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Leveraging Historical Archives with Artificial Intelligence algorithms for the Digital Reconstruction of Architectural Heritage

The preservation and digital reconstruction of architectural heritage remain a significant challenge, particularly when historical records are limited to single images or incomplete datasets. This study explores the potential of AI-driven methodologies for 3D reconstruction capable of generating detailed 3D meshes from a single image. Applying this approach to historical archives data, the model was tested on a selection of case studies in South Tyrol. The results highlight the crucial role of image resolution, detail clarity, and architectural symmetry in determining the accuracy of the reconstruction. Nevertheless, the ability to generate new views from a single image serves as a promising starting point for further model refinement. While challenges remain, particularly with irregular structures and low-quality historical images, this research demonstrates how AI can enhance the study, preservation, and public engagement of architectural heritage. The findings contribute to the ongoing discourse on digital heritage, suggesting avenues for improving AI-driven reconstructions through more diverse training datasets and hybrid methodologies. These technologies provide a framework for transforming static archival records into dynamic, interactive 3D models, offering new opportunities for research, preservation, and public engagement of cultural heritage.

Keywords:
Architectural Archive, Single Image Dataset, Artificial Intelligence, 3D Model Accessibility, Dissemination

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INTRODUCTION

The preservation and study of architectural heritage are crucial for understanding historical design processes, cultural evolution, and the socio-political contexts that shaped architectural development. However, a significant portion of historical architectural knowledge remains confined to archives in the form of sketches, technical drawings, models, photographs, and textual descriptions. These records, while invaluable, pose a major challenge for contemporary researchers due to their two-dimensional nature and the difficulties associated with reconstructing accurate 3D representations of historical structures. Many of these documents remain underutilized due to the complexity of interpreting them and the limitations of traditional methods in translating archival materials into spatially accurate reconstructions.
Recent advancements in Artificial Intelligence (AI) and photogrammetry offer promising solutions to bridge this gap, facilitating the digital reconstruction of architectural heritage from historical archives. The combination of AI algorithms with standard techniques provides new possibilities for reconstructing architectural heritage, particularly in cases where only a single image or a limited set of images is available. Traditionally, photogrammetry requires multiple images taken from different angles to create an accurate three-dimensional model. However, in historical contexts, only a single image or a limited set of images is often available, which complicates the accurate reconstruction of buildings or architectural spaces. In this context, the use of deep learning algorithms, particularly Neural Radiance Fields (NeRF) (Mildenhall, et al., 2020), has revolutionized the field of 3D reconstruction by offering a data-driven approach that directly models the volumetric scene representation (Palestini et al., 2024). These algorithms learn, through large datasets of annotated images, to predict the depth of objects and their three-dimensional structure (Hong et al., 2024; Lin et al., 2023; Liu et al., 2023; Long et al., 2023). Particularly in the context of archival materials, these models can be implemented on datasets containing historical images in order to obtain corresponding 3D models, providing a level of accuracy in reconstructing the buildings according to the quality of representation in historical documents. The ability to process and interpret archival materials in this way allows for the digital recreation of structures that may no longer exist or were never realized. This study specifically focuses on how these technologies can be applied to single-image datasets, allowing for a more precise reconstruction of architectural spaces and elements from historical photographs or drawings.
By leveraging AI algorithms, this research aims to establish a framework that enables the transformation of static historical records into dynamic, interactive 3D models. These digital reconstructions serve multiple purposes: they assist researchers and historians in understanding and analyzing historical architecture, provide architects and conservators with valuable insights into restoration processes, and enhance public engagement by making historical structures more accessible through virtual platforms and digital exhibitions. The integration of AI-driven reconstruction techniques in archival analysis not only ensures the longevity and preservation of architectural heritage but also democratizes access to historical knowledge, allowing a wider audience to explore and engage with architectural history in novel and interactive ways. Ultimately, this study contributes to the evolving field of digital heritage conservation, demonstrating how AI can play a transformative role in preserving and disseminating architectural knowledge for future generations.

STATE OF THE ART

The digital reconstruction of architectural heritage has traditionally relied on photogrammetry and laser scanning techniques, both of which require multiple high-quality images and direct access to physical structures. Photogrammetry has been extensively used in cultural heritage documentation, yet its effectiveness is limited when dataset available contain only a single image or incomplete photographic datasets. Laser scanning, while highly precise, is often impractical for reconstructing lost or inaccessible structures. However, despite recent advancements in surveying techniques, challenges remain in achieving accurate reconstructions from archival images. Historical photographs often suffer from distortions, varying perspectives, and inconsistent lighting conditions, making depth estimation and object recognition more complex. Consequently, researchers have explored the use of AI-driven algorithms, particularly those based on NeRF (Mildenhall et al., 2020) and Gaussian Splatting (Kerbl et al., 2023), enabling the creation of 3D reconstructions even in difficult context. In previous research, the author started to tested several pipeline developed for this purpose (Condorelli et al., 2024), especially based on NeRF algorithms. Recent studies have focused on implementation of both Gaussian Splatting from sparse-view images without requiring known poses (Xu et al., 2025) and from monocular (Szymanowicz et al., 2025) and on Stable Diffusion methods (Wang et al., 2025) to enhance both the geometric consistency and visual quality of the resulting reconstructions (Basak et al., 2025; Xu et al., 2025). This enables the generation of meshes, even with limited data, in situations where photogrammetric techniques cannot process images. In this research TripoSR (Tochilkin et al., 2025) was experiment with the implementation on historical single-image dataset of different cases of cultural heritage. TripoSR is a transformer architecture-based 3D reconstruction model designed to rapidly generate 3D meshes from a single image. Developed from the LRM architecture based on NeRF (Hong et al., 2023), it introduces significant improvements in data management, model design, and training techniques. Tests conducted on public datasets show that TripoSR outperforms, both quantitatively and qualitatively, existing open-source alternatives (Tochilkin et al., 2025). The aim in this paper is to test it on a challenging dataset constituted by low quality images and related to asset that are not present in the standard database used for training phase (Deitke et al., 2023).

METHODOLOGY

This study employs a multi-stage methodology that integrates AI-driven deep learning models to reconstruct architectural heritage from historical archives. The approach is structured into four key phases: data collection, preprocessing, AI model training, and 3D reconstruction. The analysis concludes with a metric analysis of the results, using as a benchmark a still-existing architecture of which a previous aerial photogrammetric survey is available. This step, although it

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cannot be implemented in cases of cultural heritage that no longer exists, serves to give a range of accuracy of the 3D reconstructions obtained by this method. Otherwise, it is emphasized that the quality of the results is closely correlated with the quality of the initial images, which are sometimes black and white and of very poor resolution, and affected by these inherent limitations. However, the goal is to obtain reconstructions of as accurate a scientific degree as possible despite the intrinsic constraints of the type of dataset being processed. The next part explains in detail the workflow of the proposed methodology, also shown in Fig. 1.

- Data Collection: the initial phase of the study focuses on the systematic collection of historical architectural records. These include high-resolution photographs, technical drawings, hand-drawn sketches, and annotated documents sourced from architectural archives, heritage institutions, and museums. The selection criteria prioritize diversity in visual material: sources are deliberately chosen to encompass a range of conditions, from pristine to deteriorated, complete to fragmentary. This approach ensures a rigorous test of the proposed AI methodology's robustness and generalization capacity. In addition, metadata such as date, author, and location are catalogued to contextualize each item historically and architecturally. Whenever possible, cross-referencing with secondary literature is employed to validate the authenticity and relevance of the visual material.

- Preprocessing: before AI-based analysis, the collected materials undergo an extensive preprocessing workflow designed to optimize them for computational modeling. This step includes: contrast enhancement to improve visibility of faded or low-light areas, especially in older photographs; noise reduction using Gaussian and median filtering techniques to remove grain and scanning artifacts; edge detection algorithms to delineate architectural contours clearly; perspective correction through homographic transformations to align skewed images, ensuring orthogonal consistency in projections. Additionally, background removal is executed using segmentation techniques to isolate architectural structures from irrelevant contextual elements. This facilitates more focused and accurate learning by deep learning models, as non-architectural noise is minimized. Where necessary, preprocessing also involves image normalization to ensure consistency in resolution and scale across the dataset.

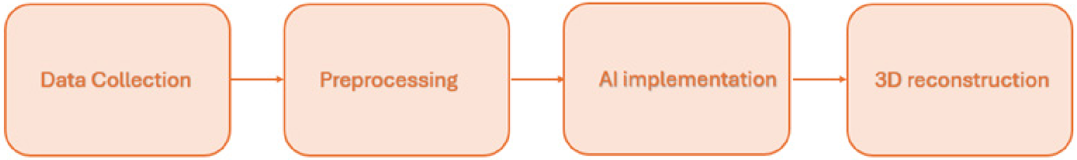

Fig. 1 - Workflow of the proposed methodology for the processing of single-image dataset from historical archives.

- AI implementation: this phase centers on implementing state-of-the-art deep learning models to interpret and reconstruct architectural forms from 2D inputs. Specifically, TripoSR—a monocular depth estimation and 3D surface reconstruction model—is utilized for its proficiency in predicting dense depth maps from single images. The model is trained and fine-tuned on a curated dataset that includes a large database of imagery. It leverages a carefully curated, high-quality subset of the Objaverse dataset (Deitke et al., 2023) —augmented with diverse rendering techniques that better mirror real-world image distributions—enhancing its generalization capabilities, especially for domain-specific objects such as those found in cultural heritage.
The learning process involves: the extraction of spatial features via convolutional encoders; depth inference using transformer-based attention mechanisms; reconstruction of occluded or missing components through learned architectural priors. TripoSR's architecture enables it to generalize from stylistic patterns and typical design elements common to specific architectural traditions, thereby allowing plausible reconstruction of incomplete segments. Transfer learning is applied where beneficial, utilizing pretrained weights from relevant architectural datasets.

- 3D recontruction: the depth maps and surface information generated by the AI are converted into 3D meshes using standard surface reconstruction pipelines, including Poisson surface reconstruction and marching cubes algorithms. These meshes are then refined through post-processing steps such as mesh simplification, hole-filling, and texture mapping. Tools like MeshLab (Cignoni et al., 2008) and CloudCompare are employed for geometric editing, scaling, and spatial alignment.
Validation of the reconstructed models is conducted through a mixed-methods approach: (1) quantitative assessment, by comparing geometric features (angles, dimensions, and volumes) with documented historical measurements where available; (2) qualitative expert review, involving architects, historians, and digital heritage professionals who assess the accuracy, plausibility, and stylistic coherence of the reconstructions.
Feedback from the validation phase is looped back into the modeling process to iteratively refine and improve the outputs. Finally, the verified 3D models are exported in interoperable formats and integrated into digital heritage platforms for further scholarly analysis, virtual restoration scenarios, and public dis-

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semination through interactive interfaces and virtual reality applications.

CASE STUDIES AND RESULTS

As a case study to implement the proposed methodology, Fortress in South Tyrol and related architectural and military elements were chosen. Fortress (Fig. 2) is one of the most important historical military sites in the region. Designed by military engineer Franz von Scholl, its construction began in 1833 during the reign of Emperor Franz I. Although designed as an advanced fortification, the fort was never used in battle, as the planned artillery was never installed. During the wars of the 19th century, some emplacements were only temporarily operational, and the site underwent transformations over time: from a depot in World War I to a defensive fortress in World War II, to becoming a powder magazine during the Cold War (Fontana, 2018). Today the fort is a provincial museum, hosting temporary exhibitions, particularly of contemporary art.
This case study is of particular interest for the research because there is historical material of different types that can be used for the purpose of applying the methodology. In particular, some elements have been selected for reconstruction in 3D that are of interest: the bridge connecting the fort, now destroyed (Fig. 3); one of the cannons that was part of the fort's armaments of which there remains a historical photograph from the 19th century in which a group of soldiers pose next to two cannons in the fort's courtyard and some design drawings of cannons typologically similar to them (Fig. 5); postcard of the Chapel of the fort (Fig. 7).

Fig. 2 - Historical photo of the Fortess and the bridge along the Brenner railway (from http://www.fortezzaopenarchive.net).

The implementation of the previously described methodology produced the results in Fig. 4, 6 and 7. The accuracy of the obtained 3D reconstruction depends on several factors, including the quality of the source image. The resolution of the image directly affects the definition of the final mesh: high resolution allows for higher fidelity in detail and more accurate reconstruction, while low-resolution images can introduce inaccuracies and artifacts. In addition to resolution, the clarity of details in the initial image is crucial: the sharper the architectural features, the better the quality of the generated model. Another determining factor is the geometry of the architecture to be represented. Symmetrical structures, as in the case of the analysed bridge (Fig. 4) and the cannons (Fig. 6), allow the algorithm to exploit this symmetry as a constraint in the generation of the model, thus achieving a more accurate reconstruction. In contrast, complex or irregular buildings can pose a greater challenge, as the lack of repeated and easily recognizable elements can lead to errors in the reconstruction (Fig. 7). Another element that influences the result is the dataset on which the algorithm was trained. Objects with common shapes, for example the bridge and the cannons, have a higher probability of being present in the images used in the training datasets, so the algorithm having references finds less difficulty in 3D reconstruction of the asset. In contrast, less common structures, such as the chapel, may not have been included in the initial dataset, the algorithm struggles to generate an accurate reconstruction. Finally, light and shadow conditions in the input images can also play a significant role in

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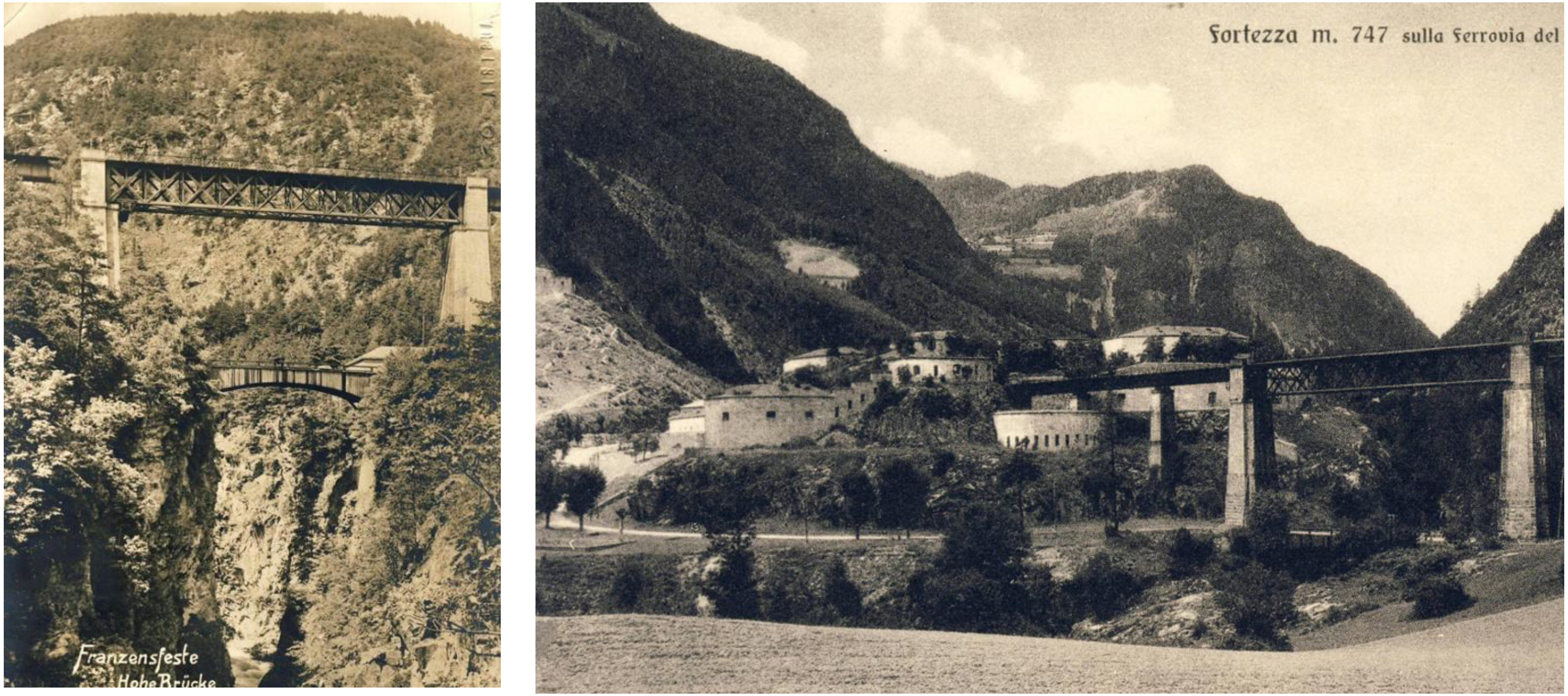

Fig. 3 - Postcards of the bridge along the Brenner railways, 1901-1913 (from http://www.fortezzaopenarchive.net).

Fig. 4 - Results of the implementation of the methodology on the dataset in Fig. 3.

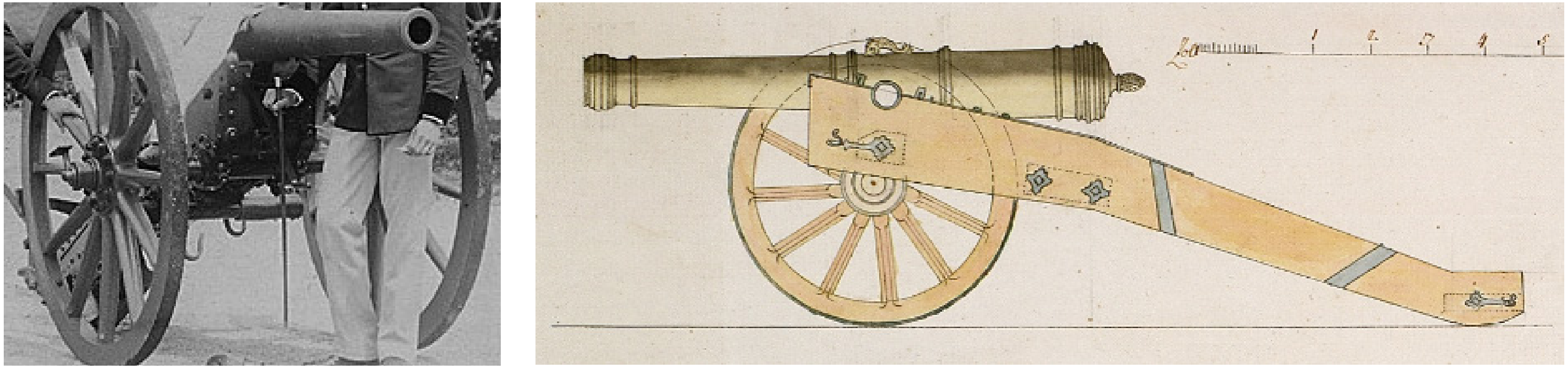

Fig. 5 - Historical image of the cannon in the Fortress and a drawing from historical documents.

Fig. 6 - Results of the implementation of the methodology on the dataset in Fig. 5.

the quality of the reconstruction. Overly pronounced shadows or lighting variations can create ambiguities in the depth data, leading to distortions in the final mesh, especially when dealing with black and white photos as in this research.

The analysis of the results was concluded with a metric comparison of the results, although this step is not always possible to accomplish, such as in cases where the objects to be reconstructed in 3D have been destroyed, as those of the bridge and the cannons. Instead, in this research the case study of the Chapel can be valid as a benchmarking to evaluate the metric quality of the results of the proposed methodology. In fact, the building is still present and thanks to a previous aerial photogrammetric survey of the area it was possible to compare the obtained model of the implementation of the proposed methodology with the existing georeferenced one. The methodology adopted for this analysis was to compare the two models using the Mesh to Cloud algorithm in the open source CloudCompare software. From the result of the analysis shown in Fig. 8, it can be seen that the model generated from the single image has concordances in shape, size and proportions of the real building, as emerges from the histogram values in which there are no outliers. The methodology is therefore reliable, although some imperfections in the model are present in this case especially in the parts not visible in the source image.

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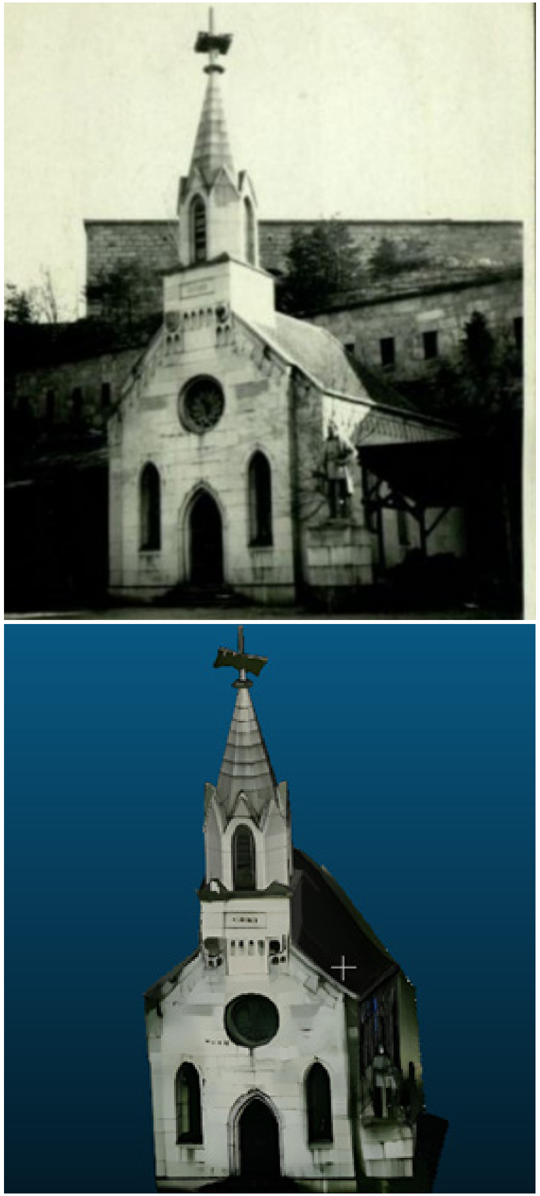

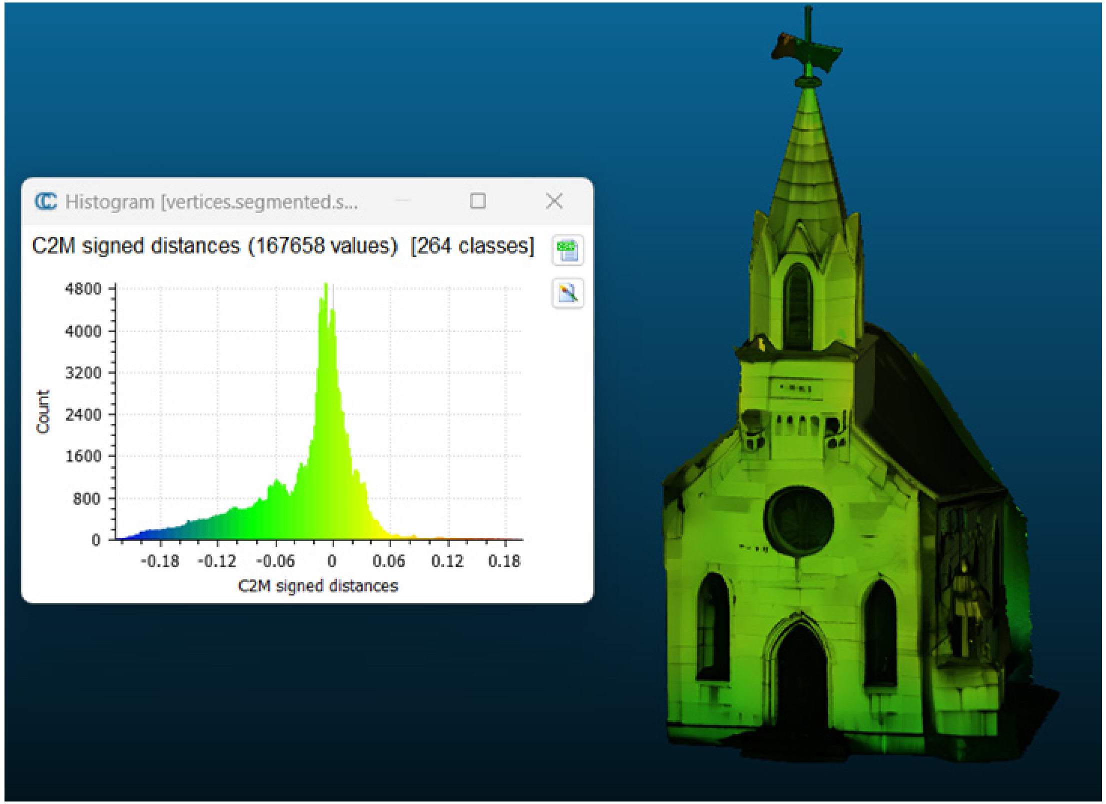

Fig. 8 - Cloud to mesh (C2M) comparison between the model obtain from a aerial photogrammetric survey of the Chapel and the model obtained from the proposed methodology.

Fig. 7 - Historical photo of the Fortress' Chapel (from Europeana) and results of the implementation of the methodology.

CONCLUSIONS

This study demonstrates the potential of AI-driven methodologies, demonstrating how NeRF based algorithms can successfully generate architectural models even from a single source image. The proposed approach addresses the challenges posed by the lack of extensive photographic datasets, offering a viable solution for digital heritage conservation when limited visual documentation is available.

The evaluation of results highlighted several key factors influencing the accuracy of reconstructions, including image resolution, architectural complexity, and the availability of relevant training data. A key takeaway from this research is the critical role played by the quality of the input images. High-resolution and well-preserved historical photographs yield more precise reconstructions, whereas degraded, low-resolution, or unclear images introduce inconsistencies in the generated 3D models. The results also highlight the influence of architectural geometry on reconstruction accuracy. Symmetrical structures, such as the analyzed bridge, benefit from their repetitive patterns, which the algorithm can effectively utilize to refine the output. Conversely, irregular or unique architectural forms, like the chapel, pose greater challenges due to the lack of pre-existing references in the training dataset. Another important consideration is the impact of the dataset used to train the AI model. Architectures that share common stylistic elements with widely documented historical structures, are more easily recognized and reconstructed. On the other hand, structures with fewer existing references, present greater difficulties, indicating a need for diversified and enriched training datasets to improve model adaptability. Additionally, lighting conditions and material properties in historical photographs contribute to variations in reconstruction quality.

A crucial aspect of this research was the validation of the proposed methodology through metric comparison. While direct validation is not always feasible—particularly for lost structures such as the bridge and cannons—the case study of the chapel provided an opportunity for benchmarking. By comparing the reconstructed model with an existing georeferenced photogrammetric survey, it was possible to assess the accuracy of the AI-generated model. The analysis using the Mesh to Cloud algorithm in CloudCompare confirmed that the model maintained consistency in shape, size, and proportions with the real-world structure. The absence of significant outliers in the histogram further supports the reliability of the method.

However, some limitations were observed, particularly in areas not visible in the source image. These imperfections highlight the inherent challenge of reconstructing missing architectural details solely from AI inference. Despite this, the methodology proved effective in generating scientifically accurate reconstructions, offering a valuable tool for historical analysis, digital heritage preservation, and architectural research. Future work could focus on improving reconstructions by integrating additional contextual information, refining AI training datasets, and incorporating hybrid approaches that combine AI with traditional photogrammetry for enhanced accuracy.

This research underscores the transformative role of AI in the field of digital heritage conservation. By leveraging AI techniques, historical structures that no longer exist or have undergone significant alterations can be revived in virtual form, providing invaluable resources for historians, architects, and the general public. The application of AI-driven reconstruction facilitates a deeper engagement with cultural heritage, allowing for immersive exploration and educational opportunities that were previously inaccessible. Future research should focus on refining AI methodologies to further improve reconstruction fidelity, particularly in cases where historical documentation is scarce. Expanding the range of training data, incorporating multi-modal inputs such as textual descriptions and technical drawings, and integrating hybrid approaches that combine AI with traditional photogrammetric techniques could yield even more reliable results. Moreover, developing adaptive AI models capable of handling extreme variations in input quality will be crucial for making these reconstruction methods more universally applicable. In conclusion, while there are still technical limitations to address, this study provides strong evidence that AI-powered techniques represent a promising frontier in architectural heritage preservation. By advancing these methodologies, it is possible to ensure that valuable historical knowledge is not only preserved but also made more accessible to future generations through interactive and scientifically accurate 3D representations.

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REFERENCES

Basak, H., Tabatabaee, H., Gayaka, S., Li, M.-F., Yang, X., Kuo, C.-H., Sen, A., Sun, M., & Yin, Z. (2025). Enhancing Single Image to 3D Generation using Gaussian Splatting and Hybrid Diffusion Priors. https://doi.org/10.48550/arXiv.2410.09467

Cignoni, P., Callieri, M., Corsini, M., Dellepiane, M., Ganovelli, F., & Ranzuglia, G. (2008). MeshLab: an Open-Source Mesh Processing Tool. Sixth Eurographics Italian Chapter Conference, 129-136. https://doi.org/10.2312/LocalChapterEvents/ItalChap/ItalianChapConf2008/129-136.

Condorelli, F., & Perticarini, M. (2024). Comparative Evaluation of NeRF Algorithms on Single Image Dataset for 3D Reconstruction. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLVIII-2-2024, 73–79. doi.org/10.5194/isprsarchives-XLVIII-2-2024-73-2024.

Deitke, M., Liu, R., Wallingford, M., Ngo, H., Michel, O., Kusupati, A., et al. (2024). Objaverse-XL: A Universe of 10M+ 3D Objects. https://doi.org/10.48550/arXiv.2307.05663.

Fontana, N. (2018). Il sistema fortificato tirolese come fattore di militarizzazione del territorio. Turris Babel, 111, 33-65.

Hong, Y., Zhang, K., Gu, J., Bi, S., Zhou, Y., Liu, D., Liu, F., Sunkavalli, K., Bui, T., & Tan, H. (2024). LRM: Large Reconstruction Model for Single Image to 3D. arXiv preprint arXiv:2311.04400.

Kerbl, B., Kopanas, G., Leimkühler, T., & Drettakis, G. (2024). 3D Gaussian Splatting for Real-Time Radiance Field Rendering. https://doi.org/10.48550/arXiv.2308.04079

Lin, C. H., Gao, J., Tang, L., Takikawa, T., Zeng, X., Huang, X., et al. (2023). Magic3d: High-resolution text-to-3d content creation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 300-309).

Liu, R., Wu, R., Van Hoorick, B., Tokmakov, P., Zakharov, S., & Vondrick, C. (2023). Zero-1-to-3: Zero-shot one image to 3d object. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 9298-9309).

Long, X., Guo, Y.-C., Lin, C., Liu, Y., Dou, Z., Liu, L., Ma, Y., Zhang, S.-H., Habermann, M., Theobalt, C., & Wang, W. (2023). Wonder3D: Single Image to 3D using Cross-Domain Diffusion. arXiv, eprint=2310.15008.

Lv, J., Guo, J., Zhang, Y., Zhao, X., & Lei, B. (2023). Neural Radiance Fields for High-Resolution Remote Sensing Novel View Synthesis. Remote Sens. 15, 3920. https://doi.org/10.3390/rs15163920.

Mildenhall, B., Srinivasan, P. P., Tancik, M., Barron, J. T., Ramamoorthi, R., & Ng, R. (2020). NeRF: Representing Scenes as Neural Radiance Fields for View Synthesis. Lecture Notes in Computer Science, 12346 LNCS, 405–421.

Palestini, C., Meschini, A., Perticarini, M., & Basso, A. (2024). Neural Networks as an Alternative to Photogrammetry. Using Instant NeRF and Volumetric Rendering. In A. Giordano, M. Russo, & R. Spallone (Eds.), Beyond Digital Representation. Digital Innovations in Architecture, Engineering and Construction. Springer, Cham.

Szymanowicz, S., Rupprecht, C., & Vedaldi, A. (2025). Splatter Image: Ultra-Fast Single-View 3D Reconstruction. https://doi.org/10.48550/arXiv.2312.13150

Tochilkin, D., Pankratz, D., Liu, Z., Huang, Z., Letts, A., Li, Y., Liang, D., Laforte, C., Jampani, V., & Cao, Y.-P. (2025). TripoSR: Fast 3D Object Reconstruction from a Single Image. https://doi.org/10.48550/arXiv.2403.02151

Wang, C., Peng, H.-Y., Liu, Y.-T., et al. (2025). Diffusion models for 3D generation: A survey. Computational Visual Media, 11(1), 1-28. doi: 10.26599/CVM.2025.9450452

Xu, J., Cheng, W., Gao, Y., Wang, X., Gao, S., & Shan, Y. (2025). InstantMesh: Efficient 3D Mesh Generation from a Single Image with Sparse-view Large Reconstruction Models. https://doi.org/10.48550/arXiv.2404.07191

Xu, J., Gao, S., & Shan, Y. (2025). FreeSplatter: Pose-free Gaussian Splatting for Sparse-view 3D Reconstruction. https://doi.org/10.48550/arXiv.2412.09573