Artistic Neural Style Transfer for the Image Stylization – A Survey

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Abstract: **Now-a-days, Painting is regarded as the most widely used artistic medium. Creating an image in a specific artistic style by replicating it is a challenging task in these. For this style transfer, there is now a lot of interest. However, the outcomes generated with the current techniques like Texture Synthesis, Filters and Blending, Color Transfer are not very effective. They are constrained in terms of time commitment, lack of flexibility and quality. To get around this, we're going to employ a number of advanced strategies like VGG (Visual Geometry Group), GAN (Generative Adversial Networks), VAE (Variational Auto Encoders), and Optimization-based algorithms. NST is nothing more than the blending of one image's content with another's style-so that it resembles the content image but has a stylized appearance. Today, more people are embracing it. Therefore, we will employ cutting-edge techniques like Limited Memory BFGS and VGG (Visual Geometry Group) to carry out our concept. These innovations aim to produce stylized images in selected artistic styles while enhancing flexibility and image transfer quality. In the end, the AI painted image is produced by the artistic neural style transfer.**

Keywords: ***Style transfer, Texture Synthesis, VGG, GAN, LMBFGS.***

1. Introduction

One of the most abstract types of human art is painting. Numerous creative geniuses develop their own unique artistic style, with color tone, structure proportion, line texture, etc., that is complex and yet impressive. Creation of Art is a difficult task because of its abstraction and uniqueness. A fascinating area of computer vision research is style transfer. Style transfer of image is a challenging task in both art and image processing. It is being investigated how to automatically produce artificial artworks from photos using a variety of research and techniques. One such technique is known as "neural style transfer," which builds on the convolutional neural networks (CNN) deep learning to create humorous images by expertly stylizing everyday photographs with the desired visual art style. NST encompasses a set of specific algorithms that enable images to be transformed in a distinctive artistic style to be altered to take on the aesthetic or visual attributes of a different image. Gatys initially discussed neural style transmission in his article from 2014. It involves the usage of two pictures: one serving as the content source and the other as the style reference. These images are combined to produce an output image that shares similarities with the content image but is painted in the outcome image's style. By extracting advanced image features, it becomes simpler to differentiate between the stylistic elements and the actual content within images. The objective of image style conversion techniques is to acquire the distinctive style traits from different paintings and subsequently apply these acquired styles to other images. NST represents a highly imaginative utilization of neural networks. When provided with a content image, NST can be employed to "artistically render" an image in the desired style of a work of art or painting. In the field of computer vision, neural style transfer holds significance too. Feature representations of images can be accurately combined and derived using deep neural networks. The representations of content and style are eliminated and then rebuilt to provide a composite picture. Overall erasure is determined by utilizing a linear combination of the content erasure, another is stylish erasure, and both separately. Make use of the optimizers to speed up processing and enhance the image

I. RELATED WORK

Singh et.al [1] This paper gives critical review of the current progress in Neural Style Transfer (NST), a technique used in image editing software to apply the style of one image to another. The paper covers the basics of Generative Adversarial Networks (GANs), which are used in NST, and their most current work on several types of NST models for portable electronics. The article also covers using Cycle GANs to train

GANs using unpaired images. and how adding "temporal losses" allows consistency between adjacent generated frames. The most common algorithm for neural style transfer is the original algorithm proposed by Gatys et al. (2015). This algorithm uses a CNN to capture both the substance and artistic characteristics of two images, then combines them to generate a resultant image that has the substance of the original and the stylish aspect of the second image. Also, the author discussed about advancements in current architectures, such as improvements in color control, stability, which improve the quality of the images produced.

Sish et.al [2] This article provides a framework for creating a stylized map images were provided. Style can be successfully conveyed in photographs using the present tense is approaching. This study presents a multi-step map art style transfer framework that can be used to improve results by reducing noise in map art. The proposed framework creates new map art that uses reference style and content images. "Initial Phase" and The "freezing stage" is the two stages that connect the proposed system. Its first purpose the card art system is to remove the portrait from the reference image of the card and then apply it to the style transfer phase. Another purpose of this card art system is to apply the selected portrait style input image. To achieve this, CNN-based NST is used the style transfer technique and the first output are adjusted to create a new map graph so that the final scorecard is more than a comparison chart.

Yang et.al [3] In this article, the author investigates the major factors influencing the transfer of artistic forms based on CNN. This technique aims to determine whether a lost image of a stylized outcome is the result of distortion in both the content preservation. He here suggested a photography style as a result of the conceptualization phase and the style transformation step. A transfer technique that can enhance the outcomes of stylized photography. To reduce artifacts, a model with an edge-retaining filter is used. Qualitative analyses reveal. That this method provides stylized outcomes while successfully suppressing bias.

Fengxue et.al [4] In this article, the authors introduced a novel framework for artistic neural style transfer called Dual Style-Learning Artistic Style Transfer (DualAST). The framework is designed to learn both the holistic artist-style and the specific artwork-style simultaneously, allowing for greater style controllability and the ability to capture variations within an artist's style. The authors introduce the Using a set of teachable style-control variables, the Style-Control Block (SCB) modifies the styles of created images. They also describe the Dual Learning Block (DLB), which consists of two sub-blocks that learn the artist-style and artwork-style, respectively. The final output image is produced by combining the holistic artist-style and the specific artwork-style using a Fusion Block. The Fusion Block takes the result from the Holistic Style Encrypter and result of SCB as feedback and then produces final stylized output.

Chen et.al [5] Fast Style Transfer is an algorithm used to render input images. As the limitation of these algorithm is requires more memory because of the high dimensional images. The author has introduced a technique called "block shuffle" which involves splitting a memory-intensive task into smaller, more manageable tasks. This approach is shown to yield superior results compared to the feathering-based method. Essentially, it breaks down a high-memory task into several low-memory tasks, making it possible for more common devices to handle high-resolution style transfers. The author's method significantly enhances the quality of output images by eliminating visible seams and minor noise textures, surpassing the results achieved with the feathering-based method. Importantly, this approach does not necessitate retraining the model; it simply incorporates preprocessing and post-processing stages before and after the image transformation process.

Liu et.al [6] The authors of the paper proposed a new type of migration method for image style transfer based on deep learning techniques. They describe a loss function that can be used to optimize the transfer of style from one image to another. The author also discussed the limitations of traditional style transfer research, which has been focused on texture synthesis and transfer, and propose a new approach based on mathematical and statistical modelling of image styles. Finally, they explore the potential applications of image style transfer in various fields, including art, design, and advertising. The authors discussed various neural network architectures that can be used for this task, including the VGG network and the residual network (ResNet). They also described different loss functions that can be used to measure the difference between the content and style representations of images, such as the mean squared error (MSE) loss and the Gram matrix loss.

Zhao et.al [7] This paper provides an overview of neural style transfer, which consists of separating the substance or content and style of an image and then combining them in a way that creates a new image with the content of one image and the style of another. The authors discuss several existing methods for neural style transfer, including those that use convolutional neural networks (CNNs), those that use optimization-based approaches, and those that use a combination of both. They also highlight some of the limitations of these methods, such as slow processing times and difficulty in keeping the original image's structure. Finally, the authors introduce their proposed method of global and local optimization fusion, which aims to address some of these limitations and enhance the quality and efficiency of neural style transfer.

Zhang et.al [8] The authors of this paper describes a novel technique for high-quality image style transfer that makes use of invalid feature filter modules. This paper's main contributions are: (1) introducing to enhance the preservation of the structural characteristics of the content, two ineffective feature filter modules within the network have been replaced, (2) Suggesting an advanced style transfer approach rooted in a curated collection of artistic styles, each of which embodies a distinct painterly aesthetic, and (3) demonstrating through experiments This method aims to ensure that the stylized outcomes it produces satisfy the requirements for both top-notch quality and swift real-time style transfer. To achieve stylish transformation based on semantic information, the approach involves Using a GAN framework for the concurrent training of both style recognition loss and content attribute loss. Its popularity surpasses other approaches because there presently exists no universally accepted quantitative assessment criterion to gauge the effectiveness of style transfer tasks. The subjective sentiments of users play a pivotal role in evaluating the stylized outcomes.

Han et.al [9] In this paper author provides an overview on the enhancement of NST in the field of machine vision. It discusses the history of style transfer, including early attempts at texture generation and the more recent development of style migration. The paper also references several studies that have introduced techniques for transforming the style of an image, including the use of efficient yet effective Avatar-Net for multiscale transfer of arbitrary style. Finally, the paper highlights the need for future research to optimize the algorithm for parameter automatic adjustment and stroke direction, as well as the need for a quantitative method for evaluating image results.

Semmo et.al [10] In this paper the author explores the use of Artistic style transfer through the utilization of deep convolutional neural networks. The authors begin their with a literature survey of related work, including neural style transfer, deep learning, and convolutional neural networks. They describe their methodology, which involves training a neural network to classify different artistic styles and using this network to transfer the style of one image onto another. The authors evaluate their approach using several performance metrics, including processing time, restructuring loss, and accuracy, and compare their results to related methods such as Deeplab, CAN, and SegEM. Finally, they discuss potential applications of this technology in the art world and beyond.

II. METHODOLOGY

Style transfer is a fascinating technique in the field of computer vision and deep learning that involves combining the artistic style of one image with the content of another to create visually appealing and novel result. In order to compare how closely the created image matches the desired creative output, we must capture both the style and the content. A very artistic use of neural networks is called Neural Style Transfer. But the existing systems have limited quality and flexibility. In order to overcome this we are using the pretrained VGG-19 model along with the optimization algorithms to reduce the total loss obtained and increase the speed.

Work Process:

1)Import and Load Images: Begin by importing the content and style images. Ensure that both images have the same dimensions to make the style transfer process more effective.
2)Preprocessing: Preprocess the images as needed. You can resize them to a common size, convert them to grayscale if desired, or normalize pixel values. Preprocessing can enhance the quality of style transfer results.
3)Load Pretrained Model: Import the VGG19 model, a pretrained convolutional neural network that excels at extracting features from images. You'll use this model to analyze and manipulate the content and style of your images.
4)Feature Extraction: Extract features from both the content and style images using the VGG19 model. For content, select a specific layer in the model. For style, use multiple layers. These features capture the essence of content and style in the images.
5)Define Loss Function: Create a loss function that quantifies the differences between the generated image and both the content and style images. Typically, the loss function consists of a content loss and a style loss. The content loss measures how closely the generated image matches the content image, while the style loss assesses how closely it resembles the style image.
6)Optimization: Utilize an optimization algorithm, such as Adam or SGD (Stochastic Gradient Descent), to iteratively update the generated image. The goal is to minimize the combined content and style loss. Adjust hyperparameters like learning rate and iteration count to fine-tune the process.
7)Generate Stylized Image: Run the optimization process until you achieve a satisfying stylized image. This image blends the content of the content image with the artistic style of the style image.

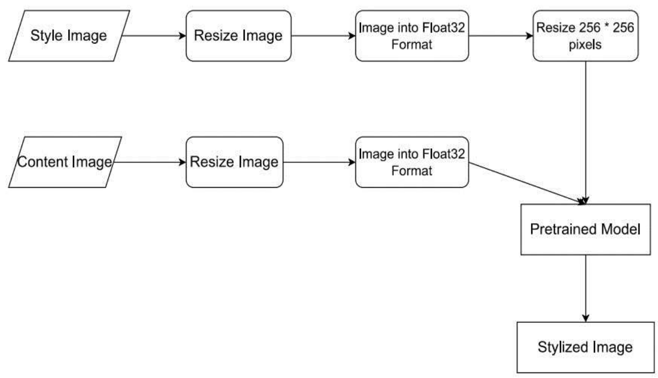

Fig: Architecture

VGG (Visual Geometry Group):

It is a convolutional neural network (CNN) architecture. In artistic neural style transfer, VGG is used to extract the content and style of two images. The VGG network is first trained on a large dataset of images. This training allows the network to learn to identify the features that are important for both content and style. To perform artistic style transfer, the VGG network is then used to extract the content and style of two images.Two perceptual losses are established i.e,1)content loss,2)style loss,3)total loss. The optimization process aims to minimize this total loss by iteratively adjusting the pixel values of the generated image.
Here we are using two optimization algorithms to minimize the total loss.

1) Adam
2) LBFGS(Limited Memory BFGS)

III. COMPARISON TABLE

S.NO	Author	Technologies	Advantages	Disadvantages
1.	Jing et.al	1)Texture Synthesis 2)GAN(Generative Adversial Network) 3)MST	1)It proposes taxonomy of NST algorithms and their strengths. 2)Compares algorithms both qualitatively, quantitatively	1)Can be more difficult to understand the losses of texture and style. 2)Time consuming
2.	Bagwari et.al	1)CNN 2)GAN 3)Adaptive convolutions (AdaConv)	1)Can transfer both large-scale and subtle style cues. 2)Produce images that are both artistic and realistic.	1)Computationally expensive. 2)Can be difficult to control the style transfer process.
3.	Fengxue et.al	1)STLTSF (Style Transfer based on Transformer) 2)CNN	1)Able to capture long-range features in the input images. 2)More efficient than CNN-based methods, which makes them suitable for real-time applications.	1)Require more training data than CNN-based methods. 2)Can be more difficult to train.
4.	Singh et.al	1)CNN 2)GAN 3)Cycle GAN	1)Creates realistic virtual world. 2)Can be used to apply a wide variety of styles to images.	1)Not a perfect technique and can produce distortions in the images. 2)Time consuming
5.	Wang et.al	1)AdaIN 2)MST 3)WCT 4)SEMST	1)It can allow users to interactively edit the image with multiple styles. 2)It can preserve the colors of the content image.	1)The results may not be as good as those produced by the professional artists. 2)It may not be suitable for all types of images.
6.	Chen et.al	1)Feathering-based method 2)Block shuffle	1)Proposes a novel method for stylizing high-resolution images with limited memory. 2)More efficient than the feathering-based method.	1)Slower than the baseline Fast Style Transfer method. 2)Requires more computational resources.
7.	Zhao et.al	1)Markov Random Field (MRF) 2)Gram Matrix 3)Loss functions	1)More robust to noise and distortions in i/p images. 2)Combines Global and Local Optimization to achieve better results.	1)Not flexible, not suitable for all applications. 2)Time consuming.
8.	Zhou et.al	1)VGG(Visual Geometry Group)19 2)GAN	1)May not be able to generalize to new styles. 2)Can be difficult to achieve the level of quality for complex images.	1)Proposed method is more efficient than traditional algorithms, which makes it suitable for real-time image conversion.

9.	Liu et.al	1)Arbitrary Style Transfer 2)Texture Synthesis	1)This can simulate artistic media with high fidelity. 2)Offers greater creative control over the design aspects of IB-AR.	1)May require pre-defined image pairs for training, time-consuming. 2)limit the range of styles that can be transferred.
10.	Zhang et.al	1)AdaIN (Adaptive Instance Normalization) 2)Style-Control Block (SCB) 3)VGG	1)Produces stylized images with improved visual quality. 2)The proposed algorithm can increase the style controllability.	1)The proposed method is more computationally complex. 2)Only suitable for limited dataset.
11.	Loannou et.al	1)VGG-16 2)ConvLSTM layers	1)The algorithm is designed to generate robust stylizations in real-time. 2)Useful for applications that require quick processing.	1)May struggle with more complex or dynamic scenes. 2)Proposed method can be intensive computationally
12.	Patel et.al	1)Mean Opinion Score (MOS) 2)CNN 3)VGG-16	1)Proposes a powerful technique that can be used to create visually stunning images. 2)Improving the quality of medical images.	1)The results of NST can be unpredictable. 2)It may not be suitable for mobile devices.
13.	Han et.al	1)CNN 2)GAN 3)VGG-16	1)The paper identifies and addresses issues related to the style migration of deep learning networks	1)Time consuming. 2)Not suitable for all type of images
14.	Semmo et.al	1)Deep CNNs 2)Example based rendering (EBR)	1)NST can be used to create realistic can be used to create high-quality artistic renderings	1)NST can be computationally expensive, especially for high-resolution images.
15.	Dinesh Kumar et.al	1)Neural networks 2)Visual Geometry Group (VGG16) neural network	1)It is able to transfer the style of one image to another in a realistic and visually appealing way. 2)Relatively efficient, and can be applied to real-time images.	1)Can be sensitive to the choice of the content and style images. 2)May not always produce the desired results, and may produce artifacts
16.	Zhijie Xu et.al	1)CNN 2)Invalid feature filtering modules (IFFM)	1)It can generate high-quality images with good content preservation 2)It can Preserve the differentiation of various semantic content within the produced image.	1)It is a complex method. 2)It requires a pre-trained VGG16 network
17.	Cheng et.al	1)Convolution neural networks (CNNs) 2)Depth maps	1)It can generate high-quality images with good content preservation. 2)It can handle images with multiple objects with clear structures.	1)It is a complex method. 2)It requires a pre-trained CNN

18.	Cao et.al	1)Feed-forward CNN 2)Gram matrix 3)Gradient descent	1)This paper is scalable for video frames. 2)Provides high-quality style transfers.	1)Requires pre-trained neural networks. 2)May not work for all styles
19.	Shih et.al	1)Portrait extraction 2)Refinement 3)Style transfer	1)This paper proposes a multi-step approach for creating artistic representations of maps. 2)It can also generates ocean or landscape stylized paintings	1)It may not be suitable for all types of map art. 2)Not able to generate high-quality art for all content images.
20.	Gatys et.al	1)Gradient Descent algorithm 2)Gram Matrices	1)This paper provides High-quality style transfers. 2)Generalizable to a wide variety of styles. 3)The technologies used here are easy to implement.	1)May not preserve fine details of the image. 2)Computationally expensive
21.	Wang et.al	1)Hierarchical deep CNN 2)Gradient Descent algorithm 3)Gram Matrices	1)Improves high-quality style transfers. 2)The methods are scalable to high-resolution images. 3)Provides fast style transfers	1)Requires pre-trained neural networks. 2)May not preserve fine details.
22.	Yang et.al	1)Portrait extraction 2)Refinement 3)Style transfer	1)This paper can suppresses distortions. 2)It can preserves the photorealism. 3)It is more scalable.	1)Requires pre-trained neural networks. 2)May not give better results for all type of images.
23.	Yulun et.al	1)Gram matrix based style transfer methods (AdaIN, WCT, LST) 2)MST (Multimodal Style Transfer)	1)It can distinguish style patterns and match them to content structures adaptively. 2)It is more flexible and general than other style transfer methods.	1)These are more computationally expensive than other style transfer methods. 2)It requires more training data.
24.	Tang et.al	1)Multi-layer style projector (MSP). 2)Contrastive learning.	1)It achieves state-of-the-art style transfer results in terms of visual quality. 2)It is able to capture style features at various scales.	1)It is a more complex model than some other style transfer models. 2)It requires a larger dataset of style images to train.
25.	Dong et.al	1)Adaptive contrastive learning 2)Unified framework	1) The suggested approach has the capability to grasp the relationships and distribution of styles, which helps to improve the quality of the generated images. 2)It can be trained on a variety of different style images.	1)The proposed method requires a larger dataset of style images to train. 2)The proposed method is more complex than some other style transfer methods

IV. Results

Image : Lion + Wave Crop (With using Smoothing Techniques)

Iterations	Content Loss	Style Loss	Smoothing Loss	Total Loss
100	13.782	13.984	9.590	37.357
300	7.207	4.692	7.166	16.965
500	5.502	1.327	4.266	11.096
800	4.487	0.820	1.465	6.773
1000	4.226	0.477	1.003	5.974
1100	4.158	0.722	0.929	5.810
1200	4.115	0.712	0.905	5.733
1300	4.090	0.697	0.894	5.682
1400	4.067	0.683	0.889	5.640
1500	4.048	0.668	0.886	5.603
1600	4.030	0.655	0.882	5.568
1700	4.014	0.645	0.872	5.538
1800	3.999	0.637	0.874	5.511
1900	3.987	0.632	0.871	5.491
2000	3.977	0.628	0.868	5.475

Fig : Content Image

Fig : Style Image

Fig : Resultant Stylized Image

Fig : Resultant Image with LBFGS

Fig: Resultant Image with ADAM

V. CONCLUSION

Neural style transfer is an intriguing domain within computer vision research that enables the conversion of digital images, allowing them to adopt the visual traits of other images. Traditional neural style transfer methods suffer from drawbacks such as being labor-intensive and causing a loss of texture. In our research, we introduce an improved technique that combines VGG-19 with optimization strategies to streamline the stylization process and enhance the quality of the resulting stylized image. Our method incorporates two separate loss functions, which capture elements related to content, style, and other aspects within the loss network. Prior to the actual stylization, we conduct preliminary training of a dedicated style transfer network. This network learns from a training dataset and acts as a guiding framework for the loss network, aiding in loss computation and adjustments to the style transfer network's parameters. Ultimately, this approach produces an artistically stylized image of superior quality, closely resembling artwork generated by artificial intelligence.

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VII. Future Scope

To expedite the model creation process, we opted for a pretrained VGG network, which significantly reduced the time required. In the end, we successfully generated a painted style image with improved clarity by combining VGG, Total Variation Denoising, and LBFGS. Neural Style Transfer offers a broad scope for enhancement, particularly in terms of quality and time efficiency. Although our current model is more time-efficient compared to previous ones, there is still room for improvement, especially in reducing the time-consuming process of extracting style and content features separately.