

AI-ASSISTED 2D-3D SEMANTIC SEGMENTATION FOR STONE LEVEL HBIM

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Abstract

The Scan-to-HBIM process plays a central role in documenting heritage buildings by converting unstructured reality-capture data into semantically enriched BIM models. However, automating this conversion remains challenging, particularly for historic structures with complex and irregular stone masonry. This paper investigates the use of Convolutional Neural Networks (CNNs) to support the segmentation of photogrammetry-derived point clouds from Romanesque stone masonry, aiming to automate the data-processing stage of Scan-to-HBIM workflows. A dual 2D–3D pipeline is proposed in which high-resolution façade images are segmented using U-Net and the Segment Anything Model (SAM) to identify stone blocks, mortar joints, and openings. In this framework, U-Net is trained to classify point-cloud data into defined masonry-related classes, while SAM is employed either to generate training masks for U-Net or to directly project selected segmentations onto the 3D point cloud. The workflow enables the creation of a model capable of automatically segmenting point-cloud data and assigning semantic attributes to specific classes. Applied to a Romanesque church in Portugal, the approach shows that AI can reliably detect primary masonry components and reduce the labour required for detailed classification, although challenges persist in fine-grained stone delineation and model generalisation across diverse datasets. Overall, the study demonstrates a complementary dual-CNN strategy with strong potential to support the generation of high-detail HBIM models.

1. Introduction

Over the past two decades, interest in the preservation of historical architectural heritage has grown steadily [1], [2]. Within this context, Heritage Building Information Modeling (HBIM) has emerged as an adaptation of BIM methodologies to heritage conservation needs, such as documentation, analytical processing, and management of architectural heritage sites [3].

Despite these advances, one of the main bottlenecks in HBIM remains the Scan-to-HBIM process: the transformation of point clouds and images into structured, semantically enriched BIM models. The conventional Scan-to-BIM workflow involves data acquisition, data processing, and BIM-based modeling [4], yet semantic segmentation of survey data remains the key obstacle to automation [5]. It is a slow, interpretive process that struggles to keep pace with the vast volume of unstructured spatial data produced by photogrammetry and laser scanning [6]. Various scholars have proposed fully automated [7], [8], [9] and semi-automated approaches to address this complex process [10], [11], that requires overcoming numerous difficulties, ranging from the irregular geometry of historic structures and rich semantic complexity demanded by HBIM models, further compounded by the scarcity of labeled training datasets [12]. However, most existing automated solutions focus on coarse semantic classes, such as walls, floors, roofs, windows, and doors [11], [13]. Detailed segmentation at the level of individual building components, particularly masonry elements, is often not considered, which significantly limits the applicability of such methods to HBIM tasks and detailed analyses of historical structures. For HBIM tasks focused on assessing the technical condition and structural reliability of historic structures, segmentation at the level of individual masonry elements is a prerequisite. It enables monitoring of the load-bearing capacity of each structural component particularly where data on specific vulnerabilities, typical failure mechanisms, and deformations already exist [14]. The neglect of which may lead to progressive deterioration or localized damage. Artificial Intelligence offers new opportunities to address the segmentation gap [15]. This study proposes a dual 2D-3D Deep learning (DL) workflow combining U-Net and the SAM to enable stone-level segmentation of photogrammetric data. The approach is tested on a Romanesque-period stone masonry building, the church of São João de Calvos, characterized by irregular masonry, to evaluate the feasibility of the AI-Assisted semantic enrichment and segmentation workflow for high-detail HBIM applications.

2. Related Work

Reality-capture data integrated with parametric object libraries forms the foundation of HBIM workflows [16]. Subsequent reviews have highlighted HBIM's role in supporting conservation-oriented workflows, while emphasizing that the automatic transformation of point clouds into BIM components remains limited [3], [17]. Scan-to-HBIM procedures are now widely adopted in restoration practice [11], yet persistent challenges include insufficient automation, lack of standardization (OIR/LOIN, LOD/LOG), and difficulties in structuring semantic information for heritage applications [18], [19].

From a geometric processing perspective, research on automation has focused on procedural modeling and point cloud segmentation for Scan-to-BIM applications [20], [21]. In masonry contexts, automated segmentation of rubble walls has been explored using geometric and rule-based approaches [22], while other studies have applied thematic mapping within HBIM to document material decay [23]. However, most existing approaches target coarse architectural classes (e.g., walls, floors, openings) rather than fine-grained stone-level components.

The integration of artificial intelligence has introduced new possibilities for semantic segmentation. CNNs, such as U-Net, have demonstrated strong performance in image-based masonry segmentation tasks [23],[24], while foundation models like the SAM offer scalable mask generation capabilities [26]. Recent systematic reviews of TLS and photogrammetry in

HBIM [27] further underline the need for automated semantic enrichment to bridge the gap between dense survey data and information-rich models. Table 1 presents recent image-based segmentation approaches to masonry segmentation. Although DL techniques such as U-Net and related CNN architectures have demonstrated strong performance in masonry segmentation tasks, existing studies predominantly focus on regular brick patterns or coarse architectural classes (e.g., walls, openings, roofs).

Table 1: Comparative analysis of masonry segmentation methods in similar case studies

Author	Segmentation type	Tools applied	Masonry type
[28]	Manual/rule-based modeling	thermography, HBIM modeling	Irregular, curved, non-rectangular
[22]	Automated (rule-based, CWT)	Continuous Wavelet Transform (CWT)	Irregular, joints narrow, and boundaries blurred
[29]	DL-based (CNN)	U-Net, GANs, watershed transform	Stones and bricks
[24]	DL-based (CNN)	U-Net, DeepLabV3+, U-Net (SM), LinkNet(SM), FPN(SM))	Nearly rectangular bricks
[15]	Semi-automated	k-NN	Nearly rectangular
[25]	DL-based (CNN)	U-Net	Irregular
[30]	Comparison of rule-based and AI methods	Thresholding, YOLO, Weka, SAM	Stones and bricks

Stone-level segmentation of irregular historic masonry, particularly in Romanesque and heterogeneous stone structures, remains insufficiently explored. Most approaches do not address the level of detail required in conservation-oriented HBIM workflows, in which individual stone blocks and joints constitute semantically meaningful structural units.

While image-based semantic segmentation has advanced significantly, limited research addresses the consistent transfer of 2D semantic labels into 3D point clouds in a manner aligned with HBIM requirements. The projection, validation, and semantic consolidation of multi-view 2D segmentations into structured 3D representations remain underdeveloped in heritage-focused workflows. Stone-level labeling of historic masonry is particularly challenging due to poorly defined inter-element boundaries and highly variable surface appearance. Existing studies largely rely on manually curated datasets and rarely evaluate scalable annotation strategies. In particular, the use of foundation models, such as SAM, for batch mask generation and dataset acceleration in HBIM-oriented segmentation pipelines remains insufficiently investigated.

Therefore, a methodological gap persists between image-based segmentation research and the practical requirements of high-detail, conservation-grade HBIM applications demanding stone-level granularity, scalable annotation strategies, and semantically consistent 2D-3D integration.

3. Materials and Methods

This study presents a hybrid AI-assisted Scan-to-HBIM workflow designed for stone-level masonry segmentation and scalable dataset generation. In addition, a 2D image-to-point-cloud semantic projection method is proposed and preliminarily tested. The proposed approach emphasizes the segmentation of stone masonry into individual stone blocks as distinct entities. To perform 2D image segmentation, two CNNs were applied, specifically, U-Net and SAM, which can operate either independently or in a complementary manner. In the current implementation, a U-Net architecture is applied to façade orthophotos for the semantic segmentation of stones and masonry joints. However, this method is also applicable to models involving a larger number of semantic classes. While the U-Net was primarily employed for semantic segmentation, SAM demonstrated strong performance in instance segmentation. The complementary strengths of both methods suggest integrating them into a unified workflow, as proposed in Figure 1.

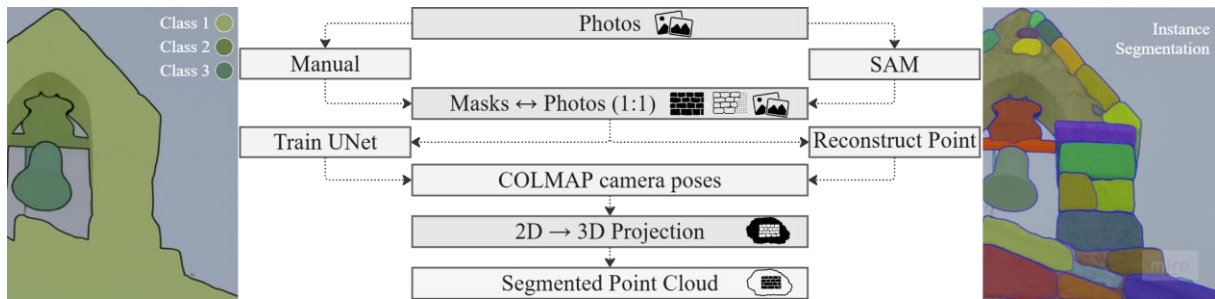


Figure 1: Difference in results obtained from both U-Net and SAM approaches

The 2D masonry mask dataset developed for training the U-Net model in the case study initially consisted of manually annotated images (Figure 4). As the need to expand the dataset became evident, additional masks were automatically generated using the SAM [26], specifically the ViT-H variant, the largest and highest-accuracy configuration available in SAM 1, with SamAutomaticMaskGenerator and the parameters listed in Table 2. SAM 1 is designed for static image inputs, making it well-suited to the 2D photogrammetric data used in this pipeline.

Table 2: SAM 1 configuration parameters used for image segmentation

points_per_side	pred_iou_thresh	stability_score_thresh	min_mask_region_area
32	0.86	0.92	400

3.1 Case Study

The Church of São João de Calvos, situated in the parish of Serzedo and Calvos (Guimarães, Braga district), is a representative monument of Romanesque religious architecture that occupies an important place in the historical landscape in northern Portugal. Since 1955, it has had the protected status of ‘IPP - property of public interest’ (IIP - Imóvel de Interesse Público), established by Decree No. 40 361 of 20 October 1955. It is also listed in the national cultural heritage register in the ‘Monument’ category. The church is characterized by irregular stone masonry, featuring heterogeneous block sizes, non-standard geometries, and visible mortar joints typical of Romanesque construction. Stratigraphic analyses conducted within the

IN2PAST research framework identified multiple construction phases and subsequent interventions, revealing a complex material history. Additionally, several stone-level degradation mechanisms have been documented. These characteristics, combined with the documented degradation pathologies and complex construction history, make São João de Calvos a particularly demanding and representative testbed for evaluating stone-level semantic segmentation and AI-assisted enrichment workflows to support high-detail HBIM applications.

3.2 Data Acquisition stage of the case study building

High-resolution façade images were captured using close-range terrestrial and aerial photogrammetry techniques on 4 November 2024. To ensure interior-exterior alignment between terrestrial and aerial campaigns, 7 CGPs were placed inside and around the building. The images were processed using Agisoft Metashape Pro 2.2 software to estimate camera parameters and to generate the dense point cloud required for subsequent 2D-to-3D projection [31]. Figure 2.a. shows the dense point cloud of São João de Calvos church before segmentation.

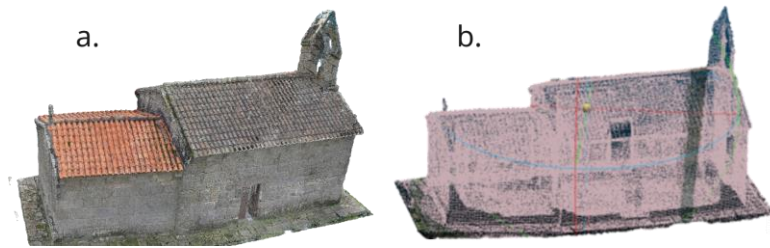


Figure 2: a. Point cloud created in Agisoft Metashape environment (cloud.ply) [31];
b. Projection of SAM-generated masks onto the point cloud.

3.3 2D Image Segmentation

U-Net, a CNN trained on manually annotated façade images, was used for supervised semantic segmentation of façade photographs into three classes: background (0), stone (1), and masonry joint (2).

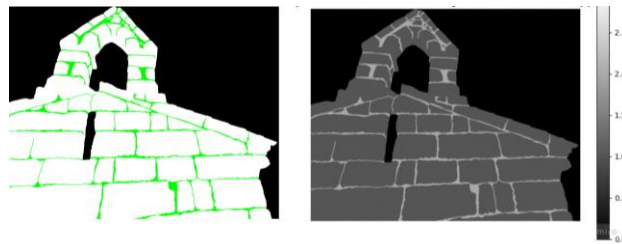


Figure 3: Grayscale masks with class IDs background (0), stone (1), and masonry joint (2)

A U-Net-style encoder-decoder was used to generate per-pixel class labels from RGB inputs. The proposed approach was designed to analyze 2D images and transfer 2D labels (classes) onto a 3D point cloud using COLMAP camera poses; however, the implementation was limited to the U-Net model training stage. The dataset is one of the most critical components in CNN model training. For the case study building, the dataset comprised 80 image-mask pairs, representing the minimum recommended sample size. As illustrated in Figure 4.b, multiple data sources were incorporated to enhance dataset variability and improve class discrimination. Following the initial training stage, the mask generation process was automated using SAM,

enabling efficient mask generation for subsequent training stages without manual labeling. A total of 2,371 photographs acquired during the data acquisition stage were used for 2D image segmentation (Table 3).

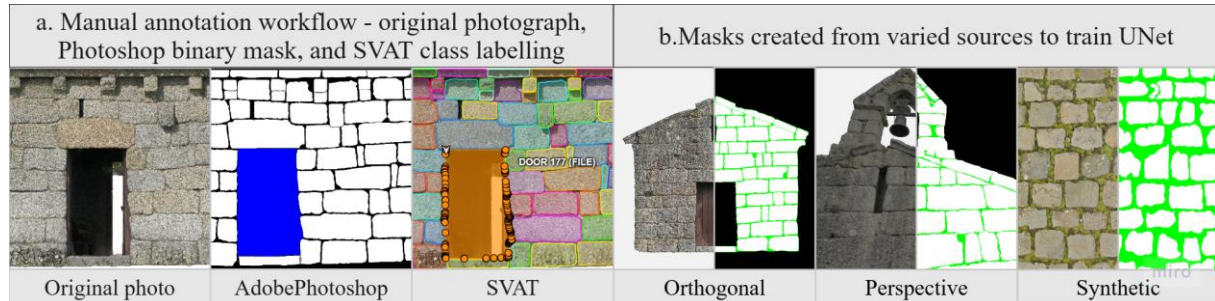


Figure 4: a. Manually created dataset labeling 3 classes (stones, masonry joint, and background); b. Masks created from varied sources to train the U-Net

3.4 Projection of 2D Masks onto a Point Cloud

In an initial experiment, all SAM-generated masks were projected onto the photogrammetric point clouds using COLMAP camera calibration data. For each 3D point, semantic labels were assigned via multi-view voting using the corresponding pixels across multiple images. However, the resulting segmentation did not produce reliable results (Figure 2.b.). This limitation is attributable to inconsistencies in the delineation of stone boundaries within some masks. A subset of SAM-generated masks met the quality threshold for reliable projection: out of 2371 photographs processed, 450 masks were identified as true positives (Table 3), while the remaining masks exhibited incorrect boundaries delineation as shown in Figure 5.



Figure 5: Example of masks generated in batches by SAM

The U-Net model, trained on a limited dataset of 80 manually created image-mask pairs, produced imprecise boundary predictions and has not yet reached the capacity to reliably detect and classify masonry into the defined categories. Consequently, U-Net-generated masks were not projected onto the point cloud in the current state of the research. A selective approach that retains only accurately defined SAM-generated masks may improve segmentation outcomes by constituting a refined dataset for U-Net retraining. Expanding the training set in this manner is identified as the primary direction for improving projection accuracy. Upon retraining, U-Net-generated masks could be projected onto the point cloud, producing a semantically enriched representation in which each point carries a class label. The resulting semantic information can then support high-detail 3D reconstruction and subsequent integration into HBIM systems.

4. Results

The U-Net model demonstrated reliable performance in identifying primary masonry components when trained on a limited but carefully annotated dataset. As seen in the graph (Figure 6) during U-Net training, there was a rapid improvement until roughly epoch 14, after which the model remained on a clear plateau around $mIoU \approx 0.78$ – 0.80 , with small oscillations. The best checkpoint is $mIoU = 0.8047$ at epoch 26 among the 50 epochs run, with representative points near the plateau shown in Figure 6.

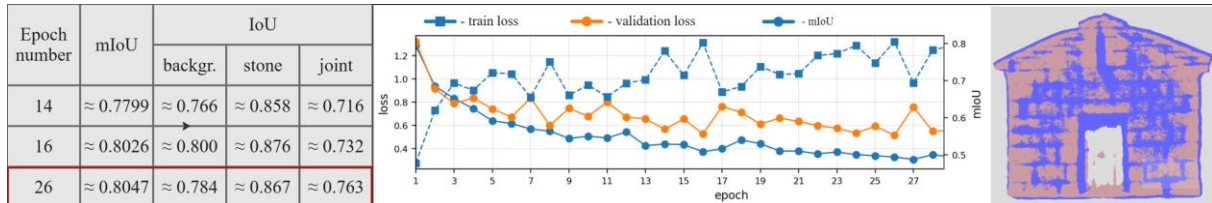


Figure 6: Example of U-Net model training with a minimal dataset of 80 images

SAM provided flexible segmentation results, particularly useful for exploratory analysis and rapid mask generation, though with less control over class consistency.

Table 3: The total number of 450 correct true positive masks generated by SAM in ≈ 2 hours

Photographic material	Total number of photos used	The number of true positive masks generated by SAM
Nikon Z6II	1375	147
DJI Mavic 2 Pro	996	303

The current implementation status of the proposed pipeline can be summarised as follows. U-Net training and inference are fully implemented, though the model was trained on a minimal dataset of 80 annotated image-mask pairs and requires further training. SAM-based automatic mask generation is fully operational and has demonstrated its utility as a dataset acceleration tool, producing 450 validated masks from 2371 photographs (Table 3) in approximately two hours; these masks are directly available for U-Net retraining. It is also noted that adjusting certain photogrammetric image parameters, such as contrast enhancement, prior to SAM processing, may further increase the yield of high-quality masks. The 2D-to-3D semantic projection via COLMAP camera poses has been implemented and tested; however, in the current experiment, all SAM-generated masks were projected without prior quality filtering, which contributed to unreliable results. Selective projection of validated masks is expected to improve outcomes. Stone-level instance segmentation, full IFC-compatible HBIM integration, and end-to-end pipeline automation remain planned for future work.

5. Conclusions and discussion

This study demonstrated the feasibility of a hybrid AI-assisted Scan-to-HBIM workflow for stone-level semantic segmentation of historic masonry. By combining U-Net for supervised segmentation with SAM for scalable mask generation, the approach addresses a critical gap

between coarse architectural classification and conservation-grade heritage documentation. Applied to a Romanesque church case study, the method confirmed that AI can reliably detect primary masonry components while substantially reducing the effort required for manual annotation.

Several limitations remain. Model performance is constrained by dataset size and projection accuracy, and stone-level segmentation is not yet sufficient for fully automated conservation-grade applications. The immediate next step is to retrain U-Net on the 450 high-quality masks generated by SAM, which are already available, and to improve 2D-to-3D projection quality through selective mask filtering. Once these steps are completed, the semantic output — a per-point labelled point cloud with stone, joint, and background classes — will be directly compatible with downstream HBIM workflows, with individual stone instances mappable to IfcBuildingElementProxy objects and semantic attributes exportable to IFC property sets.

Further research will focus on expanding the number of segmentation classes and on integrating the enriched outputs into parametric HBIM environments to support conservation planning and structural assessment.

Acknowledgments

This initiative was supported through the Multiannual Funding of the Landscape, Heritage and Territory Laboratory (Lab2PT), Ref. UID/04509: Laboratório de Paisagens, Património e Território (Lab2PT/UM), financed by National Funds (PIDDAC) through the FCT/MCTES. The authors gratefully acknowledge BUILT CoLAB for their guidance and constructive feedback during the development of this research.

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