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GAN-based automated generation path of teaching resources for Wuhu iron painting art style migration and innovation design

Shuwei Xia[1,*]

[1] School of Design, Hefei University, Hefei, Anhui, 230601, China

SUMMARY: *Under the background of the digital era, Wuhu iron painting, as one of the traditional Chinese folk art forms, needs to undergo digital transformation for its artistic inheritance and innovative development. This paper explores the automated generation path of digital teaching resources for Wuhu iron painting, proposes an art style migration model based on the improved CycleGAN model, and uses the Kano model to analyze the demand level of digital teaching resources for Wuhu iron painting, so as to realize the automated generation of digital resources for Wuhu iron painting in line with the needs of teachers and the actual teaching. It is shown that compared with the original CycleGAN model, the SSIM and PSNR index values of the images generated by the improved CycleGAN model in this paper are improved by 11.61% and 1.53% on average, and the FID index value is decreased by 47.76% on average, meanwhile, the improved CycleGAN model performs better than CycleGAN in the retention of color features, which proves the effectiveness of this paper's model in the migration of Wuhu iron painting art style. In addition, this paper constructs a demand model for digital teaching resources of Wuhu Iron Painting, which can be used as an important basis for the automated generation of teaching resources.*

KEYWORDS: *CycleGAN; Wuhu iron painting; style migration; digital teaching resources; Kano model*

1 Introduction

As a traditional craft with a long history, Wuhu iron painting is rooted in the deep cultural soil of China, which originated in the Song Dynasty and has a long history, and has gradually formed a unique artistic style through the accumulation of long years. Wuhu iron painting has become an outstanding representative of Chinese traditional arts and crafts and is regarded as a treasure of intangible cultural heritage for its exquisite craftsmanship, unique modeling design and profound cultural connotation [1]. Under the modern art appreciation and demand, the time cost of talent cultivation of traditional handmade crafts is measured in years, and there are very few contemporary young inheritors, and the contemporary Chinese iron painting design needs to be developed innovatively [2].

Digital technology provides new possibilities for the inheritance and development of traditional handicrafts. Wuhu iron painting non-heritage is no exception, and the introduction of digital technology has injected new vitality into it [3]. The combination of traditional crafts and digital technology can not only maintain the unique flavor of traditional handicrafts, but also improve the production efficiency and quality, so that Wuhu iron painting can better adapt to the needs of contemporary society. Literature [4] points out that three-dimensional scanning,

*x15755175251@163.com
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virtual reality and other technologies promote the digital preservation, personalized information pushing and design optimization of the Wuhu iron painting non-legacy, effectively expanding its dissemination scope and mass base. Literature [5] utilizes a hierarchical visual converter framework to effectively capture its unique artistic characteristics and realize the style transformation of Wuhu iron painting by designing a local attention decoder and a content correction module. Literature [6] explores the path of digital creative technology and educational innovation to collaborate to protect and revitalize Wuhu Iron Painting, and proposes a comprehensive strategy combining digital platforms, immersive learning and teacher training, which effectively promotes the inheritance and sustainable development of this non-heritage project.

With the development of deep learning technology, Generative Adversarial Network (GAN) has become a highly influential technique in the field of deep learning since it was proposed in 2014 [7]. GAN is capable of generating high-quality data such as images, audio, and text through the adversarial training of generators and discriminators. In the field of image generation, GAN is particularly widely used, for example, it shows great potential in art creation, game design, medical image synthesis, etc. [8]. GAN shows strong advantages in style migration. Literature [9] proposes a GAN-based controlled style migration method specifically for the Chinese painting style migration problem, which is to optimize the visual effect by introducing the constraints of brushstroke and ink diffusion, and combining with the stream-based optimization strategy to ensure the consistency of video content and time. Literature [10] constructed a depth-extraction GAN based on multiple feature extractors, which significantly improves the aesthetic quality and structural fidelity of the generated images by fusing color, texture, depth and shape features for artwork style migration. Literature [11] compares the performance of U-Net and ResNet generators in Cycle-GAN for style migration, ResNet outperforms U-Net in terms of image fidelity, generation speed and naturalness, while the latter is prone to introduce too many details leading to complex images. Literature [12] reported that GAN can implicitly learn complex data distributions, but its training faces challenges such as pattern collapse and non-convergence, which are rooted in the design flaws of the network architecture, objective function and optimization algorithm. Moreover, there is a lack of evaluation criteria and originality regulations for GAN-based style migration artworks.

Application of GAN in Teaching Resource Generation and Teaching Assistance. Literature [13] proposes a GAN-based method to automatically synthesize realistic cultural heritage scene images driven by semantic ontology, which helps to assist cultural heritage scene understanding. Literature [14] creates a two-stage GAN model for style recommendation and simulation of handmade artworks, and introduces a genetic algorithm to optimize the self-attention module, which significantly improves the realism and diversity of the generated images. Literature [15] proposed a GAN for Chinese art based on the attention mechanism, and by constructing an exclusive dataset and fusing the content and attribute space, the generated Chinese traditional paintings are of high quality, improved resolution, and diverse styles. Literature [16] developed an architecture that fuses multi-scale attention convolutional neural network and Transformer, combined with improved GAN to generate non-heritage image samples, and constructed a digital teaching system with a resource library, personalized recommendation and interaction, with a recognition rate of 92.3% on the self-built dataset, which effectively improves the efficiency of non-heritage protection and inheritance. Literature [17] constructed a GAN-based educational assistance system that utilizes a hybrid GAN architecture to achieve sketch generation and style migration to support art creation and learning, which can significantly improve the quality of students' creativity and participation, and provides an adaptive tool for art education.

In this paper, we innovatively design the automatic generation path of teaching resources based on the art style migration of Wuhu iron painting, introduce the relativistic discriminator, and improve the CycleGAN style migration model, so as to realize the automatic generation of digitized teaching resources for Wuhu iron painting, and compare it with the models of Gatys, DualGAN, and CycleGAN, to validate the effectiveness of the model. On this basis, based on the Kano model, the demand level of Wuhu Iron Painting digital teaching resources is explored, and a digital teaching resources demand model containing 24 elements in four dimensions, namely, practicality, usability, reliability, and accessibility, is constructed, and the demand attributes and levels are divided to provide guidance for the automated generation of teaching resources.

2 Improved CycleGAN-based Wuhu iron painting art style migration

Aiming at the Wuhu iron painting art style migration problem, this chapter proposes an improved generator based on CycleGAN and applies the relativistic discriminator technique to improve the generation of antagonistic loss, so as to realize the automated generation of Wuhu iron painting teaching resources.

2.1 Artistic style migration based on generative adversarial networks

2.1.1 Principles of style migration in generative adversarial networks

Generative Adversarial Networks (GANs) use two neural networks for adversarial training to generate new, synthetic instances of data, these two neural networks, the generator network and the discriminator network, respectively, we can think of GANs as being the antithesis of the thief and the cop in a game of cat-and-mouse, where the thief is learning stealing techniques, and the cop is learning how to spot the thief. The whole process is dynamic, i.e., both the police and the thief are training, and both of them are learning from each other to improve themselves.

A discriminator network is a standard convolutional network that can categorize the acquired images, using a binomial classifier that can make an identification of the image as true or false. In a sense, a generator network is a transposed convolutional network. A standard convolutional classifier typically performs downsampling of the image and generates classification probabilities. A generator, on the other hand, performs up-sampling of random noisy images to generate images, the first by discarding the data using down-sampling techniques such as maximum pooling, and the other by generating new data. Both types of network models strive to achieve the optimal solution in a zero-sum game, i.e., minimizing the generative adversarial loss function. The generator changes as the discriminator changes and vice versa. Their loss functions interact with each other. The basic structure of GAN is shown in Fig. 1.

The objective function of GAN is as follows:

$$\begin{aligned}\min_G \max_D V(D,G) = &\mathbb{E}_{x\sim p_{data}(x)}\left[\log D(x)\right] \\ &+\mathbb{E}_{z\sim p_z(z)}\left[\log\left(1-D\left(G(z)\right)\right)\right]\end{aligned} \tag{1}$$

where $D(x)$ is the discriminator's estimate of the probability that x is true for real data instances. E_x is the expectation over all real data instances. Given noise z, $G(z)$ is the output of the generator. $D(G(z))$ is the discriminator's estimate of the probability that the false instance is true. E_z is the expectation over all random inputs to the generator, i.e., over all generated false instances $G(z)$. Since the generator cannot directly affect the $\log(D(x))$ term in the function, minimizing the loss for the generator is equivalent to minimizing $\log(1-D(G(z)))$.

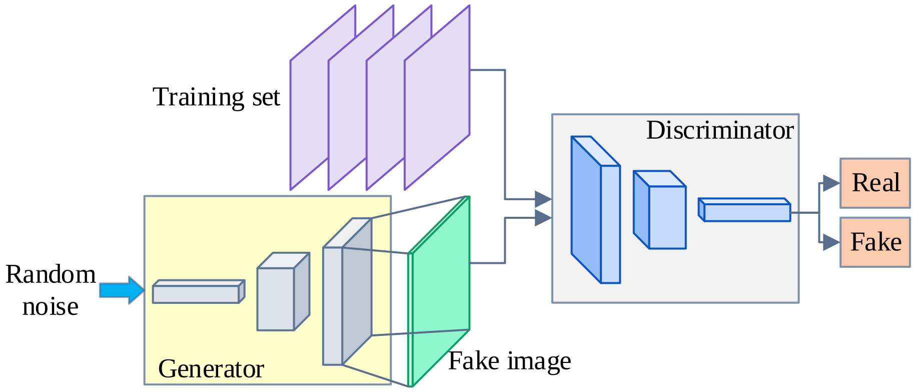


Figure 1: Generative adversarial network structure

In GAN for style migration, the generator generally consists of a convolutional neural network that learns the generation of image styles. Then a discriminator provides a style objective function for the learning of the model, thus learning against each other with the generator. A content loss function is also generally introduced as a constraint so that the content of the image does not change significantly. Finally, the generator and the discriminator optimize each other against each other, and the generated images become more and more realistic until the learning of image styles is achieved.

2.1.2 CycleGAN style migration network based modeling

The CycleGAN model is shown in Fig. 2, which achieves image style migration under unsupervised learning with significant results.CycleGAN migrates the task of language translation to image translation. For example, in language translation, a good translation is to be able to translate sentences over and back. In this way, an image is able to be generated by a generative network to produce another image, which is then slewed back to the original image by another generator. This is the cyclic consistency principle of the CycleGAN network model. The specific operation is: given two image sets A, B, build two generators G, F, and correspond them to $G: A \to B$ and $F: B \to A$. Specifically, the generator G is used to transform the real image I_A in the image set A into the false image I_B in the image set B, and then the generator F is used to reconstruct the false image I_B to obtain the reconstructed image $I_{B'A}$, which preserves the information of the original image. Then I_B and the real image I_B are fed into a discriminator to identify its truth or falsity. This constitutes a complete single-direction generative adversarial network. The training of this model is supervised by the cyclic consistency loss. CycleGAN, on the other hand, connects these two identical unidirectional GANs and supervises the model training by cyclic consistency loss. The loss function formula for this network model is as follows:

$$Loss_{cycle} = \mathbb{E}_{x\sim p_{data}(x)}\left[\left\|F(G(x))-x\right\|_1\right] + \mathbb{E}_{y\sim p_{data}(y)}\left[\left\|G(F(y))-y\right\|_1\right] \quad (2)$$

$$\begin{aligned} Loss_{GAN} &= L_{GAN}(G, D_Y, X, Y) + L_{GAN}(F, D_X, X, Y) \\ &= \mathbb{E}_{y\sim p_{data}(y)}\left[\log D_Y(y)\right] + \mathbb{E}_{x\sim p_{data}(x)}\left[\log\left(1 - D_Y(G(x))\right)\right] \\ &\quad + \mathbb{E}_{x\sim p_{data}(x)}\left[\log D_X(x)\right] + \mathbb{E}_{y\sim p_{data}(y)}\left[\log\left(1 - D_X(F(y))\right)\right] \end{aligned} \tag{3}$$

where $Loss_{cycle}$ is the cyclic consistency loss and $Loss_{GAN}$ is the adversarial loss. The total loss function can be found by adding the cyclic and adversarial losses.

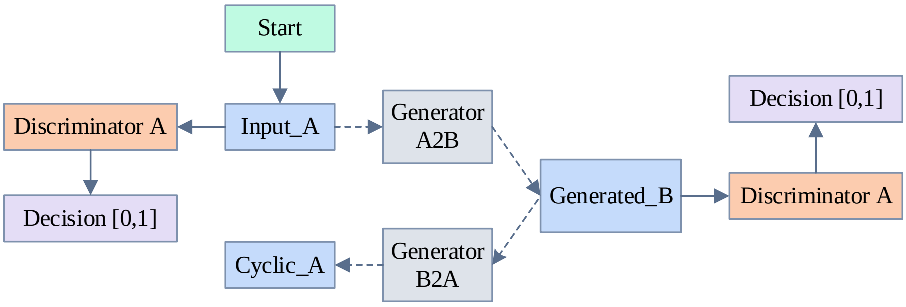


Figure 2: The basic structure of CycleGAN

2.2 Relativistic discriminator

In this paper, we argue that the key missing property of standard GAN is that as the probability of fake data becoming real $(D(xf))$ increases, the probability of real data becoming real $(D(xr))$ should decrease. In a standard GAN, the discriminator can be defined as $D(x) = Sigmoid(C(x))$ based on the non-transformed layer $C(x)$. A simple way to improve the discriminator to a relativistic discriminator is to sample (x_r, x_f) from the real/false data and define it as $D(x) = sigmoid(C(xr) - C(xf))$. By this method the improved discriminator can estimate the probability that the given real data is more real than the randomly sampled pseudo data. Therefore, the loss functions of the discriminator and generator of the relativistic standard GAN can be changed from Eqs. (4) to (5) to Eqs. (6) to (7):

$$\begin{aligned} L_D &= -\mathbb{E}_{x_r\sim P}\left[\log\left(sigmoid\left(C(xr)\right)\right)\right] \\ &\quad -\mathbb{E}_{x_f\sim Q}\left[\log\left(1 - sigmoid\left(C(xf)\right)\right)\right] \end{aligned} \tag{4}$$

$$L_G = -\mathbb{E}_{x_f\sim Q}\left[\log\left(sigmoid\left(C(xf)\right)\right)\right] \tag{5}$$

$$L_D^{RGAN} = -\mathbb{E}_{(x_r, x_f)\sim(P,Q)}\left[\log\left(sigmoid\left(C(xr) - C(xf)\right)\right)\right] \tag{6}$$

$$L_G^{RGAN} = -\mathbb{E}_{(x_r, x_f)\sim(P,Q)}\left[\log\left(sigmoid\left(C(xf) - C(xr)\right)\right)\right] \tag{7}$$

where x_r, x_f denote real data and fake data respectively, and P, Q denote real dataset and fake dataset respectively. $C(x)$ is the output of the transform-free layer discriminator.

In addition, in order to make the relativistic discriminator more useful in its original definition, this paper goes a step further and proposes the average relativistic discriminator with the following formula:

$$L_D^{RaGAN} = -\mathbb{E}_{x_r \sim P}\left[\log\left(\bar{D}(xr)\right)\right] - \mathbb{E}_{x_f \sim Q}\left[\log\left(1-\bar{D}(xf)\right)\right] \tag{8}$$

$$L_G^{RaGAN} = -\mathbb{E}_{x_f \sim Q}\left[\log\left(\bar{D}(xf)\right)\right] - \mathbb{E}_{x_r \sim P}\left[\log\left(1-\bar{D}(xr)\right)\right] \tag{9}$$

Among them:

$$\bar{D}(xr) = \mathrm{sigmoid}\left(C(xr) - \mathbb{E}_{x_f \sim Q} C(xf)\right) \tag{10}$$

$$\bar{D}(xf) = sigmoid\left(C(xf) - \mathbb{E}_{x_r \sim P} C(xr)\right) \tag{11}$$

2.3 CycleGAN-based improved generator

Generator is the most important part of GAN, the final result of GAN is to get a trained generator and use it to generate various images, and the merit of the loss function in the process of training the generator is the deciding factor of the final result. Therefore, this section improves the CycleGAN style migration model through the perspective of generator and generation against loss function.

2.3.1 Improvement of the generator

The generator of CycleGAN consists of residual network, the advantage of residual network is that it is easy to extract features and easy to train, the main steps are to first downsample the image, then change the image features by transforming the network, and finally restore back to the complete image by up-adopting it.The specific structure of Cycle GAN contains two down-sampling convolutional layers with step size 2, nine residual modules, two step size 1/2 upsampling convolutional layers. In order to input texture features to the generator as additional conditions, the input to the generator needs to be changed to four channels, while the output remains unchanged at three channels. The structure of the improved CycleGAN model is shown in Figure 3.

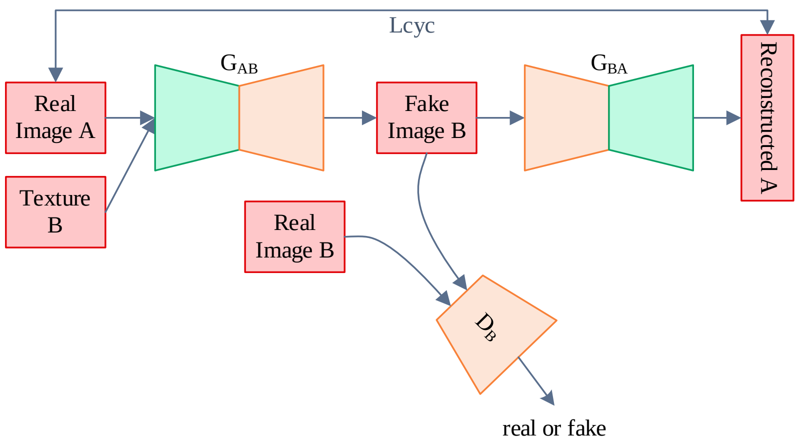


Figure 3: Improved CycleGAN model structure

2.3.2 Generating the Adversarial Loss Function

In this section, the discriminator of CycleGAN is modified to a relativistic discriminator, and the loss function is modified as well. The discriminator model adopts PatchGAN used in the original method, which is, in brief, a rather novel and powerful discriminator that cleverly designs the input as a $n \times n$ matrix, which effectively improves the quality of the generated image compared to the original discriminator that only outputs one piece of data.

The experiments in this chapter will use the L2 loss as the adversarial loss for the modified CycleGAN with the average relativistic discriminator loss. The modified discriminator loss and the adversarial loss are shown in Eqs. (12) to (13):

$$\begin{aligned} L_D = &\mathbb{E}_{x \sim p_{data}(x)}\left[\left(D(X) - \mathbb{E}_{y \sim p_{data}(y)}\left[D(G(Y))\right] - 1\right)^2\right] \\ &+ \mathbb{E}_{y \sim p_{data}(y)}\left[\left(D(G(Y)) - \mathbb{E}_{x \sim p_{data}(x)}\left[D(X)\right] + 1\right)^2\right] \end{aligned} \tag{12}$$

$$\begin{aligned} L_{GAN}\left(G, D_Y, X, Y\right) = &\mathbb{E}_{y \sim p_{data}(y)}\left[\left(D_Y(G(Y)) - \mathbb{E}_{x \sim p_{data}(x)}\left[D_Y(X)\right] - 1\right)^2\right] \\ &+ \mathbb{E}_{x \sim p_{data}(x)}\left[\left(D_Y(X) - \mathbb{E}_{y \sim p_{data}(y)}\left[D_Y(G(Y))\right] + 1\right)^2\right] \end{aligned} \tag{13}$$

L_{cyc} and L_{idt} are not changed, so the total loss of the model is shown in equation (14):

$$\begin{aligned} L_{GAN}\left(G, F, D_X, D_Y\right) = &L_{GAN}\left(G, D_Y, X, Y\right) + L_{GAN}\left(F, D_X, X, Y\right) \\ &+ \lambda_1 L_{cyc}\left(G, F\right) + \lambda_2 L_{idt}\left(G, F\right) \end{aligned} \tag{14}$$

2.4 Wuhu Iron Painting Experimental Data Set

2.4.1 Classification of sample resources

As a representative branch of Chinese traditional crafts, Wuhu Iron Painting has profound research value in terms of its representational features and cultural connotation. By collecting and extracting the original line drawings, collecting the pattern forms and color values for model training and innovative design, so as to establish a special network model for Wuhu iron painting, which can not only promote the inheritance and protection of iron painting, but also solve the current situation of the rapid loss of iron painting resources.

In order to ensure the authenticity and accuracy of image resources, through literature review and field research, the high-definition electronic version of Wuhu iron paintings is finally selected as the initial data set, which contains: landscape iron paintings, bird and flower iron paintings, figure iron paintings, calligraphy iron paintings, animal iron paintings and other iron paintings in six categories totaling 120 Wuhu iron paintings. By acquiring its electronic resources through high-definition scanner, the high-definition images of Wuhu iron paintings will be acquired, and the collected electronic resources of Wuhu iron paintings will be archived in the categories of iron paintings information, iron paintings samples, iron paintings colors and so on, and the subsequent researches and designs of the topic will be carried out gradually on the basis of this dataset.

2.4.2 Pattern Feature Acquisition

Wuhu iron paintings are classified in detail and all kinds of works have their unique stylistic characteristics. Before training the model, it is necessary to standardize the collection and systematic storage of its contour, pattern, color and other information, and extract the resources of the line drawings and patterns by means of the design software and the adaptive threshold edge detection, and then standardize the storage and establish a special dataset for Wuhu iron paintings.

(1) Outline Acquisition

The reference images of line drawings mainly come from two aspects, the first one is the physical version of iron paintings treasured by iron painting artists. The other one is the line drawing extraction of existing coloring iron paintings. In this project, adaptive threshold edge detection is used for batch extraction of iron painting line drawings. The photographs of iron paintings with colors are converted into grayscale maps, the contour maps are obtained by edge detection technology, and the grayscale maps are binarized by the average calculation method of adaptive threshold:

$$T(x,y)_{\text{Average}} = \frac{1}{B^2}\left[\sum_{i=x-\text{int}\left(\frac{B}{2}\right)}^{x+\text{int}\left(\frac{B}{2}\right)} \sum_{j=y-\text{int}\left(\frac{B}{2}\right)}^{y+\text{int}\left(\frac{B}{2}\right)} image(i,j)\right] - C \tag{15}$$

where B is the pixel block size, C is a constant, $image$ is a grayscale map, and $T(x,y)$ is the adaptive threshold of (x,y) coordinate pixels in the grayscale map.

The adaptive threshold is obtained by calculating the weighted mean value of the pixel blocks of size around each pixel and subtracting the constant C, and finally it is obtained by further refinement through the drawing software. The adaptive threshold edge detection method has obvious advantages compared with the traditional drawing software to extract the line drawings, and its short time, good real-time performance, and adaptive advantages overcome the traditional algorithms need to artificially adjust the threshold value.

(2) Color Collection

The colors of Wuhu iron paintings have gone through many changes, from the initial silver-gray and black-gray of the iron material itself, to the red, green, blue and other embellishment colors supplemented by baking lacquer process, as well as modern innovations such as gold foil, cumulative colors and other multi-colors, which are all distinctive. The collection of the color values of the works of iron paintings of different periods in the process of inheriting iron paintings is not only helpful for analyzing the characteristics of the pigments and the laws of color setting, but also lays a foundation for the establishment of a special color card for Wuhu iron paintings in the future. This not only helps to analyze the pigment characteristics and coloring rules, but also lays the foundation for the establishment of a special color card for Wuhu iron painting.

In order to verify whether the color in the subsequent migration effect can maintain a high degree of consistency with the color scheme of iron paintings, some of the colorful works in the initial data set were selected for color collection, and the color scheme of the selected works included the commonly used colors of iron paintings; the color of the physical version of iron paintings was extracted by spectrophotometric colorimeter, while the electronic version of the iron paintings was used to extract the colors by Photoshop color picker, and the CIEL*a*b* values were recorded.

Through the above two approaches to collect at the same time, can increase the maximum range of effective experimental data, making the results more accurate. A total of 120 physical Wuhu iron paintings and 84 electronic iron paintings were collected, and all the measured data were recorded in LAB format.

2.4.3 Classification of experimental data

This project establishes three different experimental datasets of Wuhu iron paintings through on-site collection, network crawling and data augmentation:

(1) Original Iron Painting Data Set: The initial data set collected through writings review and field research are all original artifacts collected by iron painting artists and local museums, totaling 204 iron painting works. The data of iron paintings are replaced with a unified background and stored in png format.

(2) Network crawling data set: In order to further enrich the data set of Wuhu iron paintings, we collect a total of 650 electronic resources of iron paintings on the Internet through network crawling technology, and also replace their backgrounds in a unified way, and then process all the pictures into the same pixel size, naming them with the numbers 1-650 and storing all of them in png format.

(3) Iron painting expansion dataset: The training network model has a large demand for datasets, and it is difficult to achieve accurate style migration with more than a hundred photos, so it is necessary to continue to expand the dataset in the way of data expansion in order to achieve a large volume of data requirements. The common way of data augmentation is based on geometric transformation, in the form of flipping, scaling, translating and rotating. The OpenCV function warpAffine is used to realize the remapping and the rotation matrix is obtained by getRotationMatrix2D. The augmented dataset is more than 7200 frames, all of which are named with “number-aug-augmentation factor” and stored in png format.

2.5 Experimental results and analysis

This section is the experimental part, which focuses on verifying the feasibility of the proposed CycleGAN improved model architecture. The experimental results are derived by comparing the effects with the classical style migration model to verify the superiority of the CycleGAN model.

2.5.1 Experimental environment

The experimental environment of this article is an Intel(R) Xeon(R) CPU E7-4809V3 with a clock speed of 2.00GHz, 8GB of memory, equipped with a NVIDIA GeForce RTX 2060 graphics card, running on the Windows 11 operating system, and using the programming language Python 3.14. There are numerous learning frameworks in the current direction of deep learning, such as Pytorch, Tensorflow, Caffe, and MXNet.The deep learning framework in this paper is the Keras framework with Tensorflow as the backend, and GPU acceleration is achieved using CUDA version 13.1 and CuDNN version 9.18.0.

2.5.2 Experimental dataset and parameter configuration

(1) Parameter Configuration

In this paper, the two datasets of style migration are divided into four parts: trainA, trainB, testA, and testB, in which the allocation ratio of training and testing is 80% and 20%, and the uniform size is $128 \times 128 \times 3$. The parameter configurations of model training are shown in Table 1. 600 epochs are trained in the pre-training phase and 4000 epochs are formally trained.

Table 1: Parameter configuration

Type	Value
Image size	(128×128×3)
Optimizer	Adam
Batch	1
Pre-training cycle	600
Formal training cycle	4000
Learning rate	0.0001

(2) Experimental data set

In the selection of dataset, this paper chooses the homemade Wuhu iron painting dataset, as well as the photographic image dataset made by randomly selecting landscape photographic images, building images and so on. The Wuhu iron painting is used as a style feature for the network to learn, and the photographic images are used as the input raw images for style migration, and the output images are with Wuhu iron painting style features.

2.5.3 Experimental results and comparative analysis

Wuhu iron painting teaching resource images have high detail requirements, so in the conversion process, not only the task of style migration should be accomplished, but also the pixel-level detail features of the original iron painting images need to be preserved.

In this paper, we first take landscape iron painting, figure iron painting and animal iron painting as the training dataset for style migration. No human intervention is made to the training set during the model training process, and the goal of style migration is to realize style migration on the basis of retaining the semantic information of the original images, which should not be distorted greatly and the coloring should be in line with the actual situation.

In order to compare the objective assessment of the art style migration effect between different models, this section divides the art style into texture features and color features for evaluation, using three indicators: structural similarity (SSIM), peak signal-to-noise ratio (PSNR), and Frechette's distance (FID) to evaluate texture features, and color histograms and pixel RGB values to evaluate color features.

(1) Evaluation of texture features of generated images

The quantitative analysis results of texture features of generated images are shown in Table 2. The larger the value of SSIM, the smaller the image distortion and the more similar the two images are, the larger the value of PSNR, the smaller the noise of the generated image and the better the image effect, and the lower the FID, the higher the degree of correlation between the two images and the better the similarity, and vice versa, the worse it is.

From the comparison of the experimental results, it can be found that: the improved model in this paper compares with the original CycleGAN on the migration of three types of art styles, namely landscape iron painting, figure iron painting and animal iron painting, and the two indexes, FID and SSIM, indicate that the quality of the image has been improved. Among them, SSIM is improved by 4.78%, 7.98%, and 6.20% on the three styles of landscape iron painting, figure iron painting, and animal iron painting, respectively.FID is decreased by 18.77%, 51.17%, and 52.22% on the three styles of landscape iron painting, figure iron painting, and animal iron painting, respectively. And the peak signal-to-noise ratio is slightly decreased compared with the original network CycleGAN. The style migration is realized under the premise of retaining the semantic information of the original image, and the quality of the generated images in this paper is better compared to other methods.

Table 2: Quantitative analysis of three types of iron painting style transfer images

Style	Evaluation index	Gatys	DualGAN	CycleGAN	Our
Iron painting of landscape	SSIM↑	0.5524	0.4213	0.8562	0.8971
	PSNR↑	15.78	12.06	26.47	27.95
	FID↓	325.16	369.45	19.87	16.14
Iron figure painting	SSIM↑	0.5123	0.7244	0.7732	0.8349
	PSNR↑	15.26	15.31	20.15	19.64
	FID↓	315.48	104.32	168.57	82.31
Iron painting of animals	SSIM↑	0.6154	0.3527	0.8722	0.9263
	PSNR↑	15.12	20.35	23.84	22.43
	FID↓	258.76	220.52	65.47	31.28

In this paper, the improved models are compared longitudinally, and it is found that the migration results of all the models retain the contour structure of the original image, but the model proposed in this paper is more brilliant in color and more obvious in line features. Not only the clear texture information is retained, but also the boundary color distinction between different objects in the image is obvious and the hue is more prominent. Taking the three photographic images of clouds, castles and the Great Wall as examples, the generated images are quantitatively analyzed from three image evaluation indexes: SSIM, PSNR and FID, and the quantitative analysis results of the three images are shown in Table 3. Among them, RD denotes the modification of the discriminator into relativistic discriminator, MGL denotes the modification of generator and loss function, and RD-MGL-CycleGAN denotes the improved CycleGAN model in this paper.

By comparison, it can be seen that compared with the above two style migration methods, the CycleGAN style migration model designed by combining the relativistic discriminator in this paper can effectively improve the image quality. The RD-MGL-CycleGAN model in this paper improves the SSIM and PSNR by an average of 11.61% and 1.53%, respectively, and the FID value decreases by an average of 47.76% for the same set of generated images compared to the CycleGAN model.

Table 3: The quantitative analysis results of three images

Image	Evaluation index	CycleGAN	RD-CycleGAN	RD-MGL-CycleGAN
Clouds	SSIM↑	0.8125	0.8207	0.8914
	PSNR↑	28.94	29.72	29.35
	FID↓	129.67	105.24	99.75
Castle	SSIM↑	0.8231	0.9613	0.9179
	PSNR↑	28.64	29.51	29.68
	FID↓	239.17	139.58	123.46
The Great Wall	SSIM↑	0.8035	0.8419	0.9127
	PSNR↑	29.53	28.65	29.39
	FID↓	193.28	122.47	54.45

(2) Evaluation of color features of generated images

This subsection mainly compares the color information of CycleGAN and RD-MGL-CycleGAN, because these two methods can generate texture features with more Wuhu iron painting art style compared to other methods. So this section further explores the learning ability of different models for color features when the texture style has been achieved. In this section, both color histogram and pixel RGB values are used to compare the color information of the input photographic image and the generated iron painting style image.

Four parts of the input image and CycleGAN and RD-MGL-CycleGAN output images are selected as the comparison range and their corresponding RGB values are represented by parts 1 to 4, respectively, and the statistics of RGB values for the comparison methods are shown in Table 4. The mean value of the Manhattan distance of the four parts is used to represent the color differences:

$$c = \frac{\sum_{i=1}^{4}\left(\left|r_{1i} - r_{2i}\right| + \left|g_{1i} - g_{2i}\right| + \left|b_{1i} - b_{2i}\right|\right)}{4} \tag{16}$$

where r, g, and b are the gray values of the R, G, and B channels, and i is the ith set of RGB values in the same image. The smaller c is, the smaller the color difference between the input photographic image and the output ferrotypical style image is, and the output image is more capable of retaining color features.

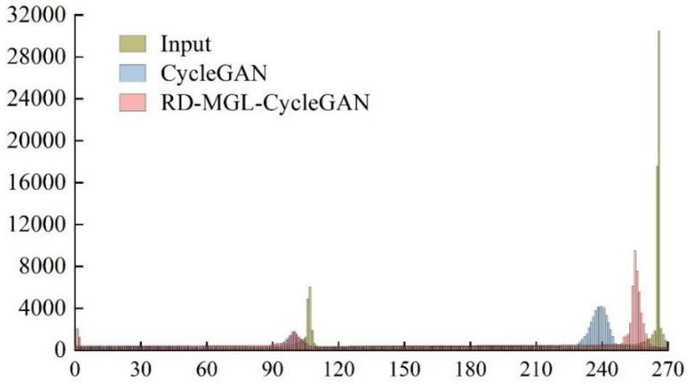
It can be seen that the RGB values of both images of RD-MGL-CycleGAN are closer to the RGB values of the input image, and the Manhattan distance calculated by Eq. (16) is much smaller than that of CycleGAN (38.00 < 83.25, 35.50 < 78.50). This indicates that RD-MGL-CycleGAN does a much better job of preserving image color information and learning color features due to the improvement of the generator and the setting of the relativistic discriminator, and produces iron painting style images that are better than CycleGAN in terms of visual quality.

Table 4: RGB value statistics of the comparison method

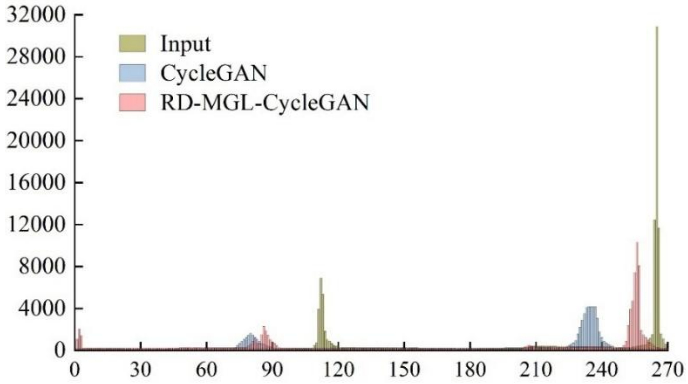
Comparison image	Part 1	Part 2	Part 3	Part 4	c
Input Image 1	(267,243,164)	(265,220,217)	(265,263,263)	(154,85,51)	-
CycleGAN	(234,201,158)	(226,194,202)	(231,224,231)	(131,96,84)	83.25
RD-MGL-CycleGAN	(258,235,192)	(253,220,214)	(248,257,258)	(150,111,85)	38.00
Input Image 2	(253,176,195)	(114,118,135)	(262,262,262)	(234,175,186)	-
CycleGAN	(211,162,175)	(102,85,94)	(238,231,237)	(200,161,162)	78.50
RD-MGL-CycleGAN	(235,176,183)	(102,90,100)	(255,255,258)	(231,174,171)	35.50

The color histogram comparisons of the experimental images of group 2 are shown in Fig. 4, where (a) ~ (c) represent the color histogram comparisons of the R, G, and B channels, respectively.

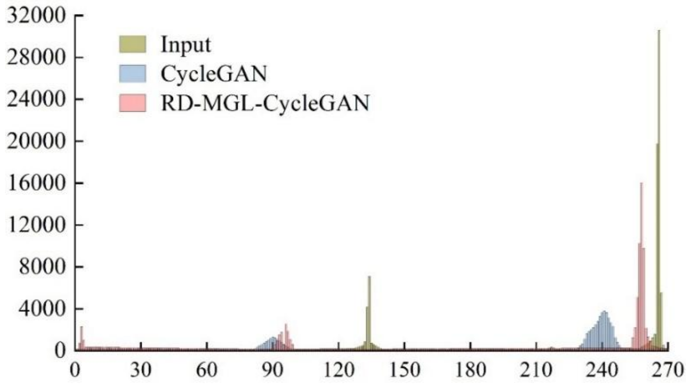
Since the color histogram represents the proportion of different colors in the whole image. It can be seen that in the R, G, and B channels, the peaks in the histograms of RD-MGL-CycleGAN are closer to the peak positions of the input photographic image, which represents that the gray values of most of the pixels of RD-MGL-CycleGAN in the three channels are closer to the gray values of the input image and the brightness of the image is more consistent. So RD-MGL-CycleGAN performs better than CycleGAN in the retention of color features, which proves the effectiveness of setting relativistic discriminator in RD-MGL-CycleGAN.



(a) R channel



(b) G channel



(c) B channel

Figure 4: Comparison of RGB three-channel color histograms

3 Digital Teaching Resources Generation for Wuhu Iron Painting

In order to better utilize the CycleGAN improvement model to automatically generate teaching resources for Wuhu Iron Painting, this chapter uses the Kano model to explore the demand level of digital teaching resources for Wuhu Iron Painting.

3.1 Kano model

3.1.1 Kano model concept

Kano model is a classic model for studying the correlation between user needs and satisfaction, which is mainly used to analyze the impact of customer needs on customer satisfaction, so as to classify and prioritize customer needs.

Kano model divides the demand characteristics of services or products into five categories: charisma demand (A), expectation demand (O), basic demand (M), undifferentiated demand (I) and problem demand (R), poses positive and negative questions for each service element, detects the psychological feelings of the customer when the service element is provided or not provided, and categorizes the demand into one of the five demand types based on the customer's answer.

(1) Charisma demand, also known as excitement demand, can bring high emotional value to the customer and belongs to the demand beyond the customer's expectations. When the company provides this type of service to the customer, it can bring surprise and great satisfaction, and if the company does not provide this type of service, the customer will not have a significant sense of dissatisfaction.

(2) Expected demand, also known as willingness to demand, the degree of customer satisfaction with the degree of provision of service elements in direct proportion to the change in the company to meet this type of demand when customer satisfaction is significantly increased, when the company can not meet this type of demand when customer satisfaction will also be significantly reduced.

(3) Necessary demand refers to the basic elements that the customer thinks the service or product should have, and it is the minimum requirement of the customer for the service or product provided by the company. If the company provides such service or product elements, customer satisfaction will not be significantly increased. But if the company can not provide such services or product elements, customer satisfaction will be significantly reduced.

(4) Non-differentiated demand refers to service elements that are of little concern to the customer. Customers themselves do not demand services in this area, and customer satisfaction fluctuates little regardless of whether such services are provided or not, and what the quality is.

(5) Problem demand refers to the service elements that cause customer dissatisfaction in the opposite direction. Customers do not have such needs, the provision of elements and customer satisfaction is negatively correlated, once the provision of the opposite will lead to a decline in customer satisfaction.

3.1.2 Operationalization of the Kano model

Kano model is based on user needs, designing a set of structured questionnaires, launching a survey through the questionnaire, and categorizing the attributes of each index element in the statistical results, so as to determine the various types of needs affecting user satisfaction and the priority of the needs, in order to help formulate the corresponding countermeasures to improve the quality of service. The specific operational steps are as follows:

(1) Determine Kano elements

Combined with the actual situation of the product or service, start from the user to determine the Kano elements.

(2) Design of Kano questionnaire

The design of Kano questionnaire is based on Kano elements.Kano questionnaire is designed using both positive and negative aspects for the same element, i.e. for a particular service, positive and negative questions are asked. Positive questions are about how users feel when a service exists and negative questions are about how users feel when a service does not exist. The users' feelings are generally expressed through five categories: "satisfied", "essential", "no difference", "tolerable", and "unsatisfied".

(3) Implementation of questionnaires

Questionnaire survey, need to be carried out in a reasonable way to ensure that the questionnaire survey respondents real and effective. After the questionnaires are collected, it is necessary to pay attention to data cleaning and eliminate all the questionnaires that choose “satisfied” or “unsatisfied”.

(4) Kano analysis of the survey results

The results of the questionnaire survey were summarized to calculate the proportion of each indicator in A, O, M, I, R, Q. Based on the proportion of these indicators in the classification table, the factor attributes were classified into categories.

The Kano model is used to analyze and determine the core factors, and the satisfaction (SI) and satisfaction (DSI) of customer service indicators are discussed in depth.SI (Better) indicates the degree of increase in customer satisfaction if a service or function is provided, and DSI (Worse) indicates the degree of decrease in customer satisfaction if a service or function is not provided, and the absolute value of the values of SI and DSI ranges from 0 to 1, and the formula is as follows. The absolute values of SI and DSI values are between 0 and 1, and the formula is as follows:

$$SI(Better) = \frac{A+O}{A+O+M+I} \tag{17}$$

$$DSI\left(Worse\right) = -\frac{O+M}{A+O+M+I} \tag{18}$$

Among them, A, O, M and I represent charm quality attribute, expectation quality attribute, essential quality attribute and undifferentiated quality attribute respectively.

(5) Combined with the actual situation, analyze the actual problems and put forward relevant suggestions based on the prioritized order of user requirements identified by the Kano analysis method.

3.1.3 Feasibility analysis of Kano model applied to this study

Although the Kano model cannot directly measure user satisfaction, it can categorize the content of user needs, which in turn can identify and prioritize the elements that have a greater impact on user satisfaction. For the automatic generation of digital teaching resources in Wuhu Tiehua, the use of Kano, a model specializing in the study of demand prioritization, can identify different aspects of the needs of users of teaching resources and analyze the extent of the impact of different demand elements on user satisfaction, which helps us to understand the needs of users at different levels, directionally determine the elements of demand for teaching resources and the prioritization of the provision of teaching resources, and improve the user's user's experience.

3.2 Kano-based Digital Teaching Resource Requirement Model Study

3.2.1 Initial Digital Teaching Resource Requirements Modeling

On the basis of the pre-research, this study explored the concept of a digital teaching resources demand model by drawing on the classification and expression of demand in related theoretical models, then formulated the dimensions and elements of the digital teaching resources demand model through literature research and content analysis, and revised the model with the help of expert consultation and focus groups, adjusting the names and attributions of the dimensions and elements in the model, as well as the connotation of the elements of each dimension and the explanation of the boundaries. The model was revised with the help of expert consultation and focus groups, and the names and attributions of the dimensions and elements in the model, as well as the connotations of the elements in each dimension, were adjusted, and the boundaries of the model were explained, and the initial digital teaching resources demand model was constructed, including 24 elements in four dimensions of utility (A1), usability (A2), reliability (A3), and availability (A4): pedagogical reasonableness (B1), content relevance (B2), type variety (B3), structural completeness (B4), personalization of styles (B5), and contextualization of applications (B6), Interactivity (B7), Pleasantness (B8), Ease of Learning (B9), Memorability (B10), Low Error (B11), Media Rationality (B12), Responsiveness (B13), Supporting Services (B14), Compatibility (B15), Authority (B16), Normative (B17), Generative (B18), Reuse (B19), Incentive Security (B20) , retrieval efficiency (B21), accessibility (B22), sharing (B23), universality (B24).

3.2.2 Research Design

(1) Questionnaire Design

The 24 elements in the initially constructed digital teaching resource demand model were elaborated and described in an expansive manner, resulting in the design of the "Digital Teaching Resource Demand Preference" questionnaire. In the KANO questionnaire, for each quality characteristic, two corresponding positive and negative questions were designed. At the same time, the options were set at five levels, namely "very dissatisfied", "not very satisfied", "indifferent", "relatively satisfied", and "very satisfied".

(2) Data collection

In this study, with the help of online questionnaire platform to the teachers were issued questionnaire link, which lasted for a week after the recovery, got 726 questionnaires, eliminated invalid questionnaires 98, finally got 628 valid questionnaires for the next step of data analysis.

3.2.3 Data analysis

In this study, 628 valid questionnaires obtained after screening were statistically processed with the help of SPSS and Excel, and the analysis process is as follows.

(1) Reliability and validity test

The collected questionnaire data were tested for reliability and validity by SPSS, and the Cronbach's alpha coefficient of the questionnaire was 0.926 greater than 0.6, which is a very high value, indicating that the questionnaire's internal consistency reliability is good. At the same time, the KMO value of the questionnaire is 0.945 greater than 0.7, with a high value, and the significance of the Bartlett sphericity test is 0.000 less than 0.05, which reaches the significance level, indicating that the questionnaire has good structural validity.

(2) Descriptive statistical analysis of research subjects

The objects of this research were art teachers from several cities within the three provinces of Shandong, Jiangsu and Sichuan in China, and the basic information of the teachers is shown in Table 5.

It can be seen that the teachers in this research basically cover all school segments, and the proportion is more appropriate, which makes the research data more representative. Teaching experience of 9-25 years of experienced teachers, the title of the more senior teachers of the first level, which makes the research data more analytical significance.

Table 5: Basic information of the research subjects

Basic Information	Category	Number of people	Proportion
Gender	Female	435	69.27%
	Male	193	30.73%
School stage	Primary school	183	29.14%
	Junior high school	257	40.92%
	High school	188	29.94%
Teaching experience	1~4 years	138	21.97%
	5~9 years	96	15.29%
	9~25 years	309	49.20%
	>26 years	85	13.54%
Professional title	Senior	22	3.50%
	Associate senior	74	11.78%
	Level 1	186	29.62%
	Level 2	237	37.74%
	Level 3	109	17.36%

3.2.4 KANO Model Traditional Classification

The KANO 2D matrix is shown in Table 6, which can be used to statistically process the responses to the forward and reverse questions in the KANO questionnaire, e.g., in determining the type of need for a particular element, based on a teacher's responses to the forward and reverse questions for that element, the location of the combination of the forward and reverse responses should be found in the KANO 2D matrix to identify the type of need for that element by that teacher. Forward questions

Table 6: KANO two-dimensional matrix table

		Reverse question				
		Very satisfied	Relatively satisfied	It doesn't matter	Not very satisfied	Very dissatisfied
Positive questions	Very satisfied	Q	A	A	A	O
	Relatively satisfied	R	I	I	I	M
	It doesn't matter	R	I	I	I	M
	Not very satisfied	R	I	I	I	M
	Very dissatisfied	R	R	R	R	Q

The type of need of a teacher for the element was obtained through the above approach, and after repeating the process to obtain all the types of need of the element in the teacher group, then the type of need with the highest frequency of occurrence was taken as the final type of need of the element, and so on, to determine the type of need of the 24 elements in the need model as shown in Table 7.

Table 7: Demand classification based on the traditional KANO model

Element	A	O	M	I	R	Q	Maximum value	Total number	Demand type
B1	127	265	58	174	2	2	265	628	O
B2	134	247	83	161	1	2	247	628	O
B3	217	235	31	138	3	4	235	628	O
B4	241	101	48	224	3	11	241	628	A
B5	161	138	50	260	5	14	260	628	I
B6	169	178	52	227	1	1	227	628	I
B7	163	137	41	277	4	6	277	628	I
B8	241	148	42	193	3	1	241	628	A
B9	124	209	61	230	2	2	230	628	I
B10	77	154	120	259	6	12	259	628	I
B11	80	284	113	124	4	23	284	628	O
B12	139	210	64	212	2	1	212	628	I
B13	146	187	55	228	2	10	228	628	I
B14	173	174	61	218	1	1	218	628	I
B15	198	232	59	132	2	5	232	628	O
B16	201	37	19	353	8	10	353	628	I
B17	86	312	70	145	5	10	312	628	O
B18	239	205	28	142	5	9	239	628	A
B19	164	188	61	205	6	4	205	628	I
B20	161	162	48	250	1	6	250	628	I
B21	76	248	100	186	6	12	248	628	O
B22	94	90	58	335	23	28	335	628	I
B23	203	174	50	190	6	5	203	628	A
B24	175	152	50	234	8	9	234	628	I

Based on the data in Table 7, the results of the requirements classification of the 24 elements in the Wuhu Iron Painting Digital Teaching Resources Requirements Model are collated as shown in Table 8.

It can be seen that no elements are classified into the essential needs (M) in the demand hierarchy obtained through the traditional classification of Kano model. Expected needs (O) elements include pedagogical soundness (B1), content relevance (B2), type diversity (B3), low error (B11), compatibility (B15), and standardization (B17). There are four elements of charismatic needs (A): structural completeness (B4), pleasantness (B8), generativity (B18), and universality (B24). All other elements are undifferentiated needs (I).

Table 8: The demand hierarchy based on the traditional classification of the KANO model

M				
O	B1, B2, B3	B11	B15, B17	B21
A	B4	B8	B18	B23
I	B5, B6, B7	B9, B10, B12, B13, B14	B16, B19	B20, B22, B24

3.2.5 Better-Worse coefficient analysis

The traditional classification of KANO model is not sufficient for the use of data, while the Better-Worse coefficient analysis can further quantitatively analyze the relationship between the quality characteristics of the product and the user's satisfaction, which makes the classification of demand more scientific.

Based on formulas (17)~(18) and the data in Table 7, the Better-Worse coefficients of the 24 elements in the Wuhu Iron Painting Digital Teaching Resource Demand Model are calculated as shown in Table 9. Where, horizontal coordinate = absolute value of Worse coefficient - average value of absolute value of Worse coefficient, vertical coordinate = Better coefficient - average value of Better coefficient.

Table 9: Demand types based on the analysis of the Better-Worse coefficient

Element	Better coefficient	Worse coefficient	Horizontal coordinate	Vertical coordinate	Demand type
B1	0.6282	-0.5176	0.1193	0.0703	O
B2	0.6096	-0.5280	0.1297	0.0517	O
B3	0.7279	-0.4283	0.0300	0.1700	O
B4	0.5570	-0.2427	-0.1556	-0.0009	I
B5	0.4910	-0.3087	-0.0896	-0.0669	I
B6	0.5543	-0.3674	-0.0309	-0.0036	I
B7	0.4854	-0.2880	-0.1103	-0.0725	I
B8	0.6234	-0.3045	-0.0938	0.0655	A
B9	0.5337	-0.4327	0.0344	-0.0242	M
B10	0.3787	-0.4492	0.0509	-0.1792	M
B11	0.6057	-0.6606	0.2623	0.0478	O
B12	0.5584	-0.4384	0.0401	0.0005	O
B13	0.5406	-0.3929	-0.0054	-0.0173	I
B14	0.5543	-0.3754	-0.0229	-0.0036	I
B15	0.6924	-0.4686	0.0703	0.1345	O
B16	0.3902	-0.0918	-0.3065	-0.1677	I
B17	0.6493	-0.6232	0.2249	0.0914	O
B18	0.7231	-0.3795	-0.0188	0.1652	A
B19	0.5696	-0.4029	0.0046	0.0117	O
B20	0.5201	-0.3382	-0.0601	-0.0378	I
B21	0.5312	-0.5705	0.1722	-0.0267	M
B22	0.3189	-0.2565	-0.1418	-0.2390	I
B23	0.6110	-0.3631	-0.0352	0.0531	A
B24	0.5352	-0.3306	-0.0677	-0.0227	I

Based on the data in the above table, the results of the demand classification of 24 elements in the Wuhu Iron Painting Digital Teaching Resource Demand Model are collated, and the final digital teaching resource demand model is obtained as shown in Table 10.

It can be seen that ease of learning (B9), memorability (B10) and retrieval efficiency (B21) belong to the required needs (M), which indicates that at this stage, primary and secondary art teachers believe that Wuhu Tiehua digital teaching resources must be in the usability aspect, and that a qualified resource should be at least easy to use, so the automated generation of Wuhu Tiehua digital teaching resources should increase the attention to usability. At the same time, teachers are very sensitive to the issue of the workload of filtering resources, and they are eager to get the resources they want quickly, so they can not just generate Wuhu Tiehua digital teaching resources, but they have to remove the roughness and extract the essence of the Wuhu Tiehua digital teaching resources by introducing the teachers' after-use evaluation of the resources.

Pleasure (B8), generation (B18) and sharing (B23) belong to the charm demand (A), which fully reflects that if Wuhu Tiehua digital teaching resources want to win the favor of teachers, they should improve the interest and beauty of the resources, and allow teachers to participate in the co-construction and sharing of the resource generation, and promote the integration and innovation of the digital teaching resources of Wuhu Tiehua by the popularization and application of the improved CycleGAN model. Integration and Innovation.

In the dimension of practicality demand (A1), structural completeness (B4), style personalization (B5), application context (B6) and interactivity (B7) are all classified as undifferentiated demand, which in fact shows that teachers don't have too many requirements for the functionality of Wuhu Tiehua digital teaching resources, and that the quality of the resources is often not reflected in the uniqueness of the functionality, so that the development of Wuhu Tiehua digital teaching resources is shifting from dedicated resources to universal resources. Therefore, the development of digital teaching resources for Wuhu Tiehua is in line with the teachers' voices by changing from specialized resources to general resources.

Table 10: Digital teaching resource demand model

	A1	A2	A3	A4
M		B9, B10		B21
O	B1, B2, B3	B11, B12	B15, B17, B19	
A		B8	B18	B23
I	B4, B5, B6, B7	B13, B14	B16	B20, B22, B24

4 Conclusion

This paper achieves an innovative design for the automated generation path of digital teaching resources for Wuhu iron painting, which is realized by an art style migration model based on improved CycleGAN and guided by Kano's demand hierarchy model.

The improved RD-MGL-CycleGAN model in this paper achieves optimal results in the migration of three types of art styles: landscape iron painting, figure iron painting and animal iron painting. Compared with the original CycleGAN, the SSIM values of the RD-MGL-CycleGAN model are improved by 4.78%, 7.98%, and 6.20%, and the FID values are decreased by 18.77%, 51.17%, and 52.22%, respectively, whereas the PSNR values are only slightly decreased, which indicates that it realizes the style migration under the premise of retaining the semantic information of the original images, and the generated images with better texture features. Meanwhile, in terms of color features, the RGB values of the generated images by RD-MGL-CycleGAN are closer to the RGB values of the input images, and it has done a better job in retaining the color information of the images, and the generated images of the iron painting style are better than CycleGAN in terms of visual quality, which verifies the effectiveness of this paper in improving the model by setting the relativistic discriminator.

In addition, this paper constructs a Kano-based hierarchical model of Wuhu Iron Painting digital teaching resources requirements, in which ease of learning, memorability and retrieval efficiency belong to the essential requirements, which need to be focused on in the automatic generation of Wuhu Iron Painting digital teaching resources. Pleasantness, generativity and shareability belong to the charm demand, indicating that the generation of teaching resources needs to enhance the interest and beauty of the resources, and allow teachers to participate in the co-construction and sharing of resource generation to promote the integration and innovation of Wuhu Iron Painting digital teaching resources. And by analyzing the undifferentiated demand, it is found that teachers prefer to change the digital teaching resources of Wuhu Iron Painting from dedicated resources to general resources.

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