# Seg4D: An Open-Source Solution for Supporting the Diagnosis of Historic Constructions Using 3D Point Clouds — A Case Study Application

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**Abstract**

This paper presents the application of the open-source software Seg4D® for the automated diagnosis of historic constructions using 3D point clouds. Seg4D® integrates machine learning, deep learning as well as several ad-hoc algorithms within the CloudCompare® interface to segment construction systems and detect damage. This software has been tested on the 13th-century Church of San Pedro in Becerril del Carpio, Spain. This building shows prominent structural problems, with relevant out-of-plane deformations. A 3D point cloud containing 33 million points was used as input. The construction systems of this building have been identified by applying the Random Forest algorithm implemented in Seg4D, achieving an average precision of 95%. Subsequent geometric analyses identified out-of-plane displacements, buttress inclinations, and arch deformations. These results demonstrate Seg4D's potential as a holistic tool for semantic segmentation and damage assessment, which facilitates structural diagnosis and conservation in cultural heritage contexts.

## 1. Introduction

### 1.1 Introduction

3D point clouds have become fundamental to the construction industry (Morel et al., 2022), as they are widely used in 3D reconstruction, safety assessments, and building performance evaluations. In the field of Cultural Heritage (CH), they are essential for documenting geometry, dimensions and damages (Xiao et al., 2018).

While they were originally used for generating plans and 3D models (di Filippo et al., 2018; Sánchez-Aparicio et al., 2021), advances in Artificial Intelligence (AI) now enable them to be used for semantic segmentation and damage detection through Machine Learning (ML) and Deep Learning (DL) (Yang et al., 2023). Common methods include unsupervised ones (K-means, fuzzy K-means and DBSCAN) (Galantucci et al., 2023) and supervised ones, especially Random Forest (RF) (Teruggi et al., 2020), but these require multiple software tools and lack standardized labelling. DL methods based on neural networks (NN) face similar issues (Matrone et al., 2020; Pierdicca et al., 2020). It is also worth mentioning the lack of standarisation in the labels used for these types of segmentations. Within this context, Matrone et al., (2020) propose a classification system for construction systems, but mostly focused on masonry elements.

Recent studies have demonstrated the value of combining semantic segmentation and damage detection algorithms to support the structural diagnosis of historical constructions (Santamaria-Maestro et al., 2025; Sanz-Honrado et al., 2025a, 2025b). These studies emphasize the potential of automated analysis to simplify decision-making in heritage conservation, where dense and complex datasets typically necessitate extensive manual interpretation. In parallel, the growing availability of public datasets—such as ArCH (F. Matrone et al., 2020) or other GitHub-hosted repositories—has facilitated the training of robust models for semantic segmentation of architectural and structural elements.

In this context, various software tools have been developed to implement these research advances and make them accessible to users. For instance, Ramírez Eudave et al., (2023) developed an open-source platform for evaluating the conservation state of earthquake-vulnerable historical buildings, integrating geometric inspection with structural indicators. More broadly, Sánchez-Aparicio et al. Sánchez-Aparicio et al., (2023) conducted a review of 3D point cloud–based damage detection methods, proposing a unified classification framework that distinguishes between geometric-driven approaches (e.g., deviation maps and curvature analysis) and radiometric-driven ones (e.g., RGB/IR anomalies). This review highlighted the need for tools that bridge the gap between academic research and practical diagnostic workflows.

In response to these challenges, new software solutions have emerged that integrate segmentation and damage detection algorithms within a unified, user-friendly environment. One such solution, based on the well-known CloudCompare® library for 3D point clouds, is the open-source software Seg4D®, (Sánchez-Aparicio et al., 2025), which extends CloudCompare's capabilities and enables end-to-end automated damage detection from 3D point clouds. Seg4D consolidates multiple ML/DL models, offers standardized class labelling and provides a complete workflow for historical building diagnostics. It addresses many of the limitations identified in current methods.

### 1.2 Objectives

As discussed in the previous section, the main objective of this study is to assess the potential of the open-source solution Seg4D in supporting the diagnosis of historic constructions. This overarching goal is addressed through several specific objectives:

- The application of AI-driven methods to segment the construction into its constituent structural elements.
- The implementation of geometry-based damage detection techniques to aid in the diagnostic process.
- The evaluation of the overall performance and effectiveness of the Seg4D software.

## 2. Seg4D software

Seg4D (Segmentation for Diagnose) is open-source software that is compiled and based on the CloudCompare's library (https://www.cloudcompare.org/), a popular open-source platform for managing and processing 3D point clouds. Seg4D provides a unified environment combining ML, DL, as well as ad-hoc algorithm to analyze 3D point clouds for supporting the diagnosis of historic constructions. More specifically, the software includes:

- Supervised and unsupervised ML/DL tools, including Point Transformer NN as well as Automated machine learning (AutoML) method.
- Computation of geometric, statistical, and color-space features;
- Modules for analyzing deflections, inclinations, and out-of-plane deformations;
- Voxelization, noise reduction, and web-based 3D visualization tools;

It also includes integrated classification trees and guides for construction system segmentation and damage detection.
The UI of the software was structure in order to be user-friendly (Figure 1). It is structure in different tabs that are described as follows: i) construction system segmentation, ii) damage detection and; iii) other methods.

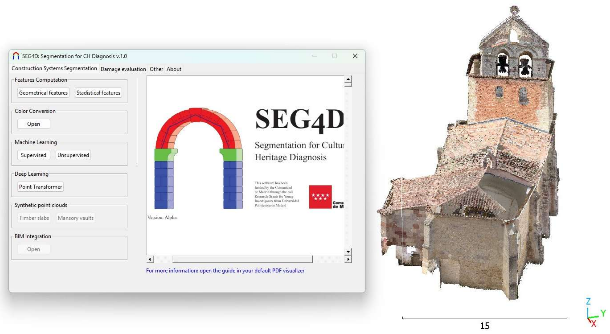



Figure 1. Seg4D interface.

## 3. The Church of Becerril

Built in 1262, the Church of San Pedro in Becerril del Carpio (Palencia, Spain) combines late Romanesque and Gothic elements. It has a single nave with a barrel vault and a ribbed apse vault, supported by columns with Gothic capitals. The building is affected by biological growth, moisture and structural deformations impacting the arches, main nave vault and tower, which are particularly noticeable on the north façade (Figure 2). For further details, see Sánchez-Aparicio et al., (2021).

a)
b)

Figure 2. Current conservation status of the Church: a) structural movement of the tower; b) large deformation in the main nave. Adapted from Sánchez-Aparicio et al., (2021).

### 3.1 Data acquisition and 3D point cloud pre-processing

Sánchez-Aparicio et al., (2019) conducted a digitization campaign of the church using a TLS Faro Focus 120 to obtain a precise 3D point cloud for structural analysis. During this campaign the authors make a total of 15 scan stations that are registered together by using a cloud-to-cloud approach.
The resulting 3D point cloud was made up by 33 million points, equally spaced at 1 cm. This 3D point cloud was used for generating a Finite Element Model to evaluate the structural performance of the Church against different scenarios (i.e. settlements and seismic events). The 3D model was generated without the segmentation of the 3D point cloud.

For the present work, the 3D point cloud was pre-processed in accordance with the procedures outlined in the Seg4D user manual and in line with the workflow adopted in previous segmentation studies of historical construction systems (Sanz-Honrado et al., 2025b). The pre-processing stage consisted of the following: i) the removal of irrelevant or non-structural areas; ii) application of a Statistical Outlier Removal (SOR) filter; and iii) subsampling to a resolution of 1 cm. The resulting 3D point cloud after preprocessing contains a total of 9.9 million points.

a)

b)

Figure 3. 3D point cloud pre-processing workflow applied to the Becerril church: a) raw 3D point cloud and; b) processed 3D point cloud.

## 4. Diagnosis assisted by the Seg4D software

The current section will show the results obtained during the evaluation of the 3D point cloud by means of the approaches implemented in the Seg4D software. These results are structured into: i) the segmentation of construction systems; and ii) the damage detection based on 3D point clouds.

### 4.1 Segmentation of the 3D point cloud in constructive elements

Firstly, it was decided to segment the 3D point cloud into construction systems with the aim of extracting relevant elements such as walls, buttresses, arches and the vault of the main nave. The geometrical features of the 3D point cloud were computed in accordance with the possibilities offered by the plugin. More specifically, the following geometrical features were computed: Z parameter and the Sum of eigenvalues, Omnivariance, Eigenentropy, Anisotropy, Planarity, Linearity, Surface variation, Sphericity and Verticality (Figure 4a). For more information, readers are referred to Weinmann et al., (2015). These features were calculated with different search radii (from 0.1 to 3.2 for the first level of resolution (5 cm spaced between points) and 0.05 to 1.6 for the second level of resolution (2 cm spaced). Statistical features (mean value, standard deviation, range, energy, entropy, kurtosis, and skewness) have also been calculated. The statistical indices at each point's neighbors are what the statistical features are related to. Finally, the “Color Conversion” tool was also used (Figure 4b), as the 3D point cloud contains the RGB information required to use this tool.

a)

b)

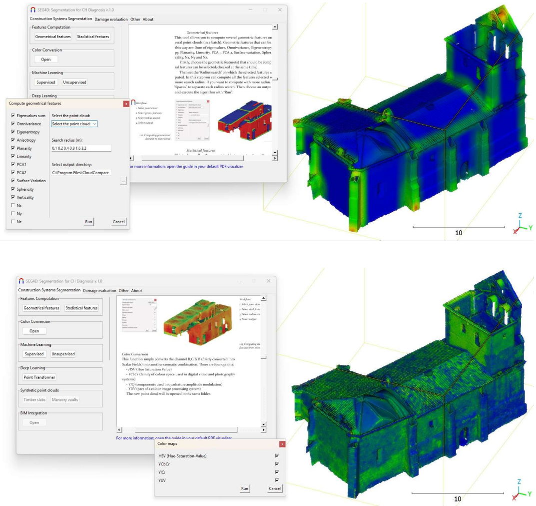


Figure 4. Seg4D computing feature extraction tools. a) Geometrical feature computation (sphericity with a 1.6-meter search radius) and b) color conversion (HSV).

Then, the 3D point cloud was manually labelled into different semantic classes (Figure 6) in accordance with the classification trees for masonry suggested in this work (Figure 5). The 25% of this dataset was used as the training subset, while the remaining 75% was reserved for evaluation purposes.

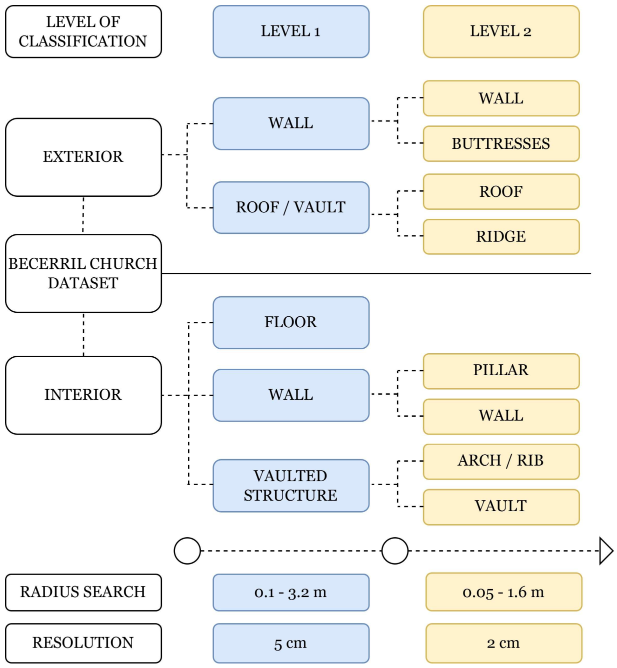



Figure 5. Classification tree for the construction system segmentation of the Becerril church following the Multi-level and Multi-resolution method offered by the Seg4D user manual.

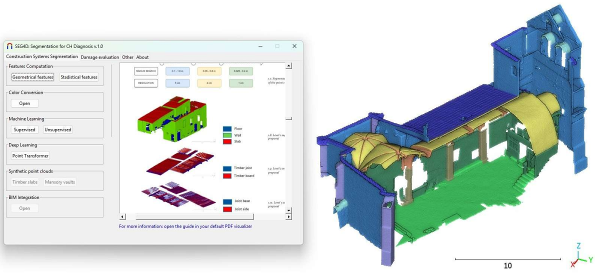


Figure 6. 3D point cloud of the Becerril´s church with labels representing the different construction systems.

The subsequent figure illustrates the outcomes obtained through the application of the multistage segmentation suggested by Seg4D (Figure 7). RF algorithm produces excellent results, with average values for precision reaching 95.2% for all classes (Figure 8).

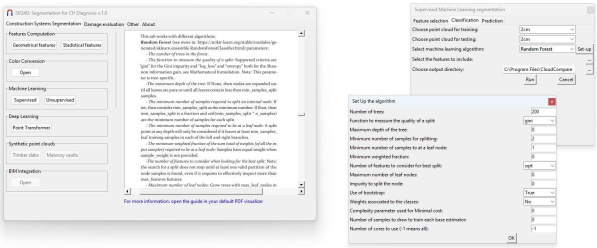
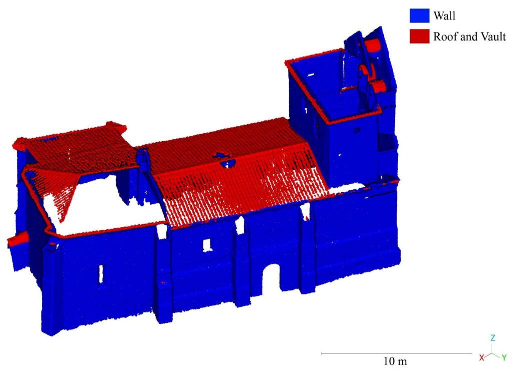


Figure 7. Construction system segmentation tab with their constituent windows of RF algorithm for parameter selection.

To run the RF algorithm for segmentation, the following inputs were required: i) 25% of the 3D point cloud for training, ii) 75% of the remainder for testing, iii) selecting the values for the Random Forest parameters (in this case, the default values were chosen).

a)

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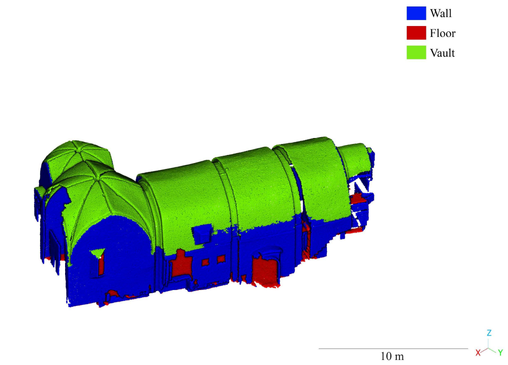


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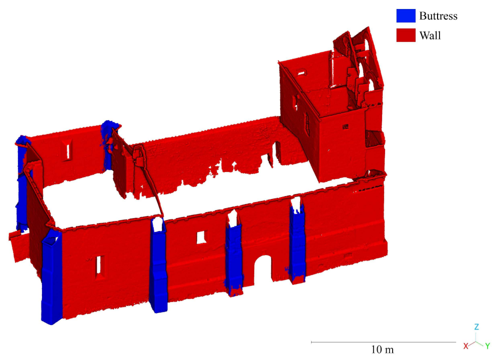


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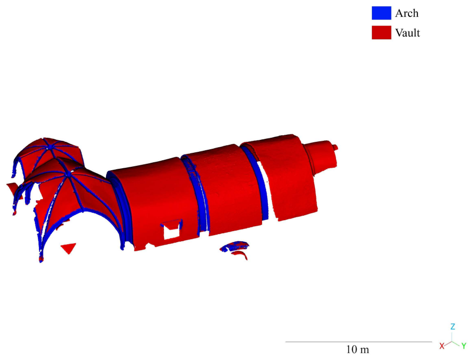


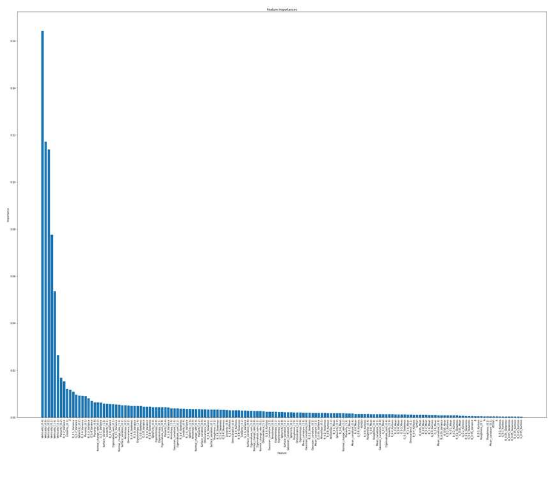

Figure 8. Prediction results obtained from the RF: a) and b) results obtained at the first level of classification; c) and d) results obtained at the second level of classification.

The outputs generated by the software were as follows: i) the point cloud used for testing segmented by classes (Figure 9), ii) the classification metric with precision, recall, and F1-Score (Figure 9a), iii) the feature importance graph (Figure 9b), and iv) the confusion matrix (Figure 9c).

a)

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 1.0 | 0.99 | 0.99 | 0.99 | 111820 |
| 2.0 | 0.98 | 0.96 | 0.97 | 35046 |
| accuracy | | | 0.99 | 146866 |
| macro avg | 0.98 | 0.98 | 0.98 | 146866 |
| weighted avg | 0.99 | 0.99 | 0.99 | 146866 |

b)



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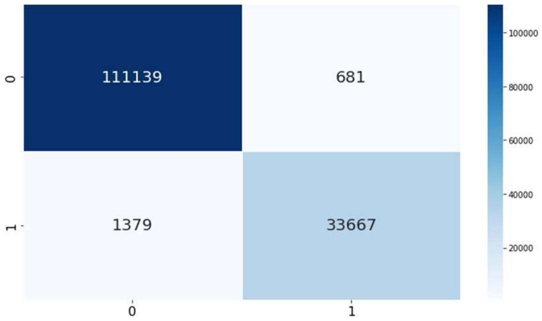



Figure 9. Metrics generated by Seg4D at first level of classification. a) Classification accuracies, b) feature importance graph and; c) confusion matrix.

The following table (Table 1) summarizes the accuracy percentages obtained at each classification level. Depending on the type of geometric difference between classes, it is possible to achieve greater or lesser accuracy. For instance, at level 1 on the exterior (Figure 8a), the accuracy was 0.99 due to the difference in verticality between the wall and the roof.

Conversely, at level 2, when segmenting between the wall and the buttress, errors are noticeable at the bases and tops of the buttresses (Figure 8c). This may be because the geometry of these junctions with the wall differs from that of the rest of the buttress. The same thing happens in other segmentation work, which also generates misclassifications at these junctions (Sanz-Honrado et al., 2025b).

| Level | Construction systems | Weighted average accuracies | | |
|---|---|---|---|---|
| | | Precision | Recall | F1-Score |
| Level 1 | Exterior (E) | 0.99 | 0.99 | 0.99 |
| Level 1 | Interior (I) | 0.944 | 0.94 | 0.94 |
| Level 2 | Wall / Buttress (E) | 0.935 | 0.933 | 0.931 |
| Level 2 | Roof / Ridge (E) | 1.00 | 1.00 | 1.00 |
| Level 2 | Pillar / Wall (I) | 0.915 | 0.883 | 0.896 |
| Level 2 | Arch / Vault (I) | 0.957 | 0.956 | 0.956 |

Table 1. Weighted average accuracies of the resulted classifications.

Other errors observed include those relating to the segmentation of the vault and the arches/ribs (Figure 10). As can be seen in the figure, this may be due to the arch's width, which differs from that of the ribs and is more geometrically similar to the vaulted panels. All of these misclassifications required manual correction to improve the performance of damage detection tools.

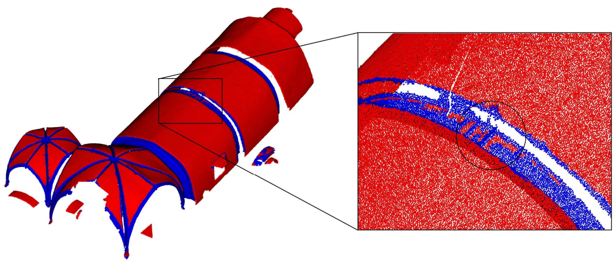


Figure 10. Classifier mismatches in the predictions using RF algorithm.

## 4.2 Damage detection based on the 3D point cloud

The classes identified as walls, buttresses, vaults and arches were used as inputs for the subsequent damage assessment. More specifically, the following geometric-based methods were implemented (Sánchez-Aparicio et al., 2023):

• A point-to-primitive distance strategy to evaluate the out-of-plane movements of the north façade and the tower.

• An analysis of sections to estimate the inclination of the buttresses.

• A curve-fitting strategy to estimate the deformations present in the arches and vault of the main nave.

**4.2.1 Out-of-plane movements of walls:** The evaluation of the inclination and out-of-plane movements experienced by the north façade wall and the tower was performed by extracting the best-fit plane for each wall. To this end, it was required to perform an instance segmentation by using the RANSAC Shape Detector implemented in CloudCompare. The hyperparameters for this study case were set as follows, a maximum distance to primitive of 0.05 metres and a maximum normal deviation of 25 degrees (Santamaria-Maestro et al., 2025).

This algorithm provided the best-fit planes to compute both point-to-primitive distances and normal vector angles. The first output allows for the observation of possible out-of-plane movements, such as those observed on the last wall of the main nave (Figure 11). The second output enables the evaluation of the inclination of the walls, as well as the leaning angle of the tower. The average inclination angle was 1.38º, a value that does not compromise the stability of these elements. The tower presented a leaning angle of 1.37º, which lies within the safety limit according to the classical recommendations of Heyman, (1966).

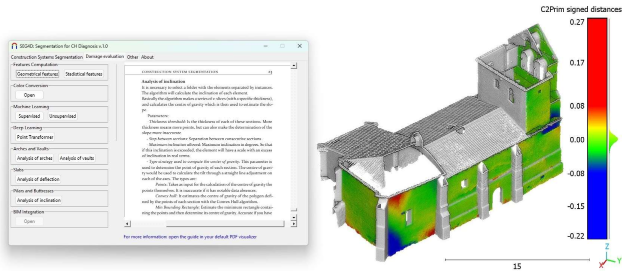



Figure 11. Results of the distance point to plane to evaluate the out-of-plane movements of the walls.

**4.2.2 Buttress inclination analysis:** The second stage of the damage assessment focused on evaluating the inclination of the buttresses. In this case, the points used as input were all those labelled as buttresses by the RF, shown in blue in Figure 8c. Before computing their inclination, instance segmentation was required. In this case, the DBSCAN algorithm implemented in the Seg4D plugin was used, with a maximum inter-point distance (ε) of 2 meters.

The inclination of each buttress was then computed using the "inclination analysis" tool implemented in Seg4D (Figure 12). The inputs for this algorithm were a distance between sections of 0.5 metres and a convex hull method to extract section centroids. Three of the four buttresses presented inclination angles between 0º and 1º. However, one buttresses exhibited a tilt of 3.1º.

According to Heyman's equations (Heyman, 1966) and a graphical analysis of the buttress section, the critical inclination is estimated at 10.7º, with crack formation expected from approximately 3.6º. Thus, this buttress is close to the threshold at which the first cracks are expected to appear.

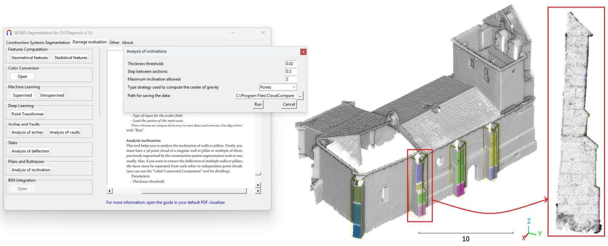


Figure 12. Appearance of Seg4D analyzing the buttress inclination.

**4.2.3 Deformations of arches and vault:** The final stage of this damage assessment concerned the analysis of deformations in the arches and the barrel vault of the main nave in order to support the decision-making of the structural engineers. All points labelled as arches and vault were used as input (Figure 8d), extracted during the second-level classification. Consistent with the other stages, the first step was to perform an instance segmentation using the DBSCAN algorithm (Figure 13).

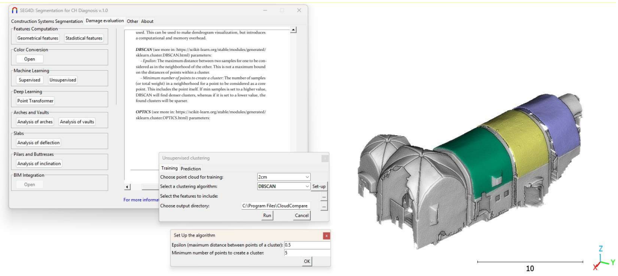
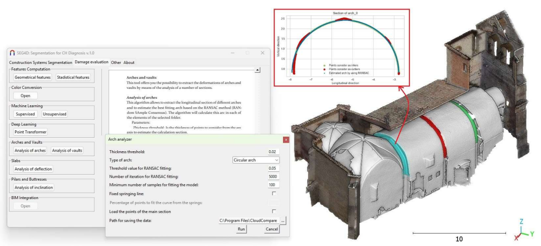


Figure 13. Instance segmentation of vaults using DBSCAN algorithm

The deformation analysis of each arch, as well as each section of the vault were analysed using the "deformation analysis" tool for arches and vaults implemented in Seg4D. Most hyperparameters were kept at their default values, with two adjustments: i) the inlier threshold for RANSAC estimation, set to 2 centimetres and; ii) the minimum/maximum Z coordinates for extracting the vault axis, defined as -0.24 metres and 0.30 metres, respectively. The fitting model used in all the cases was set to circular arches, except for one arch and the barrel vault. In both cases, the fitting model was set for pointed arches.

For the arch associated with the most tilted buttress (Figure 14a), the RANSAC outliers revealed deformation patterns indicative of the development of plastic hinges (Figure 2a). This mechanism seems to be compatible with those related to the rotation of the arch supports caused by buttress inclination (Heyman, 1966). Similar deformations were observed along the vault (Figure 14b).

a)



b)

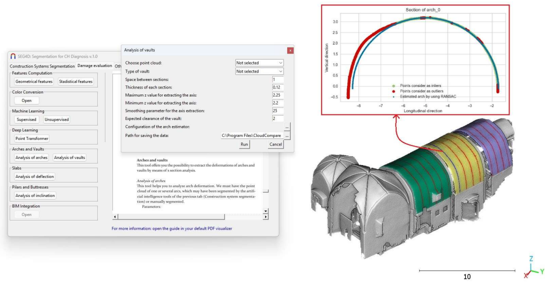


Figure 14. Results obtained with Seg4D from the analysis of: a) arch and; b) vault deformation with the best-fit model obtained through the RANSAC approach.

## 5. Conclusions

This paper describes how the Seg4D software framework can be used to diagnose the structural condition of historic buildings by automatically analysing 3D point clouds. The proposed workflow integrates artificial intelligence-based tools for segmenting construction systems, specifically using machine learning classifiers, as well as a set of geometric-based methods for detecting damage, including analysing out-of-plane displacement, tilt assessment, and curve-fitting strategies for arches and vaults.

The empirical results demonstrate that the analysed building, the Church of San Pedro, exhibits significant geometric distortions, particularly in the walls of the south façade, as well as in the arches and vault of the main nave. Seg4D enabled the quantitative assessment of wall deformations, buttress inclination, and geometric irregularities affecting the arches and vaults. These results provide valuable, objective information that improves the building's overall diagnosis, particularly with regard to its structural behaviour and potential stability issues.

Despite the high level of automation achieved, the study highlights the need for expert intervention at specific stages of the process. Manual validation is necessary to ensure the accuracy of the construction system classification, correct local misclassifications that could affect subsequent damage detection algorithm performance, and select appropriate hyperparameters for each analytical tool.

Additionally, correctly using Seg4D currently requires integrating external tools in CloudCompare for preprocessing (e.g., subsampling, segmentation and the SOR tool) and for damage detection tasks (e.g., RANSAC-based shape detection for instance segmentation). These findings suggest that automated diagnostic workflows should be considered decision support systems rather than fully autonomous solutions.

Future research will focus on reducing reliance on manual intervention by improving the robustness of classification models, generating synthetic 3D point cloud datasets of building systems and extending the framework to a wider range of building typologies and damage mechanisms.

## Acknowledgements

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