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Oil Painting Style Transfer Algorithm and Practice Based on Generative Artificial Intelligence

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Abstract: To address the challenges of unstable generated image quality and insufficient detail reproduction in oil painting style transfer methods, this paper introduces an algorithm combining a generative adversarial network (GAN) and a convolutional neural network (CNN). This algorithm optimizes the extraction of oil painting style features and image detail control to realize high-quality oil painting style transfer. This paper investigates the extraction of image content features using a CNN and the capture of image style features using the Gram matrix. The optimized loss function for the generated image incorporates deep features at the texture level, enabling style transfer. The experiments utilize Python 3.7+ and the PyTorch/TensorFlow deep learning framework for image processing. Data shows that the texture detail score for both Impressionist-style and landscape-style images is 4.6, with minimal differences between the generated and target-style images, demonstrating excellent style transfer performance. Detail control metrics such as texture reconstruction quality, color saturation, and gradient smoothness are significantly improved during the transfer of the target oil painting style.

1. Introduction

Image stylization, also known as style transfer, typically involves stylizing images through mathematical or statistical models, brushstrokes, textures, and other techniques. This paper proposes a style transfer algorithm for oil paintings based on generative artificial intelligence (AI), incorporating deep learning models (such as GANs and CNNs) to address the edge blurring and loss of style details inherent in traditional algorithms. By optimizing style feature extraction and image generation strategies, this paper transfers styles across multiple oil painting styles (such as Impressionism, Realism, and Abstract Expressionism), aiming to enhance the quality of generated images and address the style transfer challenges associated with high-resolution artistic creation. Experimental validation demonstrates significant progress in image quality and detail preservation, while also providing a new technical path for digital art creation.

This paper first explains the research background and significance of style transfer for oil painting images. It then provides a detailed introduction to the principles and workflow of style transfer algorithms. Next, it examines the specific operations of image generation and style application using CNNs, and provides a detailed analysis of the characteristics of oil painting styles. Finally, experimental verification demonstrates the feasibility of this research, and its limitations and future developments are discussed.

2. Related Works

With the development of AI and deep learning technology, oil painting style transfer, as an important research direction in image processing, has gradually become a hot topic in academia and art creation. Many scholars have proposed different algorithms and models to improve the effects of traditional style transfer methods and solve problems such as blurred image edges and loss of brushstroke details.

Chang proposed an oil painting style transfer algorithm based on the SRCNN (Super-Resolution Convolutional Neural Network) model and the UNet (U-Net) architecture. By using the Laplacian operator to enhance the image edge distribution, the problem of blurred edges in traditional image style transfer algorithms was solved. This method outperformed traditional methods in multiple evaluation indicators (such as SSIM (Structural Similarity Index Measure), PSNR (Peak Signal-to-Noise Ratio), MSE (Mean Squared Error), etc.), showing higher accuracy and effect [1]. Bai and Li extracted image quality perception features by simulating the human visual system and proposed a multi-classification CNN method based on information similarity to achieve the classification of artistic style and artist identity. Using the t database, a dataset of more than 2,000 works was constructed, and CNN achieved an accuracy of 85.75% in the artist classification task [2]. Liu et al. analyzed the brushstroke family of oil paintings, that is, the distribution of brushstrokes divided according to shapes (such as points, straight lines, curved arcs, etc.). When synthesizing new images, they ensured that the correct style of brushstrokes was used, making the output image more "painting-like" [3]. Wang et al. proposed a brushstroke style GAN called Stroke-GAN (Stroke Generative Adversarial Network), and generated pure color brushstrokes close to human artist brushstrokes by designing a three-party network, thereby improving the quality of painting details [4]. Zhang proposed a method combining CNNs and deep learning (DL), and analyzed style transfer and object detection technologies that are of great significance in visual research [5]. Zhao et al. proposed a style transfer model based on a multi-adaptive generative adversarial network (MA-GAN), which extracted features by learning aesthetic capabilities through a discriminator and passes the extracted features into a multi-attention aesthetic module, including collaborative self-attention (CSA) and self-attention normalization (SAN) modules. Experimental results showed that MA-GAN had significant advantages in visual quality and could generate artistic images with smooth brushstrokes and rich colors [6]. Li and Gao proposed a locally adjustable non-parametric neural style transfer model using a deep and shallow feature synthesis method, treating style transfer as a function matching process outside the neural network. By synthesizing the target feature map layer by layer and converting it into the target photo, the algorithm can accurately manage local rough structure, material details and texture distribution [7]. Zhao et al. extracted style and content features through a lightweight encoder based on a residual network (ResNet), and ensured the harmonious integration of global style and content semantic structure through a multi-domain structured attention module and a secondary alignment strategy. Experiments showed that BcsUST (Balanced Content and Style Transfer) can generate images that are closer to the artist's works [8]. Bai and Li proposed a multi-classification CCNN method based on information similarity to realize multi-classification tasks of artistic style and artist identity.

Using the Wiki Art database, a dataset containing more than 2,000 works was constructed. CNN achieved an accuracy of 85.75% in the artist classification task, which was better than the traditional DL network [9]. Cheng et al. used computer vision technology to establish a painting technique classification and recognition model based on multi-feature fusion. They used wavelet transform to extract color, texture, and spatial features and denoised the image. Using the WikiArt and OilPainting datasets, the neural network achieved a classification accuracy of over 95% [10]. Liu et al. analyzed the brushstroke family (such as points, straight lines, curved arcs, etc.) of paintings and sampled the brushstroke distribution when synthesizing new images to ensure that the output image has the correct style brushstrokes, making the result more "oil painting-like" [11]. The bottleneck of existing research mainly focuses on how to better preserve the details and brushstroke performance of the image, especially in complex style and high-freedom art creation, the style transfer effect still has certain blurring and distortion problems.

3. Methods

3.1 Principles and Process of the Style Transfer Algorithm

3.1.1 Working Principle of Style Transfer Algorithm

Combining the "content" of one image with the "style" of another to create a new image that both adopts the traits of the target style image and preserves the qualities of the original content is the main objective of the style transfer algorithm. In order to accomplish creative style transfer, this method separates and recombines content and style elements using deep learning models, namely CNNs.

The fundamental concept of style transfer is to take features from both the content and style images and, by means of optimization, make sure that the resulting image reproduces the target style image's colors, textures, and other visual components while preserving the content image's structure.

3.1.2 Extraction of Content Features

Assuming that the content image is $I_{content}$ and the activation output of a certain layer of the network is $F_{content}$, the extraction of content features can be expressed as:

$$F_{content}=CNN(I_{content})(1)$$

3.1.3 Extraction of Style Features

The shallow layers that compose the computer network contain the majority of the style image's features, which capture the image's local smoothness and characteristics. The Gram matrix of each neuronal layer's feature map is computed to reflect the style image's features. The correspondence between various local locations in the image is reflected in the Gram coefficient matrix, which is produced by multiplication of the matrix from the characteristic map. Assuming that the feature map of a certain layer is F_{style}, its Gram matrix G_{style} can be calculated by the following formula:

$$G_{style}=F_{style}^{T}F_{style}(2)$$

In this way, the features of the style image effectively capture the texture information in the image through the Gram matrix.

3.1.4 Training Process and Optimization Method

The core of style transfer is to use an optimization approach to reduce the disparity between the image that is generated and the subject matter and aesthetic of the images. In the actual training process, the following steps are used for optimization:

(1) Initialization of the generated image

The generated image usually uses the content image as the initial input. The initial image is continuously adjusted through back propagation so that it can not only maintain the shape of the content image but also present the visual features of the target style image.

(2) Design of loss function

Reducing the loss function is the aim of style transfer. The two components of the loss function are style loss and content loss. The difference between the image that is produced and the style image is measured by style loss, while the gap between the generated picture and the content image is measured by content loss.

Loss of content: The variations between the characteristics of the generated image and the material of the image at a particular layer is often measured using the L2 norm. The following is the formula:

$$L_{content}=\frac{1}{2}\sum_{i,j}\left(F_{content}^{(i,j)}-G_{generated}^{(i,j)}\right)^2 \quad (3)$$

Style loss: Style loss is based on the Gram matrix and is measured by calculating the difference between the Gram matrix of the generated image and the Gram matrix of the target style image. The formula is:

$$L_{style}=\sum_i \frac{1}{4N_i^2M_i^2}\sum_{j,k}\left(G_{style,ij}-G_{generated,ij}\right)^2 \quad (4)$$

(3) Total loss function

The total loss function is the weighted sum of the content loss and the style loss, and the formula is as follows:

$$L_{total}=\alpha L_{content}+\beta L_{style} \quad (5)$$

Among them, α and β are weight coefficients that determine the relative importance of the content loss and the style loss.

(4) Optimization process

A gradient descent algorithm (such as the Adam optimizer) is used to minimize the total loss function. The gradient of the loss function with respect to the generated image is calculated by backpropagation, and the pixel values of the generated image are updated so that it gradually approaches the target content and style features.

3.2 Specific Operations of Image Generation and Style Application

3.2.1 Update of Generated Image

The gradient is calculated and the generated image is updated through back propagation. The specific steps are as follows:

$$I_{generated} \leftarrow I_{generated}-\eta \cdot \nabla I_{generated} L_{total} \quad (6)$$

3.2.2 Termination Condition of Style Transfer

The style transfer process usually terminates when the loss function converges. The maximum number of iterations can be set or the change of the loss function can be monitored to determine whether the algorithm has converged.

3.2.3 Image Output

The final generated image retains the structure of the content image and the artistic style of the style image. The generated image can be used for further artistic creation or display.

3.3 Characteristics of Oil Painting Style

3.3.1 Image Characteristics and Visual Effects of Oil Painting Style

The image characteristics of oil painting style can be described by the following aspects:

(1) Rough texture

Oil painting has a relatively unique texture effect. The paint applied on the canvas often has obvious brushstrokes, showing a rough and layered surface. Especially when using thick painting techniques, the presence of brushstrokes is very strong. This effect is usually more prominent in details and has a strong visual impact.

Texture is one of the most important features of oil painting. It conveys the artist's emotions and the historical sense of painting through the processing of every detail in the picture. The style transfer algorithm needs to be able to accurately capture this sense of texture. Specifically, the algorithm can identify the visual effect of oil painting by calculating the texture features (such as texture roughness and coherence) in different convolutional layers.

(2) Color saturation and gradient

Oil painting usually uses high saturation colors. Especially when expressing light and shadow, artists use different color transitions to show the texture of the object. For example, in the shadow part of the object, the color may be darker and contain a lot of warm tones, while the highlight part may use brighter colors. The color gradient in the oil painting style shows fluidity and gradualness. For the style transfer algorithm, it is required to be able to finely handle the transition between colors when generating images.

Assuming that I_{style} represents the style image, the color gradient characteristics can be described by calculating its color gamut change. For example, in the tonal image space, color gradients can be modeled using hue, saturation, and brightness (HSB model). Gradient information can be used to capture the smooth transition of color changes in oil paintings.

$$\Delta H = \sum_i \left| H_{style}(i) - H_{generated}(i) \right| \quad (7)$$

Among them, $H_{style}(i)$ and $H_{generated}(i)$ represent the tonal values of the style image and the generated image at the i-th pixel, respectively.

(3) Direction and smoothness of brushstrokes

The direction and smoothness of brushstrokes are another important feature of oil painting style. The artist's painting skills determine the expression of brushstrokes, which sometimes appear stiff and powerful, and sometimes smooth and delicate. In style transfer, this feature requires the algorithm to consider the direction of brushstrokes and the interaction between brushstrokes during the generation process to achieve a more natural oil painting texture.

To simulate this effect, the style transfer algorithm needs to combine local feature extraction with global image modeling. During the generation process, in addition to processing texture and color, it is also necessary to model the direction of brushstrokes and make detailed adjustments to the image through gradient calculation and other means.

3.3.2 How does the Style Transfer Algorithm Handle the Unique Texture and Color of Oil

Paintings

(1) Texture reconstruction and detail enhancement

Reconstructing the texture of oil paintings is a challenge in style transfer. In order to accurately reproduce the brushstrokes and material effects in oil paintings, the algorithm needs to enhance the texture details through detailed local feature extraction. The CNN commonly used in style transfer can extract texture features from multiple layers, especially in the low-level feature map, which can effectively capture the directionality of brushstrokes and texture roughness.

In order to enhance the texture features, the optimization loss function of the generated image can introduce the deep features of the texture layer:

$$L_{texture}=\sum_{i,j}\left|T_{style}(i,j)-T_{generated}(i,j)\right|^{2}(8)$$

Among them, $T_{style}(i,j)$ and $T_{generated}(i,j)$ represent the texture features of the style image and the generated image at the i-th and j-th positions, respectively.

(2) Color harmony and saturation control

In order to ensure that the color transition in the generated image is smooth and consistent with the expression of oil paintings, the style transfer algorithm needs to accurately control the color distribution of the image. By controlling the hue, saturation and brightness of the image, the algorithm can maintain the typical color characteristics of oil paintings in the generated image. In the processing of color transition, the layering of colors in oil paintings can be imitated by enhancing local color difference and gradient.

In addition, by converting the color space into the HSV (hue, saturation, value) model, the style transfer algorithm can more accurately control the color layering and gradient effects. The formula is as follows:

$$L_{color}=\sum_{i,j}\left|H_{style}(i,j)-H_{generated}(i,j)\right|+\left|S_{style}(i,j)-S_{generated}(i,j)\right|(9)$$

Among them, H and S are hue and saturation respectively.

(3) Reproduction of brushstrokes and layering

The brushstroke direction and layering of the generated image are one of the most expressive features of the oil painting style. By comparing the local features of the generated image with the texture features of the target style image, it can be ensured that the brushstrokes and layering in the generated image are as consistent as possible with the style image.

To this end, the generative model usually combines deconvolution layers and residual networks to restore the rich layering and brushstroke direction in the oil painting through local feature learning and multi-scale modeling. For example, by weighted fusion of feature maps at different levels, the layering and texture of the oil painting can be mapped to the generated image.

4. Results and Discussion

4.1 Experimental Materials

4.1.1 Dataset Preparation

Content images: Select natural images with rich details and structures, such as landscapes, portraits, etc.

Oil Painting Style Images: Classic works from various oil painting styles (such as Impressionism, Realism, and Abstract Expressionism) were selected as target style images. Each style image included at least 10 works.

4.1.2 Experimental Environment

Hardware: A high-performance computer equipped with a GPU with at least 16GB of video memory (such as the NVIDIA RTX 3090) is used to support DL model training.

Software: Python 3.7+, PyTorch/TensorFlow DL frameworks, OpenCV for image processing, and Matplotlib for visualization.

4.2 Data Recording and Results

Evaluation metrics included SSIM, PSNR, color difference (CIEDE2000), and human-assessed texture restoration, color transfer, brushstroke directionality, and light and shadow layering. These metrics aimed to comprehensively assess the quality and detail of style-transferred images.

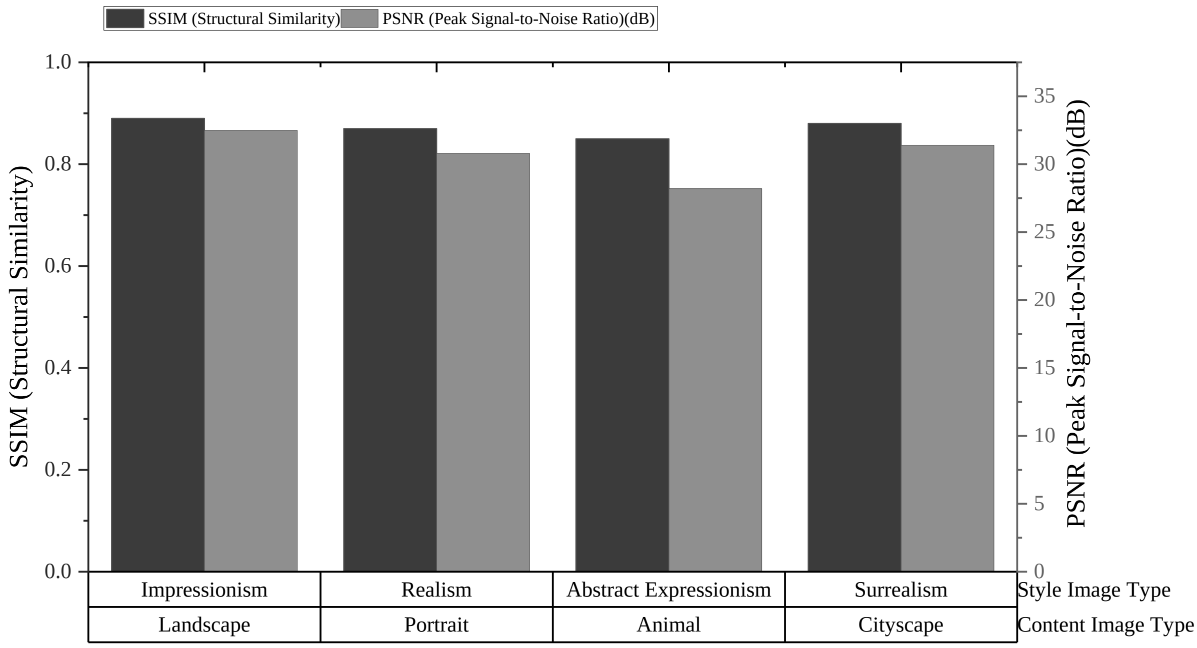

Figure 1. SSIM and PSNR of style transfer results

The generative AI-based style transfer algorithm achieved relatively stable transfer results between different style images and content images. The SSIM and PSNR values in Figure 1 indicated that the generated images generally performed well in terms of detail restoration and image quality. For example, the Impressionist style transfer results for landscape images exhibited high structural similarity (SSIM 0.89) and image quality (PSNR 32.5 dB), demonstrating a good fusion of style and content. In contrast, the Abstract Expressionist style transfer performed slightly worse, with an SSIM of 0.85 and a PSNR of 28.2 dB, indicating a lack of style restoration and detail in the generated images.

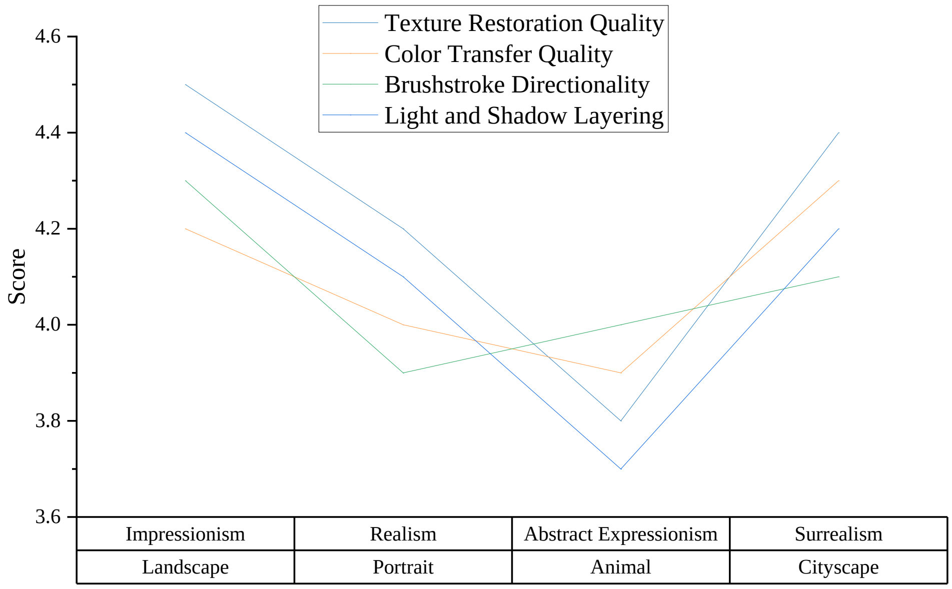

Figure 2. Human evaluation: visual quality assessment of style transfer (1-5 scale)

Note: Scoring scale: 1 (not at all consistent) to 5 (very consistent). Evaluation criteria included texture restoration, color transfer, brushstroke directionality, and light and shadow layering.

Traditional oil painting styles (such as Impressionism and Realism) performed well in texture restoration, color transfer, brushstroke directionality, and light and shadow layering, with scores close to the higher end of the range. For example, the Impressionist style transfer results received scores of 4.5, 4.2, 4.3, and 4.4 for texture restoration quality, color transfer quality, brushstroke directionality, and light and shadow layering, respectively, demonstrating that the generated image successfully reproduced detail and visual effects.

For the Realist style, while the overall performance was good, brushstroke directionality (3.9) was slightly lacking, indicating some challenges in reproducing fine details. However, other metrics (such as texture restoration quality (4.2) and color transfer quality (4.0)) performed remarkably well, resulting in an overall score of around 4.1 (see Figure 2).

The experimental results of CIEDE2000 color difference in Figure 3 show that the style transfer algorithm achieved varying color transfer performance between different style images and content images. Smaller values of color difference (ΔE\Delta EΔE) indicated better color transfer between the generated image and the target style image. Overall, the color difference between the Impressionist style and the landscape image was 5.4, demonstrating relatively ideal color transfer. This result indicates that the color gradients and tones are well matched during the generation process, and the color characteristics of the style are well preserved.

The color difference between the Realist style and the portrait image was 6.1, indicating slightly weaker color transfer. This may be due to the more complex color gradations and shading in the Realist style, which poses challenges for the algorithm in fine-tuning color blending. For the Abstract Expressionist style and the animal image, the color difference was 7.3, which was larger than for other styles, indicating significant deviation in color transfer. Due to the free and unconventional color combinations in the Abstract Expressionist style, style transfer encounters some difficulties in maintaining color consistency. The color difference between the surrealist style and the cityscape image was 5.9, slightly higher than that of the impressionist style. This indicated that during the color transfer process, the generated image's color matching with the target style was slightly off, but overall the color characteristics of the style were well preserved.

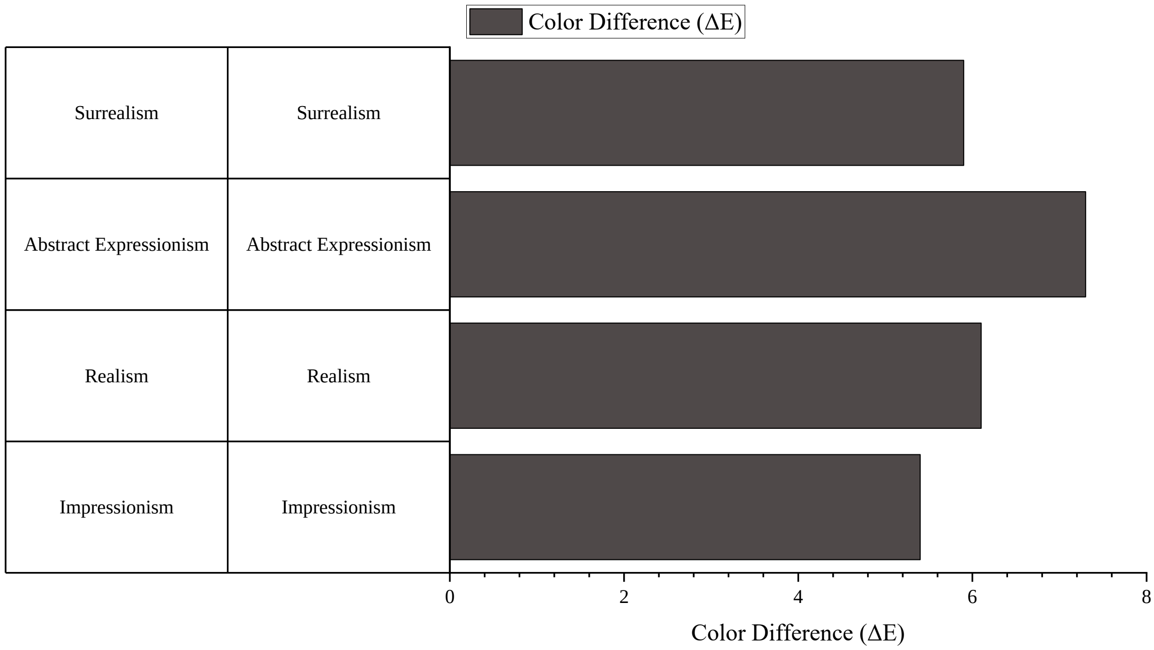

Figure 3. Color difference (CIEDE2000 color difference)

Note: CIEDE2000 color difference measures the color difference between the generated image and the target style image. Smaller values indicate better color transfer.

Table 1. Texture detail scores (1-5) for the generated image and the target oil painting style image

Style Image Type	Content Image Type	Target Style Texture Detail	Generated Image Texture Detail	Rating (1-5)
Impressionism	Landscape	4.7	4.5	4.6
Realism	Portrait	4.8	4.2	4.5
Abstract Expressionism	Animal	4.5	4	4.2
Surrealism	Cityscape	4.6	4.4	4.5

According to the data analysis in Table 1, the style transfer algorithm performed differently in reconstructing texture details across different style images and content images. Overall, the generated images in traditional oil painting styles (such as Impressionism, Realism, and Surrealism) closely matched the target oil painting style images in terms of texture detail. However, in more free and abstract styles (such as Abstract Expressionism), the texture detail reconstruction was relatively weak. First, the Impressionist style with a landscape content image had a texture detail score of 4.6, indicating relatively small differences between the generated image and the target style image, demonstrating excellent style transfer. Despite some minor differences (the target style had a texture detail score of 4.7), the generated image generally reproduced the texture characteristics of the oil painting well.

For the Abstract Expressionist style with an animal content image, the texture detail score was

4.2, indicating a significant gap between the generated image and the target style image in terms of texture representation. This may be due to the highly free and unique nature of the Abstract Expressionist style, which makes it difficult for the generated image to perfectly reproduce its texture characteristics.

5. Conclusions

This paper proposes a generative AI-based style transfer algorithm for oil painting. By combining DL models (such as CNNs and GANs), it achieves high-quality transfer of oil painting styles. Through designed experiments, the quality of generated images is evaluated using multiple metrics, including SSIM, PSNR, and CIEDE2000 color difference. The results demonstrate that the algorithm achieves significant progress in restoring stylistic details and improving image quality. However, this research still has certain limitations. First, while the generated images show significant improvements in detail and color matching, the transfer effect remains insufficient in styles that require highly creative freedom, such as Abstract Expressionism. Second, the computational performance and efficiency of the existing algorithm when processing large-scale, high-resolution images remain to be optimized. Future research can focus on improving the algorithm's computational efficiency, expanding its adaptability to a wide range of styles, and further enhancing its ability to preserve detail in complex style transfer. Furthermore, incorporating more user feedback and adaptive mechanisms may open new avenues for the customization of style transfer algorithms.

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