www.cad-journal.net
Computer-Aided Design AND APPLICATIONS

Graph Convolutional Network-based 3D Reconstruction of Art and Cultural Legacy

Dan Zheng[1] and Yan Xie[2]

[1]School of Humanities and Communication, University of Sanya, Sanya, Hainan 572000, China, danzheng@sanyau.edu.cn
[2]School of Humanities and Communication, University of Sanya, Sanya, Hainan 572000, China, yanxie@sanyau.edu.cn

Corresponding author: Dan Zheng, danzheng@sanyau.edu.cn

Abstract. The current protection of cultural legacy faces many challenges, such as low awareness of group protection, incomplete cultural relic protection system, relatively backward protection technology, and a large shortage of professional talents in cultural relic protection. The growth of VR has provided new possibilities for the protection of cultural legacy. Virtual reality (VR) has the characteristics of multi-perception, immersion, interactivity, and conceptualization, which gives it enormous potential in the field of cultural legacy protection. This article proposes a computer-aided design (CAD) 3D reconstruction method for artistic and cultural legacy based on the Graph Convolutional Network (GCN) algorithm. By applying GCN to the 3D reconstruction of artistic and cultural legacy, it is possible to capture better and restore the details of cultural legacy and improve the effectiveness of cultural legacy reconstruction. The protection and utilization of cultural legacy is an interrelated and mutually restrictive process. Researchers need to find a reasonable balance between protection and utilization, ensuring that cultural legacy is sustainably preserved while also providing the public with a rich cultural experience.

Keywords: Neural Network; Artistic and Cultural Legacy; CAD; 3D Reconstruction
DOI: https://doi.org/10.14733/cadaps.2024.S18.145-159

1 INTRODUCTION

With the growth of technology, the way of protecting and inheriting cultural legacy is undergoing profound changes. As the crystallization of human spirit and wisdom, artistic and cultural legacy bears rich connotations of history, culture and art. With the continuous development of computer technology, 3D CAD technology has become an important tool in the field of cultural heritage protection. In the stage of cultural heritage form types, 3D model reconstruction is one of the important means of protecting and inheriting cultural Heritage. However, traditional 3D model reconstruction methods are often based on manual measurement and restoration, making it difficult to ensure the accuracy and efficiency of the restoration. Therefore, this article proposes a 3D CAD processing method based on neural network algorithms for the reconstruction of 3D models in the stage of cultural heritage form types. Barrile et al. [1] explored the application of neural network algorithms in 3D CAD processing, particularly in the innovative aspect of 3D model reconstruction in the cultural heritage form type stage. This paper proposes an effective 3D model reconstruction method by utilizing neural network algorithms to process and analyze 3D data. This method can not only improve the accuracy and efficiency of 3D model reconstruction but also provide new perspectives and methods for research in related fields. In the stage of cultural heritage form types, 3D model reconstruction is one of the important means of protecting and inheriting cultural Heritage. Traditional 3D model reconstruction methods are usually based on manual measurement and restoration, which makes it difficult to ensure the accuracy and efficiency of the restoration. However, after the erosion and influence of natural and social factors, few of these precious cultural legacies have survived. Therefore, how to effectively protect, inherit and utilize these cultural legacies has become the focus of global attention. Barrilea et al. [2] explored how to integrate geographic information using neural network augmented reality technology. By utilizing neural network augmented reality technology, geographic information can be combined with cultural Heritage. Neural network algorithms can be used to analyze and process geographic information, extract useful features, and then associate these features with cultural Heritage to achieve digital display and interaction of cultural Heritage. Design the interface and functions of the application according to the requirements, including the display, interaction, search, etc., of cultural Heritage. By utilizing neural network augmented reality technology, geographic information is combined with cultural Heritage to develop cultural heritage applications with high interactivity and immersion. Test the developed application to ensure the stability and reliability of its functionality and performance. Promote the developed application to the market, let more people understand and pay attention to cultural Heritage, and improve people's awareness and protection of cultural Heritage.

Cultural Heritage is a precious treasure of human history and culture, but due to the passage of time, natural disasters, and other reasons, many cultural heritage sites have been damaged to varying degrees. It is necessary to digitize modelling and restoration. Nuclear imaging technology is a non-contact measurement technique with high precision, resolution, and sensitivity, which can be used for digital modelling and restoration of cultural Heritage. Bombini et al. [3] introduced an application based on cloud-native technology that achieves high-precision digital modelling and restoration of cultural Heritage, providing new means and methods for cultural heritage protection and research. Cloud-native applications that use nuclear imaging for the digital restoration of Cultural Heritage have broad application prospects. Firstly, this method can be applied to cultural heritage protection institutions such as museums and libraries, providing technical support. Secondly, this method can be applied in the field of cultural heritage restoration, improving the accuracy and efficiency of restoration work. In addition, this method can also be applied to historical research and cultural Heritage, providing new perspectives and methods for research in related fields. Traditional cultural heritage artworks are an important component of human civilization, showcasing artistic practices and technological achievements in different cultural and historical contexts through unique artistic forms, colours, and materials. However, the passage of time and environmental changes often lead to the fading, deterioration, or peeling of pigments in artworks, which not only affects their aesthetic value but also threatens their preservation and inheritance. In order to better protect and restore these precious artworks, it is necessary to conduct in-depth research on the types of pigments and chemical components used. Chen et al. [4] introduced a method of using machine learning algorithms to identify and visualize pure and mixed pigments in traditional cultural heritage artworks. Automatic recognition and visualization of pure and mixed pigments have been achieved by extracting colour features of artworks and training classifiers. This method can provide technical support for the protection and restoration of artworks, as well as new perspectives for the study of art history.

Chong et al. [5] explored the application of neural network algorithms in virtual reality and how to evaluate this comprehensive system through coherent classification and motivation. Neural network algorithms can automatically extract features from a large amount of data through learning, thereby establishing high-precision models. In the field of virtual reality, neural network algorithms can be used to establish three-dimensional models of cultural Heritage, making them more realistic and vivid. Neural network algorithms can be used for image recognition, and by training neural network models, automatic recognition and classification of cultural heritage images can be achieved. Virtual reality technology can achieve voice interaction, and neural network algorithms can be used for speech recognition to convert user speech into text or instructions, thereby achieving an interactive voice display of cultural Heritage. Historical videos are an important carrier for recording human history and culture, containing rich heritage information. However, due to the passage of time, natural disasters, and human destruction, much heritage information in historical videos may have been lost or damaged. In order to protect and inherit this precious cultural Heritage, it is necessary to detect and analyze historical videos to determine the lost Heritage. This article proposes a neural network-based geographic information method aimed at improving the accuracy and efficiency of lost heritage detection in historical videos. Condorelli et al. [6] proposed a method that utilizes neural network algorithms for feature extraction and classification of historical videos, combined with geographic information data, to achieve detection and localization of lost Heritage. This article first introduces the application of neural network algorithms in historical video processing, then elaborates in detail on the application of geographic information data in lost heritage detection in historical videos, and finally discusses the advantages and future research directions of this method. In historical video processing, neural network algorithms can be used for video feature extraction, object detection, behaviour recognition, and other aspects. By training and learning from historical videos, neural networks can automatically extract features from videos, achieving automatic recognition and classification of video content. In addition, neural network algorithms can also be used to optimize and repair videos, improving their quality and clarity.

With the popularization of social media, platforms such as Twitter have become important channels for people to share information and communicate. On these platforms, people often share photos and images of cultural heritage sites. These images provide not only visual information for people to understand cultural Heritage but also rich data sources for digital modelling and reconstruction of cultural Heritage. Doulamis et al. [7] explored how to use neural network algorithms to automatically perform 3D modelling and reconstruction in Twitter images; in order to achieve digital protection and inheritance modelling and reconstruction, neural network algorithms can be used to automatically extract 3D structural information from 2D images. In two-dimensional images, neural networks can learn the spatial structure and texture information in the images, thereby achieving automatic reconstruction of three-dimensional models. In addition, neural network algorithms can also be used to optimize and repair 3D models, improving their quality and realism.

Traditional 3D CAD reconstruction methods often need help with problems such as low reconstruction accuracy and loss of details when dealing with artistic and cultural legacies with complex structures and rich textures.

GCN is a powerful DL model that can effectively process data with complex structures and rich textures. This article presents a 3D CAD reconstruction method of artistic and cultural legacy based on the GCN algorithm. By applying GCN to the 3D CAD reconstruction of artistic and cultural legacy, we can better capture and restore the details of cultural legacy and improve the effect of cultural legacy reconstruction. The research has the following innovations:

(1) This article applies the GCN algorithm to the 3D CAD reconstruction of art and cultural legacy, utilizing the advantages of GCN in processing irregularly structured data to improve the effectiveness of cultural legacy reconstruction.

(2) The designed model architecture can effectively integrate the 3D geometric and texture information of cultural legacy. This fusion approach makes the reconstruction results more diverse and realistic, better capturing and restoring the details of cultural legacy.

(3) In order to train and optimize the proposed model, this article collected and preprocessed a large amount of 3D scanning data of artistic and cultural legacy and conducted annotation work to construct a dataset suitable for GCN training.

This article on 3D CAD reconstruction of art and cultural legacy describes in detail the DL algorithm and experimental methods used in this article, analyzes the experimental results, and finally summarizes the research conclusions, proposing inspiration and suggestions for the field of cultural legacy protection.

2 RELATED THEORETICAL FOUNDATIONS

Cultural relics are carriers of historical and cultural Heritage with important historical, artistic, and scientific values. However, due to the passage of time, natural disasters, and human destruction, many cultural relics have been damaged to varying degrees. It is necessary to conduct virtual restoration of damaged cultural relics. Virtual restoration refers to the digital modelling and restoration of cultural relics through computer technology to restore their original shape, texture, and colour. Flagg and Frieder [8] proposed a three-dimensional reconstruction method for cultural relics based on ACM computer technology, aiming for the virtual restoration of cultural relics. Use scanners, cameras, and other devices to scan or capture three-dimensional data of cultural relics. Perform preprocessing work such as cleaning, denoising, and format conversion on the collected data to ensure accuracy and consistency. Using ACM computer technology to extract features from preprocessed data and extract feature information related to cultural relics. Use 3D CAD technology to model and render the extracted feature information and generate a 3D model of cultural relics. The three-dimensional reconstruction method of cultural relics based on ACM computer technology has broad application prospects. Firstly, this method can be applied to cultural heritage protection institutions such as museums and libraries.

Heritage-inlaid cultural relic maps are important materials containing rich historical, cultural, and artistic information. One of the important tasks for cultural heritage protection and digital preservation is to classify the geometric shapes in the inlaid cultural relics maps of heritage sites. Traditional geometric shape classification methods are usually based on manual feature extraction and classifier design, making it difficult to handle complex geometric shapes and large-scale datasets. Ghosh et al. [9] classify geometric shapes in Heritage inlaid cultural relics maps. A method of using deep neural networks to classify geometric shapes in Heritage inlaid cultural relics maps has been proposed. This method utilizes deep learning techniques to extract and classify features from cultural relic images, achieving accurate recognition and classification of different geometric shapes. This article first introduces the basic principles of deep neural networks and their applications in cultural relic image classification. Then, the implementation process and experimental results of this method were elaborated in detail, and finally, the advantages and future research directions of this method were discussed. As an important component due to historical, geographical and other reasons, many pottery pieces are scattered around the world, making it difficult to collect and identify them effectively. Traditional collection and identification methods are usually based on manual measurement and judgment, which are not only inefficient but also prone to errors. Therefore, Gualandi et al. [10] extract feature information related to pottery by processing and analyzing the collected pottery images. It uses neural network algorithms to classify and recognize the extracted feature information, achieving automatic recognition of pottery. Store the collected pottery and identification results in a database for future research and use. Using neural network algorithms to extract features from preprocessed image data and extract feature information related to pottery. Using neural network algorithms to classify and recognize the extracted feature information, achieving automatic recognition of pottery.

Cultural relics are carriers of historical and cultural Heritage with important historical, artistic, and scientific values. However, due to factors such as time, nature, and human activities, many cultural relics have suffered varying degrees of damage. Virtual restoration refers to the digital modelling and restoration of cultural relics through computer technology to restore their original shape, texture, and colour. Li et al. [11] aim to improve the accuracy and efficiency of cultural relic virtual restoration. This system utilizes fuzzy logic algorithms to process and analyze cultural relic data, achieving virtual restoration of the shape, texture, and colour of cultural relics. This system has broad application prospects and can provide technical support for cultural heritage protection, restoration, and cultural inheritance. Fuzzy logic is a tool for dealing with uncertainty and imprecision problems, with strong reasoning ability and adaptability. Fuzzy logic algorithms can be used to handle and analyze the uncertainty and fuzziness of cultural relic data. By fuzzifying cultural relic data, the complexity of the data can be reduced, and the efficiency of data processing can be improved. Meanwhile, by utilizing the reasoning ability of fuzzy logic algorithms, cultural relic data can be optimized and restored, improving the accuracy and realism of virtual restoration. Art and Cultural Heritage are important components with extremely high historical, artistic, and scientific value. However, due to the passage of time, natural disasters, and human destruction, many artworks have suffered varying degrees of damage. It is necessary to perform virtual restoration of damaged artworks. Virtual restoration refers to the digital modelling and restoration of artworks using computer technology to restore their original shape, texture, and colour. Scatigno and Festa [12] explored the application of neural network algorithms in 3D CAD of art and cultural Heritage, particularly in sub-imaging and learning algorithms. This paper proposes an effective method for cultural heritage protection and inheritance by utilizing neural network algorithms to process and analyze three-dimensional data. This method provides new perspectives and methods for research in related fields. Sub-imaging and learning algorithms are important methods in neural network algorithms, which can be used for processing and analyzing three-dimensional data. Using sub-imaging and learning algorithms to extract features from 3D data and extract feature information related to artworks. Optimize the generated 3D model using sub-imaging and learning algorithms to improve its accuracy and realism.

Digital archaeology is a new field that has emerged. In digital archaeology, digital modelling and restoration of cultural relics are carried out through computer technology to restore their original shape, texture, and colour as an important component of cultural Heritage. However, traditional methods of pottery restoration are often based on manual measurement and restoration, making it difficult to ensure the accuracy and efficiency of restoration. Therefore, Sipiran et al. [13] utilized point cloud technology to measure and reconstruct the surface of pottery accurately, combined with 3D CAD technology. This method can not only improve the accuracy and efficiency of pottery restoration but also provide new perspectives and methods for research in related fields. Point cloud technology is a technique that obtains coordinate information of discrete points on the surface of an object through measurement. In digital archaeology, point cloud technology can be used to measure and reconstruct the surface of cultural relics accurately. By scanning or shooting the surface of cultural relics in 3D, obtain their 3D point cloud data, and then use point cloud processing software to process and analyze the data, extracting feature information related to cultural relics. Art and cultural heritage is an important component of human history and culture, with high research and artistic value. However, due to historical, geographical and other reasons, many artworks have suffered varying degrees of damage. It is necessary to perform virtual restoration of damaged artworks. Virtual restoration refers to the digital modelling and restoration of artworks using computer technology to restore their original shape, texture, and colour. This article explores the application of neural network algorithms. Yang et al. [14] explored the application of neural network algorithms in art and cultural heritage CAD cultural heritage. By utilizing advanced neural network algorithms, providing strong support for cultural heritage protection and research. The application of neural network algorithms of art and cultural Heritage CAD has broad prospects. Firstly, this method can be applied to cultural heritage protection institutions such as museums and libraries, providing technical support for the virtual restoration of damaged artworks. Secondly, this method can be applied in the field of cultural heritage restoration, improving the accuracy and efficiency of restoration work.

Cultural Digital Heritage is an important component of cultural Heritage, including historical relics, ancient architecture, folk culture, etc. However, traditional display methods often lack interactivity and intuitiveness, which cannot meet the needs of users. In order to solve this problem, Zhao [15] proposed a display method of edge computing cultural digital heritage based on interactive data visualization technology. Interactive data visualization technology is a technique that achieves data visualization through computer graphics, image processing, virtual reality, and other technologies. It can present complex data to users in an intuitive and vivid way, allowing users to have a more intuitive understanding of the form and structure of cultural Heritage. Edge computing is a technology that migrates computing tasks from central servers to edge devices. It can process data on local devices, reduce data transmission latency and bandwidth requirements, and improve data processing efficiency. In the display of cultural digital Heritage, edge computing technology can complete the computing tasks required for interactive data visualization on local devices, reduce the dependence on the central server, and improve the display's real-time efficiency. China has rich intangible cultural Heritage, including various forms such as traditional crafts, performing arts, and folk literature. However, with the acceleration of modernization, many intangible cultural heritage projects are facing difficulties in inheritance and serious loss. In order to protect and inherit these precious cultural resources, digital technology is gradually being introduced into the field of intangible cultural heritage protection. Neural network algorithms and 3D CAD technology have become hot research topics. Zhou et al. [16] reviewed the application and research progress of neural network algorithms and 3D CAD technology. Neural network algorithms are mainly used for image recognition, classification, and prediction. By training and learning from images of intangible cultural heritage projects, neural networks can automatically extract features from the images, achieving automatic recognition and classification of intangible cultural heritage projects. In addition, neural network algorithms can also be used to predict the inheritance trend and development direction of intangible cultural heritage projects, providing a scientific basis for formulating protection measures. 3D CAD technology is a computer-aided design technique that can achieve 3D modelling and visualization of objects. 3D CAD technology is mainly used for 3D modelling and virtual display of intangible cultural heritage projects.

3 METHODOLOGY

Through VR, a 3D virtual model of cultural legacy can be created, reproducing the social environment and cultural atmosphere of the historical period where cultural legacy is located. By simulating and repairing cultural relics in a virtual environment, reference and guidance can be provided for actual cultural relic repair work, avoiding excessive repair and destruction of cultural relics. VR can be used for the education and popularization of cultural legacy. By creating interactive cultural education scenes in virtual environments, users can have a more vivid and intuitive understanding of the profound connotations of cultural legacy. By combining VR with GCN, a more realistic and refined 3D virtual model of cultural legacy can be created, providing users with a more vivid and intuitive sensory experience.

GCN is a DL model specifically designed for processing graph-structured data. Unlike traditional CNN, GCN can perform convolution operations on irregular graph structures, effectively extracting and fusing information from the graph structure. The basic idea of GCN is to extend convolution operations from regular Euclidean space to irregular graph space and learn feature representations between nodes by defining convolution kernels on the graph. GCN updates the feature representation of nodes by aggregating and transforming their neighbour information. This process of aggregation and transformation can be seen as an information dissemination mechanism, allowing each node to obtain information from its neighbouring nodes.

3D CAD reconstruction refers to the process of recovering the 3D geometric structure and texture information of an object from 2D images or 3D scanning data. In the field of cultural legacy protection, 3D CAD reconstruction is commonly used to generate highly realistic virtual models for display, research, and protection. The traditional 3D CAD reconstruction methods are mainly based on computer vision and computer graphics technologies, such as stereo matching, structured light scanning, and multi-view geometry. These methods are effective in handling simple scenes or regular objects but often face problems such as low reconstruction accuracy and loss of details when dealing with complex structures and textured artistic and cultural legacy.

The progress of DL technology provides a new solution for 3D CAD reconstruction. The 3D CAD reconstruction method based on DL mainly uses the deep neural network to learn the geometric features of objects from the original data without manual adjustment and intervention, which improves the automation of reconstruction. By defining the appropriate scroll product kernel and learning strategy, GCN can better capture and restore the details and texture information of cultural legacy. GCN has strong generalization ability and can handle different types and styles of artistic and cultural legacy data. A large and high-quality 3D dataset of artistic and cultural legacy is required. This study screened data related to the task from multiple publicly available art and cultural legacy datasets. These datasets include various types of artistic and cultural legacy, such as historical buildings, sculptures, paintings, etc. Due to the possibility of some noise and missing or incomplete data in the original data, it is necessary to clean these data. The annotated content mainly includes information such as the category, era, and region of cultural legacy. The annotated data is enhanced to enhance the generalization ability of the model. In the data preprocessing stage, convert the cleaned and annotated data into a format that the model can process. For GCN, convert 3D data of artistic and cultural legacy into graph-structured data.

The GCN structure used for cultural legacy image processing is designed to handle graphic data with complex topological structures, such as images in artistic and cultural legacy. The main advantage of this network structure is that it can deeply explore the features and patterns in images. The basic components of GCN include nodes and edges, where nodes represent pixels or higher-level image elements in the image, such as superpixels or image regions, and edges represent the relationships between these elements. Each node has its own features, which can include low-level features such as pixel colour, intensity, texture, etc., as well as high-level features extracted by other DL models. Unlike traditional CNN, the convolution operation in GCN is performed on the graph structure, which can more effectively process graph data with complex topological structures. The GCN structure used for cultural legacy image processing is shown in Figure 1.

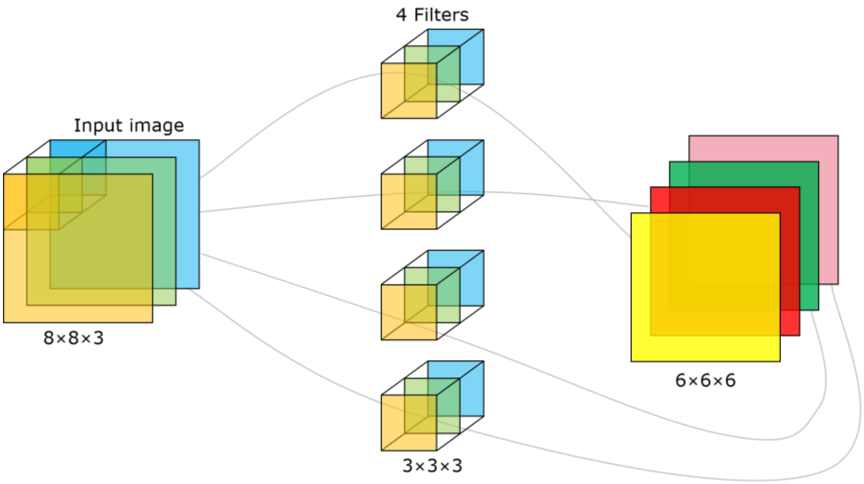

Figure 1: GCN structure for cultural legacy image processing.

The network is provided with input and the desired output. The input is represented by connections between nodes within the hidden layer. Each of these connections bears a random weight. The outputs of all layers can be determined using the formula below:

$$a_j^l = f(\sum_k w_{jk}^l a_k^{l-1} + b_j^l) \tag{1}$$

The input layer is responsible for receiving the converted graph structure data. Each node has a feature vector as input, which can contain information such as the node's 3D coordinates, colour, texture, etc. The graph convolutional layer is the core part of the model and is responsible for extracting features from graph-structured data. We adopted a spatial domain-based graph convolution method to update the feature representation of nodes by aggregating and transforming their neighbour information. The output layer is responsible for generating the results of 3D CAD reconstruction. In the part of the pooling function P, GCN uses bilinear pooling to bilinear combine the output feature vectors:

$$bilinear(f_A, f_B) = f_A \otimes f_B = u^T v \tag{2}$$

That is, they are subjected to the outer product operation to obtain the bilinear feature $bilinear(f_A, f_B)$. In order to merge all the bilinear features in the image, the bilinear features in each position are accumulated and summed:

$$\phi(f_A, f_B) = \sum_{d=1}^{D} bilinear(f_A, fB) = \sum_{d=1}^{D} u^T v \tag{3}$$

Transforms the accumulated bilinear feature matrix. Then, the vector $\phi(f_A, f_B)$ is normalized and L_2 regularized:

$$y = sign(\phi(f_A, f_B))\sqrt{|\phi(f_A, f_B)|} \tag{4}$$

$$Z = \frac{y}{\|y\|_2} \tag{5}$$

Finally, input the obtained vector Z into the classification function C for recognition and classification.

The feature detection layer is responsible for extracting pixel-level features from the original image. This can be achieved by using traditional CNN or other feature detection methods. In this layer, it is necessary to convert the extracted pixel features into graph-structured data, which means constructing a graph where each node is a pixel and edges represent the relationships between pixels. This is the core part of the entire network, responsible for performing convolution operations on the constructed graph to learn and extract structural features from the graph. Figure 2 shows GCN semantic segmentation.

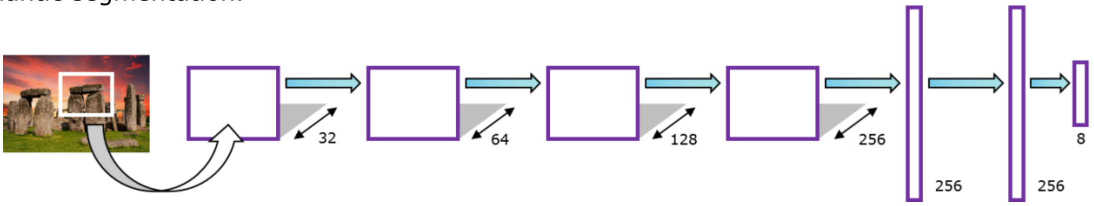

Figure 2: GCN semantic segmentation.

Add a classifier to the output of the GCN layer to classify each node. This can be achieved by using the softmax function or other classification methods. By capturing the relationships and contextual information between pixels, GCN can more accurately identify different semantic elements in images, thereby achieving high-quality semantic segmentation. If only transpose convolution is performed on the results of the last layer, the resulting segmentation map will lose too much detail information due to passing through too many pooling layers, resulting in poor detail segmentation results and obtaining relatively rough semantic segmentation results. So, the GCN in this article proposes a skip structure, which weights the previous results onto the current results and comprehensively trains to obtain the final segmentation. The specific structure is shown in Figure 3.

During the model training phase, initialize the parameters of the model. The initialization methods can include random initialization, pre-training initialization, etc. In the forward propagation stage, the input data is fed into the model, and the output results are obtained after calculation at each layer. The difference between the output result and the actual label constitutes the value of the loss function. In the backpropagation stage, the gradient of the parameters is calculated based on the value of the loss function, and the gradient descent algorithm is used to update the values of the parameters.

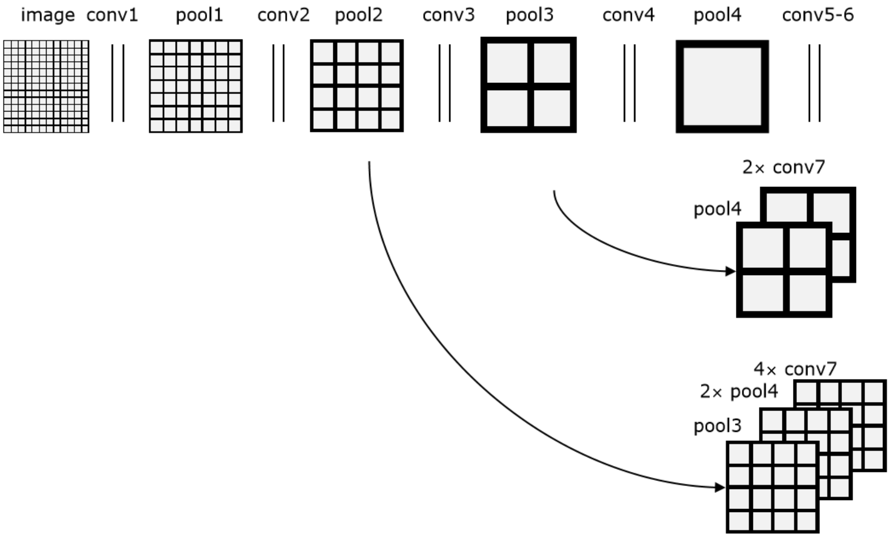

Figure 3: Jump structure in GCN.

The input projection data and entity representation are founded on the device's coordinate system. Throughout the reconstruction phase, each view is transformed into its corresponding coordinate system on the projection plane. The conversion between the coordinate system of the projection plane and that of the screen can be attained by applying specific transformation equations.

Orthographic projection plane V :

$$x^{'} = x_0 - x; z^{'} = y - y_0 \tag{6}$$

Side projection plane W :

$$y^{'} = x - x_0; z' = y - y_0 \tag{7}$$

Horizontal projection plane H :

$$x^{'} = x_0 - x; y^{'} = y_0 - y \tag{8}$$

The transformation relationship of a point in space between the world coordinate system and the camera coordinate system is as follows:

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{bmatrix} = \begin{bmatrix} R & T \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \tag{9}$$

After obtaining the output of the GCN model, use it for 3D reconstruction of artistic and cultural legacy. We consider the output of GCN as a compressed representation of the raw data, which contains rich structural and texture information. By decoding and manipulating the output appropriately, a highly realistic virtual model can be generated. This virtual model can be used to showcase, research, and protect artistic and cultural legacy. By combining the output of GCN with appropriate decoding operations, a highly realistic virtual model can be generated for displaying, researching, and protecting the artistic and cultural legacy.

4 RESULT ANALYSIS AND DISCUSSION

4.1 Dataset Introduction and Experimental Environment Configuration

A publicly available dataset containing cultural legacy images was used. This dataset contains various types of cultural legacy images, including historical buildings, sculptures, ceramics, cultural relics, paintings, and folklore. The dataset contains various types and styles of cultural legacy images, covering cultural legacy from different regions and historical periods, ensuring data diversity.

In the field of cultural legacy protection, this study built a DL-based experimental environment: in terms of hardware, a computer equipped with an NVIDIA GeForce RTX 3080 graphics card was used for the experiment. In terms of software, Python programming language and TensorFlow DL framework were used for model construction and training. Meanwhile, this study also utilized relevant image-processing libraries for image preprocessing and enhancement. The parameters were set according to the experimental requirements and the characteristics of the dataset.

4.2 Result Analysis

VR has the characteristics of multi-perception, immersion, interactivity, and conceptualization, which can be applied to the display, research, and protection of cultural legacy. It creates a social environment for the historical period in which cultural legacy is located, making it easier for learners to understand and accept historical knowledge. The growth of DL technologies, such as GCN, provides new solutions for 3D CAD reconstruction. This method can automatically learn the 3D geometry and texture information of objects from the raw data. By combining VR, more realistic and refined 3D virtual models of cultural legacy can be created.

The experiment mainly focuses on six types of artistic and cultural legacy: historical buildings, sculpture, ceramics, cultural relics, painting, and folklore. The goal is to achieve a stylistic classification of these different types of cultural legacy. To complete this task, representative material images were prepared for each style, as shown in Figure 4.

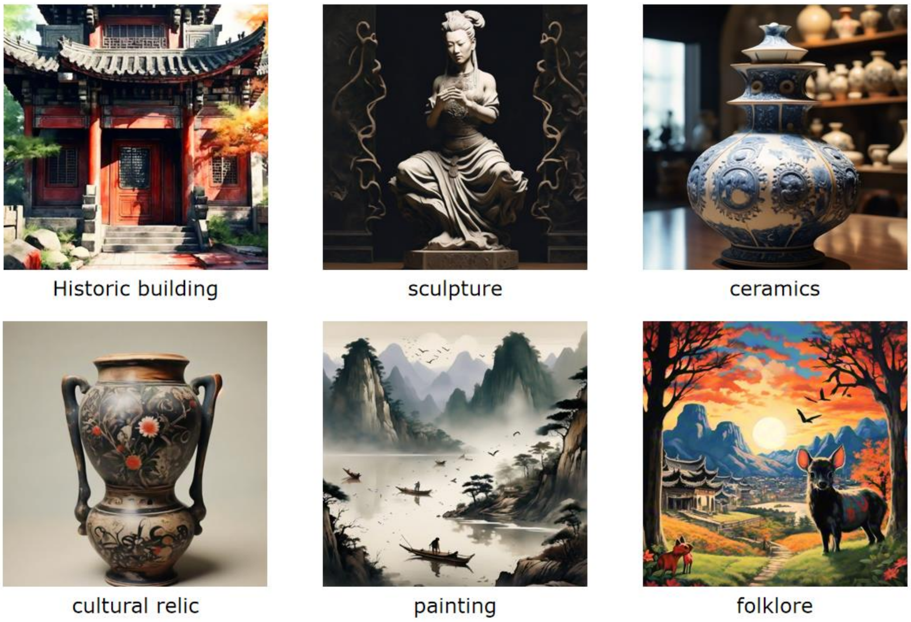

Figure 4: Representatives of different types of artistic and cultural legacy.

To ensure the effectiveness and generalization ability of the classifier, the material images of each style are divided into two sets: the training set and the test set. For each style, randomly select a certain number of sample images from all its materials as the training set. These selected images will be used to train a set of basis functions that can capture and represent the unique features of this style. Once the training set is determined and used to train the basis function, all materials that were not selected as the training set in this style naturally become the test set. The purpose of the test set is to validate the performance of the classifier, ensuring that it can accurately distinguish different styles and correctly classify new images.

By comparing the experimental results of our algorithm and the DBN algorithm, it can be found that our algorithm has significant advantages in predicting the features of cultural legacy images (see Figure 5 and Figure 6).

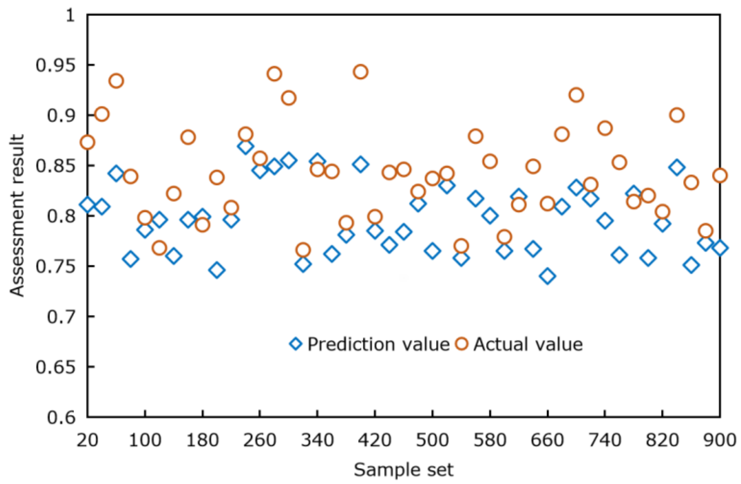

Figure 5: Feature prediction results of the DBN algorithm.

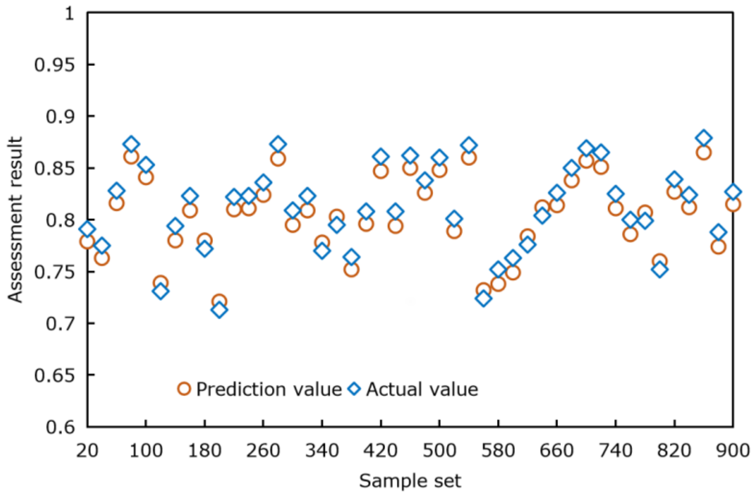

Figure 6: Feature prediction results of this method.

The accuracy of the algorithm in predicting the features of cultural legacy images in this article is significantly better at capturing and representing the details and styles of cultural legacy images. The convergence speed of the algorithm in this article is faster, which means it can achieve better predictive performance in a shorter time. When facing cultural legacy images with complex structures and rich textures, our algorithm can maintain high stability. Compared with the DBN algorithm, this algorithm provides more interpretable results. By visualizing the nodes and edges in GCN, it is possible to better understand how the model captures and is the features of cultural legacy images.

F1 value is one of the commonly used indicators to assess the performance of image enhancement algorithms. According to the experimental results, our algorithm has significant advantages in F1 value compared to the DBN algorithm, as shown in Figure 7.

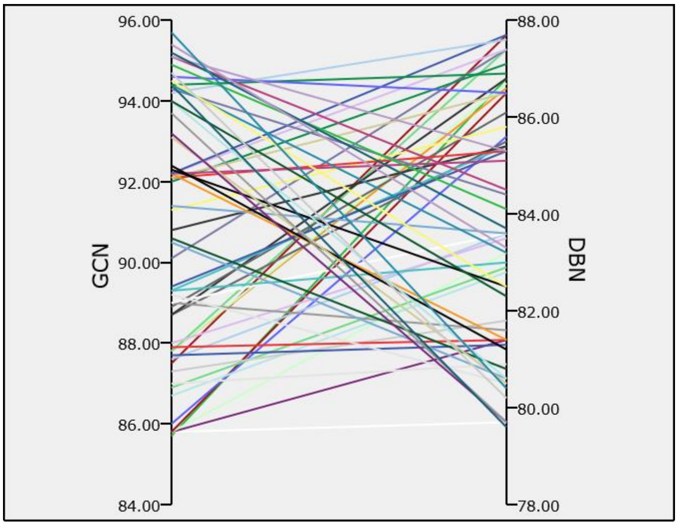

Figure 7: F1 values of different algorithms.

This indicates that the algorithm in this article has high accuracy and recall in predicting the features of cultural legacy images and can better identify and classify various types and styles of cultural legacy images.

Reconstruction error refers to the difference between the image processed by the image enhancement algorithm and the original image, which reflects the algorithm's fidelity and quality of the processed image. The smaller the reconstruction error, the more accurate the algorithm is in processing the original image. Figure 8 shows that the reconstruction error of our algorithm on various cultural legacy images is generally lower than that of the DBN algorithm. This indicates that the algorithm proposed in this article can better preserve the details and features of the original image when processing cultural legacy images and reduce the distortion and noise that may be introduced during the processing.

The DBN algorithm performs poorly in terms of reconstruction error, especially when dealing with cultural legacy images with complex structures and rich textures; its reconstruction error is relatively high. By combining the output of GCN, this algorithm can extract richer image features and contextual information, thereby more accurately reconstructing the original image.

4.3 Inspiration and Suggestions for the Field of Cultural Legacy Protection

The use of advanced technologies such as DL can more effectively identify, classify, and protect the cultural legacy. The popularization and application of DL technology have provided the possibility for public participation in cultural legacy protection. By establishing online platforms or applications, the public can participate in the digital protection of cultural legacy, such as image annotation and 3D reconstruction.

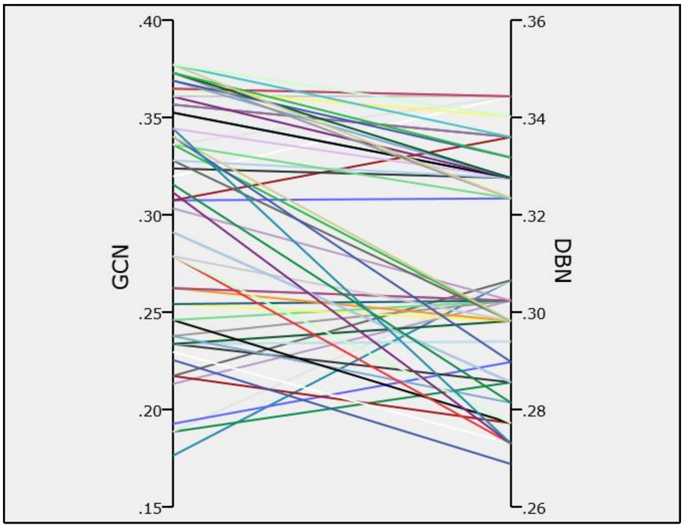

Figure 8: Reconstruction error of different algorithms.

This can not only increase public awareness and participation in cultural legacy protection but also provide more resource support for protection work. The protection of cultural legacy is not a task of a country or region but a shared responsibility of all humanity. By strengthening international cooperation and exchange, technology, resources, and experience can be shared to face the challenges of cultural legacy protection jointly.

The protection and utilization of cultural legacy is an interrelated and mutually restrictive process. We need to find a reasonable balance between protection and utilization, ensuring that cultural legacy is sustainably preserved while also providing the public with a rich cultural experience.

5 CONCLUSION

VR has the characteristics of multi-perception, immersion, interactivity, and conceptualization, which gives it enormous potential in the field of cultural legacy protection. This article proposes a 3D CAD reconstruction method for artistic and cultural legacy based on the GCN algorithm. By applying GCN to the 3D CAD reconstruction of artistic and cultural legacy, it is possible to better capture and restore the details of cultural legacy and improve the effectiveness of cultural legacy reconstruction.
Compared with the DBN algorithm, this algorithm provides more interpretable results. By visualizing the nodes and edges in GCN, it is possible to better understand how the model captures and is the features of cultural legacy images. The results demonstrate that DL algorithms have significant advantages over traditional methods in predicting and reconstructing features of cultural legacy images. This indicates that DL techniques can effectively extract and represent features of cultural legacy images. The research results not only have important implications for the field of cultural legacy protection but also provide practical suggestions for relevant practitioners.

The protection and utilization of cultural legacy is an interrelated and mutually restrictive process. In future research, DL technology will continue to play an important role in bringing more breakthroughs and innovations to the protection of cultural legacy.

6 ACKNOWLEDGEMENT

This work was supported by Hainan Provincial Philosophy and Social Sciences Planning Project: "Study on the Digital Dissemination of Hainan Intangible Cultural Heritage Skills in the Context of the Construction of Free Trade Port" (NO.HNSK(YB)23-69); Scientific Research Program of Hainan Provincial Department of Education "Research on the Application of Digital Art Design in the Intangible Cultural Heritage in Hainan Province" (NO. Hnkyzc2023-22).

Dan Zheng, https://orcid.org/0000-0001-7042-3226
Yan Xie, https://orcid.org/0009-0005-8013-124X

REFERENCES

[1] Barrile, V.; Bernardo, E.; Bilotta, G.: An experimental HBIM processing: Innovative tool for 3D model reconstruction of morpho-typological phases for the cultural Heritage, Remote Sensing, 14(5), 2022, 1288. https://doi.org/10.3390/rs14051288

[2] Barrilea, V.; Fotiaa, A.; Bilottaa, G.: Integration of geomatics methodologies and creation of a cultural legacy app using augmented reality, Virtual Archaeology Review, 10(20), 2019, 40. https://doi.org/10.4995/var.2019.10361

[3] Bombini, A.; Bofías, F.-G.-A.; Ruberto, C.; Taccetti, F.: A cloud-native application for digital restoration of Cultural Heritage using nuclear imaging: THESPIAN-XRF. Rendiconti Lincei, Scienze Fisiche e Naturali, 34(3), 2023, 867-887. https://doi.org/10.1007/s12210-023-01174-0

[4] Chen, A.; Jesus, R.; Vilarigues, M.: Identification and visualization of pure and mixed paint pigments in heritage artwork using machine learning algorithms, SN Computer Science, 4(2), 2022, 115. https://doi.org/10.1007/s42979-022-01529-8

[5] Chong, H.-T.; Lim, C.-K.; Rafi, A.: Comprehensive systematic review on virtual reality for cultural legacy practices: coherent taxonomy and motivations, Multimedia Systems, 2022(3), 2022, 28. https://doi.org/10.1007/s00530-021-00869-4

[6] Condorelli, F.; Rinaudo, F.; Salvadore, F.; Tagliaventi, S.: A neural networks approach to detecting lost Heritage in historical video, ISPRS International Journal of Geo-Information, 9(5), 2020, 297. https://doi.org/10.3390/ijgi9050297

[7] Doulamis, A.; Voulodimos, A.; Protopapadakis, E.; Doulamis, N.; Makantasis, K.: Automatic 3d modeling and reconstruction of cultural heritage sites from Twitter images, Sustainability, 12(10), 2020, 4223. https://doi.org/10.3390/su12104223

[8] Flagg, C.; Frieder, O.: Reconstruction of artifacts from digital image repositories, ACM Journal on Computing and Cultural Heritage, 16(1), 2022, 1-22. https://doi.org/10.1145/3552298

[9] Ghosh, M.; Obaidullah, S.-M.; Gherardini, F.; Zdimalova, M.: Classification of geometric forms in mosaics using deep neural network, Journal of Imaging, 7(8), 2021, 149. https://doi.org/10.3390/jimaging7080149

[10] Gualandi, M.-L.; Gattiglia, G.; Anichini, F.: An open system for collection and automatic recognition of pottery through neural network algorithms, Heritage, 4(1), 2021, 140-159. https://doi.org/10.3390/heritage4010008

[11] 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

[12] Scatigno, C.; Festa, G.: Neutron Imaging and Learning Algorithms: New Perspectives in Cultural Heritage Applications, Journal of Imaging, 8(10), 2022, 284. https://doi.org/10.3390/jimaging8100284

[13] 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

[14] Yang, S.; Hou, M.; Li, S.: Three-dimensional point cloud semantic segmentation for cultural Heritage: a comprehensive review, Remote Sensing, 15(3), 2023, 548. https://doi.org/10.3390/rs15030548
[15] Zhao, X.: The use of interactive data visualisation technology in cultural digital heritage display using edge computing, International Journal of Grid and Utility Computing, 13(2-3), 2022, 118-127. https://doi.org/10.1504/IJGUC.2022.124396
[16] Zhou, Y.; Sun, J.; Huang, Y.: The digital preservation of intangible cultural legacy in china: a survey, preservation, Digital Technology & Culture, 48(2), 2019, 95-103. https://doi.org/10.1515/pdtc-2019-0004