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A COMPARATIVE ANALYSIS OF POINT CLOUD CLASSIFICATION FOR CULTURAL HERITAGE DOCUMENTATION — THE CASE STUDY OF THE MONODRI BRIDGE, EVIA, GREECE

Abstract:

This study presents a comparative analysis of proprietary and custom point cloud classification pipelines in the context of cultural heritage documentation, using the Monodri Bridge in Evia, Greece, as a case study. The research evaluates the performance, flexibility, and suitability of commercial software solutions versus tailored, open-source workflows, focusing on their ability to accurately classify and segment complex architectural and geomorphological features for heritage-oriented applications. High-resolution point cloud data were processed through both approaches, allowing a detailed comparison of classification accuracy, computational demands, and adaptability to heritage-specific requirements. The findings highlight the potential of custom pipelines to offer enhanced methodological transparency, greater control over processing parameters, and improved reproducibility, while proprietary tools provide streamlined, user-friendly environments with simplified workflows that reduce user workload. Overall, this study contributes to the advancement of digital cultural heritage methodologies by demonstrating how different classification strategies can influence the quality and reliability of 3D documentation outputs.

Keywords: Point Cloud Classification, Cultural Heritage Documentation, Custom Pipelines, Proprietary Software, 3D Documentation, Digital Heritage, Monodri Bridge

КОМПАРАТИВНА АНАЛИЗА КЛАСИФИКАЦИЈЕ ОБЛАКА ТАЧАКА У ДОКУМЕНТАЦИЈИ КУЛТУРНОГ НАСЉЕЂА — СТУДИЈА СЛУЧАЈА МОСТА МОНОДРИ, ЕВИЈА, ГРЧКА

Сажетак:

У овом раду представљена је компаративна анализа комерцијалних и прилагођених поступака класификације облака тачака у контексту документације културног насљеђа, на примјеру моста Монодри на Евији у Грчкој. Истраживање вреднује перформансе, флексибилност и примјењивост комерцијалних софтверских рјешења у поређењу са прилагођеним токовима рада заснованим на софтверу отвореног кода, с нагласком на способност прецизне класификације и сегментације сложених архитектонских и геоморфолошких елемената за потребе примјена у области културног насљеђа. Облак тачака високе просторне резолуције обрађен је примјеном оба приступа, што је омогућило детаљну упоредну анализу тачности класификације, захтјева у погледу рачунарских ресурса и прилагодљивости специфичним захтјевима документације насљеђа. Резултати истраживања указују на потенцијал прилагођених поступака обраде да обезбиједе већу методолошку транспарентност, бољу контролу над параметрима обраде и побољшану репродуцибилност, док комерцијални алати пружају једноставнија корисничка окружења са поједностављеним токовима рада који смањују оптерећење корисника. У цјелини, овај рад доприноси унапређењу методологија дигиталног културног насљеђа, показујући на који начин различите стратегије класификације могу утицати на квалитет и поузданост резултата тродимензионалне документације.

Кључне ријечи: класификација облака тачака, документација културног насљеђа, прилагођени поступци обраде, комерцијални софтвер, тродимензионална документација, дигитално насљеђе, мост Монодри.

1. INTRODUCTION

The accelerated progression of three-dimensional (3D) data acquisition technologies has significantly transformed the field of cultural heritage documentation. Among these technologies, terrestrial laser scanning (TLS) has become a keystone for the detailed geometric recording of monuments, historic structures, and archaeological sites, due to its ability to capture high-resolution and metrically accurate point cloud datasets [1], [2]. Such datasets enable the generation of detailed digital representations that support conservation planning, structural assessment, and long-term monitoring of heritage assets.

A critical stage in the processing of TLS-generated point clouds is classification, which involves the semantic segmentation of points into meaningful categories such as architectural elements, terrain, vegetation, and structural components. Accurate classification is particularly important in cultural heritage contexts, where complex geometries, heterogeneous materials, and irregular surfaces are common [3]. Misclassification can compromise the interpretability and reliability of generated products, such as 3D meshes, 3D models or structural analyses.

The shift from traditional, labor-intensive 2D documentation to integrated 3D digital twins has been documented as a transformative process in Greek heritage management, demonstrating a radical reduction in field hours and personnel requirements over the last two decades [4].

In recent years, proprietary software solutions have dominated professional TLS workflows, offering automated or semi-automated classification tools embedded within user-friendly environments. These tools are designed to streamline processing, reduce user intervention, and deliver rapid results, making them attractive for applied documentation projects [5]. However, their underlying algorithms often operate as "black boxes", limiting methodological transparency, parameter control, and reproducibility—factors that are increasingly emphasized in scientific research and heritage-oriented studies [6].

Simultaneously, the growing availability of open-source libraries and custom processing pipelines has enabled researchers to develop tailored classification workflows that can be adapted to specific datasets and research objectives. Such approaches allow greater flexibility in algorithm selection, parameter tuning, and validation strategies, fostering reproducibility and methodological clarity [7]. Despite these advantages, custom pipelines often require increased technical expertise and extended development cycles, potentially limiting their adoption in applied heritage projects.

While previous studies have examined point cloud classification techniques in architectural and environmental contexts, comparative evaluations between proprietary and custom workflows within cultural heritage documentation remain limited, particularly for complex historic structures where architectural and geomorphological features coexist. This gap highlights the need for systematic assessments that examine not only classification accuracy, but also workflow flexibility, computational demands, and suitability for heritage-specific requirements.

This study addresses this gap by presenting a comparative analysis of proprietary and custom point cloud classification pipelines applied to the geometric documentation of the Monodri Bridge in Evia, Greece. Using high-resolution TLS data acquired with a Leica BLK360 laser scanner, the research evaluates how different classification strategies influence the quality, reliability and interpretability of 3D geometric documentation outputs. Emphasis is placed on the ability of each approach to handle complex stone masonry, multi-arch geometry, and surrounding terrain without the use of photogrammetric data.

The main objective of this paper is to assess the performance, transparency, and applicability of proprietary versus tailored classification workflows in a cultural heritage context. By systematically comparing their strengths and limitations, this study aims to support informed methodological choices in future heritage documentation projects and to contribute to best practices in point cloud processing [1].

The remainder of the paper is structured as follows: Section 2 presents the case study, including site identification and historical background. Section 3 describes the methodological framework and data collection process. Section 4 discusses the comparative results and their implications, while Section 5 concludes the paper with key findings and directions for future research.

2. CASE STUDY

The Monodri Bridge is located in Evia, Greece, spanning the Manikiatis River and connecting the Upper and Lower Monodri settlements. The bridge is a historically significant stone arch structure, exemplifying traditional masonry techniques common in the late 19th century. Its location in a rural, topographically varied environment, along with its architectural and cultural value, makes it an ideal candidate for point cloud documentation and analysis.

The bridge was constructed in 1888, according to multiple local historical sources [8][9]. The building material consisted of volcanic stone sourced from the nearby Kipos area, carefully cut and transported to the site using traditional methods. While the specific architect or engineer responsible for its construction is not documented, local tradition attributes its construction to craftsmen operating under the period of Charilaos Trikoupis.

This typological and historical profile aligns the Monodri Bridge with a broader category of "arched stone bridges" found across Greece—such as the stone bridges of the Pogoni region—where shared construction techniques, durable local materials, and a deep integration into the natural landscape define their cultural significance [10]. Like its counterparts in Epirus, the Monodri Bridge represents a synthesis of functional engineering and cultural symbolism, necessitating a comprehensive Geomatics approach for its long-term preservation and digital promotion.

The Monodri settlement has historical continuity dating back to the Byzantine period. The original settlement, located at the site known as "Trochalia", was reportedly destroyed in the 9th century by Saracen pirates, prompting the relocation of inhabitants to the current Upper Monodri area [8]. The bridge itself served as a crucial link for local transportation and commerce, connecting agricultural areas and facilitating communication between communities.

Structurally, the bridge features a two-arch design, with robust stone foundations extending approximately 10–11 meters deep, according to local tradition [11]. The design reflects both hydraulic considerations—resisting river flow pressure—and the aesthetic and technical conventions of late 19th-century Greek stone bridge construction.

From a geomatic and digital documentation perspective, the Monodri Bridge presents a number of challenges for automated point cloud classification and semantic segmentation. The structure is characterized by irregular stone masonry, non-uniform block sizes, and varying surface roughness, which complicate the reliable separation of individual architectural elements. Additionally, the presence of two proximal arches introduces complex curvilinear geometries, while the lack of strict symmetry further increases classification ambiguity when compared to more regular or modern bridge structures.

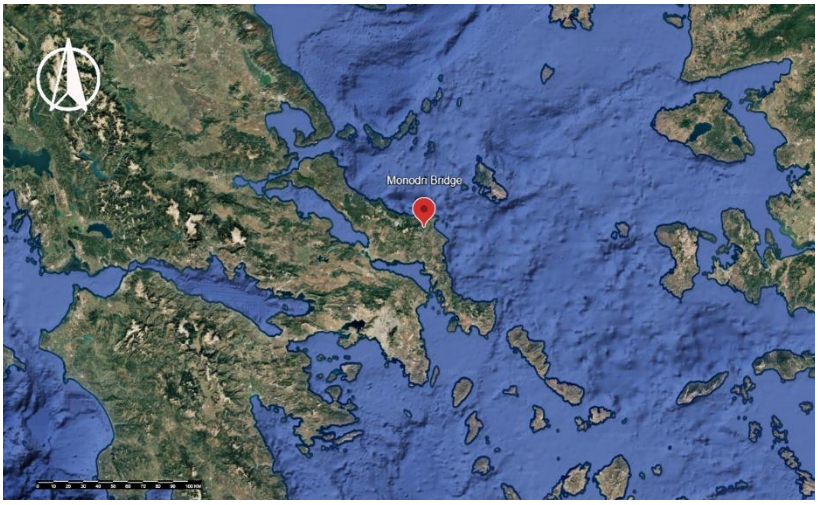

Figure 1. *Location of the Monodri Bridge, Evia, Greece [12].*

The surrounding natural environment adds an additional layer of complexity to the classification process. Vegetation growth along the riverbanks and on parts of the bridge, combined with uneven terrain and the proximity of the riverbed, results in overlapping geometric and semantic classes within the point cloud. These conditions create a challenging test case for evaluating classification pipelines, as they require the accurate discrimination between structural and non-structural elements. Consequently, the Monodri Bridge constitutes a representative and demanding case study for assessing the performance, flexibility, and transparency of proprietary and custom point cloud classification workflows in a cultural heritage context.

Figure 2.The Monodri Bridge, Evia, Greece. Detail of the two-arch stone structure highlighting the masonry and structural features of the arches [13].

3. METHODOLOGICAL FRAMEWORK

This chapter outlines the methodological framework adopted for the acquisition, processing, and classification of the point cloud data, detailing the data collection strategy based exclusively on terrestrial laser scanning (TLS) and the subsequent workflows employed for the comparative evaluation of proprietary and custom classification pipelines.

3.1. DATA COLLECTION

Point cloud data were acquired exclusively through terrestrial laser scanning (TLS) technique, using the BLK360- G1 laser scanner, a Leica Geosystems product. The selection of TLS as the sole data acquisition technique was driven by the need for high geometric accuracy, dense spatial sampling, and reliable capture of complex architectural geometries, particularly in areas characterized by irregular stone masonry, curved surfaces, and limited accessibility. No photogrammetric methods were employed in order to maintain a consistent data source and to focus the analysis on laser-based point cloud classification workflows.

The data acquisition campaign was carried out during the dry season (June of 2025), when the riverbed beneath the bridge was largely free of water. This condition allowed direct access to the riverbed and enabled scan positions to be placed beneath and in close proximity to the arches, significantly improving the coverage of the intrados surfaces and the lower structural elements. A total of 9 scan positions were established around, above, and below the bridge, following a geometry-driven acquisition strategy aimed at minimizing occlusions and ensuring sufficient overlap between adjacent scans.

Scan positions were distributed along both riverbanks, on the bridge deck, and within the riverbed, allowing the capture of the full structural extent of the bridge as well as its immediate geomorphological context. All scans were performed at high resolution, resulting in a dense and homogeneous point cloud. The acquired dataset includes a wide range of structural and non-structural features, such as stone masonry, arch spans, ground surfaces, and vegetation, providing a complex input dataset for subsequent classification and segmentation tasks.

Figure 3.Terrestrial Laser Scanning workflow in an applied heritage context. The image illustrates the positioning of the BLK360 for generating TLS-derived point clouds of the Monodri Bridge's structural elements (Authors).

3.2. DATA PROCESSING

Prior to classification, the raw TLS datasets were subjected to a series of pre-processing steps aimed at ensuring geometric consistency, noise reduction, and reliable spatial alignment. Individual scans were initially imported into the processing environment and inspected, where isolated points and scanning artefacts were identified and removed. These artefacts were primarily associated with vegetation movement, marginal surfaces, and low-incidence-angle measurements. At this stage, the individual scan positions were examined in plan-view to verify their spatial distribution and overlap (Figure 4).

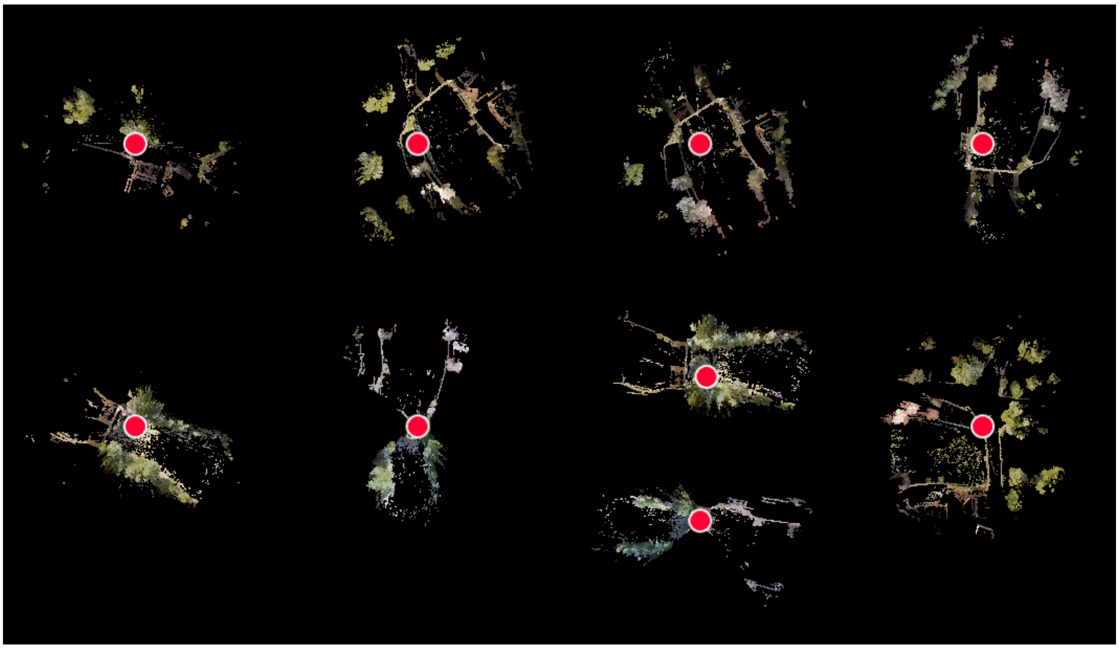

Figure 4.Individual BLK scan positions displayed in plan-view inside the Cyclone REGISTER 360 environment (Authors).

Scan registration was performed using Cyclone REGISTER 360 software, following a cloud-based registration approach that exploits geometric correspondences between overlapping scans. The acquisition strategy, which ensured sufficient overlap between neighboring scan positions, supported a robust and stable registration process. During registration, residual alignment errors were continuously monitored, and scan-to-scan constraints were refined in order to achieve optimal global consistency. The distribution of registration residuals and error metrics provided by the software are presented in Figure 5.

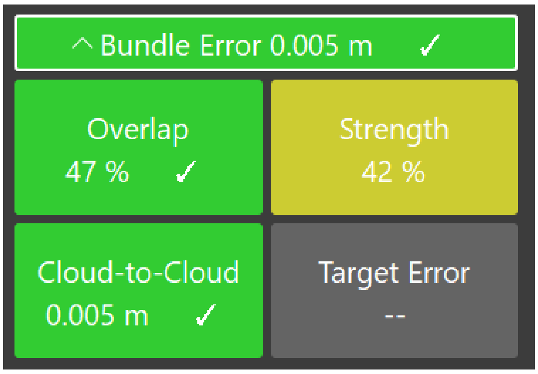

Figure 5.Registration residuals and alignment errors (Authors).

The final unified point cloud was produced after the completion of the registration and quality control procedures, resulting in a mean registration error of 0.005 m. At this stage, it is important to highlight the significance of establishing a geodetic network tied to a state projection system for cultural heritage documentation applications requiring absolute spatial positioning. Such a framework enables interoperability with official geospatial datasets, supports multi-temporal monitoring, and facilitates the long-term spatial consistency of documentation products. However, for the purposes of the present methodological comparison, a local coordinate system was adopted, as the primary objective was to ensure high internal geometric consistency for the evaluation of the classification workflows.

The merged dataset constitutes a geometrically coherent and homogeneous representation of the bridge and its surrounding environment. A plan-view visualization of the final registered point cloud is presented in Figure 6, highlighting the complete spatial coverage achieved for both the structural elements of the bridge and the adjacent terrain. Following registration, additional global filtering was applied to remove redundant data outside the area of interest, yielding a dataset optimized for subsequent classification and comparative analysis using proprietary and custom processing pipelines.

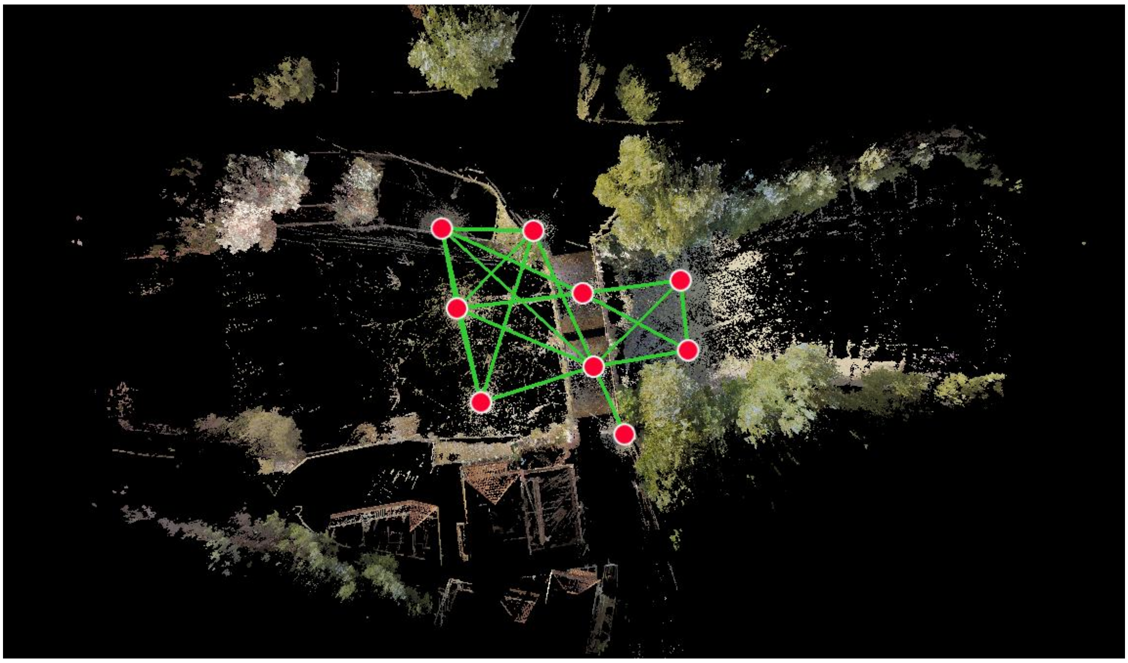

Figure 6.Final registered point cloud of the Monodri Bridge and its surrounding environment shown in plan-view (Authors).

3.3. CLASSIFICATION PIPELINES

In a general sense, point cloud classification can be described as the process of assigning each point of a 3D dataset to a predefined semantic category according to its local geometric and contextual characteristics. Formally, the classification process may be expressed as:

$$f(p_i) = c_i, p_i \in P,\ c_i \in C \tag{1}$$

where P represents the input point cloud, p_i an individual point within the dataset, and C the set of semantic classes. Within the present study, this concept was approached through two different workflow philosophies: an automated proprietary environment and a user-defined open-source hierarchical classification strategy.

Following pre-processing and registration, two distinct point cloud classification pipelines were implemented and evaluated using the same registered TLS dataset. The first pipeline follows a proprietary software approach, implemented within Cyclone 3DR developed by Leica Geosystems, while the second pipeline is based on a custom workflow developed using the open-source platform CloudCompare. The comparison focuses on differences in workflow structure, user control, transparency, and suitability for cultural heritage-oriented point cloud classification.

3.3.1. Proprietary Workflow (Cyclone 3DR)

The proprietary classification workflow was implemented in Leica Cyclone 3DR, which provides an integrated environment for point cloud processing, segmentation, and classification. The workflow relies on internally optimized algorithms and predefined processing strategies, enabling the rapid classification of large point cloud datasets.

Specifically, the classification was executed using the software's built-in "Auto Classification" command, employing the "Outdoor TLS 2.1" pre-trained model. This model is built upon machine learning algorithms trained on extensive terrestrial scan data, designed to identify real-world contexts with high precision through a "one-click" process [14]. The resulting automated classes are illustrated in Figure 7, while the final classification outputs are presented in Figure 8.

Classification is primarily driven by automatically derived geometric descriptors, such as surface orientation, local curvature, and neighborhood relationships, which are computed internally by the software to assign each point to standard ASPRS or custom classes [14]. User interaction within this workflow was limited to the configuration of high-level parameters, the selection of target classes, and the visual inspection of the classification output.

This approach offers a streamlined and efficient processing pipeline, significantly reducing manual cleaning time and minimizing the need for extensive parameter tuning. However, as the underlying decision rules and classification logic are largely abstracted from the user [14], there is a noted limit in transparency. This can restrict the customization of the workflow when attempting to accommodate heritage-specific characteristics, such as irregular stone masonry and complex structural geometries, which may require more granular control than the automated "black-box" logic provides.

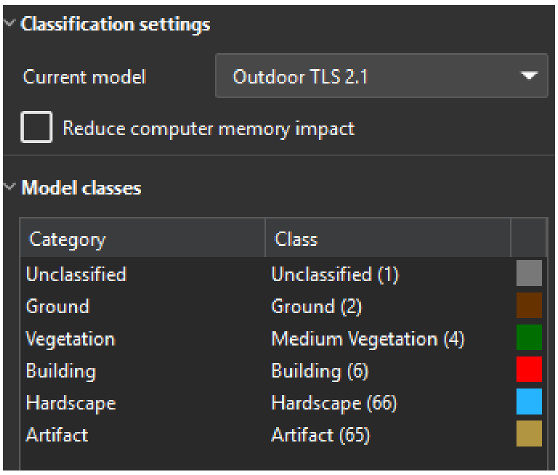

Figure 7.Automated classes generated by the Cyclone 3DR "Outdoor TLS 2.1" classification model (Authors).

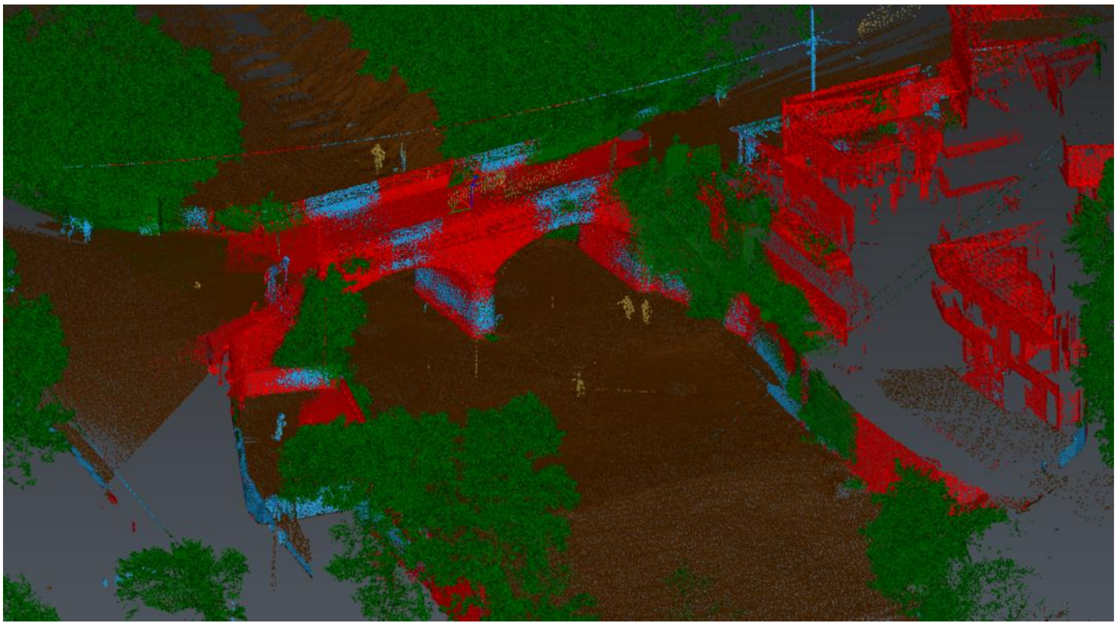

Figure 8.Results of the proprietary classification workflow on the Monodri Bridge point cloud, illustrating the automated segmentation of the structure and its surroundings (Authors).

3.3.2. Custom (Open-Source) Workflow (CloudCompare)

The custom classification pipeline was developed using open-source tools and libraries, enabling full control over each processing stage. In this workflow, the registered point cloud was processed through a sequence of user-defined steps, including feature extraction, rule-based segmentation, and classification based on geometric and contextual criteria. Parameters governing neighborhood size, feature thresholds, and class definitions were explicitly defined and adjusted according to the characteristics of the dataset and the architectural features of the bridge. This approach allows the incorporation of domain-specific knowledge, particularly relevant for cultural heritage applications involving irregular masonry, complex curvature, and mixed natural–built environments.

The custom workflow was centered on the CANUPO algorithm—an acronym for the French *CAractérisation de NUages de POints* [15]— which was integrated as a plugin within CloudCompare. CANUPO is a multi-scale dimensionality analysis method that characterizes the local geometry of a point cloud by examining its shape—specifically its tendency to be 1D (line-like), 2D (plane-like), or 3D (volume-like)—across different spatial scales [16]. This is achieved by computing a set of multiscale descriptors for each point, which are then compared against a pre-trained classifier to determine the most probable semantic class. Unlike standard automated tools, CANUPO allows the user to define the specific scales and training samples, making it particularly effective for discriminating between complex, intermingled classes.

The proposed strategy followed a hierarchical classification approach. Initially, nine representative subsets (training sets), three per each class were manually extracted from the original dataset via CloudCompare, containing: (i) vegetation, (ii) road/terrain, and (iii) bridge railings. Each training class comprised several tens of millions of points, ensuring a statistically robust dataset for the supervised learning process.

Subsequently, two distinct binary classifiers were trained using the CANUPO algorithm with a multi-scale dimensionality configuration (Min Scale: 0.10 m, Max Scale: 1.00 m, Step: 0.10 m). The classification utilized 10,000 core points and was executed using a multi-threaded approach (7/8 threads). The first model, “vegetation_road”, was trained using the vegetation and road subsets. The second model, “road_railings”, was developed using the road and railing subsets to specifically distinguish the thin, linear geometry of the metal railings from the flat surface of the road.

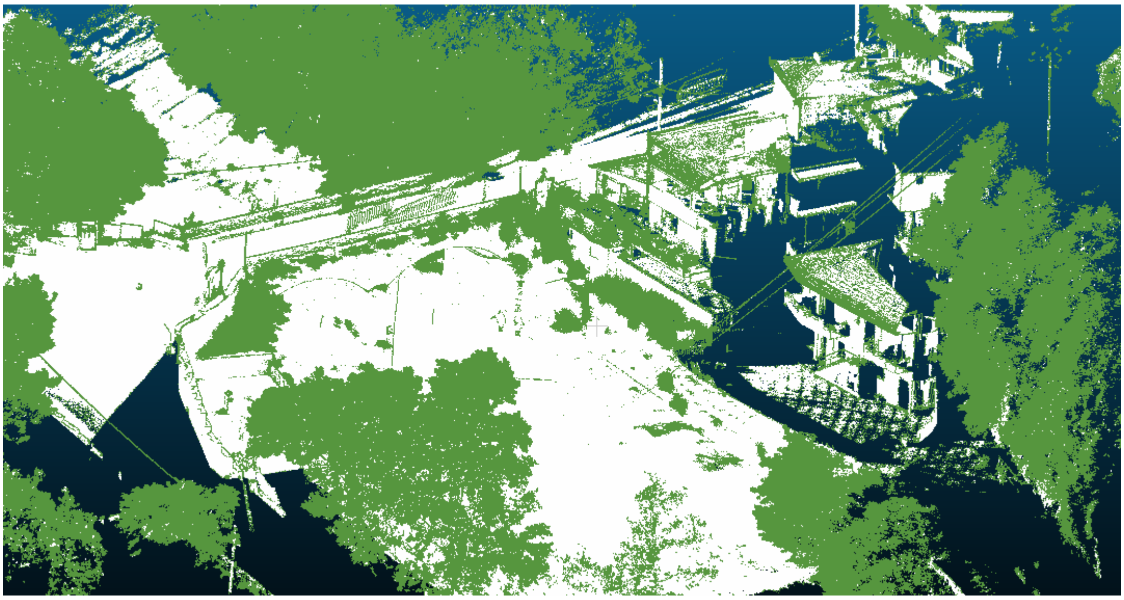

Figure 9.Results of the first classification stage using the "vegetation_road" CANUPO model: points classified as vegetation are shown in green, while points identified as road/terrain are shown in white (Authors).

The classification of the global point cloud was executed in two successive stages. In the first stage, the "vegetation_road" model was applied to the global dataset. The training of this first classifier yielded a Balanced Accuracy (BA) of 0.9594 and a Fisher Discriminant Ratio (FDR) of 2.3423, successfully discriminating between natural growth (visualized in green) and the terrain/road surface (visualized in white), as shown in Figure 9.

The resulting "road" subset was then processed using the second "road_railings" model. This stage demonstrated exceptional performance with a Balanced Accuracy (BA) of 0.9986 and a Fisher Discriminant Ratio (FDR) of 25.55. This effectively isolated the metal railings (visualized in red) from the road surface, providing a refined extraction of the bridge's structural details (Figure 10).

This sequential split allowed for a more refined extraction of architectural details that would otherwise be difficult to distinguish in a single-step process. The high internal validation metrics confirm the reliability of the custom pipeline in discriminating complex, overlapping geometries.

While the custom workflow requires greater technical expertise and longer development times, it offers increased flexibility, transparency, and reproducibility, enabling the workflow to be adapted to other heritage structures with similar geometric complexity.

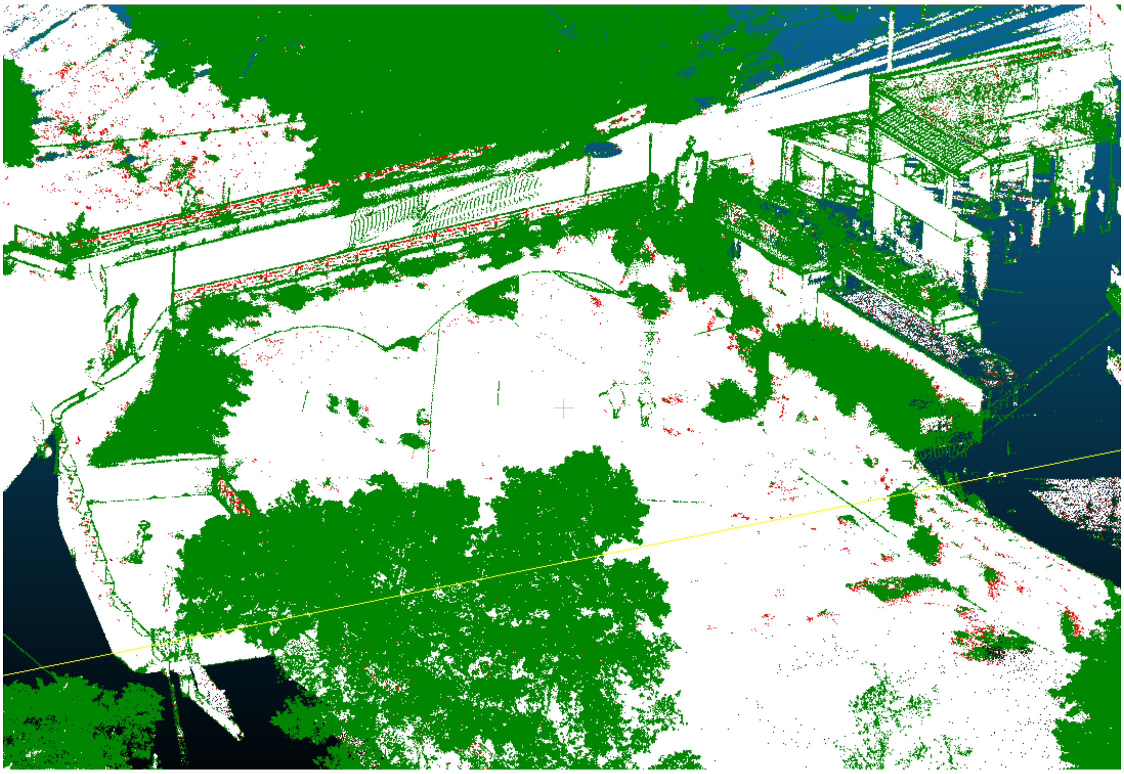

Figure 10. Results of the hierarchical classification after the second stage: vegetation remains in green, the road surface is shown in white, and the bridge railings, identified by the second "road_railings" CANUPO model, are highlighted in red (Authors).

4. DISCUSSION

The comparative evaluation of proprietary and custom point cloud classification pipelines highlights fundamental differences in workflow philosophy rather than absolute performance superiority. The proprietary workflow demonstrated a high degree of efficiency, enabling rapid classification through automated processes and reduced user intervention. The Auto Classification in Cyclone 3DR, leveraging AI-driven algorithms, was executed on a high-performance workstation (Intel i7, 64GB RAM, NVIDIA RTX 4080 16GB). Despite the robust hardware, the process required approximately 9–12 minutes, strictly adhering to the software's AI requirements for CUDA-capable GPUs and high VRAM. However, the limited access to internal classification logic restricts the ability to adapt the workflow to the specific geometric and material characteristics commonly encountered in cultural heritage structures.

This lack of transparency regarding the underlying classification logic is a common characteristic of proprietary tools. As noted by Previtali et al. [17] in a similar comparative study, such commercial solutions often behave as "black-box" due to the absence of detailed algorithmic documentation, thereby restricting the user's ability to audit or fine-tune the classification strategy for complex architectural scenarios.

In contrast, the custom open-source workflow provided increased flexibility and methodological transparency, allowing classification strategies to be explicitly tailored to the irregular stone masonry and complex geometries of the Monodri Bridge. The ability to define and adjust parameters at each processing stage facilitated a more controlled handling of ambiguous areas, such as transitions between structural elements and surrounding natural features. A key advantage observed in the custom pipeline was the successful isolation of the metal railings from the bridge deck through a hierarchical, two-stage binary classification. This level of semantic refinement was possible only because the user could explicitly "train" the algorithm to recognize the 1D linear geometry of the railings as distinct from the 2D planar surface of the road, a distinction that automated proprietary models often overlook due to their "black-box" nature.

The effective isolation of fine structural elements, such as metal railings, through multi-scale dimensionality analysis aligns with the findings of Brodu and Lague [16]. Their research demonstrated that geometry-based classification can be particularly robust in topographically complex environments.

This flexibility, however, comes at the cost of longer development times and a higher level of user expertise. The evaluation of computational efficiency revealed a stark contrast between hardware requirements and processing time. The custom CANUPO pipeline was implemented on a significantly less powerful laptop (Intel i7, 16GB RAM, Intel Iris Xe integrated graphics). Even with limited hardware resources and the absence of a dedicated GPU, the entire workflow—including the manual selection of training samples, the training of both hierarchical models, and the final classification—was completed within 1.5 hours. This demonstrates that while proprietary AI tools offer speed on high-end systems, custom geometry-based workflows can achieve superior semantic results even on entry-level hardware, provided there is expert methodological intervention.

From a cultural heritage documentation perspective, the results suggest that neither approach can be considered universally optimal. Instead, the selection of a classification pipeline should be guided by project-specific requirements, including the desired level of methodological transparency, the complexity of the object under study, and the available technical expertise. The Monodri Bridge case study demonstrates that complex heritage structures can benefit from workflows that allow greater user control, particularly when semantic consistency and interpretability of the classification results are critical for subsequent architectural analysis or restoration planning.

Despite the insights gained from this comparison, it is important to acknowledge that this research is primarily limited to a qualitative evaluation of the two workflows. Due to the absence of an objective, manually annotated ground truth dataset for the Monodri Bridge, a rigorous quantitative assessment—incorporating statistical metrics such as Precision, Recall, and F1-scores—was not feasible at this stage. Consequently, the findings reflect a methodological and visual appraisal of the classification pipelines rather than a point-by-point numerical validation. This limitation highlights the need for future efforts to establish benchmark datasets for complex heritage structures to enable more standardized performance comparisons.

Furthermore, a notable methodological limitation arises from the types of data inputs utilized. In the absence of a dedicated photogrammetric survey, the classification was primarily restricted to geometric parameters. Although the terrestrial laser scanner used (Leica BLK360) captures RGB data and provides color information to the point cloud, the proprietary software's classification logic operates as a "black-box" Consequently, it remains unclear whether or to what extent color information is integrated into its AI-driven routines. In contrast, the custom workflow was strictly based on the geometric properties and multi-scale dimensionality of the point cloud. Therefore, the potential of leveraging high-resolution spectral (RGB) data from photogrammetry to further distinguish between surfaces with similar geometries but distinct textures—such as stone masonry and dense vegetation—was not explored in this study.

5. CONCLUSIONS

This study presented a comparative analysis of proprietary and custom point cloud classification pipelines in the context of cultural heritage documentation, using terrestrial laser scanning data acquired from the Monodri Bridge in Evia, Greece. Both approaches proved capable of producing meaningful classification outputs from high-resolution TLS data, however, they differ substantially in terms of flexibility, transparency, and user involvement.

The findings indicate that proprietary workflows offer streamlined and efficient solutions, well-suited for rapid processing and standardized applications where time is a critical constraint. Conversely, custom open-source workflows—specifically those utilizing multi-scale dimensionality analysis like CANUPO—provide enhanced adaptability and methodological clarity. These features are particularly valuable for heritage-oriented analyses involving irregular geometries and heterogeneous materials, as they allow for hierarchical classification strategies that can isolate complex architectural elements, such as thin railings or intricate masonry, with higher semantic precision.

The choice between these approaches should, therefore, be informed by the specific objectives and constraints of each documentation project rather than by performance considerations alone. While automated tools reduce the manual workload, the "expert-in-the-loop" approach of custom pipelines ensures that the final classification reflects the architectural reality of the monument.

Future work may focus on the development of hybrid classification strategies that combine the efficiency of proprietary tools for initial data cleaning with the transparency and adaptability of custom pipelines for detailed feature extraction. Furthermore, a key objective for future research is the implementation of a rigorous quantitative cross-comparison between the two methodologies. By performing a point-by-point statistical analysis of the classification outputs, future work will aim to quantify the exact spatial and semantic deviations between the proprietary AI-driven results and the custom geometry-based clusters. This will allow for a deeper understanding of where each method converges or diverges in complex architectural scenarios. Additionally, extending this comparison to different heritage structures will further support the formulation of best-practice guidelines for point cloud classification in cultural heritage documentation.

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