

Retraction

Retracted: Application Model Construction of Traditional Cultural Elements in Illustration Design under Artificial Intelligence Background

Mobile Information Systems

Received 11 July 2023; Accepted 11 July 2023; Published 12 July 2023

Copyright © 2023 Mobile Information Systems. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Shi, "Application Model Construction of Traditional Cultural Elements in Illustration Design under Artificial Intelligence Background," *Mobile Information Systems*, vol. 2022, Article ID 7412066, 9 pages, 2022.

Research Article

Application Model Construction of Traditional Cultural Elements in Illustration Design under Artificial Intelligence Background

Lei Shi 

Institute of Fine Arts, Changchun University, Changchun, Jilin 130000, China

Correspondence should be addressed to Lei Shi; shil@ccu.edu.cn

Received 30 April 2022; Revised 18 May 2022; Accepted 26 May 2022; Published 14 June 2022

Academic Editor: Amit Gupta

Copyright © 2022 Lei Shi. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The sustainable development of modern illustration art needs to dig deep into traditional culture in content and, on the basis of spreading cultural forms and improving cultural influence, supplement its own creative forms. The influence of AI (artificial intelligence) on illustration design not only is manifested in the optimization of illustration design tools and the improvement of design efficiency, but also makes the illustration design methods more diverse and promotes new breakthroughs in the illustration design concept under the influence of new technologies. In this paper, combining the advantages of two activation functions, SoftSign and ReLU, a new activation function, SReLU, is constructed and applied to CNN (Convolutional Neural Network). The multimode property of color prediction is modeled by quantifying ab color channels in Lab color space, and the introduction of GAN (Generative Adversarial Network) structure can make the whole model show better generation effect and improve the generation ability of image style conversion network. *Results.* The experiment proves the effectiveness of the method with high-quality image visual effect.

1. Introduction

With the continuous development of social economy, the field of illustration began to focus on the flexibility of drawing form and content, turning illustration into a tool of expression, incorporating unique Chinese traditional elements, which made it have more aesthetic value. As a result, illustration design took on a new development face and became one of the manifestations of Chinese traditional elements. No matter whether the color matching is comfortable and eye-catching, this phenomenon begins to prove the arrival of the visual society, and the cultural industry that came into being has become the mainstream information industry in modern society. Design provides uncertainty and possibility for AI (artificial intelligence), while AI provides a new method to solve problems for design. Although it will take some time for AI to be widely used in all walks of life technically, it has already caused many discussions in the humanities, and the introduction of AI can bring

considerable application prospects to many industries [1]. However, the art development in the field of illustration needs to reinterpret the traditional cultural forms, so as to make them better carriers of Chinese cultural elements and reflect their own cultural values.

The history of illustration art is very long. Over the years, many different styles and forms of illustration works have appeared in the society, and gradually as a fashionable profession, they have quietly flourished. The domestic Illustrator China Network has gathered most of the local illustrators' works, the supply and demand of the illustration market, and so on. Vlacic has applied and innovated the local traditional cultural elements and figures and has a leading position in related research fields [2]. Through the detailed discussion of the importance of using traditional cultural elements in illustration creation, the reference points, the creation process, and the creation methods of traditional cultural elements, this paper strongly demonstrates the argument of "research on the application of traditional

cultural elements in illustration creation". Yang et al. analyzed the relationship between art design and AI, trying to find the balance between them [3]. By analyzing the influence of AI on art design, Zhang demonstrates that the combination of AI and art design can provide a more intelligent, stylized, and commercialized development path for future art design [4] with the promotion of the innovation of ideas and tools. Deng et al. discussed how to innovatively apply Chinese traditional cultural elements in contemporary illustration design and its application significance. Inject new vitality into Chinese contemporary illustration design and make it glow with vitality [5]. In view of the current situation of the domestic illustration industry, we should create a new illustration design style, such as reinterpreting the traditional Chinese culture, constantly developing diverse traditional cultural elements, and applying them innovatively, so as to complete the transformation of traditional cultural elements into commercial values [6].

AI also plays a role in the field of art generation. With the help of AI, artists' creative thinking can generate very specific works of art, such as painting works generated by deep learning algorithms and music composed by AI. These are all created by using computers as creative tools driven by our subjective consciousness. It is the combination of human creativity and human writing design codes. The creative inspiration generated by illustration design benefits more from its uncertainty, while the calculation process in which computers participate is more definite and stylized. Therefore, how to improve the design thinking of machines is one of the key points to promote the combination of AI and illustration design. In this paper, firstly, we understand the stylization principle of deep learning images from the reconstruction of CNN (Convolutional Neural Network). In stylization, we can adjust the weight ratio of content and style to get stylized images with different effects.

2. Related Work

2.1. The Development of Illustration Design. With the advent of the digital age, illustration has become a popular cultural trend and has been widely spread. Chen et al. can imitate the styles drawn by various brushes by using digital tools [7], but our aim is not to imitate but to master the characteristics of digital technology through a long-term attempt, so as to create more digital illustration identification bases with artistic value for us. Cassalho et al. [8] use the color mode on the computer to adjust the color tone and transparency of the picture, feel the rapidly changing colors and graphics, and feel the artistic effects presented to us from different angles by changing the picture composition, which greatly stimulates the creative desire and exploration spirit of digital illustrators [8]. Guo et al. [9] use 3D software and motion capture technology to depict people's facial expressions in detail, which is similar to but more expressive than photography [9]. Peng et al. [10] used hand-painting, images, and three-dimensional effects to create an elegant and long rhythm of virtual light, leaving viewers with a colorful imagination space [10]. Wu et al. [11] used spray paint or volatile pigments as tools to create graffiti on abandoned

walls, car bodies, bridge opening, passages, and telephone poles [11].

With the advent of the digital age and the convenience of information exchange, we can learn about the development of illustration art in different regions, different countries, and different cultures. Our illustrations have changed from ancient line drawing and woodcut to today's application of computer technology. The development of illustration in China requires us to develop students' creative thinking in the process of education. The lack of traditional culture makes us lose the cultural roots, and the traditional thinking mode can no longer attract the attention of the public in today's rapid development.

2.2. Research on Deep Learning in AI. Illustration design integrates knowledge from many fields. It contains both aesthetic expression and logical thinking in philosophical ideas, so it is not only the process of artists' creation, but also the process of logical thinking. AI-driven design is one of the issues being discussed in the art world. AI can help designers get rid of complicated design steps, save design time, and improve efficiency in some aspects.

Ayesha et al. [12] transformed ancient paintings into realistic natural images and put forward a novel solution to the problems caused by ancient paintings [12]. He et al. [13] proposed image style conversion based on CNN to increase multi-scale context loss [13]. In this paper, a stylized image is synthesized by constraining the high-level CNN features similar to content images and the low-level CNN features similar to style images. Badawy et al. [14] proposed a novel architecture for realizing extremely high-speed style conversion in feed-forward mode [14]. Perez-Borrero et al. [15] proposed a new method based on adaptive patch partitioning for local texture transfer, which can capture the style of the sample image and keep the structure of the source image [15].

Flah et al. [16] proposed a method that can estimate dense depth map from monocular image. In this method, a Zhang Quanjing focusing image is obtained from the multi-focusing image stack captured by the camera mounted on the mobile phone, and then the depth value on a certain focal plane can be calculated [16]. Wei et al. [17] put forward an unsupervised learning method that uses the reconstruction error of stereo image pairs as the loss function of CNN, so that CNN can train and predict the depth map without providing depth supervision information [17]. Cruz et al. [18] proposed an image texture extraction method with rotation invariance by using the eigenvalue of intensity gradient and multi-resolution analysis and used it for image retrieval [18]. Du et al. [19] proposed that deep learning technology can be applied to image texture extraction and gave a concrete model of style transfer network [19]. Thomas et al. [20] proposed a model of rapid style transfer network [20]. The network model is divided into generation network and loss network. The training and generation processes are separated. After training a certain style, the model is saved, the style rendering is performed later, and the trained model can be directly loaded.

3. Research Method

3.1. Illustration Image Classification. Based on art and culture and under the premise of folk production and living conditions, it has formed a conventional form of expression in the social environment. On the specific artistic form, artists and people will refine these cultural contents to form a complete artistic symbol. Chinese traditional culture pursues elegance and flatness and does not respect perspective and limitations in the realistic environment. Painters take this artistic conception and this so-called “beauty” as their main expression direction and goal.

In the process of combining illustration art with information technology, we constantly absorb various Chinese cultural elements to ensure that the value of illustration art itself begins to change to commercial value. As one of the four ancient civilizations, China has rich history and culture. Therefore, in the process of illustration art creation, it is necessary to vigorously develop diverse elements of Chinese traditional culture.

It provides a new design combination point for AI designers, gradually extends the traditional fixed concept of artistic creation, produces more diverse artistic creation ways, and gradually shifts from fixed mode to more diversified artistic thinking. In the color decoration, the forms of gradual strengthening, gradual weakening, transformation, repetition, rhythm, etc. are used. At the same time, the methods of harmony, fainting, and echoing are used to seek unity in the change of subject contrast, and the pictures are colorful and maintain overall harmony. Making use of the randomness of the machine algorithm interacts with people and jointly completes the creation of artistic works; the other does not require the direct participation of the artist so that the machine can understand the characteristics of the artist's works and use algorithms to generate works of art that conform to the artist's style. Theoretically speaking, it is a process of copying and reproduction, rather than complete creation.

Image classification is the basis of image understanding, and it is widely used in the field of computer vision, such as security, transportation, and Internet. Traditional image classification methods mostly use feature descriptors, but illustration images are more complicated than natural images, and the applicability of traditional image classification methods is poor. Therefore, this section puts forward the illustration image classification method based on CNN to verify the superiority of CNN in painting image classification.

Activation function is the key technology of CNN's development. Activation function introduces nonlinear elements to CNN, which makes CNN simulate the nonlinear distribution of sample data in real environment and solve the problems that linear models cannot solve. Combining the advantages of SoftSign and ReLU functions, a new activation function named SReLU is constructed. The activation function is defined as follows:

$$f(y_i) = \begin{cases} y_i, & y_i \geq 0, \\ a_c \text{SoftSign}(y_i), & y_i < 0, \end{cases} \quad (1)$$

where y_i is the input of the i th activation function f , the ReLU function value is taken when the input of the activation function layer is greater than 0, and the hyperbolic tangent function value is taken when it is less than 0. c represents different channels of picture colors, and a_c represents the values of different color channels, controlling the input of negative half axis.

The parameter a_c of the SReLU activation function can be back-propagated to be optimized, the parameter update follows the chain derivation rule, and the a_c gradient optimization is shown in the following formula:

$$\frac{\partial \varepsilon}{\partial a_c} = \sum_{y_i} \frac{\partial \varepsilon}{\partial f(y_i)} \frac{\partial f(y_i)}{\partial a_c}, \quad (2)$$

where ε represents the objective function and ∂a_c represents the gradient of the current layer.

According to the specific needs of this article, that is, according to the needs of illustration image classification, we redesigned the CNN structure. The CNN structure of this section is shown in Figure 1.

As shown in Figure 1, the network model designed in this section consists of 10 layers, with convolution and downsampling alternating three times, and finally two layers of full connection layers. The first and second pool layers are followed by LRN, and the first full connection layer is followed by Dropout.

Take the painting data set as an example; an image with a size of 225×225 is input from the input layer, the image size after the first convolution layer is 50×50 , the image size after the second convolution layer is 25×25 , and the image size after the last convolution layer is 8×8 .

3.2. Colorization of Illustration Images. Chinese traditional cultural elements are the overall representation of different ideological cultures and ideologies, nourished by more than 5,000 years of Chinese civilization. They reflect the features of the Chinese nation and constitute a national culture that people have gradually evolved into by combining their own thinking concepts, through life experience and continuous exploration and creation. For many service designs, such as interactive design, it is necessary to get the data of users' needs, preferences, and behaviors from big data and to mine, develop, and analyze the data of users' potential needs [18].

This can better analyze the user's interaction behavior and provide services for users. As a typical example of Chinese cultural characteristics, it has played an important historical role. Ink and wash art is not only in the art form of painting, but also integrated with calligraphy, seal cutting, Taoism, philosophical spirit, and other contents, being an important form of expression that gathers the core of Chinese traditional culture.

The origin of design is people's thinking problem, and it is people's cognitive problem about the use, classification, and functionality of such commodities. Generally speaking, it is an art that is close to the people and easily resonates with the public. After a long period of development, traditional

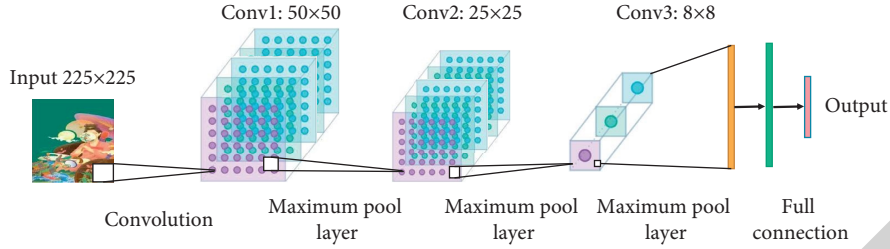


FIGURE 1: CNN structure design.

illustration has formed a variety of creative styles. On the basis of ink painting, we constantly learn from innovation, inherit Chinese traditional cultural elements, and, at the same time, make the products form a simplified ink illustration style and unique temperament [3].

Not only does the traditional coloring method of illustration images need manual intervention, which takes a long time and has poor coloring effect, but also the coloring speed decreases significantly with the increase of the size of the picture to be processed. Therefore, in recent years, the automatic colorization method of illustration images based on CNN has gradually replaced the traditional colorization method. The Euclidean distance between the color image generated by the network and the real color image is taken as the loss function. Because of the multimodal nature of color prediction, this loss function will lead to the average color of the model in many cases, which makes the whole image tend to brown tone.

Although regression seems to be suitable for this task due to the continuity of color space, in fact, the method based on classification may be better. Because color prediction is multimodal in nature, many objects can present a variety of possible colors. In this section, the probability distribution of possible colors of each pixel is predicted, and an automatic colorization algorithm is proposed. The algorithm uses the network structure as shown in Figure 2.

Distribution is trained from gray level input to quantized AB color value output. The model adopts a structure similar to VGG16 network, which contains 10 convolution groups; each convolution group contains 2 or 3 repeated convolution layers, the convolution kernel size is 5×5 , and there is a ReLU activation function behind each convolution layer.

In color prediction, this average effect will lead to desaturation of colored images. In addition, if a reasonable set of coloring is nonconvex, then the actual solution will not be in the set, thus giving an unreliable result.

Given the brightness input X , the probability distribution of possible colors of each pixel is obtained by mapping $\partial(\cdot)$ with CNN learning function:

$$\hat{Z} = \partial(X). \quad (3)$$

In order to compare the predicted color probability distribution \hat{Z} with the real color probability distribution Z , the function of converting the real color Y into the vector Z is defined as shown in the following formula:

$$Z = H_{gt}^{-1}(Y). \quad (4)$$

In this process, soft-encoding scheme [16] is used to find the five nearest neighbors of the true color $Y_{h,w}$ in the output space of 213 classes, and Gaussian weighting is carried out according to their distance to $Y_{h,w}$.

The last layer of this paper uses softmax classification function, which is the most used function in multi-classification tasks. In the field of reinforcement learning, softmax function is often used to convert a certain value into activation probability. In this case, softmax function becomes a function with temperature parameters. The formula is shown as follows:

$$\sigma_t(z)_j = \frac{\exp(z_j/T)}{\sum_{k=1}^K \exp(z_k/T)}, \quad \text{for } j = 1, 2, \dots, K, \quad (5)$$

where T is called the temperature parameter. When T is large, it tends to be positive infinity and the activation probabilities corresponding to all activation values tend to be the same (that is, the activation probabilities have little difference); When T is very low, i.e., tends to zero, the greater is the difference of activation probability corresponding to different activation values.

3.3. Image Stylized Model. The method of directly quoting traditional cultural elements in illustration creation does not mean directly copying but can be directly applied to some traditional cultural elements with beautiful forms and certain cultural connotations. To put it simply, it is to use the local traditional cultural elements and graphics as a whole, or it may be changed locally according to the needs of illustration creation and integrated into the creation of illustration works. This technique that transcends time and space needs to find the combination of traditional cultural elements and graphics and the form and content of illustration creation need to be expressed and cannot be combined arbitrarily.

Dynamic image stylization is to establish a new dynamic image stylization loss function by adding inter-frame loss function on top of the original image stylization loss function. By defining an instantaneous consistency between the two frames, the $i + 1$ frame and the stylized i frame are initialized, and the optical flow between the two frames is constrained to prevent jitter and jump.

Therefore, it is necessary to add the consistency penalty term to the loss function. In order to detect the moving

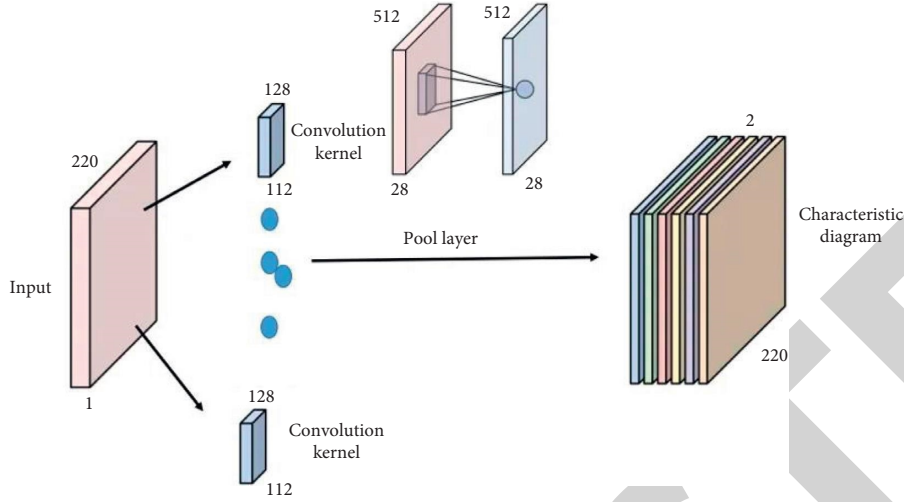


FIGURE 2: The network structure diagram of the algorithm in this section.

boundary in the two frames and the new area in the second frame, the consistency detection of the forward optical flow field and the backward optical flow field is used. The formula is as follows:

$$\bar{w}(x, y) = w(x, y) + \tilde{w}(x, y), \quad (6)$$

where $w(x, y)$ is the optical flow field in the previous frame and $\tilde{w}(x, y)$ is the optical flow field in the next frame. The estimated second frame image is obtained by adding the forward optical flow field to the first frame because the second frame is changed from the first frame image by motion.

Although the style model with histogram matching layer can adapt to more style images, there is still much room for improvement in the quality of the stylized images generated by it. Therefore, in order to further improve the performance of the model, make the generated images more authentic, and make a reasonable quantitative evaluation of the generated paintings, this section decided to introduce GAN (Generative Adversarial Network) structure.

Based on the idea of antagonistic training, a GAN consists of two small networks competing with each other. This competitive mode helps the GAN to imitate any distribution of data. The ability of GAN to imitate data makes it like a machine artist. Once successfully trained, it can create artworks. By setting a reasonable loss function and then judging the texture characteristics of the image, the GAN establishes a mapping relationship between the noisy image and the denoised image, so as to achieve the purpose of image denoising and produce a clearer image.

The overall optimization objective function of GAN is as follows:

$$\min_G \max_D (D, G) = E_{x \sim P_{\text{data}}(x)}[(\log D(x))] + E_{z \sim P_g(z)}[(\log(1 - D(G(z))))]. \quad (7)$$

For generator G , the gradient ascending method is generally used for optimization, and for discriminator D , the gradient descending method is generally used for optimization.

The introduction of GAN in this section can ensure the retention of high-level information of content images provided in the data set, and color information and texture information of style images provided [19] as much as possible. The stylized model introduced into GAN retains the original module for solving content loss and style loss, which is also very important for the training of generator network. The model frame diagram of this section is shown in Figure 3.

In the whole model, the generator acts as an “information source” from which the discriminator obtains the original unlabeled data. Unmarked data is the key to improve the performance of discriminant model. Suppose the data categories are divided into 1, 2, and 3 cases. The discriminator calculates the probability that the input image is 1, 2, 3 and 3 categories.

To sum up, the discriminator needs to have three different training data sources:

- (1) The significance of the existence of real data with labels is to serve as a standard data distribution [14].
- (2) There is no real data of the label. For these data, the discriminator knows that these data are real.
- (3) Pictures from the generator are classified as false samples by the discriminator.

Gram matrix is also needed to define the style loss function and the specific formula is as follows:

$$I_{\text{style}}^{\phi, j}(\hat{y}, y) = \left\| G_j^{\phi}(\hat{y}) - G_j^{\phi}(y) \right\|_F^2, \quad (8)$$

where F is Frobenius norm, F-norm, which is a kind of matrix norm, and $G_j^{\phi}(x)$ is the Gram matrix of the activation value of image x in the j th layer of model $\phi\phi$ and $G_j^{\phi}(x)$ is defined as follows:

$$G_j^{\phi}(x)_{c, c'} = \frac{1}{C_j H_j W_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} \phi(x)_{h, w, c} \phi_j(x)_{h, w, c'}, \quad (9)$$

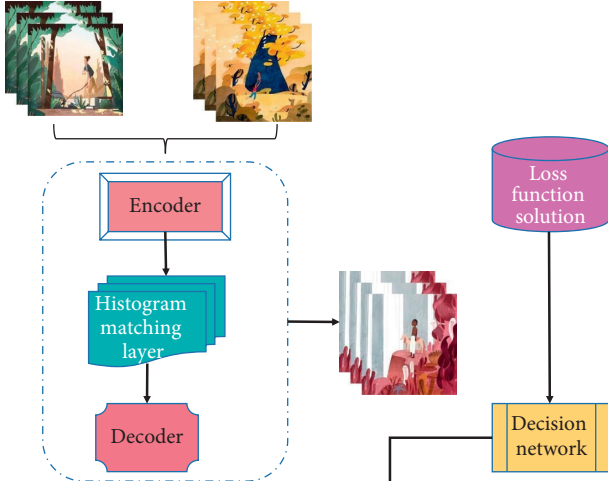


FIGURE 3: Model frame diagram.

where $G_j^\phi(x)_{c,c'}$ represents the Gram matrix correlation between the two channels of c, c' in the characteristic graph; $\phi_j(x)_{h,w,c'}$ represents the activation value of the j -layer (characteristic graph) of graph x in module ϕ ; and the height-width channel coordinates are the values of h, w, c position.

The total loss of fast style transfer network is defined as follows:

$$L_{\text{total}}(p, a, x) = \gamma_1 L_{\text{content}} + \gamma_2 L_{\text{style}}. \quad (10)$$

In the actual coding process, in order to simplify the calculation, the content loss function is usually calculated at only one layer in the network, while the style loss function is calculated at multiple network layers and then superimposed to take the average value.

4. Result Analysis

In order to verify that the activation function proposed in this section not only has certain advantages in the classification of painting data set (Data_A), but also is feasible in other data sets, the model proposed in this paper is applied to other general data sets (Data_B) for experiments.

In this paper, the best effect can be achieved when the negative semiaxis parameter $a_c = 1.5$ of the activation function SReLU is activated and the negative semiaxis coefficient of LeakyReLU is initialized to 1.5 according to experience. When using Tanh and SoftSign, the learning rate was set to 0.02, and the learning rate of other activation functions was set to 0.001; each experiment was performed for 1000 iterations. The experimental results are shown in Figure 4.

It can be seen that on Data_A, Tanh has the lowest accuracy, SoftSign has higher accuracy than Tanh and ReLU, and LeakyReLU has slightly higher accuracy than ReLU. However, the model constructed by the activation function SReLU used in this paper achieved the highest accuracy rate of 95.69%, which was 1.6% higher than that of ReLU, thus

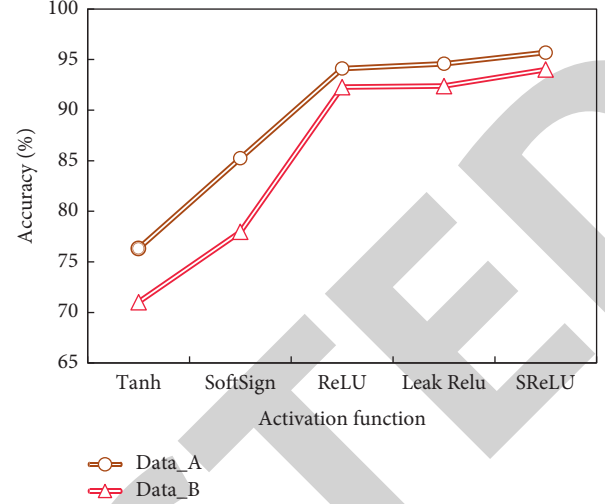


FIGURE 4: Comparison results of activation function experiment.

proving the effectiveness of the activation function in this section applied to Data_A.

It is worth noting that under the same model parameters, the activation function Sigmoid's classification accuracy of Data_A is very low, so the experimental results of Sigmoid are not included in this experiment.

Taking Data_A as an example, we compare the convergence of the network model with the increase of the number of iterations of activation functions Tanh, SoftSign, ReLU, LeakyReLU, and SReLU. The experimental results are shown in Figure 5.

As shown in Figure 5, except for the activation function Tanh, all the activation functions are iterated about 2500 times and the network model tends to converge. It can be seen that SReLU obtains a higher classification effect without affecting the convergence performance of the model, which further proves its advantages.

Next, we compare the classification performance of this network model with that of the general network model on Data_A. The experimental results are shown in Table 1.

As can be seen from Table 1, compared with LeNet, the network model in this paper has great advantages, and its classification performance is slightly higher than that of AlexNet. It can be seen that the network model designed in this paper has certain advantages in Data_A and the improved activation function plays a certain role in improving the classification accuracy.

When there are many possible colors of objects in the gray scale picture, this loss function will encourage conservative prediction in order to minimize the loss, resulting in the average coloring effect of the overall brownish color. However, the algorithm proposed in this paper adopts the cross entropy loss of classification, and the coloring model can predict the probability distribution of possible colors of each pixel. In training, the classification rebalancing technique is used to emphasize the rare color categories, so that the network model can produce vivid, full, and colorful coloring effects. Figure 6 is a graph of loss function during the training of this experiment.

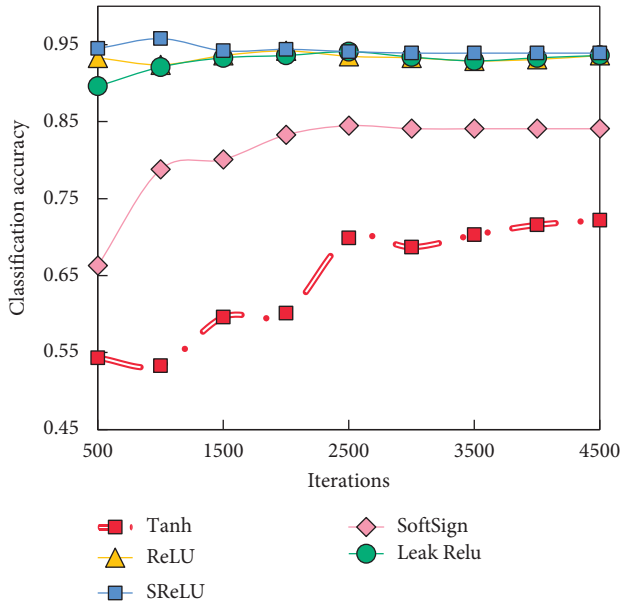


FIGURE 5: Comparison of convergence trends of activation functions on Data_A.

TABLE 1: Comparative results of different network model experiments.

Model	Accuracy (%)
Model of this paper	96.63
LeNet	66.01
AlexNet	92.18

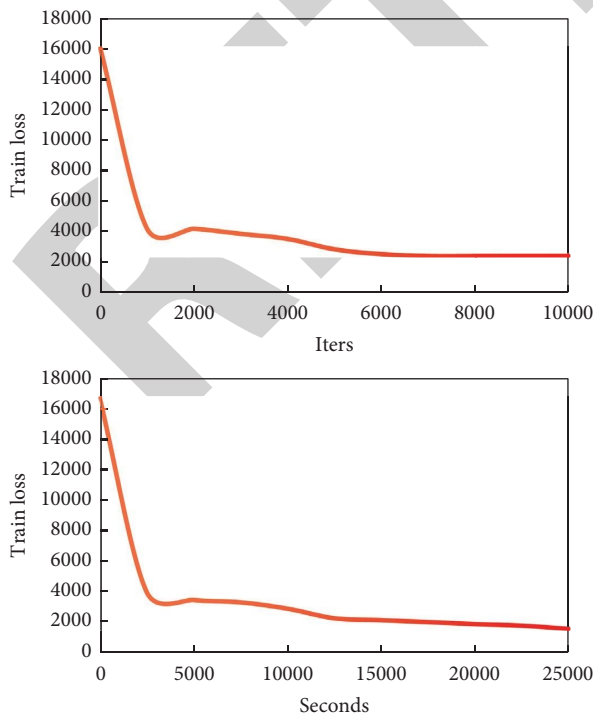


FIGURE 6: Model loss function curve.

Table 2 presents the analysis of illustration image colorization results of different algorithms under different indicators. The second column and the third column show the accuracy of the colored image and the original color image in different threshold distances, respectively. The fourth column shows the results of the coloring Turing test. For all indicators, the higher the result, the better.

It can be seen that when the threshold is set to 3%, the accuracy of the algorithm proposed in this section is 17.88%, which is higher than the 15.03% of the algorithm in [17] and 12.69% of the algorithm in [20].

When the threshold distance is extended to 5%, the accuracy of the algorithm proposed in this section reaches 39.62%, which is still higher than the 36.68% and 34.71% of [17] and [20], which shows that the color distribution in the coloring results in this paper is the closest to the original color.

The coloring result of the algorithm proposed in this paper accounts for 45.82% of the total score in the evaluation experiment, far exceeding the 25.41% of [17] and 28.91% of [20], which shows that the coloring result of the algorithm proposed in this section is closer to the real picture in terms of overall comfort and color distribution.

The experimental results prove that the algorithm proposed in this section can produce more convincing colorization results than the algorithms of [17] and [20].

There are two methods to judge the quality of stylized images, quantitative and qualitative. The qualitative method is to let the public judge which picture is better in quality from the visual angle of the public and select the best option in the public’s mind. However, as far as quantitative methods are concerned, at present, there is no unified quantitative method to judge the stylized images after migration in the field of image stylization, because the probability distribution of images of each style is different; some are cartoon paintings, some are secondary paintings, and some are landscape paintings.

200 images produced by different models were taken and sent to the two classifiers for identification. Six groups of comparative experiments were conducted, and the experimental results are shown in Figure 7.

GAN style model, histogram matching style model, multi-style generation model for real-time transmission, instance normalization model, and adaptive style model are used in this comparative experiment. The figure shows that compared with other models, except for the first group of experiments, in which the GAN stylized model is poor, the stylized models based on the GAN show good generation performance. It also proves the feasibility and effectiveness of this method.

In this paper, the network is upsampled by deconvolution layer, and features are fused twice, which causes CNN to make full use of the local information of the underlying convolution features, thus processing the local details of its output depth map better. This training process can make CNN parameters find a better local minimum point. It can be seen from Figure 8 that this network structure and its training process make the prediction result of CNN in this paper obviously superior to that of [17].

TABLE 2: Analysis of colorization results of illustration images.

Model	3% accuracy	5% accuracy	Visual authenticity (%)
Model of this paper	17.88	39.62	45.82
Reference [17]	15.03	36.68	25.41
Reference [20]	12.69	34.71	28.91

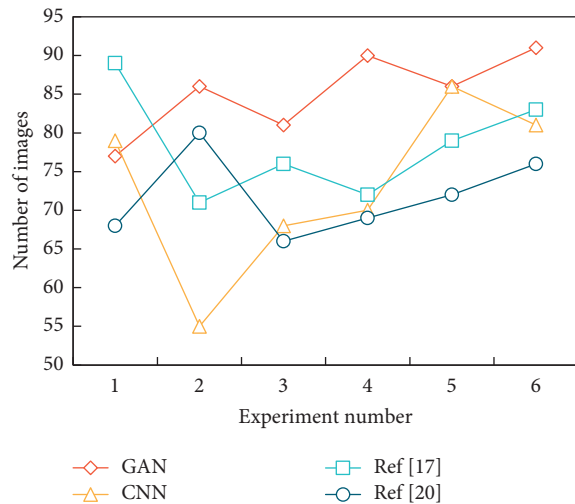


FIGURE 7: The number of images judged to be true.

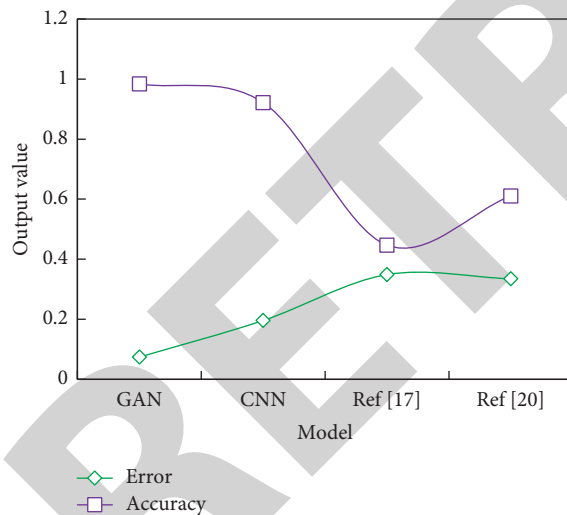


FIGURE 8: Comparison of experimental results.

Compared with other methods, this method has superior performance which is mainly due to the deeper and more complex network structure. The model avoids the super-pixel segmentation of the image and the inverse operation of large matrix in the prediction process, which not only retains the pixel-level accuracy of the image, but also makes the prediction process faster.

5. Conclusion

Different nationalities have different cultures, which is the most direct and obvious way to distinguish us from other

nationalities. Chinese traditional cultural elements with unique cultural qualities have laid the foundation of the splendid cultural treasure house of the Chinese nation. AI has a significant impact on the illustration design industry. The biggest benefit that AI brings to designers is that it can replace tedious and inefficient repetitive work and some established artistic expression methods. In this paper, based on SReLU's improved CNN model, the classification accuracy of Data_A is improved correspondingly. By quantifying the ab color channel of Lab color space, the coloring model can predict the probability distribution of ab value and select the most possible color distribution. Experiments show that the coloring results produced by the proposed algorithm are more dynamic and more real in perception. GAN is applied to the artistic model of a single model and multiple styles, which promotes better integration of different styles of pictures with the provided content pictures and generates better visual stylized pictures.

Data Availability

The figures and tables used to support the findings of this study are included in the article.

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

This work was supported by the "13th Five-Year Plan" of Jilin Provincial Education Department: "The Illustration Design Research on Brand Culture Strategy" (JJKH20200601SK) phased results.

References

- [1] J. Liu, Q. Chen, and X. Tian, "Illustration design model with clustering optimization genetic algorithm," *Complexity*, vol. 2021, no. 4, 10 pages, Article ID 6668929, 2021.
- [2] L. Vlacic, "The 2019 APEX award of excellence in the category of design & illustration? Covers goes to the IEEE? Intelligent transportation systems magazine [Editor's Column]," *IEEE Intelligent Transportation Systems Magazine*, vol. 11, no. 4, pp. 3-4, 2019.
- [3] W. Yang and X. Chi, "Cognition and design: selection of illustration style in native products packaging design based on neurocognitive science," *NeuroQuantology*, vol. 16, no. 6, pp. 385-390, 2018.
- [4] L. Zhang, "Illustration design teaching mode based on virtual wall painting technology," *International Journal of Emerging Technologies in Learning (ijET)*, vol. 14, no. 3, p. 190, 2019.
- [5] J. Deng and X. Chen, "Research on artificial intelligence interaction in computer-aided arts and crafts," *Mobile Information Systems*, vol. 2021, Article ID 5519257, 14 pages, 2021.
- [6] A. Mehndiratta and K. Asawa, "Non-goal oriented dialogue agents: state of the art, dataset, and evaluation," *Artificial Intelligence Review*, vol. 54, no. 1, pp. 329-357, 2021.
- [7] Z. Chen and Y. He, "Imitation or efficiency? aesthetics of artificial intelligence," *Foundations of Science*, vol. 26, no. 3, pp. 475-486, 2021.

- [8] F. Cassalho, S. Beskow, C. R. Mello, M. M. Moura, L. F. Oliveira, and M. S. Aguiar, "Artificial intelligence for identifying hydrologically homogeneous regions: A state-of-the-art regional flood frequency analysis," *Hydrological Processes*, vol. 33, no. 7, pp. 1101–1116, 2019.
- [9] W. Guo, Z. Wang, S. Hong, D. Li, H. Yang, and W. Du, "Multi-kernel support vector data description with boundary information," *Engineering Applications of Artificial Intelligence*, vol. 102, no. 1, Article ID 104254, 2021.
- [10] X. Peng, H. Xu, C. Diao, and Z. Ye, "Self-training-based spectral image reconstruction for art paintings with multi-spectral imaging," *Applied Optics*, vol. 56, no. 30, p. 8461, 2017.
- [11] T. Wu, X. Chen, and L. Lu, "Field coupling-based image filter for sand painting stylization," *Mathematical Problems in Engineering*, vol. 2018, no. 3, 18 pages, Article ID 3670498, 2018.
- [12] H. Ayesha, S. Iqbal, M. Tariq et al., "Automatic medical image interpretation: state of the art and future directions," *Pattern Recognition*, vol. 114, Article ID 107856, 2021.
- [13] Y. He, G. Wang, G. Dong et al., "Ghost imaging based on deep learning," *Scientific Reports*, vol. 8, no. 1, p. 6469, 2018.
- [14] S. M. Badawy, A. E. N. A. Mohamed, A. A. Hefnawy, H. E. Zidan, M. T. GadAllah, and G. M. El-Banby, "Automatic semantic segmentation of breast tumors in ultrasound images based on combining fuzzy logic and deep learning-A feasibility study," *PLoS One*, vol. 16, no. 5, Article ID e0251899, 2021.
- [15] I. Perez-Borrero, D. Marin-Santos, M. J. Vasallo-Vazquez, and M. E. Gegundez-Arias, "A new deep-learning strawberry instance segmentation methodology based on a fully convolutional neural network," *Neural Computing & Applications*, vol. 33, pp. 1–13, 2021.
- [16] M. Flah, A. R. Suleiman, and M. L. Nehdi, "Classification and quantification of cracks in concrete structures using deep learning image-based techniques," *Cement and Concrete Composites*, vol. 114, Article ID 103781, 2020.
- [17] W. U. Wei, T. L. Yang, L. I. Rui et al., "Detection and enumeration of wheat grains based on a deep learning method under various scenarios and scales," *Journal of Integrative Agriculture*, vol. 19, no. 8, pp. 1998–2008, 2020.
- [18] Y. J. Cruz, M. Rivas, R. Quiza, G. Beruvides, and R. E. Haber, "Computer vision system for welding inspection of liquefied petroleum gas pressure vessels based on combined digital image processing and deep learning techniques," *Sensors*, vol. 20, no. 16, p. 4505, 2020.
- [19] W. Du, H. Shen, J. Fu, G. Zhang, and Q. He, "Approaches for improvement of the X-ray image defect detection of automobile casting aluminum parts based on deep learning," *NDT international*, vol. 107, Article ID 1021441, 2019.
- [20] D. Thomas and S. M. Kahn, "Searching for subsecond stellar variability with wide-field star trails and deep learning," *The Astrophysical Journal*, vol. 868, no. 1, p. 38, 2018.