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Computer-Aided Design AND APPLICATIONS

Computer-Aided Design in Digital Protection of Cultural Heritage in Big Data Environment

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Abstract. This article delves into the pioneering integration of big data technology and computer-aided design (CAD) within the realm of digital safeguarding for cultural heritage (CH). Addressing current challenges in CH preservation, the study introduces a solution that harmonizes big data analytics with CAD techniques. Methodologically, four iconic CH categories—ancient architecture, archaeological sites, performance arts, and traditional crafts—are chosen, and their visual attributes are precisely discerned using advanced image recognition and processing algorithms. Experimental outcomes highlight the efficacy of our proposed algorithm in CH image feature identification, outperforming conventional methods in terms of accuracy and detail retention. Ultimately, this study demonstrates the successful deployment of big data and CAD in CH digital preservation, yielding notable outcomes. These findings not only offer a novel technical approach to CH conservation but also serve as a valuable resource for related research and practical applications.

Keywords: Big Data; Computer-Aided Design; Cultural Heritage; Digital Protection
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1 INTRODUCTION

Most existing style transfer algorithms are based on the transfer of Western oil painting styles, with excessively abstract textures that are not suitable for the expression of Chinese cultural elements such as opera. Chinese traditional culture has a long history, unique charm, and a profound mass base [1]. Opera, calligraphy, painting, and other forms are important carriers for expressing and inheriting excellent traditional Chinese culture [2]. The digitization of opera costume patterns and the generation of new styles are of great significance, but the existing digital technology forms are monotonous, and manual design is difficult and inefficient. To address the issue of flicker and jitter in video stylization, pixel-by-pixel temporal consistency is achieved, and the timing loss is calculated and added to the overall loss function to improve the style transfer effect of the video [3]. The transferable style features are single, and the jitter generated by frame-by-frame video artistic output affects the output effect. Based on convolutional neural networks, traditional culture is integrated with digital technology to innovate the styles of traditional clothing [4]. Adjusting the content loss function and style loss function to obtain images with different degrees of stylization and optimizing the selection of convolutional network frameworks and corresponding feature layers [5]. Solved the problem of single-style transmission, achieved the artistic transfer of multiple styles, and designed a new loss function to obtain a new style feature to enrich the expression of traditional culture. Changing the weight coefficients of different styles can make the final transfer style tend towards a specific style [6]. Combining style transfer with traditional clothing images, in order to better showcase its artistic effect, a new loss function was added on the basis of the original loss function [7]. Compared with Prisma's experimental results, the processed image is smoother and solves the problem of excessive abstraction caused by line distortion. In short, integrating style transfer with traditional cultural elements not only improves the generation effect but also solves the problem of video jitter. It is designed, implemented, and ultimately applied [8]. At the same time, combined with big data analysis, the project team can also monitor changes in the status of the site, predict potential risks, and propose targeted protection recommendations based on CAD design [9].

The introduction of big data technology has led to a qualitative leap in data processing capabilities during the digitization of cultural heritage. By identifying, segmenting, and classifying various elements in the raw point cloud data, CAD software can generate accurate geometric models. In this process, the reference to architectural papers and classic architectural vocabulary not only provides an important basis for shape recognition but also promotes the in-depth exploration of the cultural and historical value of the model. In H-BIM, each building component is endowed with rich semantic information, including but not limited to historical knowledge, file sources, repair records, etc. These pieces of information not only enhance the readability and comprehensibility of the model, but also provide strong support for subsequent protection decisions, repair plan design, and public education. Through H-BIM, the protection of cultural heritage can be carried out in a broader temporal and spatial context, achieving a comprehensive upgrade from physical protection to cultural inheritance. Through algorithm optimization and machine learning techniques, big data platforms can automatically identify key features in buildings, such as structural details, decorative elements, etc., laying a solid foundation for subsequent digital modelling and semantic annotation [10]. Furthermore, using advanced modelling techniques such as NURBS (Non-Uniform Rational B-splines), designers can manually adjust and optimize model details to ensure high consistency with the actual object. Intangible cultural heritage (abbreviated as "ICH") plays an important role in China's traditional culture. ICH is the core of national culture and the essence of national culture. At present, most lens boundary detection methods often rely on manually designed complex feature and similarity measurement methods, and the algorithms often have high time and space complexity, occupying a lot of computing resources. The inability to quickly and accurately segment long videos into multiple short videos based on scenes through manual operation has become a major obstacle to the dissemination of intangible cultural heritage. The disadvantage of the original SSD algorithm is that there is a large difference in the scale of the feature map when selecting candidate boxes, and the recognition effect on small targets is poor [11]. As a medium of communication, video has its unique advantages, covering both visual and auditory aspects, and being easy to produce and store. Therefore, as a medium, it holds an irreplaceable position in the inheritance, dissemination, and protection of intangible cultural heritage. By calculating the inter-frame difference, a large number of non-lens boundary frames can be discarded. The second part uses a three-dimensional convolutional neural network to identify shear in candidate boundary frames. However, the recorded products of intangible cultural heritage videos are mostly long videos with mixed semantics, based on the rapid development of short videos and data evidence. Therefore, applying lens boundary detection and boundary frame object detection techniques to intangible cultural heritage videos will be beneficial for the production of intangible cultural heritage short videos, thereby promoting the dissemination of intangible cultural heritage [12]. Shot boundary detection aims to detect the shear and gradient of shots in videos, achieving automatic segmentation of shots. The experimental results show that the shear lens detection accuracy of this model is improved by more than 10% compared to traditional methods. The experimental results show that the improved SSD object detection algorithm has a 5.2% increase in mAP accuracy compared to the original SSD algorithm, effectively improving the SSD algorithm's ability to detect objects [13]. Effective integration and utilization of these data resources, as well as the formulation of scientific, rational protection strategies, necessitate thorough research. This study aims to offer a novel approach to CH's digital preservation, contributing to the advancement of CH protection efforts. The research includes the following innovations and contributions:

(1) This study systematically discusses the all-round application of big data technology in CH protection, providing a scientific basis for precise protection.

(2) Advanced CAD technology is introduced into the research, and the restoration decision is optimized by simulating the effects of different restoration schemes.

(3) Combining big data analysis and CAD technology, a highly realistic virtual museum is built to realize the digital display of CH.

To begin, this article introduces the research background, significance, purpose, and problem definition. Following this, it reviews the current state of research in related fields and clarifies the research direction. Subsequently, a theoretical framework and methodology are established to direct empirical research. The core section delves into the practical applications of big data and CAD in CH data collection, processing, repair, restoration, and virtual museum development, assessing their impact through case studies. Lastly, the research findings are summarized, and specific policy recommendations are proposed.

2 LITERATURE REVIEW

In the big data environment, the system first obtains detailed 3D data of Terra Cotta Warriors fragments through high-precision scanning equipment. The multilayer perceptron, through its powerful nonlinear mapping ability, can automatically discover hidden patterns and relationships in data, thereby generating more representative and discriminative feature representations. Ming et al. [14] introduced an artistic generation method for the style transfer of traditional Chinese cultural elements based on convolutional neural networks. Based on the study of relevant principles and applications, it has been found that there is currently no scholar who has researched the artistic rendering of traditional Chinese cultural elements. The transferable style features are single and the jitter generated by frame-by-frame video artistic output affects the output effect. Most existing style transfer algorithms are based on the transfer of Western oil painting styles, and overly abstract textures are not suitable for the expression of Chinese cultural elements such as opera. Implemented features such as fast style transfer, multi-style fusion transfer, and video style transfer, and designed and implemented the final webpage display interface. Integrating traditional culture with digital technology, enriching the expression forms of traditional culture through style transfer, and innovating the styles of traditional clothing. The main content of Nieto et al. [15] is to develop an application for the artistic generation of traditional Chinese cultural elements, improving the relevant network structure and loss function. Firstly, the weighted sum of the content loss function and style loss function calculation results can obtain a more accurate target generation result graph with semantic information or a more intense style rendering effect.

Pierdicca et al. [16] combined style transfer with traditional clothing images and added a new loss function on the basis of the original loss function to better showcase its artistic effect. Optimize the selection of convolutional network frameworks, the calculation methods of content and style loss functions, and the selection of corresponding feature layers. Provide the transformation output of the stylized network to calculate the temporal loss, and add it to the overall loss function to improve the style transfer effect of the video. The comparison experiment results with Prisma show that the processed image is smoother, solves the excessive abstraction phenomenon of line distortion, and is more aesthetically pleasing in subjective perception. Finally, to address the issue of flicker and jitter in video stylization, pixel-by-pixel temporal consistency is achieved. By adding weight coefficients for different styles to the style loss function, a transfer effect of multiple style fusion can be obtained, which can adjust the weight coefficients of different styles and solve the problem of single-style transmission. This process begins with the construction of an intermediate knowledge system based on precise measurement surveys and greatly improves the model's ability to reproduce the materiality of buildings by integrating large-scale point cloud data and its rich texture information.

Skublewska et al. [17] carefully classified and divided various building systems to reveal their underlying technological logic and evolutionary background. Classify and archive stone masonry structures in masonry walls based on construction time, material characteristics, and other dimensions.

At the forefront of digital cultural heritage (DCH) protection, deep learning (DL) technology is gradually becoming a key driving force for 3D point cloud semantic segmentation, greatly promoting the fine recognition and classification of historical architectural elements. By combining big data and CAD technology, the digital protection of cultural heritage is no longer limited to traditional recording and display but is developing towards intelligence, dynamism, and interactivity. In addition, CAD technology also supports seamless integration with virtual reality technology, allowing users to interact with cultural heritage models in VR environments directly. This process not only relies on the powerful graphics processing and computing capabilities of computers but also requires precise analysis and intelligent matching of big data to ensure the accuracy and authenticity of reconstruction results. Activities such as roaming, measurement, and restoration simulation have greatly improved the efficiency and depth of cultural heritage protection and research. By constructing a digital twin of cultural heritage, Wang et al. [18] achieved monitoring and management of the entire lifecycle of cultural heritage, identifying and responding to potential risks and threats in a timely manner. Meanwhile, digital twins can also serve as important carriers for cultural heritage education, dissemination, and tourism, allowing more people to transcend the limitations of time and space and experience the unique charm of cultural heritage up close [19].

3 THEORETICAL FRAMEWORK AND METHODOLOGY

This section aims to explore the integrated application of CAD and virtual reality (VR) in the big data environment, especially focusing on how to optimize the interactive experience in the virtual museum through Level of Detail (LOD) modelling.

3.1 Theoretical Basis and Technical Background

First of all, it should be clear that the core goal of CH digitization is to realize the preservation and dissemination of CH information and, at the same time, provide a rich and authentic interactive experience. This requires researchers to consider not only the high-precision capture and recovery of data but also the smooth experience of users when selecting technology. As an effective resource management technology, LOD modelling can dynamically adjust the fineness of the model according to the distance between the user and the object, thus ensuring the visual effect and optimizing the system performance.

3.2 Application of LOD Modeling in Virtual Museum

(1) LOD modelling principle

LOD modelling is based on a simple and effective principle: the farther the distance, the fewer details. This principle is particularly important in the large-scale scene roaming of virtual museums because it is directly related to rendering efficiency and user experience. By creating multiple model versions with different fineness for the same object, the system can dynamically select the most suitable model to load according to the real-time position of the user, which not only saves computing resources but also ensures visual coherence.

(2) LOD modelling example of teapot props.

Taking the teapot as an example, a three-level LOD model is designed to adapt to different observation distances:

First-class LOD (Fine Model): It is suitable for users within 1 meter of the teapot. As shown in Figure 1, the model needs to be accurate to every detail, including the delicate expression of materials and textures, so as to provide a high sense of reality at close range.

Figure 1: Fine modeling.

Secondary LOD (Simplified Model): When the user is 1 to 5 meters away from the teapot, load the simplified model (Figure 2). On the basis of retaining the main features, this model greatly reduces the number of faces and texture complexity, aiming at maintaining visual consistency at a long distance and reducing the rendering pressure.

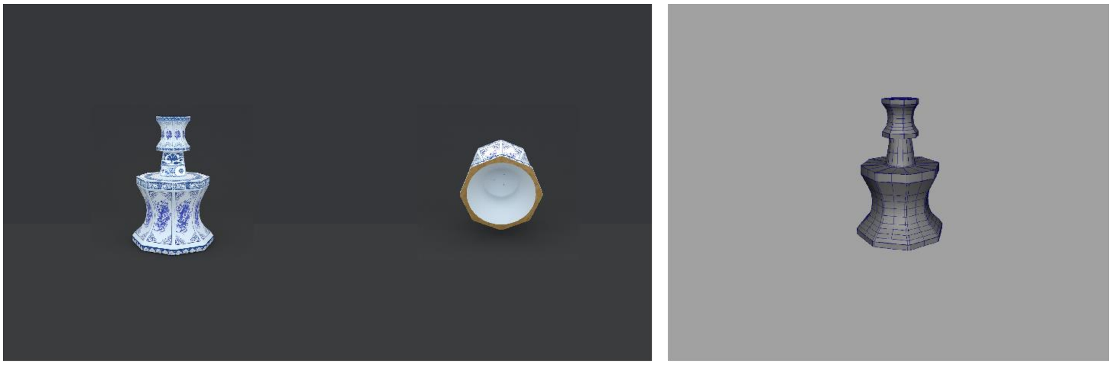

Figure 2: Simplified model.

Three-level LOD (Remote Model): For a longer observation distance, the remote model (Figure 3) is adopted, which only keeps the basic outline and colour of the teapot, and even simplifies it to geometry or points, so as to maintain the identifiability of the object with minimum resource consumption.

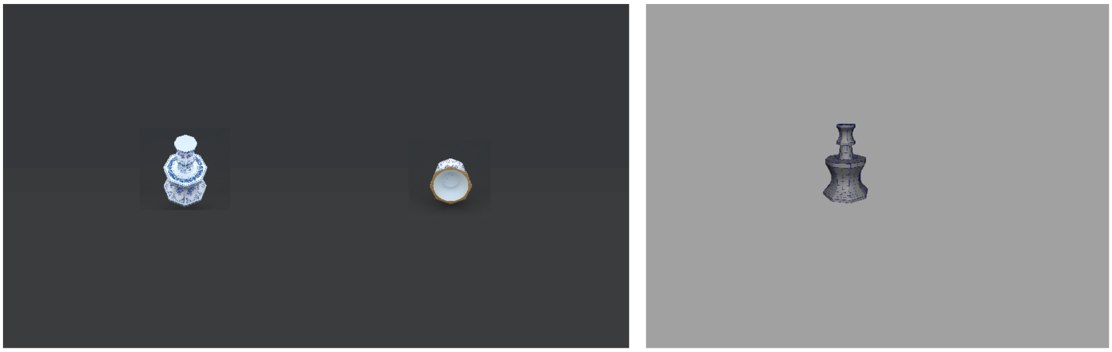

Figure 3: Remote modeling.

3.3 Construction of Theoretical Framework

(1) Data acquisition and processing

The premise of LOD modelling is high-quality data acquisition. This includes using high-precision scanning equipment to obtain 3D geometric information of CH, and high-resolution photography to capture surface texture. Subsequently, through data preprocessing techniques, such as denoising, registration, mesh simplification, etc., it lays a solid foundation for LOD modelling.

LOD strategy formulation

Based on the data collection results, specific LOD strategies are formulated. This includes determining the level of detail of LOD models at all levels, the switching threshold, and the smooth transition mechanism between models. The key is to find a balance point that can not only satisfy users' pursuit of details but also ensure the smooth operation of the system.

(3) Interaction design and user experience

LOD modelling should be closely combined with interaction design. For example, an intelligent line-of-sight perception system is designed to predict and preload the appropriate LOD model according to the user's moving speed, line-of-sight direction, and other factors to reduce the loading delay. At the same time, the LOD switching strategy is continuously optimized through the user feedback mechanism to improve the user experience.

(4) Technology integration and innovation

Combining LOD modelling with big data processing, cloud computing, artificial intelligence, and other technologies can further improve the performance and intelligence level of virtual museums. For example, machine learning can predict user behavior patterns and load areas that may be visited in advance, or cloud rendering technology can transfer some computing tasks to the cloud to reduce the burden on local hardware.

4 CH DIGITAL PROTECTION BASED ON BIG DATA AND CAD

4.1 Integration of Big Data and CAD

The swift advancement of big data technology has presented unparalleled prospects for the digital preservation of CH. By gathering, integrating, and analyzing extensive CH datasets, a more comprehensive understanding of CH's historical context, current state, and potential hazards is achievable. CAD, a crucial instrument in design and manufacturing, offers precise 3D modelling, rendering, and simulation capabilities, forming a robust basis for CH's digital representation. With the assistance of big data, CAD applications have become notably accurate and efficient. During digital restoration, CAD captures intricate details of CH's form, structure, and material, yielding highly realistic digital replicas. Furthermore, big data enriches CAD models with extensive background information, ensuring that these digital creations are not only visually convincing but also imbued with deep cultural significance.

4.2 Combination of 3D Modeling and CAD

3D modelling is one of the core technologies of CH digital protection, and CAD is an important tool for 3D modelling. Through the accurate modelling function of CAD, we can create a digital model that is highly similar to the real thing. These digital models have accurate geometric shapes and contain rich material and texture information. In the process of digital restoration, we can use the material and texture editing function of CAD to add realistic materials and textures to the digital model according to the results of big data analysis so that the model is closer to the real thing visually.

4.3 CH 3D Reconstruction Based on Graph Convolutional Network (GCN)

The 3D reconstruction algorithm is also an important part of CH digital protection. The 3D reconstruction algorithm based on big data can automatically construct a 3D model according to the point cloud data or image data of CH. This is undoubtedly an effective means of protection and display for CH that cannot be directly touched or measured.

In the workflow of CH 3D reconstruction, data acquisition is the first step. The integrity and accuracy of data can be ensured by reasonably planning the scanning and shooting paths and paying attention to the selection of parameters such as lighting conditions, scanning speed and camera settings. Subsequently, the data preprocessing stage includes denoising, registration, mesh simplification and other steps to prepare for 3D reconstruction. By combining GCN, the efficiency of 3D reconstruction can be further improved, especially when dealing with CH with complex geometry. Finally, through texture mapping and post-processing, the 3D model is more realistic and vivid. The structure of GCN used for CH image processing is shown in Figure 4.

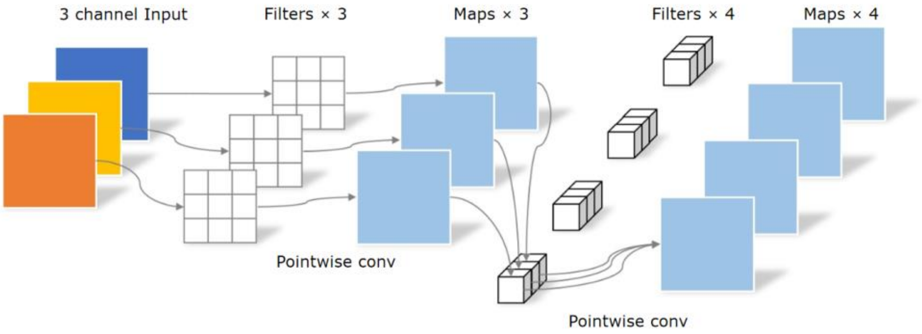

Figure 4: GCN structure for CH image processing.

During the map structure construction process, the initial step involves processing the gathered geological data to pinpoint data points and their interconnections. Each data point is designated as a graph node, while the connections between these points constitute graph edges. The construction diagram depicts node characteristics through vectors. Below is the formula illustrating the training of each GCN model layer:

$$X_{t+1} \in R^{V|\times D_{out}} = f\ D^{-1/2}\widehat{A}D^{-1/2}X_tW_t \tag{1}$$

Once the construction map is established, training is conducted using two GCN layers, culminating in the application of the Softmax function to forecast classification outcomes, as depicted in the subsequent formula:

$$Z = Soft\max\ \tilde{A}\,\mathrm{Re}LU\ \tilde{A}XW_0\ \ W_1 \tag{2}$$

Here, W_0, W_1 serves as the weight matrix. This article employs cross-entropy loss for the loss function.

Following the construction of the graph structure and extraction of node features, GCN facilitates feature learning and information dissemination. The graph convolution operation essentially functions as a message-passing process, where each node receives information from its neighbors and updates its status accordingly. The layers of GCN facilitate the dissemination of information among nodes:

$$H^{l+1} = \sigma\left(\breve{D}^{-\frac{1}{2}}\breve{A}\breve{D}^{-\frac{1}{2}}H^{l}W^{l}\right) \tag{3}$$

$$\breve{A} = A + I \tag{4}$$

Where I represents the identity matrix, $\breve{D}$ denotes the degree matrix of $\breve{A}$, defined by the formula:

$$\breve{D}_{ii} = \sum_j \breve{A}_{ii} \tag{5}$$

Here H denotes the layer-specific characteristic, H equals X the input layer, W^l represents the randomly initialized weight, and σ is the nonlinear activation function.

This article transforms and aggregates node characteristics via the graph volume accumulation layer, enabling each node to capture valuable neighbourhood information. By stacking multiple graph volumes, the receptive field of nodes expands, capturing more intricate graph structure information.

To translate the 3D model, place it on the x,y,z coordinate axis. Let $F\ x,y,z$ represent the original 3D model and $I\ x,y,z$ represent the translated model. The formula is given below:

$$I\ x,y,z\ = F\ x-m_p, y-m_p, z-m_p \tag{6}$$

Scaling involves resizing the 3D model along the three coordinate axes to prevent geometric distortion. When transforming a 3D model $F\ x,y,z$ of size $L \times M \times N$ into a new 3D model $I\ x,y,z$ of size $KL \times KM \times KN$, the process is described by the formula below:

$$I\ x,y,z\ = F\ \text{int}\ c \times x\ , \text{int}\ c \times y\ , \text{int}\ c \times z \tag{7}$$

$$c = 1 / k \tag{8}$$

The 3D model is reduced when $k > 1$, and enlarged when $k < 1$.

In the practical application of the algorithm, over-fitting is a problem that can not be ignored. It causes the model to achieve excellent recognition accuracy on the training set, but it shows low generalization ability on the unknown data. In order to effectively alleviate this problem, the Dropout method is introduced. The empirical outcomes indicate a notable improvement in model accuracy following the incorporation of the Dropout technique, along with a substantial boost in its generalization capacity for unfamiliar data.

The risk function for the 3D virtual modelling of CH is outlined below:

$$\theta^* = \arg\min_\theta \frac{1}{N}\sum_{i=1}^{N} L\ y_i, f\ x_i;\theta\ \ + \lambda\Phi\ \theta \tag{9}$$

Here, L denotes the loss function, x_i and y_i stands for the predicted and actual values respectively, f is the model's function and Φ serves as the regularization term. The logarithmic loss is computed as follows:

$$L\ Y, P\ Y \middle| X\ \ = -\log P\ Y \middle| X\ \ = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij} \log\ p_{ij} \tag{10}$$

In this context, Y represents the function's output variable, X denotes the input variable, N indicates the total input sample count, L signifies the loss function, and M stands for the number of potential categories. The 3D features of CH images are extracted using the grey difference method:

$$I_{Truth} = \begin{cases} 1 & if\ I_D \geq s \\ 0 & otherwise \end{cases} \tag{11}$$

I_D denotes the absolute difference in grey values between each pixel of the optimized and original images. For model training, the loss function employed is the weighted cross entropy, represented as L_{Mask} , and its calculation proceeds as follows:

$$L_{\text{Mask}} = -\frac{1}{C}\sum_{i=0}^{C-1} \alpha \cdot y_i \ln\ y_i'\ + \beta \cdot\ 1 - y_i\ \ln\ 1 - y_i' \tag{12}$$

y_i and $y_i^{'}$ represent the actual and predicted values of each target point within the image area, respectively, while C signifies the total number of pixels captured in each image frame.

5 APPLICATION EFFECT EVALUATION AND CASE ANALYSIS

In the broad field of CH protection and inheritance, technological innovation provides unprecedented opportunities for the reproduction and protection of ancient wisdom. This study focuses on four categories of CH: ancient buildings, ancient sites, performing arts and handicraft skills, and explores new paths in digital protection and inheritance through advanced big data and CAD technology. For each type of CH, representative material images are selected as experimental objects, as shown in Figure 5.

Ancient buildings Ancient ruins

Performing arts Handicraft skills

Figure 5: Different types of CH.

To thoroughly assess the proposed algorithm's performance in recognizing CH image features, it is meticulously compared with the classic Retinex algorithm. While the Retinex algorithm, a well-known image enhancement technique is extensively utilized for enhancing image details and restoring colors, issues like uneven lighting and complex textures frequently constrain its efficacy in handling intricate CH images. A comparison of Figure 6 and Figure 7 reveals that the presented algorithm exhibits marked superiority in terms of feature recognition precision and detail retention.

Figure 6 shows the feature recognition results after Retinex algorithm processing. Although the image contrast is enhanced to a certain extent, the recognition results are not satisfactory in terms of delicate carving textures of ancient buildings, complex landform features of ancient sites, dynamic expressions of characters in performing arts, and subtle differences in tools in handicraft skills, and some key information is blurred or over-enhanced. In contrast, the feature recognition results of this research algorithm presented in Figure 7 capture the unique features of various CH more accurately. Whether it is the cornices of ancient buildings, the historical traces of ancient sites, the emotional expression in the performing arts, and the exquisite skills in handicraft skills, they have been reproduced more delicately and accurately.

In addition to direct feature recognition, this study also explores the artistic re-creation of CH images, aiming at giving new vitality to traditional culture through technical means. Figure 8 shows a schematic process of generating stippling from a 3D solid rendering image. In the process of rendering, advanced computing technologies such as ray tracing are used to simulate the complex interaction between light and object surface, which ensures the fidelity and artistic sense of the generated image. Especially in the distribution, density, and overlapping processing of points, the final stippling not only retains the main characteristics of the original CH image but also integrates the simplicity and abstraction of modern art through fine parameter optimization.

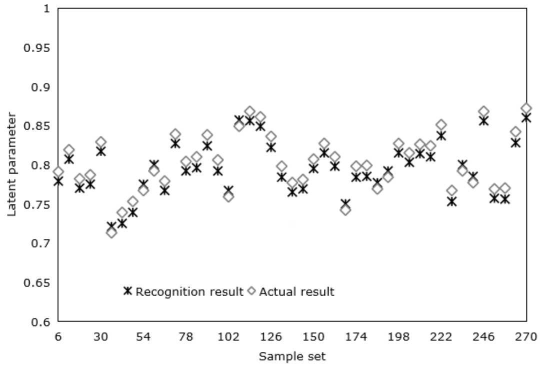

Figure 6: Feature recognition results of retinex algorithm.

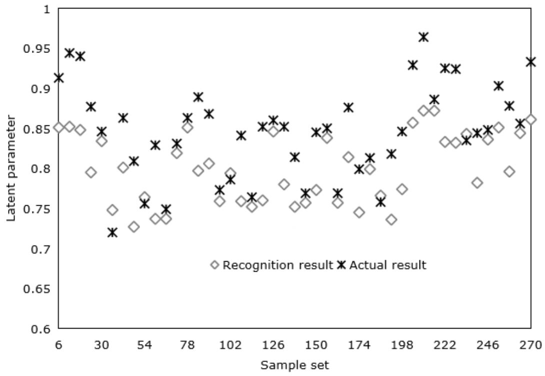

Figure 7: Feature recognition results of this algorithm.

During the practical implementation of the algorithm, over-fitting poses a significant challenge, potentially resulting in outstanding model performance on the training data but severely diminished generalization on unseen data. This research monitors the algorithm's recognition accuracy prior to incorporating fitting measures, as depicted in Figure 9. As the number of iterations increases, accuracy rises, yet it exhibits substantial variability. The subsequent improvement becomes gradual and stabilizes, suggesting the model might have entered an over-fitting condition.

Figure 8: Image generation from 3D solid rendering.

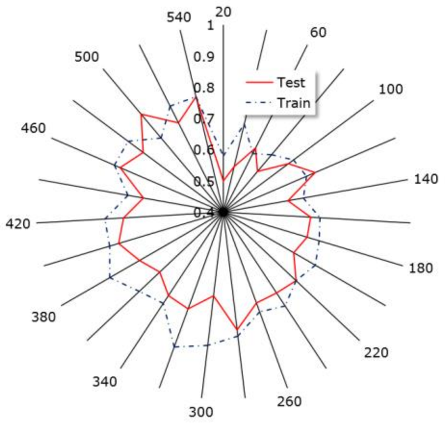

Figure 9: Accuracy before fitting measures are added.

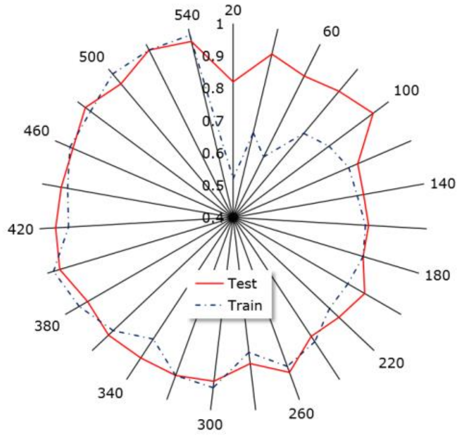

Figure 10: Accuracy after adding fitting measures.

In order to alleviate this problem, this study introduces the Dropout method, which is a strategy to reduce the complexity of the model by randomly discarding some neural network nodes and can effectively prevent over-fitting. Figure 10 shows the change curve of accuracy after adding the Dropout measure. Compared with before adding, the accuracy has been significantly improved, and the curve is smoother, which shows that the model maintains a good fitting to the training data and also enhances the generalization ability to unknown data. The successful application of this optimization strategy not only improves the performance of the algorithm in practical application scenarios but also lays a solid foundation for the further promotion of CH image recognition technology.

6 CONCLUSIONS

This research delves into the integration of big data technology and CAD for CH preservation. Through rigorous experimentation and analysis, notable achievements have been attained. Focusing on four representative CH categories—ancient buildings, ruins, performing arts, and handicraft skills—advanced image recognition and processing algorithms enable precise identification of their visual features. The proposed algorithm outperforms traditional methods in terms of recognition accuracy and detail retention. Additionally, the study explores the artistic re-creation of CH images, revitalizing their digital exhibition and dissemination through techniques like 3D solid rendering and stippling generation. In terms of algorithmic enhancement, the over-fitting issue is effectively addressed, and the algorithm's generalization is significantly enhanced by incorporating the Dropout method. Within the big data framework, CAD technology is harnessed for CH's digital preservation, yielding impressive outcomes. Future endeavours will further explore and apply these technologies, contributing substantially to CH's protection and inheritance.

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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.; Neamțu, 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 Roșie, 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] Huang, Z.-M.; Liang, Y.-M.: Digital protection and inheritance of ancient villages in southwest minority areas under the strategy of rural revitalization, Technological Forecasting and Social Change, 160(1), 2020, 120238. https://doi.org/10.1016/j.techfore.2020.120238

[10] 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

[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] 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
[13] 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
[14] 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
[15] 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
[16] 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
[17] Skublewska, P.-M.; Milosz, M.; Powroznik, P.; Lukasik, E.: 3D technologies for intangible cultural heritage preservation—literature review for selected databases, Heritage Science, 10(1), 2022, 1-24. https://doi.org/10.1186/s40494-021-00633-x
[18] Wang, Y.-C.; Chen, C.-L.; Deng, Y.-Y.: Authorization mechanism based on blockchain technology for protecting museum-digital property rights, Applied Sciences, 11(3), 2021, 1085. https://doi.org/10.3390/app11031085
[19] Zhong, H.; Wang, L.; Zhang, H.: The application of virtual reality technology in the digital preservation of cultural heritage, Computer Science and Information Systems, 18(2), 2021, 535-551. https://doi.org/10.2298/CSIS200208009Z