J. COMBIN. MATH. COMBIN. COMPUT. 127a (2025) 7747--7764

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Innovative Digital Teaching Methods for Children's Ink Painting Course for Higher Teachers Based on Graphics Algorithms

Yihong Chen[1,✉]

[1] *Quanzhou Preschool Education College , Quanzhou City, Fujian Province, 362000, China*

ABSTRACT

The article calculates the average image entropy of the image domain, quantitatively analyzes the information has richness asymmetry in the task of digitally generating ink paintings, and constructs an asymmetric cyclic coherent ink painting digital generation model based on graphical algorithms. The model integrates a generative adversarial network, and the generator is centered on the Dense Block and replaces the residual block with a dense block to improve the characterization ability. The position fusion attention network is utilized to capture the main body region of the ink painting and combined with the edge extraction technique to extract the significant main body edges of the image and simulate the salient features of the ink painting strokes. The model is integrated into the teaching of “Children's Ink Painting” course in a high school teacher, and students are instructed to use the algorithm to generate digital ink paintings to further explore the effectiveness of the teaching method. In this paper, the model is iterated for 30 times, and the total objective function converges to the minimum value of 0.85, and the measured values on PSNR, UIQM and UCIQE are improved by 4.44, 0.3 and 0.68 respectively compared with the optimal values of the comparison model, and the model can obtain the highest evaluation score (8) of the generated image at the fastest convergence speed (50 epochs), and the degree of overlap with the real image on the LPIPS distance is higher. After the experiment, the dimensions of digital pedagogical literacy level of the experimental class increased by 3.37 to 7.63 points compared with the control class and showed significant differences. As for the satisfaction of learning experience, students' satisfaction with digital teaching resources is the highest, which is 4.70 points. The experimental results show that the model constructed in this paper has good performance of ink painting image generation and can be used as a digital teaching method for children's ink painting course in high school teachers.

Keywords: Graphics Algorithm, Generative Adversarial Network, Dense Block, Edge Extraction, Ink Painting Teaching

✉ Corresponding author.
E-mail address: 15294580660@163.com (Y. Chen).

Received 01 February 2024; Revised 20 April 2024; Accepted 10 November 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-428

1. Introduction

Ink painting is a treasure of traditional Chinese art and an important part of Chinese art education. Chinese painting is an important part of the traditional culture of the Chinese nation, and since the third grade of elementary school, the art textbook has arranged the teaching of Chinese painting, an arrangement that stems from the new curriculum standard, which proposes "guiding students to participate in cultural inheritance and exchanges" [1]. In the teaching of children's ink painting, it is important to focus on cultivating students' artistic creativity and expressiveness, guiding students' perception and understanding of ink painting, and promoting traditional culture [2]. As art teachers, it is their responsibility and obligation to make children basically recognize and understand Chinese painting, and then like Chinese painting and love it, so that the excellent national culture can be inherited and developed. However, in the teaching of Chinese painting at the children's stage, due to the outdated and backward educational concepts of teachers, teachers are unable to grasp the scientific teaching direction that is in line with the times in the process of teaching, as well as the impact of the impatience produced by the society in the process of transition on teachers, which makes some of them become eager to achieve quick successes and quick profits, which leads to the emergence of mechanical imitation, passive acceptance, and "likeness" as the key factor in the teaching of traditional Chinese painting. This leads to mechanical imitation, passive acceptance, and "like" as the destination in traditional teaching of Chinese painting [3-4]. In order to improve students' interest in learning, master basic painting skills, develop personality, cultivate innovative consciousness and creative ability, as well as better disseminate the culture of traditional ink painting, it is necessary to improve teaching methods.

The new form of education in the digital era is a new trend in the current education model and an effective force currently driving the innovation of the education system [5-6]. The digital empowerment of education uses technology to shape and innovate the mode of teaching and learning, thus changing the traditional education model and moving towards intelligent integrated education [7]. Education digital transformation is the basic guarantee and core driving force to ensure the construction of a high-quality education system, and it is also a necessary path to establish a benign education ecosystem [8-9]. In the context of education informatization, digital teaching has become an important trend in the field of education. The application of digital teaching can improve the quality of teaching, enhance students' learning enthusiasm and creativity, and share good interactivity and real-time [10-11]. And graphics algorithm is an important element in the field of computer graphics, which involves the creation, display and processing of graphics. It develops a series of algorithms for implementing computer image processing based on mathematics, computer science and physics. In the field of drawing and painting teaching, graphics algorithms are used to realize digital teaching has a great potential for application.

This study proposes a graphics algorithm based on improved generative adversarial network as an innovative method for digital teaching of children's ink painting course in higher education. The algorithm calculates the average image entropy of the image domain to reflect the information richness of the image domain when generating digital ink painting images. Using a dense block generator, connecting features from different layers of the feature channel, the PatchGAN discriminator accurately calculates the probability of authenticity of each block region of the original image, enhancing the model's ability to capture the details of the original image. The saliency detection technique and saliency edge extraction module are used to depict the characteristics of the main strokes of the ink painting. The algorithm also introduces a variety of loss functions to optimize the quality of the generated ink painting images. Teaching processes such as digital creation practice of ink paintings based on the graphics algorithm are added to the children's ink painting course in senior teachers to improve students' knowledge of ink painting. Based on the teaching experiments, the impact effect of this paper's method on students' teaching literacy as well as learning experience is evaluated.

2. Digital conversion model of ink painting based on graphics algorithm

2.1. Generative Adversarial Networks

Generative Adversarial Network (GAN) [12] consists of two sub-networks: a generator and a discriminator. The two sub-networks are trained adversarially, with the generator working to generate "real" images to obtain high scores from the discriminator. The discriminator, on the other hand, is asked to give low scores to the generated images from the generator and high scores to the images from the real data distribution. Figure 1 illustrates the training process of a GAN, where a sufficiently good generator network is obtained when the model converges.The basic loss function of a GAN consists of two main components, as shown below.

$$\min_G \max_D V(D,G) = E_{x\sim p_{gt}(x)}[\log D(x)] + E_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{1}$$

where the first part of the loss term is the log-likelihood of the discriminator on the real data, representing the discriminator's ability to recognize the real data. Where x is a sample sampled from the real data, and $D(x)$ represents the probability that the discriminator believes that x belongs to the real sample. The second part of the loss term is the log-likelihood on the discriminator's generated image, representing the discriminator's ability to recognize the generated data.

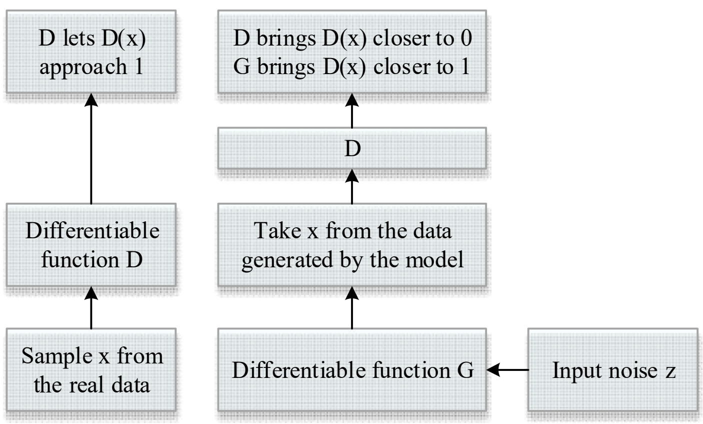

Fig. 1. GAN's learning framework

2.2. Information richness asymmetry

In order to quantitatively analyze the information richness asymmetry in the task of digitizing and generating ink drawings, the average image entropy of different image domains was calculated. Image entropy [13] is a measure of the information complexity of a single-channel image, which reflects the richness of information in the image.

For multi-channel images such as RGB images and HSI images, the average image entropy of three channels is calculated to represent the entropy value of the image. Considering the redundancy problem of image entropy in RGB color space, HSI color space with low channel correlation is used to calculate image entropy. Therefore, it is reasonable and effective to use the image entropy calculated in HSI color space to reflect the information richness of the image domain of ink painting.

Considering that an image domain contains several images, the average image entropy of all images in each image domain is calculated as the image entropy value of the domain. The image entropy of an image domain is defined as follows:

$$mEntropy = \frac{1}{N}\sum_{n=1}^{N} Entropy(img_n) \tag{2}$$

where N denotes the total number of images in an image domain, img_n denotes the image instances in the image domain, and $Entropy(*)$ denotes the image entropy value is calculated for the input image with the following formula:

$$Entropy = -\frac{1}{c}\sum_{i=0}^{255}\sum_{j=0}^{255} P_{(c,i,j)} \times \log P_{(c,i,j)} \tag{3}$$

where c denotes the channel index of the HSI color space channel, i and j denote the length and width positions of the image, and $P_{(c,i,j)}$ denotes the probability of the number of occurrences of the pixels at the corresponding position over the total number of pixels.

In order to measure the image entropy difference between the two image domains in the image conversion task more intuitively, the information entropy ratio between the two image domains is calculated, which is defined in detail as follows:

$$EntropyRatio = \frac{\max(mEntropy(X), mEntropy(Y))}{\min(mEntropy(X), mEntropy(Y))} \tag{4}$$

where X and Y denote different image domains in an image conversion task.

2.3. Asymmetric cyclic consistency structure

The Digital Generation of Ink Painting Based on Asymmetric Cyclic Consistency Structure (DMACCS) model proposed in this paper consists of two generators, two discriminators and a Significance Edge Extractor (SEE). The details are presented as follows:

2.3.1. Generators and Discriminators. In this paper, we improve the structure of the generator and discriminator for the information richness asymmetry characterizing the Chinese ink painting style migration task.

1) Generator. Dense Block [14] is used as the generator of the core conversion module, which can effectively match the conversion difficulty from the ink painting image domain with low information complexity to the real natural image domain with high information complexity. Replacing the residual blocks in the conversion module with dense blocks can effectively improve the generator's characterization ability, specifically, when migrating the style of ink painting to the real photo image domain, the dense block-based generator can consider more input feature information to enhance feature propagation. In addition, the advantages of small training parameters and fast training speed of dense blocks can improve the training efficiency of the model. The network structure of the residual and dense blocks is shown in Fig. 2. The dense block based on the dense connection mechanism, compared with the residual block based on the short-circuit connection mechanism, can splice the features of different layers in the feature channel dimensions, thus realizing the feature reuse, and improving the model representation ability while enhancing the efficiency.

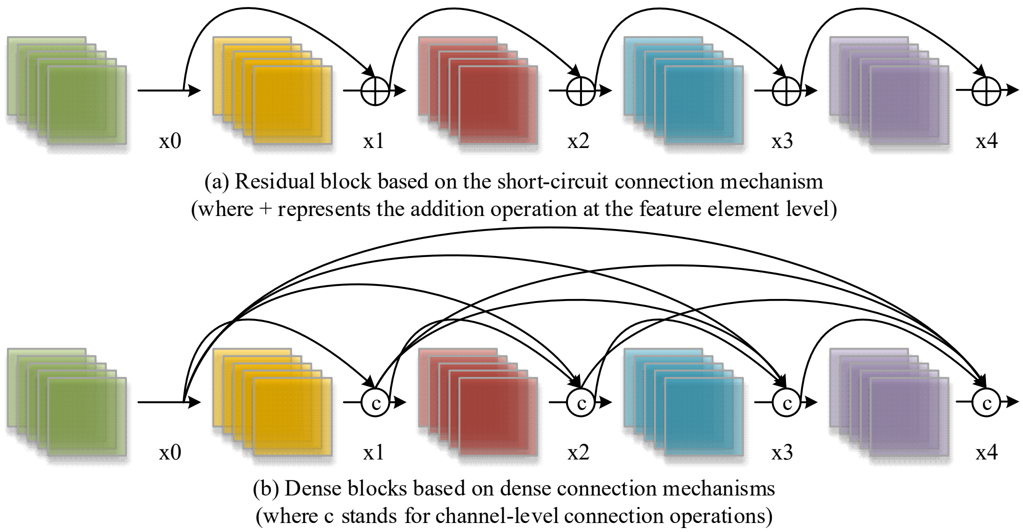

Fig. 2. Network structure of residual blocks and dense blocks

2) Discriminator. The main role of the discriminator is to distinguish between the generated image and the real image. In this paper, a 70×70 PatchGAN [15] is used as the discriminator, which consists of multilayer convolutional layers and outputs a probability matrix of 1 $n \times n$ (each value represents the probability of authenticity of a block region of the original image, which helps the model to pay more attention to the details of the image compared to the original discriminator), and finally, the average value of the whole probability matrix is used as the authenticity output result.

2.3.2. Significance Edge Extraction Module. In order to simulate the prominence of the main body strokes in ink painting, saliency edges are used to represent the main body strokes in ink painting, which are obtained by extracting the edges of the salient body in the image. A salient edge extraction module is designed, including a saliency detection part and an edge detection part. The saliency detection technique is capable of modeling the human visual and cognitive system and can detect salient regions in an image that are different from other regions. A pre-trained position fusion attention network (PFAN) is used to detect the region mask of the salient object in the image, which can effectively represent the main region of the painting in an ink drawing. The edges of the image are extracted using an excellent edge extraction network, HED, which can extract edges with different degrees of thickness, which is useful for simulating the different thicknesses of the brush strokes in ink paintings. During the training process of the model, the significant edge map obtained from the significant edge extraction module is used to calculate the significant edge loss.

2.4. Loss function

Based on the original loss of GAN, cyclic consistency loss and saliency edge loss based on feature level are introduced.

1) Adversarial loss. The main role of the adversarial loss is to be used to optimize the generator and the discriminator so as to improve the generative ability of the generator and the discriminative ability of the discriminator. Adversarial loss:

$$loss_{GAN}(G, D_Y, X, Y) = \mathrm{E}_{y \sim Y} \log D_Y(y) + \mathrm{E}_{x \sim X} \log(1 - D_Y(G(x))) \tag{5}$$

where X and Y represent the data distribution in the domain of real natural photographs and the domain of ink drawing images, respectively.

2) Identity loss. The identity loss function can help the model to avoid meaningless transformations, and at the same time constrain the model to keep the color distribution of the input image and output image consistent, the calculation is shown in Eq:

$$loss_{Identity}(G,F,D_X,D_Y)=\mathrm{E}_{x\sim X}[\|F(x)-x\|_0]+\mathrm{E}_{y\sim Y}[\|G(y)-y\|_0] \tag{6}$$

3) Cyclic consistency loss based on feature level. Feature-level based cyclic consistency loss is used, i.e., the original pixel-level based L1 loss is replaced by using the L1 loss of the pre-trained high-level features in the VGG network. The calculation is shown in Eq:

$$\begin{aligned} loss_{Cycle}(G,F,X,Y) &= \mathrm{E}_{x\sim X}[\|VGG_{conv4\_4}(F(G(x)))-VGG_{conv4\_4}(x)\|_0] \\ &+\mathrm{E}_{y\sim Y}[\|VGG_{conv4\_4}(G(F(y)))-VGG_{conv4\_4}(y)\|_0] \end{aligned} \tag{7}$$

where $VGG_{conv4\_4}(*)$ represents the output feature of the conv4_4 layer in the pre-trained VGG network, which can effectively characterize the content structure information of the image.

4) Significance edge loss. The real natural image and the generated ink painting image are input to the saliency edge module, and then the balanced cross-entropy loss is calculated on the obtained saliency subject edge map, so as to obtain the saliency edge loss. Calculation formula:

$$\begin{aligned} loss_{Salient\_Edge}(G,X) &= \mathrm{E}_{x\sim X}[-\frac{1}{N}\sum_{n=1}^{N}\alpha E(x)_n\log(E(G(x))_n) \\ &+(1-\alpha)(1-E(x)_n)\log(E(G(x))_n)] \end{aligned} \tag{8}$$

where N is the total number of pixels in the input image corresponding to the saliency subject edge map, $E(\bullet)$ is the edge extraction model HED network, and α is a balanced weight factor.

5) Total target loss. Finally, the total objective loss of the model is calculated in Eq:

$$\begin{aligned} L(G,F,D_x,D_Y,X,Y) &= \lambda_1 loss_{GAN}(G,D_Y,X,Y) \\ &+\lambda_2 loss_{GAN}(G,D_X,X,Y) \\ &+\lambda_3 loss_{Cycle}(G,F,X,Y) \\ &+\lambda_4 loss_{Identity}(G,F,X,Y) \\ &+\lambda_5 loss_{Salient_Edge}(G,X) \end{aligned} \tag{9}$$

The goal is to optimize the following objective function:

$$G^* = \arg\min_{G,F,D_x,D_r} L(G,F,D_X,D_Y,X,Y) \tag{10}$$

3. Research on the effect of digital transformation of graphic algorithm ink painting

3.1. Research data and context

3.1.1. Data set collection and organization. In order to validate the effectiveness of the network model proposed in this paper for digitized teaching of children's ink painting courses in higher education and to train and test the network model, this paper modifies and extends the original ChipPhi dataset, which is an existing dataset for studying the ink style migration task. The dataset contains two object types, real photographs and ink drawings of horses and real photographs and ink drawings of landscapes.

The ultimate goal that we want to achieve in this paper is to digitally generate ink style images and to make the network model trained in an unsupervised manner. Using the original dataset mentioned above could not achieve the task goal of this paper because it only contains less variety, so the original dataset was modified and supplemented in this paper.

First, based on the types of objects contained in the original dataset, some real photographs and a variety of ink paintings were collected and downloaded from the Internet by means of web crawlers. More than 500 real photographs and more than 1,000 ink paintings were screened by manually eliminating erroneous data samples. Duplicates in these pictures were removed, and pictures that were inappropriate for the task were eliminated. Finally, the real photographs and ink drawings after the erroneous data samples were manually eliminated were used as an expansion of the original dataset. Among them, there are 440 real photos and 735 ink paintings. In the training phase, the data samples of this type are mixed with those of the original dataset ma so that the model is no longer trained in a weakly supervised manner.

3.1.2. Experimental environment and implementation details. In this paper, the content encoder and the style encoder have three convolutional layers each, and the style features are embedded through the style weaving self-attention module. The intermediate residual network contains nine residual blocks, and the decoder contains three upper convolutional layers, each containing IN and ReLU. The discriminator consists of 70×70 patchGANs for classifying the authenticity of 70×70 overlapping image blocks. The hardware and software experimental environment for this paper is as follows:

Operating system: Windows 10 64-bit
Processor: Intel(R) Core(TM) i5-9400 CPU@2.90GHz
Graphics card: NVIDIA GeForce RTX 3090Ti (24GB)
CUDA: CUDA 11.0
Memory: NVIDIA GeForce RTX 3090Ti(24GB)
Development Environment: Pycharm
Development Language: Python 3.8.3
Deep Learning Framework: Pytorch 1.7.1

3.2. Experimental results

3.2.1. Model Training and Image Generation Quality. In order to facilitate the training of the model in this paper, these data are cleaned and preprocessed, and those images that are of low quality and do not meet the requirements are eliminated, and the images that meet the requirements are cropped and resized to 256×256 pixels.

The loss function is used to measure the difference between the generated image and the target content image and the target style image, which plays a very crucial role, the loss function can reflect the performance of the model in the training process, lower loss values usually mean that the model fits the training data better and generates more realistic and accurate samples.

The images in the dataset are split into training set, test set according to 7:3 ratio. The training process uses Adam optimizer, the learning rate is 0.001, the batch parameter is 32, the number of training rounds is 200, and the weight value λ_1、λ_2、λ_3、λ_4、λ_5 of the total objective loss function is set to 0.5, 1, 2, 3, and 4, respectively.The experimental results of the convergence speed of the total objective loss function are shown in Fig. 3, from which it can be seen that the results of the DMACCS model of this paper are basically the same for both the training set and the test set. In the early stage of training, the loss function value shows a sharp decrease, and after 20 rounds, the change in the loss function value decreases. Finally, at iteration to 30 rounds, the model completes convergence on both the training and test sets, effectively minimizing the loss function (0.85). This indicates that the model is more robust and generates images that are more in line with expectations.

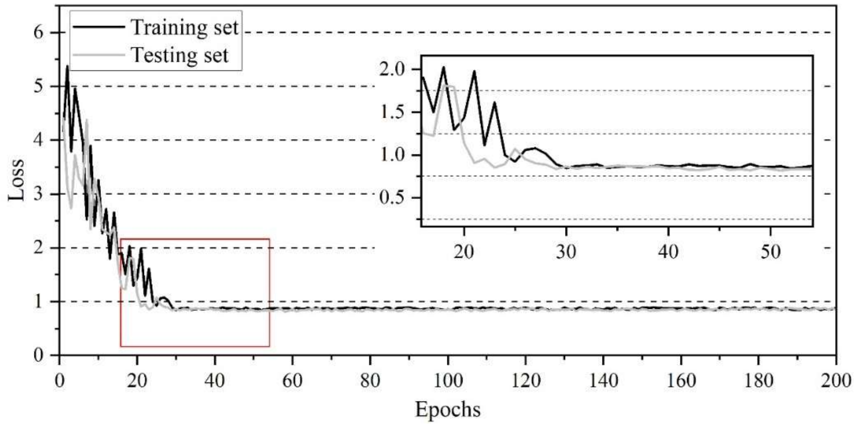

Fig. 3. The results of the experimental results of the loss function

Comparative experiments were conducted to verify the enhancement effect of the improved graphic digitization conversion DMACCS model in this paper on ink drawing graphics. Subjective qualitative evaluation relies on human eye scoring, which requires the participation of multiple observers, and the results are close to the real but time-consuming and labor-intensive. Therefore, the study uses objective quantitative evaluation to assess the quality by comparing the difference between the images before and after processing, and the evaluation indexes include:

1) Peak Signal to Noise Ratio (PSNR) is used to measure the difference between two images in terms of brightness, contrast and saturation, the larger the value indicates the higher the similarity, the calculation formula:

$$PSNR(x,y) = 10\log_{10}\frac{L^2}{MSE(x,y)} \tag{11}$$

where x and y represent the two images to be compared and L represents the maximum range of pixel values.

Non-reference evaluation methods are based on feature extraction techniques where processed images are analyzed to assess their quality. (UCIQE) and underwater image quality assessment (UIQM) are two commonly used objective evaluation metrics to assess the clarity and quality of images.

2) Color Image Quality Evaluation (UCIQE): an objective evaluation metric used to assess image clarity. Calculation formula:

$$UCIQE = b\times\sigma + c\times con + d\times sat \tag{12}$$

where b、c、d is the weighting factor, the following weighting factors are often used: b =0.0282, c =0.2953, d =3.5753. σ reflects the average gray value of the image, con reflects the contrast of the image, and sat reflects the saturation of the image. By considering these three factors together, the quality of the graphics conversion can be assessed.

3) Image quality assessment (UIQM): this metric evaluates image quality by linearly combining color, sharpness, and contrast features. Calculation formula:

$$UIQM = \alpha\times UICM + \beta\times UISM + \gamma UIConM \tag{13}$$

Wherein, the color evaluation component ($UICM$) is used to evaluate the degree of color reproduction, the sharpness evaluation component ($UISM$) is used to evaluate the sharpness of the image, and the contrast evaluation component ($UIConM$) is used to evaluate the degree of difference in color intensity in the image. α, β and γ are the weighting coefficients representing the weight of $UICM$, $UISM$ and $UIConM$ in the total evaluation with set values of 0.0282, 0.2953 and 3.5753 respectively.

To address the question of whether this paper's algorithm is superior to several more advanced and typical network models mentioned in this paper in terms of image enhancement, the improved SMBLO, traditional GAN, Star GAN, UWGAN, FUnIE-GAN, and this paper's algorithm are compared.

Fig. 4, Fig. 5 and Fig. 6 show the results of the comparison of each network model image digital conversion in PSNR, UIQM and UCIQE measurements, respectively. Combined with the data in the figures, it can be seen that through the comparison experiments, it is proved that the DMACCS model proposed in this paper performs well in the image quality assessment indexes of PSNR, UIQM and UCIQE, and improves the optimal value of each index by 4.44, 0.3 and 0.68 than the other models, respectively.The significant improvement of the image quality is attributed to the saliency edge extraction module, which enhances the richness of the image's local feature map and improves the feature extraction. Richness of the local feature map of the image, which improves the diversity and accuracy of feature extraction. Meanwhile, the loss function effectively improves the quality of the generated images and accelerates the convergence speed of the model. In addition, the loss function further improves the image quality. The function can accurately assess the discriminator's distinguishing ability, improve the performance of the discriminator by minimizing the loss, solidify the training process of the model, and enhance the authenticity and diversity of the generated samples.

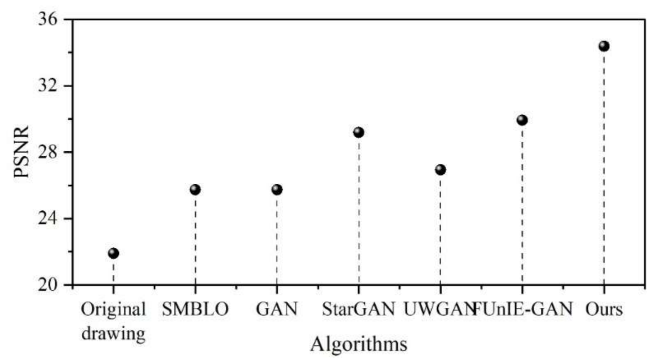

Fig. 4. Different algorithms PSNR distribution

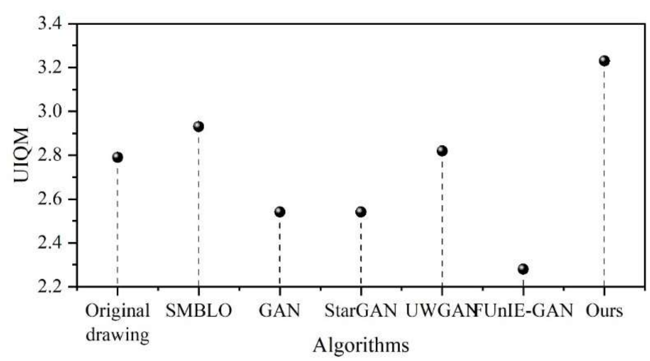

Fig. 5. Different algorithms UIQM distribution

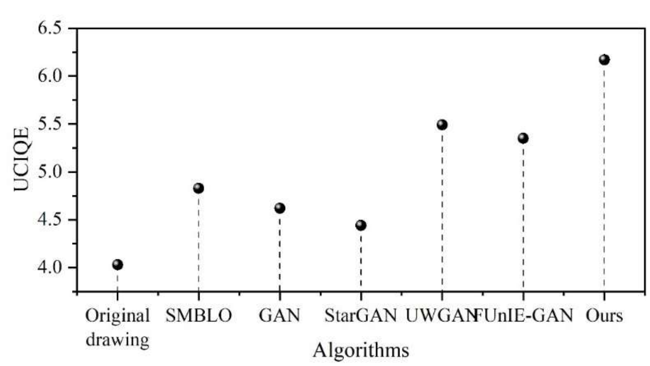

Fig. 6. Different algorithms UCIQE distribution

3.2.2. Quantitative analysis of the effect of image digital generation. In this paper, we compare the number of parameters, the size of the generating network, the average speed of generating images, and the mean square error (MSE) of DMACCS with SMBLO, GAN, StarGAN, UWGAN, and FUnIE-GAN to validate the computational advantages of DMACCS.

The results of the computational performance comparison of different algorithms are shown in Table 1. Among them, a smaller number of parameters means that the algorithm model requires relatively less computational resources during training. A smaller generative network usually means that the model complexity is lower and the network is easier to train. A shorter mean time to generate an image indicates that the model has a higher efficiency in inference. And smaller MSE indicates that the model has higher accuracy when reasoning. From the data in the table, it can be seen that the computational performance of DMACCS is significantly better than the comparison algorithm model, and its measured values in the number of parameters, the size of the generation network, the average speed of generating images, and the MSE are 4.24MB, 23.1MB, 0.278s, and 26.62, respectively.This indicates that the introduction of the idea of replacing residual blocks with dense blocks improves the overall performance of the model, and DMACCS can more quickly realize ink painting image generation.

Table 1. Performance comparison of different algorithms

Algorithms	Parameter quantity (MB)	Generated network size (MB)	Mean generation time (s)	MSE
SMBLO	5.42	30.34	0.591	31.36
GAN	7.73	39.81	0.773	38.78
StarGAN	5.15	33.92	0.558	34.12
UWGAN	6.21	32.73	0.521	33.47
FUnIE-GAN	5.62	28.99	0.436	29.05
Ours	4.24	23.1	0.278	26.62

In addition, the study adds an evaluation score (IS) to measure the quality and diversity of the generated ink painting images, which is a commonly used metric to measure the quality of the samples generated by the generative model. Under the same number of iterations, a higher value of IS indicates a higher fidelity and good diversity of the generated images, as well as a faster convergence of the model. The formula is as follows:

$$IS(G) = \exp(E_{x \sim p_g} D_{KL}(p(y|x) \| p(y))) \tag{14}$$

where $IS(G)$ represents the evaluation score of the generative model G, D_{KL} denotes the Kullback-Leibler scatter, which is used to measure the difference between two probability distributions, $p(y|x)$ denotes the category distribution generated for a given input image x, and $p(y)$ is the average category distribution of all input images.

For the ink painting style, the above algorithmic models are trained on the same dataset separately and the IS is used to measure the quality and diversity of the generated images, and the results of the experiments to evaluate the comparison of the convergence speed of the scores are shown in Fig. 7. According to the convergence curves in the figure, it can be seen that among these six algorithmic models, with the increase of the number of iterations, the FUnIE-GAN and SMBLO algorithmic models outperform the UWGAN, StarGAN, and GAN algorithmic models as a whole, while the DMACCS model of this paper is able to converge the fastest (about 50 epochs) and obtain the highest evaluation scores, and the generated images always maintain a high level in terms of quality and diversity are consistently high. Therefore, through the convergence speed comparison experiments, it can be seen that compared with the comparison models, the DMACCS proposed in this paper not only converges faster, but also generates ink painting images with better visual effects.

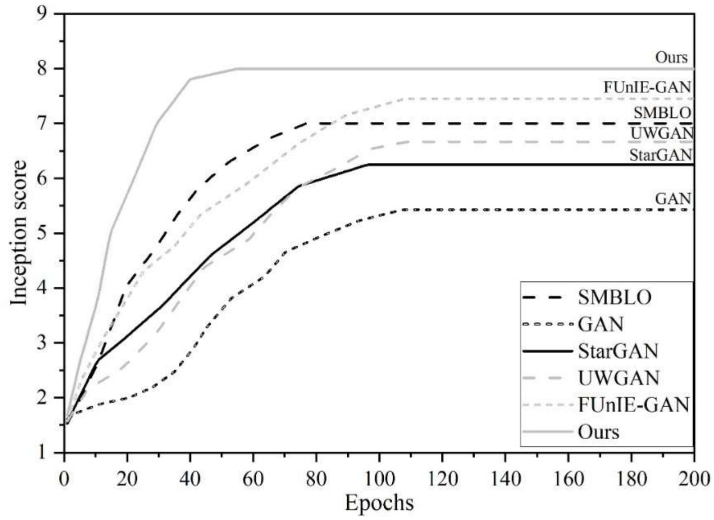

Fig. 7. Comparison results of the IS test results

In this study, the quality of the model-generated images is measured by calculating the Learned Perceptual Image Block Recognition (LPIPS) distance between the generated images and the content images. The higher the overlap of the LPIPS distance histograms between the generated image and the real image, the more similar the generated image is to the real image in terms of visual features, and the better the model performs on the style migration task. Figures 8 and 9 show the experimental results of comparing the LPIPS distance histograms between the generated images and real images of the models FUnIE-GAN and DMACCS, respectively. Comparing the two figures, it is learned that the ink painting image generated by the algorithm model of this paper has a higher degree of overlap with the real image in terms of LPIPS distance, with an overlap area of more than 50%, while the overlap area of FUnIE-GAN is about 25%. It indicates that the ink painting image generated by the algorithm model in this paper is more similar to the original image.

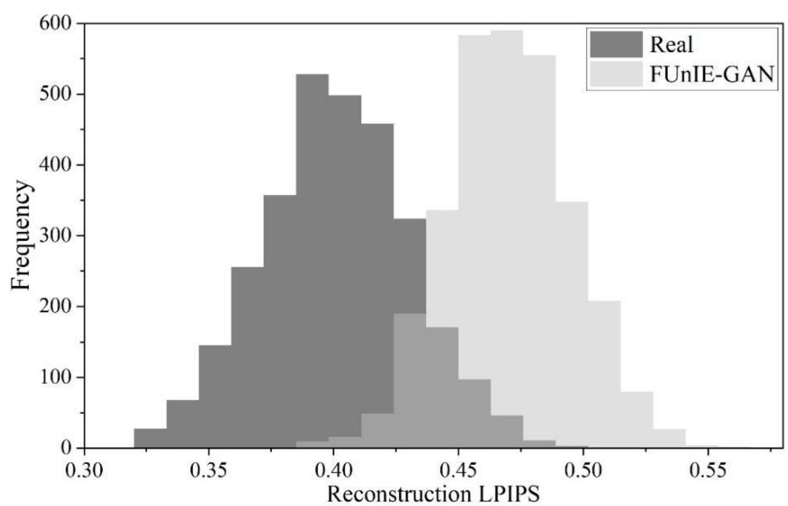

Fig. 8. Experimental results of the image LPIPS distance of FUnIE-GAN

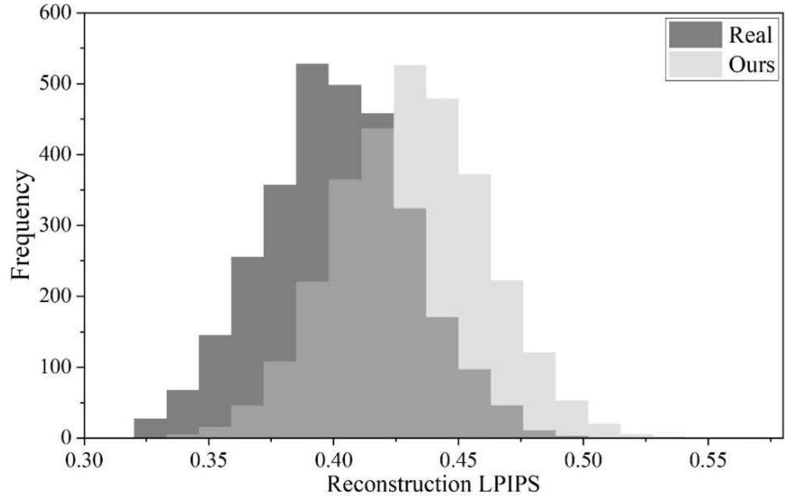

Fig. 9. Experimental results of the image LPIPS distance of DMACCS

4. Graphics algorithm-based ink painting teaching practice and effect analysis

4.1. Experimental Design of Digital Teaching in Children's Ink Painting Course for Higher Teachers

4.1.1. Purpose of the experiment. In this study, different teaching methods are used to implement teaching to students in two classes of the same level respectively, and after a period of time, the status of students' digital learning and the cultivation of creative literacy are examined to observe whether there is a significant difference. It also explores the feasibility and teaching effect of the teaching methods through classroom observation, work analysis, interviews and surveys. The purpose is mainly to verify whether this study's digital teaching method of ink painting based on imaging algorithms can effectively improve students' digital learning and innovation literacy level. Purpose two is to analyze the practicality and applicability of the digital teaching in this paper in response to the experimental results, so as to provide realistic practical support for improving and optimizing the teaching design.

4.1.2. Subjects. The subjects of the research experiment came from two classes of students in the first and second year of the sophomore year of the art education program in a high school teacher in City B, Province A. The experimental school is a public school in City B, Province A. The teaching facilities are complete, and the information technology classroom is equipped with a full set of computer equipment and multimedia equipment and so on. There are specialized creator classrooms and smart classrooms, etc., which can fully meet the hard conditions of digital teaching. The study randomly selected class 1 as the experimental class (T) and class 2 as the control class (CK). Class 1 of the experimental class used the digital teaching method based on graphology algorithms proposed in this study, while class 2 of the control class unfolded under ordinary digital learning conditions for a three-month quasi-experimental study.

The selection of the experimental classes took into account the gender status of the class and the level of digital and creative literacy. The experimental and control classes had 30 students each, and in terms of gender ratio, there were 10 boys and 20 girls in each of the two classes. With regard to the level of digital and innovative literacy, in order to ensure the accuracy of the experiment, before the experiment, the literacy level test was implemented for all the classes in the second year of art education majors in the experimental school, and the results showed that the digital learning and innovative literacy of all the classes were at the same level, and there was no significant difference between the literacy levels of the selected class 1 and class 2. As a result, a research analysis can be conducted based on the experimental data of these two experimental subject classes.

4.1.3. Experimental content. This study focuses on the teaching reality of “Children's Ink Painting” for senior teachers, and centers on the categorization and generalization of various aspects of instructional design to determine the theme of this study. In the process of collecting and organizing information, this paper exhaustively combed through the digital teaching design research materials of the “Children's Ink Painting” course published in major authoritative academic journals in recent years. It conducts research and analysis on the objectives, methods, contents, preparation, process and evaluation of activity design, from which it explores the main problems of the digital teaching design of the “Children's Ink Painting” course, and then finds out the reasons for the problems. Combined with the actual teaching and inherent requirements, the implementation strategy of digital teaching design for the “Children's Ink Painting” course for senior teachers is reasonably planned.

4.1.4. Experimental variables:

1) Independent Variables. The experimental independent variable is the teaching method, i.e. the general process of teaching. In this experiment, the experimental class adopts the teaching method constructed in this study oriented to digital learning of ink painting, while the control class chooses the form of general teaching, which constitutes the experimental conditions.

2) Dependent variable. The dependent variable of the experiment is the teaching effect, i.e. the level of students' digital learning and innovation literacy, including students' performance in digital learning awareness, digital learning cognition, digital learning ability and digital innovation thinking.

3) Interference variable. Interfering variables are variables that affect the change of the dependent variable at the same time with the independent variable, but have nothing to do with the purpose of the experiment, so they are the variables that need to be controlled in the experiment. In order to make the experimental results more scientific, this study strictly controls the interfering variables. In terms of the people involved in the experiment, the initial level of the students in the experimental classes was at the same level, and the teaching teacher involved in the experiment was the same teacher. As for the content of the experiment, it was the content of the course “Children's Ink Painting”. As for the experimental environment, the teaching was carried out in the same smart classroom.

4.1.5. Teaching and learning process. This paper integrates the digital conversion method of ink painting based on graphology algorithms into the digital teaching process of children's ink painting course for senior teachers from the following aspects.

1) Ink Painting Digital Creation Practice: in the course of Children's Ink Painting, some digital creation practical contents are added, and the algorithm of this paper is utilized to complete the process of traditional painting to digital generation. Through these contents, students can have a deeper understanding of the drawing characteristics, details, etc. of ink painting, and at the same time improve their practical ability and problem solving ability.

2) Practical guidance on digital generation of ink painting: in practical teaching, teachers can provide students with more detailed guidance on digital creation of ink painting, including the use of algorithms, image processing and other aspects of guidance. Through the guidance, students can have a more in-depth understanding of the specific steps in generating digital ink paintings based on the graphical algorithm of the ink painting digital conversion method.

4.2. Results and analysis

4.2.1. Comparative analysis of teaching literacy levels. In order to screen two classes with no significant difference in learning awareness, learning cognition, learning ability, creative thinking, aesthetic ability, and theoretical achievement as the research subjects of the teaching experiment, this paper tested the digital teaching literacy level of the “Children's Ink Painting” course on all (6) classes of the second year of the art education of this high school teacher before the experiment.

Statistically obtained test results of the dimensions of digital teaching literacy of the “Children's Ink Painting” course for the six classes are shown in Table 2. As can be seen from the table, there is a small difference between the mean and relative error of Class 1 and Class 2 in learning awareness, learning cognition, learning ability, creative thinking, aesthetic ability, and theoretical achievement, in which the absolute difference between the two classes in the mean of the dimensions ranges from 0.15 to 0.58 points. The rest of the classes have a large difference in mean and relative error, so the following is a test of significance for the scores of Class 1 and Class 2 on the dimensions to further validate that the two classes can be used as research subjects for the teaching experiment designed in this paper.

Table 2. Test results of various dimensions of digital teaching literacy

Class	Mean±1.5SE					
	Learning consciousness	Learning cognition	Learning ability	Creative thinking	Aesthetic ability	Theoretical achievement
1	64.24±1.81	67.68±1.51	66.17±1.02	69.74±1.17	65.35±1.49	67.46±1.47
2	64.82±1.77	68.08±1.49	65.92±1.13	69.59±1.54	65.65±1.62	67.68±1.33
3	71.92±2.43	73.31±2.26	66.22±1.39	63.88±1.61	70.15±1.97	71.79±1.11
4	65.57±1.53	69.01±2.43	66.13±1.64	71.48±2.23	73.43±1.84	74.71±2.25
5	67.96±1.68	64.22±1.79	65.62±1.17	64.3±2.03	65.19±2.12	71.46±2.34
6	74.23±2.64	63.51±1.43	67.53±1.65	71.6±1.79	74.74±2.65	74.84±2.46

Figure 10 shows the results of the significance test for Class 1 and Class 2 on each test dimension. The same significance labeled letters in the same test dimension in the figure indicate that there is no significant difference. As can be seen from the figure, Class 1 and Class 2 have the same significance labeled letters in learning awareness, learning cognition, learning ability, creative thinking, aesthetic ability, and theoretical achievement, and the P-value is between 0.502 and 0.783, which is greater than 0.05. It indicates that there is no significant difference between the two classes in each test dimension, and they can be used as a research object of the teaching experiment in this paper. In the following section, we will conduct the teaching experiment with class 1 as the experimental class (T) class 2 as the control class (CK) and evaluate the changes in the level of digital pedagogical literacy in the course of Children's Ink Painting in the two classes after the teaching experiment.

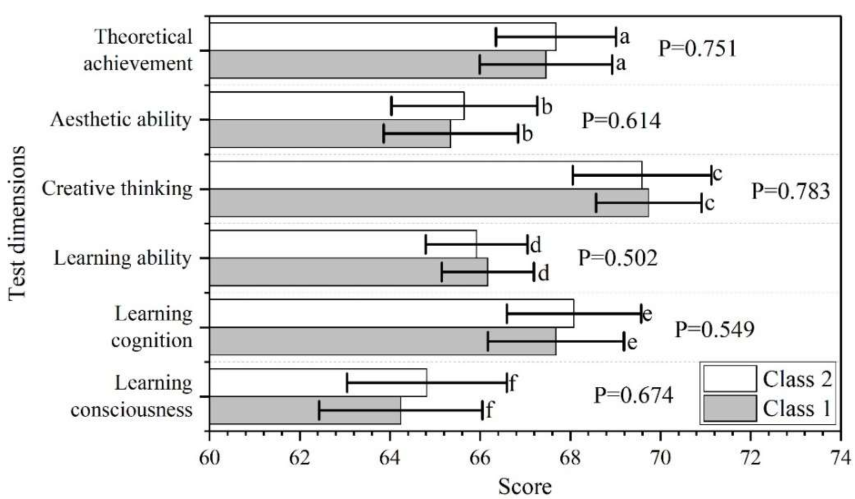

Fig. 10. Class 1 and class 2 show significant test results on each test dimension

The results of the post-test of digital teaching literacy in the two classes are shown in Figure 11. After the experiment, the results show that the level of digital teaching literacy in the experimental class “Children's Ink Painting” course is greatly improved compared with the preexperiment, and compared with the control class, its improvement is slightly lower than that of the experimental class. The mean values of learning awareness, learning cognition, learning ability, innovative thinking, aesthetic ability, and theoretical achievement scores of the experimental class were 75.83, 76.07, 70.40, 78.97, 74.53, and 80.67, respectively, which were improved by 8.39-13.21 points compared with the pre-experiment. Meanwhile, the score difference of each test dimension between the two classes after the experiment was 3.37~7.63 points, with the significance index P less than 0.05, indicating that the students in the two classes after the experiment showed significant differences in the level of digital teaching literacy.

In conclusion, in the teaching of the course “Children's Ink Painting” in senior teachers, the digital teaching method based on the graphology algorithm is more effective in improving the level of students' digital teaching literacy compared with the traditional teaching method.

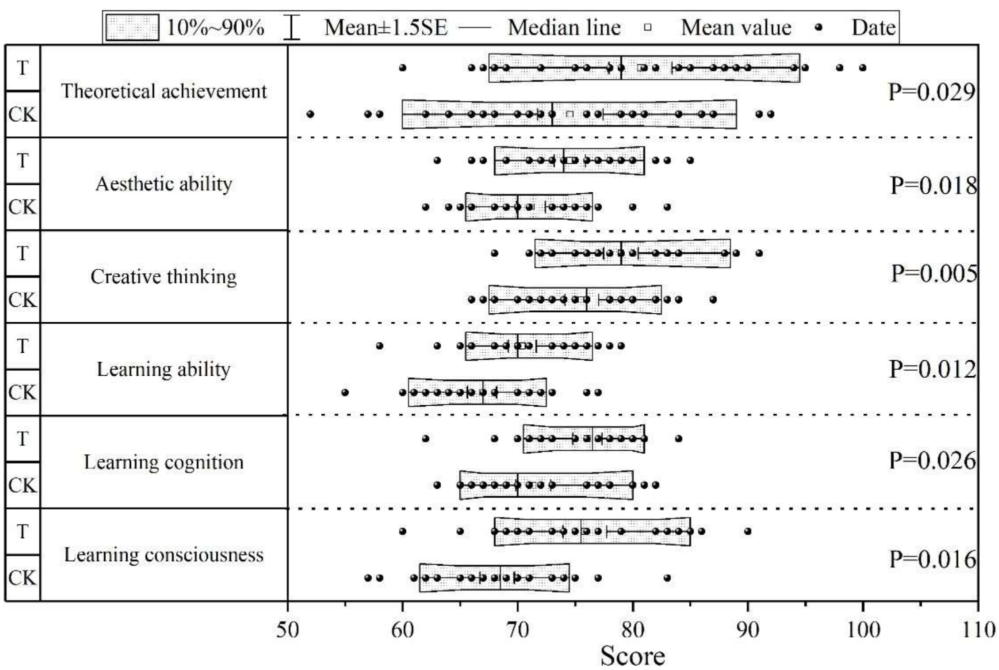

Fig. 11. The results of the digital teaching of two classes

4.2.2. Comprehensive evaluation of satisfaction with the learning experience. In the teaching method model of this paper, students' satisfaction with the learning experience is an important indicator of the effectiveness of the application of the model. In order to assess the satisfaction of the students in the experimental group with the digital teaching methodology of the course “Children's Ink Painting” based on graphology algorithms, the “Satisfaction Questionnaire of Digital Teaching Mode” was distributed and recovered from the students in the experimental group. The survey dimensions include five dimensions: course objectives, teaching content, digital teaching resources, teacher-student interaction, and course innovation. Comprehensive satisfaction, i.e., each survey dimension was added up to take the average value, was used to evaluate the students' overall satisfaction with the digital learning experience based on graphology algorithms.

To quantify students' satisfaction with their learning experience, Richter's five-level scale was adopted, with scores from 1 to 5 representing "very dissatisfied", "dissatisfied", "average", "satisfied", and "very satisfied".

Figure 12 shows the results of the survey on the satisfaction of students' learning experience under the digital teaching methods in this paper. As can be seen from the figure, the average satisfaction scores of students in the experimental group for course objectives, teaching content, digital teaching resources, teacher-student interaction, and course innovation are 4.45, 4.04, 4.70, 4.37, 4.26, respectively, and the comprehensive satisfaction has reached 4.36. Among them, the average satisfaction in the dimension of digital teaching resources is the highest, which is due to the fact that the learning platform equipped with graphics algorithms generates ink painting resources are rich and diverse, and can accurately reproduce the original painting strokes and other characteristics. In addition, students also have high satisfaction with the innovativeness of the course, which highlights the novelty of this paper's approach to digital teaching.

It can be seen that the students in the experimental group generally like the learning of this paper's digital teaching mode based on graphical algorithms, and believe that this mode can bring them an efficient and flexible learning experience and help them better master the content taught by the teacher in the classroom.

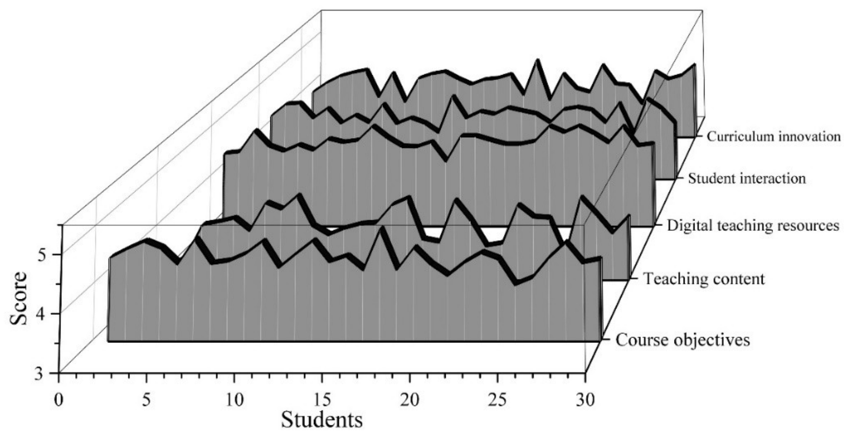

Fig. 12. Students study experience satisfaction survey results

5. Conclusion

In this paper, a digital teaching method based on graphology algorithms for children's ink painting courses in higher education is designed and implemented in a university. The graphology algorithm in this paper is based on generative adversarial network, which uses HIS color space to calculate image entropy and evaluate the information richness of the generated image. The quality of the generated image is further optimized by improving the generator and discriminator, and using position fusion attention and edge extraction network to simulate the stroke characteristics of the image subject. And on the basis of the original use of loss, the functions of confrontation loss and identity loss are incorporated to improve the robustness of the model's performance in generating ink painting images. The digital creation activities of ink painting incorporating graphical algorithms are designed in the teaching of children's ink painting courses for senior teachers to promote students' in-depth mastery of what they have learned. Finally, based on teaching experiments, the method of this paper is verified to be useful in teaching. The research results are as follows:

1) Algorithm Performance. The DMACCS model converges to about 0.85 in the total objective loss function value on both the training set and the test set when the training iteration reaches 30 rounds, and has optimal performance in the measured values on several image quality evaluation indexes. The measured values of the model in terms of the number of parameters, the size of the generative network, the average speed of the generated images, and the MSE are 4.24MB, 23.1MB, 0.278s, and 26.62, respectively, and the performance of the ink painting image generation is better than the comparison

model. In addition, the LPIPS distance overlap between its generated image and the real image is more than 50%, and the generated image is similar to the real image.

2) Teaching Effect. Before the experiment, the P-values of the experimental class and the control class in learning awareness, learning cognition, learning ability, creative thinking, aesthetic ability, and theoretical performance in the course of Children's Ink Painting are all greater than 0.05, and there is no significant difference between the two classes. After the experiment, the maximum P-value of the two classes on the above indexes is 0.29, which is less than 0.05, and the average score of the students in the experimental class rises by 3.37-7.63 points compared with that of the control class, and there is a significant difference between the two classes. The overall satisfaction of the students in the experimental class with the learning experience under the method of this paper is 4.36, reaching the level of “satisfaction”, in which the diverse digital teaching resources generated by the algorithm of this paper get the highest satisfaction from the students (4.70).

References

[1] Wu, X., Wu, H., Chang, W., & Zeng, G. (2021). The Application of Classroom Teaching Implementation of Chinese Painting in Primary and Secondary Schools in Art Teachers' Teaching Strategies. Forest Chemicals Review, 418-426.

[2] Lin, Y. (2018). Survey & Analysis on Education Status of Ink Painting's Social Value and Study on Teaching Method. Educational Sciences: Theory & Practice, 18(5).

[3] Zhang, W., & Chen, F. (2018). Teacher’s supporting behavior in kindergarten painting teaching—based on the perspective of children’s approaches to learning. International Journal of Information and Education Technology, 8(7), 10-18178.

[4] Du, J., & Song, Q. (2017, June). The Investigation and Research on the Current Status of the out-of-school Children's Art Educational Institutions-A Case Study of" Tianjin Perfect Children Paintings". In 2017 International Conference on Management, Education and Social Science (ICMESS 2017) (pp. 544-547). Atlantis Press.

[5] Nwogbo, V. N. (2024). Emerging Trends, Challenges and Innovative Approaches to Education in the Digital Era. El conocimiento a través de miradas interdisciplinares e internacionales, 37.

[6] Tereliansky, P. V., Kuznetsov, N. V., Ekimova, K. V., & Lukyanov, S. A. (2019). Transformation of education in the digital age. University management: Practice and analysis, 22(6).

[7] Fauziyyah, N. (2020). Smart Educators for Digital Age Students. INSANIA: Jurnal Pemikiran Alternatif Kependidikan, 25(1), 23-30.

[8] Quan, Z. (2023). High-Quality Development Path of Digital Transformation Enabling Basic Education: Taking the National Information-Based Teaching Experimental Areas as an Example. Frontiers of Education in China, 18(1).

[9] Hu, Y., Pan, J., & Wang, J. (2025). School’s Digital Education Ecosystem: The Practice of Digital Transformation. In Leading Smart Education: Best Practices from Chinese Schools (pp. 665-685). Singapore: Springer Nature Singapore.

[10] Tang, C., Mao, S., Naumann, S. E., & Xing, Z. (2022). Improving student creativity through digital technology products: A literature review. Thinking Skills and Creativity, 44, 101032.

[11] Claro, M., Salinas, Á., Cabello-Hutt, T., San Martín, E., Preiss, D. D., Valenzuela, S., & Jara, I. (2018). Teaching in a Digital Environment (TIDE): Defining and measuring teachers' capacity to develop students' digital information and communication skills. Computers & Education, 121, 162-174.

[12] Xin Wang,Na E & Jingbo Yang. (2025). Image clearness processing for image restoration based on generative adversarial networks. International Journal of Cognitive Computing in Engineering360-369.

[13] Qing Zhao,Jiawen Liao,Derui Zhang & Jia Feng. (2024). Grayscale Iterative Star Spot Extraction Algorithm Based on Image Entropy. Applied Sciences(20),9207-9207.

[14] Beaudelaire Saha Tchinda,Zidane Rigasse Tchoupou Segning,Daniel Tchiotsop & René Tchinda. (2025). Retinal vasculature extraction algorithm based on an improved and lightweight U-Net deep learning model using the dense block. Multimedia Tools and Applications(prepublish),1-24.

[15] Tolpadi Aniket A,Luitjens Johanna,Gassert Felix G,Li Xiaojuan,Link Thomas M,Majumdar Sharmila & Pedoia Valentina. (2023). Synthetic Inflammation Imaging with PatchGAN Deep Learning Networks. Bioengineering (Basel, Switzerland)(5).