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Neural Style Transfer Using Convolutional Neural Networks: An Experimental Study

Alaa Yousef Abu Sultan, Samy S. Abu-Naser

Department of Information Technology
Faculty of Engineering and Information Technology
Al-Azhar University, Gaza, Palestine
abunaser@alazhar.edu.ps

Abstract: *This paper presents an experimental study on neural style transfer, a deep learning technique that synthesizes a new image by combining the semantic content of one image with the artistic style of another. A pretrained convolutional neural network (CNN) is employed to transform a natural landscape photograph into a stylized image characterized by expressive brushstrokes and enhanced texture patterns. The experiment demonstrates how deep neural networks can disentangle and recombine content and style representations extracted from different layers of the network. The resulting output preserves the essential structural features of the original scene while adopting stylistic properties reminiscent of post-impressionist artwork. The findings highlight the effectiveness of pretrained CNNs for artistic image synthesis and creative visual transformation.*

Keywords*: Neural style transfer, convolutional neural networks, deep learning, image stylization, computer vision.*

1. Introduction

The rapid advancement of deep learning has profoundly impacted the field of computer vision, enabling machines to perform complex visual tasks such as image classification, object detection, and image synthesis. Among these applications, neural style transfer (NST) has emerged as a prominent technique for generating new images by combining the semantic content of one image with the artistic style of another. This approach has attracted considerable attention due to its ability to produce visually appealing results using pretrained convolutional neural networks (CNNs).

Traditional image manipulation methods rely primarily on handcrafted filters and rule-based transformations, which are limited in their capacity to model high-level artistic attributes[1-3]. In contrast, CNNs learn hierarchical feature representations from large-scale image data, capturing low-level textures, mid-level patterns, and high-level semantic structures[4]. Neural style transfer exploits this hierarchical organization by separating content and style information across different layers of a pretrained network[5-7]. Content is typically represented by higher-layer feature activations that preserve spatial structure, whereas style is encoded through correlations among feature maps extracted from multiple layers[8-9].

Despite the success of neural style transfer in artistic image synthesis, the underlying mechanism by which pretrained CNNs disentangle and recombine content and style representations remains an important area of investigation[10-12]. Many existing studies emphasize improving computational efficiency or visual quality; however, fewer works provide an explicit experimental analysis demonstrating how a fixed pretrained network can preserve semantic structure while transferring artistic texture without additional training[13-15]. This gap motivates the need for experimental studies that focus on illustrating and analyzing the behavior of classical neural style transfer frameworks.

Accordingly, this paper presents an experimental study of neural style transfer using a pretrained convolutional neural network as a fixed feature extractor. A natural landscape photograph is combined with an artistic reference image to generate a stylized output that maintains structural consistency while adopting painterly textures. The study investigates the qualitative characteristics of the generated image and examines the effect of optimization parameters, particularly the relative weighting between content and style losses, on the stylization outcome.

1.1 Objectives of the Study

The main objective of this study is to experimentally evaluate the effectiveness of neural style transfer using a pretrained convolutional neural network for artistic image synthesis. Specifically, this study aims to:

- To implement a neural style transfer framework based on a pretrained CNN for separating and recombining content and style representations from two distinct images.

- To analyze the ability of deep neural networks to preserve semantic content while transferring artistic style features from a reference painting to a natural image.
- To examine the visual quality of the generated stylized images in terms of structural consistency, texture patterns, and color distribution.
- To investigate the impact of optimization parameters, particularly the relative weighting between content loss and style loss, on the stylization outcome.
- To demonstrate the applicability of neural style transfer for digital art generation and creative image processing.
- To provide an experimental illustration of content–style disentanglement in deep convolutional neural networks without requiring additional network training.

1.2 Problem Statement

Despite the success of neural style transfer in artistic image synthesis, the underlying mechanism by which pretrained convolutional neural networks separate and recombine content and style representations remains an active area of investigation[16-17]. Many existing studies focus on improving computational efficiency or visual quality; however, fewer works provide a clear experimental illustration of how a fixed pretrained network can simultaneously preserve semantic structure and transfer artistic texture without additional training[18-20].

Therefore, there is a need for an experimental study that demonstrates and analyzes the ability of pretrained CNNs to disentangle content and style information and to recombine these representations into a visually coherent stylized image. This study addresses this need by implementing a classical optimization-based neural style transfer framework and evaluating its qualitative behavior under different parameter settings.

1.3 Research Questions

This study seeks to answer the following research questions:

- Can a pretrained convolutional neural network effectively separate content and style representations from two different images?
- To what extent can semantic structure be preserved while transferring artistic style features?
- How does the relative weighting between content loss and style loss influence the visual quality of the stylized output?
- What qualitative characteristics emerge in the generated image as a result of neural style transfer optimization?

1.4 Contributions of the Study

The main contributions of this study can be summarized as follows:

- An experimental implementation of neural style transfer using a pretrained convolutional neural network as a fixed feature extractor.
- A qualitative analysis of the generated stylized image in terms of content preservation and artistic transformation.
- An investigation of the effect of style-weight parameters on the strength of stylization.
- A visual demonstration of content–style disentanglement in deep neural networks without requiring additional network training.

1.5 Implementation Details

The neural style transfer framework was implemented using a deep learning library for automatic differentiation and tensor computation[21-23]. A pretrained convolutional neural network was employed as a feature extractor, and its parameters were kept fixed during optimization[24-26].

The content and style images were resized to a uniform resolution prior to processing[27-30]. The generated image was initialized as a copy of the content image and iteratively updated using a gradient-based optimization algorithm. During each iteration, content and style losses were computed, and gradients were propagated back to the pixel values of the generated image.

The optimization process was terminated after a fixed number of iterations when the loss values exhibited convergence[31-33]. All experiments were conducted on a standard computing environment without specialized hardware acceleration.

1.6 Limitations of the Study

Although the experimental results demonstrate the effectiveness of neural style transfer, several limitations should be noted. First, the optimization-based approach is computationally intensive and requires a relatively large number of iterations to achieve visually satisfactory results. Second, the quality of the stylized output is sensitive to the selection of CNN layers and the weighting parameters between content and style losses. Finally, the evaluation in this study is primarily qualitative and does not include quantitative perceptual metrics or user-based assessments.

Future studies may address these limitations by employing feedforward neural networks for real-time stylization, incorporating perceptual similarity measures, and evaluating results across a broader range of image categories and artistic styles.

2. Related Work

The concept of transferring artistic style between images has been studied for decades in the context of non-photorealistic rendering. Early approaches relied on texture synthesis and statistical matching of low-level image features. These methods, however, were limited in their ability to capture complex semantic content[33-35].

The introduction of deep learning brought a major breakthrough in this area. Gatys et al. proposed a neural algorithm for artistic style transfer that utilizes a pretrained CNN to represent content and style separately. Content representations are extracted from higher convolutional layers, while style representations are computed using Gram matrices of feature activations from multiple layers. This formulation enables the generation of images that merge semantic structure with artistic texture[36-38].

Subsequent studies improved computational efficiency by introducing feedforward networks trained for fast style transfer. Other works explored multi-style models, adaptive instance normalization, and transformer-based architectures to enhance visual quality and flexibility. Despite these advancements, the original optimization-based method remains a fundamental reference model due to its conceptual simplicity and interpretability[39-40].

This study adopts the classical optimization-based neural style transfer framework to highlight the fundamental principles underlying content–style separation and to provide an illustrative experimental example.

3. Methodology

3.1 Overview

The neural style transfer process consists of three main components: (1) a pretrained convolutional neural network used as a feature extractor, (2) a content image and a style image, and (3) an optimization procedure that generates a new image by minimizing a composite loss function[41]. The network parameters remain fixed throughout the process, and only the pixel values of the generated image are updated.

3.2 Feature Representation

Let C denote the content image and S denote the style image. A CNN processes these images and produces feature maps at different layers.

Content representation is extracted from higher-level layers of the network, which capture spatial structure and semantic information. Style representation is computed from correlations between feature maps using Gram matrices, which encode texture and color distributions independent of spatial arrangement[42].

For a given layer l , the Gram matrix G^l is defined as:

$$G^l = F^l (F^l)^T$$

Where F^l represents the matrix of vectorized feature maps at layer l.

3.3 Loss Function

The total loss function is defined as a weighted sum of content loss and style loss[43]:

$$L_{total} = aL_{content} + bL_{style}$$

The content loss measures the Euclidean distance between the feature representations of the generated image and the content image. The style loss measures the difference between the Gram matrices of the generated image and the style image across selected layers. The weighting coefficients a and b control the relative influence of content preservation and stylistic transformation.

3.4 Optimization

The generated image is initialized as a copy of the content image. An iterative gradient-based optimization algorithm is applied to minimize the total loss function. At each iteration, the generated image is propagated through the CNN, loss values are computed, and gradients are backpropagated to update pixel values[44-47]. This iterative process continues until convergence or until a predefined number of iterations is reached.

4. Experimental Setup

4.1 Dataset

Two images were used in the experiment:

- A landscape photograph serving as the content image.
- An artistic painting serving as the style image, characterized by expressive brushstrokes and vivid textures.

Both images were resized to a fixed resolution and normalized according to the CNN's preprocessing requirements[48-50].

4.2 Network Architecture

A pretrained convolutional neural network trained on a large-scale image dataset was employed as a feature extractor[51-54]. Several convolutional layers were selected to represent content and style features. Lower layers capture texture and color patterns, while higher layers capture spatial structure and object layout[55-58].

4.3 Training Parameters

The optimization process was run for a fixed number of iterations. Hyperparameters were chosen to balance content preservation and stylistic transformation[59-62]. The relative weighting of style loss was set significantly higher than content loss to emphasize artistic characteristics

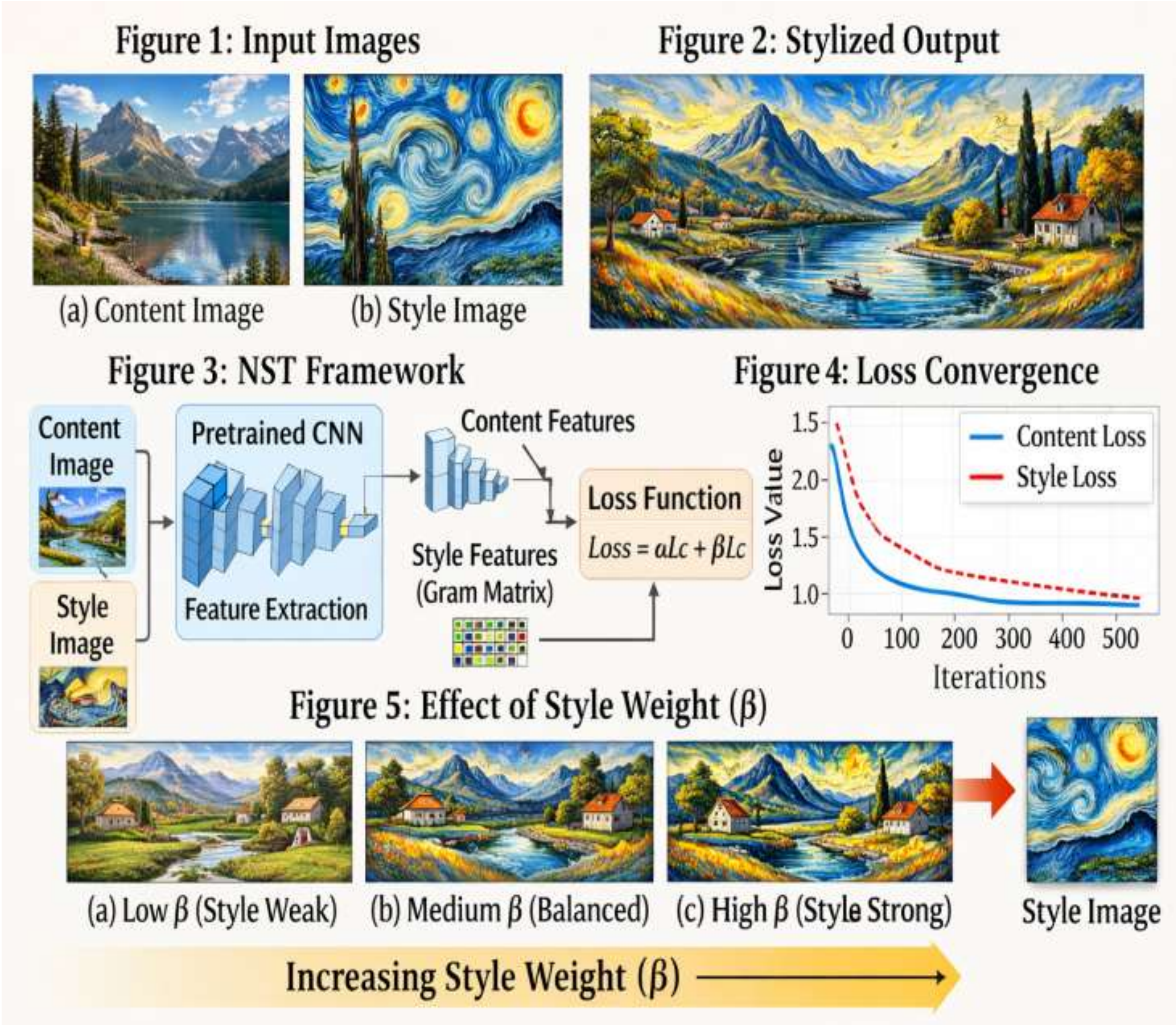
Figure 1: Input Images
(a) Content Image
(b) Style Image
Figure 2: Stylized Output
Figure 3: NST Framework
Content Image
Style Image
Pretrained CNN
Feature Extraction
Content Features
Style Features (Gram Matrix)
Loss Function
Loss = αLc + βLc
Figure 4: Loss Convergence
Loss Value
Iterations
0
100
200
300
400
500
1.5
2.0
1.5
1.0
Content Loss
Style Loss
Figure 5: Effect of Style Weight (β)
(a) Low β (Style Weak)
(b) Medium β (Balanced)
(c) High β (Style Strong)
Style Image
Increasing Style Weight (β)

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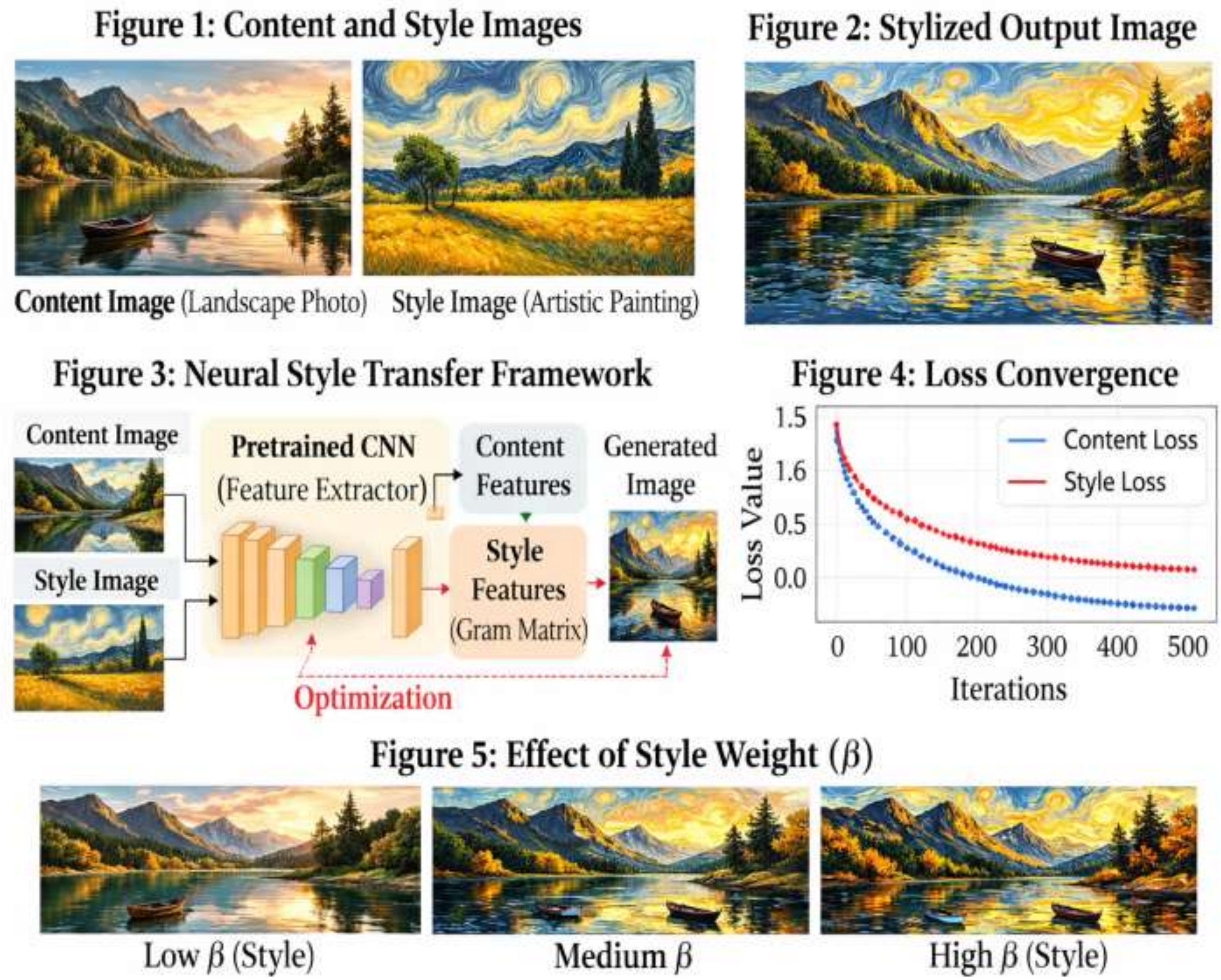

Figure 1. Input Images (Content and Style)
Example of input images used in the neural style transfer experiment. The left image represents the content image (landscape photograph), while the right image represents the style image (artistic painting).

Figure 2. Stylized Output Image
Resulting stylized image generated by the neural style transfer algorithm. The output preserves the spatial structure of the original landscape while adopting artistic characteristics from the reference painting.

Figure 3. Neural Style Transfer Framework
Overview of the neural style transfer framework. A pretrained convolutional neural network is used as a feature extractor. Content features are obtained from higher convolutional layers, while style features are computed using Gram matrices from multiple layers.

Figure 4. Loss Convergence During Optimization
Evolution of content loss and style loss over optimization iterations. Both losses decrease as the generated image is iteratively updated, indicating convergence toward a visually coherent stylized result.

Figure 5. Effect of Style Weight Parameter
Visual comparison of stylized outputs obtained using different style weight values. Increasing the style weight enhances texture intensity and artistic abstraction while reducing the preservation of fine structural details from the content image.

5. Results

The neural style transfer algorithm successfully generated a stylized image that integrates the semantic structure of the landscape photograph with artistic features derived from the style image[63-65]. As illustrated in Figure 2, major spatial elements such as the horizon line and object contours are preserved, while surface textures and color patterns exhibit painterly characteristics.

Figure 4 shows the evolution of content and style losses over the course of optimization. Both loss components decrease steadily with increasing iterations, indicating convergence of the optimization process. The gradual reduction of style loss demonstrates the effective transfer of artistic texture patterns to the generated image.

The influence of the style-weight parameter is illustrated in Figure 5. When a low style weight is used, the output image closely resembles the content image with minimal artistic transformation. Increasing the style weight strengthens the stylization effect, leading to more pronounced brushstroke patterns and color abstraction. These observations confirm that the balance between content and style losses plays a critical role in determining the visual appearance of the generated image.

Overall, the results demonstrate that pretrained convolutional neural networks can effectively separate and recombine content and style representations, producing visually coherent stylized images without additional network training.

6. Discussion

The experimental results demonstrate that neural style transfer can successfully integrate semantic content from a natural image with artistic style characteristics extracted from a reference painting. The stylized output preserves essential spatial structures such as object boundaries and horizon lines while exhibiting painterly textures and color abstractions, confirming the effectiveness of the proposed framework.

The convergence behavior observed in the loss curves (Figure 4) indicates that the optimization process is stable and capable of jointly minimizing content and style objectives. The steady reduction in both loss components suggests that the pretrained convolutional neural network provides a meaningful feature space in which content and style representations can be disentangled and recombined. This behavior supports the hypothesis that hierarchical CNN features implicitly encode semantic and stylistics elements at different levels of abstraction.

The analysis of different style-weight values (Figure 5) further highlights the importance of parameter selection in neural style transfer. When a low style weight is applied, the generated image closely resembles the original content image, with only minor stylistic modifications. In contrast, higher style weights produce stronger artistic transformations, resulting in more pronounced texture patterns and reduced structural fidelity. This trade-off demonstrates that the balance between content and style losses plays a critical role in controlling the visual appearance of the stylized output.

Despite the visually compelling results, the optimization-based approach exhibits certain limitations. The iterative nature of the algorithm makes it computationally expensive, particularly for high-resolution images. In addition, the visual quality of the generated image is sensitive to the choice of network layers and loss-weighting coefficients. These factors require empirical tuning, which may limit scalability and automation.

Nevertheless, the experimental findings provide valuable insight into the representational power of deep convolutional neural networks. The ability to transfer artistic style without explicit training for this task suggests that content–style separation emerges naturally from the hierarchical structure of CNN feature representations. This property makes neural style transfer a compelling example of creative artificial intelligence and highlights its potential for applications in digital art, design, and visual media production.

Future research may focus on reducing computational complexity through feedforward stylization networks, improving control over stylistic attributes using adaptive normalization methods, and extending the approach to video stylization and multimodal artistic generation.

7. Conclusion

This paper presented an experimental study of neural style transfer using a pretrained convolutional neural network. The proposed approach combines the content of a natural image with the artistic style of a painting by optimizing a composite loss function. The resulting stylized image preserves essential structural features while incorporating expressive artistic textures.

The findings illustrate the capability of deep neural networks to disentangle and recombine semantic and stylistic information. Neural style transfer thus represents a powerful example of generative modeling and creative artificial intelligence, with applications in digital art, design, and multimedia content generation.

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