A SCALABLE APPROACH FOR AUTOMATING SCAN-TO-BIM PROCESSES IN THE HERITAGE FIELD

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M. Avena [1,2], G. Patrucco [1], F. Remondino [2], A. Spanò [1]

[1] Department of Architecture and Design (DAD), Politecnico di Torino, Torino, Italy
Email: (marco.avena, giacomo.patrucco, antonia.spano)@polito.it
[2] 3D Optical Metrology (3DOM) unit, Bruno Kessler Foundation (FBK), Trento, Italy – Email: (mavena, remondino)@fbk.eu

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**ABSTRACT:**
In recent years, the demand for flexible and sustainable strategies in digitization processes has represented a significant challenge for the heritage documentation research community. In particular, the tasks of parametric modelling and AI-based semantic enrichment operations, necessary but traditionally time-consuming, is extremely onerous from a user-oriented perspective. Many efforts of the research community have been dedicated to enhancing efficiency through automation, and one of the possible solutions is represented by the employment of machine learning strategies. This study introduces an innovative methodology that integrates Visual Programming Language platforms and 3D Python libraries, thereby implementing the Scan-to-BIM approach. Two case studies - characterized by varying scales, resolutions, and accuracies - have been analysed to validate the proposed pipeline, demonstrating its flexibility and scalability across architectural objects and archaeological assets belonging to museum collections. The workflow involves several steps, starting from classified 3D and 2D data segmented using machine learning techniques with the aim of managing semantically enriched reality-based data in BIM/HBIM environment without scarifying accuracy criteria. Results highlight the methodology's efficiency and adaptability in diverse contexts, offering a compelling alternative to labour-intensive Scan-to-BIM processes. Ultimately, this methodology contributes to the automation in cultural heritage digitisation, underlining the need for comprehensive standards and protocols in this dynamic domain.

## 1. INTRODUCTION

In recent years, Artificial Intelligence (AI) has emerged as a transformative catalyst in the digitisation processes of Cultural Heritage (CH), assuming a pivotal role in boosting the processes associated with CH documentation, preservation and valorisation (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 digitisation 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. Surveyed point cloud can be semantically enriched using ontology-based methods (Poux et al. 2017) or adopting an ontology-based semantic conceptualisation 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 2023). The remarkable achievements obtained through these algorithms have subsequently stimulated their application in semantic modelling for CH using Scan-to-BIM approaches. Conventionally, the effectiveness of Building Information Modelling (BIM) techniques, particularly in the field of Historic Building Information Modelling (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, 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. 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.

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 emphasise 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. 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. 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).
However, 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. 2020).
In particular, the first tests carried out in the framework of this contribution have 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. 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 advantage of using VPL lies in, among others, the visual-code flexibility which can be easily adapted to heterogeneous case studies. Considering the architectural scale, this strategy can help, for example, the semi-automatic modelling of architectural elements (Roman et al. 2023) and 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, the proposed strategy represents a valuable alternative to the traditional Scan-to-BIM approach which requires significant manual involvement by the operator, consequently contributing to increasing the complexity of these modelling processes.

### 1.1 Aim of work

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. This research attempts to advance the field by developing an innovative framework that seamlessly integrates these methodologies with semi-automatic modelling, employing VPL and 3D Python libraries. Particularly, this 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 the paper is to foster automatic workflow using VPL and Python libraries to facilitate the import of reality-based semantically enriched 3D data in a BIM environment.

## 2. CASE STUDIES

Our methodology's application within the complex CH conservation field is validated through two different case studies. Each of them has been carefully selected and different scales of representation have been considered to showcase the flexibility and scalability of the proposed pipeline. In particular, the first one investigates a built heritage asset, while the second one delves into a movable heritage asset.
The first case study exemplifies the architectural scale (e.g., 1:200, 1:50, etc.), portraying a module within the cloister of the Royal Palace of Turin (Figure 1). For the 3D surveying, a FARO phase shift laser scanner is used (flash scans technology, investigated in Sammartano et al. 2024). The accuracies achieved after the registration processes are coherent with the architectural scale.

**Figure 1**. Cloister of the Royal Palace of Turin.

The second case study refers to a digital replica – characterised by a sub-millimetre resolution – of the Standard of Ur (a masterpiece of the Sumerian civilisation, actually stored in the British Museum - Figure 2). 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. 2023) 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 2**. Standard of UR.

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 cloister exhibits a centimeter-level accuracy, coherent with the architectural scale requirements, while the digital replica resolution is higher than 50,000 points/cm$^2$.

## 3. METHODOLOGY AND RESULTS

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 visualisation. 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 (LOA), according to survey aim and specifications. The proposed workflow (Figure 3) – 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.
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 first case study) to create 3D geometry compatible and manageable with the parametric environment. Alternatively, if a mesh is already available (e.g. second case study), 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 (first case study) or in the projected UV map (second case study). With this mapping process, the polygonal model's vertices inherit the corresponding radiometric RGB value from the original reality-based classified data.
**Step 5**: Semantic segmentation to segment 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. The following sections report more details of each step.

## 3.1 Data classification

In recent years, the scientific community has focused on the automatic classification of heritage point clouds and images. The most commonly used strategies are:

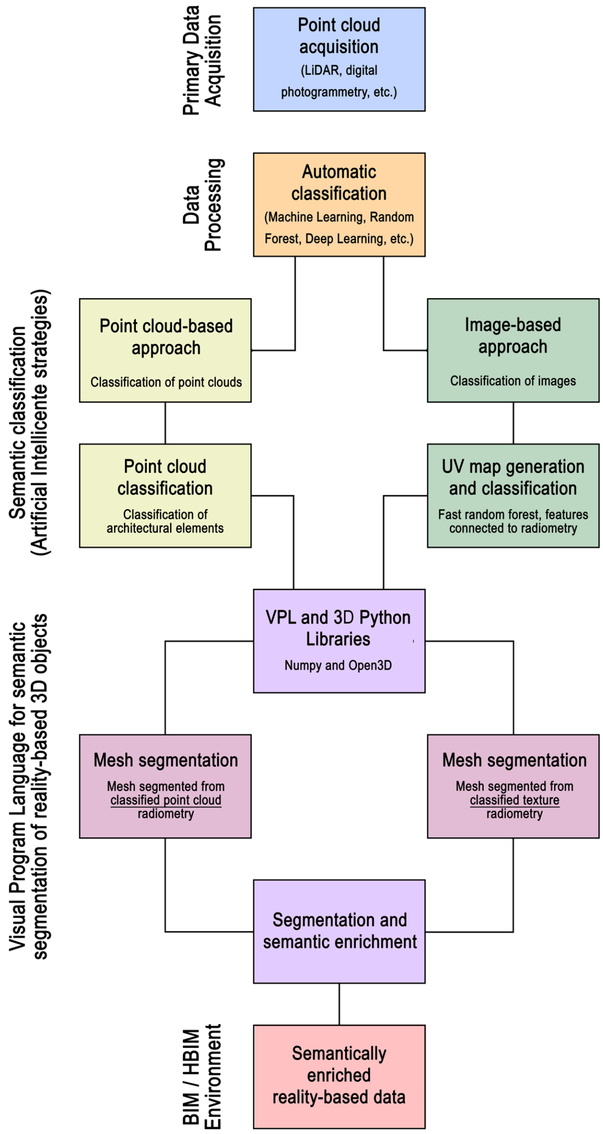

**Figure 3**. Flowchart of the proposed workflow.

- 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 point cloud is shown in Figure 4.
- Image-based approach: predictive models, such as SegNet or DeepLab V3+ for image segmentation are very well knwon (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. 2023 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 (Figure 5) is then re-project onto the geometric model, as shown in Figure 6.


**Figure 4**. RGB (above) and segmented (below) point cloud for the cloister module of Royal Palace in Turin.

### 3.2 VPL and 3D Python Libraries

The second phase of the current workflow 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 first approach);
- Mesh classification process;
- Mesh semantic segmentation process.

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

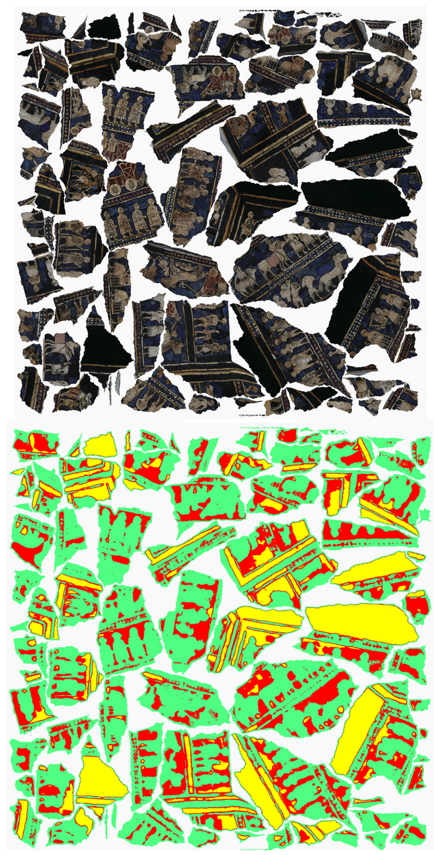

**Figure 5**. Original UV map (above) and classified UV map (below) after the ML process.

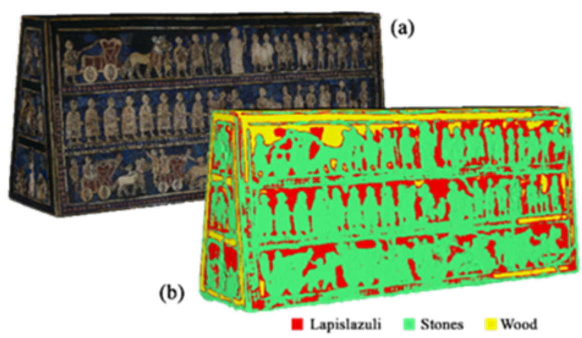


**Figure 6**. Original mesh model (a) and mesh after the reprojection of classified UV map (b).

Particularly, the first fundamental step 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.

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 parametrisation 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 allows 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. 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.
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. Results for the first case study are shown in Figure 7.

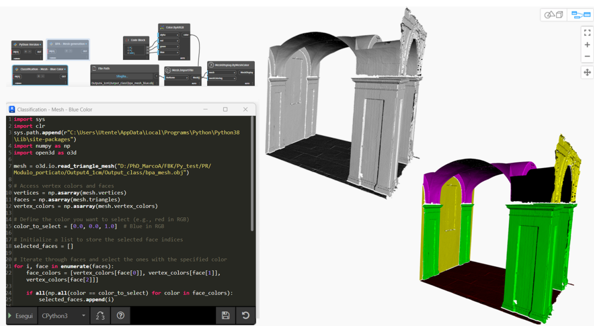

**Figure 7**. Classification of the cloister mesh in Dynamo.

For the second case study, the mesh is directly imported into the VPL environment, where its texture has been pre-classified, as described in Section 3.1. Similar to the first case study, the RGB information linked to the texture from the model's vertices and allocate it to each corresponding face are mapped on the mesh model.
Consequently, this second case study also yielded the generation of a segmented 3D model, delineated by the material consistencies it encompasses (stone, lapislazuli, wood - Figure 8).

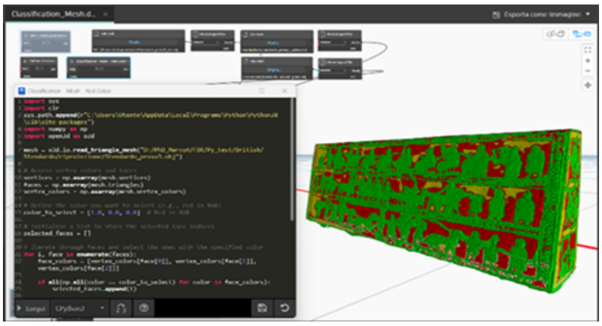

**Figure 8**. Classification of the Standard of Ur in Dynamo.

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 9a illustrates the correct assignment of the cloister columns to the "Column" family. The capability to have segmented HBIM models appropriately categorised significantly facilitates the phase of semantic enrichment (Figure 9b).

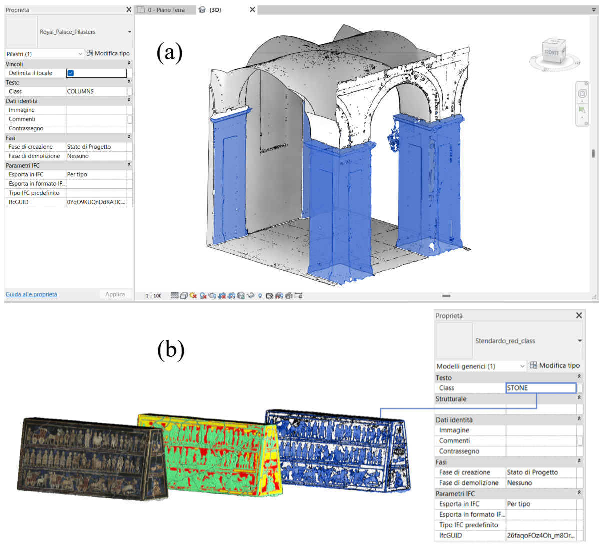


**Figure 9**. Importing the generated semantic mesh entities in a BIM environment. Each mesh is a separate parametric object able to host heterogeneous information. (a) Selection of objects belonging to the "Column" class (Royal Palace cloister module); (b) segmented 3D model (Standard of Ur) in BIM environment with true colour texture (left), classified texture (middle) and selection of semantically enriched parametric entities (right).

## 4. DISCUSSION

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 two proposed case studies). The efficiency and effectiveness of a highly automated procedure, based automatic classification algorithms and VPL, represents a significant opportunity for the operators working in CH digitisation 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 first case study (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 not only in the context of the built environment but also concerning museum collections, artworks and, in general, heritage objects requiring documentation at a larger scale. This represents a significant opportunity for enhancing parametric modelling strategies in the HBIM domain and improving the management, readability and usability of digital resources. Such resources increasingly require parametrisation and semantic enrichment operations for dissemination processes, digital cataloguing, virtual restoration and many other applications in the conservation and valorisation domain.

## 5. CONCLUSIONS AND FUTURE PERSPECTIVES

The results of this work 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 two different heritage scenarios to handle efficiently and intuitively reality-based 3D models derived from 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 heritage buildings. In this case, the specific LOD is associated with the complexity of the mesh generated GOG (Grade of Generation), as through the process of downsampling, it is possible to simplify the model by inserting the desired number of faces. As observed, the method has been developed from a multi-scale perspective, considering objects which are very different from many points of views – specifically architectural objects and museum artifacts. 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 methodology outlined in this paper in the framework of parametrisation processes of heritage objects.

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