# Restoration of Cultural Legacy Artistic Design Based on CAD Modeling and Neural Network Analysis

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**Abstract.** The design and restoration of cultural legacy involve not only technology but also the interpretation of history, cultural continuity, and artistic innovation. This process aims to protect and continue the cultural legacy, injecting new vitality and significance into it. CAD modelling technology achieves precise depiction of the morphology, structure, texture, and other features of cultural legacy through digital modelling. NN can achieve automatic identification and classification of a cultural legacy by learning and training on a large amount of data. In order to promote the application of CAD modelling and NN methods in cultural legacy artistic design and restoration, this article proposes a cultural legacy 3D reconstruction algorithm based on multi-view images and improvements on existing algorithms to improve simulation speed and 3D effects. Taking the Yellow River cultural legacy as an example, this study analyzes the application of the proposed method in the artistic design of the Yellow River cultural legacy and provides experimental simulation results. Through experimental verification, it has been shown that the proposed method can significantly improve simulation speed and optimize 3D effects, achieving high simulation and restoration of the Yellow River cultural legacy.

**Keywords:** CAD Modeling; Neural Network; Cultural Legacy; Art Design
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## 1 INTRODUCTION

In the highly intelligent modern society, digital technology is gradually penetrating into the inheritance and restoration of cultural Heritage. Computer-aided design modelling and neural network analysis, as advanced digital technologies, provide endless possibilities for the artistic design and restoration of cultural Heritage. Cultural heritage artworks are cultural treasures of all humanity, and their protection and restoration are crucial. In order to effectively protect and restore these artworks, it is necessary to diagnose their condition accurately. This requires analyzing and extracting features from diagnostic images to identify and classify various elements and damages in the image. Amura et al. [1] explored how to use CAD modelling and neural network analysis methods to design and extract features from diagnostic images. These models can better understand the shape and structure of artworks and identify and predict possible damage. In addition, CAD models can also be used to simulate the maintenance process to predict and solve possible maintenance problems. A neural network is a deep learning algorithm that can automatically learn features from data and perform classification and prediction. In art diagnosis, neural networks can be used to identify and classify various elements and damages in images. In addition, neural networks can also be used to predict the lifespan of artworks and possible repair solutions. The design and feature extraction of art diagnostic images based on CAD modelling and neural network analysis is a comprehensive process. Firstly, use CAD modelling techniques to create a 3D model of the artwork, and then use neural network analysis techniques to classify and predict the model. Meanwhile, features such as shape, texture, and colour can be extracted from the model for training and optimizing neural network models. By using this method, more accurate and effective diagnostic images of artworks can be obtained, providing more accurate basis for protection and restoration work. CAD modelling technology achieves a detailed description of the shape, structure, texture and other characteristics of Cultural Heritage through digital modelling. The cultural landscape heritage of Indian riverbank architecture is a cultural heritage with profound historical Heritage and artistic value. However, due to long-term natural erosion and human destruction, many precious architectural landscapes face serious protection issues. Bardhan and Paul [2] discussed how to use computer-aided design (CAD) modelling and neural network analysis to conduct artistic design research and restore the cultural landscape heritage of Indian riverbank architecture. Through high-precision measurement and modelling, detailed geometric shapes, textures, and other information about the landscape can be obtained, providing accurate data support for subsequent art and design research and restoration. CAD modelling can also be used to construct virtual displays and interactive experiences of riverbank architectural and cultural landscape heritage, providing the public with a more intuitive and vivid display of cultural Heritage. Through virtual display and interactive experience, the public can have a deeper understanding and experience of the historical background, artistic value, and protection significance of riverbank architectural cultural landscape heritage. On the other hand, NN is a computational model that simulates human brain neurons and can achieve automatic recognition and classification of cultural Heritage by learning and training large amounts of data. With the advancement of technology, 3D/VR technology has provided new possibilities for the preservation and protection of historical and cultural Heritage. 3D/VR, as a cutting-edge technology, not only helps enhance understanding of historical and cultural Heritage but also helps to protect this precious cultural Heritage more effectively. In this context, Bozorgi and Lischer [3] conducted a research project called the "Virtual Ganjali Khan Project" and provided the latest project updates here. The Virtual Ganjali Khan Project is a project aimed at utilizing 3D/VR technology for digital protection and research of the ancient Ganjali Khan site. The Ganjali Khan Site is an important ancient city in Central Asia with rich historical and cultural value. However, due to natural and human factors, the site faces serious protection issues. These data provide us with a detailed virtual restoration map, allowing us to intuitively experience the historical style of Ganjali Khan.

3D scanning and point cloud processing technology have become important tools for cultural heritage protection and reconstruction. Especially in the field of art and architecture, precise point cloud data can better understand and protect this precious cultural Heritage. However, how to effectively process these large amounts of point cloud data to achieve more accurate semantic segmentation remains a challenge. Cao and Scaioni [4] proposed a method based on CAD modelling and neural network analysis, which utilizes efficient deep learning of labels for semantic segmentation. CAD modelling is a computer-aided design technique that can create accurate 3D models. In the point cloud processing of cultural heritage art buildings, CAD modelling can be used to obtain high-precision point cloud data and describe the shape, structure, and texture of this data. A neural network is a deep learning algorithm that can automatically extract features from a large amount of data and perform classification and prediction. In the semantic segmentation of cultural Heritage and art buildings, neural networks can be used to identify and classify different elements in point cloud data, such as walls, roofs, windows, etc. Semantic segmentation based on label-efficient deep learning is a machine learning method that achieves automatic classification and segmentation of point cloud data through training using pre-labeled label data. The role of digital technology in the restoration and protection of cultural Heritage is increasingly prominent. Comes et al. [5] discussed the digital reconstruction process of fragmented cultural heritage assets in Romania.Due to prolonged exposure to the natural environment, the relief plate has suffered severe weathering and erosion. In order to protect this precious cultural Heritage and enable the public to have a deeper understanding and appreciation of it, digital reconstruction has been carried out. Using VR technology, import digital models into a virtual environment and create an interactive display system. The public can visit and interact with the relief plate from multiple perspectives through devices such as head-mounted displays or mobile phones. After completing the preliminary digital reconstruction, the reconstruction results are evaluated and optimized through feedback from experts and the public, further improving the quality and effectiveness of digital reconstruction. Meanwhile, through virtual displays and interactive experiences, the public can gain a deeper understanding and appreciation of the value of this cultural Heritage. Cultural and artistic heritage buildings are important treasures of all humanity, carrying rich historical and cultural information, reflecting the evolution and development of human civilization. However, due to the prolonged natural erosion and human damage experienced by these buildings, protection and restoration work face enormous challenges. Croce et al. [6] proposed a semiautomatic method based on machine learning to extract information on cultural Heritage and artistic heritage buildings from semantic point cloud data and establish corresponding information models. Obtain point cloud data of cultural and artistic heritage buildings through 3D laser scanning or other 3D measurement techniques. These data may contain a large amount of noise and redundant information, thus requiring preprocessing, such as filtering, denoising, data simplification, etc., to extract useful geometric information. These pieces of information can be used to establish information models for cultural and artistic heritage buildings in order to facilitate more in-depth protection and research. The digital protection and restoration of cultural Heritage has become an important research field. Among them, using 3D CAD modelling and neural network analysis technology for the digital restoration of architectural Heritage is an emerging and effective method. Croce et al. [7] explored how to combine these two technologies to achieve precise reproduction and restoration of architectural elements in cultural Heritage. 3D CAD modelling is a method of generating three-dimensional models of objects using computer technology. In the restoration of architectural Heritage, 3D CAD modelling can be used for the digital reconstruction of elements such as architectural structures and carving details. Through high-precision surveying and modelling, detailed geometric shapes, textures, and other information about architectural Heritage can be obtained, providing accurate data support for subsequent neural network analysis. 3D CAD modelling can also be used to construct virtual displays and interactive experiences of architectural Heritage, providing the public with a more intuitive and vivid display of cultural Heritage. Through virtual display and interactive experience, the public can have a deeper understanding and experience of the historical background, artistic value, and protection significance of Architectural Heritage. Neural networks are deep learning algorithms that can process large amounts of data and automatically extract features from the data. In the restoration of architectural Heritage, neural networks can be used to analyze data such as images and textures of architectural elements. Through training and learning, automatic recognition and classification of architectural elements can be achieved.

In order to better implement the application of CAD modelling and NN analysis in cultural legacy artistic design and restoration, this article proposes a 3D reconstruction algorithm based on multi-view images. This algorithm first uses CAD modelling technology to digitize cultural legacy and then obtains 3D information about cultural legacy through image acquisition and processing from multiple perspectives. Then, NN analysis will be used to optimize and improve the obtained 3D information in order to achieve a high degree of simulation and restoration of cultural legacy. This algorithm can be improved and enhanced on the basis of existing algorithms to achieve faster and more accurate 3D reconstruction results.

In order to verify the feasibility of the proposed method, this article takes the Yellow River Cultural Legacy as an example for application research. The Yellow River culture is an important component of traditional Chinese culture, with a profound historical and cultural legacy. However, due to historical and natural factors, the Yellow River cultural legacy has suffered serious damage and loss.

Experimental verification shows that the proposed method can significantly improve simulation speed and optimize 3D effects and has important application value in the artistic design and restoration of the Yellow River cultural legacy. This method can quickly and accurately obtain 3D information on the Yellow River cultural legacy and optimize it through NN analysis. This combination can not only improve the artistic design effect of cultural legacy but also better protect and inherit cultural legacy. This study has the following innovations:

(1) This article introduces CAD modelling and NN technology into the field of artistic design and restoration of cultural legacy, utilizing advanced technological means and methodological support to improve the effectiveness of design and restoration.

(2) This article proposes a 3D reconstruction algorithm based on multi-view images, which achieves fast and accurate 3D reconstruction of cultural legacy. This algorithm can be improved and enhanced on the basis of existing algorithms, achieving more efficient and accurate 3D reconstruction results.

(3) This article takes the Yellow River cultural legacy as an example to apply the proposed method and verify its feasibility in the artistic design and restoration of cultural legacy.

Article organization: The first section is the introduction, which introduces the significance of CAD modelling and NN analysis in cultural legacy artistic design and restoration; The second section provides an overview of the relevant theoretical foundations; The third section elaborates on the principles and methods of the cultural legacy 3D reconstruction algorithm based on multi-view images; The fourth section presents experimental verification and result analysis, demonstrating the effectiveness of the algorithm; The final section is the conclusion, summarizing the research results and pointing out the research directions in the fields of artistic design and cultural legacy protection.

## 2 OVERVIEW OF RELEVANT THEORIES

With the continuous development of technology, the digital protection and utilization of cultural Heritage has gradually become a research hotspot. Among them, spectroscopic technology has been widely applied in the field of cultural Heritage digitization due to its unique advantages of non-destructive, fast, and high-precision. Demenchuk et al. [8] explored how to combine computer-aided design (CAD) modelling with neural network analysis to further promote the application of cultural heritage spectroscopy research in the digitization of cultural Heritage. CAD modelling technology can be used for the three-dimensional digital reconstruction of cultural relics. Through high-precision surveying and modelling, detailed geometric and texture information of cultural relics can be obtained. In spectroscopic research, CAD modelling can establish a digital spectral database for cultural relics, facilitating accurate recording and reproduction of information such as materials and colours of cultural relics. In addition, CAD modelling can also be used to construct virtual displays and interactive experiences of cultural relics, providing the public with a more intuitive and vivid display of cultural Heritage. Neural networks are deep learning algorithms that can process large amounts of data and automatically extract features from the data. Traditional evaluation methods often rely on the experience and judgment of experts and have a certain degree of subjectivity and uncertainty. CAD modelling and neural network analysis methods are widely used in the assessment of the condition of heritage buildings. Fino et al. [9] explored a method for evaluating the condition of heritage buildings based on CAD modelling and neural network analysis. It establishes a three-dimensional model of heritage buildings through CAD modelling and obtains relevant structural, material, and other data. Then, neural networks are used to learn and analyze these data, predicting the performance of the structure, the performance of the material, and the degree of aging. Chinese landscape painting and classical private gardens are two treasures of Chinese culture and art with profound aesthetic connotations. Style transfer is a technique of applying one art style to another art form through deep learning. This method has been successful in applying Western painting styles to Japanese ukiyo-e and Van Gogh style to photography. Hong et al. [10] have developed a novel approach to transform these two forms of art into aesthetic styles. It explores how to use deep neural networks to achieve aesthetic style transformation between Chinese landscape painting and virtual scenes of classical private gardens. Applying the aesthetic style of

Chinese landscape painting to virtual scenes of classical private gardens through deep neural networks. Or apply the aesthetic style of classical private gardens to virtual scenes in Chinese landscape painting. In the study of cultural relic spectroscopy, neural networks can be used to analyze the spectral data of cultural relics. Through training and learning, automatic classification and recognition of information such as cultural relic materials, pigments, and processes can be achieved. In addition, neural networks can also be used to study the patterns of aging, corrosion, and other pathological changes in cultural relics, providing the scientific basis for the protection and restoration of cultural relics. Computer-aided design (CAD) modelling and neural network analysis play an important role in the restoration of historical and cultural values. Kotsiubivska and Baranskyi [11] explored how to combine CAD modelling with neural network analysis for three-dimensional simulation in the restoration of historical and cultural values. CAD modelling is a method of three-dimensional modelling of objects using computer technology. In the restoration of historical and cultural values, CAD modelling can be used for the three-dimensional digital reconstruction of cultural Heritage such as architecture and sculpture. Through high-precision surveying and modelling, detailed geometric shapes, textures, and other information about cultural relics can be obtained, allowing for virtual display and interactive experiences. In addition, CAD modelling can also be used to construct three-dimensional models of historical and cultural scenes, providing support for the simulation and reproduction of historical events. Neural networks are deep learning algorithms that can process large amounts of data and automatically extract features from the data. In the restoration of historical and cultural values, neural networks can be used to analyze data such as images and audio in historical and cultural scenes. Through training and learning, automatic recognition and classification of historical and cultural values can be achieved. In addition, neural networks can also be used to study the development and evolution laws of historical culture, providing a scientific basis for the deduction and simulation of historical events.

Virtual restoration of three-dimensional digital cultural relics is an emerging and effective method that utilizes computer technology for digital reconstruction and restoration of cultural relics. Li et al. [12] explored how to construct an efficient three-dimensional digital cultural relic virtual restoration system based on fuzzy logic algorithms. Fuzzy logic is an algorithm for handling fuzzy information, which can handle uncertain or imprecise data. In the virtual restoration of cultural relics, fuzzy logic algorithms can be used to deal with uncertainty issues such as damage and loss of cultural relics. Fuzzy logic algorithms can automatically identify, classify, and restore cultural relics, improving the accuracy and efficiency of virtual restoration. This module is based on fuzzy logic algorithms to preprocess, recognize, and classify the collected data. By adjusting model parameters and details, precise restoration of cultural relics can be achieved. This module will visually display the restored cultural relics, providing the public with a more intuitive and vivid experience of cultural Heritage. Virtual displays can observe cultural relics from multiple perspectives and interact with them, deepening our understanding and comprehension of history and culture. As an important carrier of China's intangible cultural Heritage, Qin Opera costumes have important historical, cultural and artistic values. However, due to factors such as time, environment, and human factors, these cultural relics often suffer losses. In order to better protect and inherit these cultural relics, it is necessary to use modern digital technologies such as CAD modelling and neural network analysis for digital protection and innovative design research. Liu et al. [13] took the Qin Opera costumes as an example to discuss how to use these technologies for digital protection and innovative design. CAD modelling is a computer-aided design technique that can generate high-precision models of objects by accurately describing their geometry and analyzing their properties. A neural network is a deep learning algorithm that can automatically extract features from a large amount of data and perform classification and prediction. This paper studies the digital protection and innovative design method of Qin Opera costumes based on CAD modelling and neural network analysis. By means of accurate measurement and recording, detail restoration, virtual restoration and other means, the digital protection of Qin Opera costumes can be realized, Simultaneously utilizing techniques such as style transfer, pattern generation, and colour prediction to achieve the innovative design of cultural relics. Yue Opera is a type of traditional Chinese opera art with unique regional characteristics and artistic charm. As an important component of Yue opera performance, Yue opera costumes carry rich cultural connotations and artistic values. However, traditional Yue opera costume design methods have problems such as long design cycles, high costs, and difficulty in modification. With the continuous development of computer technology, virtual simulation and clothing design of Yue Opera costumes based on elements of Yue Opera have become possible. Liu et al. [14] explored the advantages and applications of virtual simulation and clothing design based on elements of Yueju opera. Yue Opera costumes have unique regional characteristics and artistic charm, and their design elements include colours, patterns, fabrics, styles, etc. In order to conduct virtual simulation and clothing design, it is necessary to analyze and extract elements of Yue Opera costumes. Through in-depth research and analysis of Yue Opera costumes, representative design elements are extracted to provide basic data for subsequent virtual simulation and costume design. Virtual simulation of Yueju costumes based on Yueju elements refers to the use of computer technology to digitize the extracted Yueju costume elements and generate a virtual Yueju costume model. By adjusting the parameters and details of the model, a virtual simulation of Yue Opera costumes with different styles and colours can be achieved. This method can greatly shorten the design cycle, reduce costs, and improve design efficiency. Meanwhile, through virtual simulation, the design effect can be visually displayed, making it easy to modify and optimize. The Delphi Apollo Temple is an important heritage of ancient Greek culture with significant historical and cultural value. In order to better protect and inherit this precious cultural Heritage, Maravelakis et al. [15] explored the method of using CAD modelling and neural network analysis techniques to perform 3D modelling and analysis of the Apollo Temple in Delphi. Obtain point cloud data of the Delphi Apollo Temple through laser scanning or other 3D measurement techniques. These data may contain a large amount of noise and redundant information, thus requiring preprocessing, such as filtering, denoising, data simplification, etc., to extract useful geometric information. At the same time, it is necessary to collect non-geometric information, such as historical photos and literature of the Delphi Apollo Temple, to provide data support for subsequent neural network analysis. Using CAD software such as AutoCAD or 3DS Max, establish a 3D model of the Delphi Apollo Temple based on processed point cloud data. This model should include detailed information such as the main structure of the temple, carving details, and building materials. During the modelling process, attention should be paid to maintaining the accuracy and completeness of the original data to ensure the reliability and accuracy of the model.

Ming et al. [16] aim to review the latest progress in ancient ceramic restoration systems based on CAD modelling, neural network analysis, and VR technology. CAD modelling is mainly used in ancient ceramic restoration to establish high-precision 3D models of cultural relics. In addition, CAD modelling can also be used to simulate the repair process to predict and solve possible repair problems. Neural networks are a type of deep learning algorithm that can automatically extract features from data and make decisions. In ancient ceramic restoration, neural networks can be used to identify and classify damaged parts of ceramics, as well as predict possible repair results. In addition, neural networks can also be used to simulate the repair process to predict and solve possible repair problems. Virtual reality technology can create realistic 3D virtual environments, allowing users to immerse themselves in the virtual world from a first-person perspective. Digital 3D technology provides a new way of creation and display for cultural heritage art design. Through digital 3D modelling, artists can accurately restore the original form of cultural Heritage and freely create in virtual space, thus achieving innovative interpretations of cultural heritage art. In addition, digital 3D technology can also combine the artistic elements of cultural Heritage with modern design concepts to create new works with contemporary characteristics. Digital 3D technology has a wide range of applications in humanities research [17]. Wooden cultural Heritage is a carrier of history and culture with high artistic value and historical significance. However, due to various reasons, many wooden cultural heritage sites have been destroyed or lost. In order to protect and inherit this cultural Heritage, Massafra et al. [18] adopted advanced technological means for digital restoration and artistic design. Parametric 3D modelling is a 3D modelling method based on parametric design. Through parameterized design, it is possible to parameterize the shape, size, proportion and other characteristics of cultural Heritage, thereby establishing accurate 3D models. This method can not only improve the accuracy and efficiency of modelling but also provide important data support for subsequent art and design. CAD modelling is a method of three-dimensional modelling using computer technology, which is of great significance for the reconstruction of timber churches. CAD modelling can accurately measure and model the structure and details of wooden churches, providing accurate data support for reconstruction work. By learning the structural parameters of the 3D model, neural networks can predict the load-bearing capacity and stability of the structure. In addition, neural networks can also be used to analyze the performance and aging degree of materials. By learning the physical and chemical properties of materials, neural networks can predict their durability and service life [19]. Learning-based features are a method of feature extraction and classification of point cloud data using machine learning algorithms. In TLS SfM indoor point cloud registration, learning-based features can be used to evaluate the shape, texture, and other features of point clouds. In the field of cultural heritage protection, the evaluation of TLS SfM indoor point cloud registration is of great significance for the research and restoration of cultural heritage objects. By handcrafting and learning-based feature evaluation, three-dimensional data of cultural heritage objects can be obtained, and further research work such as shape analysis and structural analysis can be carried out. Meanwhile, these data can also be used to repair and restore cultural heritage objects to protect their historical and cultural value [20]. In ancient ceramic restoration, VR technology can be used to simulate the restoration process, allowing users to experience the various stages of restoration firsthand. In addition, VR technology can also be used to display restored cultural relics, allowing users to more intuitively appreciate and understand the artistic value of ancient ceramics. The restoration and protection of cultural Heritage is a complex and important task that requires interdisciplinary cooperation and advanced technology support. CAD modelling and neural network analysis are two powerful technologies that have broad application prospects in the field of cultural heritage restoration and protection. Nieto et al. [21] explore the collaborative workflow of CAD modelling and neural network analysis in cultural heritage restoration and protection. Based on historical data and photos of cultural relics, CAD modelling technology can be used to restore details and attempt to restore the original state of cultural relics. Through CAD modelling technology, virtual restoration can be carried out, that is, attempting to restore cultural relics on a computer to provide a reference for actual restoration. By utilizing neural network technology, one art style can be transferred to another artwork, providing new ideas and methods for the restoration of cultural Heritage. By training neural network models, elements and features in cultural heritage images can be identified, providing a reference for the classification and protection of cultural relics. By utilizing neural network technology, it is possible to predict the colour distribution and variation patterns of cultural Heritage based on image data, providing guidance for the restoration of cultural relics.

3D scanning and point cloud processing technology have become important tools for cultural heritage protection and restoration. Point cloud data can capture the detailed shape and structure of cultural relics, providing an accurate basis for protection and restoration work. However, processing large amounts of point cloud data is a huge challenge, which requires us to use deep learning frameworks for efficient semantic segmentation. Pierdicca et al. [22] explored how to use deep learning frameworks for point cloud semantic segmentation of cultural Heritage. The point cloud data of Cultural Heritage has unique characteristics, such as complex shapes, rich details, and large data volume, which pose great challenges to the semantic segmentation of point clouds. Firstly, it is necessary to preprocess the point cloud data, such as noise removal, registration, etc., to improve the quality and accuracy of the data. Secondly, it is necessary to design a network architecture suitable for cultural heritage point cloud data in order to perform semantic segmentation accurately. Based on the characteristics of cultural heritage point cloud data, construct suitable deep learning models, such as 3D convolutional neural networks or point cloud recurrent neural networks. Utilizing a large amount of point cloud data to train the model, optimizing network parameters through repeated iterations, and improving the accuracy and generalization ability of the model. Select a portion of test data to test and evaluate the trained model, verifying its performance and effectiveness. With the development of technology, digital museums have gradually become important places for preserving and showcasing cultural Heritage. Firstly, CAD modelling can accurately create digital copies of cultural Heritage, covering everything from architectural structures to decorative details. This not only allows the audience to visit the virtual environment without obstacles but also provides a large amount of useful data for neural network analysis. Secondly, neural network analysis is a deep learning technique that can process large amounts of data and extract valuable information from it. Radosavljevi and Ljubisavljevi [23] can use historical data to train neural networks, which include past exhibition content, time, location, promotional activities, and corresponding attendance rates. By analyzing these data, neural networks can learn various factors that affect occupancy rates and predict future occupancy rates. Overall, the potential for attendance in cultural heritage digital museums based on CAD modelling and neural network analysis is enormous.

Ranjazma et al. [24] explored a research method for the principles of geometric patterns in cultural Heritage based on CAD modelling and neural network analysis. It establishes a three-dimensional model of geometric patterns through CAD modelling and uses neural networks to analyze and identify constituent elements and patterns. This method can comprehensively and deeply study the principles and laws of geometric patterns, providing a scientific basis for the protection and inheritance of this valuable cultural Heritage. Cultural Heritage, art, and historical architecture are important treasures of all humanity, carrying rich historical and cultural information, reflecting the evolution and development of human civilization. However, over time, these buildings are often damaged by various natural and human factors, leading to their original forms and features gradually disappearing. Therefore, how to effectively identify and protect the "genes" of these buildings has become an important issue. Shao and Sun [25] used the example of Chinese Baroque architecture in Harbin to explore the method of identifying the "genes" of cultural Heritage, art, and historical buildings based on deep learning. Chinese Baroque architecture is a major feature of Harbin City, and these buildings are famous for their unique style and exquisite decoration. However, with the development of cities and the destruction of natural factors, these buildings are facing serious threats. Therefore, it is of great practical significance to identify and protect the genes of Chinese Baroque architecture in Harbin. The experimental results show that the deep learning-based method for identifying the "genes" of cultural Heritage, art, and historical buildings can effectively identify the style, features, and elements of buildings, providing important reference for protection and restoration work. Digital archaeology, which uses digital technology to measure, model, and analyze archaeological sites and artifacts, has become a hot topic in the field of archaeology in recent years. Among them, point cloud analysis is an important digital technology that can be used to obtain three-dimensional data on cultural relics, providing important data support for cultural relic restoration. Sipiran et al. [26] explored a data-driven restoration method for digital archaeological pottery based on point cloud analysis. In digital archaeology, point cloud analysis can be used to obtain three-dimensional data on cultural relics, providing accurate data support for cultural relic restoration. Point cloud analysis can obtain information on the shape, size, colour, and other aspects of cultural relics, thereby accurately restoring them. The architectural styles of Athens's cultural Heritage vary, reflecting the architectural styles and artistic characteristics of different historical periods. However, classifying and identifying so many cultural heritage buildings is a daunting task. Deep learning technology provides new possibilities for solving this problem. Siountri and Anagnostopoulos [27] explored how to use deep learning techniques to classify Athenian cultural heritage buildings. It successfully used deep learning techniques to classify Athenian cultural heritage buildings. Accurately recognize and classify cultural Heritage building images by constructing convolutional neural network models. In the modelling of three-dimensional cultural heritage buildings, object detection and image segmentation techniques are of great significance for the establishment and optimization of models. Deep neural networks, as a powerful tool for object detection and image segmentation, can be applied to the modelling of three-dimensional cultural heritage buildings. Through deep neural networks, automatic detection and segmentation of 3D models can be achieved, improving modelling efficiency and accuracy. Wei et al. [28] explored the interoperability between deep neural networks and 3D cultural heritage building modelling software and analyzed their feasibility in object detection and image segmentation. In order to protect and inherit this precious cultural Heritage, it is necessary to use digital technology to record and preserve it. Xin and Daping [29] proposed a digital system for ancient architectural decoration art based on neural networks and image features, aiming to improve the digitization efficiency and accuracy of ancient architectural decoration art. The system mainly includes data collection, preprocessing, feature extraction, classifier, and evaluation modules. Firstly, the data acquisition module is used to capture or scan the decorative art of ancient buildings, obtaining high-quality image data. Then, the preprocessing module performs denoising, enhancement, and other processing on the image data to improve the accuracy of subsequent processing. Next, the feature extraction module utilizes deep learning techniques to extract features from image data, including texture, shape, colour, and other features. Finally, the classifier module utilizes the extracted features to classify and recognize ancient architectural decorative arts, and the evaluation module evaluates and optimizes the classification results. Hakka culture is an important component of traditional Chinese culture, with a profound historical Heritage and unique artistic value. Yu and Zhu [30] explore the method of digital restoration and three-dimensional virtual space display of Hakka cultural heritage art design based on numerical algorithm optimization in order to provide new ideas and approaches for the protection and inheritance of Hakka culture. It uses reverse engineering algorithms for high-precision measurement and modelling of cultural Heritage. And use morphological algorithms to denoise and smooth cultural Heritage.

## 3 MATERIALS AND METHODS

CAD is a method that uses computer technology to assist designers in all kinds of design work. CAD modelling is the process of building a 3D model by using CAD software. In this process, designers can use various tools and methods to build a 3D model of an object. CAD modelling technology has been widely used in architecture, machinery, electronics, art, and other fields. In the artistic design and restoration of cultural legacy, CAD modelling technology plays a vital role. Through the digital modelling of cultural legacy, designers can better understand its shape, structure, texture and other characteristics, thus providing strong support for subsequent artistic design and restoration. NN is a computational model that simulates human brain neurons. By learning and training a large quantity of data, data can be automatically identified and classified. In the artistic design and restoration of cultural legacy, NN analysis can help us to automatically identify a large quantity of cultural legacy data and improve the efficiency of design and restoration. Designers can use NN analysis to process the image, text, audio, and other data of cultural legacy and extract useful information, such as morphology, structure, texture, and other features, to provide support for subsequent artistic design and restoration.

The artistic design and restoration of cultural legacy is a complex and arduous task that requires careful consideration of various factors, such as historical background, cultural connotation, artistic style, etc. In this process, it is necessary to use various technologies and methods, such as archaeology, history, art, etc., to conduct an in-depth analysis of cultural legacy. Moreover, it is necessary to use modern technological means to digitize modelling and virtual display of cultural legacy in order to improve its protection and inheritance effectiveness. As two important technical means, CAD modelling and NN analysis have played an important role in the artistic design and restoration of cultural legacy. How to integrate these two technologies to achieve efficient and accurate 3D reconstruction of cultural legacy is still a challenging problem. This section will introduce in detail the 3D reconstruction algorithm of cultural legacy based on multi-view images, which combines CAD modelling and NN technology to achieve high simulation and restoration of cultural legacy. The structure of the Deep Neural Network (DNN) proposed in this article for the 3D reconstruction of cultural legacy is shown in Figure 1.

The 3D reconstruction algorithm for cultural legacy based on multi-view images mainly consists of the following steps:

⊖ Data collection: Using multiple cameras or scanners to capture images of cultural legacy from different angles and obtain multi-view image data.

⊜ Image preprocessing: Preprocessing the collected multi-view images, including denoising, enhancement, and other operations, to improve image quality.

⊛ 3D point cloud generation: Using CAD modelling technology, generate 3D point cloud data of cultural legacy based on feature points in multi-view images.

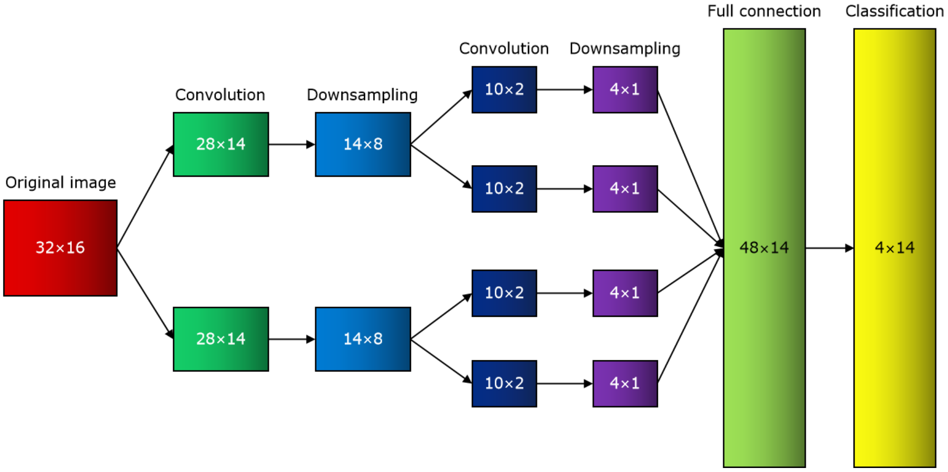


**Figure 1**: 3D reconstruction of DNN structure of cultural legacy.

④ NN optimization: Using NN analysis technology to optimize the generated 3D point cloud data, removing noise, filling missing parts, and other operations to improve the accuracy of 3D reconstruction.
⑤ 3D model construction: Based on optimized 3D point cloud data, use CAD modelling technology to construct a 3D model of cultural legacy.
⑥ Texture mapping: Maps texture information from multi-viewpoint images onto 3D models to achieve a highly realistic cultural legacy.

In the data collection stage, multiple cameras or scanners are needed to capture images of cultural legacy from different angles. In order to ensure high image quality, this study selected a suitable camera or scanner and set appropriate parameters. In addition, factors such as lighting conditions and background during collection were also considered to avoid interference with subsequent 3D reconstruction. In the image preprocessing stage, denoising, enhancement, and other operations are performed on the collected multi-view images. These operations can effectively improve image quality. In the stage of 3D point cloud generation, CAD modelling technology is used to generate 3D point cloud data of cultural legacy based on feature points in multi-view images. This process requires the use of professional CAD software or related algorithms for implementation. In order to ensure the high quality of generated 3D point cloud data, this study selected appropriate feature point extraction methods and performed precise matching. In the NN optimization stage, use NN analysis techniques to optimize the generated 3D point cloud data. This process can effectively remove noise, fill missing parts, and improve the quality of 3D reconstruction. The principle of rendering cultural legacy images is shown in Figure 2.

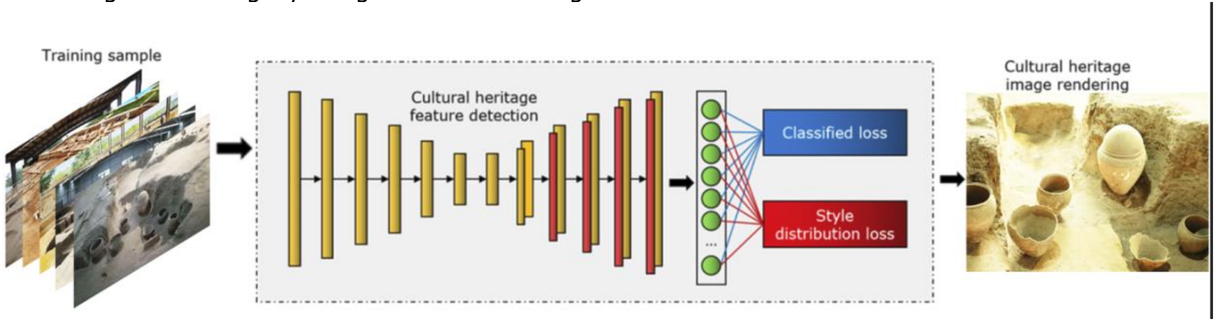


**Figure 2:** The principle of cultural legacy image rendering.

It is assumed that the number of layers of a convolution layer is then the number of layers of the pool layer below it $l+1$. To ascertain the sensitivity of the $l$ layer, this article necessitates obtaining sensitivity samples corresponding to the pooled layer, ensuring that the dimensionality of the sensitivity aligns with that of the convolutional layer:

$$\delta_j^l = \beta_j^{l+1}(f'(u_j^l) \circ up(\delta_j^{l+1})) \tag{1}$$

Where $\beta_j^{l+1}$ represents the weight corresponding to the pool layer; $up(\cdot)$ stands for up-sampling operation.

In the 3D model construction stage, it is necessary to use CAD modelling technology to construct a 3D model of cultural legacy based on optimized 3D point cloud data. This process requires the use of professional CAD software or related algorithms to ensure that the constructed model has high quality. In order to achieve high simulation and restoration of cultural legacy, it is also necessary to consider the details and texture information of the model. In the texture mapping stage, texture information from multi-view images is mapped onto a 3D model to achieve a highly simulated and restored cultural legacy.

The kd tree is a data structure used for multi-dimensional spatial data indexing, mainly for range queries and nearest neighbour queries. In 2D space, the kd-tree can be seen as a binary tree, where each node represents a 2D space partition, with the left subtree containing all points on the left side of the partition line and the right subtree containing all points on the right side of the partition line. By recursively dividing the 2D space into smaller subspaces, fast indexing and querying of data can be achieved. In the 3D reconstruction of cultural legacy, it is necessary to process a large amount of 2D image data and extract 3D information from it. This process can be seen as a mapping process from 2D to 3D. In this process, 2D kd trees can play an important role. This study utilizes a 2D kd-tree to perform spatial partitioning and indexing on 2D image data, thereby achieving fast querying and processing of image data. Through this method, it is possible to quickly locate the spatial area containing the target pixel and further analyze it. The schematic diagram for creating a 2D kd tree is shown in Figure 3.

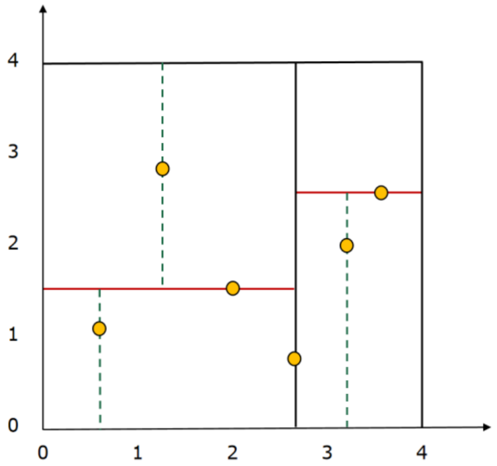


**Figure 3**: Schematic diagram of creating a 2D kd-tree.

By utilizing the kd tree for spatial partitioning and indexing of 2D image data, it is possible to locate spatial regions containing target pixels quickly. By treating image data from different viewpoints as different 2D spaces and using a kd tree to partition each space, a fast fusion of image data from different viewpoints can be achieved. The kd tree is a scalable data structure that can be easily extended to higher dimensional data spaces. This gives it greater flexibility when dealing with complex cultural legacy data.

Suppose that the coordinate of a point on the graph is $(x,y)$, and a new point $(x^{'},y^{'})$ is obtained by translating $T_x$ and $T_y$ along the $x$ and $y$ axes respectively, and the coordinate transformation is:

$$x^{'} = x + T_x, y^{'} = y + T_y \tag{2}$$

The translation transformation expressed in homogeneous coordinates is:

$$\begin{bmatrix} x^{'} \\ y^{'} \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & t \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} x + t_x \\ y + t_y \\ 1 \end{bmatrix} \tag{3}$$

Assume that the coordinate of a point on the graph is $(x,y)$, and a new point $(x^{'},y^{'})$ is obtained after scaling by $S_x$ and $S_y$ along the $x$ and $y$ axes respectively, and the coordinate transformation is:

$$x^{'} = x \cdot S_x, y^{'} = y \cdot S_y \tag{4}$$

The proportional transformation expressed in homogeneous coordinates is:

$$\begin{bmatrix} x^{'} \\ y^{'} \\ 1 \end{bmatrix} = \begin{bmatrix} S_x & 0 & 0 \\ 0 & S_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} S_x \cdot x \\ S_y \cdot y \\ 1 \end{bmatrix} \tag{5}$$

Different from proportional transformation, rotational transformation does not change the shape and size of objects, and it is a rigid transformation. Assuming that the coordinate of any point on the graph is $(x,y)$, rotate it counterclockwise by an angle $\theta$ around the origin to get a new point $(x^{'},y^{'})$, and the coordinate transformation is:

$$x^{'} = x \cdot \cos\theta - y \cdot \sin\theta \tag{6}$$

$$y^{'} = x \cdot \sin\theta + y \cdot \cos\theta \tag{7}$$

The rotation transformation expressed in homogeneous coordinates is:

$$\begin{bmatrix} x^{'} \\ y^{'} \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & 0 \\ \sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} x\cos\theta - y\sin\theta \\ x\sin\theta + y\cos\theta \\ 1 \end{bmatrix} \tag{8}$$

Figure 4 shows how different density functions affect and generate various artistic and design effects. The density function can be understood as the distribution of data points, which reflects the degree of aggregation or dispersion of data in a given space. The (a) part in Figure 4 is a uniform density function. Under this function, the data points exhibit a uniformly distributed state without obvious clustering or sparse regions. The artistic design effect generated under this distribution is relatively peaceful, with overall colours and textures presenting a harmonious sense of unity but lacking a sufficient sense of hierarchy. Part (b) in Figure 4 shows the density function of a normal distribution. Normal distribution is the most common form of data distribution, which exhibits the characteristic of having more data in the middle and less data on both sides. The artistic design effect generated under this density function usually has a more obvious distinction between the center and the edge. The design elements in the center are more abundant and prominent, while the edge is relatively simplified. Part (c) in Figure 4 shows a density function with an exponential distribution. The exponential distribution is commonly used to describe the time interval between two consecutive events, characterized by a rapid decrease in the probability of event occurrence as the value increases. Under the influence of this density function, the generated artistic design effects often have a strong sense of contrast.

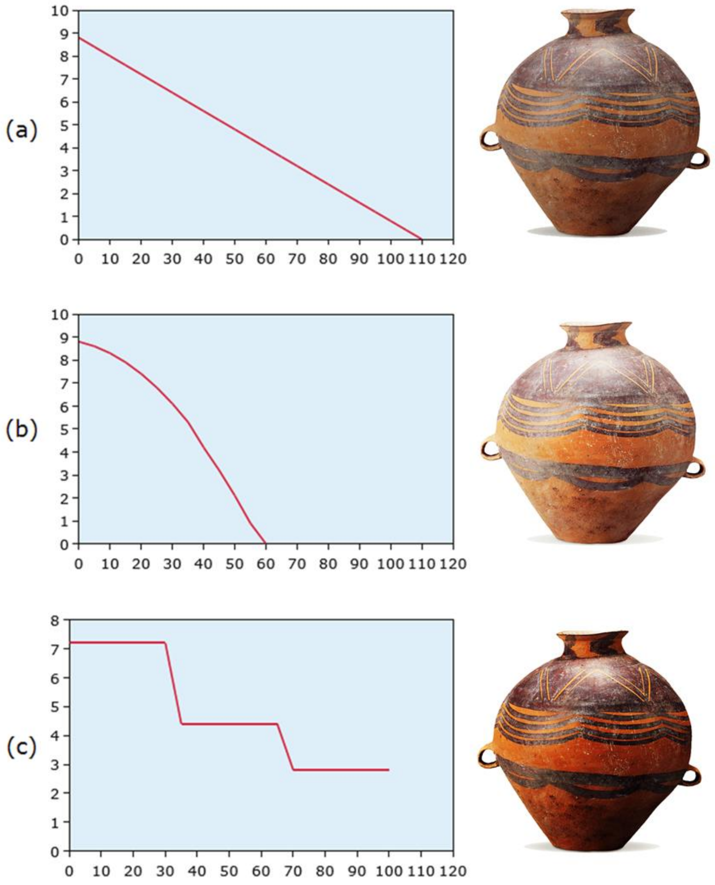


**Figure 4:** Different density functions and artistic design effects generated under these density functions.

Principal Component Analysis (PCA) is a technique that employs a selection of integral indicators to represent numerous indicators within a dataset, thereby providing an enhanced representation of the original data. In essence, the aim is to utilize the minimal quantity of variables possible to encapsulate the information contained within the original data, with the relationships between these variables being depicted through linear correlations:

$$\begin{cases} F_1 = A_{11}X_1 + A_{21}X_2 + \cdots + A_{p1}X_p \\ F_2 = A_{12}X_1 + A_{22}X_2 + \cdots + A_{p2}X_p \\ F_M = A_{1M}X_1 + A_{2M}X_2 + \cdots + A_{pM}X_p \end{cases} \tag{9}$$

Where $A_{1I}, A_{2I}, \dots, A_{PI} (I = 1, 2, \dots, M)$ represents the eigenvector corresponding to the eigenvalue of $X$, and the value of the initial variable after standardized processing is $X_1, X_2, \dots, X_p$.

$$A = (A_{IJ})_{MP} = (A_1, A_2, \dots, A_M), R_{AJ} = \lambda_I A_I \tag{10}$$

$R$ is the correlation coefficient matrix, and $\lambda_I, A_I$ is its corresponding eigenvalue and unit eigenvector.

Prior to analysis, preprocess the data within the sample array by converting the original dataset into positive indicators. Subsequently, apply the subsequent formula:

$$x_{ij}^{*}=\frac{x_0-\bar{x}i}{\sqrt{\operatorname{var}(x_j)}} \quad i=1,2,...,n;j=1,2,...,m \tag{11}$$

Where $\bar{x}_i, \operatorname{var}(x_j)$ is the average and standard deviation of the $j$ th variable respectively?

Compute the matrix of sample correlation coefficients for the aforementioned matrix:

$$R=[r_{ij}]_{p\times p}=\frac{Z^{'}Z}{n-1} \tag{12}$$

By solving the characteristic equation of the sample coefficient matrix $R,P$ , eigenvalues can be obtained.

# 4 RESULT ANALYSIS AND DISCUSSION

## 4.1 Experimental Data and Hardware Environment

(1) Experimental subjects:
In order to verify the effectiveness of the algorithm, this study selected cultural relics and landscapes with rich texture and historical significance from Yangshao coloured pottery as experimental objects. This landscape not only represents traditional Chinese culture, but its unique architectural structure and complex details also provide a good testing environment for 3D reconstruction.
(2) Data collection:
In order to obtain multi-view images, a high-resolution camera was used to capture the water wheel landscape in the Yellow River Basin under different angles and lighting conditions. In addition, for comparative analysis, multi-view image data from other cultural legacy sites were also selected from public datasets.
(3) Hardware configuration:
The hardware environment used in the experiment is as follows:
⊖ Processor: Intel Core i9-10900K.
⊜ Graphics card: NVIDIA GeForce RTX 2080 Ti.
⊛ Memory: 32GB DDR4 RAM.
④ Storage device: 1TB NVMe SSD.
(4) Software environment:
The experiment was conducted on the Ubuntu 18.04 operating system, using Python 3.7 as the main programming language and utilizing the TensorFlow 2.3 deep learning framework for model training and inference. In addition, the OpenCV library was also used for image processing and analysis.
Through the above hardware configuration and software environment, powerful computing power and a stable working environment have been provided for the experimental verification of the base algorithm.

## 4.2 Results Display

Figure 5 provides a comparison between the rendering efficiency of our model and traditional methods. In the artistic design and restoration of cultural legacy, the efficiency of rendering directly determines the speed of design and restoration work. The model in this article has significant advantages in rendering efficiency compared to traditional methods. The model requires significantly less rendering time than traditional methods when achieving the same rendering quality.

The advantages of this method are mainly attributed to a series of technical means and methodological support adopted in the model, such as the fusion application of CAD modelling and NN analysis technology and the 3D reconstruction algorithm based on multi-view images. As the complexity of rendering tasks increases, the rendering time of traditional methods shows a rapid upward trend, while the optimized model in this article shows a relatively stable growth trend. This indicates that in the face of more complex and large-scale rendering tasks, the optimized model proposed in this article can maintain high rendering efficiency, while traditional methods may exhibit significant performance degradation due to computational resource limitations.

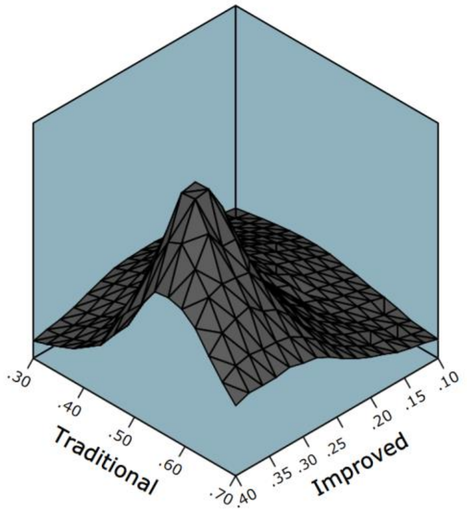


**Figure 5:** Rendering efficiency of different methods.

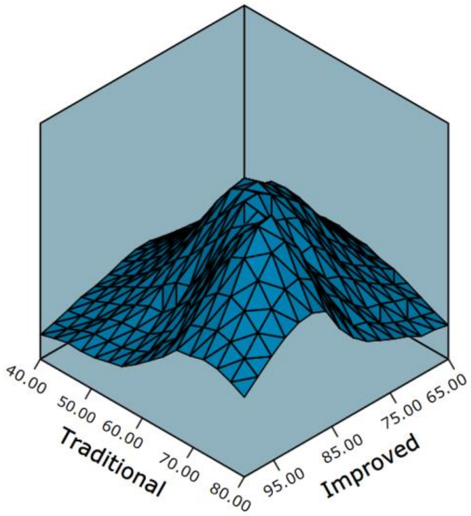


**Figure 6:** Rendering quality of different methods.

Figure 6 shows the comparison between our model and traditional methods in terms of rendering quality. Compared to traditional methods, our model has significantly improved rendering quality by more than 10%. A 10% improvement represents the comprehensive advantages of the optimization model in multiple aspects. For example, in terms of colour reproduction, optimizing models can more accurately restore the true colours of cultural legacy. In terms of texture details, optimizing the model can better preserve and display the texture information of cultural legacy. In terms of light and shadow effects, the optimized model can more realistically simulate the reflection and refraction of light and shadow on the surface of cultural legacy.

Figure 7 shows the comparison of modelling errors between the SVM algorithm, GAN algorithm, and our proposed algorithm. Modelling error is an important indicator to measure the accuracy and stability of a model, and lower modelling error usually means that the model has better generalization ability and predictive performance.

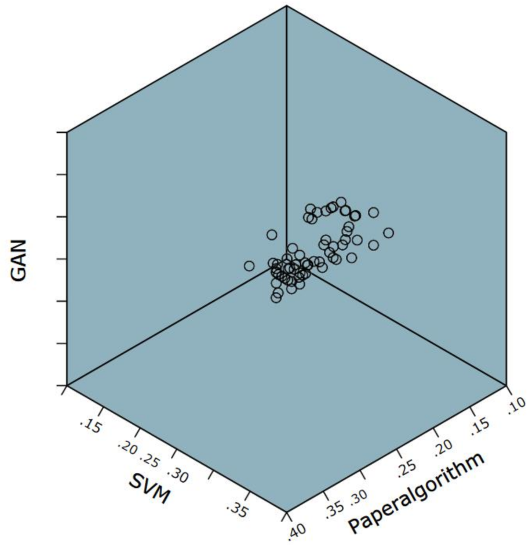


**Figure 7:** Error situation of the algorithm.

Compared to SVM and GAN algorithms, the modelling error of our algorithm is significantly lower, reducing by more than 20%. As a traditional machine learning method, SVM may be limited by the selection of its kernel function and parameter settings in some cases, resulting in higher modelling errors. As a generative adversarial network, although GAN has a strong generative ability, it may also increase modelling errors in some cases due to unstable training or pattern collapse. In contrast, the algorithm proposed in this article can more effectively reduce modelling errors and improve model stability by integrating CAD modelling and NN analysis techniques.

## 5 RESULT DISCUSSION

Based on the above analysis, this study conducted an in-depth analysis of the significant improvement in rendering efficiency and quality of our model compared to traditional methods, as well as the significant reduction in modelling errors compared to SVM and GAN algorithms. These research results not only demonstrate the effectiveness of the technical means and methodological support proposed in this article but also provide new perspectives and possibilities for the artistic design and restoration of cultural legacy.

The artistic design and restoration of cultural legacy is not only a technical process but also an interpretation of history, inheritance of culture, and innovation of art. In this process, the role of technology is indispensable, but more importantly, how to utilize these technologies to better serve culture and history. This article provides a new tool and perspective for designers and cultural inheritors by integrating CAD modelling, NN analysis technology, and 3D reconstruction algorithms based on multi-view images, enabling people to have a deeper understanding of the charm of cultural legacy.

For the field of cultural legacy art design, research results not only demonstrate the effectiveness and superiority of new technologies and methods but also indicate future research directions and development trends. With the continuous advancement of technology, the restoration of cultural legacy will become more efficient and precise.

## 6 CONCLUSIONS

The artistic design and restoration of cultural legacy is not only a technical process but also an interpretation of history, inheritance of culture, and innovation of art. In the highly intelligent modern society, digital technology has gradually penetrated into the inheritance and restoration of cultural legacy. This article proposes a 3D reconstruction algorithm for cultural legacy based on multi-view images and proposes improvements on existing algorithms to improve simulation speed and 3D effects. Taking the Yellow River cultural legacy as an example, this study analyzes the application of the proposed method in the artistic design of the Yellow River cultural legacy and provides experimental simulation results. By integrating CAD modelling, NN analysis techniques, and 3D reconstruction algorithms based on multi-view images, this method has achieved significant improvements in rendering efficiency. This means that within the same amount of time, the model can complete more design and restoration tasks. Moreover, the model has also made significant improvements in rendering quality, including colour reproduction, texture details, and lighting effects. In the comparison of modelling errors with SVM and GAN algorithms, this algorithm reduces modelling errors and improves model stability by introducing a 3D reconstruction algorithm for multi-view images and NN analysis technology. This study not only demonstrates the superiority of new technologies and methods but, more importantly, provides a new perspective for the artistic design and restoration of cultural legacy.

## 7 ACKNOWLEDGEMENT

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## REFERENCES

[1] Amura, A.; Aldini, A.; Pagnotta, S.; Salerno, E.; Tonazzini, A.; Triolo, P.: Analysis of diagnostic images of artworks and feature extraction: design of a methodology, Journal of Imaging, 7(3), 2021, 53. https://doi.org/10.3390/jimaging7030053

[2] Bardhan, S.; Paul, S.: The cultural landscape of the Bhagirathi-Hooghly riverfront in Kolkata, India: studies on its built and natural Heritage, Journal of Cultural Legacy Management and Sustainable Development, 13(2), 2023, 219-237. https://doi.org/10.1108/JCHMSD-08-2020-0119

[3] Bozorgi, K.; Lischer, K.-Z.: Using 3D/VR for research and cultural legacy preservation: project update on the virtual Ganjali Khan project, Preservation, Digital Technology and Culture, 49(2), 2020, 45-57. https://doi.org/10.1515/pdtc-2020-0017

[4] Cao, Y.; Scaioni, M.: 3DLEB-Net: Label-efficient deep learning-based semantic segmentation of building point clouds at LoD3 level, Applied Sciences, 11(19), 2021, 8996. https://doi.org/10.3390/app11198996

[5] Comes, R.; Neamţu, C.-G.-D.; Grec, C.; Buna, Z.-L.; Găzdac, C.; Mateescu, S.-L.: Digital Reconstruction of Fragmented Cultural Heritage Assets: The Case Study of the Dacian Embossed Disk from Piatra Roşie, Applied Sciences, 12(16), 2022, 8131. https://doi.org/10.3390/app12168131

[6] Croce, V.; Caroti, G.; Luca, L.; Jacquot, K.; Piemonte, A.; Véron, P.: From the semantic point cloud to heritage-building information modeling: A semiautomatic approach exploiting machine learning, Remote Sensing, 13(3), 2021, 461. https://doi.org/10.3390/rs13030461
[7] Croce, V.; Caroti, G.; Piemonte, A.: From survey to semantic representation for Cultural Legacy: the 3D modeling of recurring architectural elements, ACTA IMEKO, 10(1), 2021, 98. https://dx.doi.org/10.21014/acta_imeko.v10i1.842
[8] Demenchuk, E.; Camelia, I.-D.; Wendt, J.-A.: Spectroscopy study of heritage objects for the digitization of cultural legacy, Environmental Engineering and Management Journal, 19(6), 2020, 1057-1066. https://doi.org/10.30638/EEMJ.2020.100
[9] Fino, M.; Galantucci, R.-A.; Fatiguso, F.: Condition assessment of heritage buildings via photogrammetry: a scoping review from the perspective of decision makers, Heritage, 6(11), 2023, 7031-7066. https://doi.org/10.3390/heritage6110367
[10] Hong, S.; Shen, J.; Lü, G.; Liu, X.; Mao, Y.; Sun, N.; Tang, L.: Aesthetic style transferring method based on deep neural network between Chinese landscape painting and classical private garden's virtual scenario, International Journal of Digital Earth, 16(1), 2023, 1491-1509. https://doi.org/10.1080/17538947.2023.2202422
[11] Kotsiubivska, K.; Baranskyi, S.: 3D simulation in the restoration of historical and cultural values, Digital Platform Information Technologies in Sociocultural Sphere, 3(1), 2020, 59-68. https://doi.org/10.31866/2617-796x.3.1.2020.206109
[12] Li, F.; Gao, Y.; Candeias, A.-J.-E.-G.; Wu, Y.: Virtual restoration system for 3D digital cultural relics based on a fuzzy logic algorithm, Systems, 11(7), 2023, 374. https://doi.org/10.3390/systems11070374
[13] Liu, K.; Gao, Y.; Zhang, J.; Zhu, C.: Study on digital protection and innovative design of Qin opera costumes, Heritage Science, 10(1), 2022, 127. https://doi.org/10.1186/s40494-022-00762-x
[14] Liu, K.; Zhou, S.; Zhu, C.; Lü, Z.: Virtual simulation of Yue Opera costumes and fashion design based on Yue Opera elements, Fashion and Textiles, 9(1), 2022, 31. https://doi.org/10.1186/s40691-022-00300-0
[15] Maravelakis, E.; Giannioti, G.; Psalti, A.; Tsakoumaki, M.; Pocobelli, D.-P.; Xinogalos, M.; Stavroulakis, G.: 3D Modeling & Analysis Techniques for the Apollo Temple in Delphi, Buildings, 13(7), 2023, 1730. https://doi.org/10.3390/buildings13071730
[16] Ming, Y.; Me, R.-C.; Chen, J.-K.; Rahmat, R.-W.-O.: A systematic review on virtual reality technology for ancient ceramic restoration, Applied Sciences, 13(15), 2023, 8991. https://doi.org/10.3390/app13158991
[17] Muenster, S.: Digital 3D Technologies for humanities research and education: An overview, Applied Sciences, 12(5), 2022, 2426. https://doi.org/10.3390/app12052426
[18] Massafra, A.; Prati, D.; Predari, G.; Gulli, R.: Wooden truss analysis, preservation strategies, and digital documentation through parametric 3D modeling and HBIM workflow, Sustainability, 12(12), 2020, 4975. https://doi.org/10.3390/su12124975
[19] McLennan, S.; Brown, A.: A smart heritage system to re-generate New Zealand's 19th century timber churches, Heritage, 4(4), 2021, 4040-4055. https://doi.org/10.3390/heritage4040222
[20] Markiewicz, J.; Kot, P.; Markiewicz, Ł.; Muradov, M.: The evaluation of hand-crafted and learned-based features in Terrestrial Laser Scanning-Structure-from-Motion (TLS-SfM) indoor point cloud registration: the case study of cultural heritage objects and public interiors, Heritage Science, 11(1), 2023, 254. https://doi.org/10.1186/s40494-023-01099-9
[21] Nieto, J.-J.-E.; Farratell, J.; Bouzas, C.-M.; Moyano, J.: Collaborative workflow in an HBIM project for the restoration and conservation of cultural Heritage, International Journal of Architectural Heritage, 17(11), 2023, 1813-1832. https://doi.org/10.1080/15583058.2022.2073294
[22] Pierdicca, R.; Paolanti, M.; Matrone, F.; Martini, M.; Morbidoni, C.; Malinverni, E.-S.; Lingua, A.-M.: Point cloud semantic segmentation using a deep learning framework for cultural Heritage, Remote Sensing, 12(6), 2020, 1005. https://doi.org/10.3390/rs12061005

[23] Radosavljevi, Z.; Ljubisavljevi, T.: Digitization of cultural legacy as a potential for increasing museum attendance in Central Serbia, Bizinfo Blace, 10(1), 2019, 53-67. https://doi.org/10.5937/bizinfo1901053R

[24] Ranjazma, A.-M.; Bemanian, M.; Mahdavinejad, M.; Körner, A.; Knippers, J.: Application-based principles of islamic geometric patterns; state-of-the-art, and future trends in computer science/technologies: a review, Heritage Science, 11(1), 2023, 22. https://doi.org/10.1186/s40494-022-00852-w

[25] Shao, L.; Sun, J.: Identification of historic building "genes" based on deep learning: a case study on Chinese baroque architecture in Harbin, China, Heritage Science, 11(1), 2023, 241. https://doi.org/10.1186/s40494-023-01091-3

[26] Sipiran, I.; Mendoza, A.; Apaza, A.; Lopez, C.: Data-driven restoration of digital archaeological pottery with point cloud analysis, International Journal of Computer Vision, 130(9), 2022, 2149-2165. https://doi.org/10.1007/s11263-022-01637-1

[27] Siountri, K.; Anagnostopoulos, C.-N.: The classification of cultural heritage buildings in athens using deep learning techniques, Heritage, 6(4), 2023, 3673-3705. https://doi.org/10.3390/heritage6040195

[28] Wei, C.; Gupta, M.; Czerniawski, T.: Interoperability between deep neural networks and 3D architectural modeling software: affordances of detection and segmentation, Buildings, 13(9), 2023, 2336. https://doi.org/10.3390/buildings13092336

[29] Xin, W.; Daping, Q.: Digitalization system of ancient architecture decoration art based on neural network and image features, Journal of Intelligent & Fuzzy Systems, 40(2), 2021, 2589-2600. https://doi.org/10.3233/JIFS-189251

[30] Yu, Q.; Zhu, G.: Digital restoration and 3D virtual space display of hakka cardigan based on optimization of numerical algorithm, Electronics, 12(20), 2023, 4190. https://doi.org/10.3390/electronics12204190