as walls, roofs, and floors, and for architectural decorative

apparatus, such as altars or statues. In addition, other plug-ins implement the editability of the imported point clouds and make it possible to manipulate data to return objects, directly modelling on the surveying datasets. The most common surface representations are the boundary-based descriptor (B-Rep), in which boundaries are generated by algorithms (Maalek et al. 2019) or by cell decomposition methods (Becker et al. 2006; Kada & McKinley 2009; Wang et al. 2017; Tran et al. 2020).

- **volumetric modelling** (e.g., Constructive Solid Geometry (CSG) representation, Procedural Modelling (PM), Finite Cell Method (FCM)): it generally requires different types of prior knowledge to be applied (Tang et al. 2010). For this reason, this method is only partially used for 3D restitutions.

In general, there are two main approaches for building 3D models deriving from point cloud data: the direct modelling and the parametric one (Tommasi et al. 2016). In the direct modelling process, the point cloud is used as a reference for the 3D vectorization of the profiles. This process is manual and time-consuming. The operator needs to create several horizontal and vertical sections of the elements to analyze their complexity and extract the main profiles. In this case, generated 3D elements have fixed dimensions and cannot be easily adapted for representing similar objects. As an alternative approach, in parametric modelling, pre-built and modifiable models can adapt to broader cases by modifying the associated parameters. A more deeply classification includes *parametric-generative modelling* and *parametric object-oriented modelling*. In the first strategy the models are editable at any step of the modelling process by changing the parameters' value. This type of modelling is typically operated using different interfaces, such as Grasshopper for Rhino 3D (Guidara 2011). The second one refers essentially to the BIM working process, where the modelling phase is based on pre-built libraries and basic construction elements. The most known software using this process are ©Revit, ©Archicad, ©Allplan. In recent years, parallel to these BIM authoring software, there has been an increasing effort to promote approaches that do not depend on the use of a software from a single manufacturer with a single native proprietary format for data exchange (Panah & Kioumars 2021). As a result, the concept of Open BIM has emerged (Salzano et al. 2023), a methodology distinguished by the implementation of open and standardized data exchange formats. Generally, in the BIM domain, the Industry Foundation Classes (IFC) are a widely adopted open data transfer standard. This format enable seamless communication and information sharing, making the construction process more transparent, efficient, and collaborative among all parties involved. Its flexibility allows for the transfer of a wide range of information, encompassing attributes from various fields, including geometric and semantic data, mechanical and physical properties, cost details, construction schedules, and other relevant aspects (Okonta et al. 2024).

2.1.1 Different levels of automation in Scan-to-BIM approach

Modeling strategies and approaches can be categorized based on the level of automation involved:

- **Manual approaches:** In these methods, sections are typically extracted from point clouds or meshes. Non-uniform rational basis splines (NURBS) are then used to model masses within the BIM environment (Banfi et al. 2018), from which parametric elements, such as slabs, pillars, and other components, are derived (Figure 2_6).

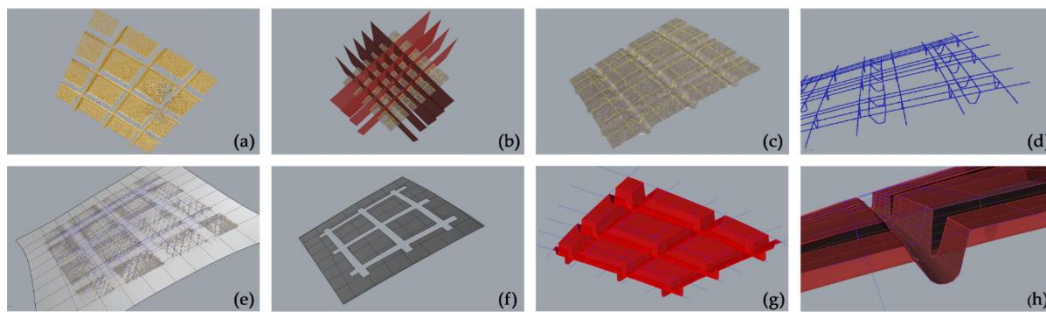


Figure 2_6: a) Segmented point cloud; (b) 3D mesh (computed from the point cloud) with the planes for the automatic extraction of the significant profiles; (c) 3D mesh and automatically extracted profiles; (d) Geometrised profiles; (e) NURBS surface interpolated from the sections; (f) 3D modelling phase; (g) Final NURBS model; (h) Detail of the final NURBS model. (Spanò et al. 2023).

- **Semi-automatic approaches:** These involve the use of VPL and one or more Python scripts (Andriasyan et al. 2020) to automate specific tasks within the modeling process. Semi-automatic methods are often implemented via software plug-ins, such as Rhinoceros with Grasshopper or Dynamo for Revit, and are applied during phases like pre-processing, mesh creation, or geometric extrapolation (Figure 2_7). The approach described later in paragraph 2.3 belongs to this category.

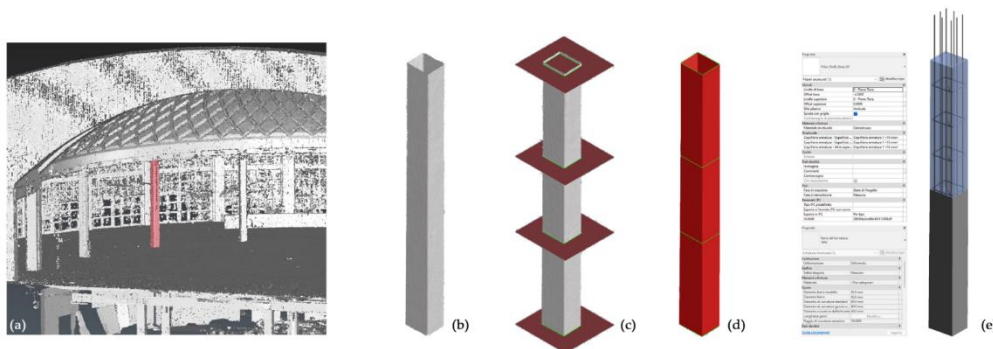


Figure 2_7: (a) Three-dimensional point cloud of the apse (the considered pillar is evidenced in red); (b) 3D mesh of the pillar; (c) 3D sections for the extraction of the significant profiles; (d) Generation of the NURBS surface from the extracted profiles (e) BIM object with the related properties table. (Spanò et al. 2023)

- **Automatic approaches:** These rely on advanced processing of point clouds using machine learning (ML) or deep learning (DL) algorithms. The aim of these methods is to detect features such as openings or automatically create watertight volumes for spaces, allowing for the automatic definition of structural elements like walls and floors. These automatic methods often build upon semi-automatic workflows.

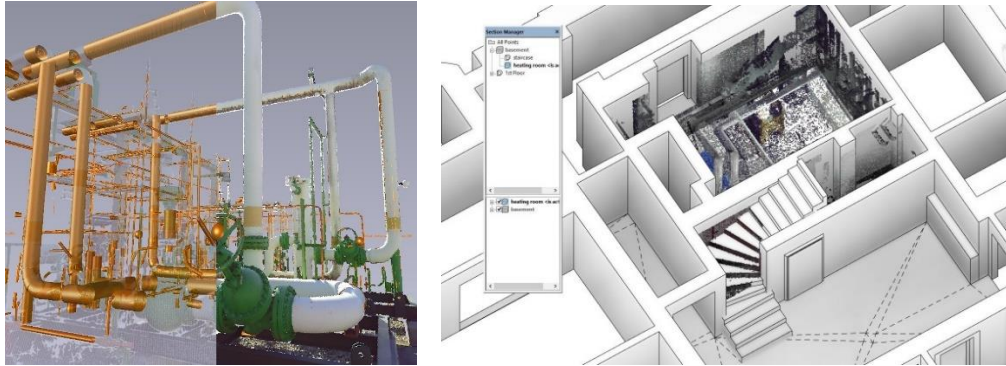


Figure 2_8: Examples of the use of FARO As Built plugin for Revit (www.faro.com 2025).

In recent years, several software developers have introduced semi-automatic plug-ins to facilitate the modeling process. Examples include PointSense and the As Built Suite, both developed by FARO Technologies (Figure 2_8). These tools enable the recognition of elements directly from point clouds and the association of predefined primitives and shapes to the detected components, improving the overall efficiency and accuracy of the modeling process.

2.1.2 The VPL approach supporting Heritage documentation

Visual programming languages (VPLs) were first introduced in the 1970s as a result of advancements in computer graphics, programming languages, and human-computer interaction (Boshernitsan & Downes 1998). Unlike traditional textual programming languages, where users must first learn and apply specific syntactical rules, VPLs facilitate programming through graphical representations, making them more intuitive and accessible. In VPL environments, programs are constructed using diagrammatic structures known as graphs (Figure 2_9). These graphs are composed of interconnected elements called nodes, each encapsulating specific functions or predefined programming structures.

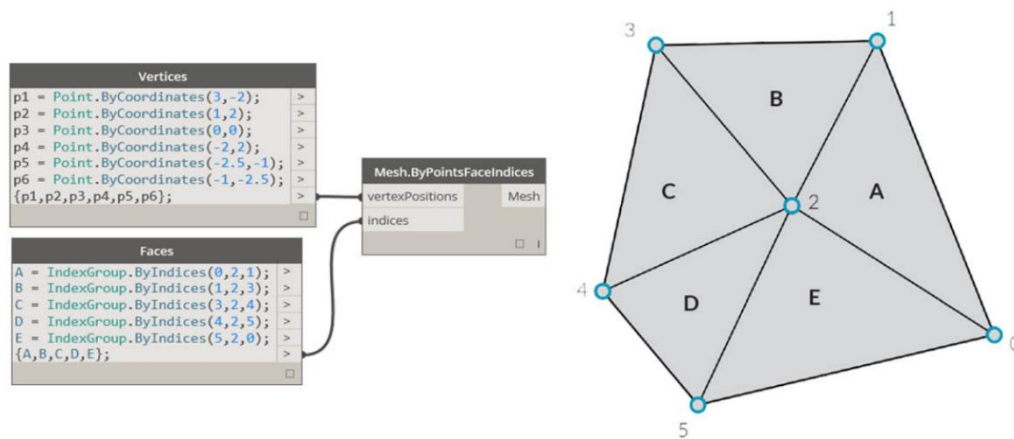


Figure 2_9: An example of graphs and nodes in the VPL environment.

As users build a program by assembling nodes within a graph, they indirectly generate the underlying code, which remains embedded within the visual components. This abstraction reduces the cognitive load associated with learning a textual language while enabling complex computational logic to be executed through an intuitive interface (Monteiro 2016). An example of this approach, specifically applied to point cloud, is illustrated in Figure 2_10, which presents a program graph created in Dynamo for Revit®. When executed, the graph processes the embedded code within its nodes, generating a corresponding three-dimensional geometry. This demonstrates how VPL tools not only simplify the programming process but also enhance real-time computational design by allowing users to manipulate data visually. Overall, VPLs provide a more user-friendly programming paradigm, particularly beneficial for beginners and non-programmers, while still offering the computational power required for advanced applications. By bridging the gap between human cognition and machine logic, VPL tools contribute to a more accessible and efficient approach to programming. In this context, by replacing traditional code with intuitive and visual interfaces, VPL supports the user in handling intricate design tasks more efficiently. For that reason, this approach has allowed engineering and architectural design professionals to automate repetitive tasks, simplify complex workflows, and increase overall project accuracy. Consequently, VPL has become a vital tool in modern design, empowering professionals to create more sophisticated models and achieve higher levels of precision and innovation in their work.

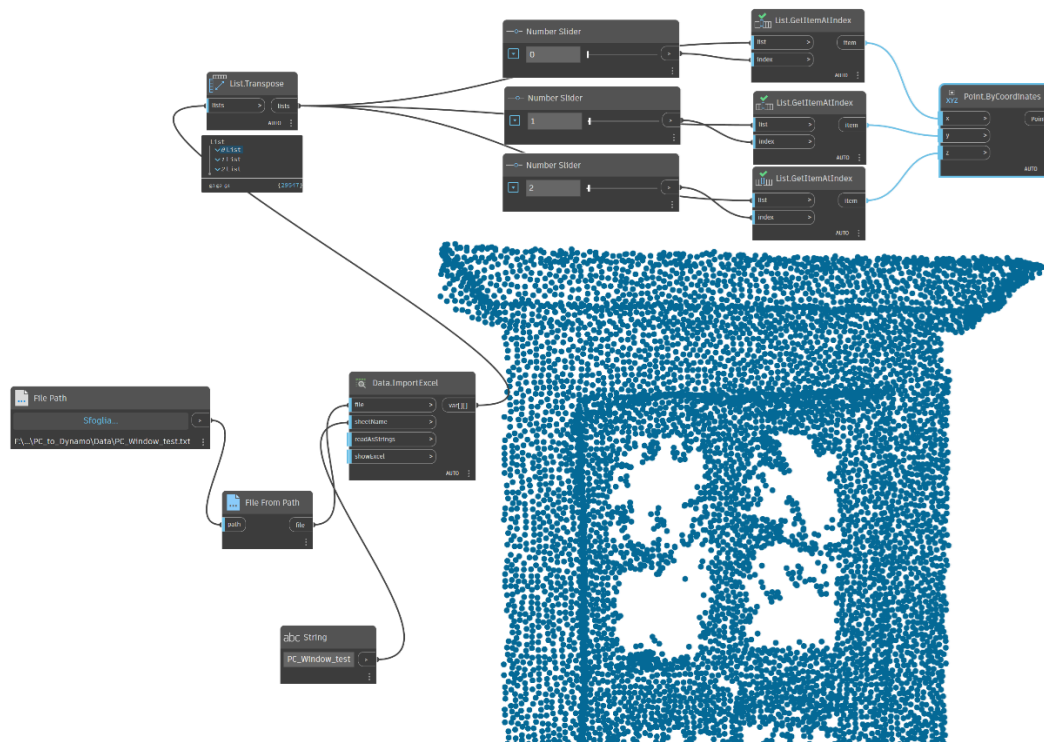


Figure 2_10: An example of a Dynamo script for reading the point cloud directly within the VPL environment.

The advantages of utilizing automation processes to support the documentation of Cultural Heritage are immediately apparent. In general, reality-based data obtained from 3D metric surveys – typically optimized 3D point clouds – are highly heterogeneous and present significant challenges for modeling. In historical contexts, architectural elements often exhibit a high degree of complexity and variability, requiring careful and precise manual modeling to accurately capture their intricate geometries and stylistic details. In the literature, the process of surface generation from reality-based data is generally classified into point-based and profile-based approaches. These methods rely on interpolation techniques, either using discrete points or profiles derived from generative geometries. These typical modeling processes based on the extrapolation of geometric features from a point cloud – such as points, NURBS and surfaces – can be automated through the use of VPL. There have been several examples in recent years that have attempted to implement visual programming-based approaches within CH documentation processes: the transformation of mesh models into BIM objects in a semi-automatic manner, facilitating the conversion process for various components, including for example structural elements (Spanò et al. 2023); the creation of direct and coherent connections between alphanumeric DBs and geometric objects, facilitating the generation of enriched BIM models (Sammartano et al. 2021b); the development of VPL rules-based algorithms able to create an advanced modeling tool for intelligent excavation safety planning, enhancing automated design processes and assisting decision-makers in formulating more efficient and practical safety plans (Khan et al. 2019).

2.1.3 Validation procedures for HBIM models

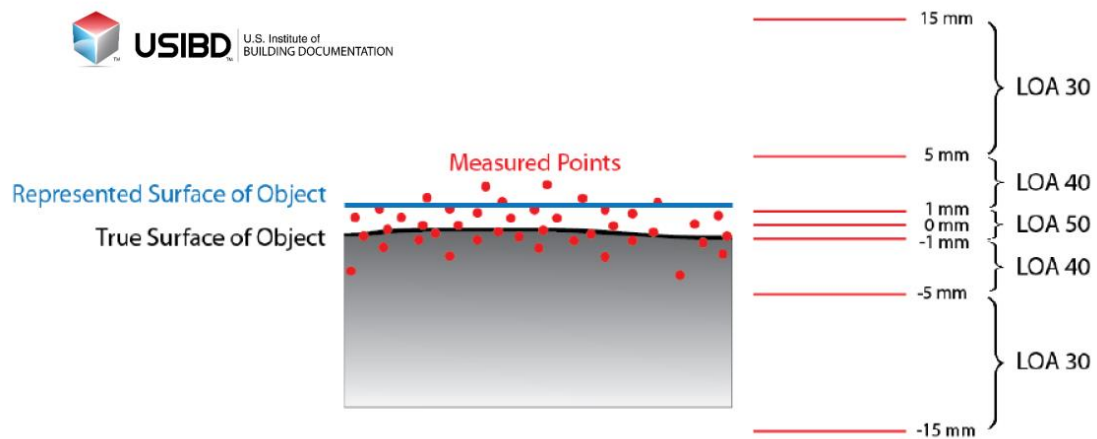
The use of Point Cloud data to validate BIM and HBIM models has become a widely adopted practice across the AEC industry. This technology offers numerous benefits for capturing and documenting the as-built conditions of structures with high precision (USIBD 2019). Both laser scanners and photogrammetric 3D metric surveys provide an efficient and accurate method to gather detailed information about existing Heritage, making it invaluable for documentation, conservation, enhancement, and management projects.

However, while the advantages are clear, the process of validating these enriched BIM models against point cloud data presents a series of significant challenges. One major difficulty arises from the fact that real-world conditions are often far from ideal; they may include complex, irregular, out-of-plumb (not perfectly vertical) or out-of-plane (not perfectly flat or aligned) elements. These deviations from idealized geometry must be compared against BIM models, which are typically created with orthogonal and simplified design assumptions. This mismatch between the complexity of real-world geometry and the idealized nature of BIM models can complicate the validation process and requires careful handling to ensure accuracy in the model representation. To enhance processes related to the modelling of built heritage, in recent years, internationally recognised guidelines have been developed, introducing the concept of Level of Accuracy (LOA) (USIBD, 2019). Specifically, it is a guideline that enables professionals in the Architectural, Engineering, Construction, Owner (AECO) industry to clearly specify and articulate the precision criteria and methods for accurately representing and documenting existing buildings (Table 2_1 and Figure 2_11). Similar to Level of Detail (LOD), the LOA is a scale that prescribes five levels of accuracy in terms of standard deviation between point clouds and 3D models.

Table 2_1: The five levels of accuracy of USIBD Guidelines.

Level	Upper Range	Lower Range
LOA10	User defined	5cm *
LOA20	5cm *	15mm *
LOA30	15mm *	5mm *
LOA40	5mm *	1mm *
LOA50	1mm *	0 *

*Specified at the 95 percent confidence level.

**Figure 2_11:** Graphic representation of LOA concept. (USIBD 2019).

2.2 Methodology: a proposal of semi-automated HBIM modeling strategy

In the field of HBIM, the digital reconstruction of complex shapes is recognized as a demanding task. This process, as mentioned in the paragraph 2.1, typically begins by capturing a detailed point cloud, and the following steps involve identifying and isolating individual structural elements and establishing their spatial and functional relationships within the overall model. However, upon examining this process, several critical issues emerge that warrant further analysis. First of all, approaching the problem of HBIM modeling in a traditional way involves a considerable expenditure of energy and time for the operator, who is called upon not only to perform routinary technical operations typical of 3D modelling, but above all to interpret a reality-based data (point clouds) that is not always easy to interpret. Point clouds imported into BIM environments could be affected, for example, by incomplete parts (lack of data, occlusions, etc.) or, as typically happens, turn out to be of considerable size (in terms of GB, Giga Byte), greatly complicating the processes related to its management. In this scenario, it thus becomes evident that the choices that the operator has to make to model an element from a point cloud are very complex and do not always lead to adopting the best strategies. The main consequences can be found in the oversimplification of 3D models or, in the worst case, in the misinterpretation of data, a factor that causes the generation of 3D models far from reality. In addition, another risk closely related to the problem just described of simplification is that related to generalization. An approximate interpretation of reality-based data can, in fact, lead to the generation of 3D models that do not faithfully follow the geometries and shapes of the original elements, a factor that causes the loss of basic geometric information for the purpose of Heritage documentation. A striking example is characterized by all those elements that in architecture turn out to be produced in a repetitive manner. Typical elements of this type might be, for example, the columns of a portico, the decorative elements of a series of windows on the facades of a building, or even all the elements from which a balustrade of a staircase of a historic building is composed. All these elements turn out to be similar, but not identical, as each element is unique in that it is uniquely produced by the craftsmen of the time.

In general, once these elements and relationships are defined, the operator has several consolidated approaches for the modelling phase:

- Constructing an in-place family directly within the project environment. This option allows the user to develop unique components specifically tailored to the project, facilitating the accurate representation of complex shapes and details within the specific HBIM model.
- Creating standardized and parametric components that can be reused in other projects. This approach is valuable when recurring elements are identified, as it enables efficient resource sharing across different HBIM projects. However, many BIM platforms restrict the direct import of

point clouds into the Family Editor, which is typically where reusable components are developed; specialized plugins may be necessary to work around this limitation.

- Designing 3D objects using alternative software and importing them into the BIM environment as mesh or surface models, enhancing the accuracy and Level of Detail (LOD) in the final HBIM representation.

Therefore, in the field of Cultural Heritage, in order to preserve and promote the authenticity and universality value of any asset, there is a need to favor Scan-to-BIM approaches that are able to distance themselves from the paradigm of classical BIM modeling, which was born and developed to serve the AEC sector for new construction. In addition, there is a need to develop automatic or semi-automatic modeling strategies that can assist modelers in the management and interpretation of point clouds by providing appropriate tools useful for the extraction of geometric features from point clouds directly in the BIM environment. For these reasons, in this work of thesis, the adoption of methods to simplify and automate data modeling, integration, and management processes has gained significant traction. The approach adopted to promote the automation of Scan-to-BIM processes centres on the implementation of visual programming algorithms, which are increasingly transforming conventional methodologies within the field (Collao et al. 2021). In more detail, the following paragraphs illustrate how the use VPL has significantly contributed to the development of this doctoral research by enabling the semi-automatic generation of architectural elements from point cloud data directly within the BIM environment. This approach builds upon the research conducted by our team, as presented in Roman et al. (2023).

In general, considering the digital reconstruction of a complex HBIM model, the proposed methodology establishes a well-structured workflow capable of generating 3D objects from NURBS and 3D profiles derived from a point cloud while adhering to specific geometric rules to ensure accuracy and consistency. The extraction of closed polylines that define profiles can be usually classified as a Boundary-Representation (B-Rep) method, eliminating the need to generate meshes or surfaces before profile extraction.

In this context, the proposed workflow offers several key contributions that aim to enhance the integration of reality-based data within BIM and HBIM workflows:

- **Generation of BIM and HBIM elements:**
BIM and HBIM elements are generated directly from photogrammetric or LiDAR-derived point clouds through the development of custom modelling tools within a VPL environment, thereby streamlining the transition from reality-based data acquisition to 3D model generation.
- **Integration of heterogeneous information:**
A diverse range of attributes – including material properties, state of preservation, and other semantic data – can be associated with the

generated objects. These attributes are recognized and managed within both the VPL environment and the BIM Authoring tool.

- **Export and reuse of reality-based Families:**

The resulting HBIM models can be exported as individual families, facilitating their reuse across different BIM project files and promoting efficiency in Heritage documentation processes.

Overall, this workflow not only improves the efficiency of 3D model generation from point cloud data but also ensures a richer, more semantically meaningful representation of existing assets within the BIM environment.

In this scenario, Visual programming platforms—such as Dynamo for Revit—are commonly used to automate workflows and streamline repetitive, replicable operations. However, there are currently limited applications specifically dedicated to 3D modeling from point clouds. The existing nodes designed for this purpose struggle to effectively manage the reconstruction of complex and irregular architectural elements. Therefore, a key objective of this study is to develop specialized VPL nodes capable of directly modeling architectural elements from point clouds within the BIM environment, enhancing accuracy and efficiency in the digital reconstruction process. The overall workflow for the proposed semi-automatic BIM reconstruction approach is illustrated in Figure 2_12.

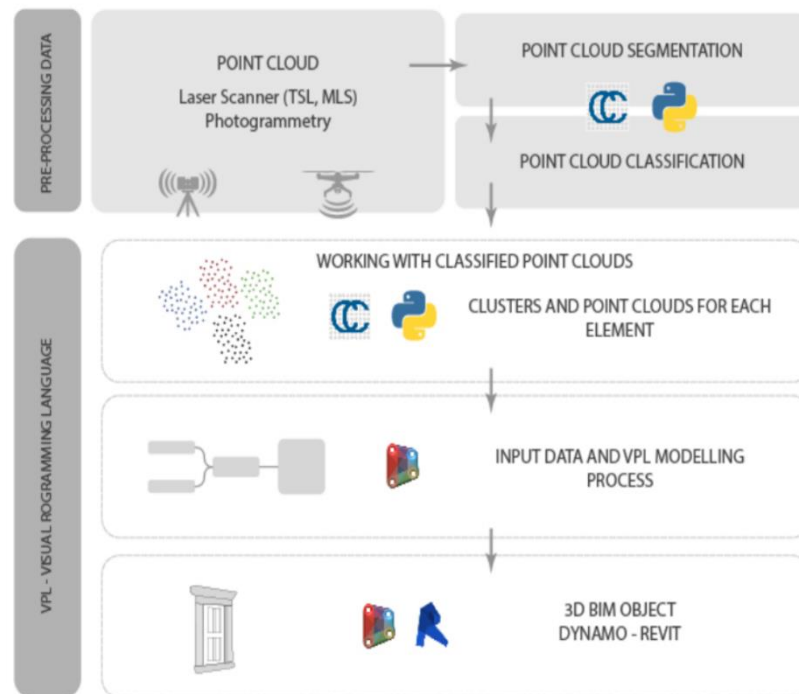


Figure 2_12: General workflow for the presented semi-automatic BIM reconstruction approach. (Roman et al 2023).

2.2.1 Data pre-processing phase

The initial step of this proposed workflow focuses on the accurate and consistent processing of survey data. At this preliminary stage, it is crucial to structure the data rigorously and in accordance with specific rules to ensure a seamless transition to the subsequent modeling phases. For this reason, the implemented workflow (Figure 2_14) begins with three essential preliminary phases:

- **Classes identification phase**, in which the categories of architectural elements that constitute the object of study are identified;
- **Data Segmentation phase**, in which the point cloud is segmented in order to distinguish and isolate objects and individual elements for modeling;
- **Data Classification phase**, in which the categories of elements designated for semantic enrichment are identified, by integrating semantic, positional, and geometric data, including point coordinates, normals, and RGB values.

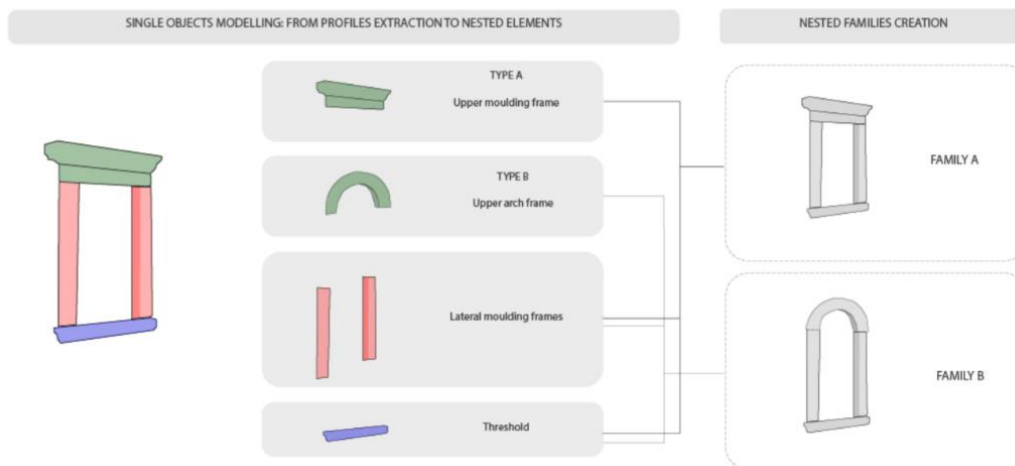


Figure 2_13: General workflow applied to the windows in order to obtain BIM/HBIM elements. (Roman et al. 2023).

A properly classified point cloud, structured according to the various component classes of the identified architectural elements, provides significant advantages. Firstly, it streamlines the subsequent modeling stages by simplifying the identification of geometric shapes and their corresponding categories, known as *Element Families* in the BIM environment. Secondly, it reduces the computational load on VPL algorithms when processing the point cloud. Given that point clouds typically contain millions of points, their size has a major impact on the modeling process within BIM environments, which are not inherently designed for direct point cloud management. Therefore, structuring, segmenting, and classifying data appropriately enhances the efficiency of BIM authoring software in handling point clouds and enables the development of more optimized and fluid modeling

workflows. After being properly segmented and classified, architectural elements are individually exported in an ASCII format (.txt file). This step ensures that the data is structured in a clear and organized manner, facilitating the data manipulation and features extrapolation process (Figure 2_13).

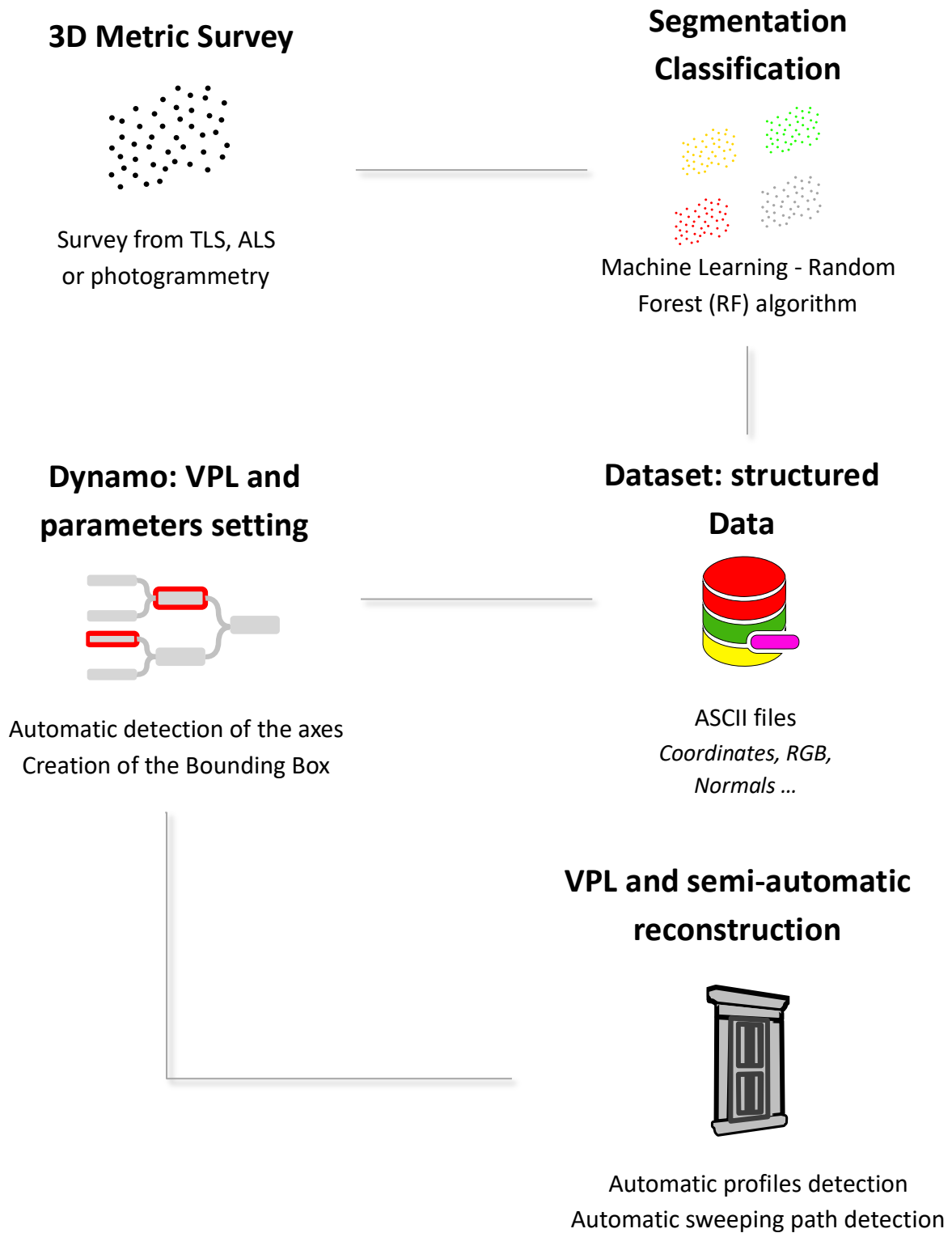


Figure 2_14: General workflow regarding the phase of pre-processing data. (Roman et al. 2023).

2.2.2 VPL custom nodes: a possible application in the cases of the Pretorio Palace and Duomo of Trento

Before delving into the core of this innovative workflow – specifically, the development of tailored VPL nodes designed to automate Scan-to-BIM processes – it is essential to provide a brief introduction to the case study. This case study served as the initial testing ground for the methodology, allowing for its validation and a clearer understanding of its practical benefits. The implemented workflow was tested using the photogrammetric 3D reconstruction of Piazza Duomo in Trento, comprising buildings of various architectural styles and historical periods, including the medieval Praetorian Palace, the City Tower, and the Cathedral dating from the 12th to 13th centuries (Grilli and Remondino 2020) (Figure 2_15).



Figure 2_15: The Trento square. (heliopolis.eu 2024).

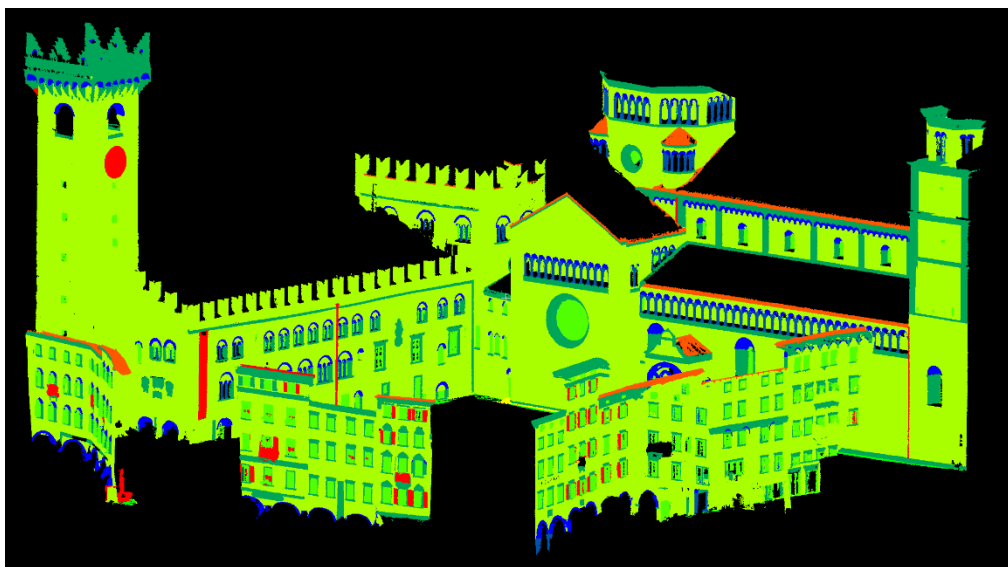


Figure 2_16: Classified point cloud of the Trento square, containing both the Pretorio Palace and the Duomo. (Grilli and Remondino 2020).

To evaluate the effectiveness of the proposed reconstruction pipeline, specific architectural elements from the Pretorio Palace and the Duomo were selected. The dataset used for this study (Figure 2_16) consists of 11 million points and has a spatial resolution of 1.3 cm. For the segmentation and classification of architectural elements, a set of carefully chosen covariance features was applied. By following this classification approach, individual window elements were identified and categorized as a preliminary step in the 3D modeling phase, which was carried out using Dynamo scripts.



Figure 2_17: Test dataset: Windows typologies of the southern façade of Pretorio palace (01-04), and Arcades on the western façade of the Duomo of Trento. (Roman et al. 2023).

Segmented and classified single elements (like window sills or frames) are imported as separated Excel files in Revit's Dynamo VPL environment for the reconstruction phase (Figure 2_18). The following operations consist in:

- extracting the plane, using points normals values, on which the profile path of the elements will be generated with best-fitting line algorithms;
- generating a customized clipping box collecting points used to define closed polyline profiles automatically;
- creating the HBIM element, sweeping the profile along the profile path;
- assigning the element to a specific Revit Family category.

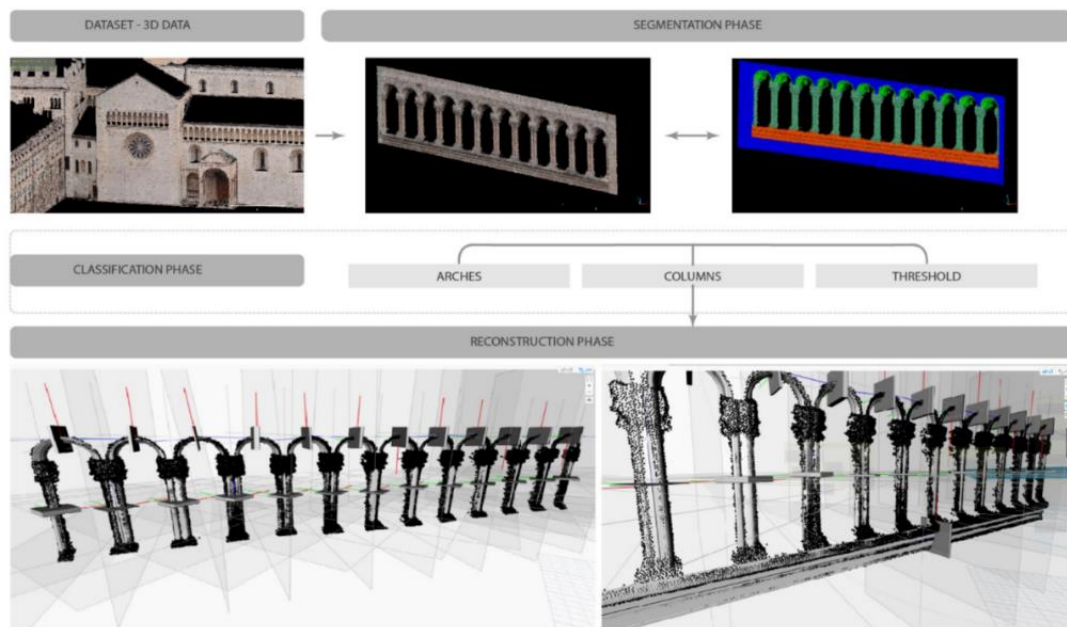


Figure 2_18: Generating parametric 3D models of the arcades in the western façade of the Duomo of Trento. (Roman et al. 2023).

The described workflow results in a complex, flexible, and generalized Dynamo script capable of generating different architectural elements in a semi-automatic way. Based on the complexity of the element to model and the point cloud density, two parameters were created to be manually set and modified (Figure 2_19):

- **Clipping Box Depth:** to better intercept all the points in a selected area/volume;
- **Normal Values Filter:** to select, in a defined range, only the points lying on a specific plane.

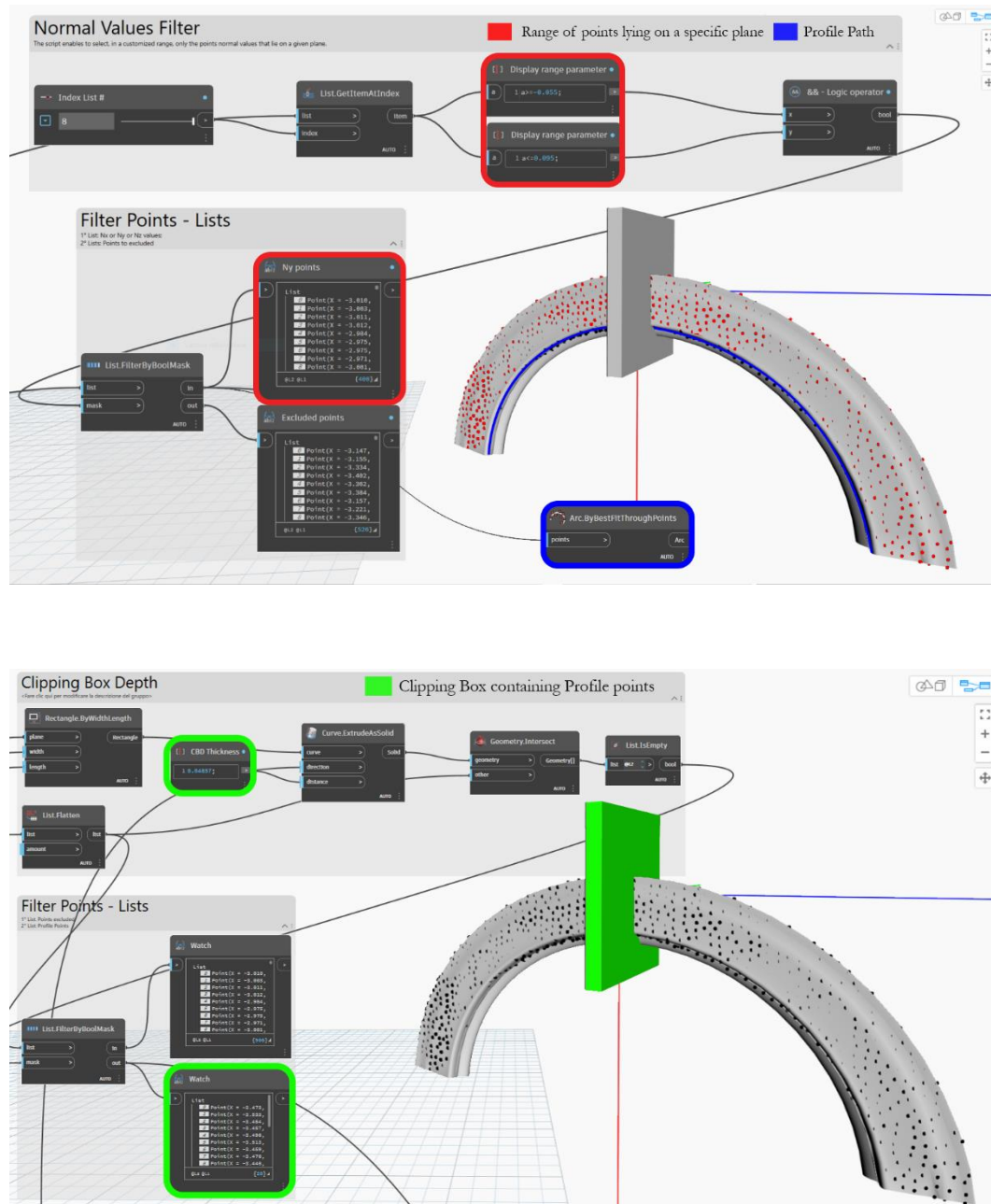


Figure 2_19: VPL schema with *Normal Values Filter* and *Clipping Box Depth* customized parameters.

The proposed tools (Figure 2_20) makes it possible to model also elements featured by more complex primitives such as arches, vaults, and moulding frames. The entire code, made up of nodes, has been entirely developed inside the Dynamo environment. The code is structured in a visual language, where wires link nodes. The workflow enables preserving the original points coordinates, and this aspect simplifies the positioning of separately modelled elements in the final BIM model. Also points normals (nx, ny, nz) are preserved, and this is particularly helpful in improving the position of the best-fit line in the sweep operation. The sweeping line, in fact, is computed as the best line through points, orthogonal to the extracted

element profile (Figure 2_21). The *Normal Values Filter* is used to filter points based on the irrespective normal values. Preserving only points with coherent normal values improves the quality of the plane extracted for the generation of the profile path. The thickness of the clipping box rules the number of points the algorithm uses to create the elements' profile. By increasing the thickness value, the profile will feature more details. The final step of the workflow enables the creation of Custom Nodes, which are helpful for effectively organizing visual scripts within the working environment. The visual scripts are composed of a considerable number of differently complex nodes, which can be grouped and customized. In this work, some custom nodes have been designed to group all the nodes useful to merge related functions. As an example, the custom node called *CutRefPlane_ByBestFitPoints* simplifies the automatic generation of a cross-section plan. In this case, this type of custom node contains eight single nodes and functions. Finally, custom nodes allow all Dynamo users – also visual programmers – to understand, use and also implement a code graph that is clean and intuitive, manipulating only customized graphic elements.

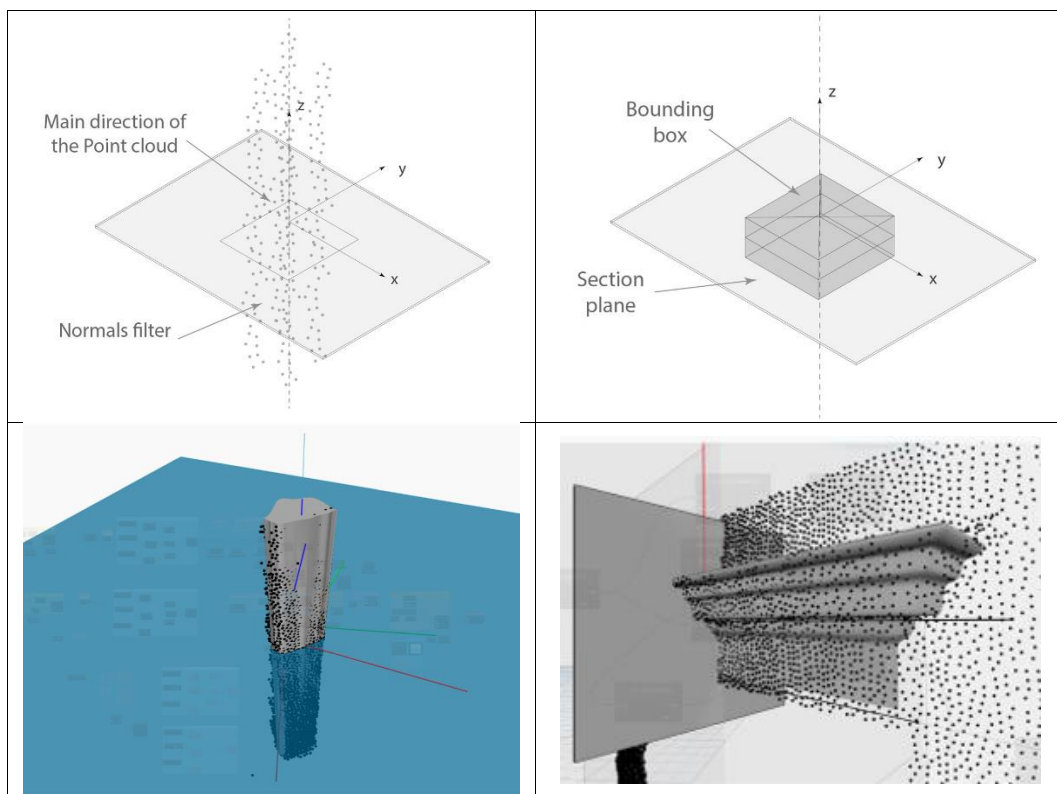


Figure 2_20: The automatic rotation calculated from the input data used to define the correct sweeping path (Romain et al. 2023).

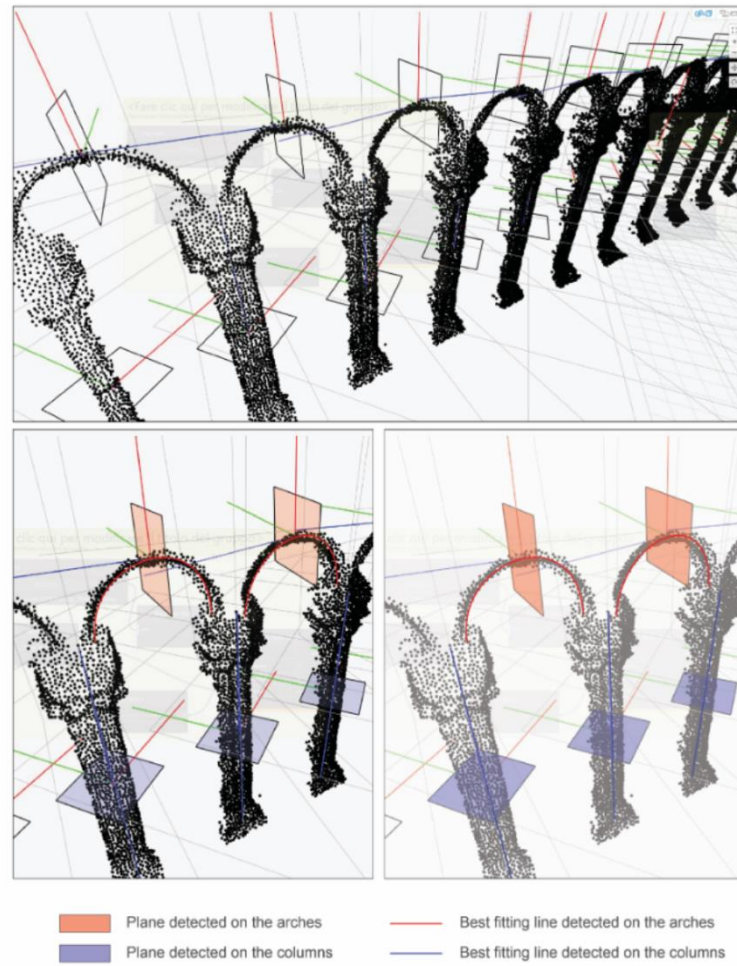


Figure 2_21: The planes and the best-fitting lines detected by the Dynamo script used for the workflow (Romain et al. 2023).

2.3 Evaluation of the results

Windows and arcades were selected among the architectural elements as test-case for the higher level of modelling complexity. In particular (Figure 2_17):

- a) Four types of windows from the main façade of Pretorio palace, located on the southern part of the building:
 - Typologies 01 and 03 are featured by more regular elements, such as linear frames and moulding frames;
 - Typologies 02 and 04 present an arch in the upper moulding;
- b) Arcades in the façade of the Duomo of Trento, located on the western front of the monument, and overlooking both the rose window and the entrance. The arcade is featured by twelve repeated arches with an average height of 0,63 m (arc radius), a total height of 2.53 m (column) and a total length of 11.52 m.

The HBIM model, generated with VPL approach, was examined to evaluate the quality of the obtained results and the reliability of the adopted workflow. In this evaluation process, for each architectural element analysed, the Ground Truth (GT) is represented by the original classified point cloud (Grilli & Remondino 2020) (Figure 2_16). The metrics used to assess the overall quality of the parametric model include:

- **C2M**: the comparison between the original point cloud, used as the ground truth, and the mesh obtained from the model within the Revit environment (*Cloud-to-Mesh*);
- **C2C**: the comparison between the original point cloud, used as the ground truth, and the cloud obtained from the model within the Revit environment (*Cloud-to-Cloud*);
- **M2M**: the comparison between the mesh obtained from the original point cloud, used as ground truth, and the mesh obtained from the Revit model (*Mesh-to-Mesh*).

Table 2_2, 2_3, 2_4, 2_5 and Figure 2_22 as well as Table 2_6 and Figure 2_23 report the results for the Pretorio palace windows and for the Duomo arcades, respectively.

Table 2_2: Results of the tests conducted on the Window 1.

WINDOW 1				
Test#	Average distance signed [mm]	Standard deviation signed [mm]	Average distance [mm]	Standard deviation [mm]
C2M	-5.9	14.5	12.1	10.1
C2C	-	-	15.9	4.8
M2M	9.2	7.7	10.3	6.1

Table 2_3: Results of the tests conducted on the Window 2.

WINDOW 2				
Test#	Average distance signed [mm]	Standard deviation signed [mm]	Average distance [mm]	Standard deviation [mm]
C2M	2.1	8.8	6.5	6.2
C2C	-	-	15.1	5.2
M2M	2.5	16.7	11.8	12.0

Table 2_4: Results of the tests conducted on the Window 3.

WINDOW 3				
Test#	Average distance signed [mm]	Standard deviation signed [mm]	Average distance [mm]	Standard deviation [mm]
C2M	0.2	11.8	6.2	10.0
C2C	-	-	13.8	5.8
M2M	0.2	10.6	6.2	8.5

Table 2_5: Results of the tests conducted on the Window 4.

WINDOW 4				
Test#	Average distance signed [mm]	Standard deviation signed [mm]	Average distance [mm]	Standard deviation [mm]
C2M	-4.1	14.6	9.7	11.7
C2C	-	-	18.5	10.7
M2M	0.7	20.8	13.2	16.1

Table 2_6: Results of the tests conducted on the Arcades.

ARCADES					
Test#	Element	Average distance signed [mm]	Standard deviation signed [mm]	Average distance [mm]	Standard deviation [mm]
C2M	Arches	14.5	16.9	17.9	14.2
	Complete	17.1	25.6	19.2	24.1
C2C	Arches	7.1	13.3	10.13	11.1
	Complete	-	-	22.7	17.6
M2M	Arches	2.8	23.1	18.1	14.7
	Complete	-4.7	28.4	28.8	18.8

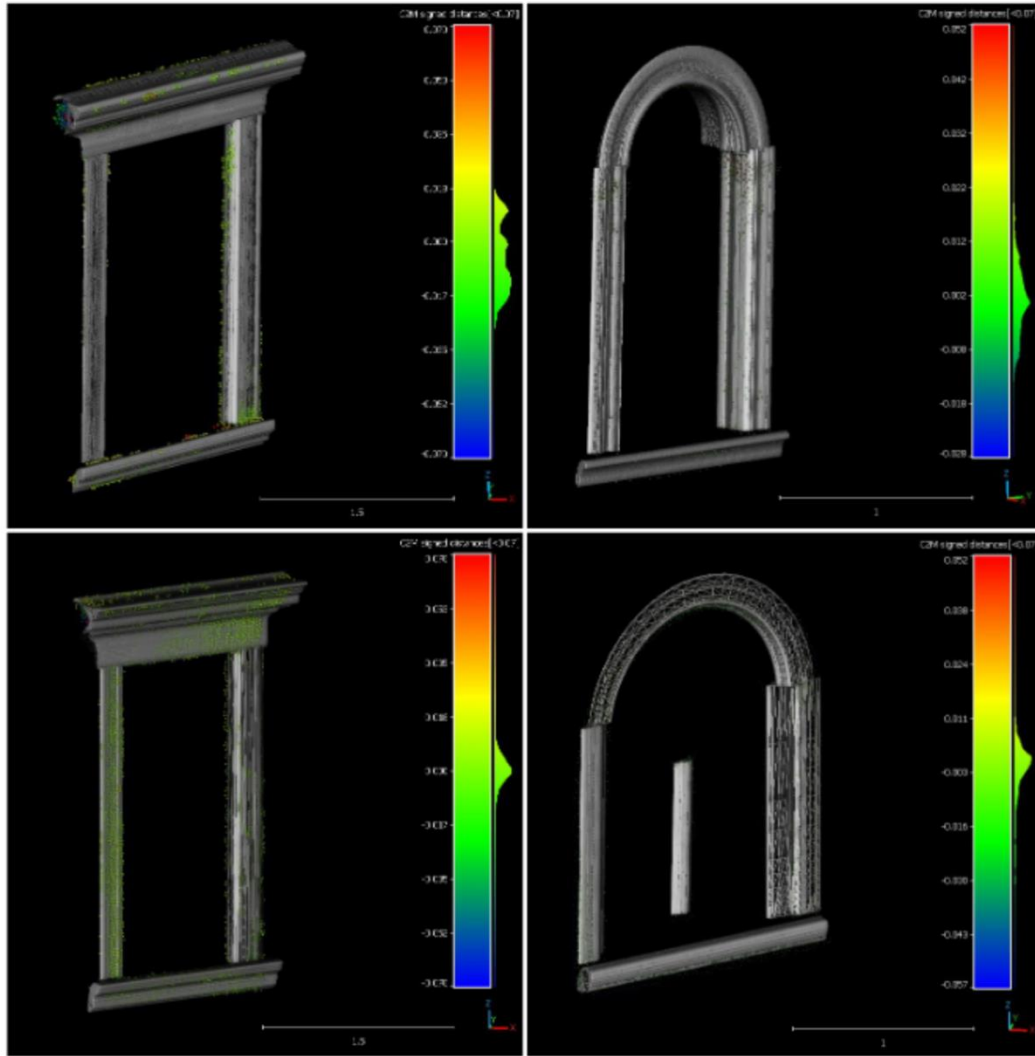


Figure 2_22: Cloud to mesh (C2M) distances results [m] for the windows of the Pretorio palace façade. (Roman et al. 2023)

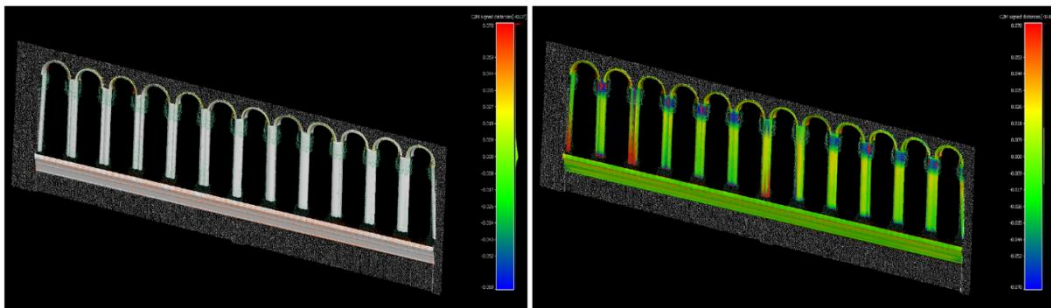


Figure 2_23: Cloud to mesh (C2M - left), Mesh to mesh (M2M - right) distances results [m] for the arcades of the western façade of the Duomo of Trento. (Roman et al. 2023).

2.4 Discussion on the VPL-based semi-automatic modeling strategy

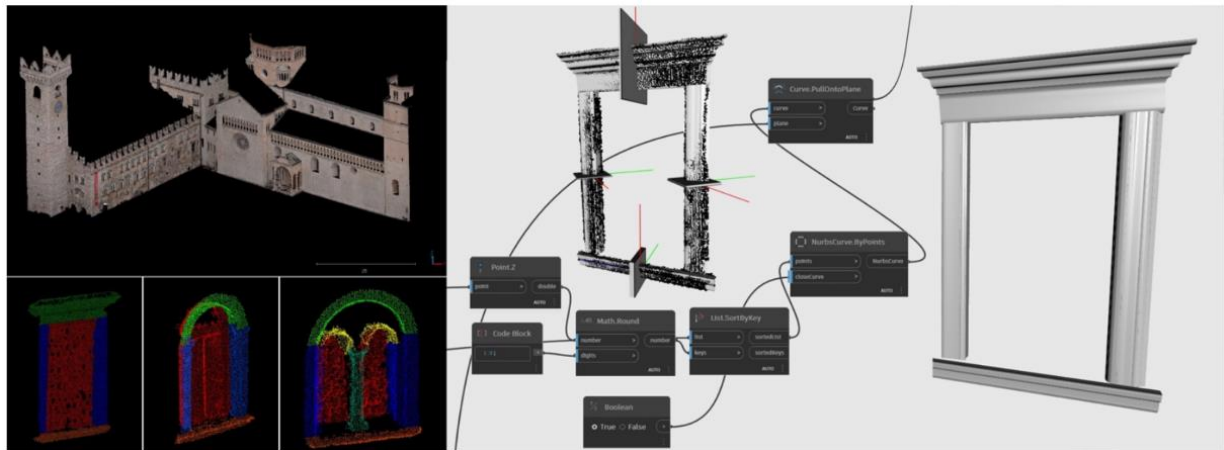


Figure 2_24: Main steps of the implemented semi-automatic Scan-to-BIM modelling workflow: the architectural elements segmentation and classification (bottom left), the VPL structure node (middle), and an example of HBIM element modelling results (right). (Roman et al.2023)

The results of this work consist of a set of complete and customizable visual programming nodes for BIM and HBIM modeling (Figure 2_24), which can be summarized as follows:

- The possibility to import point clouds (with an Excel file as input, derived from the segmented point cloud dataset) directly within the VPL environment (Dynamo), without overloading the BIM authoring software (Revit);
- The automatic extraction of profile path and orthogonal sweeping lines makes it possible to model complex shapes, while using point clouds' normal information increases the precision of the reconstructed geometries. As mentioned above, the precision of the algorithm is related to thickness of the clipping box used during the 3D modeling phase and the 3D model obtained inside Revit is more detailed the greater is the thickness itself. In addition, incrementing the number of points inside the clipping box, the Level of Detail (LOD), especially the Level of Geometry (LOG) of the returned objects will reach higher precision, since the profiles are closer to the reference point cloud. Figure 2_25 shows, in fact, the final HBIM object obtained using the proposed Dynamo VPL script within the Revit environment, offering also a comparison between the 3D model elements and the Ground Truth point cloud;
- The possibility to save time in modelling complex objects, since the modelling phase is substituted by a semi-automatic process to return objects. The main operations are focused, in fact, on the preparation of the data of the point cloud and the input data. The implemented solution

can be easily expanded and replicated for managing different architectural elements with additional nodes and directly modelling in BIM environment from 3D reality-based data, realizing different libraries of customizable nodes for modelling heterogeneous and complex architectural elements.

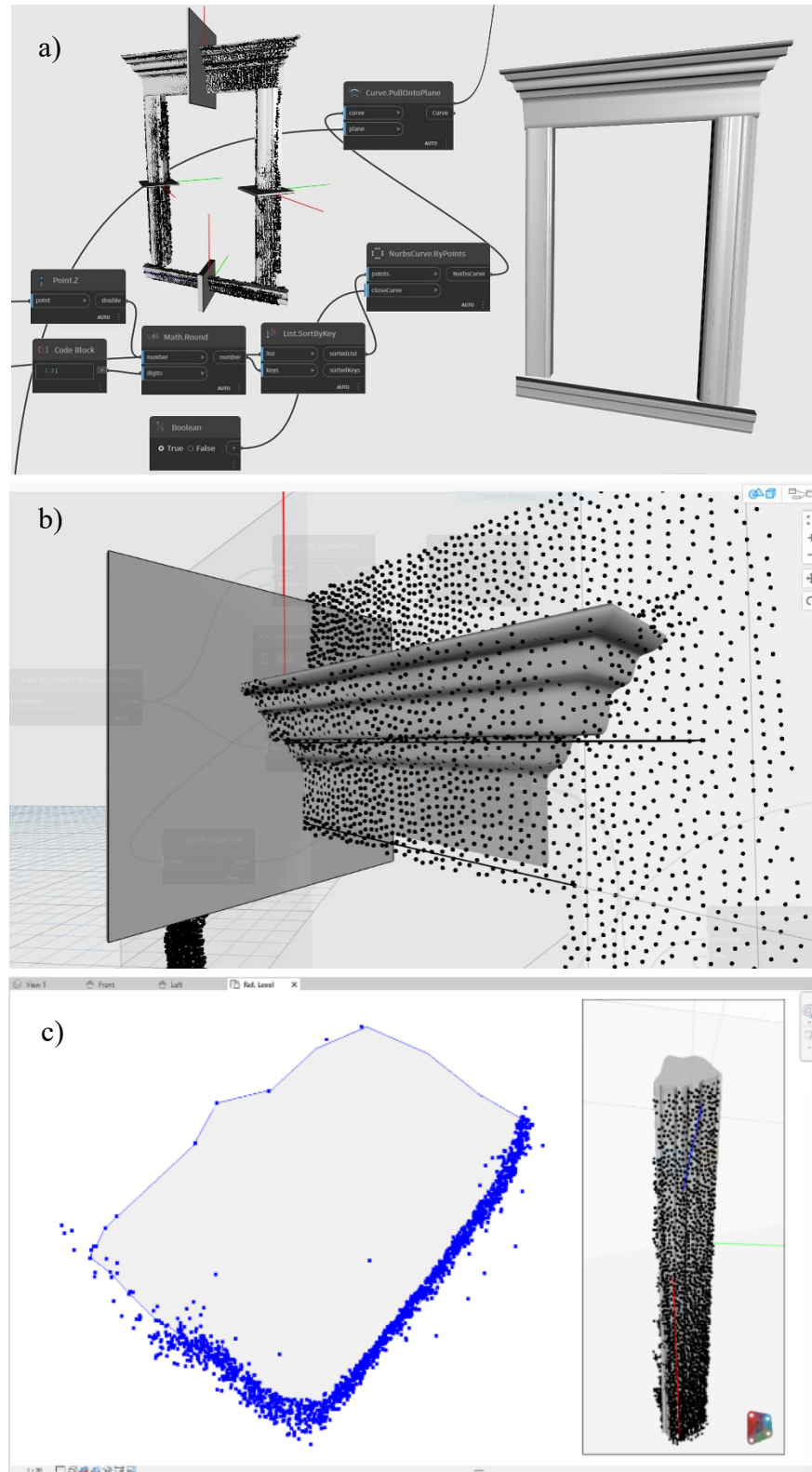


Figure 2_25: The proposed semi-automatic VPL tool: (a) the Window 3 reconstructed by VPL tool; (b) the detail of the HBIM model of the upper moulding frame; (c) the comparison between the HBIM model of a lateral moulding frame and the corresponding Ground Truth point cloud.

Chapter 3

Scan-to-BIM process optimization using AI-based semantic enrichment strategy



Classification - Mesh - Blue Color

```
import sys
import clr
sys.path.append(r"C:\Users\Utente\AppData\Local\Programs\Python\Python38\Lib\site-packages")
import numpy as np
import open3d as o3d

mesh = o3d.io.read_triangle_mesh("D:/PhD_MarcoA\FBK\Py_test\PR\Modulo_porticato/Output4_1cm/Output_class\bpa_mesh.obj")

# Access vertex colors and faces
vertices = np.asarray(mesh.vertices)
faces = np.asarray(mesh.triangles)
vertex_colors = np.asarray(mesh.vertex_colors)

# Define the color you want to select (e.g., red in RGB)
color_to_select = [0.0, 0.0, 1.0] # Blue in RGB

# Initialize a list to store the selected face indices
selected_faces = []

# Iterate through faces and select the ones with the specified color
for i, face in enumerate(faces):
    face_colors = [vertex_colors[face[0]], vertex_colors[face[1]], vertex_colors[face[2]]]

    if all(np.all(color == color_to_select) for color in face_colors):
        selected_faces.append(i)
```

Create a mesh with the selected faces



In recent years, the increasing demand for flexible and sustainable strategies in digitization processes has posed a significant challenge for the research community engaged in the field of Cultural Heritage documentation. This complexity is particularly evident in tasks such as parametric modeling and AI-based semantic enrichment, which, despite being essential for structuring and enhancing digital heritage assets, have traditionally been highly time-consuming and resource-intensive. From a user-oriented perspective, the substantial manual effort required for these processes often limits efficiency and scalability, especially in large-scale digitization projects.

To address these challenges, extensive research efforts have been dedicated to optimizing and automating such workflows. Among the most promising solutions are machine learning and deep learning techniques, which offer substantial improvements in efficiency and accuracy. Machine learning facilitates the automation of various decision-making processes, enhancing the categorization and interpretation of digital assets. Meanwhile, deep learning, with its advanced neural network architectures, enables more sophisticated pattern recognition, automated segmentation, and the generation of highly accurate models.

The integration of these technologies not only accelerates the digitization of cultural heritage but also introduces new possibilities for more accessible, dynamic, and interactive documentation. As these methodologies continue to evolve, they pave the way for more scalable, efficient, and sustainable approaches to heritage preservation in the long term.

3.1 Contribution of AI algorithms in a HBIM scenario: related works

The remarkable achievements obtained through these AI algorithms have subsequently stimulated their application in semantic modelling for CH using Scan-to-BIM approaches. Conventionally, the effectiveness of Building Information Modelling techniques, particularly in the field of HBIM, relies on the geometric complexity of the data and the expertise of the BIM operator, who is tasked with interpreting the survey data. These processes are typically repetitive and time-consuming, necessitating manual operations that are often impractical, primarily when implemented within the framework of CH digitisation projects. To enhance processes related to the modelling of built heritage, as seen above in paragraph 2.1.3, internationally recognised guidelines have been developed, introducing the concept of LOA (USIBD 2019), in order to clearly specify and articulate the precision criteria and methods for accurately representing and documenting existing buildings. As a result of these considerations, the ongoing refinement and advancement of AI techniques within the Scan-to-BIM field, with the objective of autonomously and comprehensively extracting BIM/HBIM objects from 3D surveying datasets, is becoming an increasingly attractive and promising research investigation area (Yang et al. 2020). However, it is crucial to emphasize the notable

absence, within the extant IFC standard, of specific digital descriptive classes – geometric/semantic features, 3D dataset classification, etc. – for assets associated with the HBIM domain, a facet increasingly deemed essential within the field of Cultural Heritage (Diara & Rinaudo 2020; Banfi et al. 2020; Cui et al 2023). In this context, it is evident that a critical void exists concerning the establishment of comprehensive standards and protocols intended to provide a systematic framework for the modelling and reconstruction processes and the assessment of their outcomes. In this context, numerous research efforts aim to bridge this gap by generating digital twin models capable of archiving heterogeneous information – geometric and semantic - translated into appropriate classes of the IFC standard (Colucci et al. 2020). This ensures that these models can meet the requirements of replicability within the CH domain and interoperability concerning the subsequent phases outlined in preservation plans (Spanò et al. 2023; Oostwegel et al. 2022).

It is essential to underline that before proceeding with an HBIM modelling, the recognition process of elements composing a real scenario in different domains, with automated approaches of semantic classification, is a crucial step (Moyano et al. 2021). The semantic classification of data related to CH is therefore of fundamental importance to promote the generation, understanding and analysis of digital twins of this heritage, contributing to the processes of conservation and enhancement (Matrone et al. 2020b).

The approaches grounded in VPL strategies, as seen above in paragraph 2.1.2, stand as a continuously advancing domain within the Scan-to-BIM field, presenting the opportunity to automate various operations concerning the interpretation and modelling of 3D metric data surveys. In the Chapter 2, it was shown how, from a geometric perspective, the VPL can be effectively used to support modelling activities based on point clouds. However, it can also be highly valuable for several other purposes within Scan-to-BIM processes. Considering the architectural scale, this strategy can help, for example, the semi-automatic mapping of material decay of historical buildings (Lanzara et al. 2022). At city scale, VPL strategies were used to support the parametric CIM modelling from segmented point clouds (La Russa et al. 2023). Following these premises, and considering the great potential offered by visual programming, the proposed strategy aims to provide an alternative method capable of leveraging the flexibility of VPL scripts to facilitate the generation of semantically enriched HBIM models.

3.2 Methodology: integration of enriched classified 3D models in a parametric environment

This paragraph of the thesis has the aim of proposing an innovative and flexible methodology for integrating 3D Python libraries and VPL platforms, focusing on the complex 3D reconstruction of different objects linked to CH using pre-segmented/classified 3D survey data. A portion of the work outlined in this section was published in Avena et al. (2024).

In the realm of conservation, enhancement and management of CH, methodologies such as BIM and HBIM have gained prominence. These methodologies provide a structured framework for creating and managing digital models that extend beyond visual representation, incorporating detailed information about geometries and semantic enrichment of CH's elements. In this part of the dissertation, it is intended to draw attention to the possibility of developing an innovative framework that seamlessly integrates these methodologies with semi-automatic modelling, employing VPL and 3D Python libraries. Particularly, the proposed approach not only expedites the model creation process but also facilitates in-depth analysis and efficient data management directly in BIM environment. The aim of this part of the work is to foster automatic workflow using VPL and Python libraries to facilitate the import of reality-based semantically enriched 3D data in a HBIM environment. The proposed workflow is illustrated in Figure 3_1.

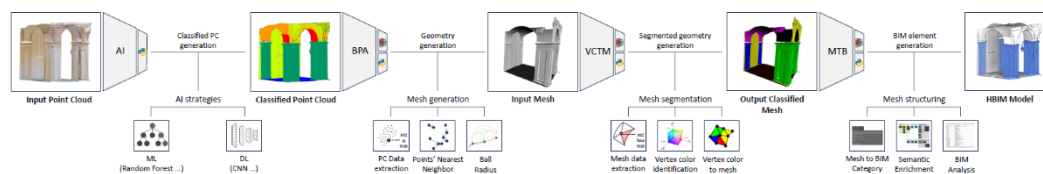


Figure 3_1: The proposed workflow for integrate semantically enriched 3D models into parametric environment.

The effectiveness of the proposed methodology within the complex field of Cultural Heritage conservation is demonstrated through two main application cases developed in this research, each based on a different type of input data. The first case, focused on the Royal Palace of Turin and detailed in the following sections, adopts a point cloud-based approach and fully aligns with the HBIM domain. The second case, concerning the Standard of Ur and presented in Appendix A, is instead based on an image-derived mesh generation model and represents a more peripheral, yet promising, application of the methodology within the HBIM framework. The proposed workflow – common to both cases – is structured into a sequence of steps implemented using Dynamo and Python scripts. However, some phases, specifically Steps 3 and 4 described in section 3.2.2, involve different operational procedures depending on the data type used. Finally, this paragraph provides a

comprehensive overview of the entire workflow, discussing both methodological paths, but in this phase of the thesis work, it focuses exclusively on the Royal Palace application case. A full description of the complementary application case of the Standard of Ur is provided in Appendix A. Together, the two cases highlight the flexibility and scalability of the methodology across different data sources and representation scales.

3.2.1 The courtyard of Royal Palace of Turin application case

This specific application case exemplifies the architectural scale (e.g., 1:200, 1:50), focusing on a modular portion of the courtyard of the Royal Palace of Turin (Figure 3_2). In this context, 3D digitization has, for some years, benefited from the introduction of Mobile Mapping Systems (MMS) based on SLAM (Simultaneous Localization and Mapping) technology (Sammartano et al., 2021), which expand the range of applications to indoor or underground environments where traditional positioning and navigation systems such as GNSS (Global Navigation Satellite System) sensors are ineffective. The continuous evolution of these technologies has led to the development of hybrid solutions that integrate different types of sensors, with the overarching aim of accelerating data acquisition and storage processes, enabling more user-friendly and robotic systems, and ultimately increasing the efficiency of the operator's role. For the 3D survey, a FARO phase-shift laser scanner was used, employing Flash Scans technology, as investigated in Sammartano et al. (2024). In this specific metric survey, a novel Hybrid Reality Capture™ (HRC) system based on Flash Technology was tested. This system acquires 3D scan data (68 scans) enriched with panoramic imagery, enabling rapid data capture while also implementing upsampling algorithms to enhance the density and quality of the acquired point clouds (Figure 3_3). Finally, the point cloud and all outputs linked to the courtyard exhibits a centimeter-level accuracy, coherent with the architectural scale requirements (Figure 3_4).

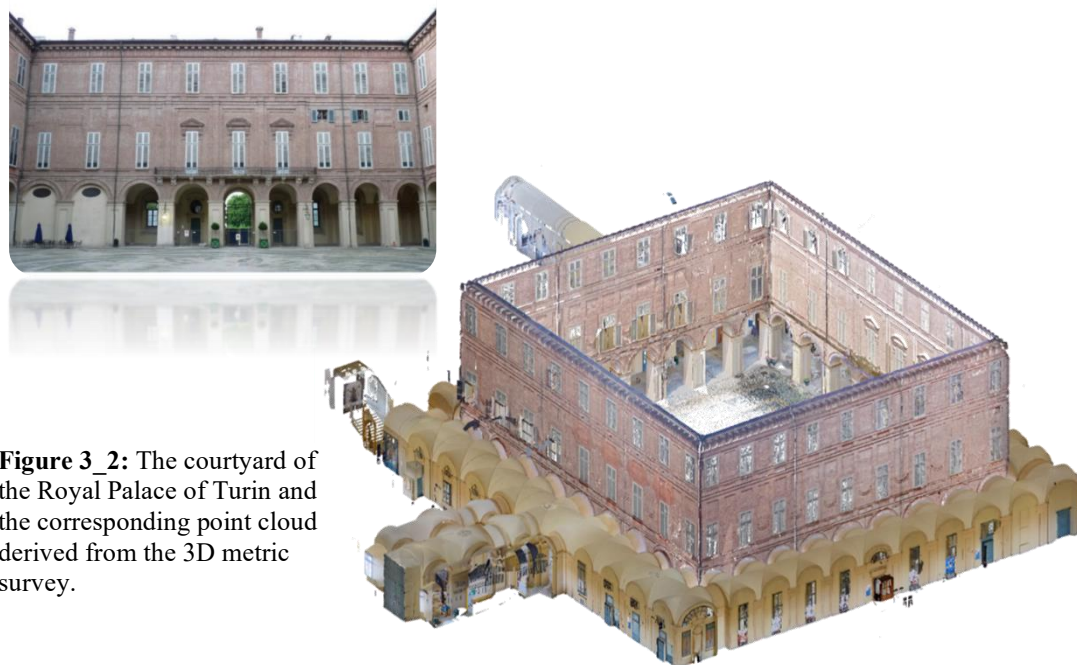


Figure 3_2: The courtyard of the Royal Palace of Turin and the corresponding point cloud derived from the 3D metric survey.

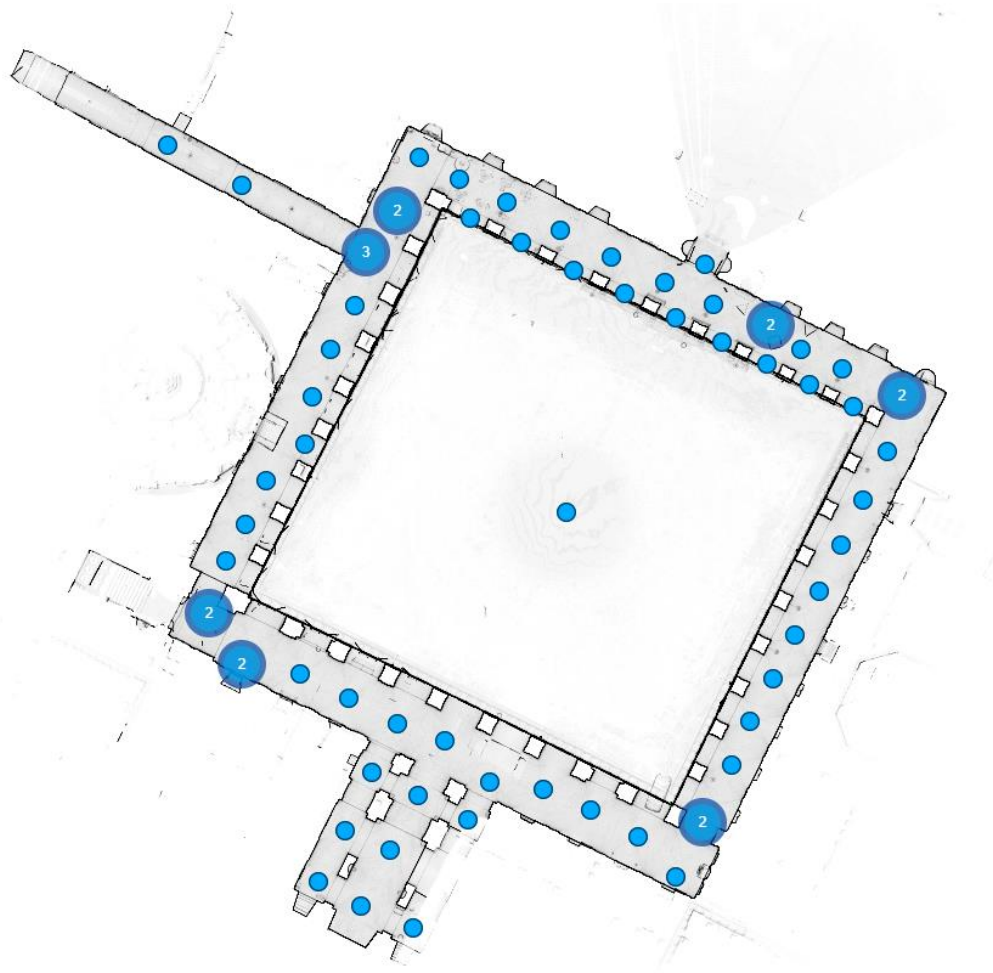


Figure 3_3: Laser scanning survey using Flash technology of the courtyard of the Turin Royal Palace. Plan view of the point cloud with positions of the Flash scans. (Sammartano et al. 2024).

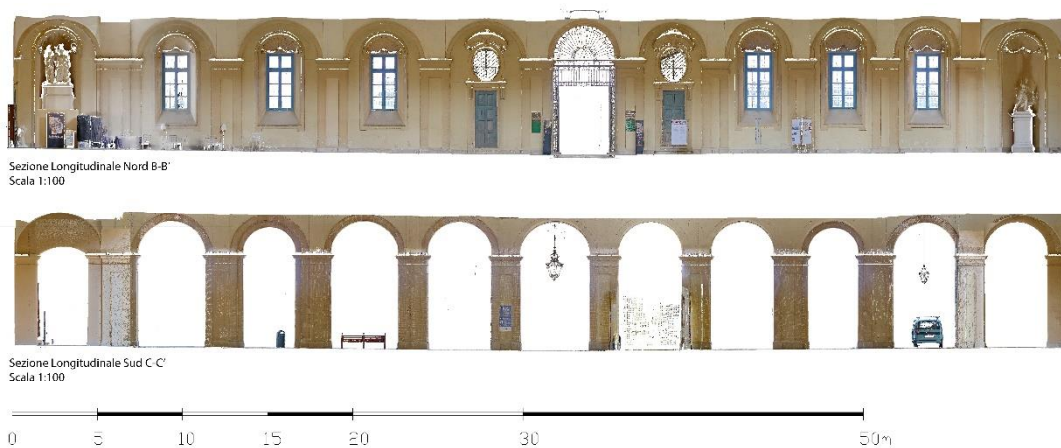


Figure 3_4: Example of planar projections of point cloud sections used to represent the inner and outer façades of the Royal Palace portico.

3.2.2 3D Python Libraries implementation strategy in VPL environment

A common practice in the AECO industry is to represent 2D or 3D complex data – derived from an integrated metric survey – using a classical approach that traditionally involves an orthogonal type of visualization (architectural drawings). Since, real-world existing conditions are rarely orthogonal, this feature represent a significant issue heavily limiting the possibilities connected to the management of these data. Adding to the complexity, numerous contemporary design software packages have limitations in accurately representing the CH shape complexity. The challenge is therefore represented by the desire to avoid Scan-to-BIM approaches that overly simplify reality-based models, making the most of the high level of detail derived from 3D metric surveys and ensuring an appropriate Level of Accuracy, according to survey aim and specifications. The proposed workflow (Figure 3_5) – based on the use of the VPL platform Dynamo for Revit and Python scripts retrieved from open repositories and adapted for specific use – enables the integration of classified 3D models (namely, mesh) in a parametric environment as categorised BIM objects. This approach enables the generation of 3D databases for improving the study and the management of heritage assets. The generation and application of categorised meshes directly within the BIM environment allow for the automation of the modelling process of complex elements – typically a manual and time-consuming task – while maintaining the level of detail of the original model unchanged. The use of 3D Python libraries within the VPL platform avoids overloading the BIM authoring software excessively during mesh generation and segmentation processes, as these meshes are managed in a separate environment. These models can then be converted into HBIM objects, subsequently categorised within the BIM environment, and finally semantically enriched with all relevant information to support conservation, enhancement, and management processes (e.g., materials, quantities, state of preservation etc.). Ultimately, the modelled objects can be exported as IFC files, generating specific Property Sets capable of retaining all associated geometric and semantic information, promoting interoperability and collaboration among field experts.

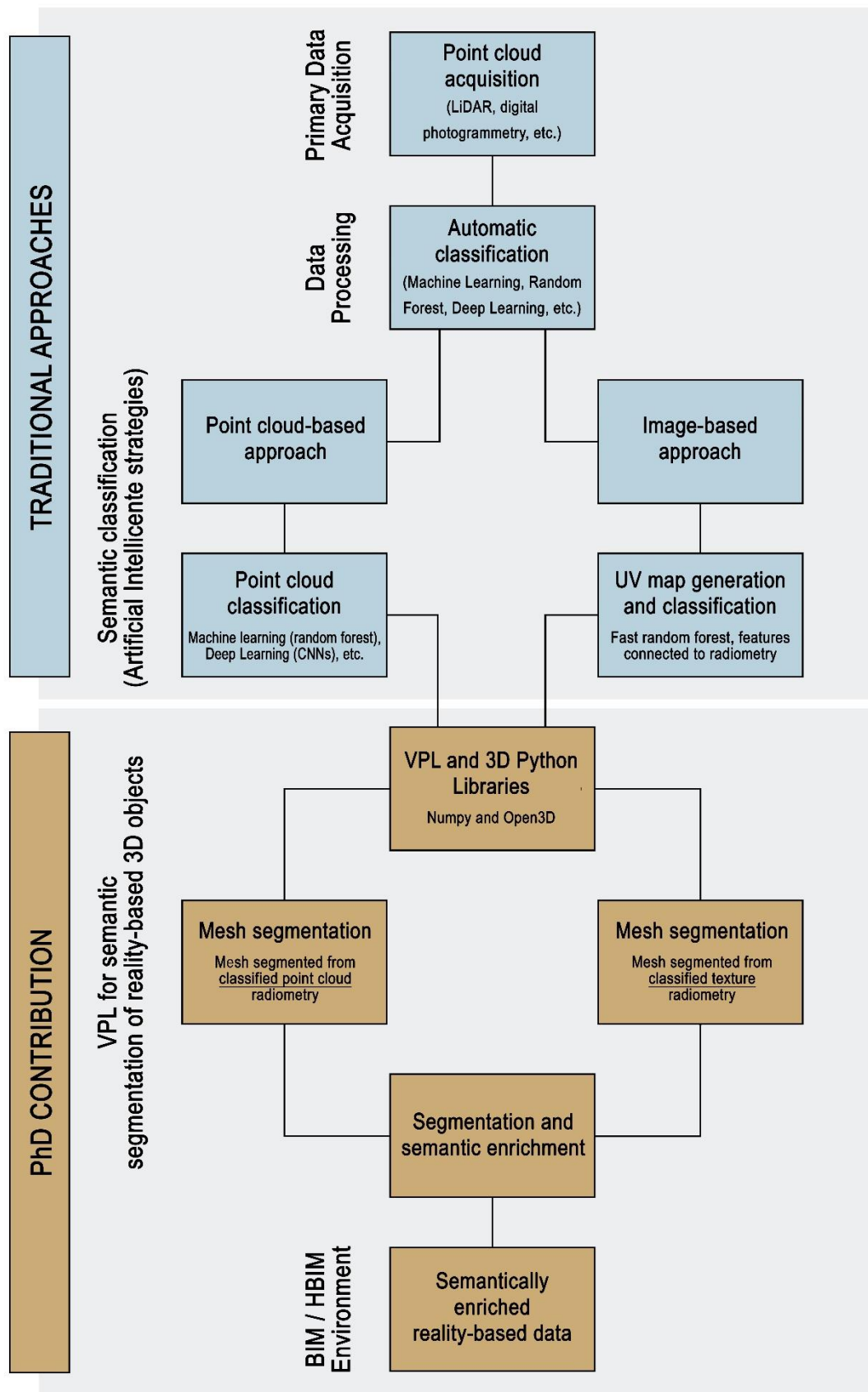


Figure 3_5: Flowchart of the proposed workflow.

The proposed workflow, based on Dynamo and Python scripts, consists of the following steps:

- **Step 1:** Classification of the reality-based data (point clouds or mesh model) using a machine learning approach (Grilli & Remondino 2019);
- **Step 2:** Importing 3D classified data in VPL environment (Dynamo for Revit);
- **Step 3:** Mesh generation (this applies if the workflow processes point clouds, e.g. in the Turin Royal Palace application case) to create 3D geometry compatible and manageable with the parametric environment. Alternatively, if a mesh is already available (e.g. in the Standard of Ur application case, Appendix A), it is necessary to convert the polygonal model to be properly read by the parametric software;
- **Step 4:** Mesh re-texturing to assign the radiometric values corresponding to each specific class. This is necessary in order to subsequently perform a segmentation procedure based on unique RGB values. The class information is stored in the original point cloud colour (the Turin Royal Place application case) or in the projected UV map (the Standard of Ur application case, Appendix A) With this mapping process, the polygonal model's vertices inherit the corresponding radiometric RGB value from the original reality-based classified data.
- **Step 5:** Each class is segmented in N mesh models (where N is the number of considered classes) according to the radiometric value corresponding to a specific class and separately imported into Revit as a parametric entity, associated with a specific category able to host semantic heterogeneous information. The pipeline carried out in the proposed research can be observed in Figure 3_5.

The following sections provide more details of each step applied to the Turin Royal Palace application case.

Data classification

The first phase of the current workflow pertains the classification of the reality-based data. In recent years, the scientific community has focused on the automatic classification of heritage point clouds and images. The most commonly used strategies are:

- **Point cloud-based approach:** the data is represented by an unstructured point cloud, usually acquired with a LiDAR system or generated using photogrammetry. A popular method is represented by ML methods, in particular with Random Forest algorithms (Grilli and Remondino 2020). Recent research experiences have shown that these methods generate results characterised by high accuracy (Tang et al. 2023). Deep learning methods have also proven to be particularly

effective (Guo et al. 2021) although, in heritage, classes and needs vary and are generally project-related. For our first case study, the dataset has been labelled based on common classes used in the architectural representation domain, which has been adopted by the ArCH dataset, a well-known benchmark dataset composed of 17 annotated heritage point clouds (Matrone et al. 2020b). The segmented courtyard module point cloud is shown in Figure 3_6.

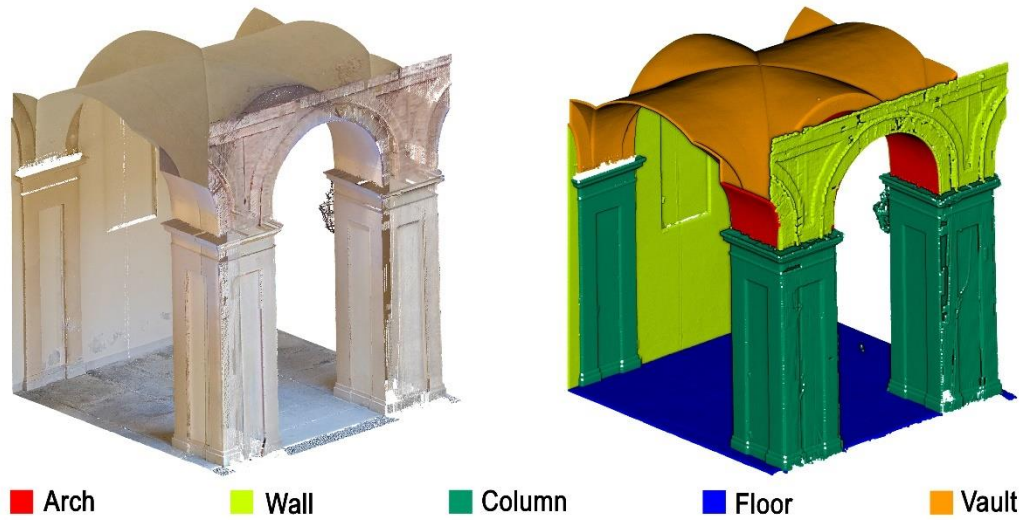


Figure 3_6: RGB (left) and segmented (right) point cloud for the courtyard module of Royal Palace in Turin. (Avena et al. 2024).

- Image-based approach: predictive models, such as SegNet or DeepLab V3+ for image segmentation are very well known (Badrinarayanan et al. 2017; Chen et al. 2017). In the domain of 3D heritage documentation, these applications are often developed in parallel with the photogrammetric process, in order to classify photogrammetric blocks or 3D model derived from SfM applications (Murtiyoso et al. 2022). For the second case study, we build upon Patrucco et al. 2023a exploiting the high-resolution UV map generated in the 3D surveying and modeling process. A material-based classification is carried out using a machine learning-based algorithm (the Fast Random Forest classifier implemented in Weka Trainable Object, a open source plugin of Fiji: ImageJ platform) (Grilli & Remondino 2019; Adamopoulos 2021). The classified UV map is then re-project onto the geometric model. For in-depth analyses and related images of the present case study, the reader is referred to the Appendix A.

VPL and 3D Python Libraries

The second phase of the current workflow, corresponding to Steps 2 through 5, pertains to the integration of classified 3D survey data directly into the BIM environment, specifically utilising Autodesk Revit and Dynamo. Within the VPL environment, specific nodes employing Python are utilised. These scripts facilitate the replacement of numerous nodes typically found in a .dyn file with succinct and well-organized lines of code.

Additionally, it extends Dynamo's capabilities by enabling the creation of tailored instructions. This pivotal aspect enables the automation of both the import and management phases of classified data. Generally, this process involved four main steps:

- Python environment setting;
- Mesh generation process (applicable exclusively for the point cloud-based approach);
- Mesh classification process;
- Mesh semantic segmentation process.

Except for the second step in the list above, all other steps are common to both considered case studies.

Particularly, the first fundamental step of this phase is setting up the Python environment. The two libraries Numpy and Open3D are added for managing a point cloud and automatically generating a 3D mesh. They are open-source library that allows the use of a set of efficient data structures and algorithms designed for 3D data processing. In particular Numpy library is the primary array programming library for the Python language (Pérez et al. 2011; Harris et al. 2020); in the other side Open3d represents an open-source library designed to enable the efficient development of software applications that process 3D data (Zhou et al. 2018).

In this context, reality-based 3D data are usually characterised by a higher metric accuracy compared to modelled geometries. And, since advanced modelling tools are not embedded in most of the widely used BIM/HBIM platforms (e.g., Revit), when a high-accuracy digital replica is demanded it is necessary to adopt alternative strategies for the generation of the parametric model. A consolidated method relies on NURBS modelling (Barazzetti et al. 2016; Spanò et al. 2023), which allows the generation of digital models characterised by a high metric accuracy using reverse modelling strategies (e.g., extracting section profiles from a point cloud or a 3D mesh). However, these processes are significantly time-consuming and demanding due to manual human operations. Additionally, further parametrization processes are required to implement these models in a parametric environment. For this reason, the possibility of generating semantically enriched 3D polygonal models and importing them in a HBIM project can represent a significant opportunity in order to optimise modelling processes from a time-saving perspective, without scarifying accuracy criteria. Additionally, this approach hallows to implement the radiometric information in the generated polygonal

models. The strategy used for the mesh generation is the Ball-Pivoting Algorithm (BPA - Bernardini et al. 1999), which generates a mesh from a point cloud simulating the use of a virtual ball (Figure 3_7). BPA iteratively pivots the ball around edges of existing triangles, adding new triangles and points to the mesh until the entire surface is reconstructed. The relevant information derived from the original point cloud (e.g., coordinates, RGB values, normals, etc.) is embedded in the vertexes of the generated surface model. It's worth noting that the size and the radius of the virtual ball are crucial parameters in the algorithm, as they define the shape and resolution of the resulting mesh. Following the mesh generation, the extraction of RGB values from classified point cloud is achieved through the application of concise Python code. These values were subsequently reprojected onto the 3D model (Figure 3_8). For the mesh segmentation, the initial procedure consists of filtering the mesh based on the desired colour, followed by the storage of the selected model faces in dedicated lists (dictionaries). This methodology facilitates the generation and export of a 3D model composed by segmented meshes representing different classes of architectural elements.

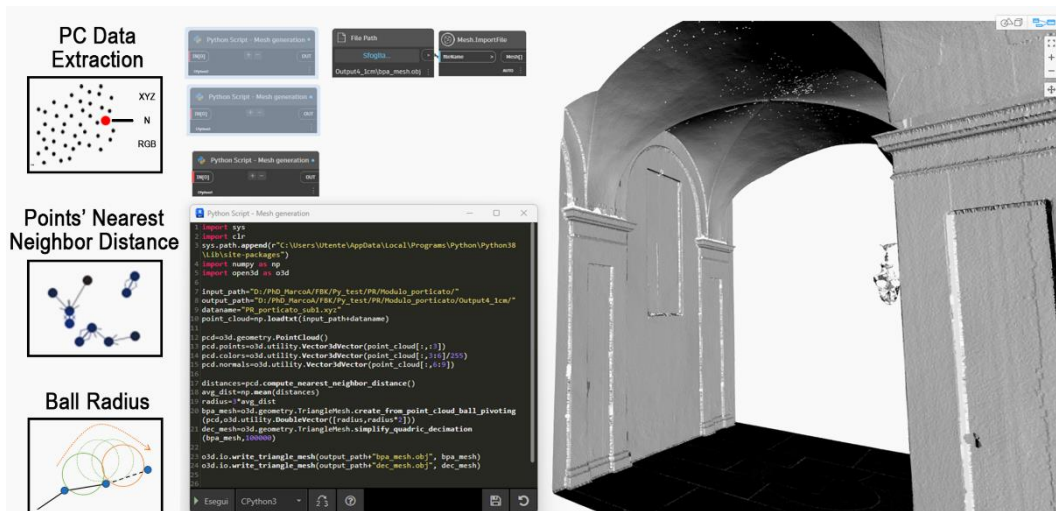


Figure 3_7: Mesh generation of the Turin Royal Palace courtyard module using BPA algorithm directly in Dynamo environment. (Avena et al. 2024).

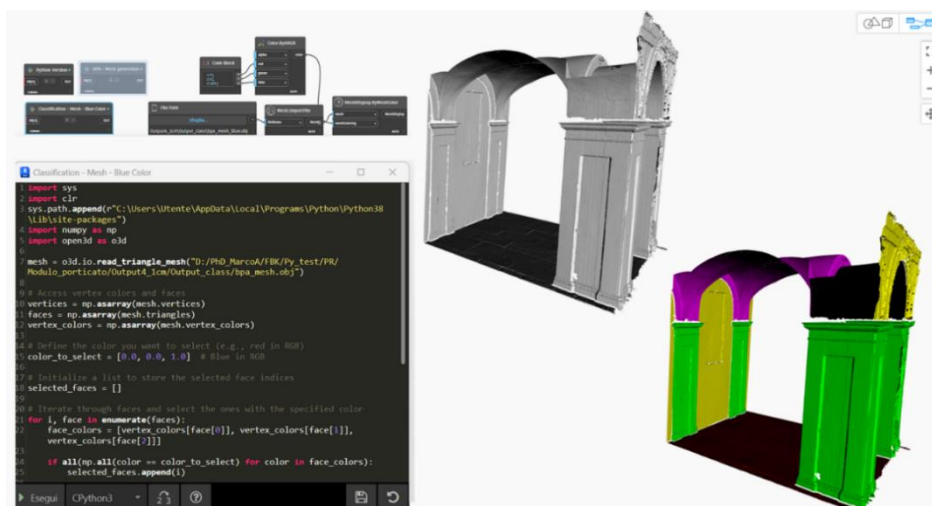


Figure 3_8: Segmentation of the mesh based on the RGB values projected onto it directly in Dynamo environment. (Avena et al. 2024).

Finally, the last step of the workflow enables the conversion of the generated and semantically enriched meshes into a HBIM environment. The mesh conversion phase, coupled with the process of assigning specific BIM categories to the model, plays a pivotal role in the proposed methodology. Typically, such geometries do not inherently represent entities found by default in 2D and 3D collections stored within major BIM software. This conversion ensures seamless model management and complete utilisation. The proper categorisation of an element also allows to inherit all the properties that the BIM software assigns to entities belonging to that category. Figure 3_9a illustrates the correct import of the mesh within the BIM environment, while Figure 3_9b the correct assignment of the cloister columns class to the *Column* family. The capability to have segmented HBIM models appropriately categorized, as shown in the Table 3_1, significantly facilitates the phase of semantic enrichment.

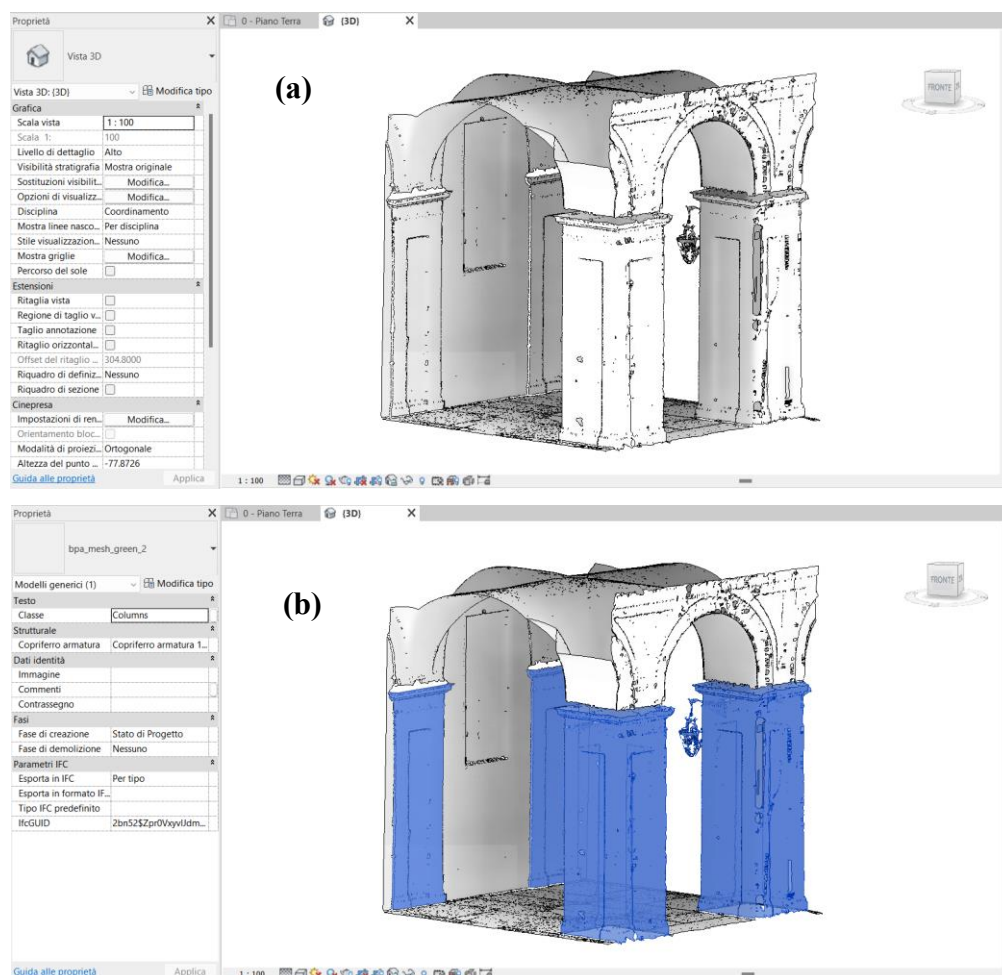
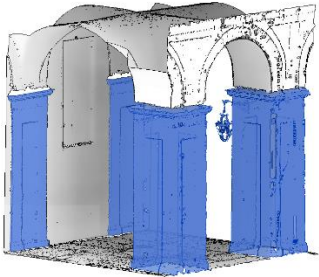
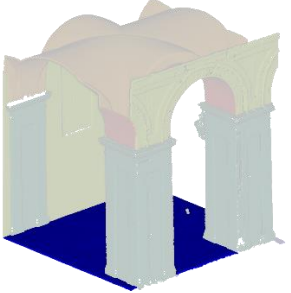
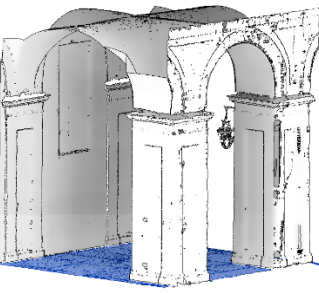
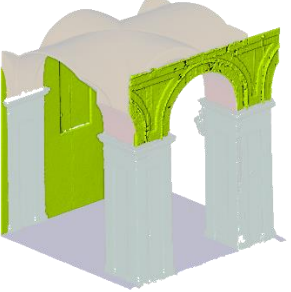
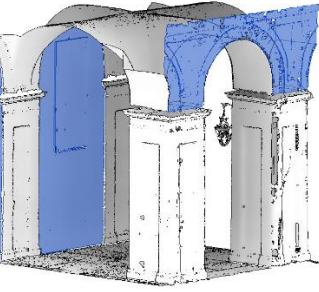
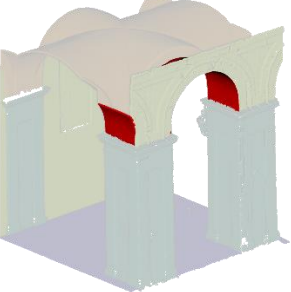
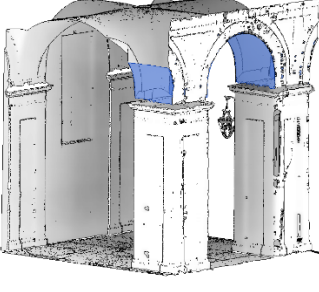
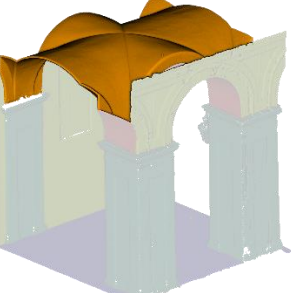
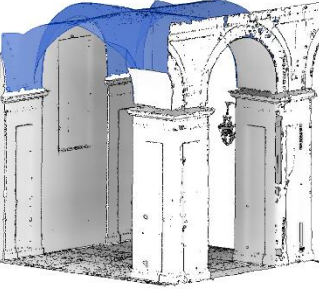


Figure 3_9: Importing the generated semantic mesh entities in a BIM environment. Each mesh is a separate parametric object able to host heterogeneous information. (a) The semantically enriched mesh imported in BIM environment; (b) Selection of objects belonging to the “Column” class (Royal Palace cloister module). (Avena et al. 2024).

Table 3_1: Point cloud classification and conversion of semantically enriched meshes in HBIM elements.

CLASSES OF ARCHITECTURAL ELEMENTS	POINT CLOUD CLASSIFICATION	HBIM ELEMENTS
Column		
Floor		
Wall		
Arch		
Vault		

3.3 Evaluation of the results

The achieved results highlight the flexibility and replicability of the proposed methodology, which proved to be effective when applied to a complex architectural context such as the Royal Palace of Turin. This case study, situated at the architectural scale, demonstrated the method's capacity to manage heterogeneous semantic, geometric, and topological features, despite the variations in resolution and accuracy typical of real-world 3D acquisition processes. The implementation of a highly automated workflow, based on classification algorithms and VPL, offers significant benefits to professionals operating in the digitization of Cultural Heritage. Notably, this approach has the potential to significantly reduce modelling times, particularly in the case of complex architectural elements, while preserving the high level of geometric detail enabled by advanced 3D metric survey techniques.

In many CH scenarios, strategic decision-making or condition assessments do not necessarily require fully parametric models (i.e., models in which users can adjust parameters to modify geometry or dimensions), especially at a preliminary knowledge stage of the asset. What is often needed instead is a highly faithful digital replica of the object or structure, enriched with semantic information and suitable for a range of analytical and management tasks. In this context, semantically enriched mesh models offer a powerful and innovative alternative: they retain the high-accuracy geometry captured through 3D surveys and, at the same time, provide structured interpretive layers for enhanced understanding and use.

One particularly innovative aspect of the proposed approach lies in the generation and semantic management of these mesh models outside traditional BIM authoring environments. Using Python scripting within a VPL framework, it becomes possible to process and enrich even highly complex and data-heavy mesh models – often several gigabytes in size – without overloading BIM platforms, which are not inherently designed to handle point clouds or high-resolution meshes. This strategy not only ensures smoother processing and greater efficiency, but also maintains full interoperability between VPL-generated models and those imported into BIM environments, preserving both geometric accuracy and semantic richness across platforms.

As demonstrated in the case of the Royal Palace, this strategy supports the classification of architectural elements for HBIM integration, as well as the representation of material or degradation-related features. Moreover, due to its inherent flexibility, the methodology shows promise for application beyond the architectural scale, potentially extending to museum collections and other heritage artefacts. Further reflections on its scalability and performance in different contexts are provided in the conclusions of Appendix A.

3.4 Discussion on integrating semantically enriched 3D models into a parametric environment

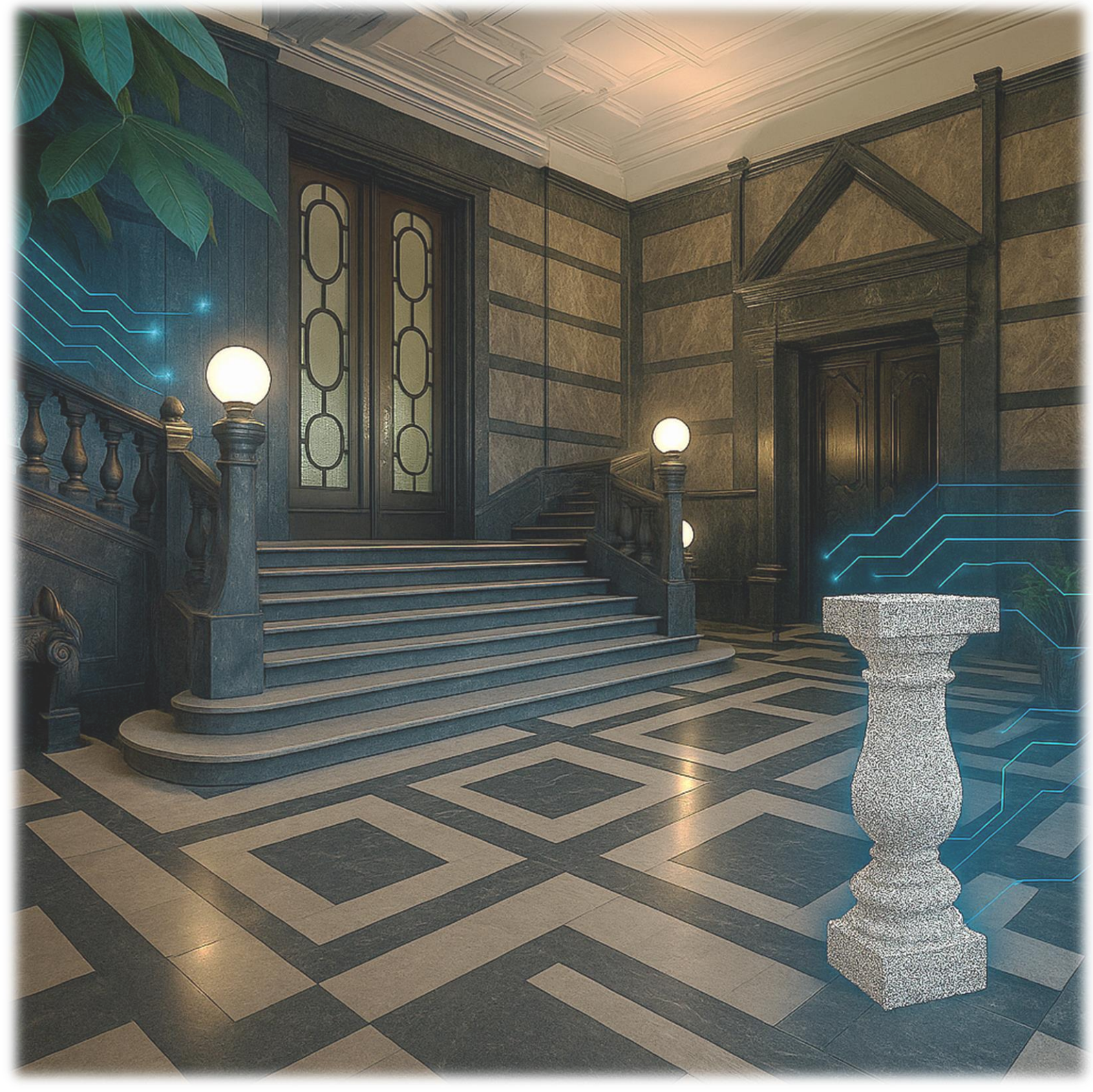
The results of methodology comprises the proposal of an innovative methodology capable of integrating Python 3D libraries with customizable nodes of VPL to facilitate the automation of processes for BIM and HBIM modelling. Specifically, the core of the workflow involves the use of segmented 3D data directly within parametric BIM environment. The approach was tested on a specific architectural scenarios to handle efficiently and intuitively reality-based 3D models derived from 3D surveying data. This was achieved through the use of VPL scripts created specifically for various stages of data pre-processing (point cloud management) and for generating HBIM models from segmented meshes (mesh generation – mesh segmentation). The choice to employ Python 3D libraries within Dynamo enabled the automation of the process, making it feasible to use the original reality-based data directly within the BIM authoring platform. This not only helped avoid unnecessary platform memory overload, attributed to the management of complex and large 3D data, but also ensured the generation of an HBIM model with an appropriate LOA, according to survey aim and specification. This goal is challenging to achieve using conventional Scan-to-BIM techniques. The use and management of classified meshes at a high LOA in the BIM environment offer additional advantages. Firstly, the generated 3D element can be converted into a geometry readable by the program and assigned to a specific BIM category, inheriting all relevant properties and characteristics. Furthermore, the generation and import of classified meshes provide the additional benefit of structuring various elements based on their radiometric information, enabling various types of analyses (e.g. degradation analysis, material studies etc.) and facilitating differentiated semantic enrichment operations. This methodology ultimately saves time in the modelling phase, as the operator is assisted by semi-automatic tools that replace typically manual and laborious operations. At the same time, the adopted VPL systems prove to be highly flexible and adaptable to various situations and case studies, being based on easily implementable visual nodes. As future research avenues, we are firstly considering the possibility of managing different LODs by downsampling the geometric information of the imported 3D models while conserving the semantic informative contents. This could allow for an effective multi-scale modelling and documentation of cultural heritage. In this case, the specific LOD is associated with the complexity of the mesh generated GOG (Grade of Generation) (Banfi 2020), as through the process of downsampling, it's possible to simplify the model by inserting the desired number of faces. This method can be seen and developed from a multi-scale perspective, considering objects which are very different from many points of views – for instance architectural objects and other heritage artifacts, as investigated in Appendix A. This implementation for the management of multi-resolution data could be a next

step with the aim of improving the efficiency, manageability and sustainability of these semantic enrichment processes.

Another interesting research perspective involves the exploration of generative AI technologies (e.g., super-resolution, GANs, and other generative approaches) to densify and/or complete missing data. In particular, when free-form elements (typically part of the decorative apparatus of a heritage building) are surveyed, generative AI can represent a significant opportunity for filling gaps that arise depending on the 3D sensing strategies employed. The implementation of generative technologies would greatly contribute to increasing the level of automation introduced in the proposed methodology in the framework of parametrization processes of heritage objects.

Chapter 4

GenAI approach for 3D survey data completing and optimization



Building upon the potential of Generative AI technologies to address challenges in data densification and completion, this chapter delves into the comparative evaluation of approaches for reconstructing incomplete 3D data. Specifically, the focus is on point clouds and polygonal surfaces (meshes) in the context of Cultural Heritage (CH) digitization, with the aim of enhancing reality-based modeling techniques within HBIM workflows through Scan-to-BIM processes. Despite the advancements in these methodologies, significant challenges persist due to the limitations of 3D metric surveys, which often yield incomplete datasets caused by instrumental and operational constraints. This chapter seeks to assess the effectiveness and accuracy of 3D reconstruction techniques by juxtaposing traditional geometry-based methods with innovative generative AI algorithms. Through a critical analysis of the strengths and limitations of the main completion methods, these approaches are tested and compared using a variety of objects characterized by diverse shapes, scales, and surface properties.

4.1 3D models completion techniques: related works

In this context, drawing inspiration from the growing interest in digitizing CH domain through polygonal representation of three-dimensional objects (Pérez et al. 2016), advances in hole-filling methodologies complement efforts directed at point cloud completion (Schnabel et al. 2009). These methodologies exploit computer graphics and artificial vision techniques to fill gaps and inconsistencies within digitized models, generated from integrated 3D metric surveys (LiDAR, aerial/UAV photogrammetry, MMS systems etc.). By addressing common issues such as noise, holes, and topological discrepancies (Vetrivel et al. 2015; Adamopoulos et al. 2021; Yang et al. 2022), hole-filling techniques (Xie et al. 2004) help improve the overall quality and fidelity of the point cloud. In this context, the completion of point clouds and polygonal meshes are often intertwined with the task of hole filling, as both endeavors share the common objective of refining the geometric representation of three-dimensional shapes (Park et al. 2020). Deep learning-based methods have gained prominence in recent years for their efficacy in addressing these challenges. However, existing methodologies frequently encounter hurdles stemming from the discrete nature of point clouds and the unstructured prediction of points within local regions, especially if the holes are very large (Podolak and Rusinkiewicz 2005). These challenges impede the preservation of well-organized structures and hinder the accurate delineation of local geometric details and structural characteristics, such as smooth regions, sharp edges, and corners, during the completion of partial 3D shapes. At this point, a comprehensive overview of existing methods of 3D model completion is conducted, incorporating the two main approaches in this field: Geometric-based and GenAI-based completion approach.

4.1.1 The Geometric-based completion approach

The data acquired from 3D scanners are typically unstructured and heterogeneous. It's crucial in the initial phase to study the raw data and understand what type of lack we are faced with. Typically, indeed, the holes can exhibit simple or complex shapes, gaps, islands, holes with accentuated curvature and incomplete topology. Before the raw input data can be used for 3D reconstruction, a preprocessing phase is necessary to structure these data. The repair phase, approached from a geometric perspective, involves two main steps: hole boundary detection and hole filling. In the hole boundary detection step, the algorithms identify the boundaries of the holes in the point cloud or mesh. Subsequently, in the hole filling step, these algorithms either triangulate the boundary points or generate new interpolated points within the holes to reconstruct a complete and continuous surface. Although a wide range of hole-filling algorithms have been rigorously tested, a comprehensive solution that effectively addresses every situation and case has yet to be developed. Given the heterogeneity of the input data, hole filling algorithms can be divided into two categories:

- point cloud-based methods;
- mesh-based methods.

The following sections will delve into these two categories, exploring their principles and applications.

The completion algorithms in point clouds

Geometry-based methods primarily use geometric cues from the incomplete input data to deduce the shape of the missing part, without relying on external auxiliary data to complete the overall shape of the data model. Before closing a hole within a point cloud dataset, it is crucial to identify and select all the points that delineate the boundary of the gap. Numerous researchers have experimented with various algorithms aimed at automating this process. Bendels et al. (2006) introduced a method integrating multiple criteria into a unified boundary probability for each point. This probability is computed using the angle criterion, which categorizes points as either boundary or interior. Subsequently, exploiting the coherence among these points, a straightforward boundary loop for the hole is extracted. This approach establishes a robust and automated hole detection algorithm by capitalizing on both the boundary probability and coherence properties. To ascertain whether a set of points forms part of the boundary, employing kD-tree, octree, or BSP-tree algorithms becomes imperative to facilitate neighborhood searches around a point. Similarly, Tran et al. (2015) experiment the extraction of reliable geometric primitives from unstructured point clouds. Initially, focusing on robustly extraction of curved planes, spheres, cylinders from the point cloud data, in order to facilitate 3D surface reconstruction operations. More recent

studies have also tested the possibility of extracting point cloud boundary by fitting a least squares plane to the point cloud data, computing the normal vector of the plane, and analyzing the characteristics of the point cloud (Kai et al. 2020).

Taking into consideration the hole-filling process, it can be divided into *volume-based* and *surface-based methods*, as proposed by Guo et al. (2018). The volume-based approach typically involves subdividing the point space into atomic volumes using an octree grid. Each volume grid must ascertain whether the individual volume lies inside or outside the point surface and generate signs for the grids requiring processing. Xie et al. (2004) initially organize the input point set using an octree and determine the inside/outside orientation of each point cluster through a robust voting algorithm. This algorithm blends the implicit quadric surface of each octree cell to reconstruct noisy and defective datasets. Additionally, another option is to segment input point objects into 3D uniform grids to handle large unorganized point sets, representing an alternative to hierarchical octree grids for constructing volume grids (Franchini et al. 2010; Ansary et al. 2024). This uniform grid approach simplifies computation but requires uniform sampling of the input data. Sharf et al. (2004) fill holes with a smooth patch copied from valid regions of a given surface. This method partitions point clouds by constructing an octree, then works top-down to build a local implicit approximation of the shape from points inside a cell, classifying cells into valid or invalid cells, and computes patches by copying part of the surface around the filled region using an iterative closest point procedure. On the other hand, the surface-based methods mainly focus on different surface characteristics, including boundary curvature, topology, and similar properties. Initially, all researchers involved in this research topic focused on repairing small holes in the point cloud datasets. Kazhdan & Hoppe (2013) proposed methods based on the original Poisson surface reconstruction algorithms, enhancing the technique by explicitly incorporating the points as interpolation constraints. Therefore, another research team introduced a *3DPatchMatch* (Cai et al. 2015) algorithm designed to enhance the efficiency of point cloud completion by rapidly identifying suitable matches. This algorithm leverages point cloud consistency to minimize convergence time through processes of random initialization and propagation. They also incorporated a random Gaussian process to help the algorithm escape local minima. Considering instead larger missing areas, Schnabel et al. (2009) proposed a method that allows the extraction and use of the primitives from which the 3D models were composed (planes, cylinders, cones, etc.) to identify the missing areas and facilitate the point cloud-based reconstruction process. Further exploring the geometric relationships among the orientations, positions, and equality of primitives during the reconstruction process, Li et al. (2012) designed a RANSAC-based algorithm. This algorithm aimed to acquire fundamental primitives for local adaptation, progressively assimilating the connections among these primitives and adjusting the model accordingly.

Filling holes in 3D meshes

The input of mesh-based hole filling methods is a mesh consisting of vertices set and triangles set. In creating a polygonal mesh, stringent geometrical and topological standards must be upheld. Geometrically, polygons must accurately represent the object's outer surface, requiring a closed, intersection-free, and singularity-free polygonal surface (Perez et al. 2016). Topologically, it is imperative that the mesh conforms to connectivity rules (watertight mesh), avoiding errors like redundant handles and disconnected patches that add unnecessary complexity and complicate subsequent parametrization and segmentation tasks. Maintaining topological integrity, including features like handles and connected components, is fundamental to ensure the robustness and usability of the model in cultural heritage preservation and analysis.

These mesh-based hole filling methods utilize strict mesh structure principles to detect hole boundaries and efficiently fill in the missing regions. Also in this specific case, hole-filling algorithms can be divided into *volume-based* and *surface-based methods*. The volume-based method is typically related to highly distorted or inconsistent meshes with multiple types of defects that require global approaches to be repaired. In the field of hole-filling, the term *global* means that the approach is applied broadly rather than focusing on the area around each specific hole. Typically, volumetric models, which are stored as a volume buffer of voxels, are used for synthesizing, manipulating, and rendering objects. For hole restoration, volumetric solutions often involve completely re-meshing the input or utilizing an intermediate data structure different from a polygonal mesh. Davis et al. (2002) proposed a technique based on a signed distance function whose zero set defines the surface. Initially, this function is only defined near observed surfaces, and a diffusion process extends it through the volume to bridge the holes. The algorithm is straightforward to implement, ensures manifold non-interpenetrating surfaces, and is efficient for large datasets since computations focus on areas near the holes. Following a different strategy, Podolak et al. (2005) proposed a complex hole-filling method based on decomposition of the space in atomic volumes. In the first part of the process the input mesh is enclosed in a cube and partitioned into atomic volumes, which are classified as either inside or outside the mesh to ensure the final model is watertight. Then, the algorithm labels these volumes by computing a minimum-cost cut in a graph representation, patching holes globally. User control allows for different valid ways of filling holes, and an octree decomposition ensures efficient computation. The solution proposed by Paulsen et al. (2010) tried to adapt the Markov Random Field (MRF) based regularization method to the distance field. This approach allows for the integration of both the prior knowledge about the surface type to be reconstructed and the data observations in an orthogonal manner. The goal is to generate surfaces without self-intersections and non-manifold edges while accurately following the input data and filling holes. This method is highly effective for small to medium-sized holes and can maintain simple and smooth features. Finally, the research proposed by He et al. (2023) integrates a hole-filling

method into the Bi-directional Evolutionary Structural Optimization (BESO) framework to control the complexity of 3D structures by managing cavities and tunnels, enabling the design of efficient, topologically controlled structures that balance architectural creativity with structural performance.

4.1.2 The GenAI-based completion approach

The Generative AI represents a specialized area within deep learning focused on the creation of novel content by learning patterns and structures from training datasets. This technology is highly versatile, allowing for its application across a wide range of data modalities, such as textual information, visual imagery, three-dimensional data, and more, enabling innovative solutions in diverse fields. Examples of such advancements include DALL-E, which generates highly detailed images from textual descriptions (Ramesh et al. 2021); ChatGPT, designed to produce human-like text for conversational and creative writing tasks (OpenAI 2023); and SORA, which facilitates 3D content generation, showcasing the breadth of generative AI's capabilities across different domains (Liu et al. 2024).

Over the last decade, significant progress in computer vision has enabled the exploration of point cloud and 3D shapes completion using both traditional machine learning techniques and deep learning methods (Wen et al. 2021a; Wen et al. 2021b; Han et al. 2019). Traditional approaches relied on the assumption that 3D shapes possessed regular surfaces, which restricted the complexity of the shapes they could produce. Benefiting from large-scale point cloud datasets, deep learning-based methods for point cloud completion have garnered increased research interest. However, initial deep learning models struggled with the unstructured nature of point clouds, making it challenging to accurately represent detailed local geometric features such as corners, edges, and planes during completion. This contrasts with the capabilities of convolutional neural networks, which excel at handling such tasks in 2D image processing.

Current methods for point cloud generation typically impose constraints by utilizing a hierarchical rooted tree structure (Wang et al. 2020) or by making assumptions about the specific topology of the target shape (Yang et al. 2018). Despite these efforts, most approaches face significant challenges due to the inherently discrete nature of point clouds and the unstructured manner in which points are predicted within local regions. This lack of structure often makes it difficult to maintain a well-organized and coherent arrangement of points in localized patches. Furthermore, accurately capturing the intricate local geometric details and structural characteristics of the complete shape – such as smooth and continuous regions, sharply defined edges, and distinct corners – remains an ongoing and complex problem in the field.

In recent years, numerous researchers have explored various approaches to address these challenges. One promising solution has been the application of Transformer technology – originally revolutionary in the field of Natural Language Processing (NLP) – to the domain of point clouds. Briefly, the Transformers are

advanced attention-based machine learning models that were introduced by Vaswani et al. (2017). These models have revolutionized the field of NLP, offering a more efficient and scalable alternative to the previously dominant recurrent neural network (RNN) architectures (Zhao et al. 2021). Their introduction marked a significant shift in how sequential data is processed and understood. The core innovation of Transformers lies in their use of attention mechanisms to process input sequences, such as text or other forms of sequential data. Unlike traditional methods, attention enables transformers to assign different levels of importance to various parts of the input, allowing the model to prioritize relevant information while minimizing the influence of less critical elements. This selective focus not only enhances the model's ability to understand context and relationships within the data but also significantly improves its performance on complex tasks. In this scenario, PointNet++ (Qi et al. 2017) incorporates these concepts within a hierarchical spatial structure to enhance its sensitivity to local geometric layouts. This hierarchical approach allows the model to effectively capture fine-grained geometric details by progressively analyzing smaller regions of the point cloud.

A further step forward in this research was conducted by Xiang et al. (2021). This researchers' team introduced SnowflakeNet, an innovative network designed to enhance the decoding process for completing partial point clouds. The core of SnowflakeNet is the Snowflake Point Deconvolution (SPD) layers, which model the generation of complete point clouds by emulating the growth pattern of a snowflake in 3D space. Points are progressively generated through successive SPD layers, where each layer produces child points by splitting parent points while inheriting the shape characteristics encoded in the parent points. This technique laid the groundwork for investigating the application of GenAI to CH, which constitutes the research question of Chapter 4 of this thesis. As we will examine in detail, this approach was carefully analyzed and adapted to the specific context of completing point clouds associated with cultural heritage assets. These topics will be further explored in Section 4.2.

In parallel with the specific methodological advances presented in this chapter, the broader evolution of GenAI and Large Language Models (LLMs) has opened promising avenues for the reconstruction and enrichment of incomplete heritage data. As emphasized by Hagos et al. (2024), LLMs – initially developed for tasks in Natural Language Processing – have undergone a rapid transformation into multimodal generative frameworks, capable of synthesizing content across various data types, including text, images, and even three-dimensional structures. Their underlying attention-based architectures offer high flexibility, making them increasingly relevant in tasks involving unstructured spatial data, such as point clouds.

The adaptation of these technologies to the Cultural Heritage domain, however, raises several critical challenges. Beyond the risk of hallucination and inaccuracy, a number of structural and systemic barriers have been identified in recent literature. For example, ethical concerns related to authenticity, cultural sensitivity, and subjectivity in AI-generated reconstructions have become increasingly prominent,

especially when reproducing heritage artifacts from marginalized or underrepresented communities (Tiribelli et al. 2024). Legal and policy ambiguities further complicate the picture, particularly regarding copyright restrictions and the permissibility of text and data mining for heritage applications (Westenberger et al. 2025). In addition, the scarcity of high-quality, interoperable datasets remains a major obstacle to training domain-specific models in the cultural heritage sector. This limitation is compounded by inconsistent digitization practices, lack of standardized metadata, and insufficient interconnectivity among collections, which collectively hinder the effective application of AI technologies in this domain (Foka & Griffin 2024). Furthermore, the integration of ML and DL into geomatics has raised significant concerns regarding algorithmic fairness (Petrocchi et al. 2024). Although these technologies aim to enhance accuracy and efficiency, they often reproduce or amplify existing social biases. Research has shown that predictive models tend to disproportionately yield adverse outcomes for disadvantaged groups, not only in terms of accuracy but also in the type of errors generated (e.g., over-pessimism for minorities, over-optimism for advantaged groups). Compounding this issue is a significant digital skills gap among cultural heritage professionals, which limits the sector's ability to integrate AI technologies meaningfully and sustainably (Griffin et al. 2024). These challenges highlight the importance of interdisciplinary collaboration, institutional capacity building, and the development of ethical and technical frameworks tailored to the needs of the heritage sector.

To address some of these limitations, researchers have proposed hybrid frameworks that integrate Retrieval-Augmented Generation (RAG) methods. These combine LLMs with structured external knowledge sources to enhance factual grounding and reduce erroneous outputs (Fan et al., 2024). In a CH context, such frameworks could, for instance, reference validated textual corpora or image archives to constrain the generative model within historically plausible boundaries.

Furthermore, ongoing research into resource-efficient architectures seeks to lower the barriers to adoption by reducing memory and energy requirements while maintaining high performance. This line of inquiry is especially relevant for all the experts that work in the CH domain, which often operate with constrained technical infrastructure yet require robust and adaptable digital tools for documentation and restoration. In light of these developments, the exploration of GenAI tools for 3D point cloud completion – such as those described in this chapter – should be situated within this larger technological and ethical landscape. The integration of multimodal LLMs holds significant potential for context-aware reconstruction, where textual descriptions, historical metadata, and partial geometric information can be jointly leveraged to inform plausible completions. However, as argued in Section 4.2, this potential must be balanced with methodological transparency, interdisciplinary collaboration, and the development of domain-specific validation protocols to ensure that generative outputs remain interpretable, verifiable, and aligned with heritage conservation principles.

4.2 Methodology: the GenAI as support for the digitization process

As previously anticipated, starting from 3D metric surveys and point clouds, it is feasible to generate accurate HBIM models of the existing built heritage. These advanced informational-management models can provide methods for prevention and conscious management, aimed at promoting processes for the preservation, conservation, and enhancement of CH. Nowadays, through the integration of informational models with ML (*Machine Learning*) and DL (*Deep Learning*) algorithms, it has been possible to enhance the efficiency of both metric survey processes and consequently parametric 3D modeling, thereby promoting the level of automation in the digitalization process. However, in the domain of 3D computer vision, raw point clouds captured by different 3D sensors and depth cameras often exhibit sparsity and incompleteness due to occlusion and limited sensor resolution. Consequently, hole filling, alongside point cloud and polygonal mesh completion, emerges as a critical endeavor aimed at rectifying missing or occluded regions within the point cloud representation. The completion approach, also known as point cloud repair or 3D shape completion, assumes paramount importance for a plethora of downstream applications, including visualization, object recognition, and virtual environment construction.

4.2.1 Acquisition phase issues

During the phases of acquiring in a multi-scale 3D metric survey, depending on the scale of representation intended to be achieved, various reasons can lead to a lack of both geometric and semantic information within the point clouds.

Considering a larger scale of representation than those traditionally used in the architectural domain, useful, for example, when aiming to obtain a digital replica of an object characterized by sub-millimetric resolution, the main acquisition techniques used are very close-range photogrammetry (macro photogrammetry) (Apollonio et al. 2021; Patrucco et al. 2023a), triangulation-based laser scanners (mechanical arms, etc.) (Balletti & Ballarin 2019), and structured light scanners (Kersten et al. 2018; Tucci et al. 2023; Bitelli et al. 2025). In this specific scenario, the presence of gaps, holes, and overall missing information can be attributed primarily not to the chosen acquisition strategy, but rather to the following reasons:

- Morphological complexity, when a particular object is characterized by complex geometries that make it difficult to entirely cover its shapes;
- Operational impediments, when it's not possible to reach all parts of an object (cavities, lumps, shadow areas, etc.) or it's not feasible to move/relocate the object being surveyed (static or heavy statue, highly sensitive artifacts that cannot be handled due to their intrinsic fragility etc.).

Then, considering the large-medium scale (architectural scale), it is easy to understand that it is not always feasible to encompass all the surveyed surfaces, especially due to operational constraints. In this scenario, it is necessary to analyze the different acquisition methods to fully comprehend the reasons for the presence of incomplete survey data. The main acquisition methods and their critical issues are the following:

- **TLS systems.** Following established practices, static lidar scans are typically closely spaced and exhibit a high degree of overlap to facilitate subsequent registration operations based on ICP methods. While this approach may result in redundancy due to the overlap, the 'static' nature of the acquisition often leads to numerous gaps or surfaces that are not properly captured due to occlusions, recesses, or the presence of objects between the sensor and the target surface. Additionally, the angle of incidence relative to the surface affects this aspect, particularly when overhanging elements are present on the upper parts of the buildings to be surveyed. The only solution would be to elevate the position of the laser scanner, but this is not always feasible for operational reasons (Di Pietra et al. 2017; Donadio et al. 2018);
- **Close-range photogrammetry.** The considerations mentioned above can also apply to photogrammetry. Moreover, in this case, geometric reconstruction is significantly influenced not only by the angle of incidence but also by the radiometry of the photogrammetric block. Consequently, if areas are underexposed or improperly acquired, it is likely that the geometric reconstruction will be incomplete or will present topological errors. Although this method offers greater flexibility, instrumental accuracies and the achievable level of detail are lower compared to TLS solutions (Donadio 2018);
- **UAV photogrammetry.** Images captured with nadir angles often exhibit significant gaps on vertical surfaces, i.e., those perpendicular to the sensor's positioning plane. Although images acquired with oblique angles can alleviate this issue, gaps persist in areas occluded by projections such as roofs and balconies. Additionally, it is widely acknowledged that oblique images have non-uniform spatial resolution (GSD) (Lingua et al. 2017).

In this regard, the integration of multiple sensors and data types emerges as a preferred solution. However, it should be emphasized that this approach entails significant costs in terms of data acquisition and processing, as well as considerable investment of time and computational resources. Furthermore, it is important to note that, despite integration, gaps in information may persist, an aspect that often becomes apparent during the data processing phase.

4.2.2 The proposed strategy for point cloud completion supporting Scan-to-BIM processes

In previous chapters (Chapters 2-3), we demonstrated that generating accurate HBIM models can significantly enhance the documentation of cultural heritage by providing information models enriched with both geometric detail and semantic information. Although well-established processes exist for the semantic enrichment of HBIM models – employing traditional techniques and Business Intelligence methods (Sammartano et al. 2023; Spanò et al. 2023) – substantial gaps remain in the geometric reconstruction from point clouds. In canonical HBIM modeling processes, replicating elements with complex morphology, as often encountered in the cultural heritage sector, is challenging even under optimal conditions, where the 3D metric survey data is complete and well-structured. In scenarios where the survey data is incomplete, these modeling processes prove even more limited, lacking the tools necessary for the faithful replication of such elements. In this complex context, the integration of GenAI technologies into Scan-to-BIM processes emerges as an especially innovative approach, offering promising alternatives to address some of the persistent challenges in HBIM modeling techniques. The following sections emphasize how GenAI techniques can be integrated at the beginning of the workflow discussed in Chapters 2 and 3, focusing on automating the post-3D metric survey phase and introducing a novel pipeline to streamline data processing.

To validate the aforementioned claims and demonstrate how the proposed approach facilitates documentation, preservation, and enhancement of cultural heritage – as discussed in prior chapters – a detailed application case will be presented in paragraph 4.3. This application case was carefully selected to highlight the methodology’s scalability and flexibility in reconstructing different geometries, from simple to complex forms. In particular, the case focuses on an architectural element that exemplifies the cultural heritage field, both for its widespread occurrence in architectural works and for its unique morphological characteristics. In this section, the application case selected to evaluate the applicability of generative algorithms within the parametric modeling process from incomplete point clouds is presented. The section outlines the adopted strategy – explained in the flowchart proposed in Figure 4_1 – and the primary experimental activities conducted as part of this research.

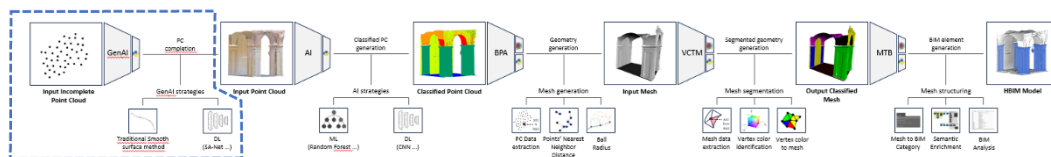


Figure 4_1: The GenAI proposed pipeline.

4.3 Application case: integrating GenAI for staircase baluster reconstruction

The application case used to test the methodology proposed in this chapter was identified on the repetitive elements constituting the balustrades of the staircase leading to the main floor of the historical headquarters of INRIM (National Institute of Metrological Research) in Turin (Figure 4_2). In this chapter, which focuses on the integration of Generative AI techniques, a third and distinct application case was selected with the specific aim of testing a further stage of the proposed Scan-to-BIM workflow. While the previous two cases addressed earlier phases of the pipeline, this third case was designed to evaluate its performance on a different category of architectural elements, characterized by unique morphological and semantic features. This choice reflects the overarching intention of the thesis to validate the methodology in a modular and progressive manner, ensuring that each stage can be effectively adapted to a variety of architectural typologies and heritage conditions.

The selection of this architectural feature was guided by the following criteria:

- An element that is easily recognizable within most historical buildings;
- A repetitive and serially replicable element, yet characterized by varying shapes, ensuring that the proposed method remains adaptable and versatile;
- A feature belonging to a well-defined category of architectural elements commonly included in BIM-oriented software libraries, thereby facilitating Scan-to-BIM workflows.

For these reasons, the vertical elements typically forming the balustrades of historical staircases were identified as the most suitable candidates for the initial experimental activities. These elements provide an ideal testbed for evaluating the proposed innovative pipeline which will be elaborated upon in the subsequent paragraph.



Figure 4_2: The INRIM Building entrance with the main staircase and balausters.

However, at this early stage, it's necessary to address the issue related to representation scales. When discussing Scan-to-BIM approaches, the concept of multiscale is typically associated. In fact, to effectively model historical buildings, it is essential to plan on-site surveys according to a logic that first and foremost considers the scale of representation required during the data restitution phase. Therefore, in an integrated 3D metric survey, this choice inevitably influences the selection of specific sensors rather than others. This consideration is closely linked to the aforementioned issue of data gaps resulting from occlusions or various obstacles encountered on-site during data acquisition. For example, if the goal of the 3D metric survey is to produce a representation at a scale of 1:200 of a building and its connected parts, the presence of incomplete data might be deemed insignificant for achieving the intended purpose. Conversely, as the scale increases (1:100, 1:50, 1:20, etc.), thereby enhancing the resolution of the survey, the survey campaign must be more thorough. For instance, in the case of a survey using TLS technology, it would be necessary to arrange more stations and perform a greater number of scans. However, this leads to increased effort during the survey campaign, extended acquisition times, and a substantial volume of data (in terms of GB) to be processed during post-production.

Secondly, a critical consideration in selecting this particular architectural element as the application case was the inherent difficulty encountered in achieving comprehensive documentation during field surveys. In conventional 3D speditive architectural survey practices, the primary focus is on capturing the main structural elements of a building – such as walls, floors, ceilings, doors, and windows – while

often neglecting decorative components that require more detailed survey. The vertical elements of balustrades fall into this category of accessory and detailed architectural features. This is due to both their complex shapes and the practical challenges associated with capturing their complete geometry. Specifically, static laser scanners, typically mounted on tripods and positioned at multiple stations along a staircase, are often unable to fully document all surfaces of these elements. As a result, the point cloud data obtained is frequently incomplete, with specific areas of the vertical balusters remaining incomplete.

These limitations underscore the importance of developing a flexible and adaptable generative modeling pipeline, capable of compensating for the incomplete datasets that are commonly encountered in architectural heritage documentation. For these reasons, the primary aim of the proposed strategy was to develop a pipeline that seamlessly integrates with the Scan-to-BIM workflow presented in the preceding chapters of this thesis. This innovative workflow is specifically designed to be applicable when data from 3D metric surveys are incomplete or present gaps. In particular, the adopted pipeline – based on GenAI algorithms – consists of the following steps:

- **Step 1: Benchmark preparation**
Preparing dedicated benchmark for shape completion of specific architectural elements;
- **Step 2: Application of an existing Predictive Model of GenAI**
Using a specific predictive model (SnowflakeNet) without making any changes on the code;
- **Step 3: Fine tuning and implementation dataset**
Adapting SnowflakeNet to our application context by implementing 50 (1st phase) and 150 (2nd phase) elements to the starting benchmark and re-training the pre-trained model;

Finally, at the conclusion of Step 2 and 3, a comprehensive experimental evaluation was conducted to validate the effectiveness of the proposed workflow. The results of this validation will be discussed in detail in Section 4.4. Subsequently, the forthcoming sections provide a comprehensive explanation of the steps outlined above.

4.3.1 Benchmark preparation

The present paragraph is specifically dedicated to providing a detailed analysis of Step 1. In particular, the aforementioned starting dataset was acquired using TLS technology with the FARO FOCUS X 330 scanner. A total of four scans were conducted with the aim of simulating a rapid survey to capture only the main architectural elements of the analyzed staircase segment. Consequently, the vertical components of the balustrade were intentionally left incomplete in certain sections. To further enhance the realism of the simulation and to rigorously test the

effectiveness of the generative algorithms, it was decided to increase the presence of gaps within the point cloud. Specifically, after isolating the vertical elements of the balustrade, random gaps were introduced to better simulate different types of incomplete data. In this context, three types of gaps were identified and generated, as summarized in Figure 4_3:

- **Gap 1 < 5cm**
A small-sized gap located in the upper portion of the object, where no significant morphological variations are observed, is taken into consideration;
- **Gap 2 between 5-15cm**
A medium-sized gap located in the upper portion of the object, where a morphological variation is observed, is taken into consideration;
- **Gap 3 > 15cm**
A large-sized gap extending along the entire length of the object, where a substantial morphological variation is observed, is taken into consideration. In this specific case, it was decided to remove the two mirrored scans from the four acquired, in order to simulate a realistic scenario that could occur during a survey of this nature.

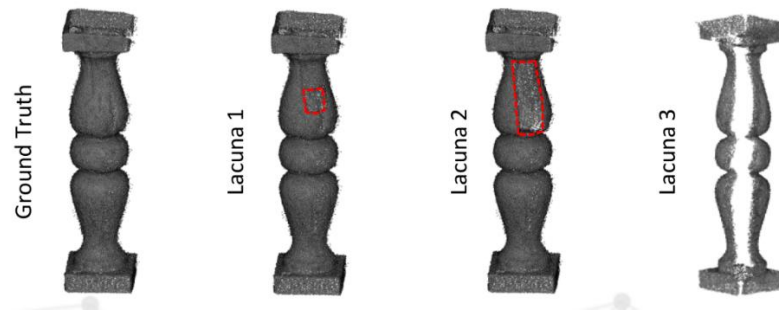


Figure 4_3: Three different types of gaps identified on the vertical elements of the balustrade.

The next step, once these gaps were generated within the point cloud of the vertical element, was to test the SnowflakeNet generative network without making any kind of adaptation of the source code provided by the developers.

4.3.2 Application of an existing Predictive Model of GenAI

As mentioned earlier, SnowflakeNet constitutes a deep learning architecture for point cloud completion, characterized by its innovative approach to modeling the generation process as a hierarchical, snowflake-like expansion of points. The network is designed to address the intrinsic challenges of the discrete and unstructured nature of point clouds, particularly in terms of capturing fine local geometric details. In particular, this section is dedicated to highlighting the distinctive features of the SnowflakeNet predictive model and detailing how it was evaluated for the completion of point clouds derived from our application case, during the experimental activities of Step 2.

SnowflakeNet consists of three components: Feature Extraction, Seed Generation, and Point Generation (Figure 4_4). The input is a point cloud requiring completion, and the output is a completed point cloud that retains the same geometric characteristics as the input, both locally and globally. Each component is defined by parameters that are tuned during the training phase to optimize the desired output.

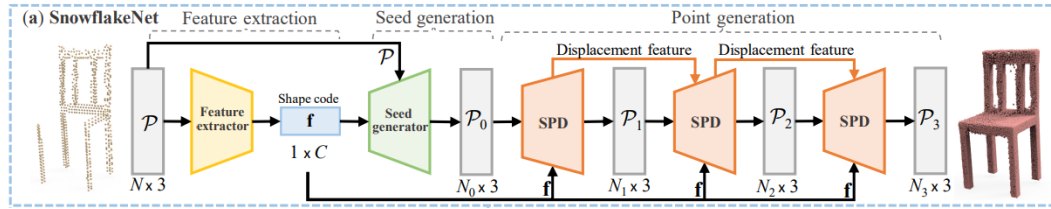


Figure 4_4: The overall architecture of SnowflakeNet, which consists of the following three modules: feature extraction, seed generation and point generation. (Xiang et al. 2021).

The first part of the network takes as input an incomplete point cloud of shape $N \times 3$, where N is the number of points composing the cloud and 3 are the spatial coordinates. It produces a $1 \times C$ vector (shape code) that captures both the global structure and local patterns of the target shape. The shape code can be seen as a concise numerical representation of all the information needed to reconstruct the cloud. This is done using the techniques presented in the pioneering works on PointNet++ and Point Transformer.

The vector produced by the Feature Extraction module serves as the input for the subsequent Seed Generation module, whose objective is to generate a coarse yet complete point cloud (of dimensions $N_0 \times 3$, where $N_0 < N$) of the target shape, approximately capturing its structure and geometry. The points in this cloud, referred to as seeds, are later multiplied in the final stage to achieve the density of the output point cloud. The shape code (Figure 4_5) is fed into a point-wise splitting (PS) operation—a deconvolution process that generates, for each vector element, a feature vector representing both the existing and missing structures of the shape. Each feature vector is then concatenated with the same shape code and provided as input to a multi-layer perceptron (MLP), a simple neural network with a single hidden layer, to produce an intermediate point cloud of dimensions $N_c \times 3$. This

intermediate cloud is concatenated with the input cloud, and the combined result is subsampled to N_0 points, yielding the point cloud P_0 as shown in the figure. The subsampling is executed using Farthest Point Sampling (FPS). Consequently, P_0 is a coarse point cloud that includes points in the missing regions, with these points serving as the seeds from which the final point cloud will be generated.

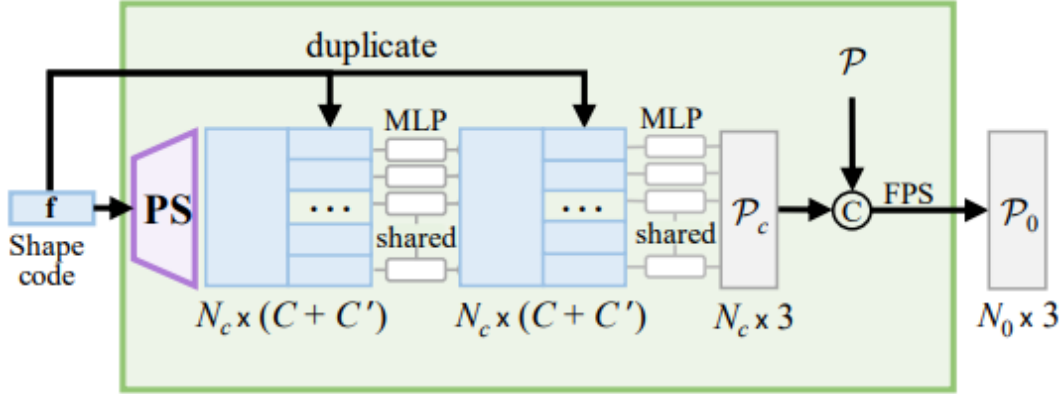


Figure 4_5: The details of the seed generation module. (Xiang et al. 2021).

Once the point cloud P_0 , which provides a rough approximation of the complete target shape, has been obtained, the Point Generation module aims to produce a more detailed final point cloud. This is done by concatenating three Snowflake Point Deconvolution (SPD) modules. Each module receives the point cloud from the previous stage and generates an upsampled version (P_1 , P_2 , P_3 , as shown in Figure 4_6).

The SPD module constitutes the truly innovative component of SnowflakeNet. Its objective is to increase the number of points, thereby revealing the detailed geometry of the point cloud. This is achieved by oversampling the input point cloud and adding displacements to each point, which are derived from the initial shape code and from the information produced by the preceding SPD layer, preserved through the skip-transformer. The skip-transformer is employed to facilitate cooperation among the three SPD modules. For the mathematical details regarding the functionality of this module, please refer to the paper of Xiang et al. (2021).

The i -th SPD module receives as input the point cloud generated by the previous layer along with the shape code produced by the Feature Extraction module. These inputs are processed by a PointNet that generates a per-point feature vector Q . Subsequently, the skip-transformer takes the vector Q and the displacement features produced by the preceding layer and, using an attention mechanism, produces a new vector of shape context features H . As in the Seed Generation module, a point-wise splitting operation is applied to this vector, and the result is fed into a multi-layer perceptron (MLP) to produce the displacement features K . The vector K is then employed to generate the point displacement ΔP via another MLP. It is noteworthy that K will subsequently be processed by the skip-transformer in the next SPD layer. Finally, the displacements are added to an

oversampled version of the input point cloud, resulting in a new point cloud that is forwarded to the subsequent layer.

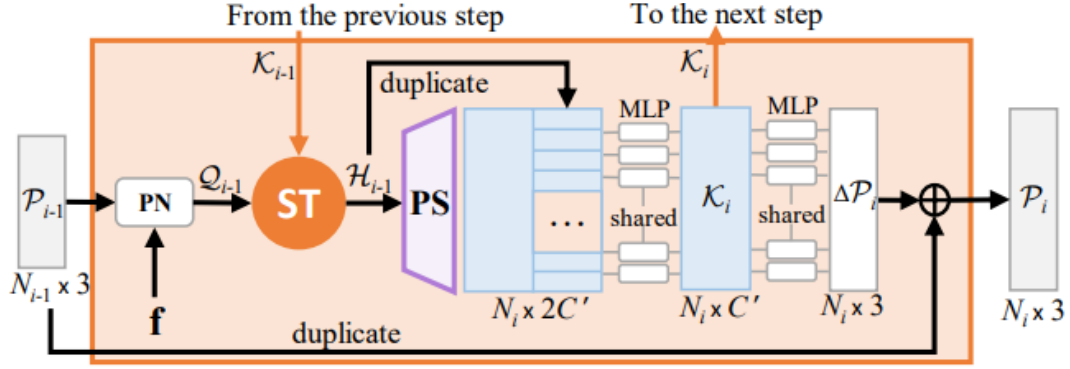


Figure 4_6: Snowflake point deconvolution (SPD). (Xiang et al. 2021).

The neural network was subsequently tested to automatically complete the incomplete point clouds derived from the benchmark associated with our application. In general, the ultimate goal of training a neural network is to minimize a loss function that quantifies the discrepancy between the network's output and the expected ground truth, by measuring the difference between the target point cloud and the one generated by the network. In our specific case, during training, portions of the point clouds are randomly removed and provided as input to the network. The network's output is then compared to the complete original point cloud, and the loss function is computed. Subsequently, using a backpropagation algorithm, the network parameters are adjusted to minimize this loss.

In summary, SnowflakeNet advances the state-of-the-art in point cloud completion by modeling the generation process as a progressive, tree-structured expansion of points. This approach not only preserves global coherence but also faithfully reproduces fine-grained local details, thereby offering significant promise for applications that demand precise reconstruction of complex geometries, such as in the documentation and preservation of cultural heritage.

4.3.3 Fine-tuning and implementation dataset

This paragraph provides an in-depth analysis of Steps 3. At this juncture in the workflow, we sought to enhance the predictive capabilities of the neural network by tailoring it more specifically to our application context. To achieve this goal, we have chosen to adopt the fine-tuning technique, adapting an existing predictive model to a specific dataset that represents our application context. Before diving into the methodological section, it's necessary to briefly introduce the concept of fine-tuning and how this approach can benefit the present strategy.

The Fine-tuning approach could be described as adapting a pre-trained model so it fits particular needs, tasks or applications. It's a critical deep learning technique, especially in training foundation models for generative AI. The Fine-tuning approach could be seen as part of transfer learning, which utilizes knowledge

from an existing model to start learning new tasks (Yosinski et al. 2014). Fine-tuning a predictive model on one's own dataset involves adapting a pre-trained model (already trained on a large, general dataset) to the specific data associated with a particular problem or application context. In other words, a model that has already acquired general knowledge is refined to specialize in the unique characteristics and nuances of one's own data. Various research has shown how fine-tuning offers several advantages (Yosinski et al. 2014; Donahue et al. 2013; Devlin et al. 2019):

- **Time and Computational Efficiency:** starting from a pre-trained model eliminates the need to train a model from scratch, significantly reducing both computational costs and development time;
- **Improved Accuracy:** by adapting the model to domain-specific data, better performance can be achieved compared to using a generic model;
- **Contextual Specialization:** fine-tuning allows a model trained on general data to be adapted and specialized for specific tasks or domains, enhancing its ability to perform effectively in the target context.

In this particular thesis work, a dedicated dataset was generated to effectively apply the fine-tuning technique. This specific dataset was constructed by merging the LiDAR point cloud of the application case with N point clouds representing various types of vertical elements that can form a balustrade. By providing the neural network with a larger number of similar elements from which to learn, its predictive capacity can be improved.

Due to the impossibility of acquiring an adequate and high number of such models – each distinct from the others – a semi-automatic generation of this supplementary dataset was chosen. To this end, and in accordance with the experiments described in Chapters 2–3, specific VPL nodes were employed to semi-automatically generate a series of repetitive elements whose morphology continuously varies, starting from an initial point cloud. In particular, the ground truth representing the typical vertical element of the detected balustrade was used as the input point cloud. Dedicated cutting planes were first generated to section the point cloud, and subsequently, nodes were created to extract only those points necessary to form the generative profiles of the primary geometry. Finally, leveraging libraries such as Numpy and Python 3D implemented within the VPL environment, an algorithm was developed to take the aforementioned profile points and randomly alter their positions. In this way, by merely modifying certain variables within the code, it became possible to automatically generate similar elements with ever-changing morphology. As will be further detailed in the following section on result validation, an initial synthetic dataset comprising 50 elements generated via the VPL approach was produced (Figure 4_7). Subsequently, to further enhance the learning of the generative network, the dataset was expanded with an additional 150 elements.

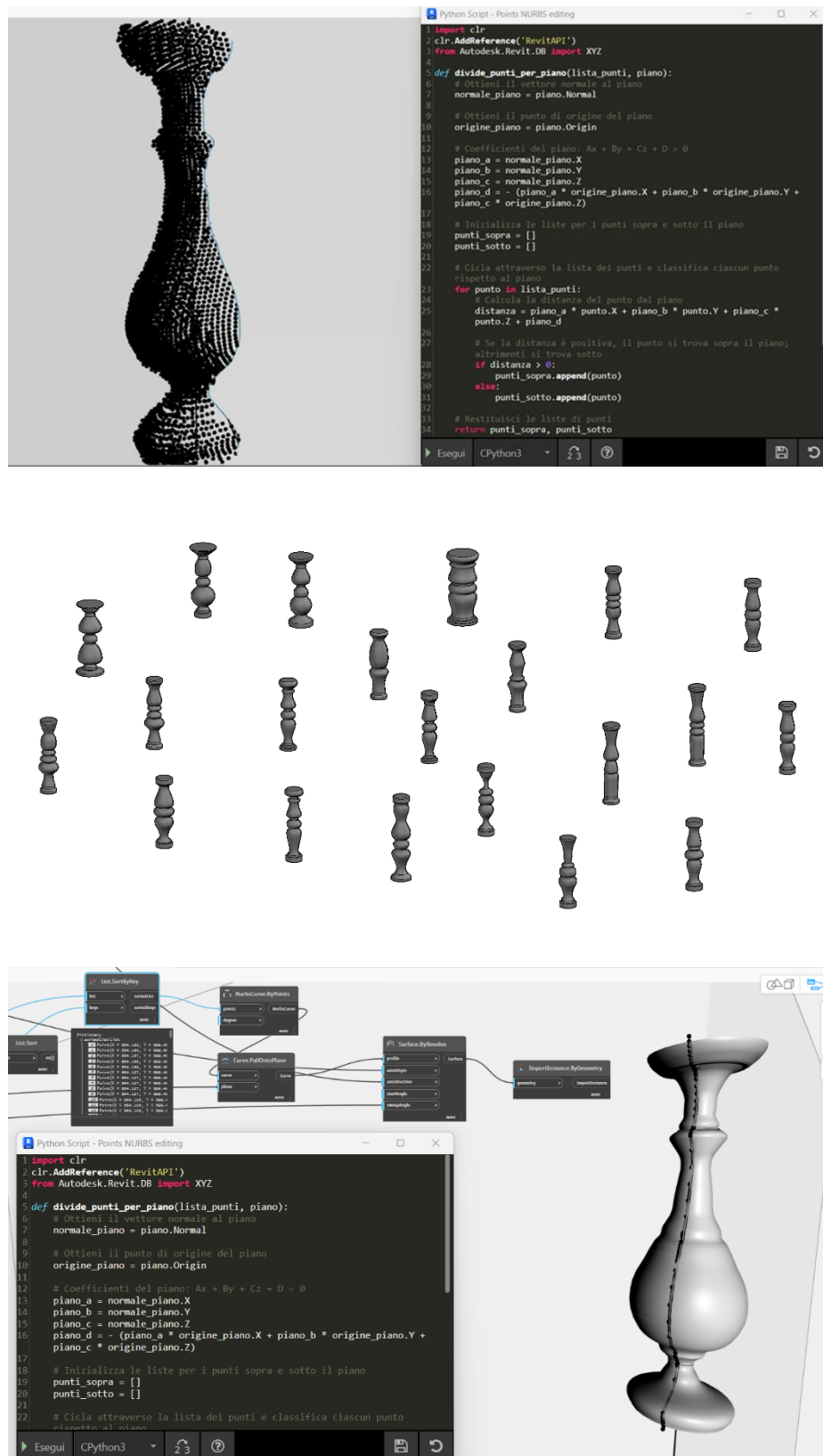


Figure 4_7: Example of semi-automatic generation of essential elements for fine-tuning using VPL.

4.4 Evaluation of the results

To evaluate the effectiveness and accuracy of the proposed method, a comprehensive analysis of the results was conducted. In this context, Chamfer Distance (CD) and Cloud-to-Cloud (C2C) analysis were employed as the primary metrics to quantitatively assess shape similarity and geometric accuracy. In particular, the CD metric was adopted in continuity with the approach proposed by Xiang et al. (2021), while the C2C metric was selected due to its widespread use in point cloud analysis within the cultural heritage domain.

Among the various loss-related metrics used in point cloud analysis, the F1 score is sometimes applied – particularly in segmentation or classification tasks – where it operates on a point-by-point basis by comparing predicted and ground-truth labels. Recent surveys such as Zhuang et al. (2024) have also acknowledged the use of F1 in point cloud completion tasks, provided that a clear point-wise correspondence between the generated output and the reference data is preserved. However, this condition does not apply to the generative approach adopted in this study, where the input geometry is transformed into a newly synthesized structure without maintaining one-to-one correspondence with the original point cloud. As a result, standard classification-based metrics like the F1 score are not suitable for this evaluation context. Instead, metrics such as CD and C2C – which assess global spatial and morphological similarity – offer a more robust and meaningful means of evaluating the geometric fidelity of the reconstructed shapes.

The following section presents a detailed discussion of the obtained results, highlighting the performance and accuracy of the proposed approach through CD and C2C metrics.

In particular, the CD analysis is widely used to measure the similarity between two point clouds by calculating the average distance from each point in one cloud to its nearest neighbor in the other cloud (Wu et al. 2021). Specifically, given two point clouds P and Q , CD is computed as:

$$CD(P, Q) = \frac{1}{|P|} \sum_{p \in P} \min_{q \in Q} \|p - q\| + \frac{1}{|Q|} \sum_{q \in Q} \min_{p \in P} \|q - p\|$$

This bidirectional calculation ensures a symmetric measure of similarity, making it particularly effective for comparing geometric structures. CD is commonly used in computer vision and 3D modeling due to its computational efficiency and ability to capture subtle geometric differences. In the specific case of SnowflakeNet, the CD is employed to compare point clouds. The loss function to be minimized is defined as the sum of a completion loss and a preservation loss. The completion loss measures the quality of the completion and is calculated as the sum of the CD between the point clouds produced by the various SPD layers (P1, P2, and P3) and the original point cloud, which is subsampled to be comparable

with the outputs from the different layers. In contrast, the preservation loss is obtained by comparing only the original points with their nearest neighbors in the completed point cloud – rather than performing a bidirectional comparison as in the CD – thus measuring how well the structure of the incomplete input has been preserved.

On the other hand, the C2C analysis measures the distance between corresponding points in two point clouds, providing a direct quantification of geometric deviations. In C2C analysis, each point in the source cloud is paired with its nearest neighbor in the target cloud, and the Euclidean distance between these pairs is calculated. The resulting distances are then statistically analyzed to assess the overall accuracy and identify potential geometric discrepancies. This metric is especially useful in evaluating the precision of reconstructed models, as it provides a detailed spatial distribution of errors.

Therefore, it can be concluded that the metrics are grounded in the same underlying principles, justifying their integration in our analysis of the results. By leveraging these two complementary metrics, the evaluation framework ensures a comprehensive and robust analysis of shape similarity and geometric accuracy.

The results obtained through the conducted experimental activity will be critically analyzed below. As introduced in Section 4.3, three different tests were carried out:

- **Test 1**
Application of the original SnowflakeNet model for filling gaps in point clouds from our benchmark dataset;
- **Test 2**
Fine-tuning using a synthetic dataset consisting of 50 new point clouds of vertical baluster elements with varying morphologies;
- **Test 3**
Fine-tuning using the same synthetic dataset as before, expanded with an additional 150 elements.

Within each test, different specific cases – (A) (B) and (C) – were also analyzed, each corresponding to a distinct type of gap, as previously outlined in Section 4.3.1.

The following workflow was used for each test:

- **Feature Extraction & Seed Generation**: The incomplete point cloud is processed to extract features and generate the seed cloud P0;
- **Iterative Transformation**: For N times (three in this case), the seed cloud P0 is progressively transformed into new clouds (P1, P2, P3);
- **Final Output**: The last generated cloud (P3) serves as the final output of the neural network;

- **Training Phase:** During training, each generated cloud is compared with the GT to improve the network's performance;
- **Evaluation Phase:** During the evaluation of the trained network, only the final output is considered, while the intermediate clouds are ignored.

Regarding Test 1, the objective was to evaluate how the SnowflakeNet neural network performs in completing an architectural benchmark, which differs from the datasets for which it was originally designed. Specifically, without making any modifications to the original code, this initial experiment focused on generative completion. The training process was conducted using a pre-trained model on ShapeNet, the most widely used dataset for point cloud completion (Chang et al. 2015). The process begins with the Feature Extraction Module, where an input point cloud is analyzed to derive a shape code. Once the shape code is extracted, the Seed Generation Module constructs a coarse but complete point cloud that approximates the overall geometry of the target shape. The final step is the Point Generation Module, which progressively refines the seed point cloud through three Snowflake Point Deconvolution (SPD) steps. Through this iterative approach, the module ensures that the final point cloud faithfully reconstructs the complete geometry of the target shape. The number of points in the completed point cloud is 16'384, which is the maximum allowed by the pre-trained models available for this specific neural network. Consequently, the input point clouds were downsampled to the same number of points.

As illustrated in Table 4_1, the neural network successfully filled the gap in the incomplete point cloud. However, it is evident that, depending on the gap considered, the generated output cloud is highly noisy (Figure 4_8). As the gap size increases, the generative algorithm faces greater challenges in reconstructing the missing part, leading to the generation of random noise with varying intensity. While the main geometry of the reconstructed vertical baluster element is still recognizable in all gap cases, the background noise produced by the neural network is significantly high in two of them, as demonstrated by the cases of gap (B) and (C). Therefore, a noise removal process was necessary, applying a Statistical Outlier Removal (SOR) filter using a dedicated tool provided by the open-source software CloudCompare©.

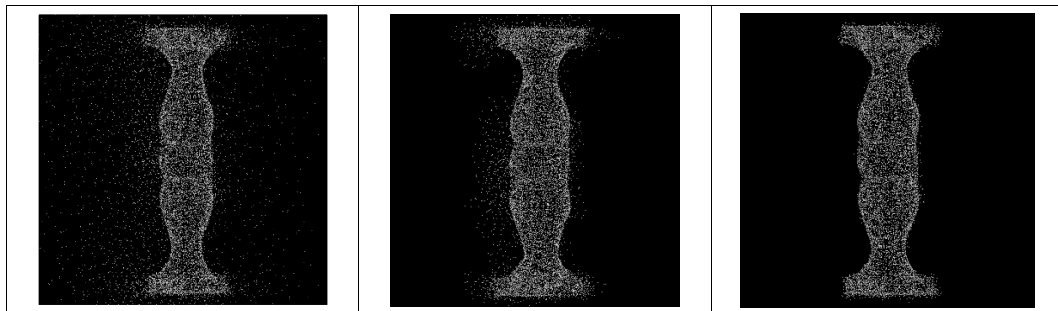
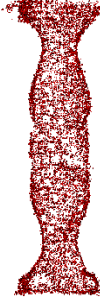
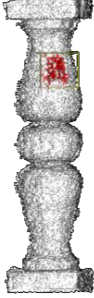
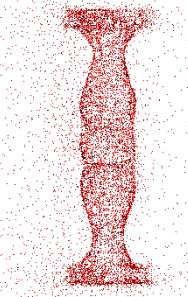


Figure 4_8: Various noise patterns predicted by the original SnowflakeNet.

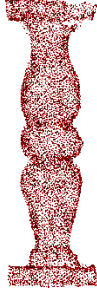
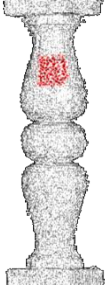
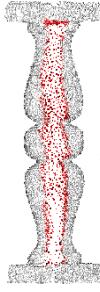
This approach allowed for the identification and isolation of the main geometry of the analyzed element, enabling the subsequent comparison phase between the ground truth (GT) cloud and the point cloud generated by the network. The Table 4_1 presents also the results of the metrics applied in this first experiment. The Chamfer Distance (CD) value was directly extracted from the network, following the guidelines provided by the original code developers, while the Cloud-to-Cloud (C2C) value was obtained using the CloudCompare software. Specifically, by analyzing both metrics, in the gap case (A) the deviation between the GT cloud and the network-generated cloud was found to be less than 7.5 mm. In the case of gap (B), due to its larger extent, the metric results are, as expected, less favorable. Specifically, the values of Chamfer Distance (CD) and Cloud-to-Cloud (C2C) remain below 10 mm, whereas for the largest gap (C), this deviation increases to 15 mm. These results, considering that this initial test was conducted without any modifications to the original code and that training was performed using a pre-trained model on ShapeNet, a dataset composed of elements far removed from the architectural domain, can be considered promising. It provides valuable insights and contributes to facilitating modeling processes in Scan-to-BIM approaches.

Table 4_1: Performance elevation metrics of the generative neural network training applied to Test 1.

	GT	Point Cloud Gap	Point Cloud Prediction	C2C/CD (Absolute Distance)
(A) Gap < 5cm				 < 7.5 mm
(B) 5cm < Gap < 15cm				 < 10.0 mm
(C) Gap > 15cm				 < 15.0 mm

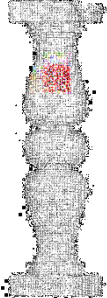
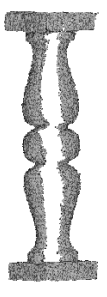
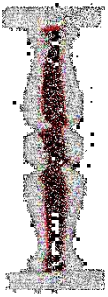
Similarly, the same types of gaps were considered for the generative experimental tasks in Test 2. However, unlike the previous test, an initial fine-tuning phase, described in Section 4.3.3, was performed using an expanded synthetic dataset consisting of 50 new elements. This approach aimed to minimize loss values and enhance the predictive capabilities of the neural network. As shown in Table 4_2, this refinement led to improved results across all gap types, as the network was able to better learn the possible morphological variations of the architectural element under analysis. Specifically, the CD and C2C values decreased from 7.5 mm to 2.5 mm in case (A), from 10.0 mm to 5.0 mm in case (B), and from 15.0 mm to 10.0 mm in the most complex case (C).

Table 4_2: Performance elevation metrics of the generative neural network training applied to Test 2.

	GT	Point Cloud Gap	Point Cloud Prediction	C2C/CD (Absolute Distance)
(A) Gap < 5cm				 < 2.5 mm
(B) 5cm < Gap < 15cm				 < 5.0 mm
(C) Gap > 15cm				 < 10.0 mm

For the final experimental task, Test 3, additional fine-tuning was applied to the original SnowflakeNet code. The primary objective was to determine whether a threshold existed beyond which further training would no longer yield improvements in the network's learning capabilities. Specifically, after expanding the synthetic dataset from 50 to 150 elements, the results did not exhibit significant differences. As shown in Table 4_3, the network demonstrated improved performance only in the case of the largest gap (C), where the CD and C2C values decreased from 10.0 mm to 7.5 mm. However, for the remaining cases (A) and (B), the gaps were filled in a similar manner, yielding results comparable to those obtained in the previous experiment.

Table 4_3: Performance elevation metrics of the generative neural network training applied to Test 3.

	GT	Point Cloud Gap	Point Cloud Prediction	C2C/CD (Absolute Distance)
(A) Gap < 5cm				 < 2.5 mm
(B) 5cm < Gap < 15cm				 < 5.0 mm
(C) Gap > 15cm				 < 7.5 mm

Ultimately, these metrics were compared with the Levels of Accuracy (LOA) to better assess whether this approach, leveraging GenAI algorithms for the completion of incomplete point clouds, can effectively support modeling activities in Scan-to-BIM processes. As shown in Table 4_4, the results are highly promising. In particular, considering only the best outputs obtained from the generative network (Test 3), the results indicate that, in this specific application, very high LOA levels were achieved: LOA40 for cases (A) and (B) and LOA30 for case (C).

Table 4_4: Comparison of generative metrics and Levels of Accuracy (LOA).

TEST 3	(A)	(B)	(C)
C2C/CD	< 2.5 mm	< 5.0 mm	< 7.5 mm
LOA	LOA40	LOA40	LOA30

These results support the conclusion that the methodology proposed in this chapter can be seamlessly integrated into Scan-to-BIM processes when gaps are encountered in point clouds derived from 3D metric surveys. In this context, the proposed workflow can contribute to providing a precise approach for accurately representing and documenting existing buildings within the HBIM framework.

4.5 Discussion on GenAI proposed approach

The pipeline presented in this section, based on the use of GenAI to support established Scan-to-BIM processes, represents a promising and scalable method capable of bridging the gap between parametric modeling and the documentation of cultural heritage. The results and metrics discussed in the previous section confirm the validity of this innovative approach, which currently remains a preliminary study in this field.

Based on the findings obtained, the proposed method allows for the following considerations regarding its scalability and replicability:

- **Enhancement of the neural network's efficiency and predictive capability**

To improve the learning process of the neural network, an increase in the volume of training data would be ideal, ensuring access to a significant number of point clouds of the target element. However, this condition is often difficult to achieve and not cost-effective. In the case study analyzed, for instance, reconstructing the vertical elements of a balustrade would have required a dataset comprising point clouds from N staircases of different buildings. Since access to such heterogeneous datasets is not always feasible, alternative strategies must be considered. The conducted experiments have demonstrated that, in these contexts, the use of synthetic datasets represents an effective and functional solution, offering a viable alternative to traditionally generated and labeled data.

- **Integration of established semi-automatic modeling processes**

The adoption of GenAI techniques can enhance the scalability of established semi-automatic modeling methods within Scan-to-BIM approaches. The simulation of well-known issues in 3D metric surveys – such as incomplete point clouds due to occlusions, physical obstructions, or sensor limitations – has demonstrated that these techniques can contribute to narrowing the gap between parametric modeling and architectural heritage documentation. The results obtained are consistent with major architectural representation scales, highlighting how these methodologies can be

effectively incorporated into a semi-automatic workflow for HBIM modeling, as proposed in Chapters 2 and 3 of this thesis.

- **Limitations related to the analysis of a single architectural element**
The proposed strategy requires further validation across a broader range of architectural elements, extending beyond the decorative features of historic buildings to include other categories such as pillars, floors, doors, and windows. As discussed in this thesis, the adoption of advanced techniques such as fine-tuning on extensive datasets—both synthetic and real—can further optimize the generative completion process. In future research, this could enable the application of the proposed methodology to different

Chapter 5

Conclusions and future perspectives

The primary objective of this research was to experiment with and validate innovative methods to optimize and enhance the efficiency of the Scan-to-BIM workflow applied to architectural heritage. All proposed methodologies share a common goal: improving parametric modeling by intervening in different phases of data acquisition, processing, and modeling. In particular, this study has explored three key aspects:

- **Semi-automatic modeling of architectural elements from classified point clouds using Visual Programming Languages (VPL)**

The methodology developed in this study has proven to be highly effective in optimizing Scan-to-BIM procedures, enhancing their efficiency and automation. At the core of the proposed workflow is the automatic modeling of architectural elements, which leverages Visual Programming Languages (VPL) to streamline the transition from raw survey data to structured HBIM models. This approach enabled the development of dedicated tools designed to support modeling operations, complementing the standard functionalities provided by conventional BIM authoring software. By reducing reliance on manual interventions, this method significantly accelerates the modeling process while maintaining a high level of accuracy.

- **Semantic enrichment of HBIM models by leveraging classified data and integrating VPL environments with Python libraries for managing 3D data**

A fundamental aspect of this approach is the efficient use of classified data, where ML and DL algorithms play a crucial role in structuring the extracted information from point clouds. Through automated classification, architectural components can be systematically identified and categorized, ensuring a more structured and efficient modeling process. Building on this structured classification, the semantic enrichment phase ensures that HBIM models go beyond mere geometric representation. The semantic information derived from classification is

integrated into the BIM environment through the combined use of VPL and 3D Python libraries, enabling an enriched model that embeds meaningful metadata. This step is essential for restoration, conservation, and heritage management, as it facilitates interoperability and enhances the usability of HBIM models for interdisciplinary applications. By linking classified point cloud data with structured information inside the BIM environment, this methodology strengthens data consistency and accessibility, making heritage documentation more robust and insightful.

- **Optimization and completion of primary data, with a specific focus on filling gaps in point clouds using Generative Artificial Intelligence (GenAI)**

Finally, to improve the overall quality and completeness of the dataset, the workflow incorporates the optimization of primary data. This phase focuses on refining point clouds obtained through terrestrial laser scanning (TLS), digital photogrammetry, and mobile mapping systems (MMS SLAM) by employing Generative AI for gap completion. Addressing the common issue of missing data, this step enhances the reliability of the dataset, ensuring that the resulting HBIM models achieve greater accuracy and consistency. The integration of these processes has led to a more efficient, structured, and automated Scan-to-BIM pipeline, reducing processing time, minimizing errors, and significantly decreasing the need for manual interventions. By adopting AI-driven techniques, this study demonstrates the potential of automated workflows in enhancing the precision, scalability, and applicability of heritage BIM modeling, paving the way for more advanced and data-driven digital heritage documentation.

Despite the promising results, the research also highlights significant challenges, chiefly the limited availability of training data for AI models in the heritage BIM domain. Training state-of-the-art AI algorithms (such as deep learning models or even classical machine learning classifiers) requires large, high-quality datasets with comprehensive annotations. In the context of historic buildings, creating such datasets is difficult. Architectural heritage structures are often unique, with complex and irregular features, resulting in a scarcity of publicly available datasets suitable for AI training. Nevertheless, considerable efforts are currently underway to bridge this gap (ISPRS Working Group II/6). During the course of this work, it became evident that obtaining enough labeled examples (for instance, point clouds with each point labeled by architectural element type) is a time-consuming and labor-intensive process. The lack of data can lead to models that do not generalize well beyond the specific case study they were trained on. In

practice, this means an AI model trained on one building might struggle when applied to another building with different styles or levels of ornamentation. Overcoming the data scarcity problem is thus a major hurdle: it may involve generating synthetic data, augmenting existing scans, or encouraging the sharing of annotated datasets within the research community. Until more extensive training datasets become available, the full potential of AI in Scan-to-BIM will be difficult to achieve, as models might remain limited in their accuracy or scope of applicability.

Another challenge identified is the high level of expertise required to effectively implement AI-driven Scan-to-BIM processes. This field sits at the intersection of several disciplines – architectural conservation, geometric modeling, computer vision, and machine learning – and leveraging AI in HBIM demands knowledge in all these areas. Practitioners need to understand not only the architectural domain (to correctly interpret building elements and historical construction techniques) but also possess skills in data science and programming to train and fine-tune AI models. For example, preparing a dataset for machine learning involves specialist tasks like point cloud processing, annotation of architectural features, and choosing appropriate features or network architectures for classification. Similarly, interpreting the output of an AI model in a meaningful way (e.g. validating that the automatically classified elements make sense in architectural terms) requires domain expertise. This thesis underlines that a multidisciplinary collaboration is often necessary: architects, heritage experts, and BIM specialists must work alongside AI researchers or software engineers. However, such collaboration can be challenging to organize, and there is a learning curve for all parties involved. The need for specialized knowledge may also act as a barrier for wider adoption of AI tools in everyday professional practice. It suggests that as these AI tools evolve, efforts should be made to simplify their use (for instance, through user-friendly interfaces or training programs) so that the benefits of AI can be accessed by practitioners without extensive programming background. In summary, building effective AI-driven HBIM solutions is not just a technical endeavor but also an educational one, requiring capacity building and knowledge exchange across traditionally separate fields.

The findings of this work open several promising avenues for future research and development. One promising direction for further automation of Scan-to-BIM workflows involves leveraging Visual Programming Languages (VPLs) to develop customizable libraries of tools tailored to specific categories of architectural elements. By organizing tools according to recurring morphological patterns—such as cornices, columns, arches, or window frames—researchers could create flexible, reusable modules capable of accelerating and standardizing modeling operations across similar typologies. These libraries would enable more efficient adaptation of automated processes to a wide variety of heritage structures, facilitating both precision and scalability in HBIM production.

A secondary recommendation is to focus on expanding and improving training datasets for heritage AI applications. This could involve creating open repositories

of labeled point clouds or images of historic architectural elements, enabling researchers worldwide to train more generalized models. Techniques such as transfer learning and data augmentation could be further explored to make the most of limited data – for instance, adapting models trained on contemporary buildings or synthetic data to work with heritage structures.

Another promising area of research concerns the enhancement of Scan-to-BIM workflows through the integration of Generative AI algorithms. The present thesis has only begun to explore this topic—such as the completion of deficient point clouds—addressing selected aspects and offering an initial contribution. However, the field remains wide open, with numerous challenges and opportunities yet to be addressed. One particularly relevant direction involves improving the predictive performance of such algorithms through the creation of tailored datasets of architectural elements. By enabling the algorithm to better learn the formal and semantic features specific to cultural heritage, such datasets could significantly increase the contextual accuracy and reliability of the predictions.

A major barrier in this respect is the lack of benchmark datasets specifically designed for architectural applications. Most of the benchmarks currently used in generative point cloud modeling—such as ShapeNet or ModelNet—contain mainly generic, object-level categories (e.g., furniture, tools, vehicles) that do not reflect the morphological complexity or material characteristics of built heritage. This mismatch reduces the applicability of existing models to real-world cultural heritage scenarios. Developing benchmarks focused exclusively on architectural components—especially those with historical or stylistic significance—would make it possible to train and evaluate models on more relevant tasks, such as the reconstruction of decorative frames, arches, capitals, or vaults.

In this sense, creating well-structured, open-access repositories of labeled architectural data would support not only improved algorithmic performance, but also encourage reproducibility and comparability across studies. This would represent a significant step toward the development of more robust and heritage-aware generative tools. Ultimately, it would enable the generation of HBIM models from predicted point clouds that are more accurate, semantically rich, and faithful to the physical and historical reality of architectural assets.

Still within the scope of Generative AI, in this work of thesis was adopted only Chamfer Distance (CD) and Cloud-to-Cloud (C2C) as validation metrics to assess the quality of the predictions. However, recent studies – such as Xiao et al. (2024) – have demonstrated the potential value of incorporating additional evaluation criteria, including Earth Mover's Distance (EMD) and the F1 Score. Integrating such metrics into future analyses could significantly enhance the robustness of the evaluation framework by capturing different aspects of geometric similarity and structural correspondence. This multi-metric approach would help reduce the risk of overestimating or underestimating prediction accuracy, thereby providing a more comprehensive and reliable assessment of generative model performance

More broadly, refining AI algorithms to better accommodate the inherent complexities of historic architecture remains a crucial research objective. This may

involve the development of dedicated neural network architectures or the integration of domain-specific features capable of addressing challenges such as irregular geometries, ornamental detailing or the presence of material degradation typical of heritage structures. Additionally, future research should evaluate how well these AI-driven methods scale and transfer to different contexts: applying the developed workflow to a variety of buildings (different historical periods, styles, or materials) will test its robustness and versatility. It is also worth exploring the integration of AI-driven Scan-to-BIM workflows into commercial BIM software and heritage management practices. For AI tools to gain wider adoption, they must be accessible to practitioners; thus, creating plug-ins or modules for existing BIM platforms, or even standalone user-friendly applications, would be a valuable step. Moreover, interdisciplinary research teams including architects, conservators, data scientists, and software developers should continue to work together to bridge the gap between technical innovation and practical application on site. Field testing on live projects (such as restoration or renovation projects) can provide feedback on what improvements are needed for AI tools to be truly effective in practice. In summary, while AI-driven methodologies for Scan-to-BIM are still evolving, their potential to revolutionize heritage building modeling is evident. By addressing current challenges – particularly the scarcity of training data and the steep expertise requirements – and pursuing the outlined future directions, researchers and professionals can unlock more robust, accurate, and efficient HBIM processes. This will not only streamline the creation of digital models for historic structures but also enhance our capacity to analyze and preserve architectural heritage. Despite the challenges that remain, the proposed approach constitutes an important step towards the efficient digitization of architectural assets, allowing sustainable documentation, preservation, and enhancement of cultural heritage.

Appendix A

6.1 Complementary application case: The Standard of Ur

As outlined in Chapter 3, the methodology proposed in that phase was tested on two distinct application cases in order to assess its flexibility and scalability across different data sources and representation contexts. While the main body of that chapter focuses on the Royal Palace of Turin – representing a point cloud-based, architectural-scale scenario within the HBIM framework – this appendix presents the second application case, concerning the Standard of Ur. Unlike the first, this case is based on an image-based mesh model and addresses the potential extension of the methodology to object-scale heritage artefacts. Although more peripheral to traditional HBIM applications, it serves as a valuable complement to the primary study, enabling further exploration of the workflow’s adaptability to different input types, geometric resolutions, and conservation scenarios. The following sections provide a complete overview of the process and results related to this second application case.

The second application case, briefly introduced in Section 3.2, has been included to further explore the adaptability and scalability of the methodology proposed in Chapter 3, within a different Cultural Heritage context, thereby complementing the analysis developed in the main chapters. Unlike the primary case study presented in Chapter 3, which focuses on architectural scale (a courtyard module of Royal Palace in Turin), this additional application case refers to a digital replica – characterized by a sub-millimetre resolution – of the Standard of Ur (a masterpiece of the Sumerian civilisation, actually stored in the British Museum - Figure 6_1). The two case studies are different not only in terms of size and resolution but also regarding the achieved metric accuracy (this is strongly influenced by different needs related to the application areas of 3D metric documentation at an architectural scale and museum assets digitisation). Consequently, the point cloud of the courtyard exhibits a centimeter-level accuracy, coherent with the architectural scale requirements, while the digital replica resolution is higher than 50,000 points/cm².

In this specific case, the task is to evaluate the suitability of the proposed workflow when larger scales than those traditionally used in the architectural framework. The 3D surveying of the object (Patrucco et al. 2023a) is performed by integrating a Faro Quantum Max S Model 2.0m Arm – equipped with a Faro xP Lase Line (LLP) – scanner and a close-range photogrammetric survey (288 images with a Canon EOS 5DSR equipped with a 50mm macro lens from an average shooting distance lower than 50 cm).

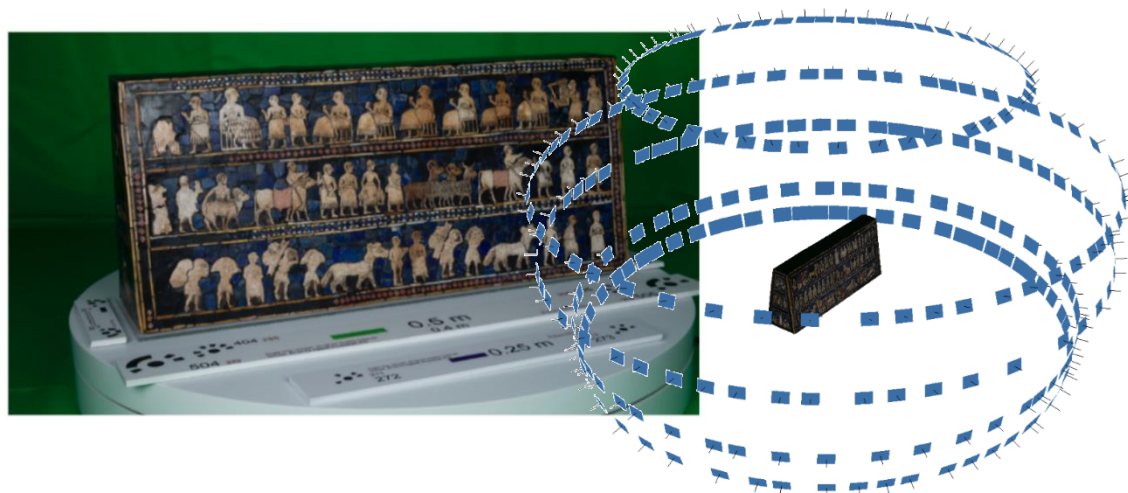


Figure 6_1: Standard of UR. (Patrucco et al. 2023a).

With reference to the workflow steps described in Section 3.2.2, the first operation consisted in classifying the reality-based dataset according to a material recognition criterion. For the second case study, a material-based classification was performed using a machine learning algorithm, specifically the Fast Random Forest classifier implemented through the Trainable Weka Segmentation (TWS) plugin, an open-source component of the Fiji distribution of ImageJ. This tool enables pixel-wise supervised classification of image-based datasets by allowing the user to train models on manually annotated regions and apply them to the entire image or 3D stack (Figure 6_2). TWS integrates a wide range of feature descriptors (e.g., texture, intensity, edge filters) and supports various classifiers provided by the Weka library. Its intuitive interface, flexibility, and seamless integration into the Fiji environment make it particularly suitable for rapid, non-destructive classification tasks on heritage artefacts derived from photogrammetric imaging. Finally, the classified UV map is then re-project onto the geometric model, as shown in Figure 6_3.

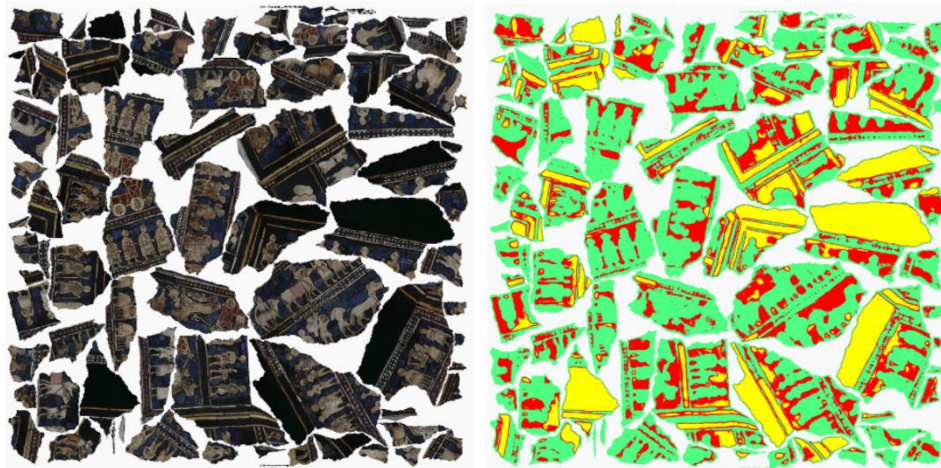


Figure 6_2: Original UV map (left) and classified UV map (right) after the ML process. (Avena et al. 2024).

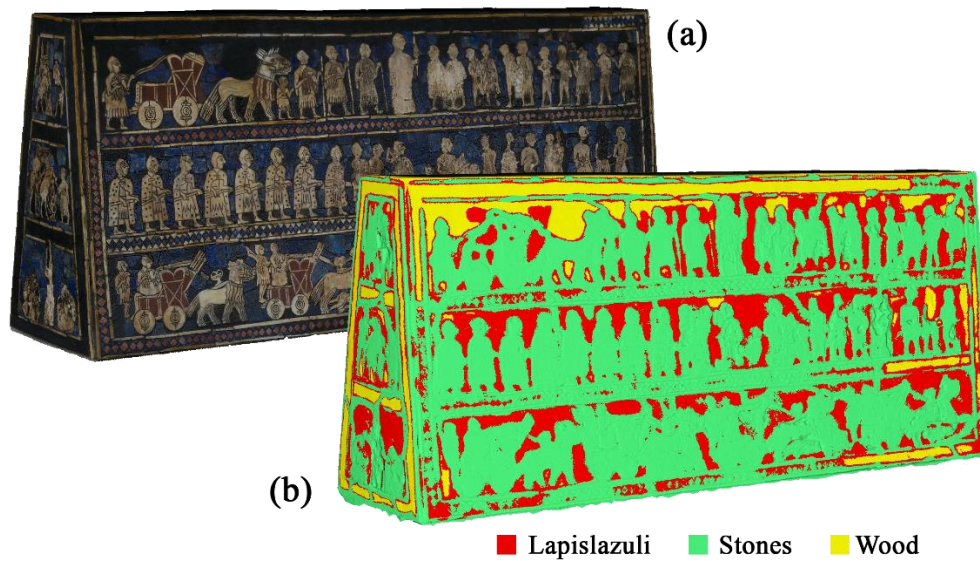


Figure 6_3: Original mesh model (a) and mesh after the reprojection of classified UV map (b). (Avena et al. 2024).

In this application case, the mesh is directly imported into the VPL environment, where its texture has been pre-classified, as described earlier. The process begins with the extraction of RGB values from the classified image, which are subsequently reprojected onto the mesh model by assigning the corresponding colour information to each vertex (Figure 6_4). Similar to the Royal Palace application case, this RGB data is then mapped onto the faces of the mesh. Based on this transfer of information, it becomes possible to segment the 3D model by filtering the mesh according to the desired RGB values, effectively isolating specific material categories (Wood, Stone and Lapislazuli) (Figure 6_5).

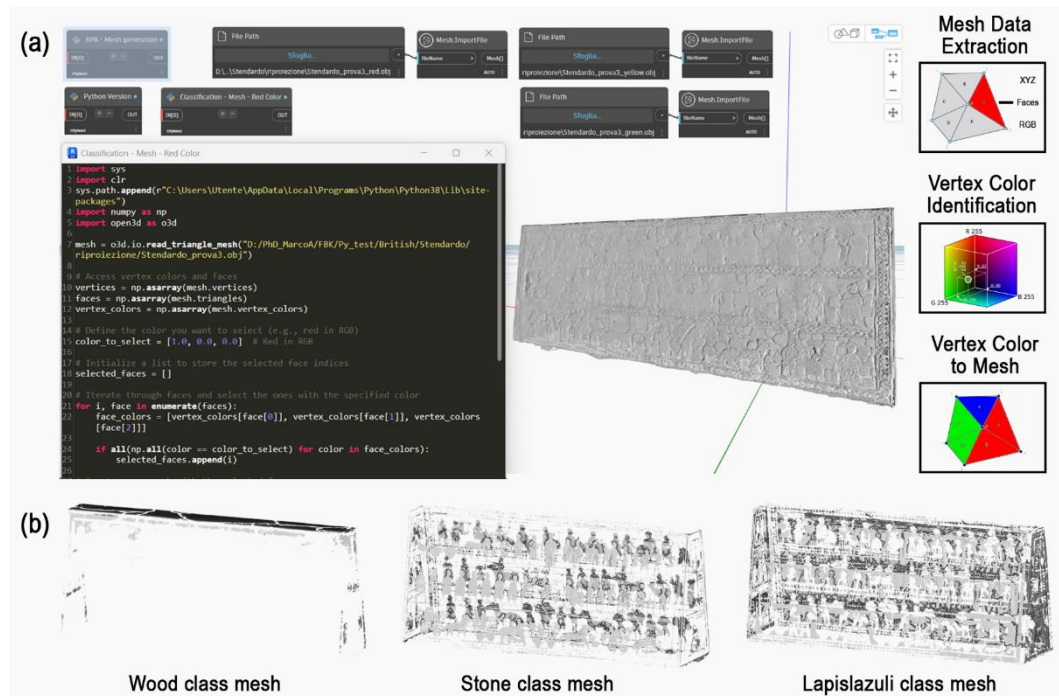


Figure 6_4: (a) Python script for re-classification of the Ur Standard mesh ; (b) examples of meshes obtained according to specific classes.

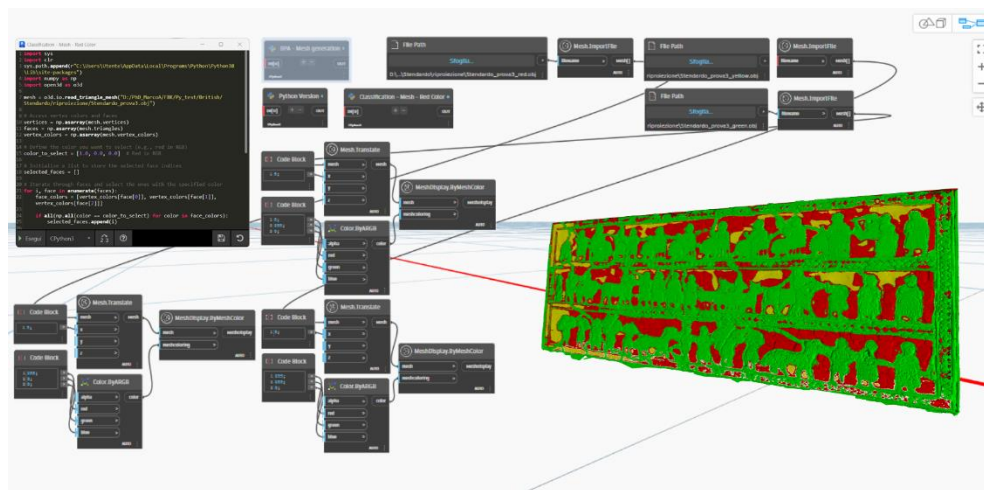


Figure 6_5: Reclassifying and segmentation processes carried out using Open3D Python Libraries in Dynamo environment (Avena et al. 2024).

As discussed in Chapter 3 with reference to the Royal Palace case study, the final stage of the workflow involves transferring the semantically enriched mesh into a BIM environment. A similar operation has been carried out for the Standard of Ur, despite the different scale and typology of the object. Once classified and segmented, the mesh model was converted and imported into the HBIM platform, where specific BIM categories were assigned to its components (Figure 6_6). Accurate categorisation within the BIM environment allows the assigned elements to inherit parametric properties and behavioural rules associated with their respective families.

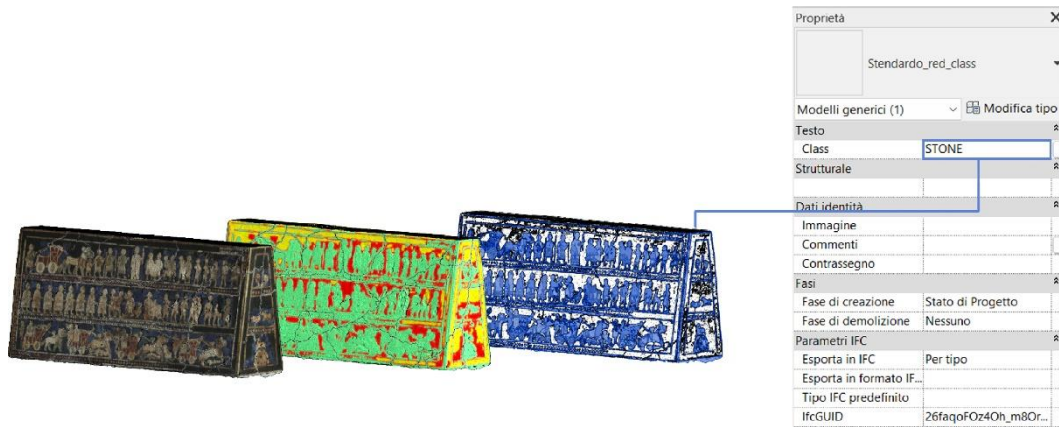


Figure 6_6: segmented 3D model (Standard of Ur) in BIM environment with true colour texture (left), classified texture (middle) and selection of semantically enriched parametric entities (right). (Avena et al. 2024).

The complementary case study of the Standard of Ur demonstrates the potential of the proposed pipeline for the digitization and management of specific heritage components embedded within the built environment, such as museum collections.

The achieved results show the flexibility of the proposed methodology and, specifically, replicability of the method, which has been proven suitable and effective in different transversal contexts characterised by heterogeneous semantic, scales, geometric and topological features (considering also the different scales, resolutions, and accuracies of the different surveying data). The efficiency and effectiveness of a highly automated procedure, based on automatic classification algorithms and VPL, represents a significant opportunity for the operators working in CH digitization domain. It can be observed that the proposed strategy can be efficiently applied in a wide range of application scenarios on very heterogeneous 3D models, depending on the type of preliminary classification. The semantic segmentation and representation can involve various aspects and features, as evidenced by the application of the method to the Royal Palace of Turin application case illustrated in Chapter 3 (architectural scale object): classification of architectural elements, in order to facilitate parametric modelling processes during the generation of HBIM models, but also degradation analysis, material studies, and other features connected to build heritage assets. However, due to the flexibility and adaptability of the proposed strategy, it becomes evident that a similar methodology holds significant potential in different contexts. For example, these models may serve as valuable repositories of architectural components, which can be integrated as needed into larger building information models. Their integration contributes to enriching the BIM environment not only from a geometric perspective – by adding high-fidelity representations of complex forms – but also from a semantic standpoint, by embedding metadata relevant to material composition, conservation status etc. Additionally, such semantically enriched models can also play a crucial role, for example, in supporting the management of museum buildings and, more significantly, the collections housed within them. They act as comprehensive

information containers, not limited to geometric data but extending to material properties, historical metadata, conservation states, and more. In this sense, they contribute meaningfully to a variety of museum operations, ranging from documentation and conservation planning to inventory control, exhibition design, and digital cataloguing.

In conclusion, this approach represents a significant opportunity to advance parametric modelling strategies within the HBIM domain and to enhance the management, interpretability, and usability of digital resources. These resources increasingly require operations of parametrization and semantic enrichment to support dissemination, digital cataloguing and a wide range of applications within Cultural Heritage conservation and digitization workflows.

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