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Combining CAD and Deep Learning Models for Style Recognition and Transformation of Arts and Crafts

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Abstract. This article provides new insights into art and design methods for protecting styles in deep learning by preprocessing and technical identification of comprehensive datasets of different arts. This article plans a craftsman recognition style for artistic processing. The training set process of feature recognition uses algorithm recognition to accurately recognize the expected style of the model classifier of the source image. It uses a classifier to train a recognition model for precise style transfer based on the framework of handmade works. At the same time, it utilized the transfer algorithm of the target style to perform simple training model style optimization on the classifier. The research results are presented in the table. With the combination of cultural and artistic model image content, the DL model in this paper has a relatively high advantage in image accuracy recognition. This not only enriches the target style conversion of handicrafts but also protects and overlaps the artistic style of the model's image with digital craftsmanship. The foundation has been laid for the recognition of image styles to protect traditional art.

Keywords: Arts and Crafts; Style Recognition; Style Conversion; Deep Learning
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1 INTRODUCTION

The foreground and background separation technology in videos not only provides artists with more creative inspiration and possibilities but also plays a crucial role in practical applications. These advanced models, originally designed for image classification, have now been cleverly applied to foreground and background separation in videos. Nowadays, this skill has crossed the traditional boundaries of painting and is integrated into video processing in the digital age. Akilan et al. [1] proposed an innovative solution - a 3D Convolutional Neural Network (3D CNN) combining Long Short Term Memory (LSTM) pipelines. These methods are often based on pixel-level processing, assuming that the foreground (FG) and background (BG) have significant visual differences. The strategy of relying solely on single-frame object detection to segment the foreground has its limitations, as it often ignores valuable temporal information during the separation process, resulting in an inaccurate depiction of the foreground area. Therefore, the in-depth study of the arts and crafts style is of great significance for understanding human culture, promoting artistic innovation and promoting the development of the arts and crafts industry. In the vast world of digital art, digital watermarking technology is like an invisible umbrella, guarding the creative achievements and intellectual property rights of artists. Bansal et al. [2] proposed a novel watermarking scheme that combines the intelligence of fuzzy logic and particle swarm optimization (PSO). In this rapidly changing digital age, the importance of ownership and copyright protection is becoming increasingly prominent, and digital watermarking technology is a shining gem in this field. These studies focus on the development of technology and algorithms, which is not only a technological challenge but also a pursuit of the spirit of arts and crafts. The cutting-edge research of digital watermarking technology is like a master of arts and crafts who constantly pursues the perfect integration of technology and art. In the magical world of discrete cosine transform (DCT), we extracted sensitive features of three human visual systems (HVS) from each main image - brightness, edge sensitivity, and contrast sensitivity. This plan is like an artist who perfectly combines traditional and modern techniques, fully utilizing the flexibility of fuzzy logic and the optimization ability of particle swarm optimization.

CAD, as a versatile tool, has found extensive application in the arts and crafts domain. Designers utilize CAD software to create and refine designs with precision and efficiency, significantly diminishing errors and redundant tasks inherent in traditional hand-drawing methods. In the delicate world of arts and crafts, every detail contains the wisdom and emotion of the craftsman. Traditional frequency domain-based robust watermarking techniques, like traditional techniques in arts and crafts, rely directly on the balance of robustness and invisibility for their efficiency. Robust digital image watermarking technology, a treasure in the field of information security, has attracted the attention of countless people with its unique charm. Similarly, in the vast universe of digital art, robust digital image watermarking technology safeguards the uniqueness and originality of each artwork in its unique way. The efficiency of this technology, just like fine carving in arts and crafts, not only requires exquisite craftsmanship but also pursues showcasing the craftsman's ingenuity in subtle details. Cedillo et al. [3] adjusted the key parameters and often required craftsmen to manually adjust based on experience and intuition when searching for the optimal carving angle and intensity. By introducing optimization techniques such as particle swarm optimization, we can adjust the key parameters of watermark technology in a more intelligent and automated manner. Moreover, CAD's integration with cutting-edge technologies like virtual reality and 3D printing opens up new avenues for artistic creation. Nevertheless, CAD's current usage in arts and crafts primarily remains at the assisted design level, while deeper issues such as artistic style recognition and adaptation are yet to be fully explored. Electronic devices are the foundation of this painting, carrying endless creativity and imagination; Sensors, like brushstrokes in a painting, are delicate and sensitive, capturing every subtle change in the real world. Earnshaw [4] proposed an improved spread spectrum-based discrete Fourier transform robust watermarking algorithm. These components are not only the stacking of technology, but also the perfect combination of art and technology, providing us with an unprecedented experimental platform to showcase the endless creativity of the present and future. It uses a particle swarm optimization algorithm to optimize key operational parameters, especially the number of frequency bands, frequency coefficients, and watermark intensity factor. This innovative approach, like the cross-border integration in arts and crafts, combines traditional techniques with modern technology, bringing a more comprehensive and efficient solution for the protection of digital artworks.

In the world of arts and crafts, seeking innovation and perfect integration has always been a challenge. In arts and crafts, different materials, colours, and textures have their unique "group contribution" properties, which together determine the final effect of the work. Frutiger et al. [5] proposed a method that combines fluid property uncertainty to explore new possibilities for computer-aided molecular design (CAMD) and process design models in the field of arts and crafts. Through regression analysis, we asymptotically approximated the covariance of model parameter estimation errors, thereby gaining a more accurate understanding of the sources and ranges of these uncertainties. However, the uncertainty of these properties, like the fluid properties in molecular design, often makes it difficult for designers to accurately predict and control the final product. Just as in molecular design and process design, we seek the best combination to achieve specific functions or aesthetics, process artists are also pursuing the perfect integration of materials, technology, and concepts. Driven by the wave of digitization, digital video has surged like a tide and become an indispensable part of our lives. Guo and Li [6] proposed a revolutionary method of directly extracting I frames in the compressed domain, completely overturning the cumbersome process of traditional video retrieval algorithms that require decompression before processing. From the perspective of the scene, it further discusses how to use I frames to synthesize the scene summary and skillfully splices the essence fragments in the video. This new model not only brings technological innovation to the field of video processing but also has a profound impact on art and design activities. They form short and pithy video clips, presenting the essence of art to the audience. This method not only improves retrieval efficiency but also preserves the original quality and artistic value of the video. Recent advancements in DL technology have been notable, especially in image recognition and manipulation. Through extensive data training, DL models can grasp intricate patterns and rules within images, enabling highly accurate image recognition and manipulation. In the realm of arts and crafts, DL offers innovative approaches for identifying, categorizing, generating, and adapting artistic styles, thereby injecting fresh perspectives and techniques into artistic creation and research. As computer technology advances, the integration of CAD and DL technologies has emerged as a focal point of research. Currently, scholars are examining how DL can enhance CAD design, aiming to boost automation and intelligence in the design process.

From ancient paintings and sculptures to exquisite prints, to today's digital media, art and technology have always been indispensable elements in Buddhist learning tools. Karnchanabayap and Chaetnalao [7] studied the perfect combination of VR art, arts and crafts, and Buddhist beliefs. In this virtual world of arts and crafts, audiences can immerse themselves in exquisite and delicate Buddhist art, experiencing an unprecedented journey of learning. They inject endless vitality into the dissemination and learning of Buddhist beliefs with their unique style of arts and crafts. Through the sensory perception of VR, the audience can "remember" the details and essence of Buddhist art. In VR, viewers can observe the lines, colours, and changes in light and shadow of Buddha statues up close, and feel their unique artistic style. The aim of this research is to integrate CAD and DL technologies for the purpose of recognizing and adapting various arts and crafts styles. This involves constructing a DL-based model that can accurately pinpoint distinct artistic styles and facilitate their conversion from one to another. The model's efficacy has been empirically validated.

The novelty of this undertaking is rooted in the unique amalgamation of CAD and DL, which is then harnessed for artistic style recognition and adaptation. Through the creation of a DL-driven model tailored for arts and crafts style identification and transformation, our study can precisely discern and seamlessly shift between intricate and evolving artistic styles. This offers fresh perspectives and techniques for artistic endeavours and scholarly explorations. We anticipate that our work will carry significant academic weight and practical relevance within the artistic sphere.

This article is organized in the order of introduction, related theory and technical foundation, style identification and transformation model design of arts and crafts, simulation experiment and result analysis, conclusion and prospect. The logic among the chapters is clear and distinct, which together constitute the research framework and system of this article.

2 RELATED WORK

When exploring the depth and breadth of art and craft styles, although current online solutions attempt to simulate or surpass the real experience of visiting, many virtual tours of online museums and art galleries often appear too static and lack interaction. Meinecke et al. [8] proposed an innovative virtual museum experience centred around the art and craft style, integrating multiple visualization technologies. In order to attract and expand the audience, museums and art galleries need to go beyond traditional online display methods and provide more engaging and interactive experiences. Utilizing the vast dataset of WikiArt, which contains over 200000 images, it covers a rich and diverse range of arts and crafts from classical to modern, and from the East to the West. It cleverly contextualizes digital artworks in galleries and related works in large-scale image archives.

These data not only provide tourists with endless visual enjoyment but also provide rich metadata to guide them in visual exploration and comparison. In the field of arts and crafts, every detail and every plan embodies the wisdom and craftsmanship of craftsmen. In order to better capture and showcase this ingenious process, Ormaz and Sarkar [9] proposed a novel upper ontology, semantic integrated manufacturing planning model. On a philosophical level, with its unique OWL-DL axiom form, it reveals to us the deep connection between manufacturing and arts and crafts. Images are composed of low-level visual features such as colour, texture, and shape, and humans cannot recognize the objective subject they depict. Emotional recognition of abstract images can not only promote research progress in the fields of art and psychology. In previous studies, traditional methods have struggled to bridge the emotional semantic gap, while neural network-based methods have been limited by the difficulty of training on small datasets. To classify abstract images based on emotions, it is necessary to establish a connection between low-level visual information and human cognitive emotional semantics and to cross deeper emotional semantic gaps. The image style concept in the style transfer task defines the low-level visual information contained in the image, which is semantically similar to abstract images. Pallasena et al. [10] introduced the idea of style transfer into the problem of abstract image emotion recognition and proposed a new solution. Moreover, it can expand the application scenarios of abstract images and visual elements in daily life, and assist in the creative work of generative AI, which has important theoretical and practical significance. Universal image emotion recognition methods often focus too much on high-level semantics and overlook the characteristics of abstract images themselves, lacking differentiation from large-scale AICA tasks in terms of thinking. Including two modules: style transfer data augmentation and classification models that integrate style features. SAR cleverly integrates virtual content into physical space with its unique display form, breaking the boundary between reality and virtuality. In the architecture of SAR, we can see the mutual resonance between technical principles and artistic styles [11].

Augmented Reality (AR) technology, like a skilled artist, redefines the way people interact and communicate with technology through its unique brushstrokes. Rarenko [12] follows the guidelines of Design Science Research (DSR) and designs, develops, and evaluates AR works with the craftsmanship of craftsmen, just like carefully laying out and polishing every detail on a canvas. This design makes AR no longer just a pile of technology but a bridge that connects with the user's mind. This visual feast not only immerses users in the virtual world but also allows them to feel the perfect combination of technology and art. Let the AR experience be like a smooth dance, which not only conforms to the user's natural habits but also allows for flexible adaptation in different situations. In the creation of visual canvases/clues, we pursue realistic 3D models, rich visual and audio clues, and elegant aesthetic expression. Traditional arts and crafts emphasize the delicacy of handicrafts and the uniqueness of creativity, but digital manufacturing technology has the ability to integrate virtual and reality perfectly. In the dazzling world of arts and crafts, digital manufacturing technology is not only remarkable for its astonishing development speed. With its increasingly user-friendly and cost-effective nature, it has brought unprecedented opportunities to the education sector. Song's [13] research results show that digital manufacturing technology has a positive impact on the learning of pre-service teachers in multiple aspects. This has brought a new experience of learning while doing arts and crafts education. Especially in the fields of arts and crafts and design education, these technologies inject new vitality into traditional teaching methods.

The computer-aided process planning (CAPP) system, like a highly skilled master of arts and crafts, is quietly changing the traditional face of manufacturing engineering. Faced with various complex problems and challenges in production engineering, The CAPP system is like a thoughtful artist, meticulously crafted using optimization techniques, striving to improve the efficiency of the parts production process. It can be combined with advanced technologies such as artificial neural networks and cloud manufacturing systems to share the advantages of different CAPP systems in different industry applications. This ultimate pursuit of efficiency is like the pursuit of perfection and harmony by masters of arts and crafts in their creations, striving to achieve the best possible state in every process. It is like a bridge that cleverly connects the fields of computer-aided design (CAD) and computer-aided manufacturing (CAM), making the transition from creative thinking to actual production smoother and more efficient. This kind of cross-border integration thinking is a reflection of diversity and inclusiveness in the style of arts and crafts [14]. In the wave of diversified arts and crafts styles, environmental art design is integrating advanced 3D virtual reality technology in an unprecedented way, injecting new vitality into modern display design. Wang and Hu [15] adopted 3D virtual reality technology, which is usually achieved by wearing special glasses. This technology not only allows environmental art and design to be freely displayed in virtual space but also allows the audience to experience the charm of arts and crafts firsthand. Finally, the principle of quantity inspection is used to verify the feasibility and effectiveness of the design scheme through rigorous data analysis. Secondly, the principle of formal application should serve the needs of art and design, rather than becoming a shackle of design. Not only focusing on technological innovation but also committed to combining modern technology with the essence of traditional arts and crafts to achieve the modern integration of traditional environmental art, thereby promoting the economic and cultural development of cities and society.

In the arts and crafts hall independently designed by robots, visual synchronous positioning and mapping technology, like a craftsman who focuses on details, has long been committed to interpreting and constructing the environment through the geometric features of images. Semantic synchronous localization and mapping are not only simple geometric analyses of images but also the integration of deep semantic information behind images. Xia et al. [16] discovered a more advanced and diverse approach - semantic synchronous localization and mapping, which injects soul colours into the robot world. In this process, it proposed the concept of a "semantic extractor", which is like an artist proficient in image semantics, able to extract key semantic information from complex images. It can effectively estimate the robot's posture, detect loop closure, and even construct a 3D map with rich semantic information. At the same time, a framework of "simultaneous positioning and mapping of modern vision" has been constructed, which is like an exquisite handicraft, perfectly integrating semantic information with modern visual technology. In the field of arts and crafts, the emotions and inspiration of designers are often closely related to the final presentation of their works. Zhou et al. [17] An innovative approach has been developed that combines the emotions of designers with their activities in computer-aided design (CAD) software. In the process of creating arts and crafts, every emotional response of a designer may be a unique interpretation of design elements or a momentary capture of inspiration. Its method not only utilizes automatic facial emotion detection software but also combines cursor tracking technology, providing a unique perspective for understanding the psychological state of designers during the creative process. Through logistic regression analysis, we revealed a significant statistical trend between designer emotions and CAD events. These activities may include navigating in the model tree, drawing detailed sketches in the graphic area, making choices in the functional menu, or using chat windows to communicate ideas with team members. Through our method, we can correspond these emotional responses to their specific activities in the CAD environment.

3 DESIGN OF RECOGNITION AND TRANSFORMATION MODELS

3.1 Style Recognition of Arts and Crafts

Within DL algorithms, the Backpropagation Algorithm stands as a pivotal component of the training process, optimizing model performance by updating model parameters based on the loss function's gradient.

Arts and crafts style refers to the unique expression and artistic characteristics of arts and crafts works in form, colour, and material. Different regions, nationalities, and times have their own unique arts and crafts styles. The classification of arts and crafts styles can be carried out according to different standards, as shown in Table 1.

Style classification	*Style Description*	*Example*
Regional style	Reflect the natural	1. Chinese traditional style: With Chinese

	environment and cultural characteristics of different regions	traditional culture as the background, it integrates elements such as mountains, rivers, flowers, and birds. 2. Greek and Roman style: Based on ancient Greek and Roman architecture and sculpture, pursuing harmony, symmetry, and perfection. 3. Arabic style: Using rich geometric patterns and curves to reflect Islamic aesthetic concepts.
National style	Reflecting the traditions and aesthetic concepts of different ethnic groups	1. Tibetan style: Based on Tibetan Buddhist culture, using elements such as Tibetan architecture and clothing. 2. African tribal style: Bright colours and complex patterns reflect the primitive and natural beauty of African tribes. 3. Nordic style: minimalist, natural, and practical, emphasizing the harmonious coexistence between humans and nature.
Times style	Reflecting the social background and aesthetic trends of different historical periods	1. Renaissance style: Based on ancient Greek and Roman culture, pursuing humanistic spirit, expressing the perfection and proportion of the human body. 2. Baroque style: Emphasizing dynamic, exaggerated, and complex decorations, reflecting the mystery and majesty of religion. 3. Modernist style: minimalist, practical, and highly functional, pursuing innovation in technology and materials.
Style fusion	Integrating stylistic elements from different regions, ethnicities, and eras	1. Chinese Western fusion style: Integrating traditional Chinese elements with modern Western design to form a unique aesthetic style. 2. Retro style: Drawing on the style of a certain period or region in history, re-creating and interpreting. 3. Cross-disciplinary style: Integrating elements from different art fields, such as incorporating art forms such as painting and sculpture into craft works.

Table 1: Classification of arts and crafts styles.

Recognizing and transforming styles represents a significant aspect of arts and crafts research. When it comes to identifying styles, extracting and analyzing various features, such as shapes, lines, colours, and materials, allows us to categorize the style of arts and crafts works. Leveraging DL and other cutting-edge technologies, we can construct an identification model capable of automatically recognizing and classifying different arts and crafts styles.

In the aspect of style transformation, one style of arts and crafts can be transformed into another, thus creating new artistic effects. This can be achieved by changing some characteristic information of arts and crafts works, such as changing the thickness of lines and adjusting the brightness of colours. In order to realize style transformation, it is needed to study the mapping relationship between different styles and build the corresponding transformation model. These models can be trained and optimized based on DL and other technologies to achieve a high-precision style conversion effect.

Before identifying the styles of arts and crafts, the first task is to build a comprehensive and high-quality data set. Ensuring the diversity and accuracy of data sets is very important for subsequent model training. In this article, many factors are considered when choosing a DL model suitable for arts and crafts style recognition. First of all, the model should have a strong feature extraction ability to capture complex visual features in arts and crafts works. Secondly, the model should have sufficient generalization ability to deal with different styles and types of arts and crafts works. Finally, considering factors such as computing resources and training time, we should choose a model with both performance and efficiency. Drawing from this, the present article opts for the convolutional neural network (depicted in Figure 1). This neural network stands as a prevalent DL model structure in recognizing arts and crafts styles. CNN extracts layered features from images through a combination of numerous convolutional layers, pooled layers, and fully connected layers. Taking into account the specifics of arts and crafts style recognition, this article formulates a CNN-based model framework. This framework employs the pre-trained ResNet model as a feature extractor and integrates it with a fully connected layer for classification purposes. The functional relationship formula is as follows:

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

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

Where X_i^k is the input sum of the k layer neurons i; Y_i^k is the output; W_{ij} is the weight from $k-1$ layer neurons j to k layer neurons i.

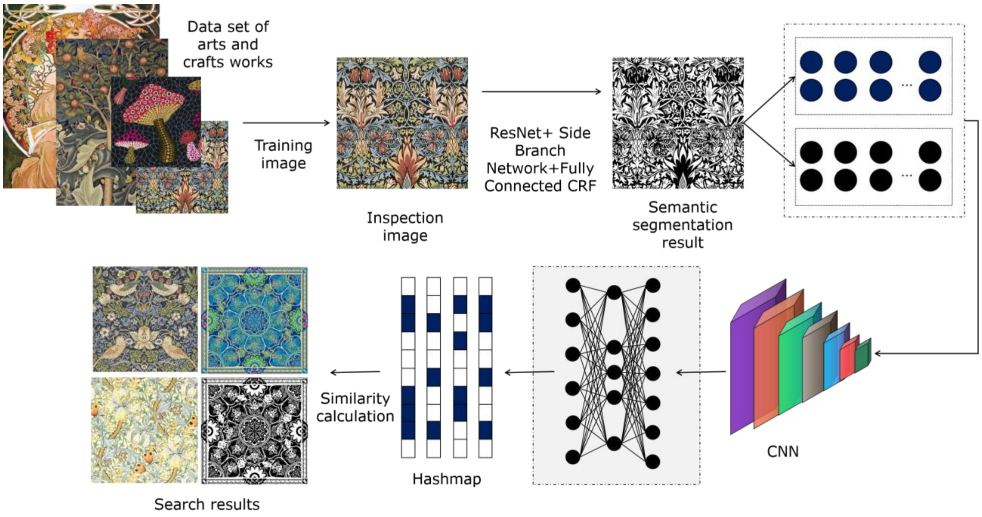

Figure 1: Style identification and transformation model of arts and crafts.

Feature extraction plays a pivotal role in the style recognition model of arts and crafts. Apart from leveraging CNN for automatic image feature extraction, we integrate edge detection technology to capture specific feature types. The Sobel operator functions based on gradient computations of the image brightness function. It identifies edges by evaluating the grayscale weighted difference of four adjacent pixels situated above, below, left, and right of each pixel point in the image. Precisely, the Sobel operator comprises two sets of 3x3 matrices, one for horizontal and another for vertical detection. Through the planar convolution of these matrices with the image, we can derive approximate values for horizontal and vertical brightness disparities, ultimately yielding the image's edge details.

$$Sobel\ x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{3}$$

$$Sobel\ y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{4}$$

Where x and y represent Sobel operators in horizontal and vertical directions respectively. These operators perform convolution operations with the image to highlight the edges.

Optimizing the extracted features is essential to enhance the precision of arts and crafts style recognition. This optimization can be accomplished through diverse tactics. In this article, regularization technology serves to avert overfitting. Additionally, the dropout technique is employed to decrease the model's reliance on particular features. Furthermore, a feature fusion approach is utilized to amalgamate distinct types of feature information.

Suppose there are n neurons in the L layer of the model and Dropout is applied. In the training process, for each input instance, a probability p is randomly selected to "turn off" each neuron. "Off" here means that the output of this neuron will be set to 0 during the backward propagation. The formula can be expressed as:

$$P_{\text{Dropout}}\ l = p \tag{5}$$

$$\text{Output}_l\ \text{Dropout} = \begin{cases} 0 \quad \text{with probability p} \\ \text{Input to the neuron} \quad \text{with probability 1-p} \end{cases} \tag{6}$$

Therefore, if p is set to 0.5, then each neuron has a 50% probability of being "turned off" during training. In practical applications, Dropout is utilized in all hidden layers, excluding the input and output layers. This approach ensures that Dropout prompts the model to acquire more resilient features while diminishing its reliance on individual neurons.

3.2 Style Transformation of Arts and Crafts

The theoretical foundation for art style transformation predominantly stems from computer vision and DL research. Drawing upon the theory of image generation and style transfer, it accomplishes style conversion by altering the visual attributes of images. Essentially, this can be perceived as a procedure for amalgamating and rearranging the content from the source image with the style of the target image. In selecting a style transfer algorithm tailored for arts and crafts style transformations, both the efficiency and effectiveness of the algorithm must be taken into account. With a focus on the task of transforming the style of arts and crafts, this article devises a DL-based style transformation model. This model comprises a generator network tasked with converting the source image into a fresh rendition bearing the target style and a discriminator network tasked with assessing whether the generated image aligns with the desired style. The process of style conversion is achieved through training these two networks.

The style conversion model based on DL uses the position-color space vector to complete the initial sample construction;

$$v = \ ax, ay, R, G, B \tag{7}$$

The 5-dimensional vector represents the pixel color R,G,B at the $P = \ x,y$ position. Mean-shift segmentation method can be defined as an iterative process of searching the position of the central point:

$$u_{k+1} = \frac{1}{n_k} \sum_{\|v_i - u_k\| \le \delta} v_i \tag{8}$$

Let's assume that AA denotes the data distribution of the authentic image BB, CC signifies the data spread of the produced image DD, EE signifies the prior distribution FF of the random noise vector GG, while HH and II symbolize the generator and discriminator networks correspondingly, with JJ considered as a binary classifier. The model's optimization goals are as follows:

Let's assume that P_r denotes the data distribution of the authentic image x, P_g signifies the data spread of the produced image $G(z)$, P_z and signifies the prior distribution $N(0,I)$ of the random noise vector z, while G and D symbolizes the generator and discriminator networks correspondingly, with D considered as a binary classifier. The model's optimization goals are as follows:

$$\min_G \max_D V(G,D) = E_{x\sim P_r}\left[\log D(x)\right] + E_{z\sim P_r}\left[\log(1 - D(G(z)))\right] \tag{9}$$

The style conversion model based on DL alternately improves the performance of generating networks and discriminating networks through a clever minimax game strategy until they reach a stable Nash equilibrium. During this conversion process, the generator network demonstrates expertise not only in transforming images of varying artistic styles but also possesses the capability to replicate and refine images within the same stylistic domain. This ensures that the network can precisely acquire the essential characteristics of the intended style (refer to Figure 2).

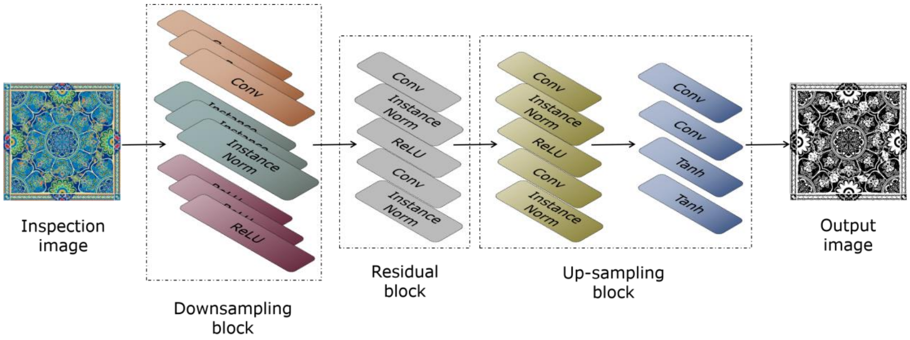

Figure 2: Generator network structure.

To accomplish this objective, this article employs a particular approach during the training of network parameters. Firstly, the real embroidery image and texture image are input into the generator respectively, and the generator tries to imitate the styles and textures of these images. Furthermore, the low-frequency L1 loss function is used to finely adjust the output results of the generator to ensure that they are consistent with the input original image in style, texture and details. The specific calculation method of this step aims to make the GAN generator not only keep the core features of the original image but also integrate the unique charm of the target style in the process of arts and crafts style transformation. The specific formula is as follows:

$$L_i = \left\|x - \hat{x}\right\|_1 + \left\|y - \hat{y}\right\|_1 \tag{10}$$

Where x stands for arts and crafts image, $\hat{x}$ is arts and crafts image generated by x through generator G_c, y is real texture image, and $\hat{y}$ is texture image generated by y through generator G_s.

In order to transfer the artistic style of the arts and crafts style image $\vec{a}$ to the content of the content image $\vec{p}$, we need to carefully and synchronously match the unique style features of the arts and crafts style image $\vec{a}$ and the core content features of the content image $\vec{p}$, so as to synthesize a brand-new image $\vec{x}$ with the essence of both.

In this process, this article pays special attention to minimizing two key losses: one is the content loss feature representation of the content image $\vec{p}$ obtained from a certain layer of the DL model, which ensures that the new image $\vec{x}$ can retain the core elements of the original content image; The second is the representation of the total style loss characteristics of the arts and crafts style image $\vec{a}$ obtained from multiple layers of the DL model, which ensures that the new image $\vec{x}$ can accurately show the artistic style of the arts and crafts style image $\vec{a}$. The concrete realization of this optimization process, as shown in Formula (10), through fine algorithm adjustment, this article tries to find the best balance between style conversion and content preservation.

$$L_{total}\ \vec{p},\vec{a},\vec{x}\ = \alpha \times L_{content}\ \vec{p},\vec{x},l\ + \beta \times L_{style}\ \vec{a},\vec{x},l \quad (11)$$

In order to assess the effect of the style conversion model of arts and crafts, it is necessary to design reasonable evaluation indicators. Commonly used evaluation indicators include subjective evaluation and objective evaluation. Subjective evaluation is achieved by inviting experts or ordinary users to score or sort; Objective evaluation can use some quantitative indicators to assess the similarity and quality of the generated image and the target style image. By comprehensively considering the results of subjective and objective evaluation, we can get a comprehensive evaluation of the performance of the style conversion model of arts and crafts, which will be explained in detail in the next section.

4 SIMULATION EXPERIMENT AND RESULT ANALYSIS

4.1 Style Recognition Experiment

Firstly, we filter and obtain image data from a carefully planned dataset. Next, we introduced a pre-trained deep learning model and configured and initialized the model according to the specific needs and objectives of the experiment. These configurations include adjusting model parameters, optimizing algorithms, etc. to ensure that the model can learn and work according to our expectations. Through deep learning and computation of the model, we can extract key feature information from images. To ensure the accuracy of the experiment, we performed necessary preprocessing on these images to standardize the input data and ensure that the model can receive images of uniform format and quality. This feature information can accurately reflect the style characteristics of the image. We encapsulate this feature information into feature vectors for subsequent classification operations. After obtaining the feature vectors, we use them to train the classifier. Through training, the classifier can learn the feature differences of images with different styles and accurately classify images based on these differences. This article provides detailed documentation of the experimental data and conducts an in-depth analysis of the results. Refer to Figure 3 for the model's classification accuracy.

Figure 3 shows the classification accuracy of the proposed deep learning model in style recognition tasks. The horizontal axis in the figure represents different testing stages or sets, while the vertical axis reflects the classification accuracy of the model. Each testing stage (such as "Test 10", "Test 50", etc.) represents the performance evaluation of the model on a test set containing different numbers or styles of images. Specifically, "Test 10" represents a test set containing ten different styles of landscape images, while "Test 50" is a test set containing fifty different styles of landscape images. As the style types covered by the test set increase, the classification task of the model becomes more complex, as the model needs to distinguish more subtle style differences. The high accuracy of the model on "Test" may be attributed to the relative simplicity of style types and the effective learning of the model. As the complexity of the test set increases, the model needs to handle more style differences and possible confounding factors, which may lead to a decrease in classification accuracy.

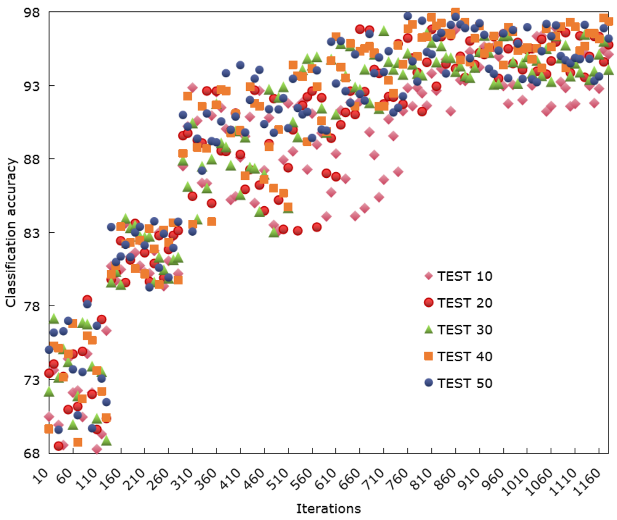

Figure 3: Classification accuracy of the model.

However, the model can still maintain high classification accuracy on more complex test sets, which further verifies the effectiveness and robustness of the model. Figure 4 illustrates the model's classification recall rate.

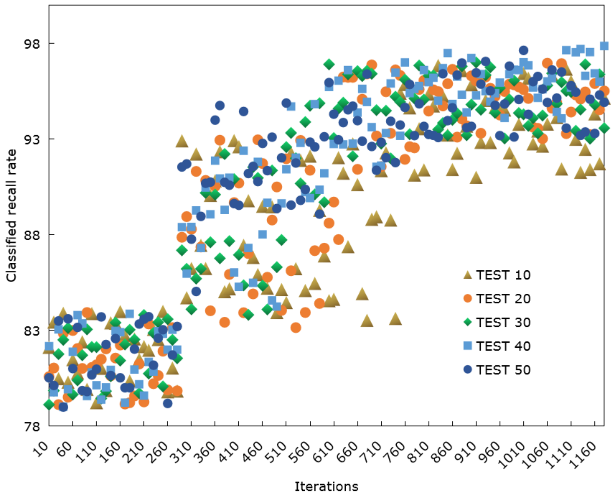

Figure 4: Classification recall rate of the model.

Figure 4 shows the recall rate of the deep learning model in the style recognition experiment in this article. This graph intuitively reflects the accuracy and comprehensiveness of the model in identifying different types of styles when identifying different numbers of test sample sets (i.e. "Test 10", "Test 20", "Test 30", "Test 40", etc.). From the graph, it can be seen that as the complexity of the test sample set increases (from "Test 10" to "Test 50", etc.), the recall rate of the model fluctuates, but overall remains at a gradually increasing level. This indicates that the model has strong generalization ability and robustness when recognizing images with different styles. Figure 5 shows the output error of the model.

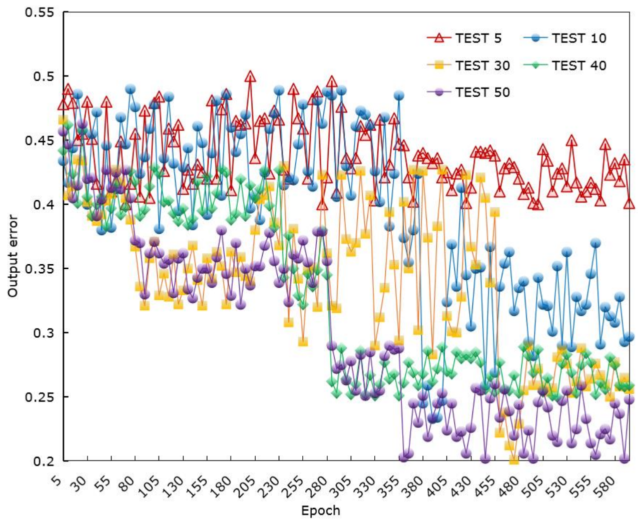

Figure 5: Output error of the model.

Figure 5 shows the trend of output error of deep learning models in style recognition experiments as the number of test samples increases. Output error is an important indicator for measuring the accuracy of model predictions, which reflects the difference between the predicted and actual values of the model. From the graph, it can be observed that as the number of test samples increases, the output error of the model shows a gradually increasing trend. In cases where the number of test samples is small (such as Test 10), the output error of the model is relatively small, indicating that in a small number of samples, the model can accurately recognize image styles. However, as the number of samples increases, the model needs to handle more diverse image styles and more complex feature combinations, which may lead to a decrease in the model's predictive ability and an increase in output errors. Through the comparison and discussion of experimental results, it is found that this model has achieved good performance in the task of style recognition and can accurately classify the styles of arts and crafts works.

4.2 Style Conversion Experiment

For the style conversion experiment, the following experimental framework was devised:

Picking a style transfer methodology: Taking into account the specifics of the task and algorithm efficacy, this article settles on an appropriate style transfer technique (a DL-driven style conversion model).

Compiling the dataset: Assemble a dataset encompassing source images and target style images for training and evaluating the style conversion model.

Training the model: Utilize the chosen style transfer method to coach the style conversion model, aiming to impart the desired style to the generated images via iterative refinement.

Assessment and validation: Feed the test dataset into the model to produce style-converted images, and evaluate the conversion quality using both subjective assessments and objective metrics.

This section presents a selection of style-converted images (refer to Figure 6) and provides a comprehensive analysis of the conversion outcomes.

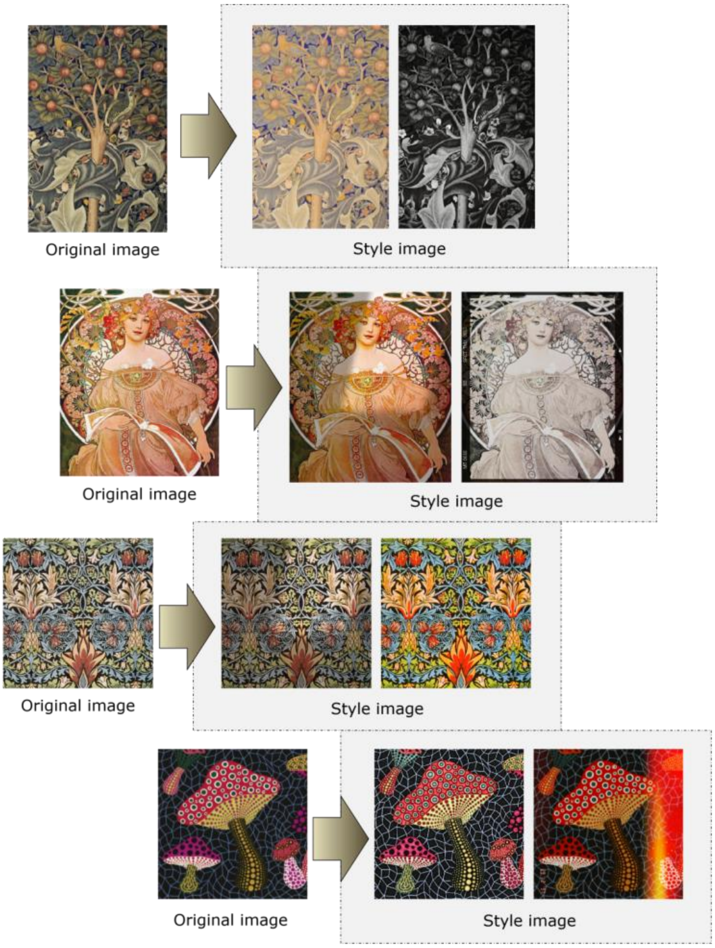

Figure 6: Partial style conversion image example.

The degree of resemblance and the quality between the generated image and the target style image are exhibited in Figure 7.

Figure 7 visually illustrates the similarity and quality evaluation results between the generated image and the target style image. The horizontal axis represents different test samples or conditions, while the vertical axis corresponds to graphical indicators, which may combine the evaluation of image similarity and quality. Through Figure 7, we can observe the similarity between the images generated by the model under different testing conditions and the target style images, as well as the overall quality of the images. The graphical indicators increase with the increase of test values, which usually means that the model is improved or optimized. The generated images are getting closer to the target style while maintaining their content, and the image quality is also improving. The scoring situation of experts and users is shown in Figure 8.

Figure 8 provides a detailed record of the ratings of experts and users on the images generated by the model. The horizontal axis may represent the number of test samples, while the vertical axis displays the score obtained for each test sample. By comparing the ratings of experts and users, we can understand the differences in the evaluation of model-generated images among different groups. Expert ratings are usually based on their in-depth understanding of image style, content, clarity, and artistic effects.

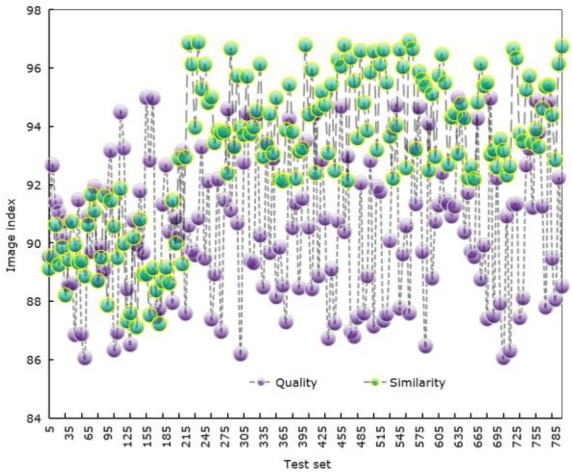

Figure 7: Similarity and quality of images.

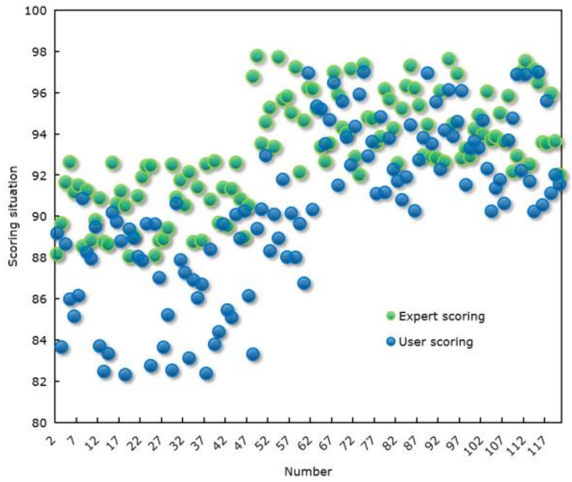

Figure 8: Scoring by experts and users.

If the expert ratings are generally high, it indicates that the images generated by the model have achieved a high level of style fusion, content preservation, and overall quality. By comparing the original image with the converted image, this article finds that the model can successfully fuse the content of the source image with the target style to generate a new image with the target style. Furthermore, the image generated by the model has high similarity and good quality with the target style image, and the scores of experts and ordinary users are high.

4.3 Experimental Summary and Discussion

This experiment validates the efficacy of DL in identifying and transforming the styles of arts and crafts. The findings reveal that the DL model outlined here performs admirably in recognizing styles and accurately categorizing the various styles of arts and crafts pieces. Additionally, in the realm of style conversion, the model adeptly blends the content of the original image with the intended style, thereby creating a fresh image bearing the desired style.

5 CONCLUSIONS

The core objective of this study is to explore and design a deep learning (DL) model to identify and transform the styles of arts and crafts and verify their practical effectiveness through simulation experiments. After rigorous experiments, we are pleased to find that the designed DL model has demonstrated excellent accuracy in recognizing the style of arts and crafts, and can accurately perform style transitions, successfully generating works that meet the expected style. This article aims to develop more accurate and efficient style recognition and transformation models to better adapt to real-world application needs. We will focus on the integration of multimodal data and explore the integration of visual elements with various art forms such as text and audio to achieve more comprehensive and in-depth style recognition and transformation. The plan is to apply the research results to a wider range of art disciplines, promote the digital preservation and renewal of traditional art through interdisciplinary integration and innovation, and inject new vitality into traditional art. This breakthrough achievement not only brings enormous value to digital research in the field of arts and crafts but also opens up new paths for the protection and inheritance of traditional art forms. The study highlights the enormous potential of deep learning in the recognition and transformation of art and craft styles and points out new directions for research in this field.

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