Art Design Style Mining Based on Deep Learning and Data Mining

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Abstract. The art design style is a unique visual feature formed by an artist or designer in the process of creation, which embodies the artistic accomplishment, aesthetic concept, and technical means of the creator. In this article, deep learning (DL) and data mining (DM) technologies are combined to mine art design style information and integrate it with computer-aided design (CAD) systems so as to realize the intelligent upgrade of CAD systems. Through real-time style suggestions and design scheme optimization, designers can find the design style that meets their needs more quickly. In order to achieve this goal, a series of optimization strategies are proposed, including improving feature extraction methods, introducing more effective learning algorithms, and adjusting parameters. Through experimental verification, it is found that these strategies significantly improve the accuracy of artistic style transfer and greatly shorten the processing time. The optimized algorithm can learn and express the characteristics of artistic style more accurately while maintaining high efficiency when dealing with large-scale data. The research results have laid a solid foundation for the growth of CAD art design and provided valuable reference and enlightenment for future research.

Keywords: Deep Learning; Art Design; Data Mining; CAD; Style Transfer
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1 INTRODUCTION

With the rapid growth of computer technology, AI has gradually penetrated into all fields of society. As an important branch of AI, DL has made remarkable achievements in image identification, natural language processing, and speech identification. The research, protection, and management of rock art are gradually receiving attention from people. As a new type of detection and analysis method, hyperspectral imaging technology has the characteristics of high spectral resolution and multispectral imaging, providing a new approach for the research, protection, and management of rock art. Bayarri et al. [1] explored how to combine deep learning techniques with hyperspectral imaging technology to study, protect, and manage rock art. Deep learning techniques can help us better understand and analyze rock art. By training deep learning models, we can automatically classify and recognize

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hyperspectral images and extract features and styles of rock art. In addition, deep learning can also be used for the automatic recognition and classification of rock paintings, providing more accurate data and stronger support for research. Hyperspectral imaging technology can provide high-precision detection and analysis of rock art, discovering its microstructure and composition. This helps us to better understand the production methods and techniques of rock art, providing a more scientific basis for its protection. Meanwhile, hyperspectral imaging technology can also be used for disease detection and prevention in rock art, timely detecting and dealing with potential diseases, and extending the service life of rock art. The art design style is a unique visual feature formed by an artist or designer in the process of creation, which embodies the artistic accomplishment, aesthetic concept, and technical means of the creator. Art design style is not only epochal, regional, and national but also an important driving force for continuous innovation in art and design. The digital twin technology based on operation images in deep learning-based art design of large-scale structures is an emerging technology with broad application prospects. By combining deep learning and digital twins, we can better achieve real-time monitoring, safety evaluation, performance optimization, and artistic design effect evaluation of large structures. Digital twin technology has been widely applied in various fields, especially in the field of artistic design of large structures. Digital twin technology achieves real-time monitoring, prediction, and optimization of physical objects by establishing a close connection between physical objects and virtual models. Deep learning technology provides powerful analysis and processing capabilities for digital twins, making their application in the art and design of large-scale structures more extensive and in-depth. Deep learning can automatically optimize the model parameters of digital twins by analyzing historical data, improving the prediction accuracy and stability of the model. Deep learning can automatically detect abnormal situations and issue timely warnings through the analysis of real-time data, providing a basis for maintenance and management. It can also provide scientific decision support for decision-makers by mining and analyzing a large amount of data, improving the accuracy and efficiency of decision-making [2].

Art design based on deep learning provides artists with a brand new creative platform, especially by constructing virtual spaces on the canvas, which can create unique works of art and enhance the experience. Deep learning technology has brought revolutionary changes to art and design. By training deep neural networks, artists can automatically generate unique artworks, greatly improving the efficiency and diversity of their creations. Building a virtual space on the canvas can expand artistic works from traditional two-dimensional planes to three-dimensional space. This virtual space can not only display static artwork but also bring a more immersive experience to the audience through dynamic visual effects and interactive design. Artists can use technologies such as virtual reality and augmented reality to bring audiences into a completely new world of art. The combination of deep learning and virtual space can capture the artist's creative information and intention, bringing a more in-depth "enhanced" experience to the audience. For example, artists can use deep learning techniques to analyze audience behavior and feedback, continuously optimizing the display effect and interaction design of virtual spaces. At the same time, the audience can also gain a deeper understanding of the artist's creative process and intention through interaction with the virtual space, improving their understanding and appreciation of artistic works [3]. However, the traditional art design style analysis method mainly relies on experts' subjective judgment and experience summary, lacking objectivity and quantification. CAD technology supports designers to carry out efficient and accurate design work through digital means. In historical painting, big data mining and analysis techniques provide new perspectives and tools for studying the evolution of Suzhou's artistic design style and living environment during the Ming and Qing dynasties. Ding et al. [4] explored how to use big data technology to deeply explore and analyze information in historical paintings in order to reveal the evolution of Suzhou's artistic design style and living environment during the Ming and Qing dynasties. Big data technology provides massive data resources and analysis tools for historical painting research. Through data mining and analysis of a large number of historical paintings, rich information on artistic design styles and living environments can be obtained. These pieces of information can provide us with a deeper and more comprehensive understanding of the social, cultural, and artistic landscape of Suzhou during the Ming and Qing dynasties. Through big data

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technology, in-depth analysis can be conducted on the art and design styles of Suzhou during the Ming and Qing dynasties. For example, analyzing the styles, colors, and compositions of elements such as architecture, gardens, and clothing in painting, exploring the cultural connotations and social significance behind them. In addition, big data technology can also be used for style classification and trend prediction, providing reference and inspiration for modern art and design. However, the traditional CAD system mainly focuses on the modeling of geometric shapes and functional requirements and relatively little consideration is given to art design style. How to integrate the art design style information mined by DL with CAD systems to provide designers with more comprehensive and intelligent design support is a challenging research topic.

With the continuous development of digital image processing and computer vision technology, understanding artistic image scenes has become a highly focused research field. Deep learning, especially convolutional neural networks (CNNs) and object detection algorithms provide powerful tools for understanding artistic image scenes. Gu et al. [5] explored how to use deep learning techniques for art scene classification and object detection. The application of deep learning in image classification has achieved significant results. By training deep neural networks, we can automatically extract features from images and classify them based on these features. In art image scene classification, deep learning can help us identify scene types in images, such as landscapes, still life, people, etc. By training large-scale art image datasets, we can develop deep neural network models with high generalization ability for the automatic classification of art image scenes. Deep learning has broad application prospects in understanding artistic image scenes. In addition to scene classification and object detection, deep learning can also be used in fields such as scene segmentation, sentiment analysis, and style transfer. Automatic painting refers to the process of generating artistic works using computer algorithms and robot technology. Compared with traditional art creation, automatic painting has higher efficiency and richer creative possibilities. Through programming and algorithm design, painting robots can mimic the painting techniques and styles of human artists and even create new artistic styles. Artificial creativity refers to the use of computer technology to simulate and realize human creativity. In the field of painting, artificial creativity can achieve collaborative creation between machines and human artists through collaboration with artists. This collaborative creation can not only improve the efficiency and quality of artistic creation but also provide artists with new creative inspiration and ideas. Gülzow et al. [6] explored more artistic styles and techniques through collaboration with painting robots, thereby enriching their artistic language. Machine learning is a computer science that learns from data and makes predictions or decisions. In the application of painting robots, machine learning can help us explore and understand the artistic style of robots. Through data analysis and learning of a large number of artworks, machines can identify different artistic styles and features and apply them to the creation of painting robots. Some researchers have made useful attempts to apply DL to art design style mining.

Digital art and virtual reality technology provide new possibilities for the innovation of traditional art forms. Chinese landscape painting and classical private gardens, as representatives of traditional Chinese art, have always received attention for their unique artistic style and aesthetic value. Hong et al. [7] explored how to use deep neural networks to achieve artistic aesthetic style transformation between Chinese landscape painting and virtual scenes of classical private gardens. By training deep neural networks, one can learn the features and forms of various artistic styles and use these features for style transformation. In virtual scenes, deep neural networks can be used to generate images, textures, and lighting effects with specific artistic styles to create unique virtual environments. Chinese landscape painting and classical private gardens share common artistic styles, such as emphasizing natural beauty and pursuing profound artistic conception. Through deep neural networks, we can quantitatively analyze and extract features of these art styles. With the rapid development of digital technology and the Internet, the dissemination and display of artistic images are also constantly changing. In order to better understand and appreciate art images, Jaspe et al. [8] proposed a web-annotated multi-layer reimaginable art image model based on deep learning. The application of deep learning in the field of image processing has achieved significant results. By training deep neural networks, it is possible to automatically extract features from images and perform tasks such as classification, recognition, and generation. In art image processing, deep

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learning can help us achieve automated annotation, style conversion, content generation, and other functions, providing new ideas and methods for art creation and appreciation. This model has broad application prospects in the field of art. For example, museums, galleries, and art websites can use this model to provide users with a more intelligent and interactive art appreciation experience. Artists and educators can use this model to assist in creation, teaching, and presentation. Ordinary users can also better understand and appreciate artworks through this model, improving their aesthetic level. The application of computer-aided design software in the field of environmental art design is becoming increasingly widespread. This software provides designers with powerful tools that enable them to carry out design work more efficiently. In environmental art design, computer-aided design software also plays an important role. Jin and Yang [9] discussed the application of computer-aided design software in environmental art design. Computer-aided design software provides precise drawing tools and parameter settings, enabling designers to express design intentions more accurately. This helps to better grasp the accuracy and detail handling of design during the learning process. With the rendering function of the software, designers can generate realistic renderings that showcase the colors, lighting, and texture of the design.

At present, the research mainly focuses on the identification and migration of a single artistic style, but the excavation and application of multiple art design styles are still insufficient. In this article, an integrated application method of art design style mining and CAD based on DL is proposed. Firstly, DL technology is used to study and analyze a large number of works of art, and the characteristics of the art design style are excavated. Then, these style features are combined with a CAD system to provide real-time style suggestions and design scheme optimization for designers. The significance of this study lies in:

(1) This article proposes to automatically extract and analyze the characteristics of art design style through DL technology, which reduces the dependence on the experience of traditional experts and provides a more objective and quantifiable method for the study of art design style.

(2) Integrating the art design style information mined by DL with the CAD system will help to realize the intelligent upgrade of the CAD system and provide designers with more comprehensive and intelligent design support.

(3) Through real-time style suggestion and design scheme optimization, designers can find the design style that meets the requirements faster and improve the design level.

This article will study the following aspects: first, build an image data set containing various art design styles for training the DL model; Secondly, by improving and optimizing the CNN model, the ability to extract art design style features is improved. Then, it studies how to combine the excavated art design style characteristics with a CAD system to realize real-time style suggestions and design scheme optimization. Finally, the practicability of this method is verified by experiments.

2 RELATED WORK

Graphic art design style refers to a unique visual expression that typically includes features such as color, layout, font, and image. By utilizing data mining and machine learning techniques, various styles of features and patterns can be extracted from a large number of flat artworks. For example, by analyzing works from different periods, genres, or regions, the characteristics and evolution process of different styles can be discovered, providing inspiration and reference for designers. Kovacs et al. [10] explore how to combine these two to achieve the mining of graphic art design styles and effective search for design assets. Context-aware technology is a technology that enables intelligent judgment and response based on factors such as environment, context, and user behavior. In the field of graphic art and design, context-aware technology can help designers better understand contextual information such as design requirements, target audience, and design limitations, thereby making better design decisions. By combining context-aware technology and data mining technology, it is possible to better understand design requirements and target audiences, quickly locate relevant design assets, and improve design efficiency and quality.

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With the rapid development of deep learning and machine vision technology, we have gained a deeper understanding of the processing mechanisms of human visual information. Especially in the perception of abstract works of art, deep learning frameworks provide us with new perspectives and tools. Lelièvre and Neri [11] explored how to use deep learning frameworks and machine vision techniques to study human perception of abstract artworks. By training deep neural networks, we can extract rich features and style information from abstract works of art. These features can be further used to classify, recognize, and compare different works of art, thereby gaining a deeper understanding of human perception mechanisms towards abstract art. Machine vision technology provides powerful tools for abstract art research. Through computer vision algorithms, we can automatically analyze and extract visual features such as geometry, color, and texture from artworks. These features can be used to construct machine-learning models to simulate human perception of abstract art. In addition, machine vision can also be used for the automatic classification of artistic works, style recognition, and simulation of the creative process. Rural courtyard art landscape design has become an important means to improve the quality of rural tourism. However, there are many problems in the current rural courtyard art landscape design, such as a single design style and a lack of uniqueness and innovation. To address these issues, Li and Liang [12] proposed a menu-based design method for rural courtyard art landscapes based on deep learning. It utilizes deep learning techniques to train and learn a large number of rural courtyard art landscape images. So as to automatically identify and classify different design styles. This helps designers quickly locate the target style and improve design efficiency. Through deep learning models, key features of successful rural courtyard art landscape design can be extracted, such as color matching, element layout, etc. Based on these characteristics, the system can provide personalized design suggestions and recommendations for designers. In rural courtyard art landscape design, the menu style design method can preset a series of representative design elements and styles based on regional characteristics, cultural background, and functional requirements.

By intelligently upgrading CAD systems, we can not only improve design efficiency and accuracy but also explore a new interdisciplinary aesthetic style, injecting new vitality into artistic creation. McCartney and Tynan [13] discussed how to achieve intelligent upgrades of CAD systems for contemporary art and how such upgrades can promote interdisciplinary aesthetic style mining in art and design collaboration. In order to break through the limitations of traditional CAD systems, we need to upgrade them intelligently. By introducing artificial intelligence (AI) technology, we can enable CAD systems to have the ability for autonomous learning and aesthetic style mining. Specifically, we can use deep learning algorithms to train a large number of artworks, enabling CAD systems to automatically recognize and generate patterns, colors, and compositions with specific aesthetic styles. The intelligent upgraded CAD system will provide strong support for interdisciplinary aesthetic style mining in art and design cooperation. Artists and designers from different fields can explore new aesthetic styles together by sharing the same CAD system. This collaborative approach will promote interdisciplinary knowledge exchange and collision, inspiring more creative and diverse works of art. In art painting, style extraction is a crucial step in analyzing and understanding works of art. However, various defects may occur during the style extraction process, such as color distortion, loss of details, etc. In order to better identify and handle these defects, Nordin et al. [14] proposed using derivative-oriented thresholds for feature extraction. The derivative-oriented threshold method is an effective feature extraction method that extracts important features from images by analyzing their edges and textures. This method is based on the gradient information of the image and distinguishes different regions by setting a threshold to extract important features from the image. In art painting, the defects in style extraction often manifest as color distortion, loss of details, and other issues. These issues can lead to inaccurate extracted style features, affecting subsequent analysis and understanding. The derivative-oriented threshold method can effectively extract the features of style extraction defects. By analyzing the edges and textures of images, problems such as color distortion and detail loss can be detected, and the nature and degree of these problems can be further analyzed. The experimental results show that this method can accurately extract the features of style extraction defects and help further analyze and understand the nature and degree of these defects.

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Compared with traditional feature extraction methods, it was found that derivative-oriented threshold methods have higher accuracy and reliability in handling style extraction defects.

Multimedia information processing refers to the process of using computer technology to collect, edit, store, transmit, and display various media information such as text, images, audio, and video. Multimedia information processing technology is also widely used in art design and teaching in universities, providing richer and more diverse means for teaching. Artificial intelligence technology has brought new opportunities and challenges to art design and teaching in universities. Through artificial intelligence technology, universities can conduct art design and teaching more efficiently, improving teaching quality and student learning outcomes. Xu and Jiang [15] use AI for image recognition and processing, which can help students better understand and apply design elements such as color and composition. Through virtual reality (VR) and augmented reality (AR) technology, students can engage in artistic design and creation in a virtual environment, improving their practical skills and innovative thinking. Future art design and teaching will place greater emphasis on digitization, intelligence, and personalization. In mural pattern design, evolutionary computer technology can be used to optimize the composition, color, texture, and other elements of the pattern, find the best combination, and achieve innovative mural design. It utilizes deep learning techniques to recognize and classify the style of the original murals, extracting key style features. Then, these features are input into the evolutionary computer system, and the mural patterns are optimized and improved through genetic algorithms or particle swarm optimization. Finally, by combining the style conversion function of deep learning technology, the optimized pattern is transformed into the target style, resulting in the final innovative design of the mural.

With the widespread application of deep learning in the field of computer vision, its potential in art processing and transformation is increasingly evident. Yaniv et al. [16] explored how to use deep learning techniques to extract and transform artistic features, particularly for landmark detection and geometric style transformation in portrait painting. By training deep neural networks, we can extract rich feature information from images, thereby achieving style and appearance extraction of artistic works. In portrait painting, deep learning can help us recognize and extract landmark features, such as facial contours, facial layout, etc. Geometric style transformation is a method of transforming an image from one style to another. In portrait painting, we can use deep learning techniques to automatically apply an artistic style (such as Impressionism, Abstractionism, etc.) to another portrait painting. This style transformation can not only change the appearance of the painting but also give it a new artistic atmosphere and expressive power. Zhang and Rui [17] discussed the application analysis of computer deep learning graphics and image-assisted design in art and design teaching. Through deep learning models, designers can extract and classify features from a large number of artworks, thereby gaining a deeper understanding of the characteristics and trends of different styles, genres, and periods. This technology can help students better grasp the laws of art and improve their ability to appreciate and analyze works of art during the learning process. In art and design teaching, image-assisted design can help students better achieve creativity and expressive forms. For example, using image processing software, students can edit and modify existing images to achieve an initial creative presentation. By utilizing deep learning techniques such as Generative Adversarial Networks (GANs), students can generate artworks with unique styles. These technologies can stimulate students' creativity and imagination and cultivate their practical abilities and innovative spirit. Ship art design is not only the combination of engineering and aesthetics but also the crystallization of technology and creativity. In contemporary times, the application of computer graphics and image software has penetrated into various aspects of ship art design, providing designers with broader creative space and implementation methods. Zhang [18] explored the application of computer graphics and image software in ship art design style graphic design. Through computer graphics, designers can create and modify complex ship models for fluid dynamics simulation and aesthetic design. By utilizing modeling techniques in computer graphics, designers can construct a three-dimensional model of the ship's hull, presenting realistic visual effects by simulating light, shadows, and reflections. In the graphic design of ship art design, image software plays a crucial role. Adobe Photoshop, Illustrator, and other software provide designers with a wealth of tools to enable efficient image processing, drawing, and layout. Designers can use this software to

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modify, enhance, and optimize ship designs to meet customer needs and aesthetic standards. In addition, image software can also help designers create visual effects and render images, providing decision-makers and customers with a more intuitive visual experience. Digital painting is a new way of painting where artists can directly draw on a computer without the need for traditional brushes and pigments. Digital painting can not only simulate the effects of traditional painting but also create unique visual effects. In addition, computer image processing technology can also combine multiple images to create brand-new images. This technology allows artists to create more freely, no longer limited by traditional painting techniques and materials [19].

3 MINING METHOD OF ART DESIGN STYLE BASED ON DL

3.1 Construction of Multi-Art Design Style Image Data Set

DL is a subset of machine learning that relies on artificial neural networks, particularly deep neural networks. The concept of DL originated from the study of artificial neural networks, and its inspiration came from the connection and working mode of human brain neurons. Compared with the traditional machine learning method, DL can automatically extract the hierarchical feature representation of input data, thus effectively dealing with complex nonlinear problems. CNN is a network structure in DL that is specially used to deal with image problems. CNN can effectively extract local features from images through local connection and weight sharing and combine these local features in a hierarchical way to form a global feature representation. Art design style refers to the unique expression and visual characteristics adopted by artists or designers in the creative process. It embodies the artistic accomplishment, aesthetic concept, and technical means of the creator and is an important driving force for continuous innovation in the field of art design. Therefore, different art design styles often have unique visual characteristics and aesthetic value.

According to different classification standards, art design styles can be divided into many types. For example, according to the characteristics of the times, it can be divided into ancient style, medieval style, and modern style. According to the regional characteristics, it can be divided into oriental style and western style. According to the national characteristics, it can be divided into Chinese style, European style, and Japanese style. In addition, there are some specific art design styles, such as abstract, impressionist, and cubist styles. These different art design styles have significant differences in visual characteristics, expression techniques, and aesthetic values.

The CAD system expresses the geometric shape, functional requirements, and manufacturing process of designing objects in a digital way and supports designers in carrying out efficient and accurate design work. Intelligent CAD systems can automatically extract the feature information of design objects and provide intelligent design suggestions and optimization schemes according to the needs of designers. This kind of intelligent design support can help designers find the design scheme that meets the needs more quickly. Intelligent CAD systems can also carry out self-learning and self-adaptive optimization according to historical data and design experience and continuously improve their own design ability.

By training the DL model, the feature information in the CAD model can be automatically extracted, classified, identified, and optimized. For example, CNN can be used to identify the CAD model or DL technology can be used to optimize and repair the CAD model automatically. In order to mine art design styles effectively, we need an image data set containing multiple art design styles. This data set should cover works of art of different times, regions, and nationalities to ensure the diversity and comprehensiveness of styles. To construct such a data set, it is necessary to collect image data from various open art resources, museum collections, historical documents, and other channels. During the collection process, it is crucial to ensure the clarity and quality of images, along with verifying their copyright and license.

When assembling the dataset, it is essential to appropriately preprocess the images, which may involve size normalization and color space conversion, to facilitate subsequent DL model training. Furthermore, to enhance the model's generalization capabilities, it is advisable to augment the

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dataset by employing techniques such as rotation, cropping, and color dithering to introduce greater diversity among the images.

3.2 Optimizing CNN Model

The CNN structure of art design style mining is usually a multi-layer neural network, which is specially designed to extract and identify the characteristics of art design style from images. In the task of art design style mining, the input is usually a color image with a specific resolution and color space. The convolution layer slides on the input image through a series of convolution kernels (also called filters) and calculates the dot product of the convolution kernels and the local area of the image to generate a feature map. The activation function introduces nonlinear factors to help the network learn and express more complex features. The fully connected layer is usually used to map the extracted features to a specific style tag or style representation space. In the task of art design style mining, the output can be the probability distribution of one or more style categories, a style feature vector, or a style image. Through the backpropagation algorithm and gradient descent optimizer, the weight parameters in CNN can be adjusted to minimize the difference between the prediction results and the real tags—art design style mining CNN structure as shown in Figure 1.

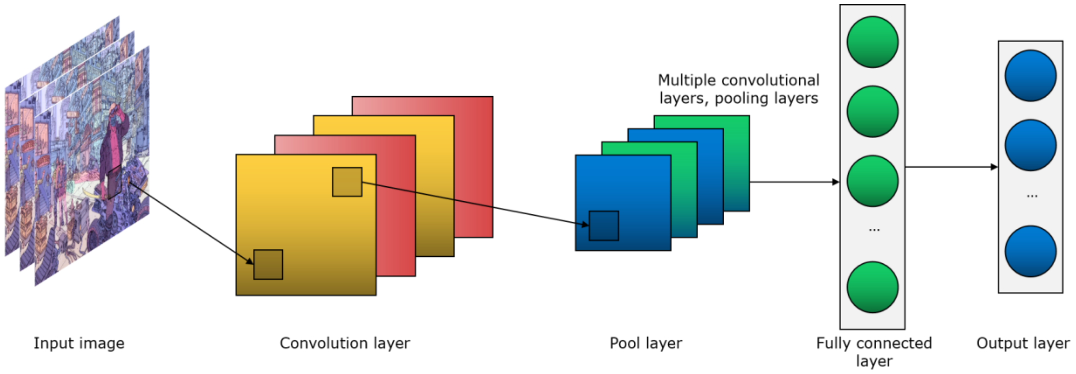

Figure 1: Art design style mining CNN structure.

By adding a convolution layer and pooling layer, the network can capture more complex features. A deeper network structure is helpful in extracting high-level abstract features from images, which is especially critical for identifying different art design styles. More convolution kernels are used in each convolution layer to increase the feature extraction ability of the network at the same level. The feature maps of different channels are weighted so that the model can focus on the channels that are more important for style identification. The attention mechanism is introduced in the spatial dimension of the feature map so that the model can pay attention to the key areas in the image. In the training process, images with different scales are input so that the model can learn style features with different granularity. This enhances the generalization ability of the model and enables it to process images with different resolutions. Construct a pyramid of input images input images of different scales into the network respectively, and fuse their features.

Let X_i^k is the sum of inputs of k layer neurons i, Y_i^k is the output, and the weights of $k-1$ layer neurons j to k layer neurons i are W_{ij}, then there is the following functional relationship:

$$Y_i^k = f(X_i^k) \tag{1}$$

$$X_i^k = \sum_{j=1}^{n+1} W_{ij} Y_j^{k-1} \tag{2}$$

Generally, f it is an asymmetric Sigmoid function:

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$$f(x_i^k) = \frac{1}{1+\exp(-x_i^k)} \tag{3}$$

If the output layer is the m layer, the actual output of the i neuron in the output layer is Y_i^m. Let the corresponding image signal be Y_i, and define the error function e as:

$$e = \frac{1}{2}\sum_i (Y_i^m - Y_i)^2 \tag{4}$$

The pre-trained CNN model is used to extract the style features of images, and the style loss between the target image and the style reference image is calculated. By minimizing the loss of style, the image generated by the model can have a specific art design style. At the same time, the content information of the image is considered to ensure that the basic content of the image remains unchanged in the process of style transfer. Content loss is usually calculated by comparing the feature difference between the target image and the original image at a certain layer of CNN. Dynamic learning rate adjustment strategies, such as learning rate attenuation or periodic learning rate adjustment, are used to optimize the training process of the model.

3.3 Extraction of Art Design Style Characteristics

After refining the CNN model, it can be utilized to extract the characteristics of artistic design styles. The preprocessed image is input into the trained CNN model for forward propagation calculation. In this stage, the CNN model will extract the feature information of the image layer by layer to form a feature map. Feature maps are extracted from different layers of the CNN model, and these feature maps are coded. In order to describe the art design style of images more comprehensively, features from different layers are fused. The fusion method can be simple splicing or weighted fusion through a full connection layer. The structure of the neural network model with multi-level semantic features is shown in Figure 2.

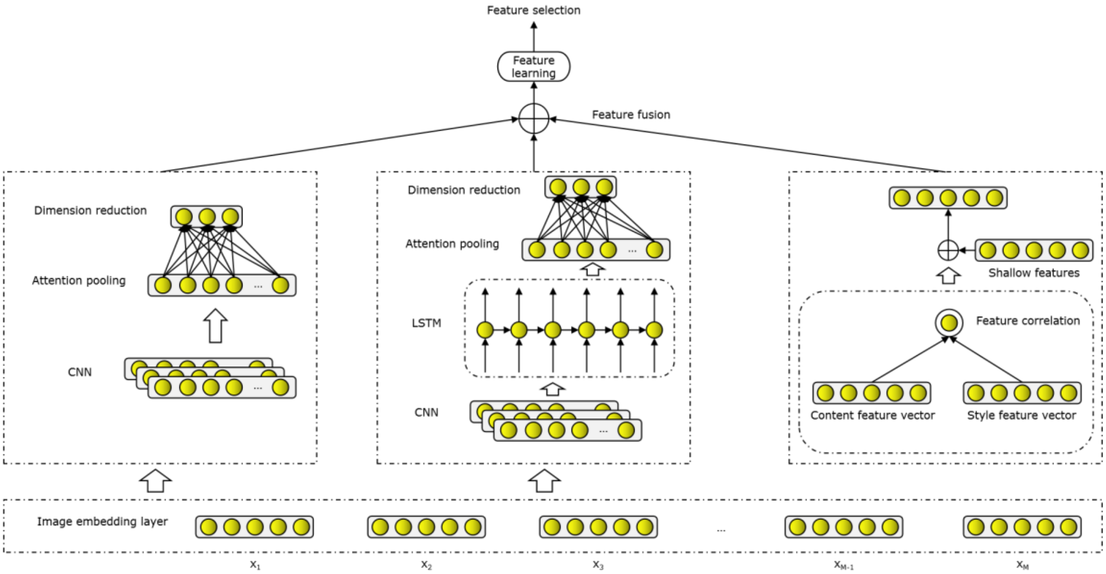

Figure 2: Neural network model of multi-level semantic features.

Visualization technology can be used to intuitively display and understand the features of the extracted art design style. For example, the feature map can be restored to the image space by

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deconvolution or gradient rise so as to observe the specific performance of different style features in the image. The correlation of these features is represented by a Gram matrix G^l, where G^l_{ij} is the inner product between vectorized feature maps i and j in l layer:

$$G^l_{ij} = \sum_k F^l_{ik} F^l_{jk} \tag{5}$$

By taking into account the correlation between multi-layer features, a robust and multi-scale depiction of the input image is achieved. This representation effectively encapsulates the image's textural details while overlooking its global structure. Subsequently, the insights gained from these style feature spaces, formed at various network layers, can be visually represented by crafting an image that aligns with the style characteristics of a given input image.

Let $\vec{a}$ and $\vec{x}$ be the original image and the generated image, while A^l and G^l respectively represent the styles of the original image and the generated image layer l. Then, the loss of layer l can be expressed as:

$$E_l = \frac{1}{4N_l^2 M_l^2} \sum_{ij} (G^l_{ij} - A^l_{ij})^2 \tag{6}$$

The total loss function has the following form:

$$L_{style}(\vec{a}, \vec{x}) = \sum_l w_l E_l \tag{7}$$

Where w_l is the weighting factor? Regarding the activation function in the layer l, the derivative E_l can be expressed as:

$$\frac{\partial E_l}{\partial F^l_{ij}} = \begin{cases} \dfrac{1}{N_l^2 M_l^2} ((F^l)^T (G^l - A^l))_{ji} & if \quad F^l_{ij} > 0 \\ 0 & if \quad F^l_{ij} < 0 \end{cases} \tag{8}$$

The minimized loss function is:

$$L_{total}(\vec{p}, \vec{a}, \vec{x}) = aL_{content}(\vec{p}, \vec{x}) + \beta L_{style}(\vec{a}, \vec{x}) \tag{9}$$

Where α and β are the weighting factors of content and style reconstruction, respectively? The gradient $\partial L_{total} / \partial \vec{x}$ of pixel values can be used as the input of the numerical optimization strategy.

Through the above steps, the art design style features in the image can be effectively extracted, and basic data support can be provided for subsequent style classification, identification, and application. In practical application, the mining of art design style may be influenced by many factors, such as image resolution, color space, lighting conditions, and so on. Therefore, when extracting style features, these factors need to be fully considered, properly handled, and controlled to ensure the stability and reliability of the extracted features. At the same time, for different art design styles and application scenarios, it may be necessary to optimize the above methods and technical parameters in order to obtain better results.

4 EXPERIMENTAL RESULTS AND ANALYSIS

By using a CAD art design data set, the original algorithm is taken as the benchmark, and the optimization strategy proposed in this article is applied to it, including an improved feature extraction method, a more effective learning algorithm, or finer parameter adjustment. In order to verify the effectiveness of the optimization strategy, a control experiment will be designed, which adopts the same data set and evaluation index but does not apply the optimization strategy. This experimental

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design is expected to verify the effectiveness of the proposed optimization strategy in improving the accuracy of artistic style learning and processing time.

Compare the performance of the method in reference [11] and the algorithm in this article on the same sample graph and target graph. The results show that when the method in reference [11] is used for style transformation, the results are different from the characteristics of the target map. This is due to the limitation of this method in extracting and transforming style features, which leads to the low accuracy of style transformation. In contrast, this algorithm can express the artistic style of the target map more accurately. The method in reference [11] may lose some important style features in the process of style transformation, but the algorithm in this article can better retain these features. This indicates that the algorithm presented in this paper exhibits a superior capability for preserving features during style transformation, thereby more effectively conveying the artistic style of the target map. Figure 3 shows a comparison of algorithm results.

(a) Sample image (b) Target image (c) Reference [11] method (d) This method

Figure 3: Comparison of algorithm results.

Figure 4 shows the interpolation results of two different artistic styles. By adjusting the interpolation ratio, different styles can be obtained. When the interpolation ratio of a certain style is low, the resulting image mainly shows the characteristics of another style. For example, if the interpolation ratio of Style 1 is low, the resulting image will show more features of Style 2, such as color, texture, or composition. On the contrary, when the interpolation ratio of a certain style increases, the resulting image will gradually show the dominant characteristics of that style. When the interpolation ratio of the two styles is close, the resulting image shows the fusion effect of the two styles. This fusion is manifested not only in visual elements, such as the mixing of color and texture, but also in composition and theme expression. By interpolating different proportions of styles, it is possible to create a unique style that does not exist originally.

(a) Style 1 (b) Style 2 (c) Style 1: Style 2 = 1: 1 (d) Style 1: Style 2 = 4: 1

Figure 4: Two style interpolation examples.

At the beginning of the style transfer process, the generated picture is a combination of content picture and noise. Therefore, the initially generated picture is visually very similar to the content picture. Although the generated picture is similar to the original content picture in content, its style is far from the target style picture. This is because the algorithm of style migration has not yet begun to integrate the characteristics of the target style into the generated pictures in the initial stage. When

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the iteration goes to the 200th time, it can be clearly seen that the generated pictures begin to change in style. These changes indicate that the style migration algorithm has begun to integrate the characteristics of the target style into the generated images. After 1000 iterations, the generated picture is not only visually attractive but also achieves the expected effect in content and style. It closely fits the original content picture in content and is highly consistent with the target style picture in style. Figure 5 shows the influence of iteration times on the effect of image style transfer.

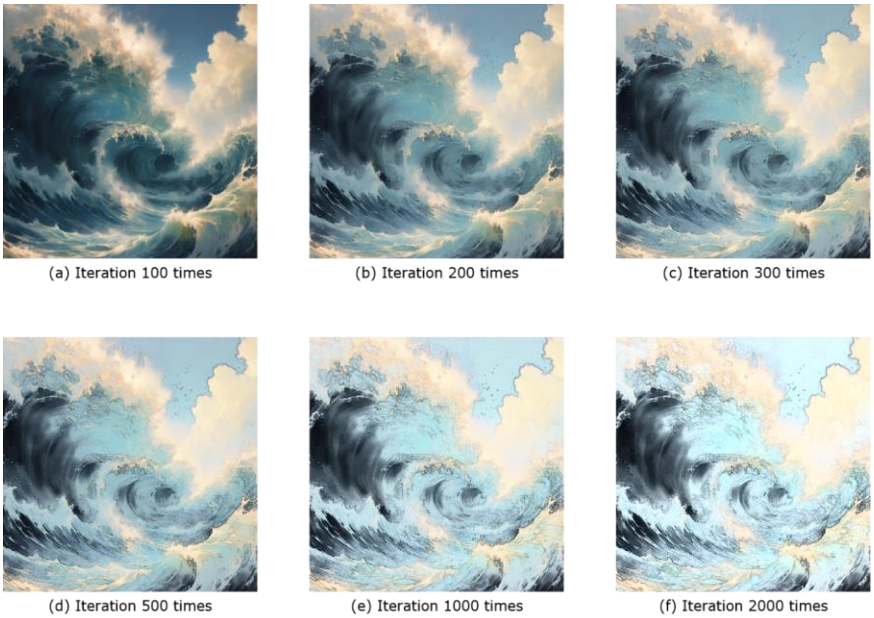

Figure 5: Image style transfer effect.

The result shows how the style transfer algorithm can effectively transfer styles while maintaining the consistency of content. By adjusting the number of iterations, the intensity and effect of style transfer can be controlled. More iterations usually lead to more obvious style changes.

Figure 6 shows the accuracy of the algorithm for artistic style learning before and after optimization. Before optimization, the original algorithm showed a certain accuracy in the task of artistic style learning, but the overall effect was not ideal. After optimization, the new algorithm has significantly improved the accuracy of artistic style learning. This promotion shows the effectiveness of the optimization strategy and the advantages of the new algorithm in dealing with and learning complex artistic style characteristics. By comparing the accuracy indexes before and after optimization, it can be observed that the accuracy of CAD art design has been significantly improved after using this strategy.

Figure 7 shows the comparison of the time required to deal with artistic style learning tasks before and after algorithm optimization. Before the optimization strategy is adopted, it takes a relatively long time for the algorithm to deal with the task of artistic style learning. After the optimization strategy processing, it can be obviously observed that the processing time of CAD data is greatly shortened.

Shortening the processing time not only means more efficient use of computing resources but also means that it can respond to users' needs faster in practical applications and improve user experience. For scenes that need to process a lot of CAD data, this efficiency improvement will bring great practical value and economic benefits.

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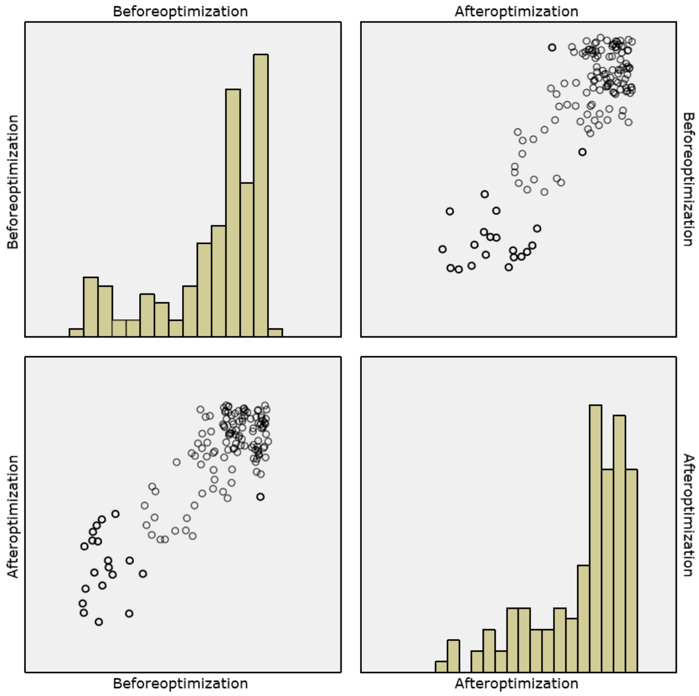

Figure 6: Accuracy of artistic style learning.

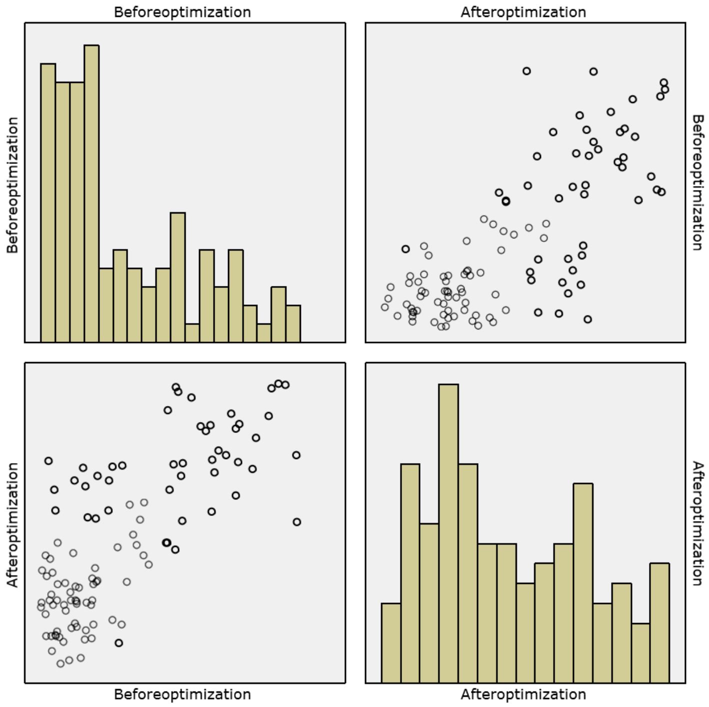

Figure 7: Processing time of artistic style learning.

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By improving the feature extraction method, introducing a more effective learning algorithm, and adjusting parameters, the accuracy of the new algorithm in artistic style learning has been obviously improved. This means that the optimized algorithm can capture and express the characteristics of artistic style more accurately, thus achieving a higher quality of style transfer. This result not only proves the effectiveness of the optimization strategy but also shows that the new algorithm has advantages in dealing with and learning complex artistic style characteristics. After the optimization strategy, the processing time of CAD data is obviously shortened. This time reduction is of great significance in practical application. First of all, it improves the efficiency of computing resources and enables the algorithm to complete the task of style transfer in a shorter time. Secondly, shortening the processing time is helpful to improve the user experience, especially in application scenarios that need rapid response. For scenes that need to process a large amount of CAD data, this efficiency improvement will bring significant economic benefits.

5 CONCLUSION

The art design style is a unique visual feature formed by an artist or designer in the process of creation, which embodies the artistic accomplishment, aesthetic concept, and technical means of the creator. This article focuses on the optimization of style transfer algorithms in CAD art design, puts forward a series of effective optimization strategies, and verifies the effect of these strategies in improving the performance of the algorithm through experiments. The findings reveal that enhancing the feature extraction technique, incorporating more efficient learning algorithms, and fine-tuning parameters can elevate the precision of artistic style transfer. This means that the optimized algorithm can capture and express the characteristics of artistic style more accurately, thus achieving a higher quality of style transfer. After the optimization strategy, the processing time of CAD data is obviously shortened. This method not only improves the utilization efficiency of computing resources but also helps to improve the user experience.

With the increasing diversity and complexity of artistic style, improving the adaptability and generalization ability of the algorithm is a problem worth studying. How to apply the optimization strategy in this article to other similar tasks or fields is also a direction worth exploring. Future research can focus on these challenges and problems and further promote the growth of CAD art and design.

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