Beyond Traditional H-BIM: AI-Powered Modeling for Heritage Bridges

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Abstract

Heritage Building Information Modeling (HBIM) is the methodology that addresses the growing needs in the management and preservation of Cultural Heritage, by integrating three-dimensional digital models with spatial, temporal, organizational, operational, and other types of information. The digital model, derived from a 3D survey, requires significant time and training efforts when transitioning to the HBIM methodology. Moreover, this process often leads to substantial geometric approximations, due to the limited flexibility of converting point clouds into BIM during manual modeling.
In this context, artificial intelligence plays a fundamental role through the development of algorithms specifically designed to transform project documentation or point clouds into semantic three-dimensional models exportable in IFC format. The proposed case study explores this experimentation applied to an ancient bridge, where infrastructure and culture converge in a perfect dialectical and formal expression of heritage.
The three main phases of the proposed workflow, photogrammetric acquisition via drone, semantic segmentation of the point cloud using AI models (RandLA-Net), and generation of the parametric model in a BIM environment through tools such as AtlasNet, Rhino, and Revit, have led to a significant reduction in BIM modeling time without compromising the final geometric quality.

1. Introduction

The management and preservation of cultural heritage require the adoption of advanced digital tools capable of integrating geometric precision, operational efficiency, and long-term sustainability. This study stems from the need to optimize and accelerate the process of creating semantic BIM digital models. Previous experiments conducted on other case studies with the same goal have revealed challenges that are not always easy to overcome and have produced results that were not entirely satisfactory.

The proposed case study, a bridge from the early 20th century originally built to serve a railway connection, proved particularly suitable for repeated experimentation, due to its geometric characteristics, accessible location (easily reachable and isolated from other structures), and its clear semantic structure. Furthermore, the choice was driven by the uniqueness of an infrastructure that is also a historical artifact, part of the Cultural Heritage. In this case, engineering and culture converge in a single structure, offering visitors both historical and technical insights.

Lastly, the superficial deterioration of the stone structure often leads to rapid aging of the artifact, presenting local administrations with significant challenges in terms of its preservation and management.

A well-constructed BIM digital model, understood here as a model that meets specific quality standards in terms of geometry, metrics, and material definition—enables the development of a BIM platform in which routine and predictive maintenance, cost management, inventory control, inspection data mapping, and integrated dashboards are effective and sustainable (Inzerillo et al., 2023). This, in turn, ensures the long-term preservation of an asset that belongs to the collective heritage (Blake, 2000; Jeon et al., 2023).

In the field of Cultural Heritage (CH), artificial intelligence algorithms are becoming increasingly widespread, significantly reducing the steep learning curves typically associated with BIM software for the creation of three-dimensional models. However, the coding of the algorithms that drive this implementation has been applied primarily to the representation of relatively simple residential buildings and, to date, has not been extended to CH applications involving infrastructures such as ancient bridges. In this study, models generated through a traditional BIM methodological process will be compared with those produced by artificial intelligence, in order to assess the reliability of the latter (Kutlu, 2025).

2. State of the art

The application of advanced semantic segmentation and automatic classification techniques has proven extremely useful in overcoming the main limitations of traditional manual modeling, drastically reducing the time required to generate detailed digital models and improving the accuracy of documentation (Pan et al., 2024).
Recent developments in machine learning have enabled new possibilities for automating the Scan-to-BIM process. For instance, rule-based logic and supervised learning approaches have been used to extract architectural elements from point clouds and generate corresponding BIM families (Patil and Kalantari, 2025).

In the domain of cultural heritage, Croce et al. (2021) proposed a semi-automatic pipeline based on supervised classification to derive H-BIM models from heritage buildings, demonstrating the effectiveness of machine learning methods in reducing manual modeling efforts. Similarly, Banfi and Mandelli (2021) showed how UAV-based photogrammetry can be integrated into HBIM workflows to capture inaccessible or complex heritage structures.

Another notable contribution is GeoTransformer by Qin et al. (2023) which uses geometric inpainting and transformer-based networks to infer missing parts of objects in large-scale scenes.
Building on these advancements, Hu et al. (2019) introduced RandLA-Net, a lightweight yet powerful model for real-time semantic segmentation of large-scale point clouds. This architecture, which combines random sampling and local feature aggregation, has proven particularly effective in scenarios such as heritage masonry structures, where high-density geometry and complex morphology are common.

In terms of mesh reconstruction and surface completion, AtlasNet (Aubry et al., 2018) has emerged as a benchmark solution, using patch-based learning to reconstruct detailed 3D surfaces from sparse or incomplete point clouds. Its generative capabilities make it suitable for modeling irregular or degraded structures, such as historic stone bridges.

3. Methodology

The adoption of Heritage Building Information Modeling (H-BIM) in cultural heritage management offers significant advantages in terms of operational efficiency and process optimization. One of the fundamental principles of H-BIM, interoperability, facilitates multidisciplinary collaboration through advanced and interactive digital platforms. It improves data sharing and integration, ensuring a more coordinated approach to documentation, restoration, and maintenance of historical architecture. H-BIM also assists in monitoring restoration activities and organizing operational phases, creating a structured and accessible archive (Baik, 2024).
However, challenges remain, particularly in adapting H-BIM for historical heritage conservation. A key issue is defining the level of detail (LOD), as achieving the required "as-built" model is difficult due to constraints in data acquisition and modeling. The transition from LOD to Level of Information Need, introduced by ISO 19650 (International Organization for Standardization, 2018a, 2018b), offers better compatibility with conservation requirements. Depending on specific project needs, various approaches are employed, including conventional BIM tools and customized solutions. The workflow shown in Figure 1 illustrates the traditional process of building an H-BIM model (Lovell et al., 2023).

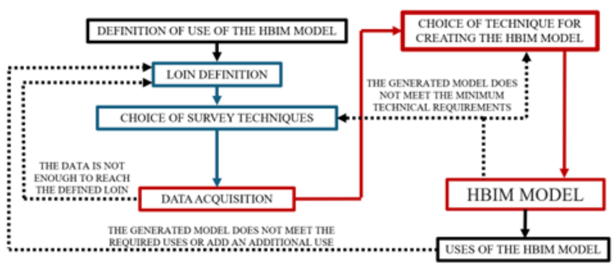

Figure 1. Traditional H-BIM workflow.

The most widespread technique for creating Heritage Building Information Modeling (H-BIM) models still involves manual modeling from point clouds generated through laser scanning (and more generally, point clouds from 3D surveys), a process known as Scan-to-BIM. This methodology is effective but has significant limitations related to the time required for modeling and the potential introduction of human errors during the process. In recent years, however, the development and introduction of advanced software and specific digital tools have substantially simplified the BIM modeling process, facilitating a transition from a predominantly manual process to a partially automated one.

Simultaneously, the rapid evolution of machine learning (ML) techniques has opened new opportunities to significantly enhance efficiency and accuracy in BIM modeling. For example, applying semantic segmentation algorithms allows for automatic classification of architectural elements within point clouds, greatly accelerating the overall process.

Although fully autonomous systems capable of self-learning and continuous improvement without human intervention do not yet exist, it is possible to develop "AI-powered" workflows where artificial intelligence (AI) plays a central role. In these workflows, AI is not merely supportive but acts as a driving force that guides, optimizes, and adaptively automates modeling, significantly reducing errors and increasing operational efficiency.

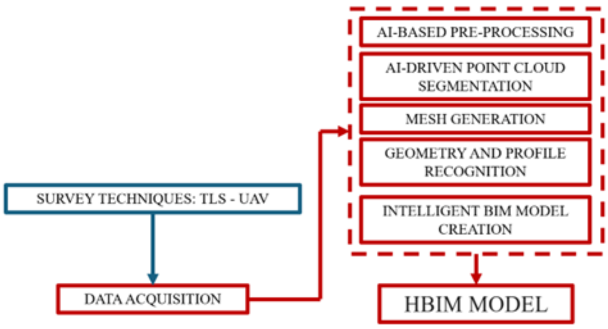

Figure 2. AI-powered BIM workflow.

4. Case study

A stone bridge located along a historic railway line in Sicily, Italy, was selected as a case study. Specifically, the bridge is situated on the Castelvetrano–San Carlo–Sciacca railway line, near the municipality of Sambuca di Sicilia (Figure 3). The railway network was decommissioned between 1959 and 1968, partly due to the seismic event in the Belice Valley, which caused severe damage to the infrastructure. The bridge structure is currently intact, with all its components in generally good condition, as shown in Figure 4 (F. Agnello, 1912).

The decommissioning of this railway network occurred between 1959 and 1968, coinciding with the catastrophic earthquake that struck the Belice Valley, causing significant damage to the railway infrastructure. Along the route, several important engineering structures are still present, including bridges, viaducts, tunnels, and minor civil works, as well as various railway workers' houses. Today, the railway line has been converted into a cycling path, and most of the engineering structures remain in relatively good condition. The application of advanced digital methodologies for the management and preservation of this historic infrastructure could provide substantial support to the responsible authorities, enhancing decision-making processes related to maintenance and restoration activities. Such strategies are essential to ensure the long-term preservation of a heritage of significant historical and engineering value.

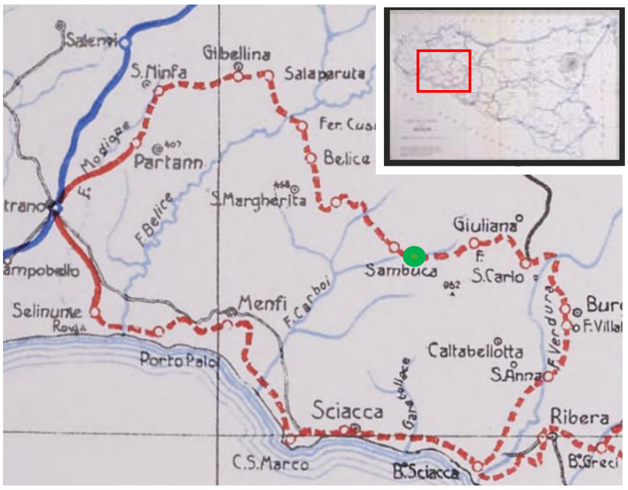

Figure 3. Location of the bridge within the historic railway infrastructure (F. Agnello, 1912).

Figure 4. Aerial photo of the stone bridge under study.

The survey of the infrastructure was carried out using aerial photogrammetry with a DJI Mavic 2 Pro drone. The use of UAVs enables the acquisition of high-resolution photogrammetric data even in areas that are difficult to access from the ground. The collected images were processed with Agisoft Metashape software using the Structure from Motion (SfM) method, which allows the reconstruction of dense three-dimensional point clouds from two-dimensional images (Figure 5). This technique, already well-established in the geomatics field, enables effective 3D modeling of complex structures, reducing both time and costs compared to traditional laser scanning surveys.

Figure 5. Dense point cloud obtained from the UAV survey after post-processing with Metashape.

5. Results and discussion

The generated point cloud was exported in *.ply format and subsequently processed with Open3D using a dedicated Python script. The main operations included translating the point cloud to its centroid to facilitate geometric operations, removing outlier points using the Statistical Outlier Removal (SOR) algorithm, and reducing point density through voxel downsampling (Hackel et al., 2017). These operations significantly reduce the computational load in subsequent processing stages. Artificial intelligence further enhanced the preprocessing phase. The PointCleanNet model was able to learn the characteristics of point clouds, intelligently removing noise and outliers.

In addition to the use of software tools and the application of an AI solution such as PointCleanNet (Guerrero et al., 2019), which significantly simplified the process, manual intervention was still necessary at certain stages, particularly for cleaning unwanted portions of the point cloud, such as the ground, and for performing selective cropping (Figure 6).

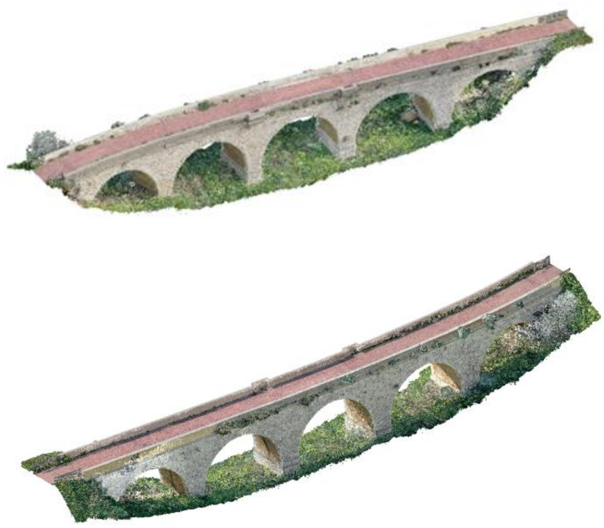

Figure 6. Cleaned point cloud obtained through SOR filtering and the application of PointCleanNet.

Point cloud segmentation is a critical phase for identifying the structural components of the bridge. In this study, segmentation was carried out by identifying the types of elements based on the guidelines provided by the Bridge Management System (BMS) methodology (Tyvoniuk et al., 2024) (Table 1).

Element	Description
Piers	Vertical supports between arches
Impost blocks	Elements between arch and support
Arch	Main load-bearing structure
Vault	Underside of the arch seen from below
Tympanum	Lateral closure of the fill
Deck	Traffic-bearing surface
Coping	Uppermost part of abutments/piers
Parapet	Lateral protective barrier
Fill	Infilling material under the Deck

Table 1. Types of elements for masonry bridges in accordance with the Bridge Management System (BMS).

Due to persistent inaccuracies in the results produced by the adopted algorithms, an initial manual segmentation was carried out to distinguish the terrain from the infrastructure (Figure 7).

Figure 7. Manual terrain-infrastructure segmentation.

At this stage of the study, a semi-automatic segmentation technique was initially adopted. It is based on clustering by elevation levels (Z-level), integrated with the DBSCAN algorithm (Escudero et al., 2024). This approach was chosen not only to divide the point cloud into horizontal bands (Figure 8), but also to facilitate the automatic identification of distinct objects within each band (Figure 9).

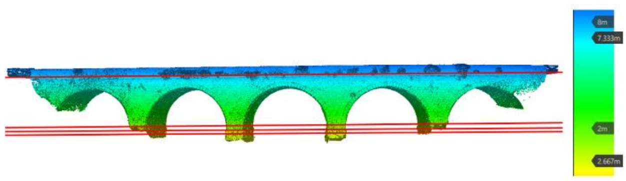

Figure 8. Stratified analysis of the point cloud using elevation-based clustering (Z-axis).

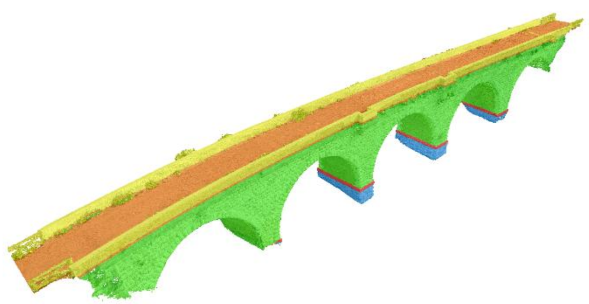

Figure 9. Initial point cloud segmentation obtained using level-based clustering algorithms (Z-level + DBSCAN).

The adoption of elevation-based clustering segmentation (Z-axis) integrated with the DBSCAN algorithm resulted in a classification error, due to the misinterpretation of the parapet as part of the roadway, since both belong to the same elevation band (Figure 10a). This ambiguity was corrected (Figure 10b) by integrating a three-dimensional segmentation algorithm into the workflow, extending the clustering analysis to include longitudinal, X-axis (Figure 11a) and transverse bands, Y-axis (Figure 11b).

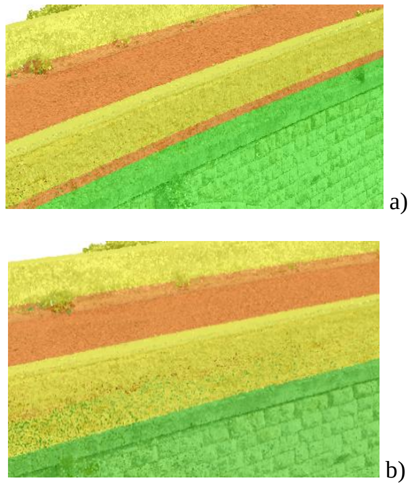

Figure 10. Semantic classification: a) error resulting from semi-automatic segmentation based on elevation clustering (Z-axis) integrated with DBSCAN; b) bug fix with added clustering along X and Y directions.

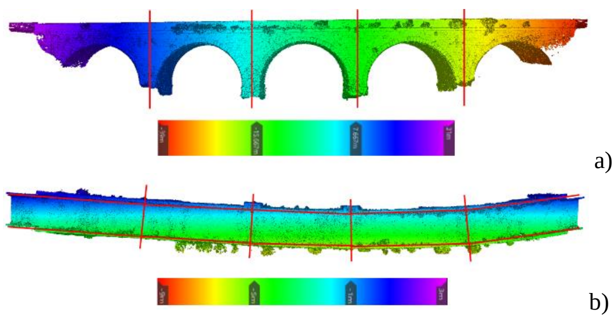

Figure 11. Stratified analysis for segmentation through clustering: a) in the longitudinal direction (X-axis); b) in the transverse direction (Y-axis).

The introduction of transverse bands enabled the segmentation of the bridge into individual spans, allowing for consideration of the infrastructure's planimetric curvature. The automatic identification of spans allowed for the implementation, via code, of the initial segmentation of the structural elements "arch" and "vault," using the arch width, measured on the two lateral elevations, as a reference parameter.

This preliminary segmentation into coarse regions served as the basis for generating an annotated dataset required for the model training phase. Each identified portion was assigned a semantic class corresponding to the main structural components.

In parallel, an artificial intelligence–based approach was developed by integrating the RandLA-Net model (Hu et al., 2019), designed for real-time semantic classification of point clouds. Similar to PointNet++ (Cai and Pan, 2022) and KPConv (Thomas et al., 2019), RandLA-Net enables point-wise semantic labeling by leveraging the local geometry of the point cloud, ensuring high performance even in complex scenarios, such as that of a historic masonry bridge. Following the creation of the annotated dataset, subsequent iterations of the segmentation process were carried out almost automatically, thanks to the direct application of the RandLA-Net model.

At the end of this semi-automatic process, an accurate segmentation of the point cloud was achieved, enabling the partially automated identification of the bridge's various structural components (Figure 12).

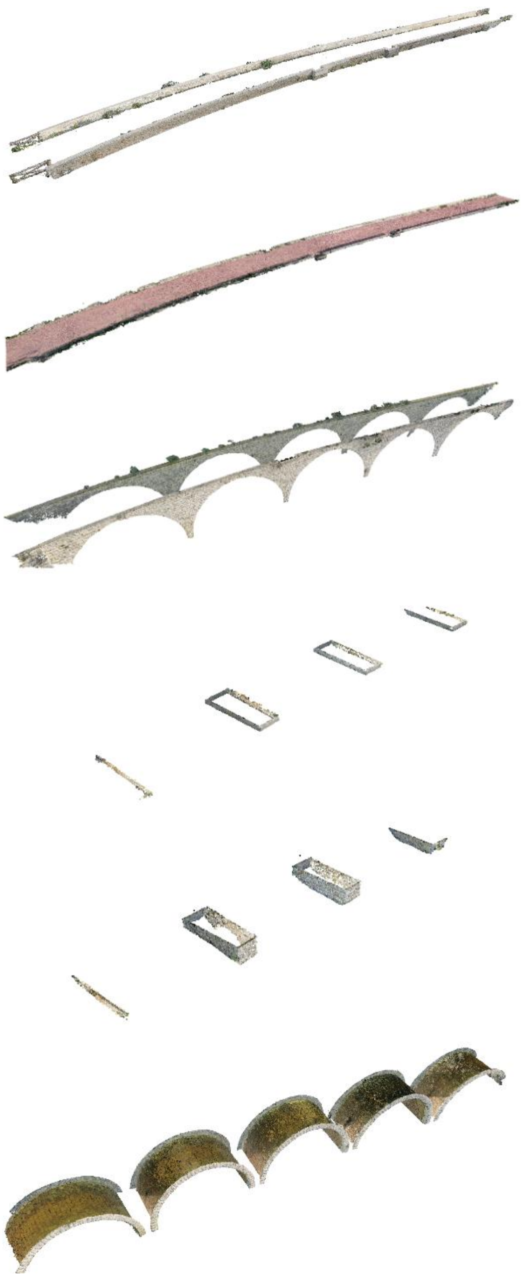
a)
b)
c)
d)
e)
f)

Figure 12. Bridge segmentation obtained through a semi-automatic clustering process (X+Y+Z + DBSCAN) and an AI-based approach (integration of the RandLA-Net model): a) parapet; b) deck; c) tympanums; d) impost blocks; e) piers; f) arches and vaults.

The proposed workflow, although advanced, is not yet fully automated and presents certain limitations, particularly in the removal of vegetation interfering with structural elements and in the accurate segmentation of the terrain.

Figure 13 shows the semi-automated segmentation, with AI-based classification, applied to the main span under study. The same view also includes the segmentation of additional secondary bridge elements, obtained using the same approach described in the previous sections.

In the context of point cloud analysis acquired through architectural surveys, one possible strategy for segmentation consists in decomposing the cloud into elementary surfaces, such as planes or other geometric primitives.

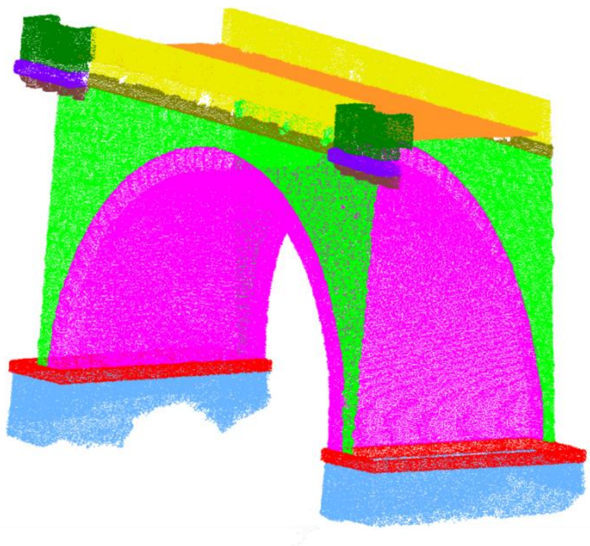

Figure 13. Final segmentation of a bridge span using the (X+Y+Z + DBSCAN) algorithm and an AI-based approach (integration of the RandLA-Net model).

Among the methods that can be adopted, the RANSAC algorithm has proven effective in robustly and parametrically identifying the main geometrically regular components of the structure, such as flat surfaces and simple curvature arches (Croce et al., 2021) (Figure 14a).
This procedure was implemented using the Open3D library in a Python environment, with the aim of isolating dominant surfaces and subsequently generating more accurate 3D meshes associated with each segmented element (Zhou et al., 2018). Mesh generation was carried out using the Alpha Shapes method (Edelsbrunner and Miicke, 1992), which proved particularly suitable for reconstructing the complex geometry of historical masonry structures.

To support this traditional geometric approach, an artificial intelligence component was integrated. Specifically, the AtlasNet (Aubry et al., 2018) model was adopted, a deep learning architecture designed for 3D surface generation from partial point clouds. The use of AtlasNet significantly improved reconstruction quality, particularly in the presence of incomplete or deformed geometries, thanks to its ability to learn coherent shapes from local morphology (Figure 14b).
This integration between deterministic approaches and AI models represents a significant methodological advancement in the processing and digital reconstruction of complex architectural artifacts.

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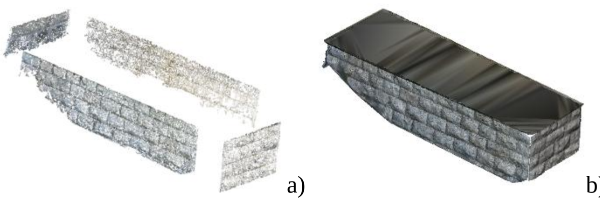
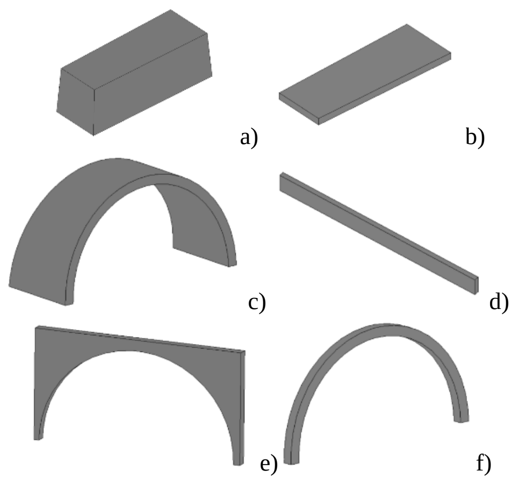


Figure 14. a) Segmentation of the point cloud into planar surfaces using the RANSAC algorithm implemented in Python; b) mesh generation using the Alpha Shapes and AtlasNet methods, followed by the reassembly of elements through a Python script.

The approach based on the Alpha Shapes method proved particularly effective in reconstructing the geometry of complex architectural masonry, thanks to its ability to adapt to the irregular conformation of historic structures. The integration of artificial intelligence techniques, specifically through generative neural networks such as AtlasNet, further refined the modeling process, improving both accuracy and the level of detail in surface generation, even in the presence of discontinuities or missing portions in the point cloud.

The segmented surfaces were subsequently converted into triangular meshes, forming the basis for generating regular three-dimensional geometries compatible with information modeling environments such as BIM. Since Dynamo, in its standard configuration, does not directly support mesh formats, external tools were used to facilitate the import process. In particular, Rhino software, integrated with Grasshopper, was adopted to transfer the meshes into Dynamo.

Integration with Dynamo made it possible to automate the organization and parameterization of the imported objects, simplifying the management and documentation of the bridge's construction elements within the Revit environment. The transition from freeform geometry to parametric objects was achieved through the Rhino.Inside.Revit platform, which enables direct communication between Rhino and Autodesk Revit. To ensure a true informational level and full manipulability of the model, a custom Dynamo script was developed to automate the assignment of Revit adaptive families to the geometries imported from the meshes (Figure 15).



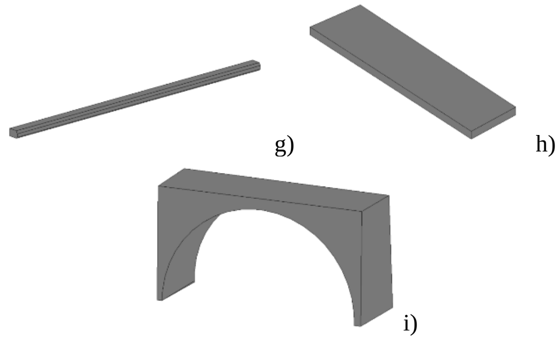


Figure 15. Adaptive parametric families created in Revit for the conversion of meshes into BIM components: a) pier; b) impost block; c) vault; d) parapet wall; e) tympanum wall; f) arch; g) coping profile; h) Deck floor; i) fill.

The process initially involved importing the three-dimensional mesh into the Revit environment as a geometric reference, using the creation of a DirectShape object. From this reference geometry, points belonging to cross-sections were extracted and used as control nodes for adapting the adaptive parametric families.

By using the AdaptiveComponent.ByPoints and FamilyInstance.ByPoint nodes available in Dynamo, it was possible to automatically associate appropriately parameterized Revit families with the actual scanned geometry, locally adapting them to the captured shapes (Figure 16).

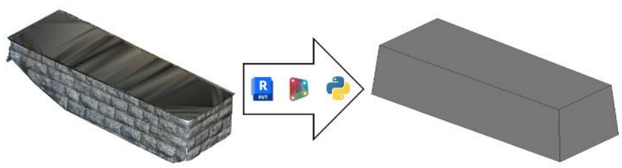


Figure 16. Illustrative visualization of the transition from mesh to parametric element.

As an alternative to this procedure, adaptive surfaces can be generated directly using interpolation features offered by Dynamo, such as Loft.ByCrossSections and Surface.ByPatch. In this case, cross-sections are connected to generate continuous surfaces, allowing a more faithful representation of the complex morphology of the historical infrastructure.
The decision to associate predefined adaptive families was aimed at geometrically regularizing the elements and achieving a more coherent and manageable model within the BIM context. The final assembly of the bridge was ensured through the definition of relational constraints between individual components, implemented via generative scripts in the Dynamo environment (Figure 17).

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Figure 17. Dynamo node sequence for the generation of adaptive components in the BIM model.

Each parametric family was assigned specific informational attributes, including construction type, material, and structural identifier, in accordance with the modeling standards. Once the semi-automatic generation of the bridge structure was completed, achieved through the integration of artificial intelligence techniques and Python and Dynamo scripts (Figure 18).
Adaptation issues with parametric families occurred in cases where the reference mesh did not provide sufficiently complete or accurate geometry. This was particularly evident for components that were partially occluded or interrupted by the presence of terrain, such as the lateral piers and impost blocks. In such cases, manual adjustment of the geometries within the modeling environment was necessary.

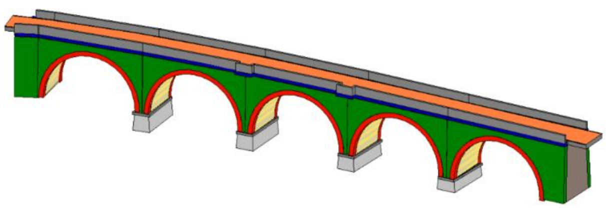

Figure 18. Digital information model obtained through segmentation algorithms and AI techniques.

The terrain modeling was carried out manually within the BIM environment, starting from the acquired point cloud (Figure 19). However, once the portion of the point cloud corresponding to the ground had been isolated, it would have been possible to apply an automated modeling procedure similar to the one used for the bridge structure. In that case, the process would have involved converting the mesh into a parametric surface, adapting the Dynamo script for direct topographic generation based on control points, without the use of predefined families.

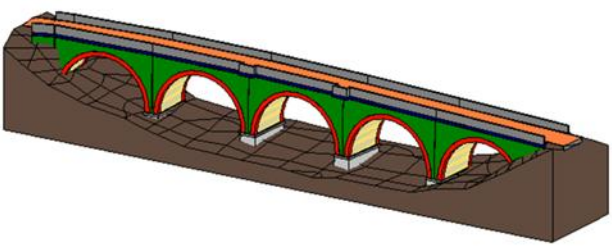

Figure 19. BIM model of the bridge including terrain morphology.

The use of the described workflow, although not yet fully automated, offers numerous advantages in both geometric and informational terms. It allows for accurate modeling that closely reflects the actual geometry captured during the survey (Figure 20), while also ensuring the necessary parameterization for consistent data management and proper export in IFC format, in accordance with BIM interoperability standards.
It is important to note that the development and initial configuration of the workflow require a certain investment in terms of time and expertise, particularly in defining segmentation logic, creating adaptive families, and optimizing scripts. However, once implemented, the system enables a significant reduction in operational time for future applications, thanks to the reusability of components and the partial automation of modeling phases. This approach is therefore particularly advantageous in scenarios where multiple similar structures need to be modeled or when periodic updates of the information model are required.

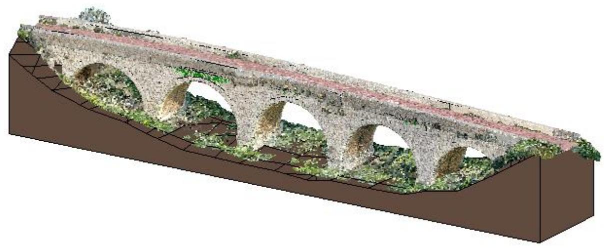

Figure 20. Overlay between the BIM model and the point cloud for geometric consistency verification.

6. Conclusion

The adoption of HBIM enhanced by artificial intelligence techniques represents an innovative and highly effective solution for the management and preservation of historical and CH. The development of the algorithm has undoubtedly led to the expected results, although there is still room for improvement.
Numerous technical and methodological challenges remain. In particular, the adaptability of AI systems to the specific characteristics of historical infrastructures.

The validation of models produced by AI algorithms often requires accurate and specialized human intervention, which is essential to ensure precision and reliability. Moreover, full autonomy and continuous self-improvement of AI systems have not yet been achieved, making it necessary to integrate AI techniques with well-established traditional workflows.
Despite the promising results obtained, full automation of the process remains an open challenge, requiring further studies to ensure the reliability and autonomy of AI systems applied to cultural heritage conservation

The results highlight the potential of this approach in the digitization of cultural heritage, while also acknowledging certain technical limitations, such as the automatic management of vegetation and the segmentation of morphologically similar elements. The methodology represents a concrete step toward a smarter, more adaptable, and scalable HBIM system for future applications in the conservation of collective heritage.
To overcome these difficulties, it is essential to intensify research and development efforts in the field of machine learning, promoting the creation of more sophisticated and flexible algorithms capable of better adapting to the specific nature of cultural heritage. Such developments can ensure greater management and conservation efficiency, significantly contributing to the long-term preservation of the historical, architectural, and cultural integrity of global heritage infrastructures.

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