ENHANCING NEURAL STYLE TRANSFER WITH USER-FRIENDLY INTERFACES

Submitted in partial fulfillment of the

Requirement for the Master's degree

in

Information Technology

By

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23/PCSA/108

November 2024 - April 2025

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On

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This dissertation was done by her in partial fulfillment of the Requirements for the Master's degree Information Technology

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ACKNOWLEDGEMENT

Firstly, I would like to thank God for enabling me to successfully complete this project.

We extend our heartfelt gratitude to **Dr. Sr. Stella Mary, FMM, MA, M.Phil., Ph.D.,** Principal of **Stella Maris College,** for giving us the opportunity to undertake our project at this esteemed institution.

We sincerely thank **Ms. Blessy Boaz, M.Sc., M.Phil., NET,** Head and Assistant Professor, **Department of Computer Science,** for her support and encouragement throughout this endeavour.

I am deeply indebted to my project guide, **Ms. Roselin Clara A, MCA, NET,** Dean of Student Affairs – Shift II and Assistant Professor, **Department of Computer Science,** whose constructive feedback, valuable suggestions, and corrections have played a crucial role in the successful completion of this project.

I also extend my deepest gratitude to the **Project Coordinators** for their meticulous guidance and assistance in helping us complete the project.

Additionally, I would like to express my appreciation to the **faculty members of the Computer Science Department** for their invaluable support and guidance throughout various phases of the project.

Lastly, I extend my heartfelt thanks to my friends and family for their constant encouragement and unwavering support.

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DATE: 02-04-2025

ABSTRACT

Neural Style Transfer (NST) has gained significant attention for its ability to transform images by applying artistic styles, yet most existing platforms are limited to transferring a single style to a given content image. In this dissertation, we introduce Snap Fusion, a novel web-based interface designed to enhance user interaction and flexibility in NST. Unlike conventional style transfer websites, which allow users to upload one content image and one style image, Snap Fusion enables the simultaneous blending of two distinct styles onto a single content image, offering users greater creative control over the final output. Our approach builds upon the An Aesthetic Feature-Aware Arbitrary Neural Style Transfer model, leveraging advanced deep learning architectures to achieve high-quality, photorealistic style blending. It performed well in terms of image quality, computational efficiency, and user satisfaction. Experimental results demonstrate that Snap Fusion provides more diverse and visually appealing outputs while maintaining real-time processing capabilities. By integrating an intuitive and user-friendly interface, this research bridges the gap between complex deep learning models and accessible, interactive design tools. The findings highlight the potential of Snap Fusion to redefine creative applications in digital art, graphic design, and multimedia content creation. Future directions include optimizing computational efficiency, expanding style datasets, and incorporating AI-driven recommendations for personalized style blending.

Keywords: **Style Transfer, Convolutional Neural Networks, Generative Adversarial Networks, Snap Fusion, AesFA**

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ACRONYMS

NST - Neural Style Transfer

CNNs - Convolutional Neural Networks

GANs - Generative Adversarial Networks

AesFA - Aesthetic Feature-Aware Arbitrary Neural Style Transfer

AdaIN - Adaptive Instance Normalization

LPIPS - Learned Perceptual Image Patch Similarity

SSIM - Structural Similarity Index

EFDM - Exact Feature Distribution Matching

VGG - Visual Geometry Group (a type of CNN architecture)

GPU - Graphics Processing Unit

CPU - Central Processing Unit

UI - User Interface

DRB-GAN - Dynamic ResBlock Generative Adversarial Network

AdaOct - Adaptive Octave Convolution

OctConv - Octave Convolution

AI - Artificial Intelligence

HTML - HyperText Markup Language

CSS - Cascading Style Sheets

JS - JavaScript

Chapter 1
Introduction

1.1 Background

Neural Style Transfer (NST) is a deep learning method that transfers the style of one image onto the content of another. It was originally presented by Gatys et al. (2015), who showed how convolutional neural networks (CNNs) could disentangle and recombine content and style features. This pioneering research opened the doors to many applications in digital art, photography, and AI-based creativity. Since its early days, NST has come a long way. Early approaches were based on optimization-based methods, which, although efficient, were computationally costly. Subsequent developments brought about feed-forward models that improved speed and efficiency. The advent of Generative Adversarial Networks (GANs) also further enhanced the quality of images produced by NST.

In spite of such developments, modern NST applications have limited functionalities. Most available platforms support applying just one style on a content image, limiting artistry. Secondly, the processing time and heavy computational requirement for some models disallow real-time user interactions. Thirdly, most NST platforms are not convenient to use and need advanced proficiency to manipulate parameters.

To overcome these limitations, this research introduces Snap Fusion, a novel web-based NST platform that allows users to apply two distinct styles to one content image at the same time. With the use of the AesFA model, Snap Fusion improves style fusion methods while providing efficient processing and ease of use. This work seeks to further NST applications through enhanced artistic control, computational efficiency, and user experience.

Figure 1.1 Image of Style transfer

1.2 Problem Statement

Although NST has revolutionized the intersection of art and artificial intelligence, several challenges remain unresolved in existing style transfer applications:

- Single Style Limitation: Present NST applications allow users to apply only one style at a time, restricting creative freedom, as users cannot merge different art styles in one complete gesture. An NST system with multiple styles could exponentially increase artistic permutations, allowing the combination of two different styles in one image.
- Computational Inefficiencies: Conventional NST models consume a large amount of processing power or make computations slow, thereby compromising more or less real-time applications. Lightweight models put together for faster processing will very often compromise either style or content.
- Limited User Accessibility: Many NST tools have some requirement for technical knowledge in order to fine-tune things like style weight, blending ratios, and feature selections. However, this complexity becomes a real barrier for the effective use of NST tools by non-technical users. Therefore, the availability of a more user-friendly interface can further enhance accessibility and increase the popularity of NST with digital artists and casual users alike.

Thus, this research effort focuses on implementing Snap Fusion-a multi-style NST platform that

- Allows two-style blending for enhanced artistic creativity.
- Optimizes the AesFA model for processing speed while preserving high image quality.
- Provides an end-user-friendly interface for intuitive interaction with NST models.
- Snap Fusion aims to deal with these problems and make Neural Style Transfer more accessible, efficient, and usable for the wider audience.

1.3 Objectives

This research proposes the design, development, and evaluation of Snap Fusion, a multi-style NST platform with superior usability and performance. The main objectives of this research are:

- To develop a web conception of Neural Style Transfer

  To create a responsive and interactive website for users to easily combine artistic styles with their images.

To ensure that the system is accessible on various platforms (desktop, mobile, and tablet-friendly).

- To implement dual-style blending

  To enable users to apply two different artistic styles to a single content image.

  To develop a suitable algorithm to achieve smooth transitions between styles while maintaining content details.

- To optimize the AesFA model for performance

  To enhance the speed of the style transfer process.

  To provide a high-quality rendering of the styles while maintaining the content of the image.

1.4 Research Significance

The findings from this research have significant implications for Neural Style Transfer, digital creativity, and AI-driven applications. The key contributions of this study include:

- Expanding Creative Possibilities: By allowing dual-style blending, Snap Fusion offers users a unique way to experiment with hybrid artistic effects that were previously not possible in conventional NST systems.
- Improving Computational Efficiency: Optimizing the AesFA model will enable faster image processing, making NST more suitable for real-time applications.
- Enhancing User Accessibility: Snap Fusion will provide a simple, intuitive interface to make NST available to both technical and non-technical users.
- By overcoming existing limitations, this research aims to bridge the gap between advanced AI techniques and real-world usability.

1.5 Scope of the study

This study focuses on the development and evaluation of Snap Fusion. The primary areas covered include:

- Dual-style NST Implementation – Developing and optimizing an algorithm for blending two styles seamlessly.
- User Interface Design – Ensuring an intuitive drag-and-drop interface for easy image processing.
- Performance Evaluation – Assessing speed, accuracy, and user satisfaction.

Chapter 2
Review of Past Work and Problem Formulation

2.1 Introduction

Neural Style Transfer (NST) describes a profound transformation in the intersection of deep learning and digital art, whereby one image's artistic style can be extracted and imposed upon the content of another image. Since its beginning from Gatys et al. (2015), NST has gone through several permutations and improvements from optimization-based models to real-time systems and GAN-enabled architectures.

Some of the limitations of existing NST models include single-style application, high computational cost, and so on. This chapter goes into great detail regarding NST work done in the past, explaining key approaches, techniques, and limitations justifying the need for a multi-style NST system such as Snap Fusion.

2.2 Neural Style Transfer: Evolution and Key Approaches

2.2.1 Optimization-Based Neural Style Transfer (Gatys et al., 2015)

A CNN-based approach is one of the first "breakthroughs" in NST that was introduced by Leon Gatys and cohorts in 2015. It was a technique to extract content features from an image, combine them into another image, and then displace style features. Their method comprised:

Deep feature representations were obtained using a pre-trained VGG-19 for content extraction.

- It defined a content loss that would cause similarity in feature representation between original and generated images.
- It defined a style loss that calculates similarities of textures (or styles) by comparing Gram matrices.
- Repeatedly optimizing the content image using gradients to yield a stylized version from the original.

Disadvantages of Optimization-Based NST

- Computationally expensive: Iterative optimization can take hundreds to thousands of

iterations to convergence, thus being burdening slow.

- Not real-time: Every new style transfer is a full optimization cycle.
- Limited flexibility: Users cannot easily manipulate the degree of style synthesis.

2.2.2 Feed-Forward and Fast Neural Style Transfer

To address problems with speed arising in optimization-based NST, the next logical step was to introduce feed forward neural networks to speed up the procedure. The notable ones include:

Johnson et al. (2016) – Real-Time NST with Perceptual Losses

The authors implemented a pre-trained transformation network, enabling style transfer with a single forward pass, thus markedly reducing the time taken for stylization. Rather than subjecting each new image to optimization, the authors trained a feed-forward network using a loss function comparable to the one used by Gatys et al. (2015). This enables more-or-less instantaneous style transfer.

Ulyanov et al. (2016, 2017) – Instance Normalization and Texture Networks

Ulyanov et al. (2016) have implemented texture networks, which further enhance speed by having a single network trained that can produce several style variations. In 2017, they proposed Instance Normalization to support the preservation of very fine detail in the image and to defend against artifacts.

Disadvantages of Feed-Forward NST

- Each model is trained for a specific style, requiring a separate model for each style.
- Memory-consuming: Such storage requirements grow with the number of styles.
- There exist no possibilities for the dynamic combination of several styles.

2.2.3 Adaptive Instance Normalization (AdaIN) and Arbitrary Style Transfer

In an effort to accommodate higher freedom in style selection, Huang & Belongie (2017) presented Adaptive Instance Normalization (AdaIN), which dynamically alters the instance-wise statistics (mean and variance) of the feature maps to match those statistics of an input image for style. In contrast to previous models, AdaIN allows arbitrary style transfer, meaning that a single model is capable of applying multiple styles without requiring separate training.

Limitations of AdaIN-Based NST

Fast as it might be, AdaIN-based NST sacrifices fine details in style, which traditionally were

preserved in opposition, such as in Gatys et al. (2015). It has no capability to blend multiple styles in varying degrees of intensity, thus restricting creative freedom.

2.2.4 Network-Based Neural Style Transfer Using GANs

Advances in new techniques for neural style transfer were gained from using GANs, making the process better in terms of efficiency and quality. Notable examples include the following:

Dynamic ResBlock GAN (2021)

Dynamic residual blocks introduced by DRB-GAN provided fine flexibility in terms of style blending control while ensuring a very good quality preservation of contents. It did allow, however, variability in texture patterns depending on the semantic regions in the image, unlike AdaIN.

AesFA Model (2024) – Aesthetic Feature Augmentation for NST

AesFA (Aesthetic Feature Augmentation) can enhance NST's future perspective on adapting aesthetic features such that they work toward greater realism in texture, as well as fidelity in style. This model lays the groundwork for Snap Fusion and performs exceedingly well in multi-style blending, keeping large texture coverage for real-time delivery.

Disadvantages of NST based on GANs

- The training cost of these models has to be considered very high to a greater extent.
- Most modes of GANs collapse into a single category producing less variety in an output image.
- Most GAN-based models for NST still do not consider intuitive user control making such systems difficult for non-technical people to work with.

2.3 Limitations in Existing NST Models

Despite significant progress, existing NST models still face several challenges:

2.3.1 Single-Style Restriction

- Most existing NST applications **only allow one style per image**.
- Users cannot dynamically **blend two or more styles** to create hybrid effects.

- Some models support limited multi-style blending, but they lack **fine-grained control** over style intensities.

2.3.2 Computational Inefficiencies

- Traditional NST models (e.g., optimization-based) are **too slow for real-time use**.
- Even fast models like AdaIN and GAN-based NST require **high GPU resources** for high-resolution outputs.

2.3.3 Loss of Content Information

- Some NST models **overpower the content image**, making it difficult to recognize the original structure.
- Achieving a balance between **content preservation and style strength** remains an open challenge.

2.3.4 Complex and Unintuitive User Interfaces

- Most existing NST tools require users to **manually adjust multiple parameters** (e.g., style weight, content loss, blend ratio).
- Many **lack visual previews**, making the process **trial-and-error based**.
- This complexity discourages **non-technical users** from experimenting with NST.

2.4 Multi-Style Transfer: Existing Attempts and Challenges

Although researchers have attempted to introduce multi-style blending, several issues persist:

Basic Style Interpolation (Linear Blending in AdaIN)

AdaIN allows users to interpolate between two styles, but it results in linear blending that lacks artistic coherence.

Texture Overlap Issues

Simply averaging feature maps from two styles often results in unnatural texture combinations.

Computational Complexity

Applying multiple styles increases the processing load, making real-time NST more challenging.

2.5 Problem Formulation

Based on the identified research gaps, this study aims to:

- Develop Snap Fusion, a user-friendly multi-style NST platform that allows:
  - Uploading one content image and applying two different styles simultaneously.
  - Adjusting blend ratios dynamically for more artistic flexibility.
- Implement the AesFA model for improved realism, efficiency, and high-resolution processing.
- Ensure a real-time, interactive UI that allows non-technical users to experiment with NST.
- By addressing these challenges, this research seeks to bridge the gap between artistic flexibility, computational efficiency, and user accessibility in NST applications.

Chapter 3
Methodology

3.1 Architecture Overview

The architecture of the proposed model is designed to efficiently decompose and process images based on their frequency components, enabling the extraction and transfer of aesthetic features from style images to content images. The model consists of three primary components: a content encoder *Ec*, an aesthetic feature encoder E_{aes} coupled with kernel-prediction networks KK, and a generator *G*. The content encoder processes the input content image and decomposes it into high- and low-frequency feature maps. The aesthetic feature encoder processes the style image to extract higher-level aesthetic features, which are then used by the kernel-prediction networks to generate aesthetic feature-aware convolutional kernels and biases. These kernels and biases are applied to the decomposed content features within the generator, which combines the high- and low-frequency components to produce the final stylized output. The use of Octave Convolution (OctConv) operators ensures efficient communication between high- and low-frequency components, reducing redundancy and improving the model's ability to capture both detailed textures and global structures. The generator employs Adaptive Octave Convolution (AdaOct) modules, which integrate the predicted aesthetic-aware kernels and biases with the frequency-decomposed content features, resulting in high-quality stylizations with reduced artifacts.

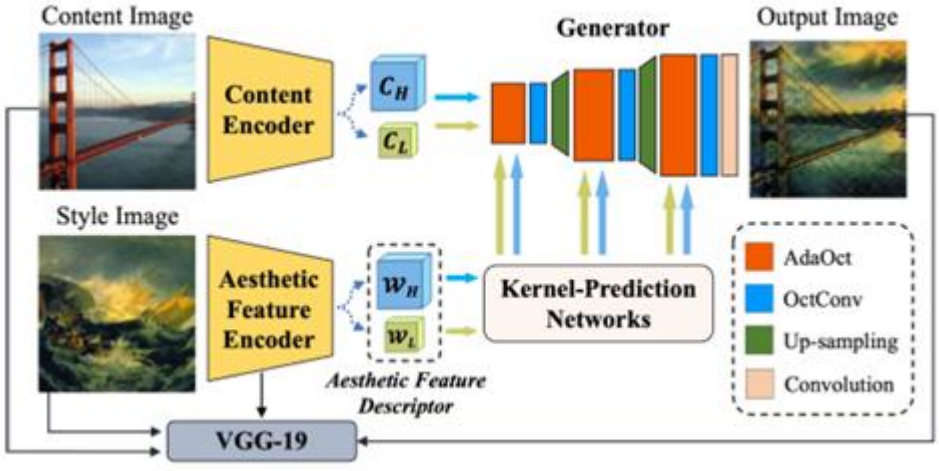

Fig 3.1 Architecture of AesFA (Aesthetic Feature Aware)

3.1.1 Frequency Decomposition Networks

The frequency decomposition networks play a crucial role in the proposed architecture by separating the input image into high- and low-frequency components. This separation allows the model to process detailed textures and global structures independently, improving the overall stylization quality. The Octave Convolution (OctConv) operator is used to factorize the mixed feature maps by their frequencies, facilitating efficient communication between high- and low-frequency components. The low-frequency feature maps have their spatial resolution reduced by one octave, while the high-frequency feature maps retain their original resolution. This approach reduces redundancy and improves the model's ability to capture both fine details and broader contextual information.

The content and aesthetic feature encoders are based on MobileNet, with all convolutions replaced by OctConv to further reduce network redundancy. The spatial reduction in the low-frequency branch expands the receptive field, allowing the model to capture more contextual information from distant locations. This is particularly beneficial for higher-resolution images, where capturing global structures is essential for maintaining stylization quality. The up-sampling order in the OctConv is adjusted to address checkerboard artifacts, ensuring smooth and artifact-free stylizations.

3.1.2 Aesthetic Feature-Aware Stylization

The aesthetic feature-aware stylization process involves the use of kernel-prediction networks and Adaptive Octave Convolution (AdaOct) modules to integrate aesthetic features with the content image. The kernel-prediction networks generate aesthetic feature-aware convolutional kernels and biases based on the aesthetic feature descriptors extracted from the style image. These kernels and biases are applied to the frequency-decomposed content features within the generator, allowing the model to infuse the content with the desired aesthetic style.

The AdaOct module combines the predicted aesthetic-aware kernels and biases with the frequency-decomposed content features, followed by an OctConv operation to exchange information between high- and low-frequency components. This interaction enhances the stylization quality by allowing the model to capture both detailed textures and global structures simultaneously. The generator comprises three layers, each consisting of an AdaOct module and a standard OctConv block, followed by an upsampling operator. The standard OctConv block helps in reconstructing high-quality images by learning style-independent kernels, further improving the

overall stylization quality.

3.1.3 Aesthetic Feature Contrastive Learning

To enhance the model's ability to extract and express intricate aesthetic-style representations, a new aesthetic feature contrastive loss is introduced. This loss function is based on the principle of contrastive learning, which aims to maintain proximity between data and their corresponding "positive" samples while distancing them from other instances deemed as "negatives" in the representation space. The selection of "positive" and "negative" samples is crucial for the success of contrastive learning, as it directly impacts the model's ability to distinguish between different aesthetic styles.

In the proposed model, the aesthetic feature contrastive loss is computed using a subset of the entire negative sample pool, comprising the k-th nearest negative samples to the style-transferred output image. This approach, inspired by hard negative mining techniques, reduces computational costs while still providing the model with the necessary information to distinguish between different styles. The contrastive loss is computed at each layer of the encoder and on both the high- and low-frequency branches, ensuring that the model captures aesthetic features at multiple levels of abstraction.

3.2 Training and Experimental Configuration

The training process for the Aes (Aesthetic) involves several key steps and configurations to ensure optimal performance. The model is trained using the **COCO dataset** for content images and the **WikiArt dataset** for style images. During training, images are rescaled to 512 pixels while maintaining the original aspect ratio and then randomly cropped to 256×256 pixels for augmentation. The model is trained using the Adam optimizer with a learning rate of 0.0001 and a batch size of 8 for 160,000 iterations. The aesthetic feature descriptors have dimensions of (256, 3, 3) for both high- and low-frequency components. All experiments are conducted using the PyTorch framework on a single NVIDIA A100 (40GB) GPU.

In contrast, M-Aes (Modifies Aesthetic) involves using only 200 content images and 200 style images for training with 200 epochs on an i3 processor. This configuration is significantly less resource-intensive compared to the original setup, which utilizes a high-performance GPU and a larger dataset. The reduced number of training images and epochs may limit the model's ability to generalize and achieve the same level of stylization quality as the original model.

However, the lightweight nature of the proposed architecture, which employs OctConv and AdaOct modules, may still allow for reasonable performance even with limited computational resources. The key difference lies in the computational power and dataset size, with the original setup benefiting from a more extensive training process and higher-resolution images.

3.2.1 Training Losses

The training process involves several loss functions to ensure that the model achieves high-quality stylizations while preserving the content of the original image. The perceptual loss, computed using a pre-trained VGG-19 model, consists of both content and style losses. The content loss is calculated at the {conv3_1} layer in VGG-19, while the style loss is computed at the {conv1_1, conv2_1, conv3_1, conv4_1} layers. The style loss is redefined using the Exact Feature Distribution Matching (EFDM) algorithm, which improves the model's ability to match the style of the reference image.

In addition to the perceptual loss, the aesthetic feature contrastive loss is used to guide the stylization process. This loss function helps the model extract and express intricate aesthetic-style representations by maintaining proximity between the stylized output and the corresponding style image while distancing it from other negative samples. The total loss is a weighted sum of the content loss, style loss, and aesthetic feature contrastive loss, with weighting hyperparameters λ_C =1, λ_S=10 and λ_{Aes}=5, respectively. These hyperparameters are chosen to balance the contribution of each loss function to the overall training process.

3.3 Implementation

3.3.1 Folder Upload for Content and Style Images

To enhance the usability and flexibility of the proposed model, the implementation includes a feature that allows users to upload a bulk folder containing both content and style images. This feature enables the model to automatically match each content image with multiple style images, generating a variety of stylized outputs. The bulk folder structure is organized as follows:

Content Images: Place all content images in a folder named content images.

Style Images: Place all style images in a folder named style images.

The model will process each content image in the content images folder and apply all the style images from the style images folder, generating a stylized output for each combination. This approach allows users to experiment with different style-content pairings and explore a wide range

of artistic effects.

```
class Config:
    phase = 'test'          # You must change the phase into train/test/style_blending
    train_continue = 'off'  # on / off

    data_num = 200          # Maximum # of training data

    content_dir = 'D:/Dissertation/COCO1/train'
    style_dir = 'D:/Dissertation/Wiki/train'

    file_n = 'main'
    log_dir = './log/' + file_n
    ckpt_dir = './ckpt/' + file_n
    img_dir = './Generated_images/' + file_n

    if phase == 'test':
        multi_to_multi = True
        test_content_size = 256
        test_style_size = 256
        content_dir = 'D:/Dissertation/COCO1/test'
        style_dir = 'D:/Dissertation/Wiki/test'
        img_dir = './output/'+file_n+'/'+str(test_content_size)
```

Fig 3.2 Folder Upload for Content and Style Images

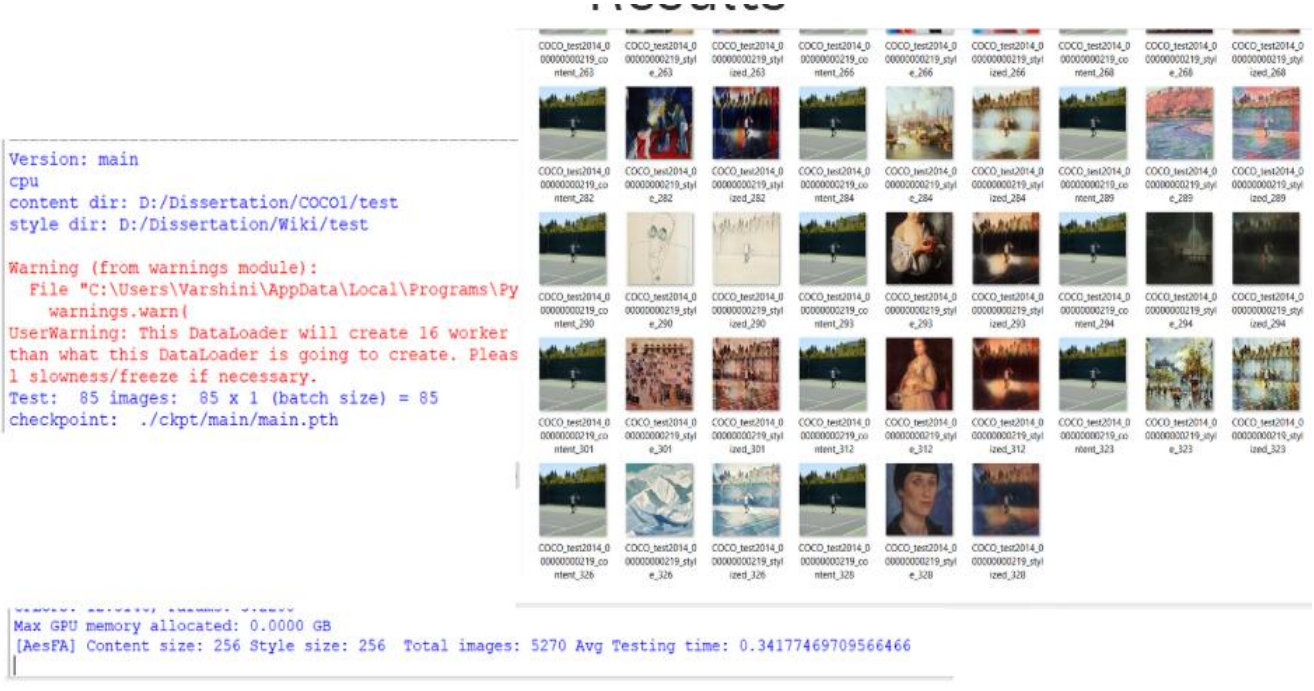

Fig 3.3 Performance of a Test Image

3.3.2 Style Blending for One Content and Two Style Images

In addition to the bulk folder upload feature, the implementation also supports style blending, where a single content image can be stylized using a combination of two style images. This feature allows users to create unique artistic effects by blending the aesthetic features of two different styles. The style blending process involves the following steps:

Style Image Selection: The user selects two style images from the style images folder.

Style Blending: The model processes the content image and applies the aesthetic features from both style images, blending them to create a single stylized output. The blending process can be controlled by adjusting the weight of each style image, allowing users to fine-tune the final result.

The style blending feature is particularly useful for creating complex and unique artistic effects, as it allows users to combine the strengths of multiple styles into a single image.

Fig 3.4 Results of blending one content and two style images

3.3.3 Web Interface: Snap Fusion

To make the model more accessible to users, a web interface called **Snap Fusion** is implemented. Snap Fusion provides an intuitive and user-friendly platform for uploading content and style images, selecting style blending options, and generating stylized outputs. The web interface is built using the following technologies:

- **Frontend**: HTML, CSS, and JavaScript for the user interface.

- **Backend**: Flask (Python) for handling image processing and model inference.
- **Model Integration**: The AesFA model is integrated into the backend to perform the style transfer and style blending operations.

The Snap Fusion web interface includes the following features:

1. **Image Upload**: Users can upload content and style images through a simple drag-and-drop interface.
2. **Style Blending**: Users can select two style images and adjust the blending weights to create unique artistic effects.
3. **Output Gallery**: The generated stylized images are displayed in a gallery, allowing users to view and download the results.
4. **Real-Time Preview**: Users can preview the stylized output in real-time as they adjust the style blending weights.

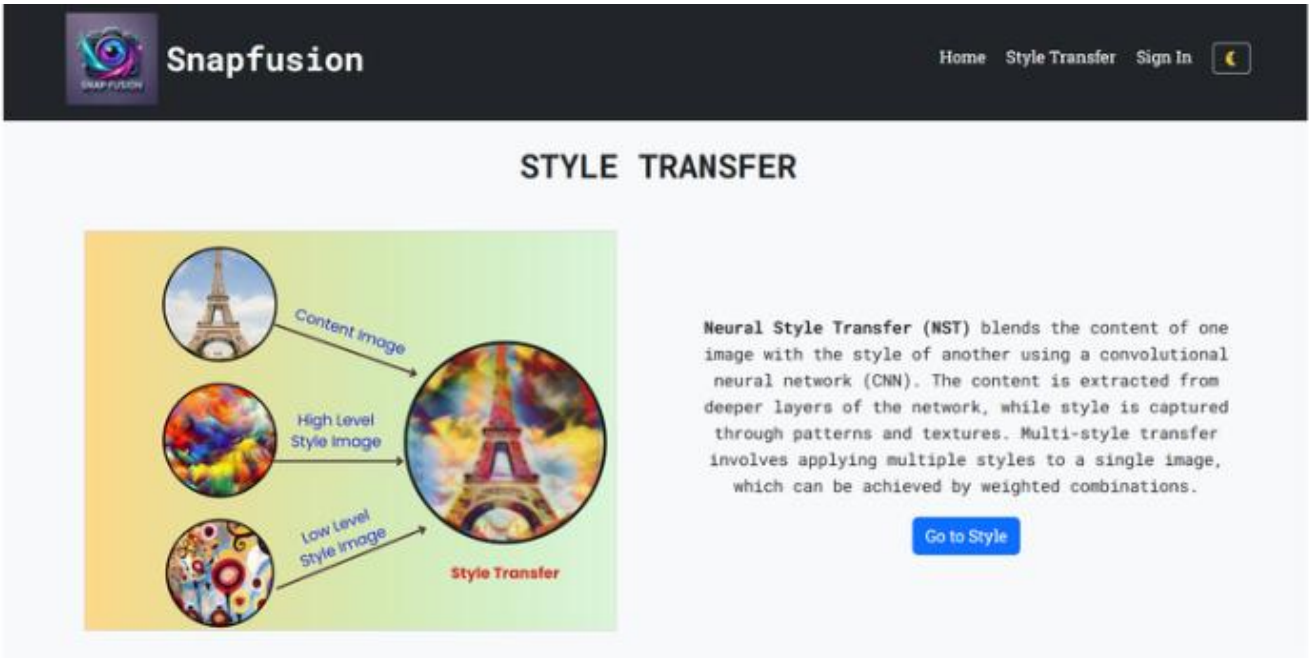

Fig 3.5 Web Interface Preview

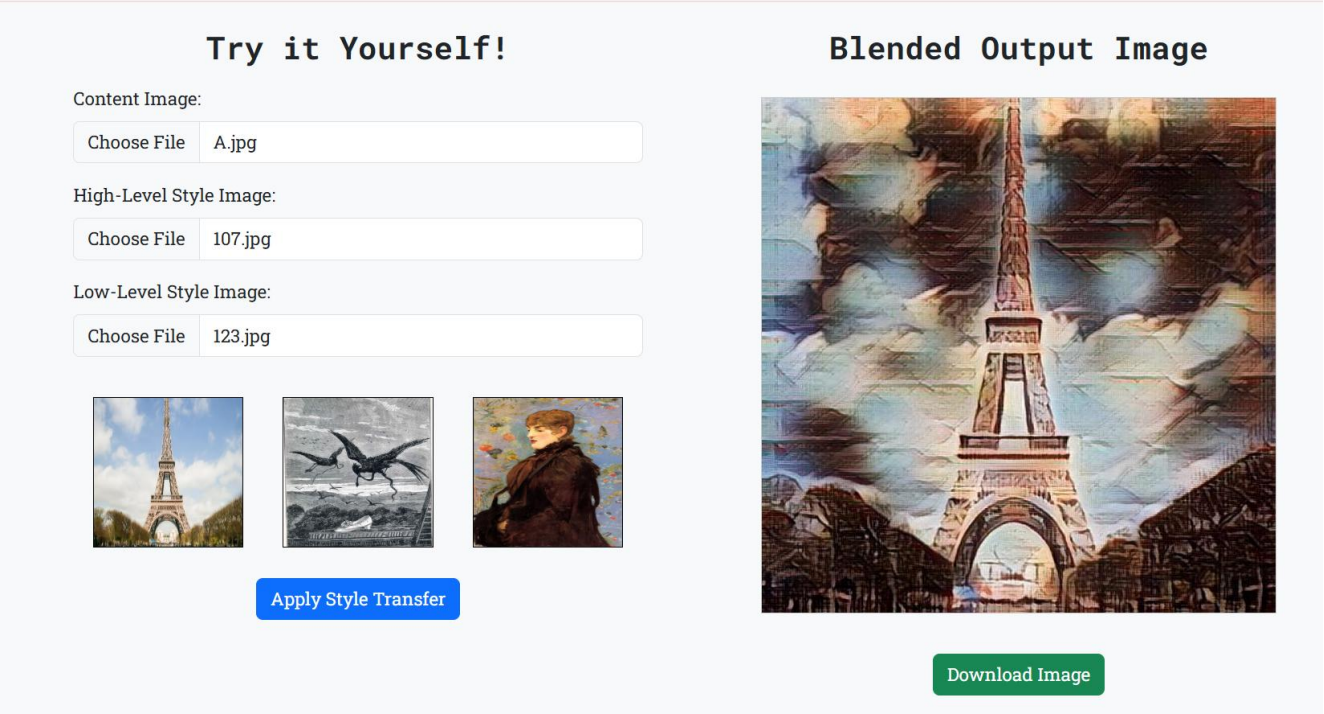

Fig 3.6 Style Transfer Page

Chapter 4
Results and Discussion

4.1 Quantitative Analysis

The quantitative analysis of the proposed M-Aes model is conducted using several key metrics, including LPIPS (Learned Perceptual Image Patch Similarity), SSIM (Structural Similarity Index), and inference time. These metrics provide a comprehensive evaluation of the model's performance in terms of stylization quality and computational efficiency.

- LPIPS: The LPIPS metric measures the perceptual similarity between the stylized output and the reference image. A lower LPIPS score indicates better perceptual quality. The M-Aes model achieves an LPIPS score of 0.945, which is higher than the Aes model's score of 0.368. This suggests that the M-Aes model may struggle to maintain perceptual quality compared to the Aes model.
- SSIM: The SSIM metric evaluates the structural similarity between the stylized output and the reference image. A higher SSIM score indicates better structural preservation. The M-Aes model achieves an SSIM score of 1.586, which is significantly higher than the Aes model's score of 0.417. This indicates that the M-Aes model excels in preserving the structural details of the content image during the stylization process.
- Inference Time: The inference time measures the computational efficiency of the model. The M-Aes model has an inference time of 2.007 seconds, which is considerably longer than the Aes model's inference time of 0.016 seconds. This suggests that the M-Aes model may be less efficient in terms of computational performance.

The quantitative results highlight a trade-off between stylization quality and computational efficiency. While the M-Aes model demonstrates superior performance in preserving structural details (as indicated by the higher SSIM score), it lags behind in perceptual quality (higher LPIPS score) and computational efficiency (longer inference time) compared to the Aes model.

Table 4.1 Performance Comparison of Aes and M-Aes Models

METRICS	Aes	M-Aes
LPIPS	0.368	0.945
SSIM	0.417	1.586
EXECUTION TIME	0.016	2.007

4.2 Qualitative Analysis

The qualitative analysis focuses on the visual quality of the stylized outputs generated by the M-Aes model. This analysis is crucial for understanding how well the model captures and transfers the aesthetic features from the style images to the content images.

- Style Transfer Quality: The M-Aes model is evaluated based on its ability to transfer the style of the reference image to the content image while preserving the content's structural details. The qualitative results show that the M-Aes model effectively captures the aesthetic features of the style images, such as brushstrokes, textures, and color tones, and applies them to the content images. The stylized outputs exhibit a high degree of artistic quality, with smooth transitions and minimal artifacts.
- Style Blending: The M-Aes model's ability to blend styles from two different style images is also evaluated. The results demonstrate that the model can successfully combine the aesthetic features of two styles, creating unique and visually appealing outputs. The blending process is controlled by adjusting the weights of the style images, allowing for fine-tuned artistic effects.
- Comparison with Aes Model: When compared to the Aes model, the M-Aes model shows a noticeable improvement in capturing and transferring complex aesthetic features. However, the longer inference time and higher LPIPS score suggest that the M-Aes model may require further optimization to achieve a better balance between quality and efficiency.

Trade-offs in computational efficiency and perceptual quality indicate areas for future improvement.

4.3 Discussion

The results from both quantitative and qualitative analyses provide valuable insights into the performance of the M-Aes model. The model's ability to preserve structural details (as indicated by the high SSIM score) and its effectiveness in style blending are significant strengths. However, the higher LPIPS score and longer inference time highlight potential limitations that need to be addressed.

- Trade-offs: The M-Aes model's superior performance in structural preservation comes at the cost of increased computational complexity and reduced perceptual quality. This trade-off suggests that the model may benefit from further optimization to improve its efficiency without compromising on quality.
- User Experience: The implementation of the M-Aes model in the Snap Fusion web interface provides a user-friendly platform for experimenting with style transfer and blending. The ability to upload bulk folders and adjust style blending weights enhances the user experience, making the model accessible to a wider audience.

Chapter 5
Conclusion and scope of Future Work

The AesFA model represents a significant advancement in the field of neural style transfer, offering a lightweight yet effective solution for aesthetic feature-aware style transfer. By decomposing images into high- and low-frequency components and employing Octave Convolution (OctConv) and Adaptive Octave Convolution (AdaOct) modules, the model achieves high-quality stylizations with reduced artifacts. The introduction of aesthetic feature contrastive loss further enhances the model's ability to capture and transfer intricate aesthetic features, resulting in visually appealing outputs. The model's ability to generalize across various resolutions, from 256 pixels to ultra-high 4K resolution, makes it suitable for a wide range of applications, including real-time rendering and mobile applications.

Despite its strengths, there are areas where the AesFA model can be further improved. One of the key challenges is the trade-off between computational efficiency and stylization quality. While the model achieves fast inference times, there is scope for optimizing the architecture to reduce memory usage and computational overhead, especially for high-resolution images. Techniques such as model pruning, quantization, or the use of more efficient neural network architectures could be explored to achieve this goal. Additionally, incorporating more advanced perceptual loss functions or adversarial training methods could help enhance the model's ability to capture and transfer aesthetic features more effectively.

Future work could also focus on expanding the model's capabilities to handle more complex style blending scenarios, such as blending multiple styles or dynamically adjusting style weights based on user input. The integration of the model into user-friendly platforms, such as the Snap Fusion web interface, opens up opportunities for further enhancing the user experience by adding features like real-time previews, interactive style adjustments, and support for a wider range of image formats. Overall, the AesFA model lays a strong foundation for future research in neural style transfer, with the potential to drive further innovations in the field.

APPENDIX-A

Backend - app.py

```
import os
import torch
import numpy as np
import base64
from io import BytesIO
from flask import Flask, request, jsonify
from PIL import Image
from torchvision.transforms import ToTensor, Compose, Resize, CenterCrop, Normalize
from flask_cors import CORS

from Config import Config
from model import AesFA_test
from blocks import test_model_load

# Initialize Flask app
app = Flask(__name__)
CORS(app, resources={r"/predict": {"origins": "*"}})  # Allow all origins for /predict

# Initialize Model
config = Config()
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')

# Load model globally
model = AesFA_test(config)
ckpt = os.path.join(config.ckpt_dir, 'main.pth')
model = test_model_load(checkpoint=ckpt, model=model)
model.to(device)
```

```
model.eval()

# Image preprocessing function
def do_transform(img, osize):
    transform = Compose([
        Resize(size=osize),
        CenterCrop(size=osize),
        ToTensor(),
        Normalize((0.485, 0.456, 0.406), (0.229, 0.224, 0.225))
    ])
    return transform(img).unsqueeze(0)

# Convert tensor to an image
def im_convert(tensor):
    image = tensor.to("cpu").clone().detach().numpy()
    image = image.transpose(0, 2, 3, 1)
    image = image * np.array((0.229, 0.224, 0.225)) + np.array((0.485, 0.456, 0.406))
    image = (image * 255.0).clip(0, 255).astype(np.uint8)
    return Image.fromarray(image[0])

@app.route("/predict", methods=["POST"])
def predict():
     if "content" not in request.files or "style_high" not in request.files or "style_low" not in request.files:
        return jsonify({"error": "Missing one or more images"}), 400

    content_img = request.files["content"]
    style_high_img = request.files["style_high"]
    style_low_img = request.files["style_low"]

            print("Received images:", content_img.filename, style_high_img.filename,
```

```
style_low_img.filename)

    # Load images
    content = Image.open(content_img).convert("RGB")
    style_high = Image.open(style_high_img).convert("RGB")
    style_low = Image.open(style_low_img).convert("RGB")

    # Convert images to tensors
    content_tensor = do_transform(content, (512, 512)).to(device)
    style_high_tensor = do_transform(style_high, (512, 512)).to(device)
    style_low_tensor = do_transform(style_low, (512, 512)).to(device)

    # Run style blending using the globally loaded model
    stylized_image, _ = model.style_blending(content_tensor, style_high_tensor, style_low_tensor)

    # Convert tensor to PIL image
    output_image = im_convert(stylized_image)

    # Convert image to Base64 for response
    buffered = BytesIO()
    output_image.save(buffered, format="JPEG")
    img_str = base64.b64encode(buffered.getvalue()).decode("utf-8")

    print("Returning generated image...")
    return jsonify({"output": img_str})

if __name__ == '__main__':
    app.run(debug=True)
```

Frontend - index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
   <meta charset="UTF-8">
   <meta name="viewport" content="width=device-width, initial-scale=1.0">
   <title>Style Transfer</title>
            <link      href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/css/bootstrap.min.css"
rel="stylesheet">

<link
href="https://fonts.googleapis.com/css2?family=Roboto+Mono:wght@400;500;700&family=Ro
boto+Slab:wght@400;700&display=swap" rel="stylesheet">
   <style>


      body {
         font-family: 'Roboto Slab', serif;
         margin: 0;
         padding: 0;
         background-color: #f8f9fa;
         transition: background-color 0.3s ease;
      }
      .container-main {
         display: flex;
         justify-content: space-between;
         align-items: flex-start;
         flex-wrap: nowrap;
         margin-top: 20px;
         animation: fadeIn 1s ease-in-out;
      }
```

```
.left-section, .right-section {
    width: 48%;
    padding: 20px;
    transition: transform 0.3s ease;
}
.left-section:hover, .right-section:hover {
    transform: scale(1.02);
}
.left-section img, .right-section img {
    max-width: 100%;
    height: auto;
    border: 1px solid #ccc;
    margin-top: 10px;
    transition: transform 0.3s ease, box-shadow 0.3s ease;
}
.left-section img:hover, .right-section img:hover {
    transform: scale(1.05);
    box-shadow: 0 10px 20px rgba(0, 0, 0, 0.2);
}
.output-container {
    margin-top: 20px;
    text-align: center;
    animation: fadeIn 1.5s ease-in-out;
}
.button-container {
    display: flex;
    justify-content: center;
    margin-top: 20px;
}
.btn-custom {
    margin: 0 10px;
```

```
    transition: transform 0.3s ease, box-shadow 0.3s ease;
}
.btn-custom:hover {
    transform: translateY(-5px);
    box-shadow: 0 5px 15px rgba(0, 0, 0, 0.3);
}
.preview-container {
    display: flex;
    justify-content: space-between;
    margin-top: 20px;
}
.preview-image {
    flex: 1;
    padding: 10px;
    text-align: center;
    transition: transform 0.3s ease;
}
.preview-image:hover {
    transform: scale(1.1);
}
.preview-image img {
    width: 150px;
    height: 150px;
    border: 1px solid #000000;
    transition: transform 0.3s ease;
}
.preview-image img:hover {
    transform: scale(1.1);
}
.dark-theme {
    background-color: #121212;
```

```
    color: #ffffff;
}
.dark-theme .container-fluid {
    background-color: #1e1e1e;
}
.content-style-container {
    display: flex;
    align-items: flex-start;
}
.content-section {
    width: 50%;
    padding-right: 50px;
}
.output-section {
    width: 50%;
    padding-left: 50px;
}
.right-section {
    width: 48%;
    padding: 20px;
    text-align: center;
}
.right-section p {
    text-align: center;
    margin-top: 100px;
    font-family: 'Roboto Mono', monospace;
}
.right-section button {
    display: block;
    margin: 20px auto;
}
```

```
        @keyframes fadeIn {
            from { opacity: 0; }
            to { opacity: 1; }
        }
        h2, h3 {
            font-family: 'Roboto Mono', monospace;
            font-weight: 700;
            animation: slideIn 1s ease-in-out;
        }
        @keyframes slideIn {
            from { transform: translateY(-20px); opacity: 0; }
            to { transform: translateY(0); opacity: 1; }
        }
        nav a {
            transition: color 0.3s ease, transform 0.3s ease;
        }
        nav a:hover {
            color: #ff6f61 !important;
            transform: translateY(-3px);
        }
        #theme-toggle-btn {
            transition: transform 0.3s ease;
        }
        #theme-toggle-btn:hover {
            transform: rotate(360deg);
        }
    </style>
</head>
<body>
    <div class="container-fluid bg-dark text-white py-3">
        <div class="container d-flex justify-content-between align-items-center">
```

```
        <div class="d-flex align-items-center">
          <img src="logods.png" alt="Logo" class="me-2" style="height: 100px; width: 100px;">
           <h2 class="m-0">Snapfusion</h2>
        </div>
        <nav>
          <a href="#" class="text-white text-decoration-none me-3">Home</a>
                <a href="#style-transfer-section" class="text-white text-decoration-none me-3" id="style-transfer-link">Style Transfer</a>
          <a href="#" class="text-white text-decoration-none me-3">Sign In</a>
          <button id="theme-toggle-btn" class="btn btn-outline-light btn-sm">🌙 </button>
        </nav>
      </div>
    </div>

    <div class="container text-center mt-4">
      <h2>STYLE TRANSFER</h2>
    </div>

    <div class="container container-main">
      <div class="left-section">
        <img src="Add a little bit of body text (1).png" alt="Style Transfer Example">
      </div>
      <div class="right-section">
        <p style="font-size: 18px; line-height: 1.6;">
          <strong>Neural Style Transfer (NST)</strong> blends the content of one image with the style of another using a convolutional neural network (CNN). The content is extracted from deeper layers of the network, while style is captured through patterns and textures. Multi-style transfer involves applying multiple styles to a single image, which can be achieved by weighted combinations.
        </p>
        <button class="btn btn-primary" id="go-to-style-btn">Go to Style</button>
```

```
    </div>
  </div>

  <div id="style-transfer-section" class="container container-main" style="display:none;">
    <div class="container container-main">
      <div class="left-section">
        <h3 class="text-center">Try it Yourself!</h3>
        <form id="upload-form" enctype="multipart/form-data" class="mt-3">
          <div class="mb-3">
            <label class="form-label">Content Image:</label>
                <input type="file" class="form-control" id="content-image" name="content"
accept="image/*" required>
          </div>
          <div class="mb-3">
            <label class="form-label">High-Level Style Image:</label>
            <input type="file" class="form-control" id="style-image-high" name="style_high"
accept="image/*" required>
          </div>
          <div class="mb-3">
            <label class="form-label">Low-Level Style Image:</label>
             <input type="file" class="form-control" id="style-image-low" name="style_low"
accept="image/*" required>
          </div>
          <div class="preview-container">
            <div class="preview-image" id="content-preview-div" style="display: none;">
              <img id="content-image-preview" src="" alt="Content Image Preview">
            </div>
            <div class="preview-image" id="style-high-preview-div" style="display: none;">
                  <img id="style-image-high-preview" src="" alt="High-Level Style Image
Preview">
            </div>
```

```
                <div class="preview-image" id="style-low-preview-div" style="display: none;">
                    <img id="style-image-low-preview" src="" alt="Low-Level Style Image Preview">
                </div>
            </div>
            <div class="button-container">
                <button type="submit" class="btn btn-primary btn-custom">Apply Style Transfer</button>
            </div>
        </form>
    </div>

    <div class="right-section">
        <h3>Blended Output Image</h3>
        <div class="output-container">
            <img id="output-image" class="img-fluid" src="" alt="Blended Style Image">
            <div class="button-container">
                <button id="download-btn" class="btn btn-success btn-custom" style="display: none;">Download Image</button>
            </div>
        </div>
    </div>
  </div>

  <script>
    document.getElementById("theme-toggle-btn").addEventListener("click", function() {
        document.body.classList.toggle("dark-theme");
        const isDark = document.body.classList.contains("dark-theme");
        document.getElementById("theme-toggle-btn").textContent = isDark ? " " : " ";
    });
```

```
document.getElementById("style-transfer-link").addEventListener("click", function() {
    document.getElementById("style-transfer-section").style.display = "block";
    window.scrollTo({
        top: document.querySelector("#style-transfer-section").offsetTop,
        behavior: "smooth"
    });
});

document.getElementById("go-to-style-btn").addEventListener("click", function() {
    document.getElementById("style-transfer-section").style.display = "block";
    window.scrollTo({
        top: document.querySelector("#style-transfer-section").offsetTop,
        behavior: "smooth"
    });
});

document.getElementById("content-image").addEventListener("change", function() {
    const contentImage = document.getElementById("content-image-preview");
    const file = this.files[0];
    const reader = new FileReader();
    reader.onloadend = function() {
        contentImage.src = reader.result;
        document.getElementById("content-preview-div").style.display = "block";
    };
    if (file) {
        reader.readAsDataURL(file);
    }
});

document.getElementById("style-image-high").addEventListener("change", function() {
```

```
    const styleImageHigh = document.getElementById("style-image-high-preview");
    const file = this.files[0];
    const reader = new FileReader();
    reader.onloadend = function() {
        styleImageHigh.src = reader.result;
        document.getElementById("style-high-preview-div").style.display = "block";
    };
    if (file) {
        reader.readAsDataURL(file);
    }
});

document.getElementById("style-image-low").addEventListener("change", function() {
    const styleImageLow = document.getElementById("style-image-low-preview");
    const file = this.files[0];
    const reader = new FileReader();
    reader.onloadend = function() {
        styleImageLow.src = reader.result;
        document.getElementById("style-low-preview-div").style.display = "block";
    };
    if (file) {
        reader.readAsDataURL(file);
    }
});

document.getElementById("upload-form").addEventListener("submit", function(event) {
    event.preventDefault();
    let formData = new FormData();
    formData.append("content", document.getElementById("content-image").files[0]);
    formData.append("style_high", document.getElementById("style-image-high").files[0]);
    formData.append("style_low", document.getElementById("style-image-low").files[0]);
```

```
        fetch("http://127.0.0.1:5000/predict", {
            method: "POST",
            body: formData,
            headers: {
                "Accept": "application/json"
            }
        })
        .then(response => response.json())
        .then(data => {
            if (data.output) {
                let outputImage = document.getElementById("output-image");
                outputImage.src = "" + data.output;
                document.getElementById("download-btn").style.display = "block";
                document.getElementById("download-btn").addEventListener("click", function() {
                    let link = document.createElement("a");
                    link.href = outputImage.src;
                    link.download = "styled_image.jpg";
                    document.body.appendChild(link);
                    link.click();
                    document.body.removeChild(link);
                });
            } else {
                alert("Style transfer failed.");
            }
        })
        .catch(error => console.error("Error:", error));
    });
</script>
```

```
<script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0/dist/js/bootstrap.bundle.min.js"></script>
</body>
</html>
```

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