A Semantic Classification Approach for the Aachen Cathedral

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Abstract

This paper presents a semantic classification workflow applied to the UNESCO World Heritage site of Aachen Cathedral, integrating 3D survey data and Machine Learning (ML) techniques. The research focuses on the Westwerk area and combines Terrestrial Laser Scanning (TLS) and photogrammetric point clouds for material and construction technique identification. A hybrid approach was adopted: 3D geometry-based classification using supervised algorithms (Random Forest) and 2D image segmentation via META's Segment Anything Model (SAM). The 3D method proved suitable for distinguishing features with strong morphological differentiation, while the 2D approach was more effective for visually subtle or geometrically similar elements. Annotated 2D masks were projected onto the 3D model to improve classification reliability.
The study demonstrates the potential of integrating spatial and radiometric data for scalable, semi-automatic classification of historic masonry. Results contribute to the development of enriched, semantically annotated 3D datasets supporting documentation, conservation planning, and future research on complex heritage sites.

1. Introduction

Aachen Cathedral, one of the oldest in Northern Europe, represents a remarkable example of medieval architecture and was inscribed as a UNESCO World Heritage site in 1978. The documentation project of the cathedral is the result of a collaboration between Sapienza University of Rome, Robert Gordon University (Aberdeen, Scotland), Rheinisch-Westfälische Technische Hochschule, and the Cathedral's own institution, the Dombauhütte Aachen (both based in Aachen, Germany).
The project focuses on the comprehensive documentation of the cathedral complex and its constituent materials using terrestrial laser scanning (TLS) and Structure-from-Motion (SfM) techniques (Pritchard et al., 2022). The models generated from the survey data have been crucial for the analysis of the monument, enabling detailed investigations of the geometry of structural components (Attenni et al., 2023) as well as the characterization of construction materials (Attenni et al., 2024).
Within this framework, this research specifically investigates the application of machine learning (ML) algorithms for the semantic classification of 3D survey data. The goal is to develop and test a workflow capable of automatically identifying architectural elements and construction techniques within the survey data. A key objective is to assess the potential of ML in recognizing structural patterns and material types, starting from the Westwerk area as a prototype, with the intention to generalize the method to other parts of the Cathedral. The work was divided into three phases: the first involved the study of the historical phases of the cathedral and the identification of materials and construction techniques; the second involved the analysis and the selection of survey data to use, and the preparation of homogeneous datasets through operations of segmentation and classification of the point cloud; the third involved extending the semantic segmentation from small portions to the entire Westwerk datasets (prediction phase).

2. Background

Recent years have witnessed significant advancements in the application of ML to the classification of architectural heritage, especially through the integration of 3D survey data.
Several researches have contributed significantly to the development of automated or semi-automated classification methods for cultural heritage, with the goal of improving the efficiency and objectivity of architectural analysis (Fiorucci et al., 2020; Croce et al., 2020; Croce et al., 2021; Lee, 2025). The main applications concern semantic modeling through knowledge-driven ontologies has laid the foundation for structured digital representations of architectural elements (De Luca, 2023) or demonstrate the potential of deep learning and data-driven approaches in classifying and interpreting 3D data derived from laser scanning and photogrammetry (Remondino, 2022).

Semantic segmentation techniques have increasingly been used to extract, label, and interpret architectural components from point clouds or textured meshes, facilitating both documentation and conservation efforts. Despite recent advances, several limitations still affect the application of machine learning to historical architecture. One key issue is the scarcity of annotated datasets specifically tailored to heritage contexts, where complex geometries, stylistic diversity, and construction techniques vary widely across periods and regions. These characteristics are seldom represented in standard ML training sets, limiting the models' ability to generalize across different sites. Another major limitation concerns the interpretability of deep learning models, which often function as black boxes. This lack of transparency poses a challenge in the field of cultural heritage, where interpretative clarity is essential for scholarly validation and meaningful analysis. Data quality also plays a crucial role: point clouds derived from terrestrial laser scanning or photogrammetric techniques often contain noise, occlusions, or uneven point distribution, especially in degraded or inaccessible areas, leading to possible misclassifications or data loss. In addition, defining semantic categories is not always straightforward. Architectural terms are deeply embedded in historical and cultural frameworks and are not easily reduced to simple geometric or textural descriptors.

To address these challenges, this study adopts a hybrid approach that combines data-driven techniques with expert architectural knowledge, focusing on construction techniques as the primary semantic layer to guide classification.

3. The Cathedral classification

The study of the Cathedral (Fig. 1) reveals the influence of different cultures and historical periods on materials and techniques. The structure, entirely built of stone, combines local and imported materials, with diverse masonry types, from compact walls with loopholes to open loggias and sculpted decorations.
The structural complexity of the building reflects both the utilization of local resources and the incorporation of construction techniques and materials originating from other regions. The masonry consists of diverse stone elements, predominantly worked through cutting, shaping, and precise installation. Certain sections are more solid and characterized by loopholes, whereas others are more open due to openings of varying geometries, including windows, loggias, and balconies. The building integrates seamlessly into its urban context, dominating the square with the bell tower on one side and the Gothic choir on the other. Sculptural elements, including architectural orders, the entablature surrounding the Westwerk and the Hungarian Chapel, as well as Gothic sculptures, indicate a high level of craftsmanship, often executed on-site prior to careful assembly. The coverings of the various spaces present multiple geometric solutions, alternating between domes and pitched roofs.
Regarding building materials, Blaustein blocks are predominantly used. This bluish stone, quarried near Aachen, was initially employed for exterior masonry and sculptural details, and has more recently been applied to reinforce the oldest deteriorated sections. It is frequently combined with limestones in different shades—brown varieties dating to the Carolingian or Romanesque periods, and gray limestone. In the Westwerk and Palatine Chapel, large and medium-sized blocks alternate with smaller limestone and sandstone units. These areas, more than others, display a high degree of material heterogeneity, including stones sourced from surrounding regions: Weiberner tuff, Lorraine limestone, Euville, Jaumont, Drachenfels trachyte, and Herzogenrath sandstone (Maintz 2009; Heckner and Beckmann 2012).
The informations on the construction techniques were grouped into seven homogeneous classes, each corresponding to a coherent set of techniques sharing similar morphological, functional, or construction-related characteristics. Some areas feature regularly arranged stone blocks of uniform size with thin, precise joints, reflecting a highly standardized construction technique. In contrast, other zones combine squared blocks with irregular stones and thicker joints, indicating a more adaptive or less refined method. Seven distinct construction techniques have been identified.

1. Small blocks with regular coursing and 4 cm joints, suggesting a slightly more relaxed construction approach.
2. Squared blocks combined with irregular stone, with joints > 2 cm, revealing a hybrid technique used where aesthetic or functional constraints required adaptation.
3. Small blocks with irregular coursing and 4 cm joints, pointing to less precise or more adaptive masonry work.
4. Precisely cut squared blocks with smoothed surfaces and thin mortar joints, typical of high-quality and structurally important areas.
5. Small blocks with regular coursing and 2–3 cm joints, indicating a refined and standardized laying method.
6. Carved and sculpted blocks, found especially for sculptural components depicting male and female religious figures
7. Carved and sculpted blocks, used both for architectural elements—such as moldings, capitals, column bases, and similar features

Figure 1. The Aachen Cathedral. Top: view of the Westwerk; bottom: view of the Hungarian Chapel, the Palatine Chapel, and the Gothic Choir (photos by the authors).

Among all these construction techniques identified, five have been detected within the Westwerk area, which constitutes the focus of the present research (Fig. 2). Alongside these, non-stone construction methods also emerged, such as those typical of carpentry or metalworking, used in secondary structural or decorative features.

Figure. 2 Identified construction technique classes. The black dots indicates that the technique was detected in the Westwerk area (elaboration by the authors).

This identification of materials and construction techniques were preliminary steps for the informed use of survey data and the subsequent thematization operations conducted on them using ML algorithms.

4. Data pre-processing

The experimental classification procedure using Machine Learning techniques relies on a database constructed from the monument’s 3D point cloud. Three data acquisition campaigns, carried out between October 2022 and December 2023, contributed to the creation of a comprehensive documentary framework by integrating Terrestrial Laser Scanning (TLS) technologies—using both static and mobile 3D laser scanners—with photogrammetric methods.

Static 3D laser scanners were used for data collection and verification to ensure complete coverage of all accessible interior and exterior areas, while a mobile scanner was employed to capture the two spiral staircases of the Westwerk and the attic spaces. Ground-based photogrammetry focused primarily on the octagonal hall, while UAV (SAPR)-based photography was used to capture all external surfaces (Pritchard, 2024).

Point clouds obtained from different survey methodologies and technologies were merged through homologous key points, using the metric reference coordinates derived from TLS data. The two resulting point clouds were then individually filtered using the Statistical Outlier Removal (S.O.R.) tool and a noise reduction filter. In the case of the photogrammetric point cloud—which was significantly sparser—lower filtering values were applied in order to preserve morphological detail and prevent excessive data loss, particularly in regions containing fine elements. In contrast, the structured point cloud underwent more aggressive filtering to remove outliers, especially in areas affected by high reflectivity due to a thin layer of rainwater present during acquisition. After filtering, both clouds were downsampled with a 1cm step to enable efficient data processing.

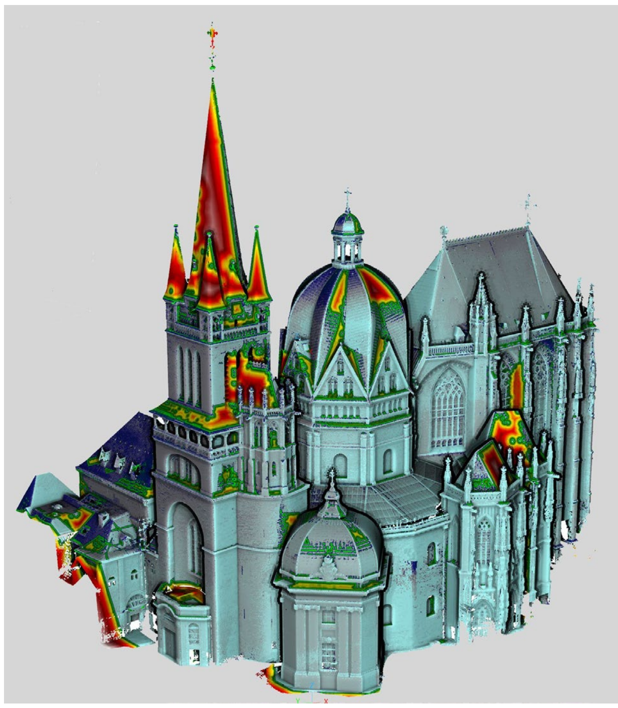

Figure 3. Cloud to cloud distance between the TLS point cloud and the photogrammetric one. Point cloud areas captured only through UAV are highlighted in green and red (elaboration by the authors).

For the experiment focused on the monument’s exterior surfaces, the selected point cloud was generated using Structure from Motion and Image Matching (SfM/IM) techniques. This dataset was created from approximately 3,000 images that fully documented the structure. Compared to the TLS-derived point cloud, the photogrammetric cloud exhibited significantly greater homogeneity in overall surface coverage (Fig. 3), point density (Fig. 4), and radiometric characteristics.

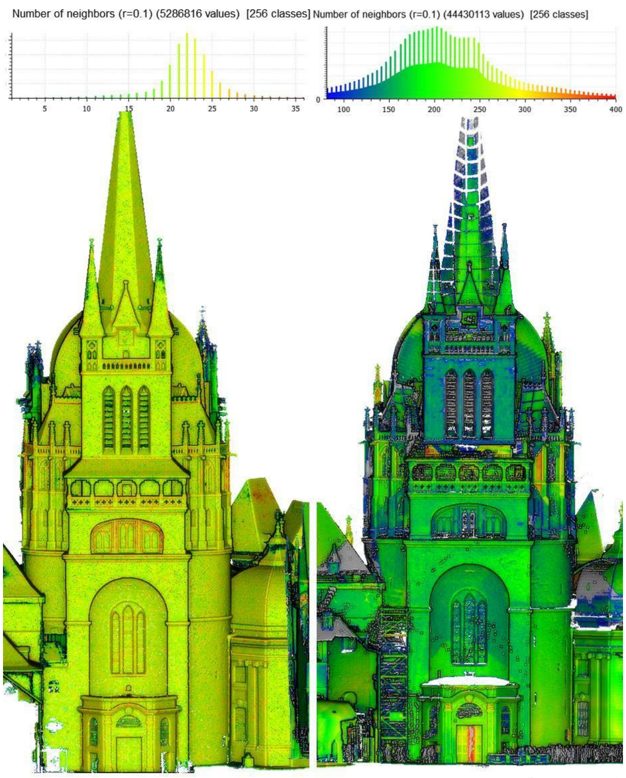

Figure 4. Number of neighbourhoods calculated on UAV photogrammetric point cloud (left) and TLS point cloud (right). Color homogeneity of SfM/IM point cloud visualization shows a more homogeneous points distribution (elaboration by authors).

As expected, the variation in data homogeneity between the two systems stems from the limited accessibility of laser scanners, particularly for capturing roof structures, compared to UAV tools. The consistency of the photogrammetric point cloud facilitates the optimization of the preprocessing phase, which is critical for designing an effective assisted classification process. Nonetheless, the reflectance values associated with TLS data substantially enrich the surface description, offering valuable input for material distinction and classification. Although a generalized calibration process cannot uniquely associate reflectance values with specific materials [Viswanath, Jiang, Saripalli 2024], the relative variation of these values can still contribute positively to the Machine Learning training process.
To this end, reflectance values from the TLS dataset were projected onto the photogrammetric point cloud. The final stage of data preparation involved identifying homogeneous regions and segmenting the point cloud accordingly. Based on the previously discussed analysis of construction techniques, seven relatively uniform zones were defined (Fig. 5):

1. Westwerk: comprising the monumental façade, bell chamber, side towers, and upper loggia, predominantly constructed with squared limestone masonry and rough stone blocks.
2. Palatine Chapel: similarly constructed with squared masonry and rough stone elements.
3. Gothic Choir: characterized by large stained-glass windows framed by sculpted stone blocks, squared-block pillars, and extensive sculptural decoration.
4. Chapel of Saints Charles and Hubert: exhibiting architectural features consistent with those of the Gothic choir.
5. Chapel of Saints Nicholas and Michael: featuring stained-glass windows and squared-block pillars.
6. Chapels of Saint Anne and Saint Matthias: likewise defined by large stained-glass windows and structural pillars.
7. Hungarian Chapel: distinguished by paired Ionic pilasters built from squared limestone blocks with matching cladding slabs.

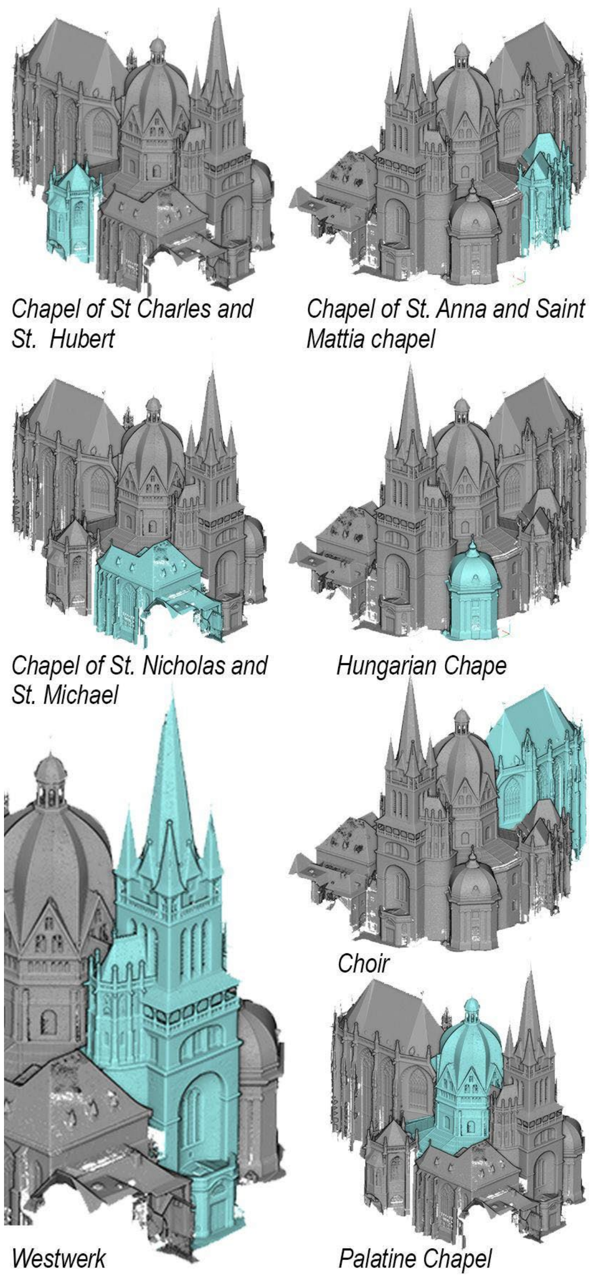

Figure 5. Identification of the 7 homogeneous areas detected (elaboration by the authors).

This segmentation into homogeneous areas supports the classification and predictive tasks performed by the Machine Learning algorithms.

5. 2D and 3D approaches for point cloud classification

In the field of semantic segmentation applied to cultural heritage and digital model analysis, two main methodological approaches can be distinguished: the 2D (Texture-based) approach and the 3D (Geometry-based) approach. Each of these presents specific advantages, limitations, and areas of application.

The 2D approach (Fig. 6) is based on the processing of photographic images or orthophotos projected onto the surfaces of digital models. In this case, semantic classification relies on radiometric information (color, texture, visual patterns) contained in the images.

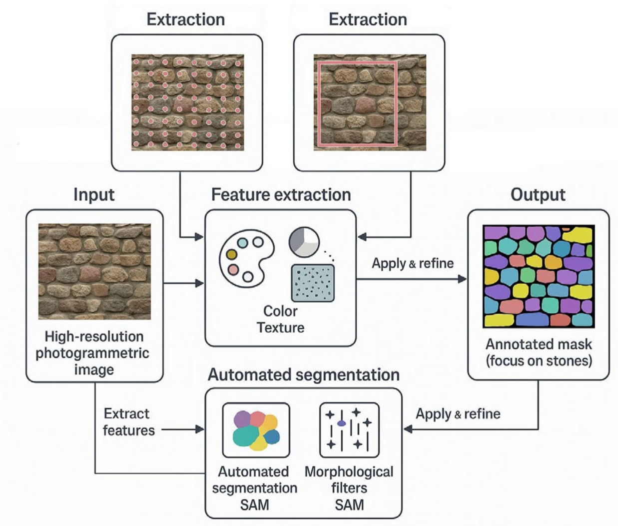

Figure 6. 2D segmentation workflow with SAM for the generation of semantic masks on photogrammetric images (elaboration by the authors).

The techniques used generally fall within the field of Computer Vision and exploit texture recognition algorithms, Convolutional Neural Networks (CNN), or supervised/trained semantic segmentation models on two-dimensional images.The 3D approach, on the other hand, directly uses the 3D point cloud as the main input, relying exclusively on the geometric and spatial information of the detected objects (such as curvature, normal orientation, local point density, surface roughness, etc.).

In this context, machine learning algorithms (such as Random Forest) are trained to recognize shapes and morphological features independently of color or texture. This approach is particularly suitable for analyzing complex architectural elements or contexts where texture does not provide sufficient information. However, the 2D approach presents some significant limitations. Firstly, the quality of the results strongly depends on the completeness and resolution of the photographic dataset: in the presence of coverage gaps, light variations, sharp shadows, or unwanted reflections, the reliability of the segmentation may be compromised. Moreover, this method cannot effectively distinguish morphologically different but visually similar elements, nor capture the spatial geometry of architectural components. Consequently, objects with the same texture but different functions or shapes may risk being incorrectly classified.

In contrast, the 3D (geometry-based) approach (Fig. 7) relies on the direct analysis of the three-dimensional point cloud and focuses on the geometric and morphological characteristics of surfaces, such as curvature, orientation, point density, and local roughness (Grilli et al., 2018). This method has the advantage of being independent of lighting conditions or chromatic variations and allows for effective discrimination of different architectural elements based on their shape, even in the absence of significant textures.

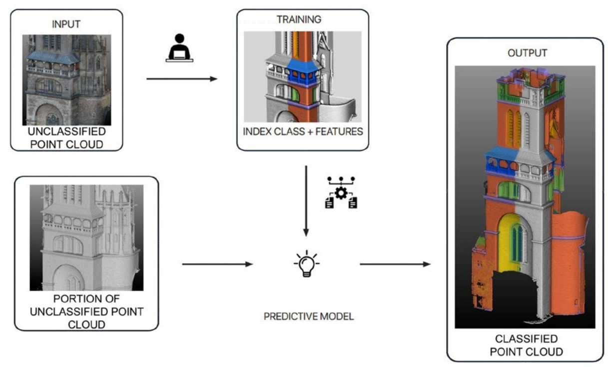

Figure 7. 3D annotation workflow on point cloud via supervised classification with Random Forest (elaboration by the authors).

Nevertheless, the 3D approach involves some complexities. It requires high-quality, high-resolution point clouds that must be subsampled to be analyzed efficiently. Moreover, the processing phase is computationally more demanding than the 2D one, as the extraction and selection of geometric features require in-depth calculations and often the optimization of numerous parameters.

6. Applied methodologies

The research focused on the recognition of construction techniques in historical masonry through semantic segmentation using point clouds and images employed for generating photogrammetric models.

Both the three-dimensional and the two-dimensional approaches were semi-automatic, aiming to create semantic classes that could be explored and consulted as three-dimensional data. The 3D approach was based on the classification of the point cloud, representing the spatial geometry of the surveyed object. The input data, in this case, consisted of the three-dimensional coordinates of the points (XYZ), enriched with intensity and color values. Classification was performed using supervised machine learning algorithms, such as Random Forest, capable of learning the relationship between the extracted geometric features (e.g., local curvature, point density, normal orientation, roughness) and the semantic classes defined by the user (Grilli et al., 2019). This method offered the great advantage of being independent of lighting conditions, chromatic variations, and photographic coverage.

Segmentation was based solely on shape and morphology, allowing for the effective distinction of architectural elements with different geometric characteristics, even in the absence of visible textures or with uniformly colored surfaces. Furthermore, it enabled direct analysis of the complete 3D model, overcoming the limitations of two-dimensional projection. However, there were cases where geometry alone was not sufficient to distinguish morphologically similar but functionally different elements, such as flat surfaces serving different roles in the architectural structure.

This limitation, which reduced the effectiveness of class recognition through machine learning applied to three-dimensional data, prompted experimentation with an approach based on two-dimensional datasets. As an alternative to using the point cloud, classification was therefore carried out directly on photographic images acquired for the SfM reconstruction. In this context, the SAM (Segment Anything) (Kirillov, A. 2023) model by META made it possible to automatically segment images (Fig. 8), generating semantic masks even with a limited number of user inputs. This enabled the rapid creation of annotated datasets, subsequently usable for training or fine-tuning neural networks dedicated to semantic classification. The 2D approach offered several advantages: primarily the ease of data manipulation and the availability of pre-trained tools, such as SAM itself, which have lowered the threshold of technical skills required as in the case of machine learning used in the three-dimensional field. Moreover, the radiometric detail provided by the images (colors, textures, moisture stains, deposits, signs of decay) proved decisive in distinguishing materials or surface conditions not identifiable through geometry alone. The processing pipeline was generally less demanding than the 3D one, and annotation was faster and more intuitive.

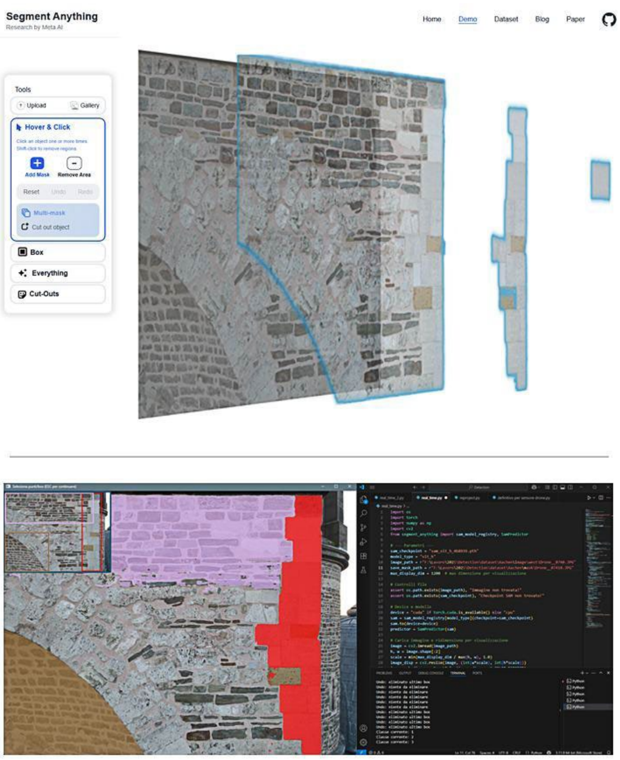

Figure 8. Demonstration of the operation of the SAM semantic mask generative model online (at the top) and on a local machine (at the bottom) (elaboration by the authors).

However, this approach also presented some critical issues. The quality of the segmentation showed a strong dependence on the completeness and consistency of the photographic set: in several cases where the pattern of the construction technique was less evident, the pre-trained model struggled to create clean masks. Moreover, light variations, shadows, or reflections—thus inconsistencies in the dataset—could jeopardize classification reliability. Additionally, the number of images acquired for photogrammetry generated a very large dataset, making full annotation impractical. For this reason, as already done for the 3D approach, it was decided to work only on the westwerk portion, annotating a smaller subset of images and reprojecting the two-dimensional masks onto the photogrammetric cloud.

7. Results Analysis

The experiments conducted on the three-dimensional and two-dimensional datasets made it possible to assess the specific capabilities of each approach in identifying and distinguishing semantic classes related to the construction techniques of historic masonry.

The 3D approach, based on point cloud classification, demonstrated a good ability to distinguish classes characterized by marked morphological differences, such as portions of masonry with different textures or architectural elements with recognizable shapes — for example, homogeneous stone blocks with mortar joints between 2 and 4 cm, and squared or carved stone blocks or slabs with thin mortar joints (Fig. 9).

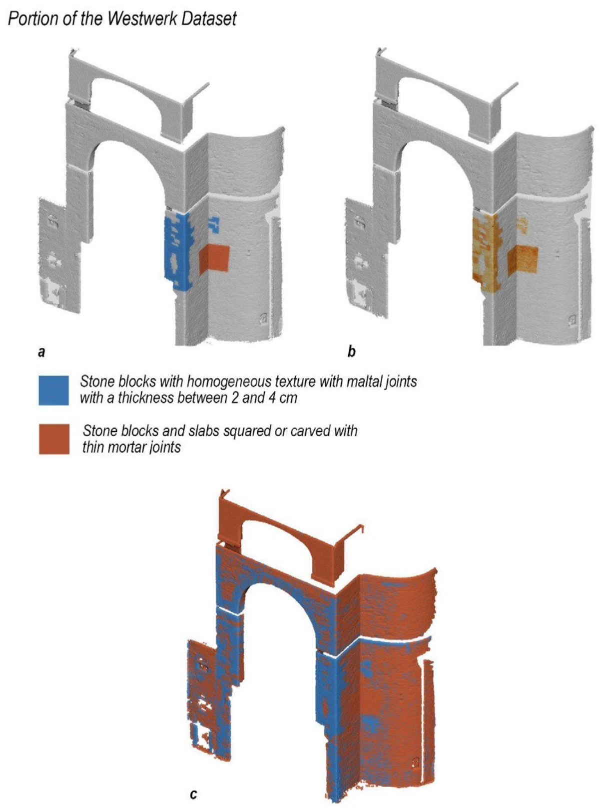

Figure 9. Manual annotation of the portion of the point cloud used as training for the recognition of construction techniques and result of the automatic classification of the predictive model (elaboration by the authors).

The extracted geometric features (local curvature, normal orientation, point density) proved effective in semantically separating these two categories. However, for classes that are less differentiated in morphological terms, the 3D method showed evident limitations, not always succeeding in correctly discriminating the expected semantic classes. The 2D approach, based on the analysis of photogrammetric images, highlighted a different mode of class distinction: the information contained in the images, such as color, shapes, and patterns, allowed the identification and recognition of a greater number of semantically different categories, even when the geometries were similar or not sufficiently distinctive.

The SAM model facilitated the initial segmentation of the images, although the quality of the masks depended on the quality of the photographic dataset and the consistency of the acquisition conditions. A critical aspect of the 2D approach was precisely the risk of confusing semantically different but visually similar classes in the presence of uniform or degraded textures, where even the pre-trained model struggled to generate clean segmentations. Moreover, the need to select a limited subset of images reduced the possibility of performing an extensive classification over the entire model. In any case, the generated semantic masks were reprojected onto the photogrammetric model so as to have a three-dimensional model with the recognized classes highlighted (Fig. 10).

Figure 10. Portion of the reprojection on the photogrammetric model of the semantic masks generated via SAM (elaboration by the authors).

For future developments, it is planned to fine-tune the SAM model using the masks already created manually, in order to adapt the algorithm to the specific characteristics of the dataset and improve the quality of the automatic segmentation. This will allow the propagation of annotations to a larger number of images and the extension of semantic classification to the entire photogrammetric dataset, reducing manual work and increasing the homogeneity of the results.

8. Possible uses of research results

The experimentation on Machine learning classification aims to enhance the management and preservation strategies of the Cathedral through a fully mapped 3D point cloud, serving as a foundation for an information system to track restorations and support maintenance planning.

One of the main challenges when working with a 3D model derived from documentation activities is ensuring its continued relevance over time. The point cloud of Aachen Cathedral captures the building’s condition at a very specific moment. By its nature, the point cloud derived from a specific survey campaign is not designed to record subsequent morphological transformations; rather, it serves as an ideal medium for examining the structure as it existed at the time of the survey.
Since the completion of the three survey campaigns, the building is constantly changing: construction interventions—such as wall maintenance and reinforcement—have already been carried out (Richarz 2024). On the one hand, this may suggest that documentation efforts become outdated almost immediately after the survey concludes. On the other hand, however, 3D survey point clouds can effectively serve as a temporal repository, capturing and preserving different stages in the life of the building.

From this perspective, the point cloud segmentation and classification can store and preserve the immanent features of the building such as its materials or its constructive techniques classification. In the same way, it is able to layer information related to constructive phases, later interventions and materials replacement. In this way the digital version of the Aachen cathedral is able to support the maintenance process and enhance site monitoring.

Beyond conservation, the classified point cloud aids scientific research on historical construction techniques and enhances public outreach. It enables broader access to the monument’s history through visual tools, making its evolution and craftsmanship more understandable to all.

9. Conclusions

This research deals with more technical aspects about ML algorithm development, highlighting potential challenges in relationship with the Aachen cathedral’s raw point cloud data and images. From a methodological perspective, the study highlights the need for hybrid approaches that combine geometric and visual data to enhance classification reliability and extend its applicability. The integration of manually annotated 2D masks projected onto the point cloud offers a promising path toward a more scalable and interpretable workflow. Moreover, the refinement and fine-tuning of segmentation models will be prioritized, aiming to automate the classification process further while improving prediction accuracy.

Following the successful testing of the workflow in the Westwerk area, the next phase of the study will focus on generalizing the methodology to additional portions of the monument, specifically the Palatine Chapel and the Gothic Choir.

The overall objective of the entire research project is to enhance knowledge of the monument’s geometry, material stratification, and construction logic. To this end, this work contributes to the broader effort of integrating advanced digital technologies into the documentation, analysis, and conservation of architectural heritage, fostering the creation of enriched 3D datasets capable of supporting informed decision-making and multidisciplinary research.

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