Challenge Journal of Structural Mechanics

Research Article

From ruins to reconstruction: Harnessing text-to-image AI for restoring historical architectures

Kawsar Arzomand [a,*], Michael Rustell [a], Tatiana Kalganova [b]

[a] Department of Civil and Environmental Engineering, Brunel University London, UB8 3PH London, UK
[b] Department of Electronic and Electrical Engineering, Brunel University London, UB8 3PH London, UK

ABSTRACT

The preservation of cultural heritage has become increasingly important in the face of conflicts and natural disasters that threaten historical sites worldwide. This study explores the application of artificial intelligence (AI), specifically text-to-image generation technologies, in reconstructing heritage sites damaged by these adversities. Utilising detailed textual descriptions and historical records, this study employed AI to produce accurate visual representations of damaged heritage sites, bridging the gap between traditional documentation and modern digital reconstruction methods. This approach not only enhances the architectural design process across various disciplines but also initiates a paradigm shift towards more dynamic, intuitive, and efficient heritage conservation practices. The methodology integrates data collection, iterative AI-generated image production, expert review, and comparative analysis against historical data to evaluate reconstruction accuracy and authenticity. By integrating AI with traditional preservation practices, this study advocates a balanced approach to conserving cultural legacies, ensuring their preservation and revitalisation for future generations. Preliminary findings suggest that AI-generated imagery holds significant promise for enhancing digital heritage preservation by offering novel approaches for visualising and understanding historical sites. These findings also highlight the need to address ethical, technical, and collaborative challenges to enhance the precision, reliability, and applicability of AI technologies in the field of cultural heritage. This study contributes to digital humanities and archaeological conservation, demonstrating AI's potential to support and complement traditional heritage preservation methods and suggests a pathway for substantial methodological evolution in the field.

ARTICLE INFO

Article history:
Received 10 April 2024
Revised 15 May 2024
Accepted 3 June 2024

Keywords:
Text-to-image synthesis
Architectural heritage
AI-assisted reconstruction
Prompt engineering
Digital archaeology
Cultural heritage preservation

1. Introduction

The architectural design process is crucial across various disciplines, from engineering and software development to the arts and humanities, and it is significantly shaped by the fusion of traditional methods and contemporary technological advancements. Recent innovations in AI, particularly text-to-image systems such as Midjourney, DALL-E, and Stable Diffusion, mark a substantial evolution in the design and heritage conservation arenas, signifying a paradigm shift towards more dynamic, intuitive, and efficient conceptualisation practices (Brisco et al. 2023; Kenig et al. 2023). This evolution reflects a broader movement to integrate cutting-edge AI tools within the architectural design process, underscoring the transition from conventional methods to more advanced, future-oriented approaches. The advent of 3D and 2D modelling tools, including Building Information Modelling (BIM) software such as ArchiCAD, AutoCAD, and SketchUp, has revolutionised architects' ability to visualise conceptual designs, while the application of AI techniques, ranging from conditional Generative

* *Corresponding author*. E-mail address: kawsar.arzomand@brunel.ac.uk (K. Arzomand)
ISSN: 2149-8024 / DOI: https://doi.org/10.20528/cjsmec.2024.02.004

Adversarial Networks (cGANs) to deep learning and machine learning algorithms, has initiated a new era in the digital preservation and reconstruction of historical landscapes and artefacts (Navarro-Mateu et al. 2021). These technological advancements are reshaping methodologies in archaeological research and conservation efforts, particularly as the architectural and cultural heritage sectors confront profound losses inflicted by conflicts and wars. Considering such destruction, AI has emerged as a pivotal tool, not only in attempting to preserve and reconstruct cultural heritage, but also to facilitate a deeper understanding of historical contexts (Kadhim and Abed 2023; Lee and Chang 2022).

The destruction of cultural heritage sites due to conflicts, natural disasters, and human activities poses a substantial challenge to preservation. Traditional reconstruction methods often rely on incomplete or damaged visual records, leading to reconstructions that may lack accuracy and authenticity. Recent advancements in text-to-image technology have introduced tools such as Midjourney and DALL-E, which have revolutionised the generation of high-quality photorealistic images from simple text prompts (Adetayo 2024; Kenig et al. 2023; Becker and Laycock 2023). AI entities can create images based on text prompts that mimic human cognitive processes (Kenig et al. 2023). Models such as Stable Diffusion, DALL-E, and Midjourney are notable in the realm of text-to-image generation (Cobb 2023; Huang et al. 2023; Lyu et al. 2022). The impact of these models is significant, influencing various fields such as neuroscience research, education, libraries, and architectural visual culture (Adetayo 2024; Becker and Laycock 2023; Steinfeld 2023). These tools have made it possible for users to create fully rendered images promptly, showcasing the potential of AI in creative endeavours (Newton and Dhole 2023).

AI-generated imagery offers a novel solution to the problem of accurately reconstructing heritage sites by leveraging detailed textual descriptions and historical records to produce accurate visual representations (Nichol et al. 2021; Ramesh et al. 2022). This study aimed to explore the effectiveness and broader implications of leveraging AI-generated imagery for the digital reconstruction of heritage sites that are significantly damaged by conflicts. By integrating the capabilities of these models with dense multi-image 3D reconstruction techniques, it is feasible to digitally reconstruct and visualise the destroyed cultural heritage sites (Rihani 2023; Wahbeh et al. 2016). In addition, the utilisation of 3D photogrammetric reconstruction methods along with AI-generated images can provide interactive and immersive experiences for visitors exploring reconstructed heritage sites (Rihani 2023; Soto-Martín et al. 2020). Employing generative adversarial networks (GANs) for heritage image super-resolution reconstruction can assist in estimating high-resolution images of ruins, thereby enhancing the visual quality of the reconstructed heritage sites (Nayak and Balabantaray 2021). Techniques such as laser scanning, photogrammetry, and UAV-based 3D reconstruction can provide detailed spatial information for large cultural heritage objects, thereby enhancing the accuracy of the reconstruction process (Xu et al. 2016; Bayram et al. 2015).

The novelty and contribution of this study lies in its innovative approach of using AI-driven text-to-image generation to reconstruct ruined heritage sites. Unlike traditional methods, which rely heavily on physical remnants or incomplete visual records, this research utilises detailed textual descriptions informed by historical, architectural, and archaeological sources to generate accurate visual representations of heritage sites. By carefully crafting text prompts based on extensive research from articles and historical sources, the AI models were able to generate images that closely resembled the original structure. This approach not only leverages the strengths of AI to produce highly accurate visual representations from textual descriptions but also bridges the gap between historical documentation and digital reconstruction. This integration offers a more reliable, accurate, and engaging method of heritage reconstruction, presenting significant advancements in the field of digital heritage preservation. This study makes several key contributions to the digital heritage preservation field. First, it introduces a novel application of text-to-image AI technologies in the context of heritage conservation, demonstrating their potential for creating accurate digital reconstructions from textual descriptions. Secondly, the study presents a comprehensive methodology that integrates AI-generated imagery with historical, architectural, and archaeological data. This interdisciplinary approach enhances the reliability and authenticity of digital reconstruction and provides a robust framework for future research. Thirdly, by producing new visual perspectives on the original states of damaged or destroyed heritage sites, the AI-generated images offer valuable insights into their architectural and cultural significance.

This method was applied to reconstruct the Buddha of Bamiyan in Afghanistan, a heritage site that was significantly damaged (Hammer et al. 2018; Grün et al. 2004). By interweaving historical narratives with AI capabilities, this study seeks to uncover new methodologies in cultural heritage preservation, contributing to the academic discourse within the digital humanities (Brisco et al. 2023; Kenig et al. 2023; Navarro-Mateu et al. 2021). This exploration is not merely a testament to technological innovation but also a commitment to bridging past and present, ensuring the enduring legacy of our collective cultural memory. By leveraging AI-generated imagery, this research offers a new avenue for the preservation and understanding of cultural heritage, addressing the profound challenges posed by conflicts and natural disasters (Kadhim and Abed 2023; Lee and Chang 2022). This study contributes to the academic discourse on digital humanities and archaeological conservation by demonstrating AI's potential to support and complement traditional heritage preservation methods (Bharati 2023; Orengo et al. 2015).

2. Methodology

In the exploration of digital reconstruction methodologies for heritage sites decimated by conflict, this study adopts a comprehensive, multi-faceted approach grounded in the latest advancements in artificial intelligence (AI) technology. The core objective centres on harnessing the potential of AI, particularly text-to-image generation models such as Midjourney and DALL-E, to reimagine and digitally resurrect heritage sites from textual descriptions informed by historical, architectural, and archaeological evidence. This methodology intersects technological innovation with historical research, aiming to reconcile the physical remnants of the past with digital reconstructions, thereby offering new avenues for understanding and preserving our cultural heritage. Architects can utilize natural language inputs to convey their design intentions more naturally, which promotes quicker revisions and reduces the obstacles usually associated with traditional design tools (Ko et al. 2023; Hsu et al. 2022). The process involves a synergistic blend of data collection, AI image generation, expert validation, and comparative historical analysis, outlined as in Fig. 1.

Fig. 1. Overview of the five-step research methodology.

Fig. 2 illustrates a detailed flowchart of the five-phase methodology for AI-driven heritage site reconstruction. This comprehensive process begins with Data Collection and Preparation, involving the detailed gathering and organisation of textual descriptions, architectural details, and historical records, which are then cross-referenced for accuracy and compiled into a structured overview. The AI Image Generation Process follows, where initial prompts are created based on the collected data, and images are generated using AI platforms such as Midjourney and DALL-E. These prompts and images are iteratively refined and meticulously documented. The third phase, Image Selection and Iterative Refinement, focuses on evaluating AI-generated images against historical benchmarks, readjusting prompts, regenerating images, and conducting internal validation with expert collaboration. Comparative Analysis and Validation is the fourth phase, involving rigorous comparison of AI-generated images with historical records, continuous refinement, and detailed documentation to address inaccuracies. The final phase, Scholarly Discussion and Practical Implications, includes engaging in discussions on the ethical and practical implications of AI in heritage reconstruction, proposing frameworks for integrating AI into preservation practices, and evaluating the educational, commemorative, and advocacy potential of the reconstructions. This flowchart provides a visual representation of the iterative and detailed nature of the research methodology, ensuring transparency and reproducibility in the AI-driven reconstruction process.

2.1. Data collection and preparation

The initial phase involves the collection and analysis of textual descriptions, architectural details, historical accounts, and existing visual records of selected heritage sites (Remondino 2011). This extensive dataset is crucial for generating detailed prompts that provide a thorough historical context to guide the image-generation process. We gathered a diverse range of historical sources, such as books, academic journals, architectural blueprints, and digital archives, to create the dataset. The incorporation of official photographs from UNESCO and other reputable institutions improved the dataset by offering authentic references that are vital for validating the accuracy of our AI-generated reconstructions and ensuring adherence to established architectural and cultural standards. The data collection process involved manually reading historical sources and articles to identify keywords related to the original construction of the heritage sites. These keywords are used to create comprehensive textual prompts for the AI generation process. The systematic extraction and organisation of specific phrases and terminology indicative of heritage sites' original construction methods were documented in a database, which was categorised by heritage site, historical period, architectural style, and other relevant factors to facilitate their effective use in prompt generation.

2.2. AI image generation process

Employing AI platforms such as Midjourney and DALL-E, this study implements a systematic approach to convert textual prompts into visual reconstructions (Horn et al. 2022; Gualandi et al. 2021). Despite extensive research efforts aimed at uncovering photographic records to inform and validate reconstructions, certain heritage sites lack definitive visual records, presenting a significant challenge for accurately reconstructing their prime versions. Considering these constraints, the methodology relies more on prompt engineering, utilising detailed textual descriptions derived from available historical documentation and expert insights. However, it is important to note that the AI-generated images produced under these conditions served as initial approximations rather than exact replicas of the original structures. The textual prompts derived from the compiled data aimed to accurately reflect the architectural and cultural aspects of the targeted heritage sites. Multiple iterations and a variety of prompts are utilized to address the multifaceted nature of each site, facilitating a broad spectrum of visual outputs (Kadhim and Abed 2023). Utilising the information presented in Table 1, initial prompts were formulated to encapsulate the fundamental architectural features, historical contexts, and cultural significance of each heritage site. For instance, the Buddhas of Bamiyan are described in terms of their monumental statues, niches, and surrounding features before they were destroyed. These prompts were iteratively fine-tuned based on AI-generated images. Each iteration involved adjusting the textual descriptions to improve the accuracy and detail of the generated images. This process has been thoroughly documented to track modifications and advancements. AI platforms generate multiple images based on refined prompts and capture diverse perspectives and details. The generated images were assessed by using historical records and visual references. For heritage sites with restricted photographic records, the methodology relies on extensive textual descriptions and expert insights to guide the AI. For instance, for Palmyra, where many structures have been damaged or destroyed, archaeological reports and historical texts provide necessary information.

2.3. Image selection and iterative refinement

The methodology employed in this phase focuses on a systematic approach for assessing AI-generated images against historical and archaeological standards. This involves refining textual prompts and regenerating new images based on evaluations, utilising prompt engineering to enhance the AI's capability to produce images that accurately reflect complex architectural designs and cultural nuances (Oppenlaender 2022). Xie et al. (2023) emphasised that crafting precise textual prompts can significantly impact the performance of AI, ensuring that the generated images closely align with architectural intent and historical context. The current approach to reconstruction is based on internal validation, but future research will involve input from historians, archaeologists, architects, and cultural experts. This expert feedback enhances the accuracy of the reconstructions and refines the prompts to align with a wider range of historical and cultural criteria. By continuing to iterate and refine the AI-generated outputs, we will improve their alignment with the historical records and architectural reliability. A systematic documentation process tracks each step of the prompt refinement and image generation, which is crucial for transparency and reproducibility. By repeatedly adjusting the textual prompts and regeneration of images, inaccuracies will be addressed, and the level of detail will be improved.

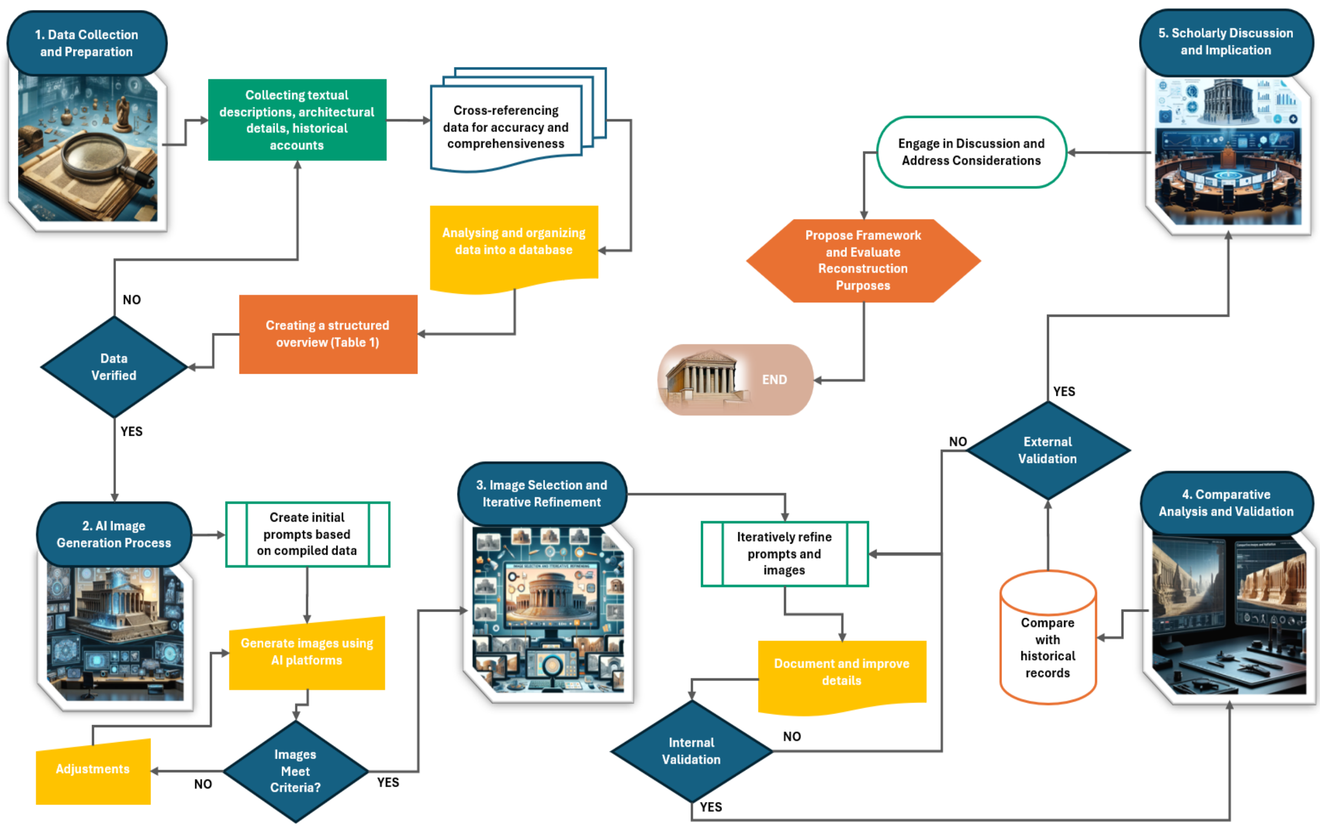


Fig. 2. Flowchart illustrating the five-phase methodology for AI-driven heritage site reconstruction.

Table 1. Overview of historical heritage sites: characteristics and conditions.

Site	Country	Period founded	Significant historical period	Main features	Destruction year	Area	Causes of damage	Current condition	Damaged parts	Key references
Palmyra	Syria	3rd millennium BC	Roman Empire, Islamic Caliphate	Temple of Bel, Great Colonnade	2015	Varies	Extremist group activities	Partially ruined	Temple of Bel, other structures	UNESCO, Britannica (Raja and Seland 2022; Elcheikh 2019)
Buddhas of Bamiyan	Afghanistan	6th century AD	Gandhara period	Two monumental statues	2001	105 hectares	Extremist group activities	Destroyed, niches remain	Two monumental statues	UNESCO (Asal et al. 2023; Toubekis et al. 2017; Grün et al. 2004)
Ancient City of Nimrud	Iraq	13th century BC	Assyrian Empire	Palaces, temples, colossal statues	2015	Over 360 hectares	Extremist group activities	Ruined	Palaces, temples, statues	UNESCO (Pollegioni et al. 2015; Reade 2002)
Pompeii	Italy	6th-7th century BC	Roman Empire	Urban infrastructure, frescoes	79 AD	66 hectares	Natural disaster (Volcanic Eruption)	Ruins preserved	Entire city	UNESCO, Britannica, (Scorrano et al. 2022; Wotzlaw et al. 2022; Senatore et al. 2014; Fulford and Wallace-Hadrill 1999)
Hampi	India	14th century AD	Vijayanagara Empire	Temples, royal complexes	1565	4187, 24 hectares	Historical Conflict	Ruins	Temples, marketplaces	UNESCO (Knell 2022; Rajangam and Sundar 2021; Powell 2018; Schettino 2016; Pakkeerappa and Thomas 2006)
Parthenon (Acropolis of Athens)	Greece	447-432 BC	Classical Greece	Doric temple dedicated to Athena	1687	69.5 by 30.9 m (228 by 101 ft)	Military Bombardment	Partially ruined	Structure, sculptures	UNESCO, Britannica (Angouri et al. 2017; Fincham 2012; Hamilakis 2002)
Temples of Thebes	Egypt	1500-30 BC	New Kingdom of Egypt	Karnak and Luxor temples	Various periods	7,390 ha with a buffer zone of 444 ha	Natural and Human Impact	Partially ruined	Karnak, Luxor temples	UNESCO, Britannica (Mahmoud et al. 2019; Manning 2012; Aubry et al. 2009)
The Great Wall	China	7th century BC and onwards	Various Chinese dynasties	Fortification system	Ongoing	21,196 km (total length)	Erosion and Human Impact	Partially ruined	Sections over time	UNESCO, Britannica (Cao et al. 2023; Shelach-Lavi et al. 2020; Yang 2017)
Maya Sites	Mexico	2000 BC to 16th century AD	Pre-Columbian Maya civilization	Temples, pyramids	Post 9th century AD	331,397 ha, surrounded by a buffer zone of 391,788 ha	Sociopolitical Decline	Ruins	Several city structures	UNESCO, Britannica (Chase et al. 2011; Scherer 2007)
Angkor Wat	Cambodia	Early 12th century	Khmer Empire	Temple complex	Not specified	Over 162 hectares	Neglect and Decay	Partially restored	Temples, infrastructure	UNESCO, Britannica (Chen 2021; Carter et al. 2019; Chen et al. 2016; Evans et al. 2013)

2.4. Comparative analysis and validation

This research incorporates a rigorous comparative analysis between AI-generated images and available historical sources, photographs, and scholarly interpretations. This validation phase assesses AI's capacity to accurately encapsulate the architectural styles, cultural significance, and ambient settings of the ruins (George 2022). The AI-generated images were evaluated by comparing them to historical records and visual references through a comprehensive analysis that included visual comparisons, consistency checks, and alignment of documentation for accuracy. Fig. 4 illustrates the AI-generated reconstructions of Palmyra, focusing on key elements such as the Temple of Bel, while Fig. 9 showcases the reconstructed images of Pompeii, highlighting hyper-realistic reconstructions of specific Roman buildings and emphasising the restoration of architectural elements and the site's historical and cultural significance. The images were assessed using photographs and descriptions to ensure accuracy. The iterative refinement process involves modifying prompts based on feedback from comparisons with historical records to ensure progressive alignment. This methodology employs prompt engineering to produce initial approximations of heritage sites, which are then refined using iterative processes.

2.5. Scholarly discussion and practical implications

The final phase of this research engages in a scholarly discussion on the implications of utilising AI for heritage reconstruction, focusing on future perspectives. This analysis employs ethical considerations, ensures historical accuracy while balancing technological advancements, and examines the interplay between digital innovation and traditional restoration practices. Key themes include the role of AI-generated imagery in enhancing educational and commemorative initiatives, and their contribution to broader heritage conservation efforts. This forthcoming discourse aims to navigate the complexities of AI applications in cultural preservation, addressing both potential benefits and challenges. This study evaluates how these reconstructions can serve educational, commemorative, and advocacy purposes within the broader framework of heritage preservation (Bharati 2023; Orengo et al. 2015). The initial phase primarily investigated the feasibility and potential of the AI-driven reconstructions. Future research should focus on specific heritage sites, such as the Buddhas of Bamiyan in Afghanistan, involving extensive collaboration with domain experts. This collaboration will aim to validate and refine the results, thereby ensuring robust and reliable outcomes. The structured approach to scholarly discussion will facilitate meaningful contributions to academic discourse on digital heritage preservation.

Subsequent validation phases will engage historians, archaeologists, and cultural experts to further refine the prompts and validate AI-generated images against a comprehensive set of historical and cultural criteria. Expert feedback enhances the accuracy and authenticity of the generated images. This multidisciplinary collaboration will significantly improve the reliability and validity of the reconstructions, ensuring that they adhere to rigorous historical and cultural standards.

By systematically employing AI-generated imagery based on historical and textual data, this study seeks to contribute to the emerging discourse on digital approaches to cultural heritage preservation and reconstruction. Prompt engineering is important for improving the generation of realistic images in text-to-image syntheses. This process involves carefully selecting and composing textual prompts to guide AI models in producing images that match the intended visual style or content described in the text (Oppenlaender 2022). The objective of strategic prompt engineering is to ensure that the generated images accurately reflect the input prompts, resulting in visually coherent and contextually relevant outputs. Designing prompts allows researchers and practitioners to influence generative AI systems to produce images with desired characteristics, such as realism, diversity, and adherence to specific visual styles (Xie et al. 2023; Rombach et al. 2022). Prompt engineering enhances the interpretability and controllability of text-to-image synthesis systems. By refining the prompts used to condition image generation, researchers can adjust output images to meet specific criteria or constraints, such as photorealism, colour accuracy, or object composition (Liu and Chilton 2021). This approach empowers users to shape the creative process of AI-generated image synthesis, allowing them to steer the output towards their desired visual outcomes (Taveekitworachai et al. 2023). The design and optimisation of prompts significantly impact the performance and capabilities of text-to-image generation systems, expanding their potential in design, art, and visual content creation. The integration of AI methodologies marks a new era in architectural conceptualisation and heritage conservation, ensuring that digital reconstructions can serve educational, commemorative, and advocacy purposes within a broader heritage preservation framework.

We employed two types of comparison methodology for our evaluation:

- Historical Accuracy Check: This involves verifying the AI-generated images against historical records and literature to ensure that the generated content aligns with the documented descriptions and visual references. This approach helps ensure the contextual and cultural accuracy of the images.
- Quantitative Metrics Evaluation: This involves utilising image quality metrics, such as SSIM, MSE, PSNR, and MAE, to quantitatively measure the similarity and fidelity of the AI-generated images. As illustrated in Figs. 11–13, these metrics offer a detailed quantitative analysis of the accuracy of the generated images compared with the original references.

By combining these two approaches, we ensured a comprehensive evaluation of the AI-generated reconstructions, balancing both qualitative historical accuracy and quantitative image fidelity.

3. Results and Discussion

This study examined the integration of 3D modelling techniques and AI in the reconstruction of heritage sites significantly damaged by conflicts and natural disasters, offering innovative solutions for cultural preservation. Drawing on the comprehensive flowchart detailed in the methodology section, this discussion enriches the narrative by incorporating additional insights into the systematic approach employed for AI-driven heritage reconstruction. Table 1 is a key resource for the AI-driven reconstruction process implemented in this study. By detailing the architectural characteristics, historical significance, and extent of damage to each heritage site, the table provides essential data that inform the development and calibration of AI models. This compilation of site-specific information ensures that AI-generated visualisations are contextually accurate and architecturally precise. For instance, the incorporation of specific architectural features and the extent of damage facilitated the AI's ability to interpolate missing data and extrapolate likely architectural elements where physical evidence is scant. Comprehensive data on the current conditions of the sites are provided in Table 1 aids in evaluating the effectiveness of AI for reconstructing various levels of decay and destruction. This evaluation was involved in refining the AI algorithms to enhance their adaptability and accuracy in dealing with the diverse preservation states found across the surveyed heritage sites. Thus, Table 1 not only informs the technical execution of AI-driven reconstructions, but also deepens the analysis of how these technologies can be leveraged to preserve and interpret cultural heritage. This methodological foundation supports the subsequent discussion on the technological approaches listed in Table 2 highlighting advancements and identifying areas for further integration of AI into heritage preservation.

Table 2. Technological approaches in heritage site reconstruction.

Site	Author and year	Photogrammetry	3D GIS	CityGML	Parametric approaches	3D reconstruction modelling software	EMF	3DMM	2D-ERT	TOF cameras	Point Cloud	Deep learning methods	MayaArch3D	Reality-based 3D documentation tools	Information system	3D WebGIS	Crowdsourcing	Panoramic imagery	Remote sensing data	3D lase-scanning/recordings	Historical photography	VR technologies
Palmyra	Pan et al. (2020) Denker (2017) Wahbeh et al. (2016)	✓				✓												✓				
Maya Sites	von Schwerin et al. (2013) Pierrot-Deseilligny et al. (2011)	✓											✓			✓						
Pompeii	Sbrogiò (2022) Mazzaglia (2021)				✓										✓							
Buddhas of Bamiyan	Spallone et al. (2022) Bevilacqua et al. (2019) Maiwald et al. (2017) Heikkinen (2009)	✓				✓														✓	✓	✓
Ancient City of Nimrud	Biljecki et al. (2015) Gröger and Plümer (2012) Remondino (2011)	✓	✓	✓																		
Hampi	Keyvanfar et al. (2022) Natampally (2014)	✓				✓																
Parthenon	Hu et al. (2013) Debevec (2004)																			✓		
Temples of Thebes	Berto et al. (2021) Meister et al. (2021) Bennoui-Ladraa and Chennaoui (2018) Hu et al. (2013)	✓					✓	✓	✓													
The Great Wall	Zeng and Jin (2023) Zhou et al. (2022) Bassier et al. (2020)									✓	✓	✓										
Angkor Wat	Wang et al. (2020) Shishido et al. (2017)		✓			✓											✓		✓			

Table 2 provides a comprehensive historical overview of the technologies used across diverse heritage sites, offering an essential context for the application of contemporary AI techniques. For Palmyra, the reconstruction process involves a combination of public domain images and professional panoramic imagery (Wahbeh et al. 2016). This approach utilises crowdsourced images and 3D photogrammetric processes to create interactive immersive experiences, particularly for the reconstruction of the Temple of Bel. These tools and techniques have enabled researchers to digitally recreate and preserve the cultural heritage of Palmyra, emphasising the importance of advanced imaging techniques in restoration efforts (Pan et al. 2020; Denker, 2017). The reconstruction of Maya sites in Mexico has been enhanced by the application of photogrammetry techniques (Pierrot-Deseilligny et al. 2011). These automated image-based procedures allow accurate 3D modelling and orthoimage generation, which are instrumental in creating detailed reconstructions. Additionally, reality-based 3D documentation techniques involving software, such as 3D Studio, Maya, and Sketchup, have enabled realistic 3D models of Maya structures (Remondino and Rizzi 2010). The MayaArch3D project further supports this by providing a 3D WebGIS platform for analysing ancient Maya architecture and landscapes (von Schwerin et al. 2013). Mazzaglia (2021) discussed the Information System of the Pompeii Sustainable Preservation Project, which plays a key role in preserving cultural heritage through effective data management and knowledge sharing. Additionally, Sbrogiò (2022) proposed a parametric approach for reconstructing timber structures in Campanian Roman houses, offering insights into the architectural elements of ancient Roman buildings in Pompeii. Advanced technologies, such as 3D laser recording, photogrammetry, and virtual reality, have been pivotal in reconstructing and preserving the heritage of Bamiyan Buddhas. Historical photography has also been crucial for providing archival images for virtual reconstruction projects (Spallone et al. 2022; Toubekis et al. 2017; Maiwald et al. 2017). The use of photogrammetry from archival imagery combined with 3D models of the current state underscores the importance of historical images in reconstruction efforts (Bevilacqua et al. 2019; Heikkinen 2009). The reconstruction of the Ancient City of Nimrud was significantly enhanced by the application of 3D GIS to archaeology. This tool is essential for urban reconstruction, modelling archaeological 3D objects, managing excavations, and analysing site development over time (Biljecki et al. 2015). In addition, CityGML supports the creation of interoperable semantic 3D city models that are vital for accurately depicting architectural elements and spatial relationships within ancient cities (Gröger and Plümer 2012). Photogrammetry and 3D scanning tools have also been integral to heritage recording and 3D modelling (Remondino 2011). This table highlights the evolution of technological applications in heritage reconstruction, showcasing both the advancements and existing gaps that AI technologies can bridge. This strategic integration of AI aligns with the current technological trends, ensuring that the study's results are innovative and grounded in proven practices.

The introduction of AI into this domain has been identified as a significant development, offering new possibilities for expediting the restoration process through predictive modelling and conceptual design ideation. This fusion of historical data with predictive AI capabilities promises to refine and accelerate the restoration workflow, facilitating a more efficient path for conserving cultural heritage (Rahim et al. 2021). Traditional architectural design, grounded in the rich tapestry of cultural and historical significance, emphasises the sustainability and artistic excellence cultivated over centuries (Liu et al. 2019). Such methods are pivotal in the context of modern architectural innovation, as they provide a sustainable framework for incorporating heritage values into contemporary designs (Hosseini et al. 2016; Mohammed and Haruna 2021). Conversely, AI-based architectural design represents a departure from conventional methods by, leveraging the power of AI to foster a more adaptable and superior architectural planning process (Li et al. 2023). Despite its transformative potential, this approach prompts critical ethical debates, particularly concerning its influence on human creativity and preservation of traditional design ethics (Hegazy and Saleh 2023). Furthermore, the role of AI in architectural education is emerging as a field of study, offering insights into how contemporary pedagogical theories can be integrated with cutting-edge technological advancements (Sadek 2023).

The AI-generated images, derived from detailed textual descriptions, provide critical insights into the original appearance of heritage sites that are significantly damaged by conflicts and natural disasters. These images function as visual reconstructions and interpretative tools, offering perspectives on sites' historical and cultural contexts that are often inaccessible through traditional architectural methods alone. For instance, the Palmyra images (Fig. 4) demonstrate AI capabilities to maintain historical accuracy, focusing on significant elements such as the Temple of Bel, the Baalshamin Temple, and ancient theatre. The photographs captured by Ko Hon Chiu Vincent and provided by UNESCO (Fig. 3) establish a baseline for the reconstruction process, ensuring that the AI models accurately represent the architectural details. Similarly, the AI-generated images of the Maya Sites (Figs. 6 and 7) highlight AI's role of AI in understanding the architectural layout and individual features of ancient cities. The prompts for these images were designed to showcase the architectural and archaeological precision of sites like Chichen Itza, thereby enhancing our knowledge and appreciation of Mayan civilisation. The Pompeii reconstruction images (Fig. 9) illustrate AI's utility in the restoration of specific historical sections, focusing on the accurate reconstruction of Roman buildings. This approach contributes significantly to the overall preservation and comprehension of the site. The AI-driven reconstruction of the Buddha of Bamiyan (Fig. 10) exemplifies the integration of deep historical research with advanced AI technologies. Fig. 10(a) provides a foundational visual reference that is essential for accurate digital reconstruction, whereas Figs. 10(b) and 10(c) illustrate the advanced capabilities of AI in recreating this cultural monument with precise detail and historical accuracy. The process of generating images using AI is rooted in extensive academic research that draws from a variety of sources including historical texts, scholarly articles, and journal publications. This approach ensures that each image produced by AI is not simply a general representation but a detailed and accurate reconstruction that is steeped in a deep understanding of the site's historical and cultural context. These reconstructions serve several objectives, including bridging the gap between the past and the present, providing educational material that enhances the understanding of the site's cultural context, and offering visual simulations for restoration projects. The use of AI in this way supports the preservation of a site's visual heritage while also contributing to the ongoing development of historical scholarship. The application of AI to interpreting and visualising historical data represents a significant advancement in the fields of digital architecture, archaeology, and heritage conservation. This demonstrates the potential of combining technological innovation with traditional historical research, thereby opening new possibilities for the preservation and presentation of heritage sites impacted by time and human conflict.

In the initial stages of this study, we used AI tools to generate prompts, and subsequently used these prompts to create images. However, the initial results were not as accurate or detailed as expected. This prompted us to delve deeper into historical records and journal articles to gather more precise information about heritage sites. For example, in the case of Bamiyan Buddhas, we discovered that the original statues were constructed using mud on rock, covered with lime plaster, and often painted with molten metal. These statues combined Indian, Persian, and Greek artistic styles, and some of the oldest Buddhist manuscripts, such as the Kharosthi scripts, were found in the surrounding caves. The evaluation metrics for AI-generated images in this study involved a multifaceted approach to ensure accuracy and alignment with historical and cultural contexts. Initially, the images were subjected to internal validation, in which prompt engineering played a critical role. This involved refining textual prompts to enhance AI's capability to produce images that closely resemble the intended architectural designs and cultural nuances. The methodology emphasises the iterative refinement process, in which prompts are continuously adjusted based on the initial outputs, leading to progressively accurate visual representations. This approach ensured that the generated images were not only realistic but also contextually relevant, accurately reflecting the architectural intent and historical context. The AI-generated reconstructions of Palmyra and Pompeii were compared with historical records and visual references, focusing on key elements such as the Temple of Bel and specific Roman buildings. Using this detailed historical information, we refined our prompts to include specific keywords and contextual information. This approach significantly improves the quality and accuracy of AI-generated images. For instance, Figs. 10(b) and 10(c) of Bamiyan Buddhas exhibit a higher degree of similarity to the original statues compared to earlier attempts.

3.1. Palmyra (Syria)

Prompt:

- A newly reconstructed Palmyra, where the essence of its ancient glory is captured in a structure that stands proud and unblemished under the clear sky. At its heart, a grand edifice, inspired by the Temple of Bel, showcases a symmetrical front view with a grand entrance. The architecture boasts complete and pristine columns rising to support a perfectly restored entablature, capped with a pediment that marries timeless artistry with contemporary innovation. This masterpiece gleams in the sunlight, reflecting a blend of historical reverence with the pinnacle of modern reconstruction. The surrounding environment is meticulously maintained, featuring a well-kept street leading to the temple's imposing steps, inviting visitors into a space where history and the present are seamlessly intertwined. Capture the essence of both ancient grandeur and modern architectural achievements, highlighting the harmony between past and future (Figs. 3 and 4).

Fig. 3. Photographs of the existing ruins of Palmyra, showcasing the Temple of Bel, the Baalshamin Temple, and the ancient theatre, taken by Ko Hon Chiu Vincent and provided by UNESCO.

Fig. 4. Midjourney and DALL-E, AI-generated reconstructions of different sections of the ancient city of Palmyra.

3.2. Maya Sites (Mexico)

Prompts:

- Chichen Itza in its heyday, focusing on the Pyramid of Kukulcan and the Great Ball Court. Show the precise architectural and astronomical alignment of the pyramid, the ornate carvings, and the surrounding temples and sacred cenotes. The lush Yucatan jungle should frame the site, highlighting the Maya's connection with their environmental, realistic, architectural design (Fig. 5).
- A detailed 3D model description of the complete architectural layout of Chichen Itza, focusing on the overall arrangement of the ancient Maya city's buildings and structures. Describe the spatial relationships

between the step-pyramids, temples, ball courts, observatory, and other key architectural features, providing information on their relative sizes, orientations, and distances from one another. Emphasize the architectural aesthetics and the visual impact of Chichen Itza's layout, allowing for a comprehensive representation of this ancient Maya city's architectural grandeur (Fig. 6).

Fig. 5. Photographs of ancient Maya archaeological sites in Mexico, captured by Community Tours Sian Ka'an and Ko Hon Chiu Vincent under UNESCO's recognition of these historical treasures.

Fig. 6. Midjourney AI-generated complete architectural layout of Chichen Itza of the ancient Maya city.

- The intricate architectural features of Chichen Itza, emphasizing the design and construction of the ancient Maya city's iconic buildings and structures. Highlight the specific elements of architecture, such as the step-pyramids, temples, ball courts, and observatory, and provide insights into their unique architectural styles, ornamentation, and any notable construction techniques or materials used. Capture the essence of Chichen Itza's architectural marvels in their prime, showcasing the cultural and artistic achievements of the ancient Maya civilization (Fig. 7).

Fig. 7. Midjourney AI-generated representations of distinctive features of Chichen Itza.

3.3. Pompeii (Italy)

Prompt:
- Create a hyper-realistic image reconstructing the specific section of the ancient Roman building in Pompeii, Italy. The reconstruction should focus only on the visible section in the original image, maintaining the same perspective and architectural elements. The mosaic patterns, column details, and architectural style should match the original as closely as possible, restored to how they might have appeared before any damage. The setting remains the same with the surrounding ruins still visible, but the specific section should appear fully restored with accurate colours and details (Figs. 8 and 9).

Fig. 8. Photographs showing the ruins of Pompeii, including detailed architectural remnants and structures. Images captured by J. Frias Velatti and Limes.Media/Tim Schnarr, as featured on the UNESCO website.

Fig. 9. Midjourney and DALL-E, AI-generated reconstructions of ancient Pompeii, showcasing its historic architecture and interiors.

3.4. Buddhas of Bamiyan (Afghanistan)

Prompt:
- Reconstruct the standing Buddha of Bamiyan, standing 180 feet tall and carved into a sandstone cliff. The Buddha is depicted in a standing posture with intricate, layered robes that showcase a blend of Hellenistic and Indian artistic influences. The statue's face reflects a serene, meditative expression typical of Indian Buddhist art. The materials used are traditional mud, straw, and lime plaster, giving it an aged yet restored look. The rugged mountainous terrain of the Bamiyan Valley surrounds the Buddha, emphasizing its monumental scale and cultural significance. Side architectures include detailed carvings and Kharosthi scripts to enhance historical accuracy (Fig. 10).

Fig. 10. Transformation of the Buddha of Bamiyan: The left image shows the original state of the statue following its destruction, while the centre and right images represent AI-generated reconstructions.

A comprehensive set of image quality metrics was employed to assess the quality and accuracy of AI-generated images. These metrics included the Structural Similarity Index Measure (SSIM), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Mean Absolute Error (MAE). Each of these metrics offers unique insights into different aspects of image fidelity and similarity.

- SSIM is a perceptual metric that quantifies the image quality by comparing the luminance, contrast, and structure between the generated and original images. SSIM values range from 0 to 1, with values closer to 1 indicating higher similarity. During the evaluation, the SSIM values ranged from 0.083 to 0.125. Fig. 13 achieved the highest SSIM value of 0.125, suggesting that it closely matches the structural characteristics of the original image. This indicates that the AI-generated image effectively preserved the structural integrity and visual information of the original heritage site.
- MSE measures the average squared difference between the pixel values of the original and generated images. Lower MSE values indicate fewer errors and better image quality. In our study, MSE values ranged from approximately 7,568,117 to 12,674,829. Fig. 13 exhibited the lowest MSE value of 7,568,117, demonstrating the smallest deviation from the original image in terms of pixel intensity, thereby indicating a high degree of similarity and reduced error.
- The Peak Signal-to-Noise Ratio (PSNR) is an engineering metric that measures the ratio of the maximum possible power of a signal to the power of corrupting noise and is usually expressed in decibels (dB). Higher PSNR values indicate a better image quality and less distortion. In our evaluation, the PSNR values ranged from 7.101 to 9.341 dB, with Fig. 13 attaining the highest PSNR value of 9.341 dB. This high PSNR value suggests that Fig. 13 has minimal noise and high fidelity, closely resembling the original image in terms of quality.
- The Mean Absolute Error (MAE) evaluates the average absolute difference between the pixel values of the original and generated images. Lower MAE values indicated better image quality and fewer absolute errors. In our study, the MAE values ranged from approximately 135.359 to 148.749, with Fig. 12 having the lowest MAE value of 135.359, indicating the least average deviation from the original image. This highlights the accuracy of the AI-generated image in maintaining the pixel-intensity distribution of the original image.

To evaluate the performance of the AI-generated reconstructions, we selected ten images of the giant Buddha statue. The choice of the Buddha statue allowed us to conduct a detailed and focused analysis utilising the metrics described above to evaluate the quality of the generated images. For other AI-generated images, such as those of the Maya, Pompeii, and Palmyra sites, our approach was primarily exploratory. We tested the AI tool to determine whether it could produce results consistent with historical records and keywords derived from journal articles and historical sources. However, our detailed metric evaluation specifically focused on the Buddha statue, allowing us to thoroughly validate one heritage site before extending the same level of evaluation to others in future research (Figs. 11–13).

Fig. 13 consistently performed well across all metrics, achieving the highest SSIM, lowest MSE, highest PSNR, and relatively low MAE values. This indicates that Fig. 13 is one of the best reconstructions, offering high structural similarity, minimal error, and high overall quality compared to the original image.

4. Limitations and Future Directions

This research highlights several limitations that impact the accuracy and authenticity of AI-generated reconstructions of heritage sites. Addressing these limitations can refine current methodologies and suggest future research directions to enhance the precision and reliability of digital reconstructions.

Lack of Original Visual References: One of the major obstacles in rebuilding damaged cultural heritage sites is the absence of original photographs or visual references, which prevents direct comparison and calculation of similarity metrics. To overcome this, evaluations rely on historical records, descriptions, and expert opinion. Future research should address this limitation by collaborating with academics and experts, whose feedback will be essential for validating reconstructions and ensuring their accuracy and validity in the absence of visual data.

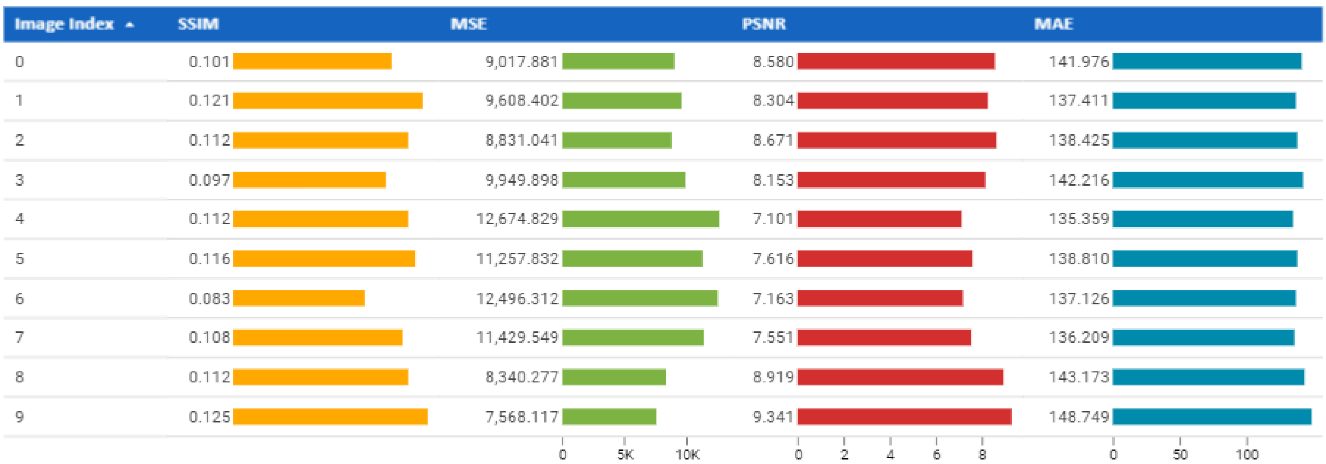
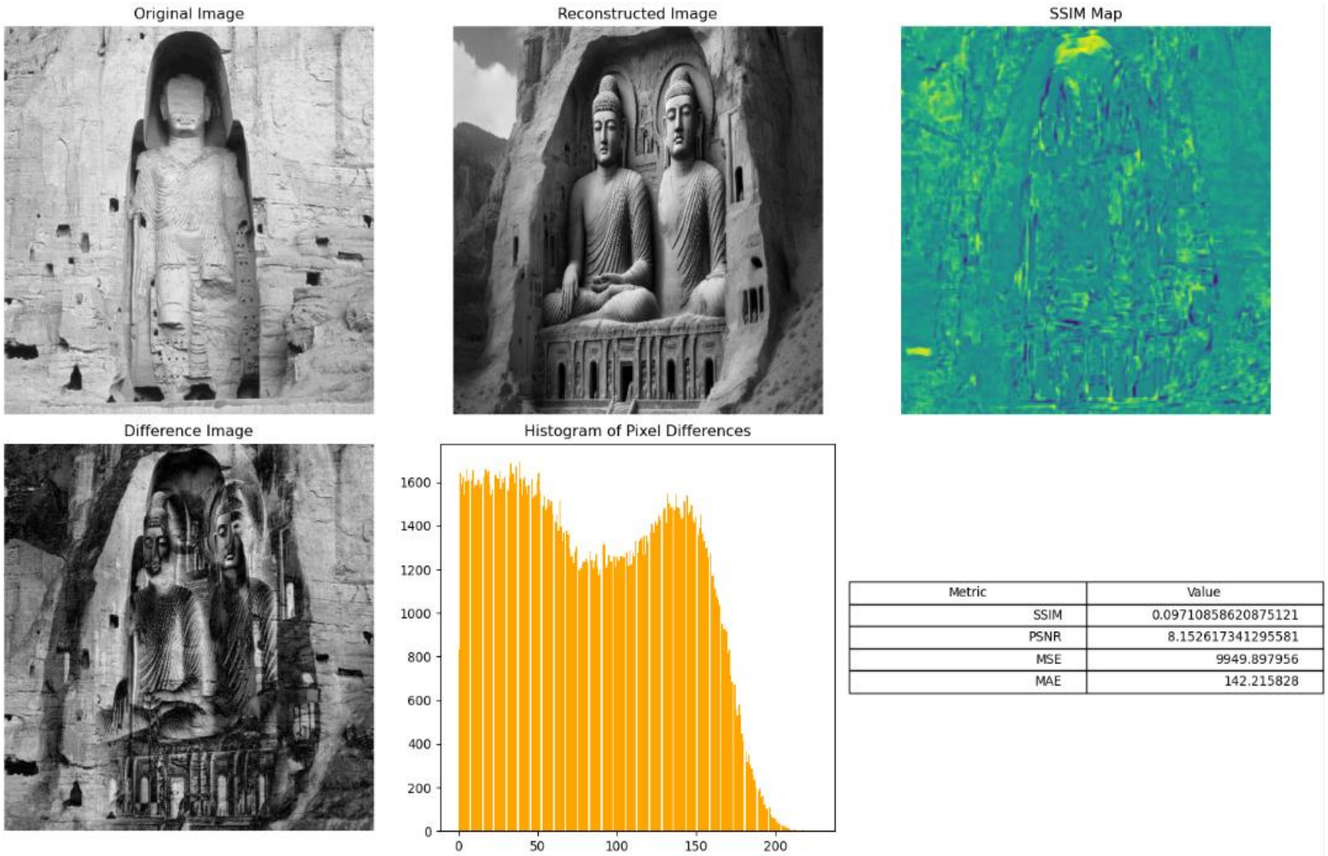
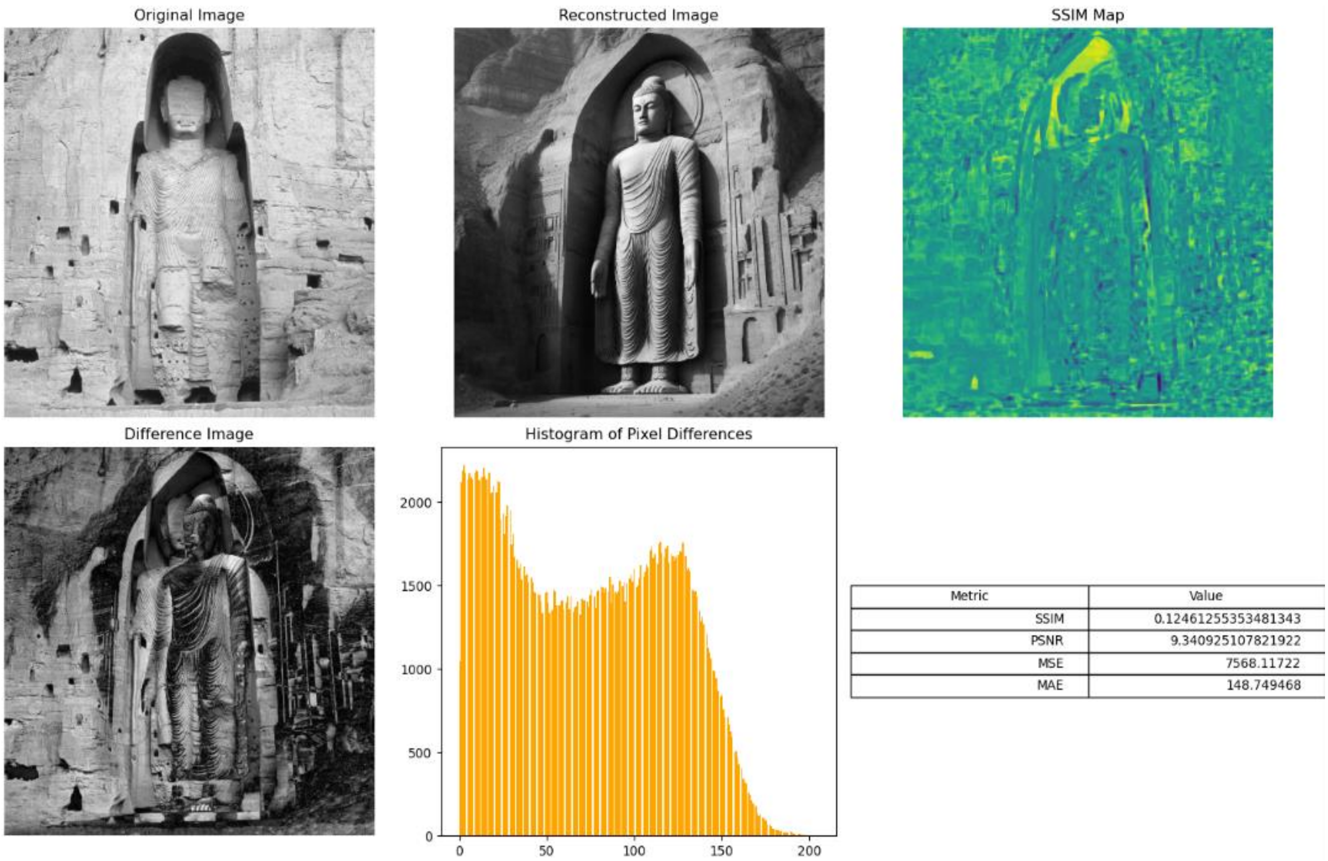


Fig. 11. Comparison of AI-generated images of the Giant Buddha Statue using evaluation metrics.



Metric	Value
SSIM	0.09710858620875121
PSNR	8.152617341295581
MSE	9949.897956
MAE	142.215828

Fig. 12. First figure displaying the evaluation of AI-generated images of the Giant Buddha statue using several comparison metrics.



Metric	Value
SSIM	0.12461255353481343
PSNR	9.340925107821922
MSE	7568.11722
MAE	148.749468

Fig. 13. Second figure displaying the evaluation of AI-generated images of the Giant Buddha statue using several comparison metrics.

Automated Information Extraction and Prompt Engineering: AI's role in reconstructing heritage sites involves challenges such as the lack of comprehensive photographic records, necessitating reliance on textual descriptions and expert insights. The dependence of the current methodology on manually curated prompts from historical documents and academic sources limits the comprehensiveness and accuracy of AI-generated images. Future research will explore automating this process using advanced AI to autonomously search, extract, and summarise relevant information, aiming to generate more detailed and precise prompts. This development could refine theoretical understanding of AI's capabilities in interpreting complex historical data and contribute to the discourse on AI's role in digital archaeology and heritage reconstruction.

Consistency and Reproducibility in AI Outputs: Variability in AI-generated images remains a significant challenge, complicating the process of achieving consistent reconstructions from multiple angles. Future research will focus on integrating advanced generative AI models, such as stable diffusion algorithms, to improve the consistency and reproducibility of AI outputs. Enhancing these aspects will make AI reconstructions more reliable for educational, cultural, and research purposes.

Enhancement of Detail-oriented Reconstructions: The accuracy of AI-generated images depends on detailed input data. Current models require explicit details regarding dimensions, materials, and spatial configurations, which are often lacking in textual descriptions. To address this, ongoing research must improve data collection methods and prompt formulation to include detailed and complex architectural and archaeological specifics. Developing AI systems capable of effectively interpreting detailed descriptive data will refine AI's ability to render accurate images, encouraging deeper integration of AI models with archaeological and architectural theories.

Acknowledged Methodological Constraints: The interpretative nature of AI reconstructions, based on incomplete data and potential biases in expert interpretations, highlights the existing methodological constraints. Continuous enhancements in AI technology and collaborative efforts with domain experts are essential to ensure that digital reconstructions closely adhere to historical accuracy and cultural authenticity. As AI technologies become more integrated into heritage preservation, they can inform policy decisions and strategies at both national and international levels, leading to the development of new guidelines for ethical and effective digital reconstruction and preservation.

This study lays the foundation for the use of AI in the digital reconstruction of heritage sites. The limitations and future directions outlined suggest a pathway for methodological evolution, aiming for more nuanced, accurate, and culturally respectful digital preservation practices.

5. Conclusions

This study highlights the significant potential of artificial intelligence (AI) in the preservation of cultural heritage, particularly through the digital reconstruction of sites impacted by conflicts and natural disasters. Utilising AI-generated imagery, derived from detailed textual descriptions and historical analyses, this research has provided new perspectives on the original appearance of heritage sites, thereby introducing innovative methodologies for architectural conceptualisation and heritage conservation. The evaluation process we conducted was comprehensive and focused on assessing the AI-generated reconstructions of the Giant Buddha statue, using key performance indicators such as the Structural Similarity Index Measure (SSIM), Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Mean Absolute Error (MAE). Among the images that were tested, Fig. 13 consistently performed the best, achieving the highest SSIM score (0.125), lowest MSE value (7,568,117), highest PSNR (9.341 dB), and low MAE (148.749). These metrics indicate that Fig. 13 closely aligns with the structural characteristics, pixel intensity, and overall quality of the original image, thereby making it one of the most accurate AI reconstructions. By integrating AI with traditional preservation practices, this research advocates a balanced approach to conserving cultural legacies, ensuring that they are both preserved and revitalised for future generations. We evaluated the performance of AI tools in generating results that align with historical records and keywords derived from journal articles and historical sources for architectural heritages such as Maya sites, Pompeii, and Palmyra. These findings underscore the need to address the ethical, technical, and collaborative challenges. Specifically, our analysis revealed that the precision of AI-generated reconstructions can be limited by the quality of the input data, underscoring the need for advanced algorithms that are capable of handling incomplete data with greater accuracy. Future research should focus on refining AI algorithms and expanding methodological frameworks to enhance the precision, reliability, and applicability of AI technologies in the cultural heritage field. This requires advancing the capability of AI systems to process and interpret complex and often incomplete data with greater accuracy and detail. The application of AI to heritage conservation presents critical interdisciplinary challenges that require collaborative approaches. Integrating the capabilities of AI with the expertise of historians, archaeologists, and architects is essential to ensure that digital reconstructions are not only technically accurate, but also culturally and historically nuanced. This collaboration is important for developing ethical standards and frameworks that guide the responsible application of AI, emphasising sustainability, and respect for the validity and integrity of cultural heritage. Furthermore, the integration of AI into heritage conservation practices has revolutionised the ways in which we interact with and understand our cultural past. By enhancing the accessibility of heritage through digital means, AI enables broader engagement and educational opportunities, thus making cultural heritage more accessible and relatable to a global audience. This transformative potential of AI not only supports preservation efforts but also enriches our collective cultural understanding. In conclusion, this research contributes to the foundational work employing AI for the digital reconstruction of heritage sites and suggests a pathway for substantial methodological evolution. By progressively addressing the outlined challenges and leveraging documented improvements in reconstruction accuracy and data handling, the field can advance towards more nuanced, accurate, and culturally respectful digital preservation practices. The continuous refinement of AI technologies and their integration into heritage conservation will be pivotal in ensuring that this new era of digital engagement with our past is marked by both innovation and respect for historical accuracy and cultural significance.

Acknowledgements

This research has previously been presented at the 2nd International Summit on Civil, Structural and Environmental Engineering (ISCSEE2024) held in Florence, Italy, on March 18-20, 2024. Extended version of the research has been submitted to Challenge Journal of Structural Mechanics and has been peer-reviewed prior to the publication.

Funding

The authors received no financial support for the research, authorship, and/or publication of this manuscript.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Author Contributions

All of the authors made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data; were involved in drafting the manuscript or revising it critically for important intellectual content; and gave final approval of the version to be published.

Data Availability

The datasets created and/or analyzed during the current study are not publicly available, but are available from the corresponding author upon reasonable request.

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