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Research on the Innovative Application of AI Painting Technology Combined with Traditional Art Teaching for Art Education

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Abstract With the rapid development of artificial intelligence technology, AI painting shows revolutionary potential in the field of art creation. In this paper, we focus on the convolutional neural network-driven AI painting generation model (FSMNet), realize image classification and style migration based on VGG-16, and construct an AI painting generation algorithm adapted to art education. Experiments show that compared with StyTr2, which has the best performance in the baseline model, the SSIM and PSNR of FSMNet are improved by 18.6% and 6.82%, respectively, and the migration time is reduced by 0.017s to reach 0.51, 12.06, and 0.079s, respectively. After the teaching experiments, the experimental group scores in the three dimensions of drawing fundamentals, color perception, and creative thinking respectively reach 25.43±1.14, 27.09±1.28, and 35.18±2.15, which are all better than the control group, and the total score of the test is higher than that of the control group by 13.68, and the standard deviation is smaller, and the overall performance is more stable.

Index Terms AI drawing technology, art education, convolutional neural network, style migration, VGG-16

I. Introduction

The emergence of new digital technologies represented by big data, artificial intelligence and blockchain has brought about a new mode of business, and also driven the iterative renewal of the traditional education model, and the digital transformation of education has become a major core strategy in the development of the country [1]-[3]. As an important way to cultivate students' aesthetic ability, innovative thinking and creativity, art education also needs to keep pace with the times and incorporate digital elements [4]. How to promote students' art practice more effectively and deeply in the context of digitalization is worth pondering. In the traditional art education model, more than 85% of institutions still use copying teaching. Due to the limitations of economic conditions and the popularity of art education, art education resources (teachers and teaching tools) are scarce in county-level institutions, and most schools only offer drawing courses, with insufficient creative courses for students [5]-[8].

In the field of contemporary art, Artificial Intelligence (AI) painting has gradually become a hot topic of research and practice.AI painting is not only an imitation of traditional painting techniques, but it also opens up a completely new way of artistic creation, which somehow transcends the limitations of human artists [9], [10]. At its core are deep learning algorithms, especially Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN). These algorithms are trained with a large amount of image data and learn the distributional features of the image so that they are able to generate new images. CNN is mainly used for image recognition and classification, while GAN consists of a generator and a discriminator, where the generator is responsible for creating the image, and the discriminator evaluates the authenticity of the generated image. Through continuous iterative training, AI is able to create more and more realistic paintings [11], [12].

Compared with traditional art, AI painting has some obvious advantages. For example, it can create a large number of works in a very short period of time, and each work is unique. However, AI painting lacks the emotion and soul of human artists, it is difficult to convey profound emotions and thoughts, the creation process lacks the intuition and inspiration of human artists, which may affect the artistic value of the works, and the creation effect of some AI painting techniques has not reached the target demand [13]-[15]. Therefore, in the digital environment of art education, how to combine AI painting technology and traditional art teaching to innovate the current art education and improve the quality of education.

In this paper, we first discuss the application of AI painting technology in traditional art, and construct an AI painting generation model based on convolutional network architecture using VGG network. The structure of the model convolutional layer and pooling layer is specifically described, and the classification model is trained by forward propagation and back propagation. An improved FSMNet model is proposed, using VGG-16 as the loss network of the model. Based on multimodal dataset experiments, the classification performance and image migration performance of the model are examined. Control experiments are set up to verify the applicability of the model in art education.

II. AI painting techniques and traditional art redesigns

II. A.Cross-border integration of AI technology and artistic creation

The rapid development of artificial intelligence (AI) technology has brought new possibilities for artistic creation, and AI technology has not only demonstrated its powerful ability in the fields of image recognition, image generation, and image processing, but has also gradually revealed its unique charm in artistic creation. Through deep learning, generative adversarial networks and other technical means, AI systems have been able to generate image works of an artistic nature, showing amazing creativity and expressiveness. This cross-border combination of AI technology and art creation not only injects new vitality into art creation, but also provides new possibilities and directions for the development of traditional painting.The application of AI painting generation technology injects a new era of connotation into traditional painting, and gives it rich forms of expression and aesthetic characteristics.

II. B.AI's Traditional Art Redesign Methods and Practices

The collision between traditional culture and new technology makes the information and meaning transmitted between cultures have a deeper and richly interesting connection. This connection is no longer the pattern information on the surface of the culture, but to make the pattern have a more profound meaning.AI painting user interaction process is shown in Figure 1, the user first selects his channel, followed by inputting instructions and selecting the style of generation to send, the AI software will be based on the user's instructions for generating the image sent, calculating and innovating the graphic. If the graphics presented at the end do not meet the user's expectations, the instructions can be meticulously entered again until a satisfactory pattern is generated.

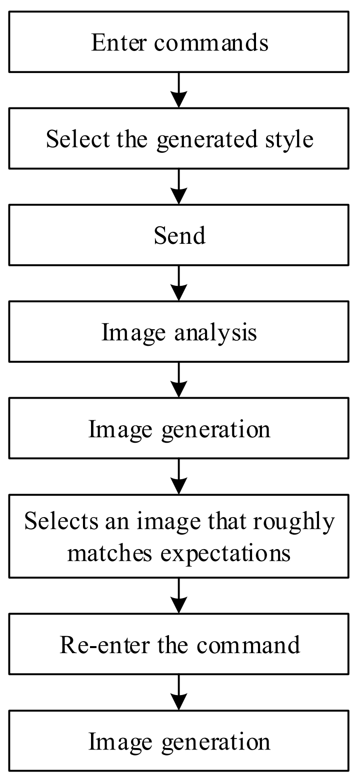


Figure 1: User interaction process

III. Convolutional neural network-based AI painting generation

The paradigm change of digital technology to reconfigure traditional art education has become an important proposition for global education innovation. Generative AI technology provides a non-linear creation path and cross-media expression tools for art creation through the ability of style migration and image generation, etc. However, there are still challenges such as insufficient technical adaptability and doubtful teaching effectiveness in its deep integration with art teaching. With the continuous accumulation of Internet data, the increasing computational power of computers, and the continuous development of neural network theory, convolutional neural networks have achieved a breakthrough. VGG network, as an improved version of AlexNet, investigates the effect of network depth on network classification ability. This study centers on how to build a lightweight AI painting model for art education, and constructs an AI painting generation model based on VGG network.

III. A. Image classification

III. A. 1) Structure

(1) Convolutional layer

In the forward propagation convolutional layer, the local region of the previous feature map is connected to the convolution kernel, and the local features are extracted by convolution operation. There are multiple convolution kernels in the convolutional layer, different convolution kernels extract different features, in the convolution operation, the same convolution kernel weights are shared, different convolution kernels have different weights, the calculation of the convolutional layer is as follows:

$$X_j^l = f\left(\sum_{m,n} X_i^{l-1} * k_{ij}^l + b_j^l\right) \tag{1}$$

where l-layer denotes the current layer, $l-1$-layer denotes the previous layer, X_j^l denotes the j-feature map of the current layer, k_{ij}^l denotes the convolution kernel that corresponds to the i-feature map of the current layer and the j-feature map of the previous layer, and b_j^l denotes the bias of the j-feature map of the current convolution layer.

The operation flow of the convolutional layer as the main feature extraction layer is shown in Fig. 2.

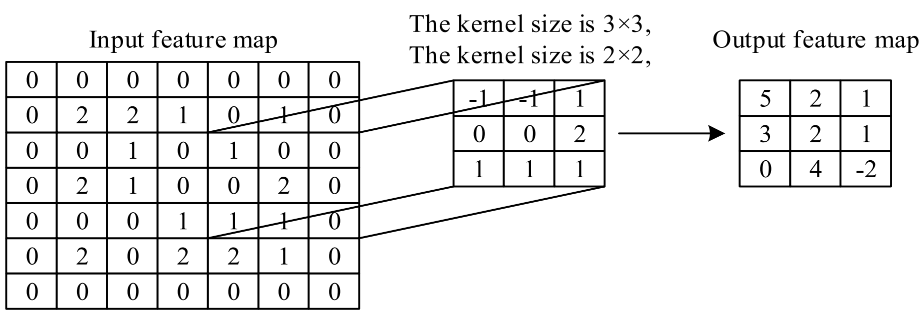


Figure 2: Operation process of the convolutional layer

In the above figure the convolution kernel is connected to the local regions of the feature map for weighted iteration computation, the size of the convolution kernel is 3×3, the step size is 2, the convolution kernel performs a sliding traversal in the previous layer of the feature map, and performs weighted iteration sequentially in all the local regions so as to compute the new feature map.

(2) Pooling layer

In the forward propagation pooling layer, the number of input feature maps remains unchanged after the pooling operation, and when the pooling step is n, the size of the output feature map becomes $1/n^2$ of the size of the input feature map. The main role of the pooling layer is to reduce the feature map resolution, reduce the feature dimension, which has a high degree of invariance to deformations in the form of translation, skewing, scaling and so on, which improves the robustness of the network model classification. The pooling layer is computed as follows:

$$X_k^l = f\left(\beta_k^l down\left(X_k^{l-1}\right) + b_k^l\right) \tag{2}$$

where X_k^l and X_k^{l-1} denote the k th feature map of the current and previous layers, respectively, $down(\cdot)$ is the downsampling function, β_k^l denotes the weighting coefficients of the k th feature map of the current layer, and b_k^l denotes the current bias of the k th feature map of the pooling layer.

The pooling layer is divided into two types: the maximum pooling layer and the average pooling layer, which are mainly used for image downsampling, taking the maximum pooling layer as an example, and its operation flow is shown in Figure 3.

Input feature map

1	0	-1	1
3	-1	1	0
0	2	-1	1
-1	1	3	2

The kernel size is 2×2,
The stride size is 2 $\longrightarrow$

Output feature map

3	1
2	3

Figure 3: Operation process of the maximum pool layer

In the above figure the maximum pooling layer selects the maximum value in each region, the region size i.e. the convolutional kernel size is 2×2 and the step size is 2, and performs a sliding traversal in the input feature maps to compute the maximum value in each region to compute the output feature maps. The pooling operation shrinks the feature map resolution and loses some detailed features, which can be attenuated by increasing the depth of the convolutional neural network structure.

III. A. 2) Training process

Convolutional neural network is a kind of supervised learning, all the training samples and test samples are labeled, using stochastic gradient descent method for training, through the network model training so that the same category of image samples are distributed in the same space, and the other image samples are distributed in different spaces. Through continuous iterative optimization, the weight parameters of the convolutional neural network classification model are constantly updated in the direction that is beneficial to image classification, so as to continuously improve the accuracy of the classification model for image classification.

The convolutional neural network classification process is essentially a mapping relationship, using the image feature extraction algorithm and according to a fixed rule to learn the mapping function: $f:R^{w\times w\times d}\rightarrow R^{K}$, which can be realized by mapping the input image into a feature vector $f(i)$ of dimension K. Continuously training the convolutional neural network classification model, constantly updating the weight parameter W of the convolutional and fully connected layers, and then going through the pooling layer and activation function can realize the mapping between the image input and output. As a supervised learning method, the convolutional neural network in the training process, in order to prevent the convolutional kernel weights and the fully connected weights because of the saturation of too large, generally in the convolutional neural network training before the random initialization of the convolutional kernel weights and the fully connected weights parameter W between 0 and 1.

Convolutional neural networks are mainly trained for classification models through two stages: forward propagation and back propagation:

First stage, forward propagation

The purpose of forward propagation is to extract data features, select a sample from the sample set as the input of the current layer l, and then through the activation function to get the output of the current layer, and then pass it to the next layer $l+1$, and so on until the end of the last layer. The current layer output calculation process is as follows:

$$Y^{l}=f(W^{l}X^{l}+b^{l}) \tag{3}$$

where the l th layer represents the current layer, X^{l} and Y^{l} represent the current layer input and the current layer output, W^{l} represents the current layer weight, b^{l} represents the current layer bias, and f represents the activation function of the current layer, and a common convolutional neural network model usually chooses the ReLU nonlinear function as the activation function.

The second stage, backpropagation

The purpose of backpropagation is to continuously update the weights of the convolutional kernel in the direction favorable to classification, generally using the error squared and loss function. For a multi-class problem with N samples and c categories, the error squared and loss functions are calculated as follows:

$$E^{N}=\frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{c}(t_{k}^{n}-y_{k}^{n})^{2} \tag{4}$$

where E^{N} denotes the N-sample total error, t_{k}^{n} denotes the k-dimensional label corresponding to the n th sample, and y_{k}^{n} denotes the k th output predicted in the corresponding output of the n th sample.

III. B. Image Generation

The task of style rendering requires feature extraction and computation for each layer of the convolution due to its each style migration from a blank noisy image, which greatly increases the computational complexity in order to get better results. This paper further describes the improved fast style migration algorithm.

III. B. 1) Generating networks

The model of Fast Style Migration Network (FSMNet) is proposed by improving on the style migration network. Its network structure is shown in Figure 4.

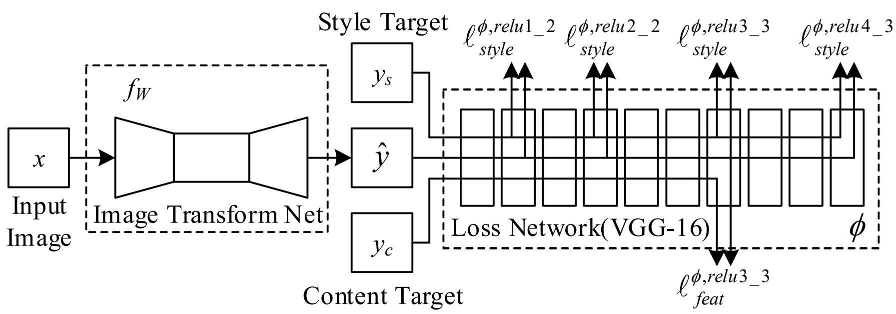


Figure 4: Fast style migration network structure

The Fast Style Migration Network structure is divided into two parts, the Image Transform Net and the Loss Network. The input to the Generative Network is a picture, and the final output after the network computation is also a picture, which has been transformed into a different style.

The generative network is actually a convolutional neural network in structure, which contains a convolutional layer, a residual layer, and an inverse convolutional layer, without any pooling operation. As can be seen from the structure of the figure, the first three layers of the generative network are downsampled, the middle part is connected by five residual blocks, and the end part uses an upsampling operation to increase the size of the image in order to keep the size of the output image the same as the input. In order to keep the pixel value of the output image in the last layer of the generative network between $[0,255]$, a Tanh function is used to compress the output value. The generative network starts with all the weight parameters randomized and as the network is trained iteratively, the weight values and bias values of all the layers in the generative network are eventually determined.

III. B. 2) Loss networks

The loss network is a pre-trained VGGNet, generally chosen as VGG-16 or VGG-19. Like the style migration network, here also no weight update is done during training, it is only used to do the computation of content loss and style loss, and back propagation is used to update the weights of the previous generated network. For calculating the content loss is the feature map of relu3_3 is extracted for comparison, relu3_3 denotes the 3rd relu layer result of the 3rd layer of the loss network. For style loss, the feature maps of relu1_2, relu2_2, relu3_3, and relu4_3 were extracted for comparison, and at the end the weighted average result was taken.

IV. Applied research on the combination of AI painting technology and traditional art teaching

IV. A. Evaluation of classification performance

To explore the image classification performance of the proposed FSMNet, this section compares the performance of FSMNet with the existing state-of-the-art methods. The comparison experiment set up consists of two parts: first, the feature learning capability of the FSMNet encoder in the self-supervised training phase is verified using linear probing, i.e., connecting a linear classification layer after the feature extraction layer of FSMNet, and using the features directly to compute the classification results. Second, a few categories with scarce samples are used as small-sample classification tasks to verify the small-sample learning performance of FSMNet.

The experiments are carried out on four widely used datasets, namely, the content image dataset MS-COCO2014, the style image dataset WikiArt, the movie and television image dataset SFEW2.0, and the video image dataset CK+, and the dataset images can be categorized into the four categories of fruits, birds and flowers, landscapes, and people.

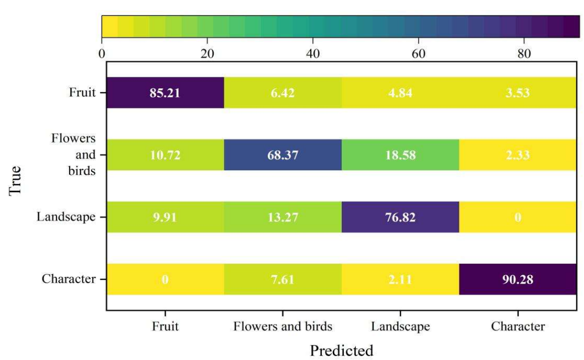
IV. A. 1) Comparison of linear detection classification results

Comparison of the classification results of different methods using linear detection is shown in Table 1.The experimental results on MS-COCO2014, WikiArt datasets show that the classification accuracy of StyTr2 is higher among the existing methods, which reaches 80.02% and 81.35%, respectively. Compared to StyTr2, FSMNet improves the accuracy by 0.15%, 2.35%. For the SFEW 2.0 dataset, PAT achieved 76.31% classification accuracy, and FSMNet improved on PAT by 2.31% to achieve 78.62% classification accuracy. On the CK+ dataset, FSMNet also performs optimally, achieving 76.82% classification accuracy. The experimental results in this section show that FSMNet can effectively extract image features with strong generalization ability.

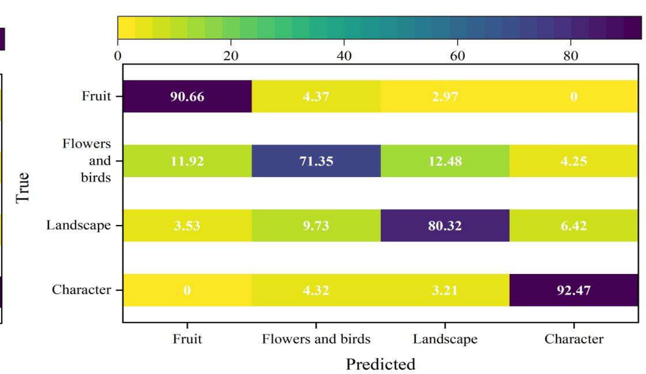
Table 1: Comparison of classification results of different methods using linear probes

Method	Backbone network	Accuracy rate/%			
		MS-COCO2014	WikiArt	SFEW 2.0	CK+
ACNN	VGG-16	66.37	67.57	53.53	50.19
RAN	ResNet-18	69.38	69.55	59.24	54.24
PASM	ResNet-34	70.08	70.97	63.58	59.21
AHA	ResNet-18	72.37	73.21	64.99	64.28
KTN	CNN	75.92	76.18	69.32	68.35
SSF-ViT	ViT	78.19	79.33	70.11	70.11
PAT	ResNet-101	79.28	80.09	76.31	74.27
StyTr2	Transformer	80.02	81.35	75.18	72.31
FSMNet	VGG-16	80.17	83.70	78.62	76.82

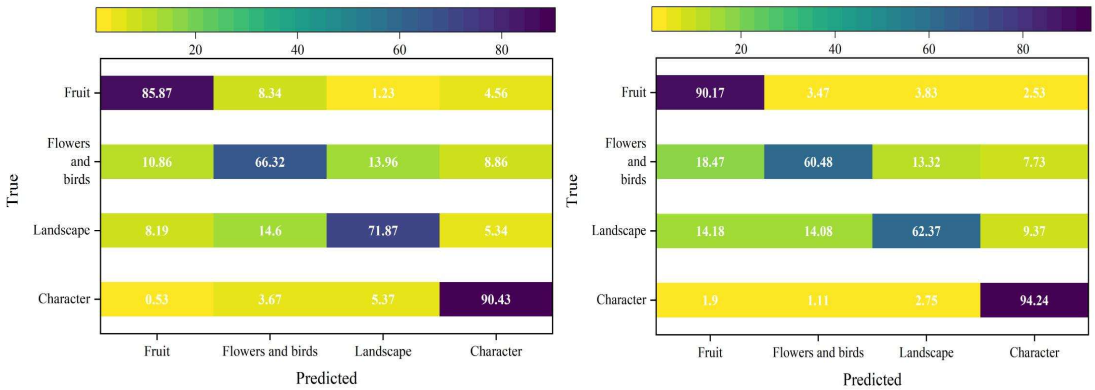
In order to target the study of which categories of images FSMNet underperforms in recognition, the confusion matrix experimental analysis is conducted in this section, and the confusion matrices on different datasets are shown in Fig. 5. As shown in Fig. 5(a), the linear detection model of FSMNet can accurately recognize most of the images in the MS-COCO2014 dataset, in which the recognition accuracy for the people category reaches 90.28%, while the recognition accuracy for the flowers and birds category is only 68.37%. As shown in Fig. 5(b), for the category of flowers and birds, which accounts for the smallest proportion in the WikiArt dataset, FSMNet also obtains only 71.35% recognition accuracy. As shown in Fig. 5(c), for the SFEW 2.0 dataset where flower and bird is also the smallest category, FSMNet only achieves 66.32% classification accuracy. For the CK+ dataset, as shown in Fig. 5(d), FSMNet performs poorly in the 2 categories of flowers and birds and landscapes, with only 60.48% and 62.37%, both of which are significantly lower than the average recognition accuracy. These phenomena are due to the low percentage of data volume of the categories in the dataset, resulting in the decreased model fitting ability. Therefore, FSMNet adopts a small-sample learning paradigm, which considers the categories with a small proportion of samples as “new categories” that the model has not seen before, and trains the model to learn to recognize these “new categories”, in order to further improve the performance of the model.



(a) MS-COCO2014



(b) WikiArt



(c) SFEW 2.0 (d) CK+

Figure 5: Confusion matrix on different data sets

IV. A. 2) Comparison of small sample classification results

The performance comparison results of small sample classification methods on CK+ dataset are shown in Table 2. The small-sample classification results of different methods are compared for two image categories, flower and bird and landscape, on the CK+ dataset. Compared with the best performing small-sample learning method PAT, FSMNet improves the 1-Shot classification accuracy by 3.76% and the 5-Shot classification accuracy by 3.64% on average, which illustrates the advanced performance of FSMNet in small-sample learning scenarios.

Table 2: Performance comparison of classification methods for small samples

Method	1-Shot/%			5-Shot/%		
	Flowers and birds	Landscape	Average	Flowers and birds	Landscape	Average
ACNN	58.38	59.93	59.16	60.21	63.21	61.71
RAN	60.38	57.38	58.88	57.28	60.72	59.00
PASM	62.86	61.99	62.43	62.97	64.18	63.58
AHA	63.11	64.38	63.75	64.22	65.85	65.04
KTN	64.97	65.79	65.38	68.18	70.19	69.19
SSF-ViT	66.08	68.11	67.10	70.36	71.77	71.07
PAT	67.37	70.28	68.83	75.31	76.38	75.85
StyTr2	69.21	66.37	67.79	72.38	73.22	72.80
FSMNet	71.29	73.88	72.59	78.86	80.11	79.49

IV. B. Evaluation of migration performance

IV. B. 1) Objective evaluation

In order to evaluate the image style migration results more objectively, two metrics, structural similarity (SSIM) and peak signal-to-noise ratio (PSNR), are used to evaluate the generated images.

The SSIM metrics are evaluated in terms of brightness, contrast, and structure of the image, using the mean value to measure the brightness of the image, the standard deviation to estimate the contrast of the image, and the covariance to measure the degree of structural similarity of the image.The closer the SSIM value is to 1, the higher the degree of similarity of the two images. Its computational expression is:

$$SSIM(c,g)=\frac{(2\mu_c\mu_g+c_1)(2\sigma_{cg}+c_2)}{(\mu_c^2+\mu_g^2+c_1)(\sigma_c^2+\sigma_g^2+c_2)} \tag{5}$$

where, μ_c, μ_g denote the mean of image c, image g respectively; σ_c^2, σ_g^2 denote the variance of image c, image g respectively; σ_{cg} denotes the covariance of image c and image g; c_1, c_2 denote constants to maintain stability and avoid divisor 0.

The PSNR metric is used to measure the signal-to-noise ratio of an image, i.e., the ratio of the effective signal to the noise in an image. It is used to measure the quality of the stylized image relative to the input image in the stylistic migration task, and a larger value of PSNR indicates that the synthesized stylized image has less distortion and higher quality. Its computational expression is:

$$PSNR(c,g)=10\log_{10}\left(\frac{255^2}{MSE(c,g)}\right) \tag{6}$$

$$MSE(c,g)=\frac{1}{xy}\sum_{i=0}^{x-1}\sum_{j=0}^{y-1}\left[c(i,j)-g(i,j)\right]^2 \tag{7}$$

where $MSE(c,g)$ denotes the mean square error of image c and image g, x denotes the height of the image, and y denotes the width of the image.

100 content style image pairs are randomly selected for the stylization test and averaged.The results of the evaluation metrics of FSMNet compared with other methods are shown in Table 3. Compared with StyTr2, which has the best performance in the baseline model, the SSIM and PSNR of FSMNet are improved by 18.6% and 6.82%, respectively, and the migration time is reduced by 0.017s, reaching 0.51, 12.06, and 0.079s, respectively.This paper's method is significantly better than other methods, and the speed of the image style migration is fast, which can realize real-time fast image style migration. The experimental results show that FSMNet can generate higher quality stylized result images and can achieve fast image style migration.

Table 3: Comparison of evaluation indicators between FSMNet and other methods

Method	SSIM	PSNR	Migration time/s
ACNN	0.23	8.93	40.372
RAN	0.25	8.99	38.434
PASM	0.27	9.27	27.376
AHA	0.28	9.58	3.282
KTN	0.32	9.92	0.091
SSF-ViT	0.35	10.28	0.082
PAT	0.37	10.85	0.073
StyTr2	0.43	11.29	0.062
FSMNet	0.51	12.06	0.079

IV. B. 2) Loss function curves

FSMNet was iterated 6000 times on the 4 datasets and the loss function curves are shown in Figure 6. As the number of iterations increases, the total loss function value tends to stabilize, and the network converges at about 1200 iterations, with the total loss stabilizing within 20%.

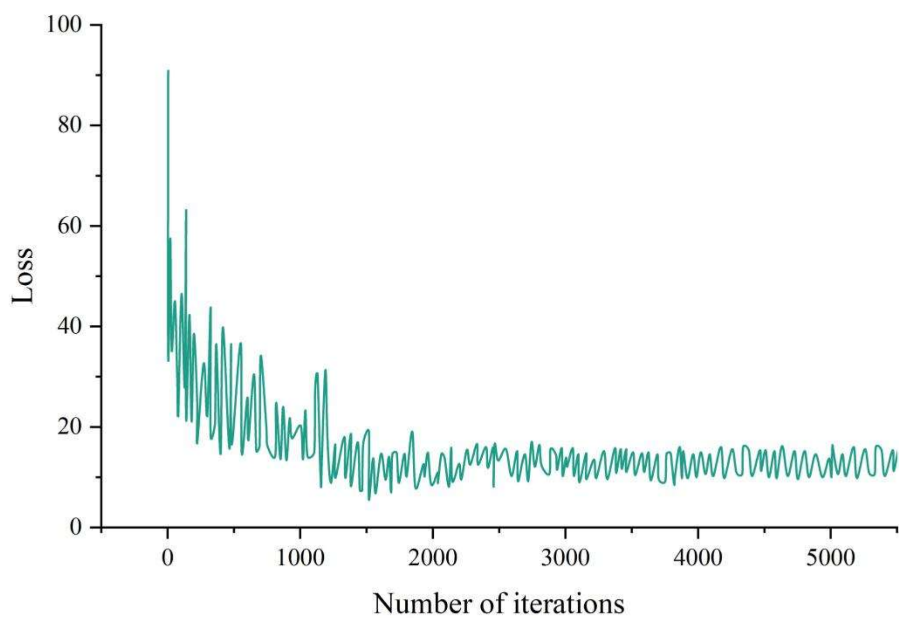


Figure 6: Loss function curve

IV. C. Analysis of application effects

In order to investigate the innovative application effect of AI drawing technology assisted art education, this paper designs a teaching experiment to compare and analyze the differences between the experimental group and the control group in terms of drawing foundation, color perception and creative thinking level. The experiment adopts a pre-test-post-test control group design, and 80 students in two classes of the second year of art majors in a university are selected as the research subjects, and are divided into the experimental group (n=40, AI drawing technology-assisted teaching) and the control group (n=50, traditional teaching) according to the random number table method. The baseline test showed no significant difference between the two groups of students in terms of the basic scores of sketching, color perception test and creative thinking level. The experimental cycle was 12 weeks (3 class hours per week), and the course content strictly followed the National Standard for Teaching Quality of Fine Arts in General Colleges and Universities.

The evaluation system takes into account the development of artistic creation ability and higher-order thinking, and the quantitative indicators include three dimensions, with a jury composed of 15 teachers from the Academy of Fine Arts, scoring according to the three-level indicators of "sketching foundation (30%)", "color perception (30%)" and "creative thinking (40%)", with a total of 20 test items, of which Q1~Q6 examines the basics of sketching, Q7~Q12 examines color perception, and Q13~Q20 examines creative thinking, with a score of 5 points for each question and a total score of 100 points.

After 12 weeks of teaching experiment, the results of the experimental and control groups' posttest scores are shown in Table 4. The experimental group scored 25.43±1.14, 27.09±1.28, and 35.18±2.15 in the three dimensions of basic drawing, color perception, and creative thinking, respectively, which were all better than the control group, and the total test score was 13.68 higher than that of the control group, and the standard deviation was smaller, and the overall performance was more stable. The teaching experiment verified that combining AI painting technology with traditional art teaching can effectively improve the teaching level.

Table 4: Post-test results of the experimental group and the control group

Dimension	Group	Number of questions	Mean value	Standard deviation
Basic Sketching	Experimental group	6	25.43	1.14
	Control group	6	21.87	1.38
Color perception	Experimental group	6	27.09	1.28
	Control group	6	20.93	1.46
Creative thinking	Experimental group	8	35.18	2.15
	Control group	8	31.22	2.22
Total	Experimental group	20	87.70	4.41
	Control group	20	74.02	4.96

V. Conclusion

In this paper, an AI painting generation model based on convolutional neural network is designed to examine the performance level of FSMNet and its application effect in art education through dataset experiments and teaching practice.

The classification accuracy of StyTr2 is higher among the existing methods on MS-COCO2014 and WikiArt datasets, reaching 80.02% and 81.35%, respectively. Compared to StyTr2, FSMNet improved the accuracy by 0.15%, 2.35%. For SFEW 2.0 and CK+ datasets, FSMNet also performs optimally, achieving 78.62% and 76.82% classification accuracy, respectively. For the two image categories of flowers, birds and landscapes on the CK+ dataset, FSMNet improves the 1-Shot classification accuracy by an average of 3.76% and the 5-Shot classification accuracy by 3.64% compared to the best-performing small-sample learning method, PAT, which illustrates the advancement of FSMNet's performance in small-sample learning scenarios. 100 content style image pairs were randomly selected for the stylization test, and compared to StyTr2, which performed optimally in the baseline model, the SSIM and PSNR of FSMNet were improved by 18.6% and 6.82%, respectively, and the migration time was reduced by 0.017s to 0.51, 12.06, and 0.079s, respectively. The network converged at an iteration number of about 1200, and the total loss stabilized within 20%.

After 12 weeks of teaching experiments, the experimental group's scores in the three dimensions of drawing foundation, color perception, and creative thinking reached 25.43±1.14, 27.09±1.28, and 35.18±2.15, respectively, which were better than those of the control group, and the total score of the test was higher than that of the control group by 13.68, and the standard deviation was much smaller, and the overall performance was more stable. The teaching experiment verified that combining AI painting technology with traditional art teaching can effectively improve the teaching level.

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