International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

A Study on Neural Style Transfer for Artistic Images

Aravind Karrothu[a*], Sanapathi Adithya[b*], Veswanth Addagarla[c*], Rudraraju Sahitya[d*], Sanapala Sai Keerthi[e*], Velagada Sravani [f*], Udarapu Sudheer [g*]

[a*]*Assistant Professor, Department of CSE, GMR Institute of Technology, Razam, 532127, India*

ABSTRACT

Painting is one of the popular forms of art. To redraw a picture in a certain style in the past required a skilled artist and a lot of work. There are so many techniques and studies researching how to automatically turn images into beautiful works of art. Among these studies, the convolutional neural network is one of the deep learning techniques used in creating artistic images by separating and recombining the content and style of the images. This image editing process is called Neural Style Transfer (NST). It's an optimization approach that combines two images known as a content image and a style reference image (say, an artwork from a painter) - so the output image resembles the content image, but appears to have been painted in a style reference image way. For images classification, Visual Geometry Group (VGG) is most popular algorithm because of its pre-trained with several classes and huge amount of data. The style will be applied to the content image effectively using this model. To get the best art image by computing the high-level features in content image and low-level features along with gram matrices in style image. This paper provides an overview of all the technical details that are used in the references, the advantages of their proposed methodology, the limitations of their work, and the gaps that need to be implemented.

Keywords: Neural Style Transfer, Transfer Learning, Visual Geometry group, Convolution neural network, Image Classification.

1. Main text

Neural Style Transfer combines two different images known as a content image and a style image, such as artwork from a well-known artist, the output image looks like a content image but is redrawn in a style image manner. The publication "A Neural Algorithm of Art Style" is where NST originally appeared. As a painting, an image of the specific content is time- consuming and cost-effective. But with the concept of neural style transfer, we can achieve this task of converting one stylized image to another type of style that appears too realistic. The first idea of neural style transfer was proposed in 2015. Since 2015, NST has become an emerging trend in deep learning. Many modifications have been applied since the beginning to modify the neural style transmission model, modify the optimizers, modify the learning speed, modify the parameters, etc. These modifications need to be done to increase the quality of the images, optimize memory usage, and reduce the losses between the input and output images. Models like CNN, VGG, and Feed Forward Neural Networks are required to perform neural style transfer. Since VGG is used for neural style transfer, most of the neural style transfer work is done using this algorithm, and using VGG will give accurate results compared to other models.

2. Literature survey

There are many existing works for Neural style transfer for images. In this survey, the different techniques of this research will be discussed.

2.1. Related works

In this paper, the author proposed a new method that divides one memory-intensive task into several smaller, less memory-intensive tasks. This Style Transfer is a collection of NST methods that render input images using feedforward neural networks. Due to the high dimension of the output layer, these networks are computationally memory intensive. Most mainstream devices cannot directly stylize high-resolution photos due to memory limitations. Fast style transfer includes a pre-trained network for loss estimation and a feedforward neural network for image transformation. It overcomes image resolution limitations so multiple devices can quickly support high-resolution style transfer without the need to retrain models. Only the transmission network is updated. The weights of the pre-trained feature extractor remain constant throughout (Ma et al, 2020).

In this post, a framework for creating stylized map images was proposed. Style can be successfully conveyed in photographs using contemporary approaches. This research presents a multi-step map art style transfer framework that can be used to improve results by reducing noise in map art images. The proposed framework creates a new piece of map art that uses reference style and content images. "Initial Phase" and "Refinement Phase" are two steps that combine the proposed system. The first purpose of this map art system is to remove the portrait from the reference map art and then use it for the style transfer stage. The second goal of this map art system is to apply the extracted portrait style to the input image. To achieve this, CNN-based neural style transfer is used as the basis for our style transfer technique, and the first result is adjusted to produce a new map drawing so that the final output map drawing is more like the reference map drawing. (Shih et al, 2021).

In this paper, the author proposed a modified Universal Style Transfer method to create visual effects for stylized images, which increases the applicability of our technology for real-world image generation. NST is a method to cleverly apply a specified visual art style to everyday images to create interesting images. In this paper, a powerful post-processing framework has been developed using a modified UST approach, image fusion, and color enhancement techniques. The problems are with the color scheme, stroke severity, and image contrast settings. This UST was presented as a solution to these problems and for the ability to colorize the image. In this study, feature transformation operations combined with style transfer are used to recreate the image. The advantage of this approach is the ability to edit photos using any visual style without having to be trained in any predefined styles. Researchers improve the learning or network architecture of CNNs by using several different methods to create additional visual effects. Meanwhile, the results of these techniques do not seem to be satisfactory. Since there is no instrument to measure the effects of artistic style transfer, qualitative assessment must be highly subjective (Lin et al, 2022).

The primary objective of the paper is to conduct a thorough investigation in order to propose a new approach that is more successful in regulating the strength of the desired style. A pre-trained convolutional neural network that is used as a feature extractor for image content and style in image classification. One method is regression specification, which regulates the output style intensity of the stylized image according to the desired characteristic function between the output style strength and the style control parameter. In order to determine the appropriate relationship between style output force and style control parameter, the style transfer network uses intermediate style anchors (Choi et al, 2020).

In this paper, single image super-resolution (SISR) is introduced to achieve smooth textures. CNN-based algorithms have shown better performance on SISR. Several lossy functions such as content loss, style loss, pre-pixel loss, and full variation control are used in this paper. This model was effectively trained as a two-phase training method. The work of the style transfer network is divided into three parts: feature engineering, style transfer, and image reconstruction. Relu3 3 and the VGG16 network were used to compute style and content information (Li et al, 2020).

This article is to generate an image whose properties are more like content images. The model in this article renders the input image to the extent of known works of art. This model mainly consists of the necessary layers that were mostly present in the VGG-16 model. The generated output will be the input for the next successive layers. With the help of these layers only can gather the features for both style and content representation. The result is a minimization of losses between the loaded style and the content representations (Dinesh Kumar et al, 2022).

In this paper, the author proposed a new Chinese painting style transfer (CPST) algorithm for transfer using the unique properties of ink and wash, which generates Chinese paintings using machine learning techniques. In Chinese painting, fine brush and hand brush are two different techniques. The Chinese Painting Style Transfer (CPST) algorithm claims to correctly transfer both painting techniques and ink tones to natural paintings. This Chinese Painting Style Transfer (CPST) algorithm aims to transfer the reference Chinese painting style to the input image without changing its shape. First, four main limitations are considered when comparing Chinese and Western paintings. The four main limitations are brush strokes, space reservation, diffused ink tone, and yellowing. A convolutional neural network (CNN) is used to incorporate these constraints into the transmission. The CNN is divided into different styles and content layers to faithfully preserve the style of the reference image (Sheng et al, 2019).

In this paper, a multi-style transfer approach is proposed that combines deep neural network (DNN)-based style transfer algorithms to achieve multiple style transfers in a single image. The author of this article designed a multi-style interactive art rendering using an image cropping tool useful for cropping content images into multiple parts. The user walks through the properties of the style and selects the style and algorithm from the manager. An interactive image cropping tool has been developed to crop content images into multiple parts. Each section has a style image and user selection algorithm. This framework includes six content images for any art style and ten typical art styles. It also allows you to add more art style to this frame (Wang et al, 2021).

In this paper, the author proposed an improvised method to mine on image style transfer mapping relations by adding L1 loss, which minimizes the difference between the input image and the output image and improves the effect of image styling. Therefore, it is important to change the image style in order to use the information effectively. The main contribution of this paper is the use of the VGG (Virtual Geometry Group) network model to find information about the content and style characteristics of an image. L1 loss and increased perceptual loss demonstrated improvement in the structural similarity between resulting and artistic images (Hong-an et al, 2021).

In this paper, the author proposed a new image synthesis method for transferring image styles. Neural image style transfer has two types of image feature representation methods used in style transfer based on deep learning and local approaches. Global style information helps eliminate patch transfer errors, such as transferring the mustache, mouth, and eyes to the wrong places. Local style loss helps preserve detailed styles better. By combining this method, patterns are transferred and artifacts are reduced. In order to incorporate these constraints into the transfer, a pre-trained VGG (virtual geometry group) mesh is useful for generating feature maps. (Zhao et al, 2019).

In this paper, the author proposed an improved method for evaluating and improvising the quality of NST stylization using various deep learning techniques. In this work, its clearly observed a few challenges, i.e., firstly, decompose design transfer quality into different quantifiable factors. Furthermore, two new methods of using factors to increase the quality of stylization are presented. The first is to use requirements to combine existing methods to improve strengths. The second is to optimize the factors to obtain better requirements (Wang et al, 2021).

In this article, the author examines the CNN-based transfer of artistic styles and explores the key reasons for this transfer. This method is intended to detect that a lost photo of a stylized result is due to distortion occurring in both the content preservation phase and the style transformation phase; therefore, here he proposed a photographic style transfer method capable of improving photographic stylized results. A total loss function is used to reconstruct content details and avoid the geometric mismatch problem, and a fused model with an edge-retaining filter is used to minimize artifacts. Qualitative evaluations show that this approach successfully suppresses bias while obtaining stylized results (Wang et al, 2020).

In this paper, the author proposed a complex multimodal style transmission network, called deep correlation multimodal style transmission. Image representation plays a key role in stylization, and by creating alternative image representation strategies, different stylization results can be generated. Compared to other correlations, the images generated by the Gram matrix are more effective in balancing performance, content preservation, and style customization. Since there is no instrument to measure the effects of artistic style transfer, qualitative assessment must be highly subjective (Tuyen et al, 2021).

In this article, the author proposed a method of image stylization in which structures are preserved and highlighted. Guided by a global texture extraction network and a local texture refinement network, they successfully preserve layout structures while applying artistic effects. Modern neural-style transfer techniques that train feed-forward neural networks or use an iterative optimization method have yielded remarkable results. It takes into account two factors and the first factor is the represented global structure (Cheng et al, 2019).

A class of algorithms known as "Image Style Transfer" renders content images in different patterns. Specifically, considering the content image (for example, the lion image) and the style image. Their research is based on the Neural Style Transfer field, which uses CNNs to transfer visual style. Style transfer procedures are used to create synthesized images and are not evaluated using any objective criteria. To demonstrate the effectiveness of our proposed strategies, we provide qualitative and quantitative analysis as well as conceptual justification. Additionally, they compare the stylized results with several benchmark methods to show how this proposed approach can produce stylized images with increased diversity. (Li et al, 2020).

In this paper, there could be a new method that allows adjusting the contribution of each lossy layer in neural transmission-type networks, where the real-time transmission depends on the hyperparameters of the model with different "optimum". Style transfer will be created as generating a stylized image p whose content is image of given content c and whose style is close to another given image style. The loss correction is not done perfectly, so the image standard is extremely low. The variable parameters were primarily introduced to manually change the loss of each individual layer. Normalized average style loss for images is 40% (Babaeizadeh et al, 2020).

In this paper, the author proposed a suitable technique for creating high-resolution stylized images based on online style transfer and super-resolution (SR). The style and image from low-res style images and content images create a lowres style image. From there, the SR network recovers the high-resolution style image from the low-resolution style image that was used. The trained SR network is unable to obtain the required information from the natural image database for high-resolution style texture recovery due to the differences between the artistic textures of stylized images and the photorealistic patterns of natural photos. In this study, the author proposed a three-step method for faster creation of highresolution stylized images. Finally, reducing the style differences between the stylized image and the LR style using style backpropagation improves the SR result. (Cheng et al, 2021).

3. Comparison table and Results

Table 1 – Comparison table of related works which consists of techniques, advantages, limitations and gaps

Year	Technique	Advantages	Limitations	Results	Gaps
2020	block shuffle	support high-resolution Fast Style Transfer without having to retrain model	cannot directly stylize high-resolution photographs due to memory constraints.	Memory consumption is high around 0.33gb	enhance quality and image speed
2021	multi-stage framework	improving harmonization and reducing noise	Analyses into the results noise and the harmonies in the art images that are produced still need to be made.	Evaluation is done using harmonization	recover the original map and use this regenerated map to produce new map art
2022	modified universal-style transfer (UST)	Faster computing speed	color scheme, the quality of image, style of the brush strokes, and the adjustment of picture contrast	there is no metric to evaluate	prevent the memory issue
2021	Method regulating the strength of the desired style.	minimize the noise of the art images and produce a better harmonization.	memory limitation on the GPU device.	zero style pictures very similar to the content pictures and full style pictures for a large range of style loss weight, $50 \leq ws \leq 10^4$	how to recover the original map successfully
2020	SISR	It breaks through the limitation of image resolution	Only works on the high resulted images which requires large memory spacing	Style loss is reduced from $50*10^3$ to $23*10^3$ with increase in parameters.	fine-tune this pre-trained SRSTN with both content information and style information to transfer the style.

2022	texture transfer for style transfer.	it can transform arbitrary visual style images without training on any predefined styles	It requires huge number of pictures for training which makes the model too complex	loss of Reconstructing of image using CAN reduces from 15% to 10%, SegEM reduces from 12% to 5% and this proposed reduces from 8.5% to 2.5%	Improve the image quality and speed
2019	Chinese Painting Style Transfer (CPST)	not only transfer ink tone but also transfer painting techniques	best results only for the paintings that are purely consists of the brush, ink, mineral.	User study results proving that paintings better reflect the style of reference.	There is a need of the artistic shapes to be transferred
2021	DNN-based style transfer	The system provides the useful image cropping tool.	Brush strokes blending procedure is not greatly concerned	The correlation of the image with colour preservation is 35% and without color preservation is 32%.	Improve the brush-stroke blending procedures by using better techniques.
2021	mining picture-style transfer	balancing the information of the style pictures and content pictures	It can only capture the low-frequency information.	Structural similarity index measure (SSIM) is 17%	Further explore the more ways to image quality for style transfer using better optimizers.
2019	New synthesized model will add the local and global style	The global style loss helps avoid patch transfer errors	Memory limitation	Changing alpha values Leads to gather content features.	To preserve the structure and color of the content image while having the style transferred, for reducing artifacts.
2021	The method decomposes the quality of style transfer into three quantifiable factors.	By adding other fine-grained factors to enrich the evaluation	The Effect of Automatic Parameter-tuning gives loss to the images during the classification of the images	Using Gatys method the quality score is 2.199	Improvement of our quality factors.

Year	Technique	Advantages	Limitations	Results	Gaps
2020	CNN-based artistic style transfer	Additional similarity loss function that constrains both the detail reconstruction and style transfer procedures	The distortions of content preservation and style transformation stages distort images to lose the photorealistic attribute.	The average scores and standard deviation for images are 2.75+-0.36	Obtaining faithful stylized results
2021	Deep correlation multimodal style transfer.	Variations of correlations	balancing the information of the style pictures and content pictures compared to other correlations.	Correlation for 100 and 1000 iteration of image is -5.28 to -5.36 and covariance is -5.03 to -5.25.	Balancing the task performance for preserving the content and quality will be improved by optimizers.
2019	Technique in which Structures are retrained and highlighted.	This approach achieves the best visual effectiveness.	This can be Adjustable to better preserve or highlight structure when stylizing pictures.	SISIM index for the method is 65%	Improvisation in image processing.
2021	A single-style input style transfer approach with an H-AI inspired design that incorporates human influence	Convenient for image acquisition and displaying.	Color is preserved perfectly, but dependencies between luminance and color are lost	Similarity 56%	Explicitly learn and extract unique perceptual attributes of a single style image, which opens a new direction towards interactive style transfer.

2020	diversified arbitrary style transfer.	original feature maps of the content image.	for instance, permutations have an impact on the original feature maps' structural consistency.	Pixel distance for WCT model is 0.124 and AdaIN+ this SP is 0.087.	Improve the image quality and speed.
2020	A new approach that allows adjustment of each loss layer's contribution in transferring the style	It allows the users to adjust the output	Loss adjustment is not done perfectly so that the quality of image is very low.	Normalized average style loss for images is 40%.	To apply the same approach for other computer vision and deep learning tasks
2022	Per-Style-Per-Model (PSPM), Multiple-Style-Per-Model (MSPM)	Style transfer and super-resolution (SR	Only applicable to the training dataset's styles.	Total time consumed to blend image for this method is around 496.3 sec for 1024*800 size	For further improving the performances, various CNN-based approaches needs to be developed.

4. Conclusion and Future scope

4.1. Conclusion

This article provides an overview of the different methods and a detailed comparison table for style transfer to identify the advantages of their methodologies, limitations of their work, and future work. Most evaluations of neural style transfer methods are qualitative, as judging image quality is primarily subjective. The most common approach is side-by-side image comparison and another common method is user study (harmonization), i.e., only the image quality will be judged based on user feedback.

4.2. Future scope

After analyzing all reference articles, some gaps are identified in the main topic, i.e., neural style transfer. It is obvious that the main thing of this research is to improve image quality. To improve image quality, you modified the SRSTN with both content information and style information to perform a style transformation. Li et al, 2020 noted that the improvement of quality factors, these quality factors can directly serve as a general measure of quality for the transfer of style and impressive visual effects must be achieved by applying some "loss adjustment" method for various fields such as computer vision and deep learning. Using various noise reduction techniques helps to minimize the noise present in the target image as well as optimizers to minimize the overall loss and increase the image quality by gathering more content information from the image.

References

[1]. Ma, W., Chen, Z., & Ji, C. (2020). Block shuffle: a method for high-resolution fast style transfer with limited memory. IEEE Access, 8, 158056-158066.

[2]. Shih, C. Y., Chen, Y. H., & Lee, T. Y. (2021). Map art style transfer with multi-stage framework. Multimedia Tools and Applications, 80(3), 4279-4293.

[3]. Lin, C. C., Hsu, C. B., Lee, J. C., Chen, C. H., Tu, T. M., & Huang, H. C. (2022). A Variety of Choice Methods for Image-Based Artistic Rendering. Applied Sciences, 12(13), 6710.

[4]. Choi, H. C. (2020). Unbiased Image Style Transfer. IEEE Access, 8, 196600-196608.

[5]. Li, Z., Zhou, F., Yang, L., Li, X., & Li, J. (2020). Accelerate neural style transfer with super-resolution. Multimedia Tools and Applications, 79(7), 4347-4364.

[6]. Dinesh Kumar, R., Golden Julie, E., Harold Robinson, Y., Vimal, S., Dhiman, G., & Veerasamy, M. (2022). Deep convolutional nets learning classification for artistic style transfer. Scientific Programming, 2022.

[7]. Sheng, J., Song, C., Wang, J., & Han, Y. (2019). Convolutional neural network style transfer towards Chinese paintings. IEEE Access, 7, 163719-163728.

[8]. Wang, X., Lyu, Y., Huang, J., Wang, Z., & Qin, J. (2021). Interactive Artistic Multi-style Transfer. International Journal of Computational Intelligence Systems, 14(1), 1-13.

[9]. Hong-an, L., Zheng, Q., Qi, X., Yan, W., Zheng, W., Li, N., & Tang, C. (2021). Neural Network-Based Mapping Mining of Image Style

Transfer in Big Data Systems. Computational Intelligence and Neuroscience: CIN, 2021.

[10]. Zhao, H. H., Rosin, P. L., Lai, Y. K., Lin, M. G., & Liu, Q. Y. (2019). Image neural style transfer with global and local optimization fusion. IEEE Access, 7, 85573-85580.

[11]. Wang, Z., Zhao, L., Chen, H., Zuo, Z., Li, A., Xing, W., & Lu, D. (2021). Evaluate and improve the quality of neural style transfer. Computer Vision and Image Understanding, 207, 103203.

[12]. Wang, L., Wang, Z., Yang, X. et al. "Photographic style transfer", The Visual computer 36, 317–331 (2020). https://doi.org/10.1007/s00371-018-1609-4.

[13]. Tuyen, N. Q., Nguyen, S. T., Choi, T. J., & Dinh, V. Q. (2021). Deep correlation multimodal neural style transfer. IEEE Access, 9, 141329-141338.

[14]. Cheng, M. M., Liu, X. C., Wang, J., Lu, S. P., Lai, Y. K., & Rosin, P. L. (2019). Structure-preserving neural style transfer. IEEE Transactions on Image Processing, 29, 909-920.

[15]. Virtusio, J. J., Ople, J. J. M., Tan, D. S., Tanveer, M., Kumar, N., & Hua, K. L. (2021). Neural style palette: A multimodal and interactive style transfer from a single style image. IEEE Transactions on Multimedia, 23, 2245-2258.

[16]. Li, P., Zhang, D., Zhao, L., Xu, D., & Lu, D. (2020). Style permutation for diversified arbitrary style transfer. IEEE Access, 8, 199147-199158

[17]. Babaeizadeh, M., & Ghiasi, G. (2020). Adjustable real-time style transfer. arXiv preprint arXiv:1811.08560

[18]. Cheng, J., Han, Z., Wang, Z., & Chen, L. (2021). "One-Shot" Super-Resolution via Backward Style Transfer for Fast High-Resolution Style Transfer. IEEE Signal Processing Letters, 28, 1485-14.