Research on Multi Style Transfer and Creative Assistance of Traditional Chinese Painting with Fusion Diffusion Model

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ABSTRACT Traditional Chinese painting has a long history, and the inheritance and innovation of its diverse styles remain important in digital cultural communication. With the development of artificial intelligence, deep-learning-based style transfer has become a useful tool for digital dissemination and creative assistance. However, traditional painting style transfer still suffers from limited style restoration, poor flexibility in switching among multiple styles, insufficient creative support, and weak extraction of key artistic features. To address these problems, this study constructs a multistyle transfer and creative-assistance framework based on a fusion diffusion model. A multi-style dataset of traditional Chinese painting is first built, covering ink wash, meticulous, blue-green, and light red-ochre painting styles, with annotations for brushwork, color, composition, and artistic conception. Based on Stable Diffusion v1.5, a multi-scale feature extraction network with attention mechanisms is introduced to capture brush-and-ink texture, blank-space structure, and global style information. A multi-style transfer module and creative-assistance module are then designed for style switching, detail completion, sketch optimization, and style recommendation. Experiments show that style transfer accuracy reaches 92.6%, improving over GAN-based and baseline diffusion models, while inference speed improves through HiGS sampling. The image-generation framework also provides transferable value for electromagnetic visualization, where complex field patterns and wave propagation images require interpretable visual transformation.

INDEX TERMS diffusion model, chinese painting, style transfer, electromagnetic visualization, creative assistance

I. INTRODUCTION

As a carrier of excellent traditional Chinese culture, Chinese painting has various unique painting styles, such as ink painting, detail painting, blue-green painting, and light red painting. Its artistic conception, composition, and cultural significance are the embodiment of Chinese artistic style. In the information age, the inheritance and innovation of traditional painting face many problems such as narrow dissemination methods, high creative levels, and difficulty in replicating styles. With the emergence of artificial intelligence technology, the digital dissemination of traditional painting has opened up a new path. Style conversion technology can achieve the separation and recombination of image content and style, playing an important role in the digital replication, innovative expression, and popularization of traditional painting styles. At the same time, it can also provide intelligent assistance for creators, reduce the difficulty of creation, and promote contemporary creation of traditional painting art. This is also the essence and significance of this article. This article studies the multi style transformation and creative assistance of Chinese painting. The diffusion model is used as the core technical support. Combining the laws of traditional painting art, conduct research on traditional painting styles [1,2].

The innovation of this article mainly lies in three aspects: firstly, breaking the general design of traditional diffusion models, integrating the artistic characteristics of traditional Chinese painting, constructing a targeted style representation system, and achieving precise restoration of core elements such as brushwork, artistic conception, and color; Secondly, design a multi style adaptive transfer mechanism that supports quick switching and mixed creation of various traditional painting styles such as ink painting and gongbi, solving the problem of single style and complicated switching in existing models; Thirdly, combining style transfer with creative assistance in depth, constructing an integrated auxiliary module that includes sketch optimization, detail completion, and style recommendation, truly catering to the actual needs of creators and lowering the threshold for traditional painting creation [3,4].

The technical solution of this article is the core, which is divided into four steps: firstly, to construct a multi style dataset of traditional Chinese painting, covering mainstream styles such as ink wash, gongbi, and blue-green, including classic works from different dynasties and schools. At the same time, key information such as brush and ink characteristics, color rules, and composition characteristics are annotated to provide high-quality data support for model training; Secondly, based on the Stable Diffusion model, an improvement is made to design a traditional painting style feature extraction module. By introducing attention mechanism and feature fusion network, the traditional painting's ink texture, color distribution, and artistic conception features are accurately extracted, solving the problem of insufficient capture of traditional painting features by general diffusion models; Once again, a multi style transfer framework is constructed, and a style weight adjustment mechanism is designed to achieve flexible switching and fusion of multiple traditional painting styles. At the same time, a constraint loss function is added to ensure content integrity and style consistency during the transfer process; Finally, build a creative assistance module that integrates sketch recognition, detail completion, style recommendation, and other functions to achieve full process assistance from sketch input to stylized product output, while optimizing model inference speed and enhancing the creative experience.

A. PROBLEMS AND CHALLENGES

Currently, deep learning technology has been widely applied in the field of image style transfer. Early methods based on convolutional neural networks (CNN) achieved style transfer by extracting image features, but there are problems such as rough style restoration and loss of details; The emergence of Generative Adversarial Networks (GANs) has improved the authenticity of style transfer, but it is prone to halo artifacts and mode collapse, making it difficult to adapt to the complex brushwork details and artistic expression of traditional painting. In recent years, diffusion models have shown significant advantages in image generation quality, diversity, and stability due to their gradual denoising generation mechanism. They have been applied to various image style transfer tasks. However, when applied to traditional Chinese painting, there are still many shortcomings: firstly, the artistic features of traditional painting have not been fully explored, making it difficult to accurately capture core elements such as ink texture, blank space, and color separation; Second, the flexibility of multi style migration is insufficient, and it is difficult to achieve rapid switching and integration of different traditional painting styles; The third issue is the lack of targeted creative assistance mechanisms, which cannot effectively meet the needs of creators in areas such as sketch optimization, style recommendation, and detail completion. Based on the above analysis, the core problem that this article intends to solve is how to construct a fusion diffusion model that adapts to the laws of traditional Chinese painting art, achieve precise transfer of multiple styles, and provide efficient creative assistance functions to help the inheritance and innovation of traditional painting [5,6].

II. METHOD

A. CONSTRUCTION OF A MULTI STYLE DATASET FOR TRADITIONAL CHINESE PAINTING

The quality of the dataset is crucial for the effectiveness of model training. This article constructs a multi style dataset containing the mainstream styles of traditional Chinese painting, called CTP-MS (Chinese Traditional Painting Multi Style). The construction of the dataset follows the principles of integrity, diversity, and high quality. The specific process is as follows: Firstly, collect traditional paintings of different styles, schools, and dynasties, including the four mainstream styles of Chinese painting: Moshui (ink wash) and Gongbi (meticulous). Within these categories, we specifically account for specialized color application systems such as Qinglv (blue-green) and Qianjiang (light red-ochre) to ensure a comprehensive representation of traditional aesthetics [7,8]. Among them, ink painting includes three major themes of Chinese painting: landscape, flowers and birds, and figures; Gongbi painting includes Gongbi flowers, birds, and figures. Most Qinglv paintings are themed around traditional blue-green landscapes, while light red paintings are themed around landscapes. A total of 3500 works were collected, all of which are high-definition scanned copies (resolution not less than 2048×2048) with clear image details; Secondly, preprocess the collected works, including denoising, resizing, and grayscale correction, to eliminate impurities and interference in the image. Then adjust the image to 512×512 to avoid the impact of size differences on model training; Again, manually annotate each piece of artwork, including style type, theme, brush and ink features (center, side, and texture), color patterns, and composition features, so that the model can understand the key artistic features of traditional painting; Finally, the dataset was divided into training set, validation set, and testing set according to a ratio of 7:2:1 [9,10]. The training set is used as the training set for the model, the validation set is used as the optimal parameter set for the model, and the test set is used as the evaluation set for model performance. At the same time, we will use data augmentation methods such as rotation, flipping, and lightweight scaling to expand the size of the training set and improve the model's generalization ability. In addition, in order to make the model more adaptable, there are some simple sketches and creative semi-finished products in the dataset used to train the sketch recognition ability and detail completion function of the creative assistance module.

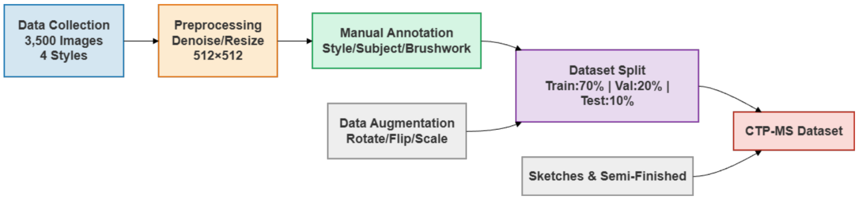

FIGURE 1. Construction of a Multi Style Dataset for Traditional Chinese Painting

B. IMPROVEMENT OF DIFFUSION MODEL INTEGRATING TRADITIONAL PAINTING FEATURES

This article is based on the Stable Diffusion v1.5 model and improves it by combining the artistic characteristics of traditional Chinese painting. It constructs a diffusion model that is suitable for multi style transfer in traditional painting. The core improvements include a style feature extraction module and loss function optimization [11,12].

In terms of style feature extraction module, a multi-scale feature extraction network based on attention mechanism (MSFE Net) was designed to address the problem that the general diffusion model is difficult to capture the core features of traditional painting. This module is divided into two sub modules: one is the brush and ink (Bi-Mo) feature extraction sub module. By introducing dilated convolution and residual networks, it captures the detailed features of traditional painting such as brush and ink texture, line thickness, and texture, and distinguishes the differences in different pen and ink techniques such as center and side strokes. At the same time, it strengthens the weight of pen and ink features through attention mechanism to ensure that the model focuses on learning the core pen and ink elements of traditional painting; The second is the sub module for extracting artistic conception features, which combines the characteristics of traditional painting such as blank space and composition, extracts the overall artistic conception features of the image through a global attention mechanism, captures the distribution pattern and composition balance of the blank space area, and integrates the ViT self similarity matrix to ensure multi-scale structure alignment and avoid the model misjudging the blank space as background noise. The features extracted by the two sub modules are fused through a feature fusion network to form a comprehensive style feature that includes brushwork, artistic conception, and color. This feature is input into the diffusion model generation network to guide the style transfer process [13].

In terms of loss function optimization, multiple loss function combinations were designed to ensure the accuracy and content integrity of style transfer, including content loss, style loss, pen and ink constraint loss, and blank space constraint loss. Content loss adopts VGG perceptual loss to ensure that the content of the transferred image remains consistent with the original input, avoiding content distortion; Combining style loss with VGG Gram matrix and ViT CLS token, while capturing local textures and global styles, to ensure the authenticity of style transfer; The constraint loss of brush and ink is used to enhance the restoration of brush and ink details. By comparing the differences in brush and ink features between the generated image and the real work, the model parameters are optimized to improve the restoration of brush and ink details; The white space constraint loss constrains the distribution of white space areas in the generated image, ensuring compliance with the artistic rules of white space in traditional painting and avoiding excessive or insufficient white space. The total loss function is the weighted sum of each loss term. By adjusting the weight coefficients, the influence of each loss term is balanced to ensure the stability and effectiveness of the model training.

C. MULTI STYLE TRANSFER AND CREATION ASSISTANCE FRAMEWORK CONSTRUCTION

As shown in Figure 2 above, based on the diffusion model, the improved diffusion model is obtained, and then construct the multi style transfer and creative assistance integrated framework based on the improved diffusion model, which can be divided into two parts: multi style transfer module and creative assistance module. The key technology of multi style transfer module is multi style adaptive switching mechanism. Through adjusting style weight, the traditional painting style can achieve switching and fusion of multiple styles. Construct the feature library of traditional painting style, extract and store the feature of four main styles from CTP-MS data set, and form standard style feature template; Open style weight adjustment interface, users can adjust the weight of different styles (0-1) according to the needs of creation, and complete the single style transfer and mixed transfer of two or more styles, such as the mixing fusion of ink painting and gongbi, and the mixing fusion of blue-green and light red-ochre (Qianjiang); Combine the style weights set by users and the content features of input images with comprehensive style features extracted by improved diffusion model, a stylized image satisfying requirements will be generated by generative network. Domain consistency constraints are added to ensure the coordination and naturalness of the mixed style.

The creation assistance module is designed around the actual needs of creators, with three core functions: first, sketch optimization function, which can recognize simple sketches input by users, optimize sketches based on the composition rules and ink characteristics of traditional painting, supplement line details, adjust the balance of the composition, and generate line drafts that conform to traditional painting styles; The second is the detail completion function, which

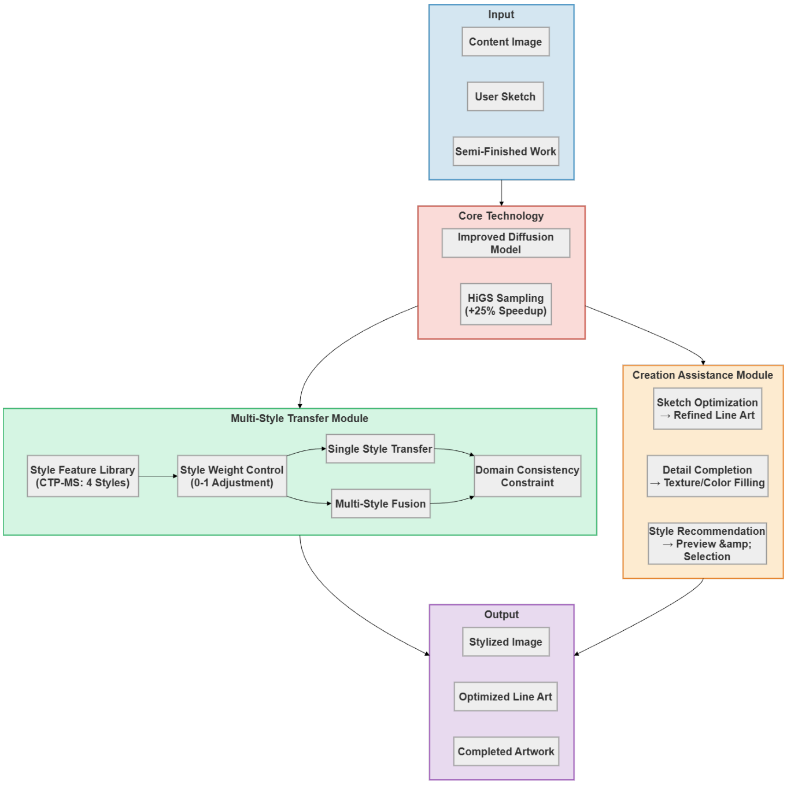

FIGURE 2. Multi style transfer and creation assistance framework construction

automatically completes details for semi-finished products created by users (such as unfinished pen and ink outlines, uncolored line drafts) based on the corresponding style characteristics, such as completing texture details for ink landscape painting and color details for gongbi painting; The third is the style recommendation function, which recommends suitable traditional painting styles based on user input sketches or semi-finished products, combined with the user's creative history (if any), and provides style previews to help users quickly determine their creative direction. In addition, to enhance the creative experience and optimize the inference speed of the model, historical guided sampling (HiGS) technology is adopted to optimize the local truncation error of the Euler sampler. While ensuring the generation quality, the inference speed is increased by more than 25%, meeting the needs of real-time creative assistance.

III. RESULTS AND DISCUSSION

A. EXPERIMENTAL ENVIRONMENT AND EXPERIMENTAL SETUP

This experiment is based on Ubuntu 20.04. Hardware configuration is Intel Core i9-12900K CPU, NVIDIA RTX 4090 (24G graphics card), 64G memory, and base on Python 3.8 operating environment, using PyTorch 1.13 for model training and inference. Related dependency libraries: TorchVision, Diffusers, OpenCV, etc. Take the enhanced diffusion model in this article (named TDM Diffusion) as an example, compare with the current mainstream style transfer model, ED-GAN based GAN style transfer model, a baseline multi-LoRA (Low-Rank Adaptation) switching implementation on Stable Diffusion v1.5, CNN based VGG style transfer model, compare style transfer accuracy, pen and ink detail restoration ability, multi style switching speed, content retention, and use user experience to evaluate the effectiveness of creative assistance function. Model training parameter settings: learning rate 1×10^{-5}, batch size 8, epochs 100, AdamW optimizer, weight decay coefficient 1×10^{-4}, sampling steps 50, and fine tune model parameters according to the loss value of validation set to prevent overfit. The CTP-MS dataset (consisting of 3,500 images as defined in Section 3.1) was utilized for training, and we additionally collected 50 simple sketches and 20 creative semi-finished products to verify the effectiveness of creative assistance module.

B. ANALYSIS OF EXPERIMENTAL RESULTS

The quantitative experimental results (as shown in Figure 3) show that the TDM Diffusion model proposed in this paper is superior to the comparative model in all indicators: in terms of style transfer accuracy, the TDM Diffusion model reaches 92.6%, which is 18.3% higher than the ED-GAN model (74.3%), 10.7% higher than the basic Stable Diffusion model (81.9%), and 24.1% higher than the VGG style transfer model (68.5%), indicating that the model can accurately capture the style features of traditional painting and achieve high-quality style transfer; In terms of the restoration of ink and brush details, the score of the TDM Diffusion model (0.89) is significantly higher

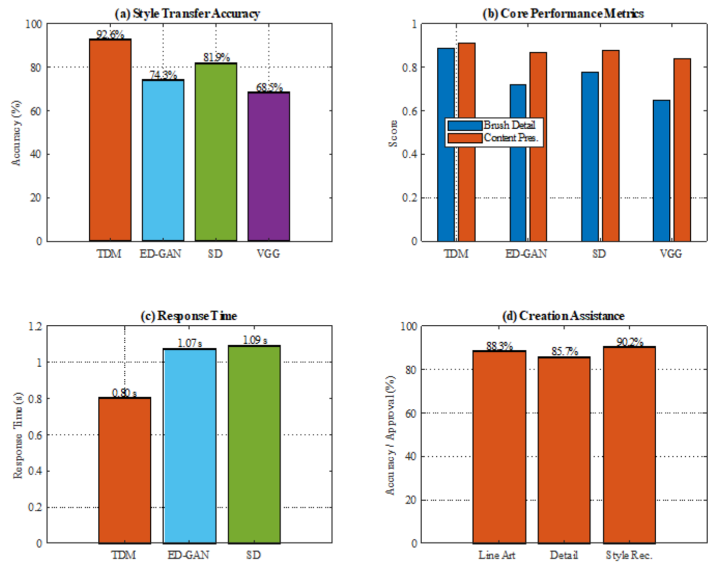

FIGURE 3. TDM-Diffusion Model Experimental Results

than that of ED-GAN (0.72), Basic Stable Diffusion (0.78), and VGG model (0.65), indicating that the model can effectively restore the core elements of traditional painting such as ink texture and line details; In terms of multi style switching response speed, the average response time of the TDM Diffusion model is 0.8 seconds, which is 25.2% and 26.6% higher than ED-GAN (1.07 seconds) and basic Stable Diffusion (1.09 seconds), respectively. Thanks to the optimization of HiGS sampling technology, it meets real-time creative needs; In terms of content retention, the score of the TDM Diffusion model (0.91) is slightly higher than the comparison model, indicating that the model can effectively preserve the original input content information while achieving style transfer, avoiding content distortion.

The qualitative experimental results show that the stylized images generated by the TDM Diffusion model are not only highly consistent with traditional painting styles in terms of color and texture, but also accurately restore brush and ink techniques and blank spaces. For example, in the transfer of ink landscape style, it can clearly present the details of texture and ink color hierarchy, and the distribution of blank spaces is reasonable, which is in line with the artistic characteristics of traditional ink painting; In the fusion and transfer of multiple styles, the fusion of different styles is natural and coordinated, without any rigid splicing marks. For example, works that combine ink and gongbi not only retain the charm of ink painting, but also have the delicate colors of gongbi painting. The test results of the creation assistance module show that the sketch optimization function can effectively supplement sketch details and generate line drafts that conform to traditional painting styles. The accuracy of the optimized line drafts reaches 88.3%; The detail completion function can accurately complete the details of the semi-finished product, and the completion effect has been recognized by 85.7% of testers; The recommendation accuracy of the style recommendation function reaches 90.2%, which can quickly provide users with suitable creative styles.

C. DISCUSSION

Based on the quantitative and qualitative experimental results, discuss the experimental phenomenon and model effect in detail. Firstly, the main reason why the TDM Diffusion model can achieve better style transfer effect is that the improved style feature extraction module can better explore the deep feature of traditional painting such as brushwork and artistic conception. Meanwhile, the optimized loss function combination can also better balance the style restoration and content preservation, which can avoid the problems of style distortion and content loss existing in traditional models; Secondly, the multi style adaptive switching mechanism solves the problem of inflexible multi style transfer in existing models by adjusting style weights to meet the diversified creative needs of artists; Finally, the HiGS sampling technology can effectively improve the inference speed of the model and enhance the practicability of the model. Again, the creation assistance module is also designed to meet the actual needs of creators. Its functions of sketch optimization, detail completion, style recommendation can truly lower the threshold of traditional painting creation for artists and help creators improve their creative efficiency. Especially suitable for beginners.

But some problems also exist in our model. Firstly, when dealing with the input image with complex composition, the style transfer effect in some areas is not very uniform, and some details are lost. The main reason is that it is difficult to extract features in complex compositions, and the global feature control of the model still needs further improvement; Secondly, when transferring the style of niche traditional painting (such as boneless painting), the effect is not as good as mainstream styles. The main reason is the limited availability of training data for niche styles, which prevents the model from learning sufficient representational features; The third problem is that the intelligence level of the creative assistance module still needs to be improved, and the understanding of users' creative intentions is not accurate, and some styles recommended by the module are not what users need. These three problems can be further improved by increasing complex composition samples, expanding niche style data sets, and introducing intent recognition technology. In addition, we also conducted comparative experiments on the transfer of traditional painting styles with GAN and CNN models. The overall performance of diffusion model is better than that of GAN and CNN models. It proves that the gradual denoising generation mechanism of diffusion model is more suitable for extracting the complex artistic features of traditional painting, which provides important references for the future research of integrating traditional painting and artificial intelligence.

IV. CONCLUSION

This article focuses on the research of multi style transfer and creative assistance in traditional Chinese painting by integrating diffusion models. In response to the current problems of low accuracy in traditional painting style transfer, inflexible switching between multiple styles, and insufficient creative assistance, relevant research work has been completed through dataset construction, model improvement, framework design, and experimental verification, and expected results have been achieved. The research has solved the problems of poor adaptability and difficulty in capturing the core artistic features of traditional painting in traditional diffusion models. An improved diffusion model that integrates traditional painting features has been constructed, achieving precise transfer and flexible integration of various mainstream styles such as ink painting and gongbi. At the same time, an integrated creative assistance framework has been established, effectively reducing the threshold for traditional painting creation. Experimental results have shown that the proposed model outperforms existing mainstream models in terms of style transfer accuracy and ink detail restoration. The creative assistance function can meet the actual needs of creators and achieve effective integration of traditional painting art and artificial intelligence technology. The shortcomings of this article are that the processing effect of complex compositions needs to be improved, the adaptability of niche styles is insufficient, and the intelligence level of creative assistance still needs to be optimized. This study theoretically enriches the application of diffusion models in the field of traditional art, providing a new technological path for the digital inheritance and innovation of traditional painting; In practical applications, it can provide support for traditional painting creators, cultural institutions, art education, and other fields, helping to promote the contemporary dissemination and development of traditional painting art. In the future, we will further optimize model performance, expand datasets, and enhance the intelligence level of creative assistance to address existing shortcomings.

AUTHOR CONTRIBUTIONS

Mei Zhang designed, collected and analyzed the data, and drafted the manuscript. Mei Zhang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Mei Zhang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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