Innovative Design Algorithm of Huizhou Bamboo Weaving Patterns Based on Deep Learning

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***Abstract*—In the field of innovative design of Huizhou bamboo weaving patterns, traditional deep learning algorithms cannot fully capture the fine structure and subtle changes of patterns, resulting in distorted or blurred results, and require a lot of computing resources and time during the training process. This paper constructs an improved ViT (Vision Transformer) model to collect diverse Huizhou bamboo weaving pattern data covering different styles and forms. In the data enhancement stage, common enhancement techniques such as rotation, scaling, flipping, and color perturbation are used to increase the diversity of training data. Based on the traditional ViT model, a local self-attention mechanism is applied to replace the traditional global self-attention mechanism. Mixed precision training and distributed training strategies are used to effectively accelerate the training process while maintaining high accuracy. The model automatically generates innovative designs by learning the style and structural characteristics of Huizhou bamboo weaving patterns, and adds a detail repair module in the generation process to enhance the detail expression of the pattern. The experimental results show that the improved ViT model tends to 0.95 after 50 training rounds, indicating that it performs well in detail preservation and structural similarity; with a sample data volume of 5000, the training time of the improved ViT model is 47.4 seconds, and the GPU memory usage is 37.1GB, providing higher computing efficiency. The experimental results prove the effectiveness of this paper's research on the innovative design algorithm of Huizhou bamboo weaving patterns.**

Keywords*—Deep learning; Huizhou bamboo weaving; bamboo weaving pattern; vision transformer; local self-attention mechanism

I. Introduction

This template, modified in MS Word 2007 and saved as a "Word 97-2003 Document" for the PC, provides authors with most of the formatting specifications needed for preparing electronic versions of their papers. Huizhou bamboo weaving art, with its unique patterns and exquisite craftsmanship, occupies an important position in traditional Chinese crafts. As an important carrier of Huizhou culture, bamboo weaving patterns carry rich local characteristics and historical and cultural connotations [1-2]. With the diversification of modern design needs, how to realize the innovative design of Huizhou bamboo weaving patterns on the basis of inheriting traditional crafts has become an urgent issue to be solved. The advantages of deep learning technology in image generation and optimization provide new possibilities for innovation in this field.

In the design of Huizhou bamboo weaving patterns, the challenges faced by traditional methods have affected its innovation and development in modern applications. Traditional design methods mainly rely on manual creation. Designers need to conceive and arrange patterns based on experience and intuition. This old method can maintain the uniqueness of handicrafts, but it has limitations in design efficiency and diversity [3-4]. The manual design process is time-consuming and labor-intensive, and it is difficult to quickly respond to the market's demand for personalized and diversified patterns. Traditional design methods are difficult to adapt to modern consumers' high requirements for personalization and innovation [5-6]. Traditional computer-aided design (CAD) can improve design efficiency to a certain extent, but it has obvious shortcomings when dealing with the complex structure and details of Huizhou bamboo weaving patterns [7-8]. Traditional CAD systems rely more on the combination and transformation of geometric figures and cannot deeply capture the delicate changes and microstructures in the patterns. The designed patterns lack detail levels and cultural depth. This limitation makes the bamboo weaving patterns generated by traditional computer technology lack artistic quality and cultural transmission [9-10], and cannot truly show the unique charm of Huizhou bamboo weaving [11]. In recent years, deep learning technology has been applied to the field of image generation. The application of existing CNNs (Convolutional Neural Networks) and Transformer deep learning models in pattern design still faces some challenges [12-13]. In terms of the balance between detail expression and model training efficiency, traditional deep learning methods require a lot of computing resources and long training time, and their ability to process complex patterns is limited. In terms of the expression of pattern details, traditional deep learning methods cannot effectively process the complex features of bamboo weaving patterns that are highly dependent on local details, resulting in distortion or blurring of the generated patterns, making it difficult to achieve the ideal design effect [14]. How to improve design efficiency while ensuring the expression of design details has become a key issue in promoting the innovative design of Huizhou bamboo weaving patterns.

This paper constructs an improved ViT deep learning model to achieve innovative design of Huizhou bamboo weaving patterns. Traditional design methods can ensure the uniqueness of handicrafts, but have significant limitations in efficiency and innovation. This paper uses the ViT model to break through the bottleneck of traditional design methods and improve the automation, refinement, and innovation of Huizhou bamboo weaving pattern design. A diverse training dataset is constructed, covering Huizhou bamboo weaving patterns of different styles and forms, and data enhancement technology is

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used to expand the diversity of training data. In view of the problem of detail loss that the traditional ViT model is prone to when processing complex patterns, a local self-attention mechanism is applied to optimize the global self-attention mechanism, enhance the ability to obtain local details, and ensure that the complex structure and delicate changes of bamboo weaving patterns can be precisely restored during the generation process. The study also focuses on solving the problem of training efficiency and adopting mixed precision training and distributed training strategies to improve the training speed and greatly reduce the demand for computing resources while ensuring model accuracy. The research goal is to realize an innovative design generation system that can automatically generate new patterns that conform to the artistic style of Huizhou bamboo weaving, and further enhance the artistic expression of the patterns through the detail repair module, providing a new solution for the modernization of traditional bamboo weaving crafts.

II. Related Work

The research on bamboo weaving pattern design has gradually attracted the attention of academia and industry. Many studies have used deep learning technology to optimize the design and generation of patterns. In view of the limitations of traditional generation methods, some studies are based on CNN [15-16] methods to capture the basic morphological characteristics of bamboo weaving patterns and generate corresponding designs. Rustandi D created an automatic recognition system for bamboo stems based on anatomical structure. The bamboo recognition algorithm was developed using macro images of cross-sectional bamboo stems, and CNN was used to identify bamboo species. The designed automatic recognition application had a high accuracy rate in detecting bamboo species [17]. However, CNN has difficulty maintaining the delicacy and clarity of the pattern when processing patterns with high detail complexity. To overcome this problem, some scholars have proposed using generative adversarial networks (GANs) for pattern design, which can effectively generate diverse patterns [18-19]. Kang X connected the deep convolutional neural network and the deep convolutional generative adversarial network. The deep convolutional neural network constructed a product image recognition model and enhanced the image recognition performance. The deep convolutional generative adversarial network learned intermediate features and automatically generated product shapes that resonated with customers' emotions, and finally generated bamboo furniture designs that met customers' emotional needs [20]. However, there is a certain degree of distortion or blur in the generated results, and the demand for computing resources during the training process is high. These studies provide innovative ideas for pattern generation, but there is still a problem of how to strike a balance between detail expression and generation efficiency, and they fail to fully utilize the advantages of modern ViT models in image processing.

Mohanarangan Veerappermal Devarajan (2022) proposed an improved Backpropagation neural network algorithm to optimize forecasting accuracy and training efficiency in intelligent cloud computing. We adopt their optimization strategies to enhance the learning performance of our deep learning model for recognizing and generating Huizhou bamboo weaving patterns which improves accuracy and faster convergence [21]. A cloud-based big data analytics framework using deconvolutional neural networks for detailed face recognition was developed to demonstrate the effectiveness of CNN architectures in extracting complex visual features, as presented by Swapna Narla (2022), we leverage this CNN-based approach to capture the intricate structural elements of bamboo weaving, enabling high-fidelity pattern recognition [22]. Venkata Surya Bhavana (2025) applied CNNs for automated skin cancer classification, highlighting CNN's ability to differentiate subtle texture variations in high-resolution images. Building on this foundation, their CNN techniques is used in our work to classify diverse weaving textures, preserving traditional aesthetic qualities while enabling innovative design variations. Our proposed study adopts the t-distributed stochastic neighbor embedding (t-SNE) and hierarchical clustering methods introduced by Rahul Jadon (2022) for enhanced machine learning pattern analysis through dimensionality reduction and clustering which supports for the systematic exploration [23-24]. Dinesh Kumar Reddy Basan (2024) presented a multi-scale fusion neural network for fault diagnosis in IoT systems, which effectively captures features across multiple granularities. Inspired by this, our method integrates multi-scale feature extraction to represent the hierarchical and multi-textured nature of Huizhou bamboo weaving, leading to more accurate feature representation [25].

In the field of image generation, the ViT model has become a research hotspot in recent years due to its strong feature extraction and long-distance dependency modeling capabilities. Compared with traditional convolutional neural networks, ViT can capture complex relationships and details in patterns in a larger range and shows unique advantages in image generation tasks [26-27]. Some studies have proposed image recognition models based on ViT, applied a global self-attention mechanism, and improved the model's understanding of global structure [28-29]. However, this may lead to poor processing results for pattern designs with rich details and frequent local changes. Drawing on existing methods, this paper proposes a new ViT model that integrates local self-attention and mixed precision training to effectively address the shortcomings of existing methods.

III. Methods

A. Data Collection and Enhancement

Diverse Huizhou bamboo weaving pattern data is collected, covering different styles and forms, to improve the model's generalization ability. In the data enhancement stage, common enhancement techniques such as rotation, scaling, flipping, and color perturbation are used to increase the diversity of training data and avoid overfitting.

1) Data collection: The data collection process focuses on bamboo weaving patterns covering various styles and forms to ensure that the improved ViT model can learn the diversity and complexity of Huizhou bamboo weaving patterns. The study collects a large number of handmade bamboo weaving patterns from multiple bamboo weaving craft museums and inheritors in the Huizhou area, including samples from different historical periods and design styles. Using digital scanning and high-resolution photography technology, detailed image acquisition of each pattern is carried out to ensure that every detail and structure of the pattern is clearly displayed. In the process of constructing the dataset, attention is paid to maintaining the diversity of the data, including different types of bamboo weaving patterns from simple geometric forms to complex natural patterns. These samples not only cover basic morphological features but also include texture details, hierarchical structures between patterns, and color distribution, ensuring the comprehensiveness of the dataset for model training.

The study also captures bamboo weaving pattern images of similar styles and forms from multiple e-commerce platforms and design websites, and labels them to improve the diversity of the data. The diverse design backgrounds and styles of these images give the dataset a stronger generalization ability. The integration of multi-source datasets ensures that the model can extract effective features from diverse and highly variable pattern images, enhancing the model's adaptability to different design styles. The study also annotates and clarifies the artistic style, historical background, and specific region of each pattern, increasing auxiliary information in the model training process.

Table I lists the data collection of various styles and forms of Huizhou bamboo weaving patterns. The number of images and data sources under each style category are counted, covering a variety of designs such as traditional, modern, retro, natural, geometric, and animal. These data mainly come from multiple channels such as traditional craft museums, design platforms, and museums, ensuring the diversity and representativeness of the training data. These collected images provide a solid foundation for subsequent pattern generation and innovative design.

TABLE I. DATA COLLECTION STATISTICS

Category	Style/Form	Image Count	Data Source	Description
Traditional	Traditional Bamboo Weaving Patterns	500	Traditional Craft Museums, Folk Artists	Classic geometric patterns with fine details, representing centuries-old craftsmanship.
Modern	Creative Modern Bamboo Weaving Patterns	400	Design Platforms, E-commerce Websites	Simplified geometric shapes combined with modern elements for innovative expressions.
Retro	Vintage Bamboo Weaving Patterns	450	Museums, Handicraft Exhibitions	Rich in historical and traditional cultural flavor, representing ancient styles.
Nature	Nature-Inspired Bamboo Weaving Patterns	550	Bamboo Craft Museums, Nature Collections	Focuses on natural elements like plants and animals, emphasizing organic forms.
Geometric	Geometric Bamboo Weaving Patterns	350	Design Platforms, Craft Companies	Features regular geometric shapes and modern minimalist design.
Animal	Animal Motif Bamboo Weaving Patterns	300	Folk Artists, Bamboo Weaving Exhibitions	Animal-themed designs, with intricate details and lifelike representations.

2) Data enhancement: Data enhancement technology is used to expand the scale of the training dataset, increase its diversity, and avoid overfitting problems caused by insufficient samples. A series of enhancement methods such as rotation, scaling, flipping, and color perturbation are used. In the process of rotation enhancement, the original image is rotated at multiple angles to generate patterns in different directions, which increases the model's adaptability to directional changes. The image scaling method randomly changes the size of the pattern image, so that the pattern structure can be effectively recognized by the model at different scales. The use of image flipping operations can not only increase the diversity of the dataset, but also effectively avoid the model from over-relying on image features in a specific direction and improve the model's generalization ability for the performance of pattern structures in different directions. During the color perturbation process, the image is randomly adjusted in hue, saturation, and brightness, which not only enhances the visual diversity of the dataset but also simulates the possible changes in pattern color in actual applications. With these enhancement operations, the diversity of the dataset is greatly increased; overfitting caused by insufficient sample size is avoided; the robustness of the model is enhanced.

For the complexity of Huizhou bamboo weaving patterns, especially the details and texture parts, local cropping, and local enhancement techniques are used. Local cropping is to crop the pattern image in a small range to generate different local area images. This technology simulates the local feature variation in pattern design and ensures the retention and diversity of local details. Local enhancement performs a separate rotation, scaling, or color perturbation on each cropped area, so that each local area has independence and diversity in the pattern generation process, so that the local features of the bamboo weaving pattern can be effectively learned, especially those details that may be ignored in the full image mode. The data enhancement effect is shown in Fig. 1.

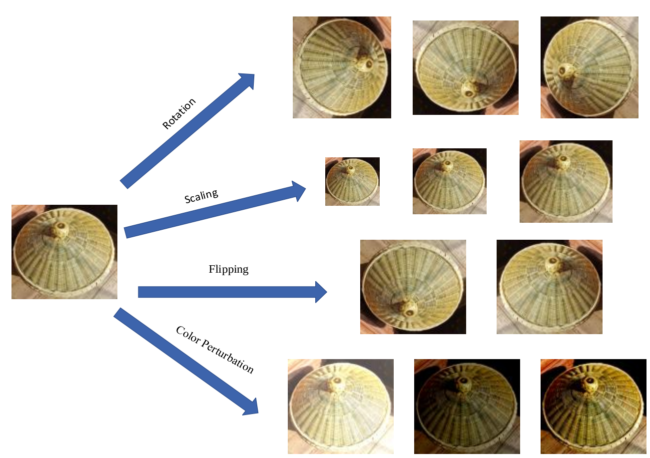

Fig. 1. Data enhancement effect.

B. Improved ViT Model Design

1) Application of local self-attention mechanism: In the traditional ViT model, the image is divided into blocks of fixed size. Each block is linearly embedded and then input into the self-attention mechanism for global calculation. This calculation model can capture the long-range dependencies in the image, but the accuracy of local detail processing is insufficient. In the Huizhou bamboo weaving pattern design with rich details and complex structure, subtle changes in the pattern may be lost. This study proposes an improved solution of the local self-attention mechanism to solve this problem. The local self-attention mechanism is applied to replace the global attention in the traditional ViT model with self-attention calculation in the local area, which can effectively enhance the ability to capture local pattern details. Unlike the global self-attention mechanism that calculates the entire image block, this method calculates in the local area, and each image block only establishes a connection with its neighboring image blocks. This method improves the accuracy of detail capture and reduces the computing complexity. The calculation formula of local self-attention is as follows:

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

In the formula, d_k is the dimension of the key matrix, and QK^T represents the attention weight calculated by the similarity between the query and the key. The local self-attention mechanism limits the calculation scope, enhances the capture of the local structure of the pattern, and ensures the clear presentation of the details in the generated pattern.

TABLE II. HYPERPARAMETER SETTINGS OF THE LOCAL SELF-ATTENTION MECHANISM

Parameter	Value	Description	Unit
Local Block Size	16x16	Size of each block for local self-attention, controls the attention region	Pixel
Self-Attention Window Size	3x3	Size of the self-attention window, affects the precision of capturing local features	Image block
Number of Attention Heads	8	Number of attention heads in each self-attention layer, controls the model's learning ability	-
Local Region Coverage	40%	Proportion of the region focused on in each computation, controls computing complexity	Percentage

In Table II, the local block size determines the size of the image area that is focused on each time the calculation is performed. Smaller blocks can capture local features more finely, but increase the amount of calculation; larger blocks reduce the efficiency of calculation. The study sets it to 16x16 pixels to balance the efficiency of calculation and the ability to capture details. The self-attention window size is 3x3, which can help the model focus on capturing subtle local changes. The number of attention heads is set to eight, which can learn different local features in multiple subspaces and improve the expressiveness of the model. The local area coverage ratio is 40%. By limiting the area involved in each calculation, the consumption of computing resources can be effectively reduced; sufficient local information can be maintained; resource waste during the calculation of the global self-attention mechanism can be avoided.

2) Mixed precision training and distributed training strategy: In terms of improving training efficiency and reducing the consumption of computing resources, this paper adopts mixed precision training and distributed training strategies. The mixed precision training method combines 16-bit floating point and 32-bit floating point calculations to reduce the computing overhead while ensuring training accuracy. Mixed precision training adjusts the calculation accuracy of each layer in the model and selects appropriate numerical representation. When the weight update process uses 32-bit floating point numbers, forward propagation and back propagation use 16-bit floating point numbers, which reduces memory usage and speeds up the training process. By automatically optimizing numerical precision, mixed precision training reduces the demand for GPU (graphics processing unit) memory and avoids numerical instability problems. The loss calculation formula for mixed precision training is:

$$\mathcal{L}_{mixed} = \mathcal{L}_{float32} + \lambda \cdot \mathcal{L}_{float16} \quad (2)$$

In the formula, $\mathcal{L}_{mixed}$ represents the loss function under mixed precision; $\mathcal{L}_{float32}$ and $\mathcal{L}_{float16}$ represent the losses using 32-bit and 16-bit floating point numbers, respectively; λ is the balance coefficient. Using this method, training stability can be ensured, and the demand for computing resources can be greatly reduced.

TABLE III. HYPERPARAMETERS RELATED TO MIXED PRECISION TRAINING

Parameter	Value	Description	Unit
Precision Type	16-bit/32-bit	Precision type used in mixed precision training	Floating Point
Learning Rate	0.0001	The learning rate used by the optimizer, controlling the step size of gradient descent	Learning Rate
Batch Size	64	The number of samples used per training step	Samples
Number of Epochs	50	The total number of training epochs	Epochs

In Table III, the Precision Type parameter determines the numerical precision used, and 16-bit or 32-bit floating point numbers can be selected. Using 16-bit floating point numbers can significantly reduce memory usage and computing time, but in some cases it may affect the model accuracy. It is dynamically adjusted during training to balance performance and accuracy. Learning Rate is the learning rate of the optimizer, which controls the pace of the gradient descent algorithm to update the model parameters. A lower learning rate helps avoid excessive gradient updates during training and improves stability. Batch Size specifies the number of samples used for each training. A larger batch size can improve training efficiency and also increase memory burden. Number of Epochs indicates the rounds of model training. The more training cycles, the stronger the model's fitting ability, but it also requires more computing resources and time.

Distributed training strategies are used to improve training efficiency. A combination of data parallelism and model parallelism is used to distribute training tasks among multiple computing nodes. Data parallelism divides the training data into multiple batches and passes them to different GPUs in parallel, while model parallelism distributes different levels or modules of the model among multiple GPUs for parallel training. This method can effectively improve training speed, reduce training time, and improve the stability and accuracy of the training process. The basic optimization formula for distributed training is as follows:

$$\text{Loss}_{total} = \sum_{i=1}^{N} \text{Loss}_i \tag{3}$$

In the formula, Loss_{total} represents the total loss; Loss_i is the local loss on each GPU node; N is the number of GPUs participating in the training. By using distributed training, this paper can significantly accelerate the convergence process and maintain efficient computing performance when training the improved ViT model on a large-scale dataset.

Combining the local self-attention mechanism, mixed precision training, and distributed training strategy, the improved ViT model can efficiently capture the details of Huizhou bamboo weaving patterns, and can also significantly shorten the training time and reduce the consumption of computing resources while maintaining high accuracy. These innovative optimization methods effectively solve the computing bottleneck problem of the traditional ViT model when processing complex patterns, and provide reliable technical support for large-scale pattern design tasks.

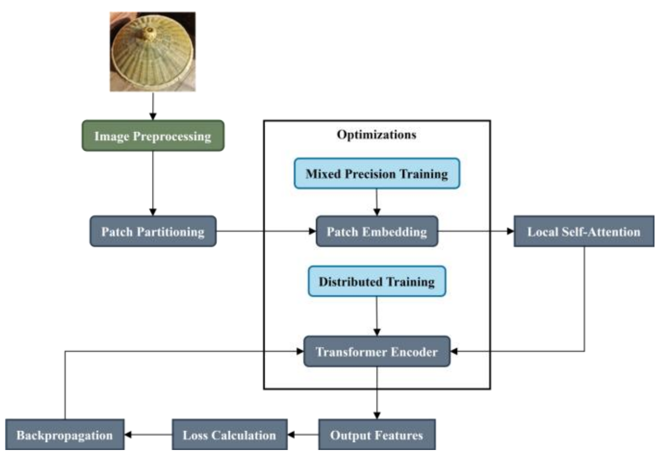

Fig. 2. Improved ViT model processing flow.

Fig. 2 shows the complete processing flow of the improved ViT model. The input image undergoes a preprocessing stage to remove noise and standardize it to ensure that the image data is suitable for model processing. The image is cut into several small blocks, each of which is converted into a vector of fixed dimension through an embedding layer as the input of the Transformer model. The core improvement is the application of a local self-attention mechanism, which significantly reduces the amount of computation brought by the global self-attention mechanism, while focusing more on capturing local features, improving the efficiency and accuracy of the model. After the local self-attention processing, the image block enters the Transformer encoder for more complex feature extraction to generate the final output features. The loss function calculation reflects the difference between the model prediction and the true label, and the network weights are adjusted through back propagation. To accelerate the training process and save computing resources, the improved model adopts mixed precision training and distributed training strategies. These optimization methods speed up the model training speed and maintain high accuracy. With this series of optimization measures, the improved ViT model improves the ability to process large-scale data while ensuring computing efficiency.

C. Innovative Pattern Generation and Detail Restoration

In the process of pattern generation, the improved ViT model first learns the style characteristics and structural layout of Huizhou bamboo weaving patterns through the self-attention mechanism to form an overall understanding of the pattern.

The model adds a detail restoration module in the design stage. The core purpose of this module is to solve the shortcomings of traditional generative models in the expression of pattern details, especially the restoration of blurred areas and missing parts of details. This measure makes the generated patterns both innovative and maintain high-quality restoration of details.

The detail restoration module is optimized based on the GAN architecture. In the generator part of the model, the improved ViT model is responsible for extracting high-level features of the pattern from the input design framework and mapping it to the innovative structure of the pattern. In the generation process, deep residual learning is applied, and the model can make detailed adjustments to the detail areas of the pattern to avoid over-smoothing or distortion in the generation of complex patterns. The loss function is designed as:

$$\mathcal{L}_{detail} = \mathcal{L}_{content} + \lambda_1 \mathcal{L}_{style} + \lambda_2 \mathcal{L}_{smoothness} \tag{4}$$

In the formula, $\mathcal{L}_{content}$ represents the content loss of the pattern; $\mathcal{L}_{style}$ is the style loss; $\mathcal{L}_{smoothness}$ is the smoothness loss; λ_1 and λ_2 are adjustment coefficients. By optimizing these losses, the generator can generate patterns similar to the training data, enhance the detail fidelity of the generated results, and avoid oversimplification of structure and texture.

During the optimization of the detail repair module, a specific region attention mechanism is applied to enhance the model's sensitivity to the pattern detail area. An adaptive weight mechanism is designed so that the model can automatically identify and focus on the key detail areas in the pattern, such as the complex bamboo weaving parts or the fine pattern boundaries during the generation process. The core of this mechanism is to calculate the feature differences of local regions, dynamically adjust the repair strategy according to the size of the difference, and achieve accurate repair of blurred areas and missing parts. The mathematical expression of the repair is:

$$\mathbf{S}_{repair} = \sum_{i=1}^{N} \omega_i \cdot \mathbf{S}_i \tag{5}$$

$\mathbf{S}_{repair}$ is the repaired pattern; $\mathbf{S}_i$ is the feature of the i-th local region; ω_i is the adaptive weight associated with the region; N is the total number of detail regions. Using the weighted summation method, the model can select the most appropriate solution from multiple repair strategies to achieve fine optimization of pattern details.

During the generation process, the artistic and structural consistency of the pattern is ensured, and the style transfer technology is used to adjust the artistic style of the generated results to be consistent with the training data. In the process of style transfer, the high-level artistic features of the pattern are guided by the style term in the loss function, so that the generated pattern has both creative design and the style characteristics of the traditional Huizhou bamboo weaving craft. The style loss calculation formula is as follows:

$$\mathcal{L}_{style} = \sum_{k=1}^{K} \|G_k - A_k\|_2 \tag{6}$$

In the formula, G_k and A_k represent the Gram matrix of the generated pattern and the real pattern at the k-th layer, respectively, and K is the number of layers. This loss compares the low-order features and high-order texture structure of the pattern, so that the generated pattern meets the morphological requirements and retains the original artistic style.

The pattern optimized by the detail restoration module uses this series of technical processing to restore the blurred areas and missing details, inject more artistic expression into the innovative design, and ensure that the pattern achieves a balance between accuracy and creativity. This optimization process improves the quality of the generated pattern, allowing it to have a deep inheritance of traditional culture and meet the aesthetic needs of modern design.

TABLE IV. DETAIL RESTORATION PARAMETERS FOR PATTERN GENERATION AND ENHANCEMENT

Parameter Name	Value	Description	Application Scenario
Detail Repair Module Weight	0.8	Controls the strength of the repair effect	Detail Repair Phase
Pattern Detail Loss Weight	0.75	Balances pattern details with overall design	During Generation
High-frequency Detail Recovery Coefficient	1.5	Enhances the recovery of high-frequency details	Detail Repair Process
Repair Image Resolution	512×512	The resolution of the output pattern	Post-repair Image
Detail Repair Iteration Count	10	The number of iterations for detail repair	During Detail Optimization
Module Activation Threshold	0.05	Threshold for activating the repair module	Repair Activation Standard

In Table IV, the weight of the detail repair module and the weight of the pattern detail loss determine the intensity and balance of the impact of detail repair on the overall design, so that the pattern has the best match between creative expression and detail accuracy. The setting of the high-frequency detail recovery coefficient can enhance the detail performance of the pattern, especially in the high-frequency area, to avoid detail loss. The repaired image resolution ensures high-quality output after the pattern is repaired, which is suitable for further application. The number of detail repair iterations controls the fineness of the repair process and increases the repair accuracy.

IV. METHOD EFFECT EVALUATION

A. Pattern Detail Retention

To evaluate the ability of the improved ViT model in capturing the details of Huizhou bamboo weaving patterns, the structural similarity index (SSIM) is used as the main evaluation indicator. SSIM is used to quantify the structural similarity between the generated pattern and the original pattern, and can comprehensively reflect the detail retention of the image in terms of brightness, contrast, and structure. An SSIM value close to 1 indicates that the pattern has a high degree of detail retention. The calculation formula for a more precise generation effect is as follows:

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{7}$$

x and y represent the images of the original pattern and the generated pattern respectively; μ_x and μ_y are the means of images x and y, respectively; σ_x^2 and σ_y^2 are their respective variances; σ_{xy} is the covariance of the two images; c_1 and c_2 are constants to avoid the denominator being zero.

During the evaluation process, the original Huizhou bamboo weaving pattern is compared with the pattern generated by the improved ViT model, and the SSIM value between each pair of images is calculated. At the same time, to ensure the comprehensiveness of the evaluation, the improved model is compared horizontally with the traditional ViT model and the GAN method. Through this comparison, the performance differences of the improved ViT model in detail retention, pattern complexity, and structural restoration are comprehensively analyzed, and the effectiveness of the model in improving detail expression is verified.

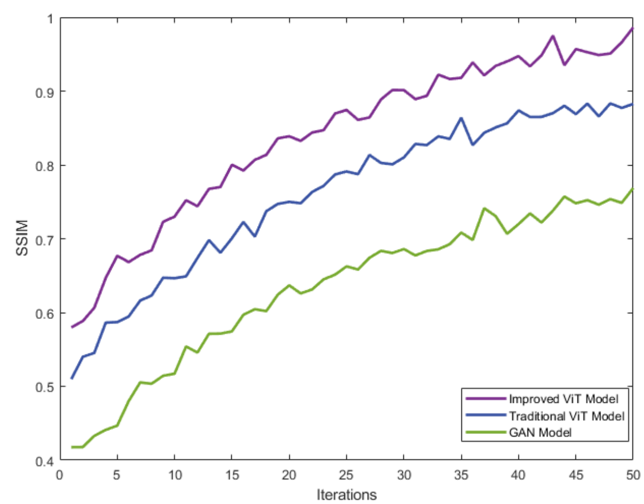

Fig. 3. Changes in SSIM values during different model training iterations.

Fig. 3 shows the changes in SSIM values of the improved ViT, traditional ViT, and GAN models at different training iterations. The improved ViT model improves rapidly in the early stage and converges stably in the later stage, tending to

0.95, indicating that it performs well in detail retention and structural similarity. The traditional ViT model tends to 0.88, showing that its ability in detail extraction is weak. Although the GAN model improves in the early stage of training, the final SSIM value is low and is not as stable as the ViT model in detail restoration. These changes reflect the differences in detail retention among different models, further verifying the superiority of the improved ViT model.

B. Computing Efficiency and Resource Consumption

To evaluate the advantages of the improved ViT model in terms of computing efficiency and resource consumption, training time and GPU memory usage are used as key indicators. Training time measures the time required for the model to complete optimization from the beginning of training, and GPU memory usage reflects the model's demand for hardware resources during training. In the comparative experiment, the same dataset and training conditions are used to train the improved ViT model, the traditional ViT model, and the GAN model, respectively, to generate Huizhou bamboo weaving patterns of the same quality, and the training time and GPU memory usage of each model at different data volumes are recorded to evaluate the computing efficiency of different models. The training time record is obtained by accurately timing the start and end of each training to ensure that the experimental results are repeatable and consistent. The GPU monitoring tool is used to collect the GPU memory usage during the training of each model in real-time. By comparing and analyzing these data, it can be determined whether the improved ViT model has advantages over the traditional ViT and GAN models in large-scale training, and whether it can effectively reduce the computing cost and improve the training efficiency.

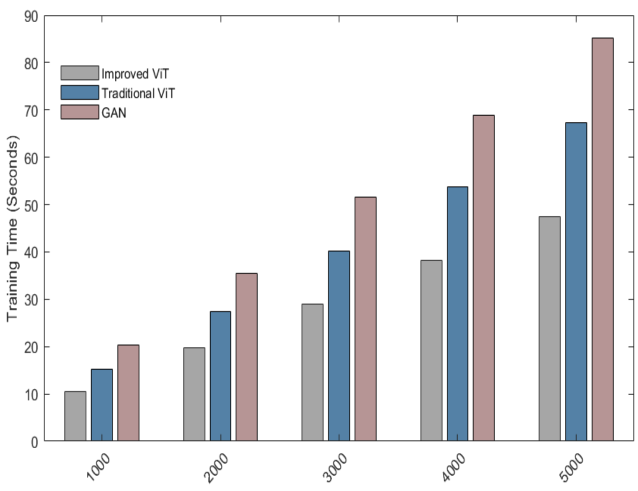

Fig. 4. Comparison of model training time under different data volumes.

Fig. 4 shows the comparison of the training time of the three models under different data volumes. As the data volume increases, the training time of all models shows an upward trend. The improved ViT model has the shortest training time, which is 47.4 seconds at a data volume of 5000. The training time of the traditional ViT model and the GAN model is relatively long, and the growth rate is large as the data volume increases. Using these data, it can be seen that the improved ViT model can effectively reduce the training time while generating high-quality patterns, and can reduce the computing cost in large-scale training, which reflects its advantage in computing efficiency.

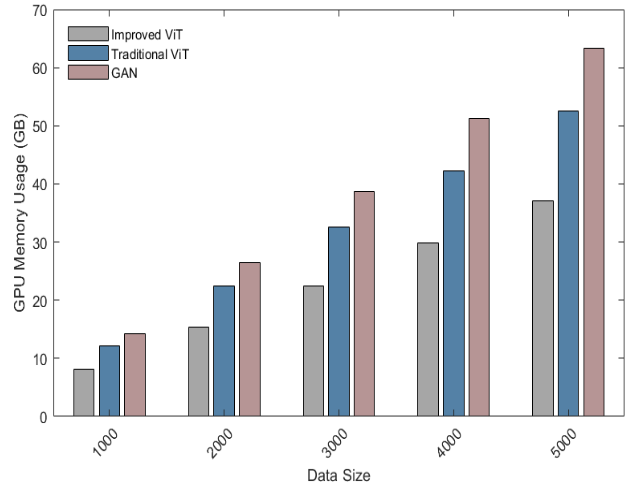

Fig. 5. Comparison of GPU memory usage of models under different data volumes.

Fig. 5 shows the GPU memory usage of the improved ViT, traditional ViT, and GAN models under different data volumes. As the data volume increases from 1000 to 5000 samples, the memory usage of the three models shows an upward trend, but the increase rate is different. The memory consumption of the improved ViT model in the entire data volume range is significantly lower than that of the traditional ViT and GAN models. When the data volume is 5000, the GPU memory usage is 37.1GB, and the memory usage advantage is more obvious. The improved ViT model can significantly reduce memory consumption and improve computing efficiency by optimizing the computing structure and applying the local self-attention mechanism.

V. Conclusion

This study constructs an improved ViT model and applies it to the generation and detail restoration tasks of Huizhou bamboo weaving patterns. By applying optimization methods such as local self-attention mechanism and mixed precision training, the improved ViT model guarantees the artistic creativity and detail expression of the generated patterns to a certain extent, and improves the performance in terms of computing efficiency and resource consumption. The experimental results show that the improved ViT model is superior to the traditional ViT and GAN models in many aspects.

From the perspective of pattern detail retention, the improved model has a significant advantage in improving the SSIM value, which tends to 0.95 after 50 training rounds, and can better retain the details of Huizhou bamboo weaving patterns, showing a relatively stable training process. In terms of computing efficiency and resource consumption, with a sample data volume of 5000, the training time of the improved ViT model is 47.4 seconds, and the GPU memory usage is 37.1GB. Under the premise of generating patterns of the same quality, the training time is reduced, providing a more efficient solution for large-scale data processing. The improved ViT model has shown strong capabilities in pattern generation and detail restoration, and has also achieved satisfactory results in optimizing computing resources. These advantages give the model broad application prospects in art design, cultural heritage protection, and other visual generation tasks. In future research, more efficient attention mechanisms and training strategies can be further explored to further improve the model's performance and scalability.

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CONFLICTS OF INTERESTS

Authors do not have any conflicts.

DATA AVAILABILITY STATEMENT

No datasets were generated or analyzed during the current study.

CODE AVAILABILITY

Not applicable.

AUTHORS' CONTRIBUTIONS

Jinjin Rong, is responsible for designing the framework, analyzing the performance, validating the results, and writing the article. Xin Fang, is responsible for collecting the information required for the framework, provision of software, critical review, and administering the process.

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