# Impact of Point Density Variation in Aerial Photogrammetric Point Clouds on Feature Extraction for the development of Cultural Heritage Digital Twin

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**Abstract**

The development of Digital Twins for cultural heritage applications depends highly on accurate and detailed 3D representations of historical structures. Aerial photogrammetry has emerged as a popular remote sensing technique for capturing such Cultural Heritage (CH) structures, primarily due to its high-resolution, detailed outputs and cost-effectiveness. However, the quality of the derived photogrammetric point clouds, particularly point density, significantly influences the efficiency and accuracy of downstream procedures such as feature extraction to be used for different applications. This research work investigates how variations in point density affect the detection and segmentation of windows and rooftops, which are two key architectural features for the development of Energy Digital Twins (EDT) for the analysis of energy consumption patterns of the CH buildings. Using aerial photogrammetric datasets, we generated point clouds using the photogrammetric images and their accurate image orientations with a bundle adjustment processing. After that, we tested the point cloud at different densities (ranging from original resolution to 1/16th of the original point density) by controlled uniform down-sampling of an original high-density cloud. We evaluated an automated deep learning-based method segmentation of the windows and rooftop features from the point cloud datasets. The investigation indicates a strong correlation between point density and feature extraction accuracy, with a clear decline in detection performance if the subsampling goes below 1/8th of the original point density, which is around 20 points/m². Rooftop features exhibited greater resilience to reduced density compared to window features and were still detected even with down-sampled point clouds. The research work proposes a density-aware workflow for CH Digital Twin development and emphasises the need for strategic planning in aerial data acquisition for heritage documentation for the optimisation of aerial photogrammetric data practices and to enhance the reliability of Digital Twins in cultural heritage conservation.

## 1. Introduction

### 1.1 Background and motivation of the work

The preservation, documentation, and sustainable management of cultural heritage sites have been significantly enhanced using digital technologies. Among these innovations, the concept of the Digital Twin has emerged as a powerful framework for multiple applications ranging from urban environments to the cultural heritage documentations. A Digital Twin is a dynamic, virtual representation of a physical structure, enriched with detailed geometric and semantic information (Abdelrahman et al., 2025; Hermon et al., 2024; Lehner and Dorffner, 2020). In the field of cultural heritage, Digital Twins facilitate monitoring, structural analysis, conservation planning, and public engagement through immersive visualizations (Dang et al., 2023). CH digital twins offer a non-invasive means of recording and assessing heritage assets, helping to minimize the risk of physical deterioration, and preserving the CH structures in a digital format also including the dynamics associated with the structures.

Airborne photogrammetry could be one of the emerging and advanced tools for the development of Digital Twins of cultural heritage sites. Using Unmanned Aerial Vehicles (UAVs) and/or manned aircraft, high-resolution imagery can be captured efficiently, even in complex or inaccessible environments as in the case of CH structures (Kong and Hucks, 2023; Vilbig et al., 2020). Processing these images through photogrammetric techniques generates dense three-dimensional point clouds, which serve as the foundation for constructing accurate virtual models(Apollonio et al., 2021; Toschi et al., 2021).

However, the density of the point cloud plays a critical role in the successful extraction of key architectural features such as windows, rooftops, and facade details(Pu and Vosselman, 2009). Variations in point density, initially caused by flight parameters, sensor limitations, and environmental factors, can significantly affect the quality and reliability of Digital Twin models (Mohammadi et al., 2021). While photogrammetric methods are widely adopted, systematic investigations into the impact of point density on feature extraction accuracy remain limited (Deliry and Avdan, 2023; Goodbody et al., 2021).

Point density is an important factor to consider when working with large-scale point cloud datasets, especially when the size of the data makes processing difficult or time-consuming (Carós et al., 2023; Jung and Lee, 2025). In some cases, using the full-resolution data may not be necessary, and lower-resolution versions can be more efficient to process. This can be useful for certain tasks such as feature extraction, where reduced point density may still provide sufficient information while improving processing speed. However, the choice of resolution of point clouds depend on the type of features to be extracted and analysed, as lower resolutions may reduce accuracy for smaller or more detailed features, while still being adequate for larger, simpler structures (Liu et al., 2019; Stilla and Xu, 2023).

The motivation behind this work is the need to investigate the trade-off between point density variations and the efficiency of the feature extraction processes from the point cloud datasets. To address this, the research work aims to contribute towards a reliable and scalable workflow for the rooftop and windows features extraction which are essential inputs for the development of Digital Twins in cultural heritage applications.

### 1.2 Related works and context

Over last decade, the application of photogrammetric methods to cultural heritage has significantly advanced the way historic sites and monuments are documented and preserved(Kong and Hucks, 2023). Aerial and airborne photogrammetry offer the possibility to acquire detailed spatial and visual information over large and complex heritage areas without direct physical contact (Remondino, 2011). The resulting three-dimensional point clouds serve as a foundation for developing precise and informative models that support conservation, restoration, and public dissemination efforts.

Several projects have utilized dense photogrammetric point clouds to reconstruct architectural features such as facades, roofs, and ornamental elements(Malihi et al., 2016). Feature extraction from these photogrammetric point clouds is critical for the generation of accurate Digital Twins, enabling detailed analysis and long-term monitoring of cultural assets (Chen et al., 2023; Konstantakis et al., 2024). Techniques based on geometric segmentation, shape analysis, and supervised classification have been employed to automate the identification of architectural components within point clouds(Moyano et al., 2024).

Despite these developments, the challenge to deal with the point cloud for different feature extraction remains open. Much of the existing work relies on high-density point clouds obtained under controlled conditions, which are not always attainable in heritage environments due to accessibility, time, or budget constraints. The impact of point density variation on the extraction of significant architectural features from aerial photogrammetry and DL methods remains insufficiently studied. Understanding this trade-off between the point density and effectiveness of feature extraction is essential for establishing reliable workflows suited to the specific demands of cultural heritage documentation and Digital Twin development (Ćosović and Maksimović, 2022; Noronha Pinto de Oliveira e Sousa and Correa, 2023).

### 1.3 Research objectives

This study aims to explore how point density variations in aerial photogrammetric point clouds affect the extraction of key architectural features for the development of Digital Twins of cultural heritage sites. The research has been motivated to investigate two main objectives:

(a) To investigate how different point densities in aerial photogrammetric point clouds affect the accuracy of feature extraction for windows and rooftops in cultural heritage buildings

(b) To investigate the performance of deep learning-based feature extraction procedure at different point density levels and determine their effectiveness for cultural heritage digital twins

## 2. Methodology and conceptual framework

### 2.1 Point cloud processing

The initial step in processing the point cloud data involved using Agisoft Metashape, a photogrammetry software that generates dense 3D point clouds from aerial photogrammetry images using their accurate exterior orientations. Metashape was used to align the images and create a dense point cloud from the camera positions. This sparse point cloud was then used to generate a dense point cloud, which represents the geometry of the heritage site. The dense point cloud is critical for accurately capturing fine architectural details, such as windows and rooftops.

To ensure data consistency and accuracy, the raw point clouds were first processed using CloudCompare. This included noise removal and the alignment of different point cloud datasets, ensuring they were properly georeferenced. Ground points were removed to focus on the architectural features, leaving only the relevant above-ground points for further analysis. The point cloud was normalized to align with a standard reference system, making it easier to compare and process across multiple datasets. This pre-processing step also included the removal of any outliers or erroneous points, ensuring a clean and reliable dataset for the following stages.

### 2.2 Down-sampling of point clouds

In this step, the point clouds were down sampled using uniform sampling techniques in CloudCompare. This process reduced the overall number of points with uniform sampling method while maintaining a representative distribution of the original dataset. Different down sampling densities were tested, including $1/2^{nd}$ , $1/4^{th}$ , $1/8^{th}$ , $1/10^{th}$ and $1/16^{th}$ to simulate varying levels of point density. The purpose of this down sampling step was to assess the effect of point cloud resolution on the accuracy of feature extraction, focused for small architectural features like windows and rooftops. Uniform sampling was chosen to maintain consistent point distribution, ensuring that the reduced point clouds still represented the spatial structure of the original dataset(Zhang et al., 2022).

### 2.3 Data preparation for DL algorithm

Data preparation for the deep learning (DL) model involved the preparation of the annotations of point cloud data for the classes of interest, specifically windows and rooftops in this research work. The goal was to create a labelled dataset that would be used for training the KPConv algorithm. In this step, each point in the point cloud corresponding to the features of interest (i.e., windows and rooftops) was manually annotated in CloudCompare. The annotation process involved selecting subsets of points that represented architectural components and labelling them accordingly.

For windows, the points that corresponded to window openings corner of frames were identified and labelled as the "Building window" class, while the points corresponding to roof surfaces, edges, and ridges were labelled as "Building rooftop" classes. These labels were crucial for training the model to distinguish between different types of architectural features based on spatial and geometric characteristics. The following classes of architectural features were annotated in this step:

| *Class ID* | *Feature class* |
|---|---|
| 0 | Non building |
| 1 | Building window |
| 2 | Building rooftop |

Table 1: Building features annotation classes.

Once the annotations were completed, the labelled point cloud data was split into training, validation, and testing sets. These sets


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were used to train the KPConv model and to evaluate its performance. In addition to the annotations, other data preparation steps included ensuring that the point clouds were scaled appropriately and converted into a format (:txt / .ply) that was compatible with the KPConv algorithm. This ensured that the model could process the data efficiently during training and evaluation of the feature extraction procedure.

### 2.4 Feature extraction with DL algorithm

The data preparation for deep learning (DL) model training involved two key steps: annotation of the point cloud data and conversion of the data into a format suitable for the KPConv algorithm. The main objective was to prepare labelled point clouds of windows and rooftops from the heritage site for feature extraction using KPConv, a point-based convolutional neural network (CNN) that directly processes 3D point cloud data.

Once the point cloud data was annotated, it was converted into a format suitable for KPConv. KPConv requires local patches of points to be fed into the model for learning. These patches consist of neighbourhoods around each point that capture its geometric and spatial properties. The point cloud data was segmented into small patches around each annotated point, ensuring that each patch included points from the surrounding neighbourhood in the cloud. These patches were organized such that they retained both the geometric features (such as position and shape) and semantic labels (i.e., whether the points belonged to a "window" or "roof").

The annotated point cloud data was then fed into the **KPConv** model, a point-based convolutional neural network specifically designed for processing irregular 3D point cloud data. KPConv operates by learning local geometric patterns and spatial relationships directly from the point cloud, without requiring a regular grid structure. Through its convolutional operations, KPConv captures key geometric features, such as the flatness of rooftop surfaces or the rectangular geometry of windows, by analysing the spatial arrangement and distribution of points within a localized neighbourhood.

As the model processes these annotated regions, it iteratively learns to extract discriminative features that distinguish between different architectural elements, such as windows and rooftops. The KPConv model's ability to directly process raw point cloud data enables it to recognize and classify complex geometric patterns based on the inherent 3D structure of the data, thereby improving the accuracy of feature extraction in the context of cultural heritage documentation.

### 2.5 Accuracy Assessment of the feature extraction

Several standard metrics were used to quantify the performance of the KPConv model in detecting and classifying windows and rooftops from the point cloud data. The primary evaluation metrics was carried out with F1-score matrix which provided insight into the model's ability to correctly identify true positives (correctly predicted features), while minimizing false positives (incorrectly predicted features) and false negatives (missed features). Additionally, Intersection over Union (IoU) was calculated for the segmented regions to measure the overlap between the predicted and annotated feature areas, providing a clear indication of segmentation accuracy.

These accuracy metrics were calculated across various point cloud densities to assess the robustness of the feature extraction process under different data resolutions. This enabled a thorough analysis of the impact of point density on the performance of KPConv in feature extraction tasks for cultural heritage applications.

### 2.6 Overall Methodology Workflow

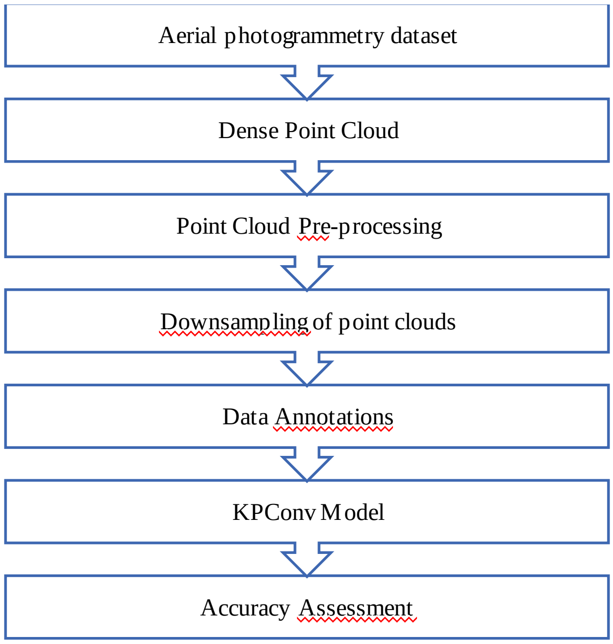


Figure 1: Methodology workflow.

## 3. Study Area and Dataset Acquisition Systems

This part of the paper includes the study area description which has been selected for this research work, followed by the details of the data acquisition and the processing tools used for this research study.

### 3.1 Study area

The selected study area for this research is the Castello del Valentino, located in Torino (Turin), Italy. This historic site encompasses approximately 2.01 hectares (20,100 square meters) and comprises around 27 rooftops (ITALY, 1997; Luigi La Riccia et al., 2024). Despite its modest size, the area exhibits a diverse array of rooftop structures and dimensions that are representative of typical urban configurations found throughout Torino.

The selected study area "Castello del Valentino" holds significant cultural and historical value. Originally purchased by Duke Emmanuel Philibert of Savoy in 1564, the castle underwent substantial renovations in the 17th century under the direction of Christine of France, transforming it into a Baroque-style residence. In recognition of its architectural and historical importance, it was designated as a UNESCO World Heritage Site in 1997 as part of the "Residences of the Royal House of Savoy" ensemble (ITALY, 1997) . Today, the castle serves as the main building for the Architecture Faculty of the Polytechnic University of Turin. Figure 1 below shows one of the images of the study area from data acquisition considered in this research work.

Figure 2: Study area image from airborne data acquisiton : Castello del Valentino, Torino, Italy

An additional factor influencing the selection of this site is the availability of comprehensive datasets and processed data products obtained through the Torino Digital Twins project (Boccardo et al., 2024). These resources provide high-resolution spatial and structural information, facilitating detailed analysis without the need for extensive new data acquisition.

### 3.2 Datasets Acquisition systems

The aerial photogrammetry dataset used in this work was collected for the Turin Digital Twin (DT) project, acquired during a dedicated aerial survey conducted in January 2022. The data acquisition was carried out using the Leica CityMapper-2, a state-of-the-art hybrid sensor system capable of capturing both high-resolution optical imagery and LiDAR point cloud data simultaneously. The sensor was mounted on an aircraft operating at an approximate flight altitude of 1,000 meters above ground level.

For the specific area surrounding Castello del Valentino, 358 aerial images were captured, preserving the GSD of 5 centimetres to ensure the detailed capture of urban environments of Torino. At each capture location, five images were taken with one nadir (vertical) and four oblique views. The acquisition pattern of the photogrammetric dataset has been illustrated in Figure 3. ensuring high spatial resolution suitable for urban-scale modeling. To ensure a sufficient image coverage and 3D reconstruction quality, the data acquisition maintained a 60% lateral overlap and 80% longitudinal overlap between consecutive images.

### 3.3 Data Processing and implementation solutions used

The following data processing tools have been used for the data processing and feature extraction procedure. Table 1 presents the various software used and their usage in the work.

| Input Dataset / Product | Software / Solutions | Usage |
|---|---|---|
| Aerial Images and orientations | Metashape | Generation of dense point cloud |
| Annotation preparation | Cloud Compare | For training of the model |
| Feature extraction | Python | Extraction of windows and rooftops |
| KPConv Model | Python | DL implementation |

Table 1: Software and tools used in the research work**.**

## 4. Results

### 4.1 Processing of the point clouds

The processing of the point clouds was carried out using the Agisoft Metashape software. The initial step involved the alignment and georeferencing of the aerial photogrammetry images to generate a dense point cloud with high spatial resolution. The dense point cloud was generated with 5,150,933 points. The point clouds were then cleaned by removing noise and ground points, ensuring that only relevant architectural features remained for analysis. Figure 3 below shows the filtered and pre-processed dense point cloud generated from the Metashape processing. This pre-processing phase ensured that the point clouds were ready for both down sampling and subsequent feature extraction using the KPConv model.

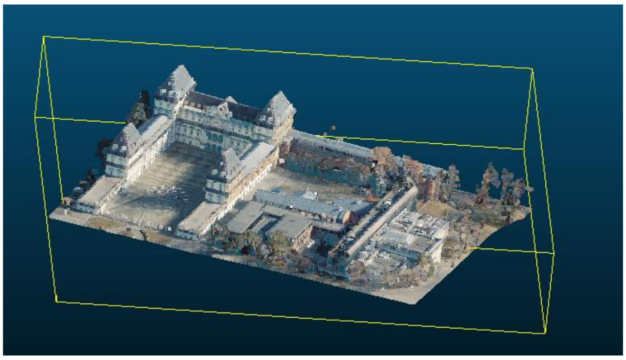

Figure 3: Pre-processed point cloud from aerial photogrammetry

### 4.2 Down-sampling of the point clouds

To evaluate the impact of point density variation, a uniform down-sampling of the original dense point cloud was performed. The original point cloud, containing approximately 5,150,933 points, was progressively reduced using uniform random sampling in CloudCompare. Down-sampling ratios of 1/2, 1/4, 1/8, 1/10, and 1/16 of the original resolution were applied.

This approach simulates practical scenarios where variations in the airborne flight parameters or environmental conditions lead to different levels of point density. The goal was to analyse how different resolutions influence the feature extraction capability of the deep learning model. Each down-sampled dataset was independently processed for training, validation, and testing in the feature extraction workflow. The final number of points in each down-sampled dataset is summarized in Table 2.

| Down sampling ratio | Number of points | Percentage of Original Points (%) |
|---|---|---|
| Original point cloud | 5,150,933 | 100 |
| 1/2nd | 2,575,466 | 50 |
| 1//4th | 1,287,733 | 25 |
| 1/8th | 643,866 | 12.5 |
| 1/10th | 515,093 | 10 |
| 1/16th | 321,933 | 6.25 |

Table 2: #points after down sampling of the point clouds.


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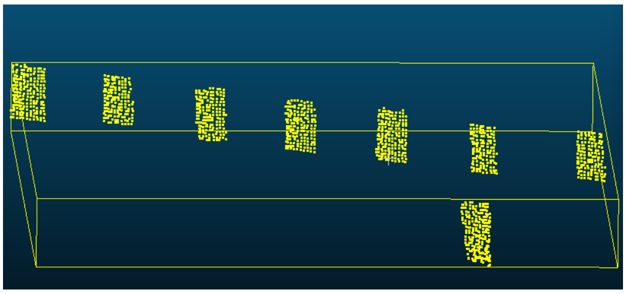
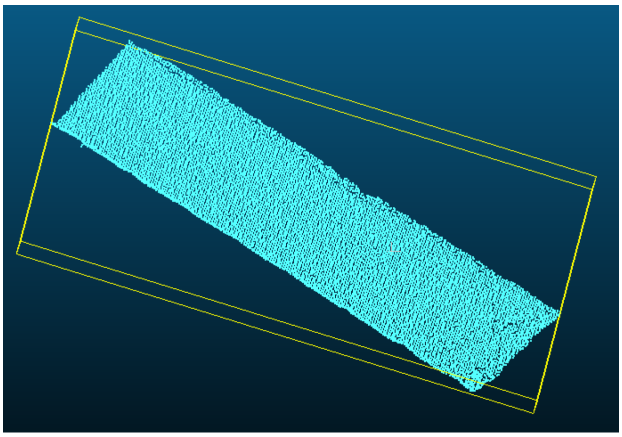
### 4.3 Annotation for DL implementation

For the deep learning implementation, manual annotation of the point clouds was carried out using CloudCompare. The annotations focused on identifying and labelling two main classes of interest: windows and rooftops. Care was taken to ensure that the annotated regions were representative of the diverse architectural features present in the study site, including variations in window shapes, sizes, and rooftop geometries.

The annotation process involved selecting groups of points corresponding to each feature and assigning them distinct class labels. Three classes namely "Non Building", "Building " and "Building rooftop" were annotated in this step. Only clean, clearly distinguishable features of interest were annotated from a selected part of the point cloud dataset to maintain high data quality. Areas with occlusions, severe noise, or incomplete structures were excluded to prevent introducing ambiguity during model training.



(a)



(b)

Figure 4: Data annotations for feature class (a) Building window (b) Building rooftop.

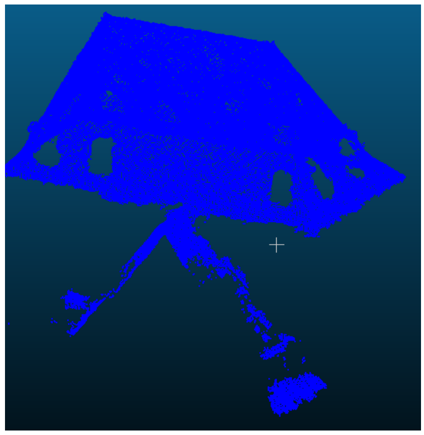
Approximately 15% of the total point cloud was annotated to create a sufficiently large and balanced dataset for the KPConv model. Annotations were prepared separately for each down-sampled version of the point cloud to evaluate the effect of reduced density on the learning and detection performance. This annotated dataset served as the ground truth for training, validation, and testing phases of the deep learning model.

### 4.4 Windows and Rooftop extraction

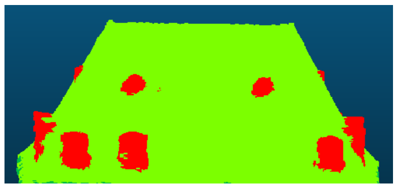
The KPConv model was trained using annotated point clouds to extract windows and rooftops from the building datasets. After training, the model was evaluated on point clouds at different down-sampling levels to assess its robustness against varying point densities.

The extraction results showed that rooftop features, due to their larger and more planar characteristics, were detected more reliably across all densities. In contrast, windows, being smaller and finer features, showed a significant drop in detection accuracy as the point density decreased.

Accuracy was assessed using F1-Score and IoU score metrics for both windows and rooftops. Figure 5 summarizes the performance results of feature extraction at different point cloud densities. Figure 5 shows a snapshot of extracted windows and rooftop features from point cloud with original point cloud density.



(a)



(b)

Figure 5: Detected (a) Building rooftop (b) windows (in red) in original point density point cloud.

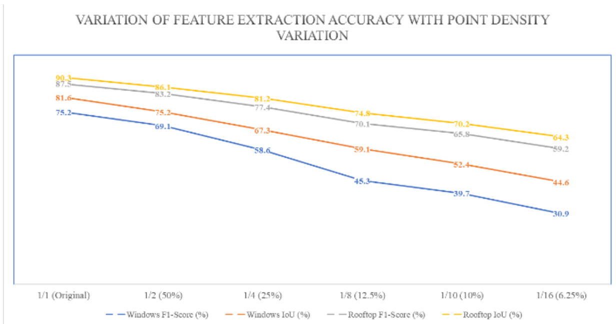



Figure 6: Results of feature extraction at different point cloud densities.

The results shown in the Figure 6 emphasize the significant effect of point cloud density on the accuracy of extracting windows and rooftop features. As the resolution decreases (from the original high-density point cloud to 1/16 of the resolution), both the F1-Score and IoU values for feature extraction decline notably. The F1-Score and IoU for windows decrease from 75.2% and 81.6% at the original resolution to 30.9% and 44.6%, respectively, at 1/16 resolution. For rooftops, the decline is less dramatic, with the F1-Score and IoU dropping from 87.5% and 90.3% at the original resolution to 59.2% and 64.3%, respectively, at 1/16 resolution.

This decrease in performance is especially evident for windows, which require high-resolution data to accurately capture fine geometric details and precise spatial positioning. In comparison, rooftops, being larger and more continuous surfaces, are less affected by the reduction in resolution. Windows are typically small, detailed, and often recessed into building facades, making their accurate detection highly dependent on fine geometric resolution and precise spatial positioning. When the resolution is reduced, much of this critical detail is lost, leading to a noticeable drop in detection performance. In contrast, rooftops are generally larger, flatter, and more continuous in structure, making them less sensitive to the loss of detail that comes with lower-resolution point clouds. As a result, rooftop extraction remains relatively stable even at reduced resolutions.

These results highlight the importance of maintaining sufficient point density, particularly when extracting detailed features such as windows in the context of CH buildings. While rooftops can be detected with reasonable accuracy even at lower densities, windows require a higher density for reliable extraction. Therefore, for cultural heritage documentation, maintaining a minimum density of 1/2 or 1/4 of the original resolution is recommended to ensure accurate feature extraction, also depending on the further application where the extracted features must be used.

## 5. Discussions

This study presents the significant impact of point cloud density on the accuracy as well as processing of feature extraction for the development of Digital Twins of cultural heritage buildings. The results demonstrate that windows, as smaller and more intricate features, are particularly sensitive to reductions in point cloud density. As point density decreased from the original 5,150,933 points to 1/16 of the original resolution, both F1-Score and IoU for window extraction dropped extremely. At full resolution, the F1-Score for windows was 75.2%, with an IoU of 81.6%. However, at 1/16 resolution, these values dropped to 30.9% for F1-Score and 44.6% for IoU, showing a 60% decrease in F1-Score and nearly 45% reduction in IoU. This significant decline indicates the challenge of accurately extracting smaller features like windows when point cloud density is insufficient, which is crucial for creating detailed and accurate Digital Twins of cultural heritage assets.

In contrast, the rooftop feature extraction was more resilient to density reduction. At full resolution, the F1-Score for rooftops was 87.5%, with an IoU of 90.3%. Even at 1/16 resolution, the F1-Score and IoU for rooftops dropped to 59.2% and 64.3%, respectively, reflecting a moderate decline of 32% in F1-Score and 29% in IoU. These results suggest that rooftops, being larger and more planar surfaces, retain enough geometric information at lower densities to maintain relatively high accuracy, which is valuable for Digital Twin development, particularly for structural analysis and conservation monitoring.

It is also worth mentioning that annotations play a critical role in the accurate extraction of windows and rooftop features from point clouds, especially as point density varies. High-quality, detailed annotations guide learning algorithms in recognizing subtle geometric and spatial characteristics which is a critical aspect particularly for windows, which are more sensitive to resolution changes. At lower point densities, where fine details are often lost, well-annotated training data becomes even more crucial to compensate for the missing information ( with points) and support the algorithm for the accurate feature detection.

In contrast, larger features such as rooftops are generally more geometrically consistent across varying resolutions, allowing for relatively coarser annotations without significantly compromising performance. Therefore, the quality and granularity of annotations must be carefully aligned with the point cloud resolution to ensure reliable and robust feature extraction.

The findings emphasize the need for high-resolution data for the extraction of detailed architectural features such as windows in Digital Twins. Given that windows are integral to the historical significance and visual identity of heritage buildings, maintaining a minimum density of 1/2 or 1/4 of the original point cloud resolution is crucial to ensure that these features are captured accurately. The results indicate that lower-density point clouds can still be useful for extracting larger, less detailed features like rooftops, but for precise documentation and preservation, high-density data is required for small-scale features.

In the context of Digital Twins for cultural heritage, which are used for structural analysis, conservation efforts, and virtual reconstruction, these results demonstrate that lower-density point clouds should only be considered for broad, coarse-scale modeling. For detailed monitoring and restoration, a minimum density of 1/4 of the original resolution, or higher, should be prioritized. Future work could focus on optimizing data acquisition strategies by combining photogrammetry with other technologies like LiDAR or terrestrial scanning to ensure that Digital Twins remain accurate, especially for capturing the fine details that are critical to cultural heritage conservation.

## 6. Conclusion

his study investigated the impact of point cloud density on the extraction of architectural features from aerial photogrammetric data for the development of Digital Twins in the context of cultural heritage. The results underline the critical role that point cloud resolution plays in ensuring the accuracy of feature extraction, particularly for smaller, detailed elements like windows. As demonstrated in the results, the extraction accuracy of windows decreased significantly with lower point cloud densities. At 1/16 of the original resolution, the F1-Score for windows dropped to 60%, highlighting the challenges in capturing fine details when the density is insufficient. These findings emphasize that high-resolution point clouds are essential for the accurate documentation and preservation of small architectural features in heritage buildings.

In contrast, the extraction of rooftops showed more resilience to density reduction. Even at lower densities, rooftops, being large and planar, maintained relatively high accuracy. This suggests that larger, more robust features can still be reliably extracted with reduced point density, which is advantageous for broader-scale Digital Twin applications. However, even for rooftops, there was a noticeable decline in extraction performance at lower point densities, underlining the need for sufficient data to ensure precision in all architectural features.

The study also highlights the potential for hybrid approaches, combining aerial photogrammetry with other technologies like LiDAR and terrestrial scans, to mitigate the limitations posed by low-density point clouds. These methods could help achieve the required detail and accuracy without the high costs associated with consistently high-resolution data acquisition.

For a takeaway from this research work, the development of Digital Twins for cultural heritage requires careful consideration of point cloud density, especially for the extraction of detailed architectural features such as windows. The results indicate that to ensure high accuracy and reliability, a minimum point cloud resolution of 1/4 of the original density should be maintained, particularly for small features. Future works could focus on optimizing data collection methods and integrating multiple data sources to enhance the accuracy and efficiency of Digital Twin creation for cultural heritage preservation.

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