Application of Regional Symbol Recognition and Collaborative Design Based on Deep Learning in Cultural Heritage

Beibei Hou[1] and Chuanyu Zhou[2]

[1,2] Department of Fashion Arts, Shaanxi Institute of International Trade & Commerce, Xi'an, Shaanxi 710048, China, [1]20171016@csiic.edu.cn, [2]20161020@csiic.edu.cn

Corresponding author: Beibei Hou, 20171016@csiic.edu.cn

Abstract. This article uses the DL (Deep Learning) model and CAD collaborative design platform to realize accurate recognition of regional symbols and multi-person online collaborative design. Firstly, the paper introduces the importance of regional symbol recognition and its application background in cultural inheritance. It also expounds on the limitations of current traditional design methods and the necessity of introducing new technologies to improve them. Then, the research methods are described in detail, including key steps such as data collection and processing, DL model construction and training, and CAD collaborative design platform construction and application. The experimental findings reveal that in comparison to PSO (Particle Swarm Optimization), RNN (Recurrent Neural Network), and BPNN (Back Propagation Neural Network), the CNN (Convolutional Neural Network) used in this study exhibits superior accuracy, recall, and F1 score, all-surpassing 90%. Notably, the recall stands at an impressive 94%, with the accuracy hovering around 92%. Additionally, user feedback indicates a widespread belief among users that this technology enhances their ability to access regional cultural information effortlessly, thereby boosting design efficiency and quality. This study offers substantial backing for the digital preservation and inventive advancement of regional cultures. Moreover, it presents innovative concepts and approaches for technological advancement and industrial upgrading in associated domains.

Keywords: Deep Learning; Convolutional Neural Network; Regional Symbol Recognition; CAD Collaborative Design; Cultural Heritage
DOI: https://doi.org/10.14733/cadaps.2024.S26.15-29

1 INTRODUCTION

As an important cultural symbol, intangible cultural heritage has showcased our Chinese nation's cultural ideas and skills for thousands of years. With the development of the times, the inheritance of intangible cultural heritage can not only meet the needs of economic and social development and serve the advancement of national strategies but also enhance the vitality and influence of traditional Chinese culture [1]. With the development of network technology and the increasing demand for

© 2024 U-turn Press LLC, http://www.cad-journal.net

intangible cultural heritage inheritance, China has been actively exploring new ways to promote the inheritance and protection of intangible cultural heritage in our country. The integration of knowledge and technology is constantly being strengthened among various fields, opening up new opportunities for the inheritance of intangible cultural heritage resources and culture. Digital narrative is a new tool and approach that expresses information through digital media and widely promotes it through storytelling. It has the characteristics of digitization, storytelling, and interactivity and can integrate elements of time, space, media, and effect narrative with a wide range of application scenarios.

Bozorgi and Lischer-Katz [2] attempted to use digital narrative as a unique perspective for studying the inheritance of intangible cultural heritage, using methods such as literature research, conceptual analysis, and case analysis. An in-depth analysis of the research background and current situation related to the inheritance of intangible cultural heritage has been conducted, and it has been found that the inheritance of intangible cultural heritage under the drive of cultural digitization strategy and emerging technologies has unprecedented development momentum and opportunities. On the basis of analyzing the concepts of digital narrative and intangible cultural heritage digital narrative, it analyzes the opportunities and challenges of inheriting intangible cultural heritage digital narrative in China from the macro environment, technological environment, and new user needs. By analyzing the elements of digital narrative in typical cases of intangible cultural heritage, we have extracted the spatiotemporal, media, and effect elements of digital narrative in intangible cultural heritage inheritance. We have constructed a path for intangible cultural heritage inheritance from the perspective of digital narrative, including spatiotemporal scenes, interactive media, and narrative experiences. This provides a reference for the dissemination and enhancement of public awareness and deep participation in the inheritance of intangible cultural heritage in China [3]. This not only improves the efficiency of embroidery production but also reduces the error rate of manual operations, injecting new vitality into the inheritance and development of embroidery skills. In recent times, the swift advancement of DL technology has sparked a transformative breakthrough in image recognition, presenting a fresh opportunity for the automated identification of regional symbols. In the digital age, artificial intelligence is gradually penetrating various fields, providing new possibilities for the inheritance and innovation of traditional art forms. As one of the cultural treasures of the Chinese nation, Xizang painting has been widely concerned with its unique artistic style and profound cultural connotation. Chen et al. [4] have provided a new idea and method for the creation of Xizang painting style fusion works with the help of circular consistency network model artificial intelligence. The cyclic consistency network model is an image processing technique based on deep learning, which can transform and fuse between different styles, achieving the transfer and fusion of image styles. This model trains a large amount of data to learn the inherent connections and transformation rules between different styles, thereby endowing it with new style features while maintaining the original image content.

With the continuous development of modern technology, people are eager to combine traditional ink painting elements with modern reality images to create novel and creative art forms. Boundary Enhanced Generative Adversarial Networks (BE-GAN) provide the possibility to achieve this vision. Chung and Huang [5] used two opposing networks - a generator and a discriminator - to achieve image generation and discrimination. On the basis of GAN, the boundary enhancement generative adversarial network further emphasizes the processing and enhancement of image boundaries. This enables the generated image to present details and boundary information more finely while maintaining the overall structure. The application of boundary-enhanced generative adversarial networks in the interactive transformation between traditional Chinese ink painting and real images not only provides new ideas and methods for artistic creation but also provides technical support for the inheritance and innovation of cultural heritage. Additionally, computer-aided design technology has gained widespread application in architecture and handicraft design fields. However, effectively integrating regional symbols with CAD technology to achieve innovative preservation and advancement of regional culture remains a pressing challenge. Parallel human-machine collaborative painting, as the name suggests, refers to the collaborative process of human artists and intelligent machines in the virtual space of the metaverse to complete the creation of painting works. This paradigm breaks the limitations of traditional painting and combines the imagination of artists with

© 2024 U-turn Press LLC, http://www.cad-journal.net

the intelligence of machines, achieving deep interaction and collaboration between humans and machines. In the metaverse, artists can enter a virtual painting space through virtual reality devices and work together with intelligent machines to conceive, design, and draw works. Intelligent machines can automatically complete some tedious painting tasks, such as outlining lines and filling colors, based on the artist's instructions and style preferences, while the artist can devote more energy to the creativity and conception of the work [6]. This study aims to investigate the identification approach of regional symbols utilizing DL and integrate it with CAD collaborative design technology. Through this, we aspire to introduce novel concepts and methodologies for the digital safeguarding and continuation of regional culture.

The core components of this study encompass: (1) Constructing a DL-driven model for recognizing regional symbols, aiming to automate their identification and categorization; (2) Investigating collaborative techniques between regional symbol design and CAD to foster the creative continuation and advancement of regional culture; (3) Validating the study's approach through simulation tests.

The study's novel contributions are highlighted below: (1) Introducing a DL-based approach for regional symbol recognition, capable of independently learning sophisticated symbol features, thereby enhancing recognition precision and durability; (2) Integrating DL with CAD for collaborative design, aiming to digitally extract and innovatively utilize regional symbols; (3) Confirming the method's effectiveness via simulation experiments, paving the way for fresh perspectives and strategies in digitally preserving and promoting regional culture.

This article comprises seven distinct sections.

Section I: The Introduction section primarily presents the backdrop and significance of the research, along with its current status, core content, innovations, and the overall structure of the article.

Section II: The recognition of regional symbols and cultural inheritance are summarized, and the role of regional symbols in cultural inheritance and the limitations of traditional recognition methods are analyzed.

The III: introduces the theoretical basis and related technologies of DL, providing theoretical support for the follow-up research.

Section IV: The method of regional symbol recognition based on DL is elaborated in detail, including key steps such as data set construction, model design and training strategy.

Section V: This section explores the utilization of CAD collaborative design technology in preserving regional culture and proposes an integration approach for regional symbols and CAD collaborative design.

Section VI: The application effect of the proposed method in cultural inheritance is demonstrated through concrete examples, and the experimental results are evaluated and analyzed.

Section VII: This section provides a concise overview of the primary accomplishments and efforts undertaken in this study, while also highlighting areas of potential improvement and future research opportunities.

2 RESEARCH STATUS

In terms of research content, discussing intangible cultural heritage from a narrative perspective can provide reference and research inspiration for subsequent researchers. Taking digital narrative as the starting point of theoretical research, innovative concepts related to the digital narrative of intangible cultural heritage were proposed, and in-depth research was conducted on the opportunities and challenges of digital narrative for the inheritance of intangible cultural heritage. In addition, a key analysis will be conducted on the elements of digital narrative, proposing narrative path suggestions for the inheritance of intangible cultural heritage from three aspects: temporal and spatial elements, media elements, and effect elements. Through continuous analysis and research, Han et al. [7]

© 2024 U-turn Press LLC, http://www.cad-journal.net

combined digital narrative theory and introduced new disciplinary foundations to establish a multidisciplinary research method. Integrating research with practice to establish a fundamental discipline for the inheritance of intangible cultural heritage. To promote the inheritance and protection of intangible cultural heritage, and provide guidance and support for the construction of related disciplines, it can make up for the shortcomings in single-discipline research. Pierdicca et al. [8] reviewed the current research status of intangible cultural heritage inheritance and digital narrative and explored the main concepts of digital narrative, intangible cultural heritage, and intangible cultural heritage digital narrative. With the development of digital technology, digital storytelling has become an inevitable trend in the inheritance of intangible cultural heritage. Digital technology not only affects the development of various fields but also has a positive promoting effect on the inheritance of intangible cultural heritage. The use of digital information technology can optimize resource management methods, create intangible cultural heritage project archives to strengthen protection efforts and use digital information systems for inheritance. Specifically, digital technology can optimize the storage methods of intangible cultural heritage resources by collecting a large amount of traditional textual information, collecting, processing, and forming a permanent database, laying a solid foundation for the inheritance of intangible cultural heritage. At the same time, digital technology can also promote in-depth research on intangible cultural heritage, and improve the research level of intangible cultural heritage inheritance through various digital resources; Finally, digital technology can further analyze intangible cultural heritage resources and related data information, ensuring that intangible cultural heritage projects can be updated and improved in a timely and effective manner. The application of digital narrative in the inheritance of intangible cultural heritage conforms to the inherent laws of the development of intangible cultural heritage in the digital era, opening up new horizons for the inheritance of intangible cultural heritage, attracting more attention and participation, and inheriting China's excellent traditional culture. Radosavljevi and Ljubisavljevi [9] digitize cultural heritage, allowing museums not only to better preserve and showcase these precious cultural relics but also to utilize advanced technological means to enhance the recognition of museum area symbols, further promoting the protection and research of cultural heritage. The digitization of cultural heritage is the process of transforming physical cultural relics into digital form. It accurately records the form, colour, texture and other detailed information of cultural relics through high-definition scanning, 3D modelling and other technical means. This digital form not only facilitates the preservation and transmission of cultural relics but also enables more people to appreciate this precious cultural heritage through the Internet and other channels. At the same time, digital technology also provides a more convenient and efficient means for the study of cultural relics. Researchers can analyze and compare digital cultural relics to deeply explore their historical background, cultural connotations, and artistic value. Driven by the digital wave, the protection of digital cultural heritage is increasingly valued. The region symbol recognition technology based on deep learning has injected new vitality into this field, helping us collaborate to discover those long-lost museum treasures. Through digital means, Schuster and Grainger [10] present cultural heritage to the public in a new way, allowing more people to understand and appreciate these treasures of human civilization. Deep learning, as a branch of artificial intelligence, plays an important role in regional symbol recognition with its powerful feature learning and classification capabilities. By training a large number of cultural relic images, deep learning models can automatically learn and extract the features of symbols, thereby achieving accurate recognition of specific region symbols. This technology not only improves the accuracy and efficiency of identification but also provides strong support for the research and protection of cultural relics.

Sun et al. [11] proposed a cultural heritage collaborative creation and drawing system based on Generative Adversarial Networks (GANs), aiming to promote innovative development and diversified applications of cultural heritage through human-machine collaboration. The system is centred around generating adversarial networks and achieves style transformation, feature extraction, and creative generation of cultural heritage images by constructing deep learning models. Specifically, the system first utilizes a large amount of cultural heritage image data for training, learning the characteristics and patterns of traditional art styles. Then, users can select the cultural heritage elements and styles they are interested in through the interactive interface provided by the system, and set

© 2024 U-turn Press LLC, http://www.cad-journal.net

corresponding parameters and conditions. The deep learning-based regional symbol recognition technology provides new possibilities for the protection and inheritance of intangible cultural heritage. However, in practical applications, the silence and memory issues encountered by intangible cultural heritage policies are worth pondering. Toji's [12] feature learning and classification capabilities using deep learning techniques provide effective analysis for regional symbol recognition. In the field of intangible cultural heritage, training cultural relics, patterns, symbols, etc. through deep learning models can achieve automatic recognition and classification of intangible cultural heritage elements in specific areas. This not only helps us better understand and document intangible cultural heritage projects but also provides a scientific basis for the protection and inheritance of intangible cultural heritage.

Artistic and cultural heritage, as a treasure of human civilization, its style and characteristics are not only a witness to history but also a source of cultural innovation. However, traditional methods of artistic style transformation often face problems such as irreversibility and limitations, which cannot meet the diverse needs of modern art creation. Therefore, Wang et al. [13] analyzed a network-based reversible art and cultural heritage style transformation method, providing new ideas for the protection and innovation of cultural heritage. During the style conversion process, users can select the target style and input the image to be converted into the network. The network performs style transformation on the original image based on the feature vector of the target style, generating an image with the target style. At the same time, in order to keep the content and structural information of the original image unchanged, this method adopts a content loss function to ensure the visual consistency of the converted image. Xu et al. [14] explored how to utilize prompt-based reinforcement learning techniques to achieve stylistic transitions between traditional classical Chinese and modern Chinese. Traditional classical Chinese, as an important component of Chinese culture, has unique language characteristics and ways of expression. At present, the digital narrative inheritance of intangible cultural heritage is facing many opportunities, including the establishment of a sound national intangible cultural heritage inheritance system and the promulgation of laws and regulations. It has laid a solid foundation for the inheritance of intangible cultural heritage, and the continuous improvement of people's awareness of inheritance and development concepts. It has awakened people's cultural confidence and interest in exploring intangible cultural heritage. With the rapid development of digital technology, the necessity of applying digital narrative in the inheritance of intangible cultural heritage continues to increase, and the application of digital narrative is a positive promotion of national policies [15]. It is the positive empowerment of digital media and a way to improve user experience needs. The cross-integration of various industries and media also provides more possibilities for the inheritance of intangible cultural heritage digital narratives.

3 REGIONAL SYMBOL RECOGNITION AND CULTURAL INHERITANCE

3.1 Concept and Classification of Regional Symbols

Regional symbols refer to graphics, patterns, symbols, or texts with specific regional cultural connotations and symbolic meanings, which are important components of the unique culture of a certain region. Regional symbols not only carry the historical memory, folk customs, and artistic style of the region but also reflect the lifestyle and aesthetic concepts of the local residents. According to different classification standards, regional symbols can be divided into multiple types, as shown in Table 1.

Division standard	*Geographical symbol type*	*Illustration*
Expression form	graphic symbol	Such as the outline of landmark buildings in a specific area.
	Pattern Symbol	Such as characteristic patterns on national costumes and carpet patterns.
	letter symbol	Such as the written expression of local dialects and ancient Chinese characters.

© 2024 U-turn Press LLC, http://www.cad-journal.net

Cultural connotation	Historical symbol	Such as historical sites and landmarks in historical events.
	Folk symbol	Such as props and folk dances during traditional festivals and customs.
	Artistic symbol	Such as facial makeup and musical instruments in local operas.

Table 1: Classification table of geographical symbols.

3.2 The Role of Regional Symbols in Cultural Inheritance

Digital media can also expand promotion and sales channels for the inheritance industry. By promoting through digital media platforms such as the internet, it is easier to attract young people, and it has included some projects for intangible cultural heritage research tours, promoting the popularization of cultural and artistic works. Intangible cultural heritage has also driven the development of the local tourism industry. Being welcomed by the public not only promotes the traditional culture of intangible cultural heritage but also promotes the development of high-tech in inheriting and developing traditional culture. The cross-integration of digital media technology and the inheritance industry will inject new vitality and energy into the inheritance and development of traditional cultural and artistic works, promoting their continued development and inheritance in modern society.

3.3 Application Potential of DL in Regional Symbol Recognition

Digital media provides various forms and channels for the digital narrative of intangible cultural heritage and achieves the inheritance and promotion of intangible cultural heritage through digital means. Specifically, the empowerment of digital media in the digital narrative of intangible cultural heritage is reflected in multimedia methods, which can be used for the inheritance and promotion of intangible cultural heritage. The combination of various forms such as text, images, audio, video, etc. enriches the presentation of intangible cultural heritage. Cross-temporal and spatial communication. Digital media can realize cross-temporal and spatial communication around the world through the Internet so that intangible cultural heritage can be spread around the world. The interactive nature of digital media enables viewers or users to communicate with intangible cultural heritage through online channels, promoting the integration of intangible cultural heritage and modern society. Digital media can digitize the management of intangible cultural heritage-related data, ensuring the inheritance and recording of intangible cultural heritage culture and also providing convenience for related research.

4 DL THEORETICAL BAS

4.1 Basic Principles of DL and NN

Each neuron within this network receives signals from its peers and produces output signals based on its internal state and assigned weights. For a visual representation of the basic neuron structure, refer to Figure 1. The learning process of NN is to minimize the loss function by adjusting the connection weights between neurons to fit the input-output relationship in the training data. According to the different network structures and training methods, NN can be divided into many types, such as feedforward NN, RNN, CNN, etc.

4.2 CNN and its Application in Image Recognition

CNN represents a specialized NN architecture tailored for image data processing. By sequentially stacking convolution layers, pooling layers, and fully connected layers, it progressively extracts and abstracts image features.

© 2024 U-turn Press LLC, http://www.cad-journal.net

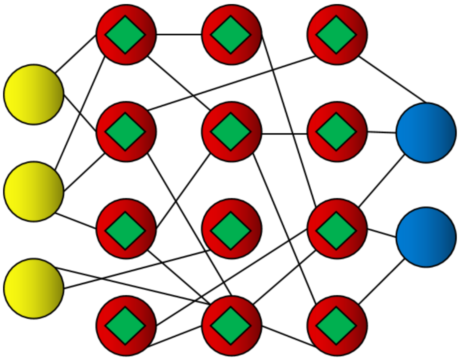

Figure 1: Basic neuron structure.

Specifically, convolution layers capture local image features by sliding convolutional operations over the image using convolution kernels, resulting in a feature map. Subsequently, pooling layers downsample this feature map, reducing data dimensionality and bolstering feature robustness. Finally, fully connected layers map the extracted features onto the sample label space, facilitating classification or regression tasks. The mathematical formulae involved in CNN training are as follows:

$$x_i = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}} \tag{1}$$

Among them, x_i is the input component, which is the i nerve cell component before pretreatment; $x_{\min}$ and $x_{\max}$ are the minimum and maximum values, respectively, and they are the minimum and maximum values of all input components of the i neuron. Because CNN can automatically learn the high-level feature representation of images, it has made a breakthrough in the field of image recognition and is widely used in tasks such as face recognition, target detection, and scene classification.

5 DL-BASED REGIONAL SYMBOL RECOGNITION METHOD

5.1 Dataset Construction and Preprocessing

In the task of regional symbol recognition, the construction of a data set is a crucial first step. In order to train an effective DL model, it is needed to collect a large number of labelled regional symbol image samples. These samples can be obtained from public databases, historical documents, field shooting and other channels. When creating a dataset, emphasis must be placed on ensuring diverse, balanced, and accurately labeled samples, thereby guaranteeing that the model can grasp the fundamental traits of regional symbols.

Data preprocessing holds the utmost importance in enhancing the model's performance. Initially, it is imperative to normalize the image, adjusting its pixel values to a standardized range. This helps mitigate the effects of illumination and contrast on recognition results. For normalization, this article adopts a formula that scales the input to fall within the [0,1] range:

$$X = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \tag{2}$$

Where X represents the normalized CNN input value; I stands for unprocessed CNN input value; $I_{\max}$ represents the maximum value of CNN input; $I_{\min}$ represents the minimum value of CNN input. The standardization process converts the pixel values of an image into a standard normal distribution. The formula is:

© 2024 U-turn Press LLC, http://www.cad-journal.net

$$x' = \frac{x - \min\ x}{\max\ x\ - \min\ x} \tag{3}$$

Where x is the average of pixel values and x' is the standard deviation of pixel values. Secondly, according to the actual needs, data enhancement technology can be used to expand the data set, such as rotation, scaling, translation and other operations to increase the generalization ability of the model. For samples with inaccurate labelling or noise, cleaning and screening are carried out to ensure the quality of training data.

5.2 DL Model Design

According to the task characteristics of regional symbol recognition, we need to design a suitable DL model. Considering the complexity and diversity of regional symbols, this article chooses CNN as the basic model and improves and optimizes it according to the actual needs. In CNN, increase the number and depth of convolution layers to extract more abstract and high-level features; The attention mechanism is introduced to make the model pay attention to the key parts of symbols; Multi-scale feature fusion strategy is adopted to capture different scale information of symbols. In the process of model design, we also need to consider the balance between model complexity and computational efficiency. Too complex a model may lead to over-fitting and waste of computing resources, while too simple a model may not fully capture the characteristics of regional symbols. Therefore, this article needs to choose the appropriate model structure and parameter settings according to the actual task requirements and computing resources. The improved and optimized CNN model is shown in Figure 2.

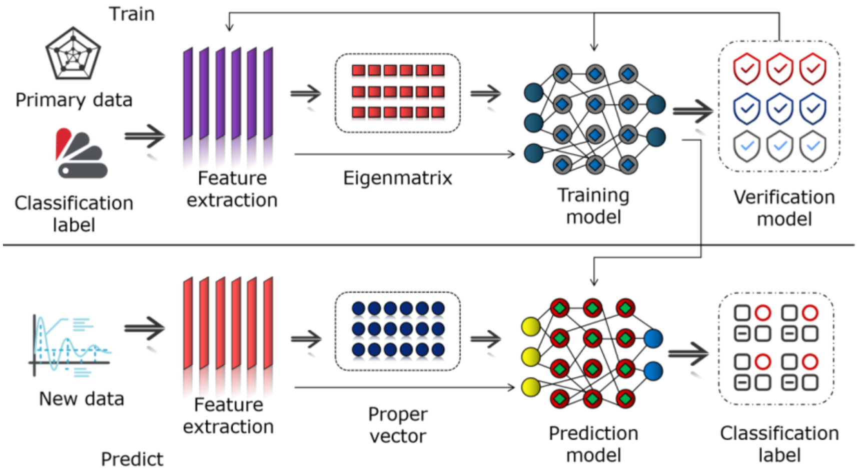

Figure 2: Improved and optimized CNN model.

During the training of the DL model, it is crucial to select an appropriate loss function that accurately quantifies the discrepancy between the model's predictions and the actual labels. For classification tasks, the cross-entropy loss function proves to be effective, while for regression tasks, the mean squared error loss function is preferred. Specifically, the cross-entropy loss function is utilized to assess the divergence between the predicted probability distribution and the true label distribution in binary or multi-classification scenarios. The formula for this function is as follows:

$$H\left(y, \hat{y}\right) = -\sum_i y_i \log\ \hat{y}_i \tag{4}$$

© 2024 U-turn Press LLC, http://www.cad-journal.net

Where y is the real label vector and $\hat{y}$ is the prediction probability vector.

The mean squared error loss function serves to predict continuous values and compute the average squared difference between the predicted and actual values. Its formula is expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} Y_i - \hat{Y}_i \ ^2 \tag{5}$$

Where n is the number of samples, Y_i what is the real value and $\hat{Y}_i$ what is the predicted value?

Furthermore, it is necessary to choose an appropriate optimization algorithm to update the weight parameters of the model. In this article, the Adam (Adaptive Moment Estimation) method is adopted. Adam is an optimization algorithm that combines moment estimation and momentum method. In this algorithm, first-order moment estimation calculates the average exponential attenuation of the gradient, which is used to capture the gradient trend. The formula is:

$$m_t = \beta_1 \cdot m_{t-1} + \ 1 - \beta_1 \ \cdot g_t \tag{6}$$

Where m_t is the first-order moment estimation at the time step t, β_1 is the attenuation coefficient of the first-order moment estimation (usually set to 0.9), and g_t is the gradient at the time step t?

Second-order moment estimation: calculate the exponential decay average of the square of the gradient, which is used to capture the change speed of the gradient. The formula is:

$$v_t = \beta_2 \cdot v_{t-1} + \ 1 - \beta_1 \ \cdot g_t^2 \tag{7}$$

Where a is the second-order moment estimation at the time step t, β_2 is the attenuation coefficient of the second-order moment estimation (usually set to 0.999), and g_t^2 is the gradient at the time step t?

Deviation correction: In order to make the average of m_t and v_t truly represent the moving average, deviation correction is needed. The deviation correction formula is as follows:

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \hat{v}_t = \frac{v_t}{1-\beta_2^t} \tag{8}$$

Where $\hat{m}_t$ and $\hat{v}_t$ are the corrected first-order and second-order moment estimates. Finally, the weights are updated by using the corrected first-order and second-order moment estimates:

$$\theta_{t+1} = \theta_t - \frac{\alpha \cdot \hat{m}_t}{\sqrt{\hat{v}_t} + \in} \tag{9}$$

5.3 Experimental Results and Performance Analysis

By comparing our approach with other DL methods, including PSO, RNN, and BPNN, we can effectively assess the model's performance. The accuracy comparison is visualized in Figure 3. The comparison of recall rates is shown in Figure 4. The comparison of F1 scores is shown in Figure 5.

The results show that compared with PSO, RNN, and BPNN, the accuracy, recall, and F1 scores of CNN in this article are better, and their scores are all above 90%. Among them, the recall rate is as high as 94%, and the accuracy rate is about 92%.

In addition, it is necessary to visually analyze the model to intuitively show the learning effect and feature extraction ability of the model. As shown in Table 2, the visual analysis results of the regional symbol recognition model are shown.

© 2024 U-turn Press LLC, http://www.cad-journal.net

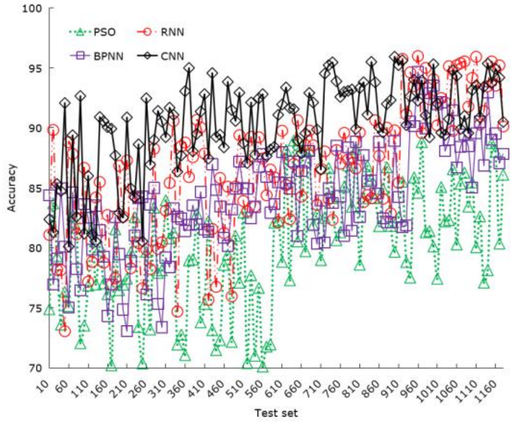

Figure 3: Accuracy comparison.

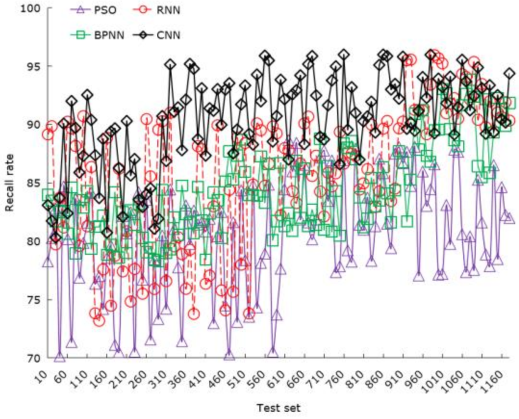

Figure 4: Comparison of recall rates.

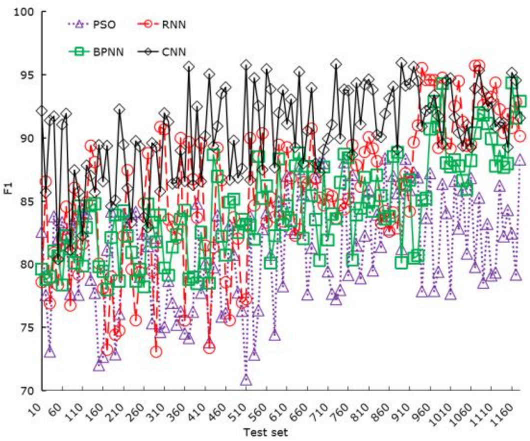

Figure 5: F1 score comparison.

© 2024 U-turn Press LLC, http://www.cad-journal.net

Visualization method	*Concerns/characteristics*	*Decision basis*	*Optimization suggestions*
Thermodynamic diagram	Symbol edge contour, colour distribution	Areas with clear edges and obvious colour contrast are more concerned	Enhance the feature extraction ability of symbol edges and colours
Saliency map	Internal texture and structural characteristics of symbols	The areas with complex textures and unique structures are more obvious	Enhance the recognition ability of internal texture and structural features
Class activation mapping	The overall shape and spatial layout of the symbols	Symbols with regular shapes and reasonable spatial layout are easier to identify	Optimization model's perception of the overall shape and spatial layout of symbols

Table 2: Visualization analysis results of regional symbol recognition model.

Remarks: Through visual analysis, we can intuitively understand the concerns and decision-making basis of the model in identifying regional symbols, and thus find out the possible shortcomings of the model and the direction that needs to be optimized. These optimization suggestions can provide guidance for further improvement of the model and improve the performance of regional symbol recognition.

6 ARCHITECTURE AND FUNCTION REALIZATION OF COLLABORATIVE DESIGN PLATFORM

As an important carrier of regional culture, regional symbols have rich cultural connotations and symbolic significance. Combining regional symbols with CAD collaborative design can realize the digital inheritance and innovative development of regional culture. Specifically, geographical symbols can be accurately modelled and rendered digitally by CAD technology and transformed into digital objects that can be edited and operated on computers. Then, using the collaborative design function of CAD, multiple designers can jointly edit and design regional symbols on the same platform, realizing the collision of design inspiration and the convergence of creativity. Finally, the design results will be transformed into actual products or buildings through CAD technology, and the modern expression and dissemination of regional culture will be realized.

In order to realize the effective combination of regional symbols and CAD collaborative design, it is needed to build a fully functional collaborative design platform. The platform should have the following basic structures and functions: firstly, it needs a stable and reliable server for storing and managing design data and user information; Secondly, an easy-to-use client interface is needed to support online editing and design by multiple people at the same time. Application of regional symbol recognition and CAD collaborative design in cultural inheritance

6.1 Application Scenario Analysis

In the development of cultural tourism products, the collaborative design technology of regional symbol recognition and CAD can help to develop tourist souvenirs and handicrafts with regional characteristics and cultural connotations. By accurately identifying regional symbols, representative cultural elements can be extracted, and creative design and product development can be carried out through CAD technology to meet the needs of tourists for characteristic cultural products and promote the spread of regional culture and economic development.

© 2024 U-turn Press LLC, http://www.cad-journal.net

6.2 Specific Implementation Steps and Processes

When implementing the application example of regional symbol recognition and CAD collaborative design technology, this article follows the following steps and processes:

First of all, data collection and processing work, including collecting relevant regional symbol sample data, sorting out and labelling data sets, etc. This step is the basis to ensure the accuracy of model training.

Next, the DL model is constructed to identify and classify regional symbols. By training and optimizing the model, the recognition accuracy and generalization ability of new data are improved.

Then, the feature elements and style information of regional symbols are extracted according to the recognition results, which provide a basis and guidance for the subsequent design work.

On this basis, a CAD collaborative design platform is built, and designers in related fields are invited to participate in the design work. Using CAD technology to make, modify and improve the design scheme, and realize multi-person collaborative editing and version control functions.

Finally, the design results will be transformed into actual products or architectural schemes, and subsequent work such as manufacturing or construction will be carried out (as shown in Figure 6).

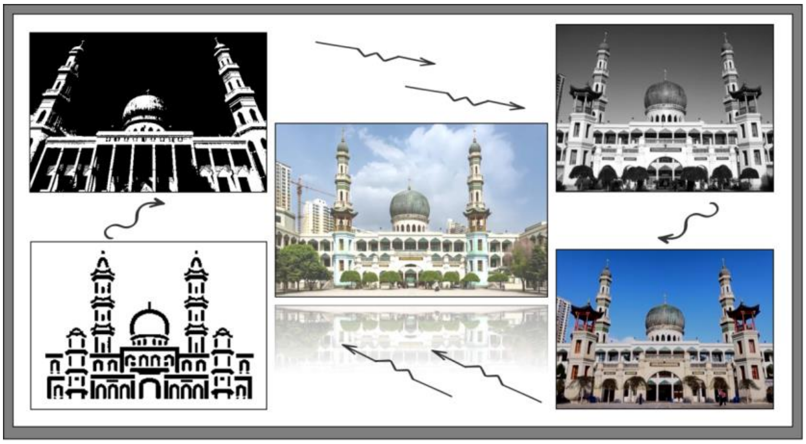

Figure 6: Display of design results.

Throughout the entire process, iterative refinement and optimization are essential to enhance design efficiency, elevate quality, and align with the practical demands of users.

6.3 Application Effect Assessment and User Feedback

After implementing an application example, it is needed to evaluate the application effect and collect user feedback. We can evaluate the application satisfaction, usability, accuracy and other indicators through questionnaires, user interviews, data analysis and other ways. Figure 7 shows the specific user feedback results. Figure 8 shows the design efficiency and quality comparison of different methods.

The assessment results show that the collaborative design technology of regional symbol recognition and CAD has achieved remarkable results in practical application. Users widely acknowledge that this technology facilitates easier access to regional cultural information while simultaneously enhancing design efficiency and quality. Additionally, they have offered valuable feedback and improvement requests, including suggestions to refine the recognition model's performance further and expand the diversity of design tools and resource libraries (refer to Table 3 for details).

© 2024 U-turn Press LLC, http://www.cad-journal.net

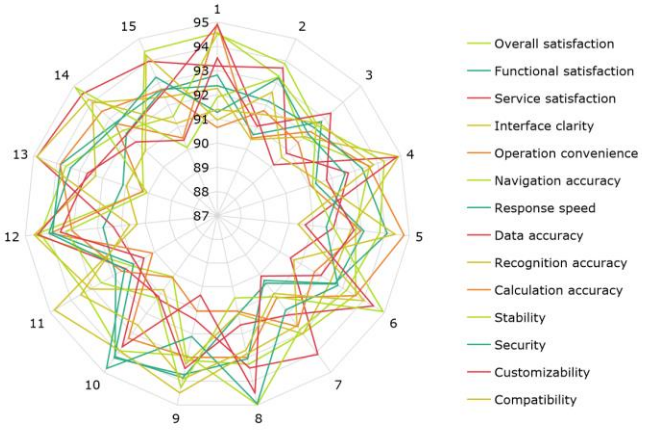

Figure 7: User feedback results.

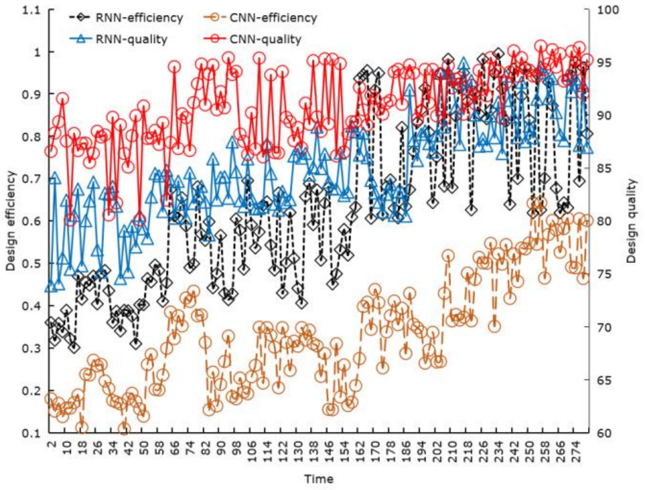

Figure 8: Comparison results of design efficiency and quality of different methods.

User Feedback	*Improvement suggestions*
The performance of the recognition model needs to be improved	Optimize model algorithms to improve recognition accuracy and speed
Insufficient richness in design tools and resource libraries	Increase the variety and quantity of design tools and resource libraries
Conflict resolution in collaborative design is not intelligent enough	Introducing more advanced conflict detection and resolution algorithms
Lack of interactivity and fun in cultural inheritance applications	Add interactive features and gamified elements to enhance user experience
Limited range of regional symbol recognition	Expand the types and scope of regional symbols in recognition models

Table 3: User feedback and improvement suggestions.

© 2024 U-turn Press LLC, http://www.cad-journal.net

According to the feedback from users, we summarized the relevant suggestions for improvement. These suggestions will serve as an important reference for the follow-up optimization work to meet the needs of users and improve the performance and user experience of the whole system.

In a word, the collaborative design technology of regional symbol recognition and CAD has a wide application prospect and great potential value in the field of cultural inheritance. By continuously optimizing and improving related technologies and platform functions, it can provide more powerful support and guarantee for the protection, inheritance and innovation of traditional culture.

7 CONCLUSIONS

This study focuses on the application of regional symbol recognition and CAD collaborative design technology in cultural inheritance. By constructing the DL model, the accurate identification and classification of regional symbols are realized, which provides strong support for the subsequent design work. Furthermore, combined with CAD collaborative design technology, multi-person online collaborative editing and version control functions are realized, which improves the design efficiency and quality. In various practical applications, this technology has found its place in diverse fields like traditional building restoration, national costume design, and cultural tourism product development, yielding impressive social and economic benefits.

During the research phase, this article tackled numerous obstacles, including intricate data collection and processing, demanding model training and refinement, and the technical complexities of establishing and managing a collaborative design platform. Through relentless experimentation and refinement, we've progressively refined our technologies and methodologies, bolstering the digital preservation and innovative advancement of regional cultures.

Looking ahead, there's potential to extend this technology's reach into other domains such as urban planning, landscape architecture, and film production, among others. This expansion would facilitate broader adoption and advancement of regional symbol recognition and CAD collaborative design technology. Moreover, it's imperative to consider the ethical and societal implications of this technology to ensure its responsible and sustainable growth.

8 ACKNOWLEDGEMENTS

This work was supported by Shaanxi Provincial Philosophy and Social Science Research Special Project: "Research on the Integration Path of Qiang Culture and Tourism in Southern Shaanxi under the Background of Rural Revitalization" (Project Number: 2023HZ1601); Shaanxi Intangible Cultural Heritage Digital Inheritance and Cultural and Creative Design Research Center, a scientific research institution affiliated with the Department of Fashion Arts, Shaanxi Institute of International Trade & Commerce.

Beibei Hou, https://orcid.org/0009-0007-9874-9827
Chuanyu Zhou, https://orcid.org/0009-0000-6269-6347

REFERENCES

[1] Bekele, M.-K.: Clouds-based collaborative and multi-modal mixed reality for virtual heritage, Heritage, 4(3), 2021, 1447-1459. https://doi.org/10.3390/heritage4030080
[2] Bozorgi, K.; Lischer-Katz, Z.: Using 3D/VR for research and cultural heritage 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
[3] Chen, L.; Su, Z.; He, X.; Chen, X.; Dong, L.: The application of robotics and artificial intelligence in embroidery: challenges and benefits, Assembly Automation, 42(6), 2022, 851-868. https://doi.org/10.1108/AA-07-2022-0183

© 2024 U-turn Press LLC, http://www.cad-journal.net

[4] Chen, Y.; Wang, L.; Liu, X.; Wang, H.: Artificial intelligence-empowered art education: a cycle-consistency network-based model for creating the fusion works of Tibetan painting styles, Sustainability, 15(8), 2023, 6692. https://doi.org/10.3390/su15086692
[5] Chung, C.-Y.; Huang, S.-H.: Interactively transforming Chinese ink paintings into realistic images using a border enhance generative adversarial network, Multimedia Tools and Applications, 82(8), 2023, 11663-11696. https://doi.org/10.1007/s11042-022-13684-4
[6] Guo, C.; Dou, Y.; Bai, T.; Dai, X.; Wang, C.; Wen, Y.: Artverse: A paradigm for parallel human-machine collaborative painting creation in metaverses, IEEE Transactions on Systems, Man, and Cybernetics: Systems, 53(4), 2023, 2200-2208. https://doi.org/10.1109/TSMC.2022.3230406
[7] Han, X.; Wu, Y.; Wan, R.: A method for style transfer from artistic images based on depth extraction generative adversarial network, Applied Sciences, 13(2), 2023, 867. https://doi.org/10.3390/app13020867
[8] 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
[9] Radosavljevi, Z.; Ljubisavljevi, T.: Digitization of cultural heritage as a potential for increasing museum attendance in Central Serbia, Bizinfo Blace, 10(1), 2019, 53-67. https://doi.org/10.5937/bizinfo1901053R
[10] Schuster, K.; Grainger, J.: Digital cultural heritage: Collaborating with students and discovering lost museums, Education for Information, 37(1), 2021, 97-111. https://doi.org/10.3233/EFI-190352
[11] Sun, L.; Chen, P.; Xiang, W.; Chen, P.; Gao, W.-Y.; Zhang, K.-J.: SmartPaint: a co-creative drawing system based on generative adversarial networks, Frontiers of Information Technology & Electronic Engineering, 20(12), 2019, 1644-1656. https://doi.org/10.1631/FITEE.1900386
[12] Toji, S.: Floating sentiments: silence and memory in the encounter between the celebration of Tooro Nagashi and the intangible cultural heritage policy in Brazil, International Journal of Heritage Studies, 29(4), 2023, 260-274. https://doi.org/10.1080/13527258.2023.2181378
[13] Wang, M.; Shao, Y.; Liu, H.: APST-flow: a reversible network-based artistic painting style transfer method, Computers, Materials & Continua, 75(3), 2023, 5229-5254. https://doi.org/10.32604/cmc.2023.036631
[14] Xu, M.; Peng, M.; Liu, F.: Text style transfer between classical and modern Chinese through prompt-based reinforcement learning, World Wide Web, 26(2), 2023, 733-750. https://doi.org/10.1007/s11280-022-01083-6
[15] Zhong, Y.; Huang, X.: A painting style system using an improved CNN algorithm, IEEE Transactions on Smart Processing & Computing, 11(5), 2022, 332-342. https://doi.org/10.5573/IEIESPC.2022.11.5.332

© 2024 U-turn Press LLC, http://www.cad-journal.net