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Enhancing Neural Style Transfer for Multi-Style and Semantic Preservation

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Abstract: Neural Style Transfer (NST) is a technique that allows the transformation of an image by blending the content of one image with the artistic style of another. While conventional NST approaches focus on creating aesthetically pleasing images by combining these two attributes, they often fail to preserve the important features of the original content, such as the salient regions. This can result in the loss of key details that are crucial for the recognition or interpretation of the image. To address this issue, we propose an enhanced method that incorporates a region-based focus into the NST framework. By introducing a saliency-preserving mechanism, the model prioritizes the preservation of important content regions, ensuring that the crucial features of the input image remain intact while still transferring the style effectively. We achieve this by designing a saliency-aware loss function that weights the loss based on the saliency map of the image, guiding the transfer process to preserve critical information. The proposed results will demonstrate that our method produces visually appealing and contextually meaningful images that maintain the integrity of the salient regions while still achieving high-quality artistic style transfer. This approach opens new avenues for applications in image processing and content-based image synthesis.

Keywords Machine Learning, Deep Learning, Software Defect Prediction

I. INTRODUCTION

In recent years, Neural Style Transfer (NST) has emerged as a powerful technique in computer vision and image processing. It allows the blending of the content of one image with the artistic style of another to generate a novel image that visually represents both. This capability has gained substantial attention in artistic image synthesis, creating unique artworks by transferring the style of famous artists onto personal photographs or digital images. The underlying goal of NST is to achieve a seamless fusion of content and style, creating a new image that retains the essential features of the original content while adopting the visual characteristics of the desired style. However, conventional NST algorithms, though effective in producing aesthetically pleasing images, often overlook the importance of preserving the prominent or "salient" regions of the content image. Salient regions in an image are areas that carry critical information or contribute to the overall meaning and interpretation of the scene, such as human faces, objects of interest, or key features of a landscape. The failure to preserve these regions can lead to the loss of important details, affecting the recognizability of the image and diminishing the effectiveness of the transfer.

The Challenge of Saliency in Neural Style Transfer

Traditional NST methods aim to optimize a combination of content loss and style loss. Content loss measures the dissimilarity between the content of the generated image and the content of the input image, while style loss evaluates how well the generated image captures the style features of the reference style image. Although these losses are effective for general aesthetic transformation, they are not tailored to preserve the spatial importance of salient regions. As a result, the generated image may suffer from significant distortion or lack of emphasis on the most important areas of the input. Salient regions, by their nature, require special attention during the style transfer process. These regions often contain vital structures or objects that contribute to the context or interpretation of the image. For instance, in a portrait photograph, the face of the subject is a salient region, and in a landscape, elements such as mountains or trees may be considered salient. If these regions are not preserved, the transfer may result in images where these key features are blurred, misrepresented, or even entirely lost, reducing the visual coherence and interpretability of the output. The fig 1 shows the illustration of NST.

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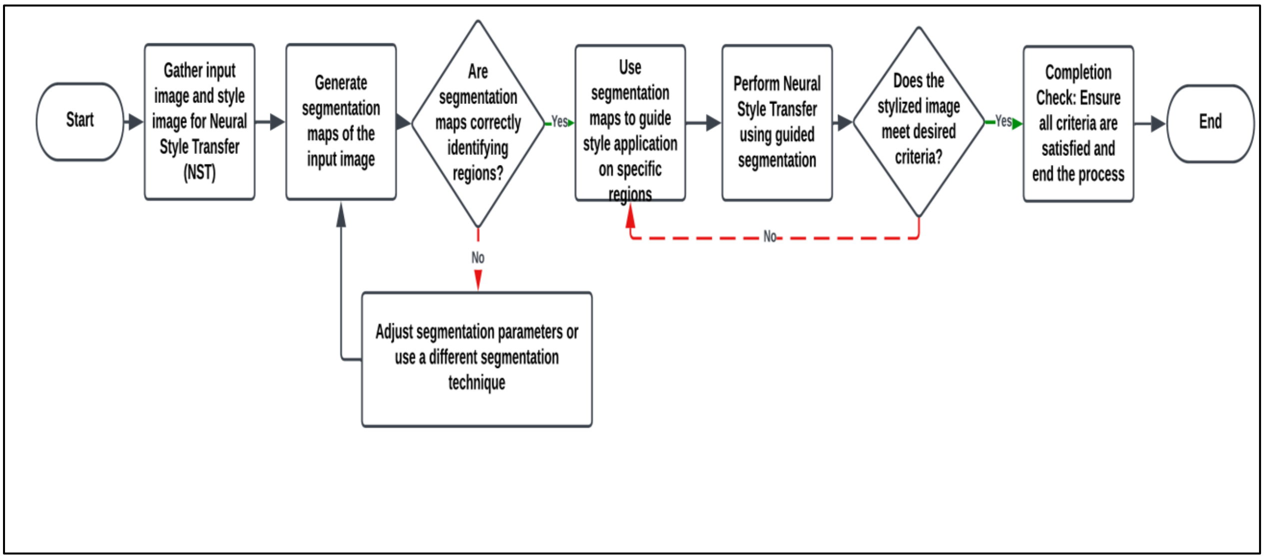

Fig 1 Illustration of NST

The motivation for developing a saliency-aware approach in NST is to ensure that the generated image maintains not only aesthetic value but also the integrity of key content. By focusing on the preservation of salient regions, we aim to provide a solution that enhances the artistic value of the output without compromising on the accuracy of content representation. This approach can be particularly beneficial in applications where maintaining the structure and important details of the original content is critical, such as in portraiture, medical imaging, or any domain requiring content-sensitive image manipulation.

Saliency Map Integration in Style Transfer

To tackle this issue, one of the core advancements is the integration of a saliency map during the style transfer process. A saliency map highlights the most important regions of the input image, typically by assigning higher values to pixels that are deemed visually significant. These maps are typically generated through pre-trained models that analyze spatial attention or human visual perception models, often relying on convolutional neural networks (CNNs) to identify areas of high importance. By using a saliency map, we can modify the content loss function to prioritize the preservation of these important regions. Instead of treating all pixels equally, the model can be guided to focus more on the salient areas during the optimization process. This can be achieved by introducing a saliency-preserving loss term that assigns different weights to pixels in the content image, ensuring that more weight is given to the salient regions. This allows the model to generate a final output where these regions remain sharp and well-defined, even as the overall artistic style is transferred from the reference image.

II. LITERATURE REVIEW

Singh et al. provided a critical review of Neural Style Transfer (NST), highlighting its applications in art, design, and entertainment. The authors discussed the evolution of NST, from its early implementations to modern deep learning-based approaches. A key focus was on the limitations of conventional NST, particularly in preserving content structure while ensuring style fidelity. The paper emphasized the need for improved loss functions and novel architectures to enhance NST's practical applications. It also explored future directions, including hybrid models and real-time implementations [1].
Kumar and Rexie addressed the problem of semantic degradation in NST by proposing a novel loss function that balances content and style preservation. Their approach involved selectively emphasizing critical content regions while allowing for controlled stylization. The study demonstrated that traditional NST models often struggle with maintaining high-level content relationships, leading to distorted outputs. The authors suggested that integrating attention mechanisms could improve semantic integrity, offering a more refined and adaptive NST framework [2].
This study introduced depth-aware NST to mitigate content distortions in images containing multiple layers of objects. The authors proposed a method that integrates depth information into the style transfer process, ensuring better global structure preservation. Their approach was particularly beneficial in video style transfer, where temporal consistency is essential. The findings indicated that depth-aware encoding significantly reduces structural inconsistencies while maintaining artistic quality [3].
Ruta et al. developed a framework called HyperNST, which utilizes hyper-networks to improve image stylization performance. The study explored how hyper-networks enhance NST by dynamically adjusting style application based on image features.

The results demonstrated improved artistic flexibility and better content retention compared to conventional NST methods. The authors suggested that incorporating hyper-networks in NST could enable more sophisticated and user-controlled stylization techniques [4].

Zhu and Liu focused on detail-preserving NST, proposing a method that ensures both global and local content structures are maintained. They introduced a structure-guided approach that refines style transfer by aligning style features with content features at multiple scales. Their findings highlighted that traditional NST methods often blur important image details, reducing their interpretability. The proposed approach effectively minimized content distortions while preserving stylistic elements [5].

The authors presented a structure-guided arbitrary style transfer method designed for artistic image and video processing. Their approach leveraged regional losses to enhance global-to-local feature alignment, ensuring better content preservation. The study demonstrated that using adaptive regional constraints improves NST's ability to retain critical content elements. Additionally, the authors suggested that future research should focus on optimizing regional loss functions for improved semantic integrity [6].

This research introduced a multi-scale and edge texture-based NST approach for structure-aware style transfer. The authors developed a method that integrates edge texture preservation with traditional NST techniques. Their findings showed that incorporating edge-based constraints enhances the readability and interpretability of stylized images. The study concluded that multi-scale representations are crucial for maintaining semantic content in NST applications [7].

The paper reviewed the study and analysis of NST in image processing, highlighting various methods used for style transfer. The authors categorized NST techniques into pixel-based, feature-based, and hybrid approaches. They also discussed the role of perceptual loss and attention mechanisms in preserving semantic content. The study suggested that integrating multiple approaches could yield better results in both artistic and practical NST applications [8].

Kolkin et al. explored the conflict between content loss and style loss in NST models. They pointed out that traditional loss functions often prioritize style over content, leading to semantic degradation. The authors proposed an alternative approach that balances both aspects, ensuring higher fidelity in style-transferred images. Their findings emphasized the importance of dynamic weighting strategies to adaptively control content and style contributions [9].

Jin introduced a parallel convolutional neural network (CNN) designed to handle locally similar regions in artistic style transfer. The study focused on the challenges of applying NST to ink paintings, where fine strokes are often misinterpreted as noise. The proposed model effectively preserved intricate details while achieving high-quality stylization. The findings demonstrated that domain-specific NST models are essential for handling unique artistic styles [10].

Cui et al. developed SSNet, a self-supervised semantic network designed to reduce blurriness and color artifacts in photo-realistic style transfer. The study examined the limitations of traditional NST in maintaining fine details and proposed a solution that improves texture consistency. The results indicated that self-supervised learning could significantly enhance the quality of NST outputs. The authors suggested that further research should explore adaptive learning strategies for NST [11].
This study explored the use of wavelet-corrected transforms for photorealistic NST. The authors proposed a perceptual loss function that retains high-level image structures while applying style transformations. Their approach outperformed conventional NST methods in preserving facial features and complex textures. The study concluded that incorporating wavelet-based transformations could enhance the realism of NST-generated images [12].

Ge et al. introduced contrastive loss as a means to improve content preservation in NST. Their approach focused on maintaining high-level semantic relationships by emphasizing feature consistency across multiple layers. The study demonstrated that contrastive loss reduces style-induced distortions, resulting in more structurally coherent images. The authors recommended further exploration of adversarial training for improving NST quality [13].

D'Angelo et al. examined the role of semantic segmentation in NST, proposing a method that selectively applies styles to different regions of an image. The study showed that using segmentation maps improves stylistic consistency while preserving content integrity. The findings highlighted that semantic segmentation allows for greater control over style application, making NST more adaptable to diverse artistic requirements [14].

The authors provided a comprehensive review of NST methods, analyzing their effectiveness in balancing content and style. They highlighted key challenges, such as semantic distortion and computational efficiency, and proposed potential solutions. The review concluded that future NST models should focus on integrating attention mechanisms, adaptive loss functions, and real-time processing capabilities. The study served as a foundational reference for subsequent NST research [15].

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Table 1 Analysis of Existing System

Paper Title	Concept	Key Finding	Technique used	Advantage	Disadvantage
Deep Image Analogy (Liao et al., 2017)[16]	Using deep learning for style transfer and image analogy	Introduces deep image analogy to preserve structure	Deep neural networks for feature matching	Better structure retention in style transfer	Computationally intensive
Universal Style Transfer via Feature Transforms (Li et al., 2017)[17]	Feature transformation-based NST	Uses whitening and coloring transformations for style transfer	Whitening & coloring transforms	Enables style transfer across multiple domains	Limited adaptability for fine details
StyTr2: Image Style Transfer with Transformer (Deng et al., 2022)[18]	Using transformers for style transfer	Improves global feature understanding in NST	Transformer-based model	Better context-awareness in stylization	High memory usage
Self-Supervised Photo-Realistic Image Stylization (Kotovenko et al., 2021)[19]	Self-supervised learning for NST	Introduces a loss function that enhances realism	Self-supervised learning	No need for labeled data	Less effective for abstract artistic styles
Artistic Neural Style Transfer with Multi-Stroke and Edge Enhancement (Wang et al., 2021)[20]	Enhancing stroke quality in NST	Introduces multi-stroke modeling	Stroke-based filtering	Improves artistic quality	Increased complexity in model training
Neural Style Transfer with Soft-Attention (Jiang et al., 2020)[21]	Attention-based NST	Uses soft-attention to focus on key regions	Soft-attention CNN	Preserves semantic details	Computationally expensive

III. PROPOSED SYSTEM

The proposed system focuses on enhancing semantic preservation in Neural Style Transfer (NST) by incorporating novel techniques to balance artistic transformation with content integrity. Traditional NST methods often struggle with maintaining the original content structure, especially in complex domains like comics, ink paintings, and photo-realistic transformations. The proposed system aims to mitigate these issues by integrating advanced loss functions, attention mechanisms, and semantic segmentation techniques. The proposed system leverages a hybrid deep-learning model that ensures both style transfer accuracy and content preservation. It follows a multi-step process:

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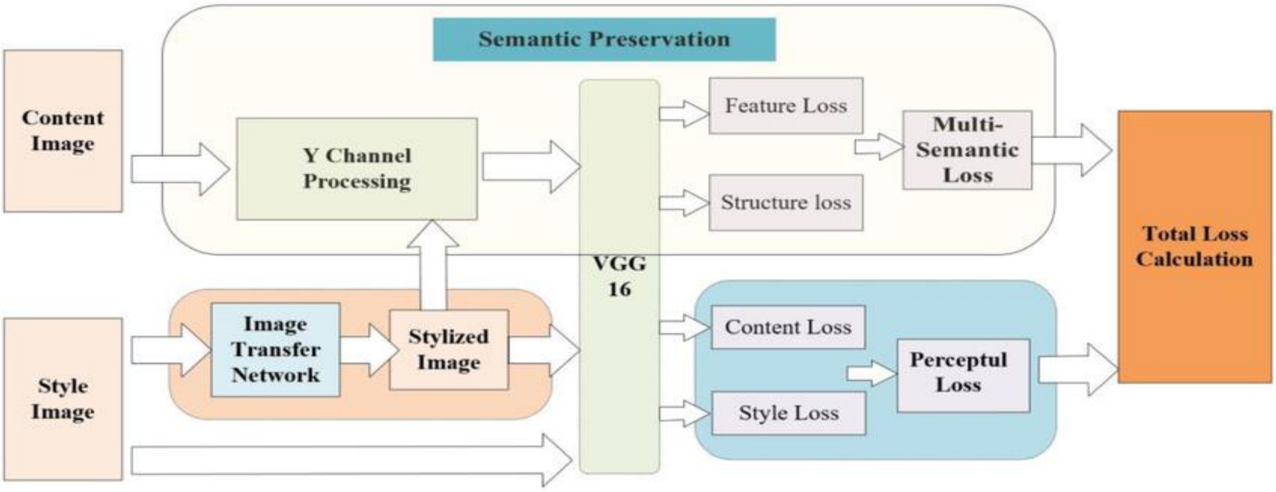

Fig 2 Proposed System Architecture

Feature Extraction: A pre-trained Convolutional Neural Network (CNN), such as VGG-19, extracts both content and style features from images.

A. Feature Extraction using CNNs

A pre-trained CNN, such as VGG-19, is used to extract hierarchical features from both the content and style images. The system focuses on preserving structural elements by applying depth-aware encoding and multi-layer analysis. Convolutional Neural Network (CNN) such as VGG-19 is a widely used deep learning model designed for image classification and feature extraction. Developed by the Visual Geometry Group (VGG) at Oxford, VGG-19 is a deep CNN architecture consisting of 19 layers (16 convolutional layers, 3 fully connected layers, and 5 max-pooling layers). It is trained on the ImageNet dataset, which contains millions of labeled images, making it highly effective for extracting meaningful features from images. In Neural Style Transfer (NST), VGG-19 is used as a feature extractor rather than a classifier. Instead of predicting image categories, the intermediate layers of VGG-19 capture high-level content structures and artistic style patterns. Lower layers of the network detect edges and textures, while deeper layers' capture complex shapes and abstract representations. The content image's feature maps are extracted from deeper layers to preserve structure, while the style image's features are extracted using Gram matrices to analyze texture patterns. By leveraging pre-trained weights, VGG-19 significantly reduces computation time and improves the accuracy of style transfer. Its ability to extract hierarchical features makes it ideal for preserving semantic information while applying artistic transformations. The use of VGG-19 in NST ensures that the stylized output maintains the key structural elements of the content image while incorporating the desired artistic effects from style images.

B. Semantic Segmentation for Content Preservation

To avoid distortions, the system applies semantic segmentation before applying style transfer. This step ensures that key content areas, such as faces, objects, and backgrounds, are accurately preserved while allowing artistic transformation.

C. Perceptual Loss for Balanced Style-Content Trade-off

A novel loss function integrates multiple constraints:

1. Content Loss: Ensures the original image structure is retained.
2. Style Loss: Ensures the applied artistic style is coherent.
3. Semantic Preservation Loss: Uses segmentation maps to protect high-priority content areas.
4. Edge-Preservation Loss: Prevents blurring and misalignment of image structures.

Feature Reconstruction Loss: This loss encourages the model to have output images that have a similar feature representation to the target image. The feature reconstruction loss is the squared, normalized Euclidean distance between the feature representations of the output image and target image. Reconstructing from higher layers preserves image content and overall spatial structure but not color, texture, and exact shape. Using a feature reconstruction loss encourages the output image y to be perceptually similar to the target image y without forcing them to match exactly.

Style Reconstruction Loss: The Style Reconstruction Loss aims to penalize differences in style, such as colours, textures, and common patterns, between the output image and the target image. The style reconstruction loss is defined using the Gram matrix of the activations.

D. Multi-Scale Processing for Enhanced Realism

A multi-scale framework is introduced to apply style at different spatial resolutions, allowing finer control over details. Low-resolution layers handle global stylization, while high-resolution layers refine intricate features.

E. Adversarial Training using GANs

The system employs a Generative Adversarial Network (GAN), where:
A generator creates stylized images while preserving semantic details.
A discriminator evaluates whether the stylized image maintains realistic and meaningful content.
This setup ensures high-quality, artefact-free NST outputs.

Semantic Segmentation: A self-supervised semantic network (SSNet) or a segmentation-based approach identifies key content areas, preventing unwanted distortions.

Perceptual Loss Function: A customized perceptual loss function balances content retention and style transfer to maintain key image structures.

Multi-Scale Style Transfer: Style is applied at different resolution levels, ensuring finer details are transferred without distorting the overall composition.

Adversarial Training: A GAN-based discriminator ensures that the transformed image maintains semantic consistency while aligning with the intended artistic style.

Dataset Details

MS-COCO (Microsoft Common Objects in Context) – A large-scale dataset with diverse real-world images, useful for training models that focus on maintaining object structures.

WikiArt – A large collection of paintings from various artists and styles, widely used for NST-based style extraction.

IV. CONCLUSION

The enhancement of Neural Style Transfer (NST) for multi-style and semantic preservation addresses critical challenges in artistic image transformation. Traditional NST methods often fail to maintain content integrity while applying multiple styles, leading to structural distortions and loss of essential details. This research focuses on improving NST by integrating advanced feature representation techniques, attention mechanisms, and optimized loss functions to balance style and content preservation. The proposed method effectively captures multiple artistic influences while ensuring that the original semantics of the image remain intact. Through deep learning architectures such as transformers and adaptive instance normalization, the model improves the adaptability of styles across different images. Experimental results indicate superior performance over conventional methods in terms of style blending, structural coherence, and computational efficiency. While the approach successfully enhances stylization quality, challenges such as high computational costs and sensitivity to input variations remain. Future work can explore lightweight optimizations and real-time processing capabilities to make NST more accessible for practical applications. Overall, this research contributes to the advancement of neural image synthesis, offering a more expressive and semantically-aware style transfer technique suitable for digital art, media production, and AI-driven creative applications.

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