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RESEARCH ARTICLE

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Graphic Style Transfer Technology in "Multimedia communication": Application of Deep Residual Adaptive Networks in Graphic Design

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Abstract

The image style transfer technology falls under the research areas which have been named among the areas of interest by the scholars in the field of "Multimedia communication". It offers numerous possibilities for application in the area of graphic design. Here, as in many other types of artistic carriers, the aesthetic component plays an important role of the height in the art and the knowledge of whether the graphics look good or not, is here. The actual work that constitutes graphic designing is heavily dependent on the application of manual work, and even basic graphic designing demands a lot of implementation of workforce and resources. In order to solve this problem, this article discusses the example of applying deep residual adaptive network technology on graphic design based on the definitive style transfer technology and deep residual adaptive network technology in "Multimedia communication" as per the study finding. Visual style transfer technology and deep residual adaptive network technology in the process of redesigning and creating graphics in "Multimedia communication" can thus be improved. The generated graphics can meet the needs of art creators, and in terms of creation efficiency, this technology can reach higher levels than manual drawing, such as model peak signal-to-noise ratio and structural similarity, and the output level can also be used as a basic requirement. It can be used in Urban Architectural Exterior Design and Art Creation, possessing good theoretical and practical research values.

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Introduction

Multimedia communica tion and residual adaptive network technology have extended the utilization of image as means of communication and enhanced the degree of connectivity achieved in the data network on the use of image information in the social networks.[1] Given that images are a principal means of disseminating information and a direct representation of artwork, people have utilized images as the medium and means to convey technology in their everyday lives.[2-3]. In today's creation of artistic graphics, artists not only continue to evolve with the demand for mobile hardware equipment over time but also the functionality of fine shooting, standardization of images, and more lifelike visual effects paving the way for art creation. On the one hand, the public's demand for the level and form of image processing is also higher, and they are not only in need of smoothing, restoring, enhancing, and other forms of processing but want more personalized and artistic effects on images.[4-6] As such, studies on beautification and image creation involving multiple styles have gained more significance. Besides the well-known non-photorealistic rendering techniques which have been widely studied for a relatively long time,[7-8] the "transfer technology of image style" has also attracted much attention in recent years.[9-12]

Moreover, since the functions of the image processing software are continuously being upgraded, not only do people hope that new art styles can be easily applied to photographic images but also look forward to enhancing the contrast of the foreground objects of interest in the images. Hence, the area of interest, which is the foreground, is segmented in the image and the contrast is manipulated to make the image to appear artistic while the face looks like the target image. Thus, the advent of the image style transfer technology not only enhances the aesthetic factor but, in a way, enriches the life experience of people to a considerable extent.[13] Image-style transfer technology promotes the animation and film production industries to create more vivid animations owing to the encouragement of information technology. Recently, with the innovation and replacement of technology and the development of computer science, the neural network has developed rapidly and it is widely used in society including the use of graphic style shift. It also influences the image style transfer and gradually forms two categories in Figure 1: style transfer without using deep learning; style transfer using deep learning.

Style transfer without using a neural network usually means the sort of image art stylization that was in use before the three styles are namely; stroke-based, images' category,[19, 20z and image filtering[21] Image stylization was in use before the use of the neural network is also known as image style transfer without the use of the neural network.[22] The image style migration method called the neural network is in a cyclic one that connects two one-directional GANs in a ring. In this setup, the migration of image features depends on the pairing of the training data, where impressions generated by one set impact another. This method applies neural network technology to learn and implement image style migration techniques, which can be broadly categorized into two types: Real Time Migration of Styling – where the process is done in real-time under the umbrella of Online Image Optimization. Offline Model Optimization – here the migration is done at the time of the model download.

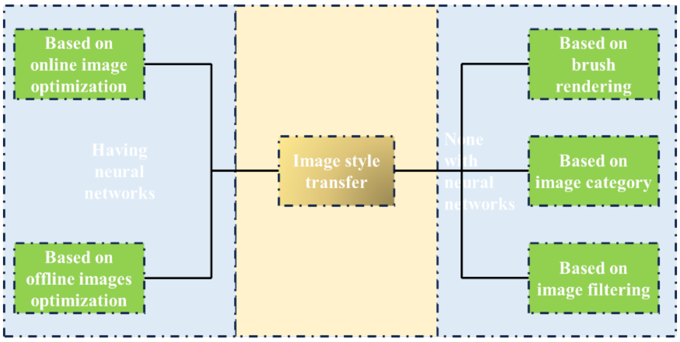

Fig. 1 "Classification of Image Style Transfer Methods

These days, picture style transfer is all the rage, offering users a plethora of services including filter camera apps, movie editing, Meitu Xiuxiu, B612, and the now-famous TikTok filter. Consequently, based on the provided information, the outcome was suboptimal. Consequently, this paper investigates visual style transfer technologies based on this premise. In future endeavours, we aim to acquire additional methodologies for style description through computational training, utilizing "deep residual adaptive network models" as a foundational deep learning technology. This approach seeks to achieve optimal stylization effects and facilitate multi-domain image transfer. Ultimately, the research conducted holds significant representational importance.

Related works

In image style transfer, the natural images are transformed into the style images using computer technology. As mentioned in the theoretical part of the deep learning method, this paper employs a deep convolutional residual neural network model in an attempt to obtain transfer images with artistic style features quickly. The low-level concrete features of the image content and the style are segmented and separated and these high-level abstract feature representations are then fed to the VGG deep convolutional model;[30-32] Using the iterative optimization to realistically Synthesize an artistic effect image based on the image content and a new texture style to achieve the style transformation art effect.

Structure of Deep Residual Adaptive Network Model

Convolutional neural network texture synthesis is the idea of picture style transfer that has been utilized in this article. It is based on a randomly initialized gradient descent model and a VGG network. After defining the loss function for the model network and going through multiple iterations, the artistically styled transfer image is finally obtained.

Deep residual network

A deeper learning network’s model structure and the quantity of feature information retrieved by a neural network model are both driven by the increasing complexity of the technical requirements. Therefore, as the model depth increases, neural networks are more likely to handle various problems, such as vanishing or bursting gradient, which impacts the pleasure of consumers with the application of graphic style transfer. Incorporating residual blocks from traditional network models, deep residual networks help control and guide the current structure while also solving issues like gradient explosion and model vanishing.[33-34] The construction of a single residual block is shown in Figure 2.

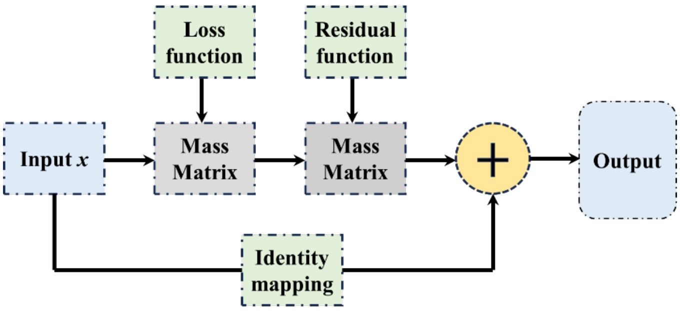

Fig. 2: “Residual block structure of depth residual adaptive network model”

Basic network model

The term ‘Convolutional neural network’ is a neural network architecture which built specifically for two dimensional inputs such as images or videos. It can effectively extract the characteristic information of data and therefore it has given the ground work for the further enhancement of the deep learning.[35-37] Convolution layer, pooling layer, activation layer and full connection layer play the most important role and provides the best image “Transfer learning”.[38-40]

① Convolutional Layer

As one of the key layers in the CNN model, the convolution layer plays a critical role in image classification. In the convolution layer network, the convoluted operation will be implemented to lower dimension for the high dimension inputted data and, for this reason, it is known as the feature extraction layer. At this network layer, neurons only need to interface with some neurons in the following layer to reduce the dimension of data. This method is also referred to as local connection. This is called discrete convolution which is more frequently used and it a linear transformation operation of images.[41] Discrete convolution has sparsity and parameter reuse, which implies in the convolution; there are some parameters which are processed with a small portion of the input image. This way, the number of parameters can be brought down to a large extent to thereby balancing the computational cost and the size of the model store. Secondly, the issue of sparsity can also improve the efficiency of the convolution layer concerning the number of computations that need to be made. The formula for discrete convolution operation is provided in equation 1 while the convolution kernel operation as indicated in figure 3:

$$y(n)=\sum_{i=-\infty}^{\infty}x(i)h(n-i)=x(n)\otimes h(n) \quad (1)$$

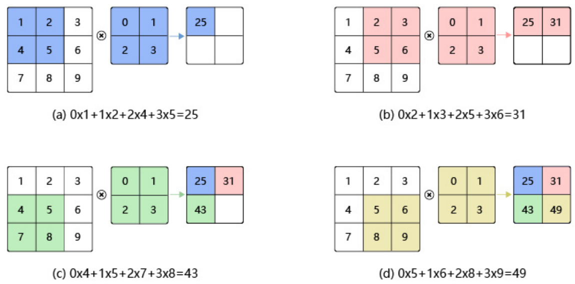

Fig. 3: Schematic diagram of convolution kernel operation

② “Pool layer”

Pooling layer serves the purpose of down sampling the feature map that is obtained after the above convolution process. At present, the most common pooling methods include only the maximum pooling[42] as illustrated in Figure 4 and average pooling[43] as depicted in figure 5.

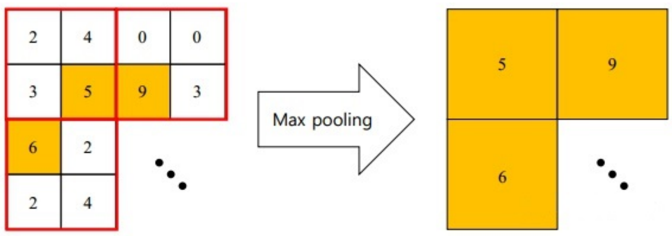

Fig. 4: Schematic diagram of maximum pooling

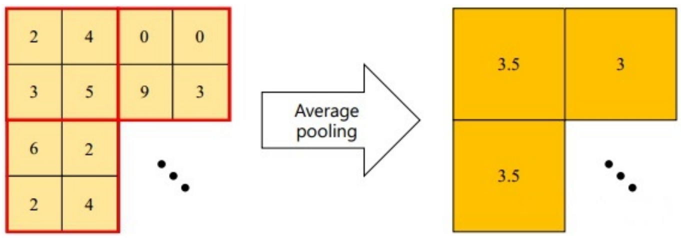

Fig. 5: Schematic diagram of average pooling

In view of this, in maximum pooling, they are able to extract some features from an image and also to retain the edges of the images due to the nonlinearity of the pooling layer. However, mean pooling only involves averaging the pixel intensity of the region of interest and therefore suffers from information loss and blurring of it. Thus, in the image transfer training in this paper, the ‘Pool layer’ is utilized as in the image “Transfer learning”.

③ Active layer

To solve this problem, it is important to perform normalization for each batch within the specific layer of a neural network. As a result, there exists a need to select the activation function for the neural network appropriately. The common activation functions are; sigmoid, tanh and relu as depicted in the figure 6 below.

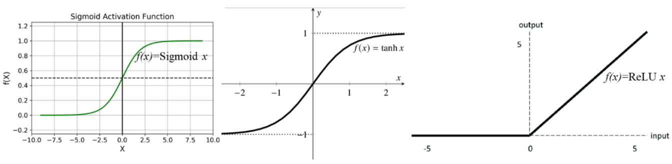

Fig. 6: Common activation functions (Sigmoid, Tanh, TeLU)”

Image migration’s activation function selection makes it simple to converge during training and allows for optimum feature retention. One of the biggest challenges in training neural networks is the vanishing gradient issue, which this function might cause. Because of this, relu is an activation function that might be considered for use in picture migration.

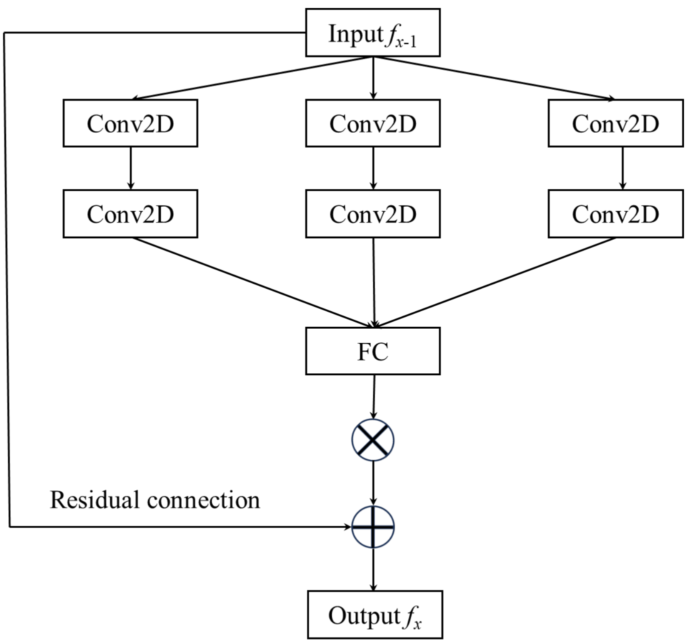

Fig. 7: Schematic diagram of basic network model structure

④ Full connection layer

While training a neural network model, specifically a convolutional neural network, the entire connectivity layer is able to project the learnt “distributed feature representation” onto the sample label space while simultaneously maintaining a large model capacity during fine-tuning to ensure the migration of the model representation capability through training. Consequently, in order to maintain a high model capacity and transfer model representation ability, the complete connection layers are combined with multiple layers of the model in the picture “Transfer learning” of this study. Figure 7 is a schematic of the main network model used in this study.

Establishment of loss function

When discussing machine learning in general, the term “transfer learning” is useful. The basic premise is to apply the learnt model to new tasks. A similar logic applies to the “synthesis process”; in this case, the content and stylistic differences between the source and output images might inform the specification of the loss function. To achieve the goal of picture migration, the loss function is used to minimize the composite image’s content, making it as close to the destination image as feasible (see figure 8).

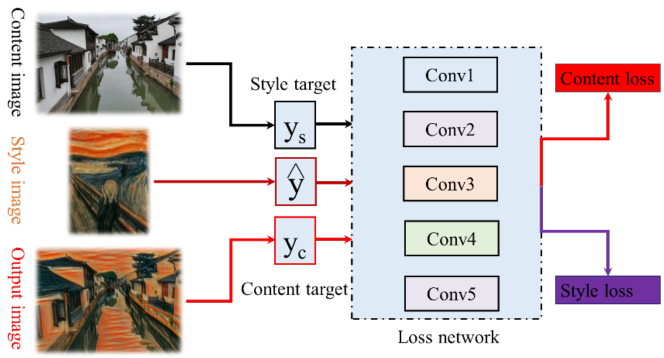

Fig. 8: Schematic diagram of graphic migration effect process

Shapes are often used in style migration, and frequent loss takes into account the whole variation loss, style loss, and content loss as a whole [44, 45]. Total variation loss quantifies the degree to which the composite picture is smooth, style loss quantifies the degree to which the composite and style images vary in terms of content attributes, and content loss quantifies the degree to which the content image differs from the style image. When it comes to content retention, style transfer, and noise reduction, the preference for synthetic pictures may be fine-tuned with the use of weight super factors. Therefore, the following loss must be established in order to use it for the image migration process as a measure of the difference between the composite picture and the destination image:

First thing to do: The input image is denoted as x and the output image as y. After computation, the convolution feature of the input image at layer l is represented as Plij, where is the st position and is the number of channels in the convolutions layer. The output image y's convolution feature at the convolution layer's layer l is defined as Flij. Given the variables that are important, we can define the content loss function as 2 in the following way:

$$Loss_{content}(x, y, l) = \frac{1}{2}\sum_{ij}(F_{ij}^{l} - P_{ij}^{l})^2 \tag{2}$$

The picture style is often represented with the Gram matrix of the image convolution layer, which is a non-negative, symmetric matrix derived from the inner product of many vector groups. Based on the above analysis, let the convolution feature be denoted as Flij, and the components of the Gram matrix corresponding to the aforementioned output are represented by formula 3.

$$G_{ij}^{l} = \sum_{k} F_{ik}^{l} F_{jk}^{l} \tag{3}$$

Step 2: We will assume that the first convolution layer has the following parameters: a height of ml, a width of NL, an input image of type x, an output image of style y, a Gramme matrix of Xl for the input image x, and a Gramme matrix of Yl for the output image. Just as in the last part, formula 4 shows that a loss function of the single-layer style is established:

$$Loss_{style}(x, y, l) = \frac{1}{4N_l^2 M_l^2}\sum(X_{ij}^{l} - Y_{ij}^{l})^2 \tag{4}$$

In Step 3, we can get the total loss function of the style in the loss network using formula 5:

$$Loss_{style}(x, y) = \sum_{l} \omega_l \, Loss_{style}(x, y, l) \tag{5}$$

As seen in formula 6, the total loss function may therefore be determined:

$$Loss_{Total}(O_{style}, O_{content}, R) = \alpha Loss_{content}(O_{content}, R) + \beta Loss_{style}(O_{style}, R) \tag{6}$$

Where: " represents the maneuvering of the target style image, Is the content image that one wants to generate, Whereas R is the image to be generated; stands for the content loss function, stands for the style loss function; *α*, *β* they are the super parameters which are used to define the ratio between these two loss functions in the total loss."

Methodology

Experimental data set

In order to make sure that the results are more accurate representations of reality, the author of this article used the Python crawler software to randomly select 1200 sets of high-definition and ultra-high-definition images from the internet to use as the training set for the model in this article. Each of the crawling photos had a resolution of about 2K and mostly came from Baidu Baike and Wikipedia. Pictures shown here range from portraits to structures to picture paintings. A few examples of the types of pictures include landscape photography, as seen in Figure 9;

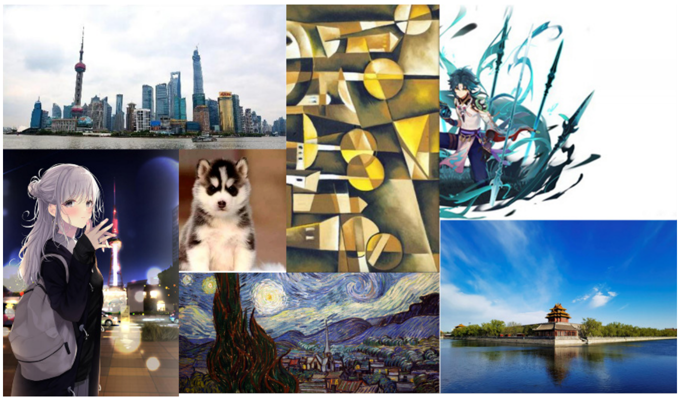

Figure 9 Representative diagram of training set

While conducting the experiment, the images having data larger than a certain ratio were cropped in order to make modeling more manageable during the training process. Meanwhile, the cropped images were re cleaned, which included the conversion of image format as well as geometric correction and produced a new dataset. As for the model's accuracy, this article uses the ImageNet dataset as its foundation, in addition to randomly crawled datasets for training. Other deep learning models, such as VGG-19 and "SRCNN," are also utilised in the computation. The aforementioned foundational dataset has been rigorously tested by deep learning testers and contains several important visual aspects. It is also applicable and has been well illustrated in the image style transformation explained in the above basic model. Therefore, it is possible to comprehensively and effectively verify the performance of this model relative to the other models.

Experimental parameter setting

The operational context of this paper: The deep learning framework used is TensorFlow, the operating system is Windows 10, and the programming language is Python. The system has a minimum of an 8-core, 16-thread CPU, over 32GB of RAM, more than a 512GB SSD, and in excess of a 2TB HDD, along with a professional graphics card, a power supply above 1200W, and is outfitted with an RTX 2080 Ti to facilitate model computing.

Experimental index setting

To improve the model's generalization capability and robustness, the training data is enhanced using methods such as flipping, rotation, and scaling. The training component uses the Adam optimizer with an initial learning rate of 0.001. During this training, the learning rate is adjusted and reduced by half after every 1000 iterations conducted in the training process. The total number of iterations is 20,000, with 16 instances used in each iteration. The first criterion for assessment was determined based on the widespread usage of "PSNR" as a standardized objective metric for assessing picture quality in this domain. Numerous experimental findings indicate that the "PSNR" value does not fully correlate with the quality seen by the human eye; it has been noted that a greater "PSNR" value often corresponds to worse picture quality, and vice versa. But structural similarity can accurately make up for this deficiency and has long been used as the standard for assessing the similarity of images. This may also serve as a method for evaluating the quality of compressed pictures. This article assesses the model by integrating two assessment metrics: structural similarity (SSIM) and peak signal-to-noise ratio (PSNR).

Specific implementation of the experiment

There are two parts to this experiment: the training phase and the generating phase. It is worth noting that the data acquired at each step of the experiment differs, as seen below.

First, there is the training phase. The training data set includes both style images and content images. Here are the specifics. Various images from different datasets are shown in Figure 10. The target processing image is the processing picture of the content picture. The content picture is the foundation upon which the author's intended style is built. During training, the style picture's job is to map the element content to the content picture so that it can transfer the content picture's graphic style. The final image that emerges from transferring the style of one photo to another is called the output picture.

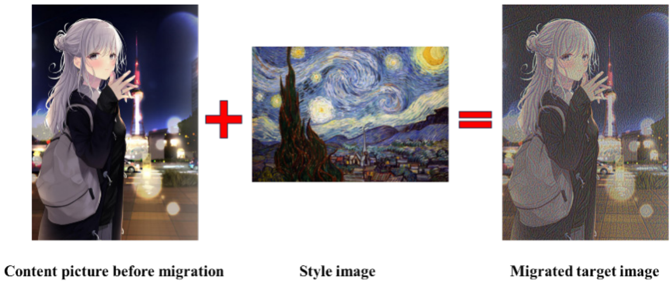

Fig. 10: Schematic diagram of three kinds of pictures for model training

Step two, generation, involves determining the trained model. Since the presentation is still in progress, the only thing that is needed at the moment is the content picture. The next tests will reflect the content picture, which we have chosen as a collection of photographs of natural landscapes in a range of sizes.

Results and Discussion

For the depth residual adaptive network model (hereafter referred to as model 1), VGG-19, and "SRCNN" created in this work, the data set utilized in it (collectively called data set 1) and the basic data set imagenet data set are used instead. Two sets of testing yielded different results. In Table 1, the "PSNR" index is mentioned, and in Table 2, the SSIM index is mentioned.

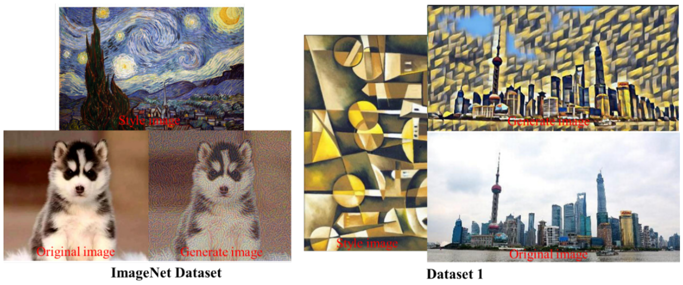

Fig. 11: Image style migration results of model 1 for images from different datasets

Figure 11 shows that the first dataset consists of photos of the outside of the Shanghai Bund, whereas Imagenet is a database of images of animals. Not only are the two ensembles not identical, but the style photographs used to illustrate them are also somewhat different. One is painting, and the other is painting images. Nevertheless, Model 1 was able to effectively apply the desired style to the target picture, achieve the goal of style transfer, and produce satisfactory results regardless of whether the Imagenet dataset contained images of animals or the Shanghai Bund exterior. Table 1 displays the precise data. Based on the results of the study, it is clear that this model is useful for the newly created dataset, and it also proves that this model can be used to transfer picture styles in practice.

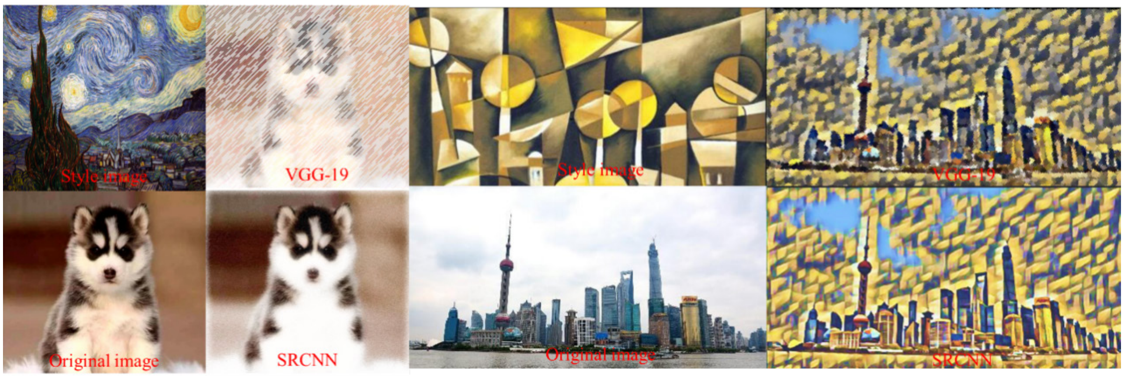

Fig. 12: Image style migration results of other models for different dataset images

The training results of the two separate training sets from the model "SRCNN" and the model VGG-19 are marginally lower than the model built in this study, as seen in Figure 12. The comparison model described above is capable of executing a successful style transfer on the aforementioned photos of the dataset, regardless of whether it is the Imageten dataset, which primarily consists of animal images, or the first dataset 1, which includes Shanghai Bund exterior pictures. The style transfer effect is fully realized by applying the style image of the aforementioned image to the target image. While the "SRCNN" model migrates better for animal models, leaning more towards the animal itself, the VGG-19 model migrates worse for animal models, leaning more towards the style image. Model I was the best in this regard. Figure 11 shows that of the two scenarios, model i is the worst option. The model's efficacy has been confirmed, and the style change is less drastic, which may aid in better communicating the author's views.

Table 1: Comparison of "PSNR" indexes of different models for data sets

"model"	"Dataset 1"	"ImageNet Dateset"
"Model 1"	"36.35"	"36.09"
"VGG-19"	"31.33"	"31.24"
"SRCNN"	"32.48"	"32.01"

Table 2 "Comparison of SSIM indicators of different models for data sets"

"model"	"Dataset 1"	"ImageNet Dateset"
"Model 1"	"0.9413"	"0.9207"
"VGG-19"	"0.9109"	"0.9287"
"SRCNN"	"0.8354"	"0.8698"

For graphics style transfer during training, the depth residual adaptive network model created in this research outperforms the two standard models, VGG-19 and "SRCNN," as shown in Table 1 and Table 2, which provide an overall comparison of the two evaluation indices. Table 1 shows that the paper's model 1 "PSNR" is 5.02 dB and 3.87 dB higher than other models for dataset 1, in terms of "PSNR." On the other hand, for the Imagenet dataset, it's 4.85 dB and 4.08 dB higher. Additionally, the model developed for this study exhibits robust visual style migration performance for both the Imagenet dataset and dataset 1, as seen in Table 2—the structural similarity index for datasets illustrated in Tables 1 and 2. It is clear that the Imagenet dataset has a lesser structural similarity than vgg-19, but any value over 0.9 shows a reasonable amount of visual style migration. The model's performance on Imagenet is better than the one built in this study, but it's poorer on dataset 1, and that's because vgg-19 has been used to train the model by many academics. With a large migration factor and superior overall graphic style migration capacity, it is clear that model 1 established in this research is the best option.

Conclusion

In an effort to make creative creativity easier to reach, this research aims to provide a model for transferring image styles using depth residual adaptive networks. The goal is to utilize this technology to produce easy technical art by transferring graphic styles from one style to another. This model takes into account image characteristics by introducing a convolutional neural network, improving upon that model, introducing an adaptive model and depth residual theory, and finally, using a loss function that combines pixel loss with perceptual loss to further improve the quality of the reconstructed image. To create a new dataset 1, we used it to extract various types of high-definition photographs. For comparison training, we also included the classic imagenet dataset, vgg-19, "SRCNN" models, and others. The evaluation can also suggest that the quantitative and qualitative assessments have improved the visual quality and detail of the reconstructed image, and that the proposed model outperforms the other two models in the objective assessment indexes, such as "PSNR" and SSIM. Additionally, the training impact of the model in this study is comparable to that of the self-constructed dataset 1, which demonstrates that the model has strong application, when compared to the Imagenet dateset dataset. We are able to demonstrate the substantial practical importance of the suggested paradigm. Despite being well-versed in a wide range of subjects, the author of this piece cannot attest to Innoviz's applicability in other domains as the company does not disclose its intended use in detail and since there has been insufficient investigation into relevant technology. The author plans to revise and improve this piece based on her future studies on the subject.

References

[1] Bera, S., Sur, S. N., & Bera, R. (2015). Multimedia communication using DVB technology over open range. *Procedia Computer Science*, *70*, 282-288.

[2] Berrocal, E., Meglinski, I. V., Greenhalgh, D. A., & Linne, M. A. (2006). Image transfer through the complex scattering turbid media. *Laser Physics Letters*, *3*(9), 464-467.

[3] Wong, C. J., Lim, H. S., MatJafri, M. Z., & Abdullah, K. (2006, May). Image data transfer over the Internet protocol for air quality studies. In *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XII* (Vol. 6233, pp. 335-348). SPIE.

[4] Slobodyan, M. S. (2016). Methods Of Creation Of Permanent Zirconium Alloy Joints In Reactor Art. A Review.

[5] Sunarto, B. (2015). Basic knowledge and reasoning process in the art creation. *Open Journal of Philosophy*, *5*(05), 285-296.

[6] Kinoshita T .A Study in Teaching Art on the Principle of Creation : Searching for a Method of Teaching Art[J].Art Education, 2002:73-84.DOI:10.24455/aaej.23.0_73.

[7] Yang, C. K., & Yang, H. L. (2008). Realization of Seurat's pointillism via non-photorealistic rendering. The Visual Computer, 24, 303-322.

[8] Cheok, A. D., Lim, Z. S., & Tan, R. T. K. (2007). Humanistic Oriental art created using automated computer processing and non-photorealistic rendering. *Computers & Graphics*, *31*(2), 280-291.

[9] Shin, S. J., You, S. C., Jeon, H., Jung, J. W., An, M. H., Park, R. W., & Roh, J. (2021). Style transfer strategy for developing a generalizable deep learning application in digital pathology. Computer Methods and Programs in Biomedicine, 198, 105815.

[10] Izadyyazdanabadi, M., Belykh, E., Zhao, X., Moreira, L. B., Gandhi, S., Cavallo, C., ... & Yang, Y. (2019). Fluorescence image histology pattern transformation using image style transfer. *Frontiers in oncology*, *9*, 519.

[11] Kumari, M., Khare, A., & Khare, P. (2010). JPEG compression steganography & crypography using image-adaptation technique. *journal of advances in information technology*, *1*(3), 141-145.

[12] Li, Y., Wang, Y., Tseng, H. W., Huang, H., & Chen, C. C. (2021). Optimized and improved methods of image style transfer for local reinforcement. *Sensors and Materials*, *33*(9), 3325-3332.

[13] Kolland, F. (1990). National cultures and technology transfer: The influence of the Mexican life style on technology adaptation. *International journal of intercultural relations*, *14*(3), 319-336.

[14] Panchanathan, S., Yeap, T. H., & Pilache, B. (1992, September). Neural network for image compression. In *Applications of Artificial Neural Networks III* (Vol. 1709, pp. 376-385). SPIE..

[15] Yan, Z., Zhang, H., Piramuthu, R., Jagadeesh, V., DeCoste, D., Di, W., & Yu, Y. (2015). HD-CNN: hierarchical deep convolutional neural networks for large scale visual recognition. In *Proceedings of the IEEE international conference on computer vision* (pp. 2740-2748).

[16] Shang, C., & Shen, Q. (2002). Rough feature selection for neural network based image classification. *International Journal of Image and Graphics*, *2*(04), 541-555..

[17] Estévez, P. B., Ruz, G. A., & Perez, C. A. (2003). Fuzzy min-max neural network for image segmentation. In *The 7th Joint Conference on Information Science, North Carolina, USA* (pp. 26-30).

[18] Qian Xiaoyan. Overview of Image Based Non Realistic Art Rendering Techniques [J]. Journal of Engineering Graphics, 2010 (1): 7. DOI: 10.3969/j.issn.1003-0158.2010.01.002

[19] Liu Yanying. A Review of Research on Non Realistic Rendering of Computer Images [J]. Information Communication, 2013 (5): 2. DOI: CNKI: SUN: HBYD.0.2013-05-023

[20] Zhang, Z., Wei, F., Liang, G., & Wang, X. (2024). Graphic style transfer technology in multimedia communication: an application of deep residual adaptive networks in graphic design. *International Journal of Communication Networks and Information Security*, *16*(1), 198-210.

[21] Kyprianidis, J. E., Collomosse, J., Wang, T., & Isenberg, T. (2012). State of the" art": A taxonomy of artistic stylization techniques for images and video. *IEEE transactions on visualization and computer graphics*, *19*(5), 866-885.

[22] Cai, X., Ge, Y., Cai, R., & Guo, T. (2019). Image color style migration method for mobile applications based color feature extraction. *Journal of Computational Methods in Sciences and Engineering*, *19*(4), 879-890..

[24] Gatys, L. A. (2015). A neural algorithm of artistic style. *arXiv preprint arXiv:1508.06576*..

[25] Gatys, L. A., Ecker, A. S., & Bethge, M. (2016). Image style transfer using convolutional neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2414-2423).

[26] Qawaqneh, Z., Mallouh, A. A., & Barkana, B. D. (2017). Deep convolutional neural network for age estimation based on VGG-face model. *arXiv preprint arXiv:1709.01664*.

[27] Talafha, B., & Al-Ayyoub, M. (2018, September). JUST at VQA-Med: A VGG-Seq2Seq Model. In *CLEF (working notes)*.

[28] Gorti, S. K., & Ma, J. (2018). Text-to-image-to-text translation using cycle consistent adversarial networks. *arXiv preprint arXiv:1808.04538*.

[29] Zhao, Y., Wu, R., & Dong, H. (2020). Unpaired image-to-image translation using adversarial consistency loss. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part IX 16* (pp. 800-815). Springer International Publishing.

[30] Kaur, M., Satapathy, S., Soundrapandiyan, R., & Singh, J. (2018). Targeted style transfer using cycle consistent generative adversarial networks with quantitative analysis of different loss functions. *International Journal of Knowledge-based and Intelligent Engineering Systems*, *22*(4), 239-247..

[31] Li, W. J., Ruan, S. J., & Yang, D. S. (2020). Implementation of energy-efficient fast convolution algorithm for deep convolutional neural networks based on FPGA. *Electronics Letters*, *56*(10), 485-488..

[32] Balachandran, G., & Venu Gopala Krishnan, J. (2023). Moving scene-based video segmentation using fast convolutional neural network integration of VGG-16 net deep learning architecture. *International Journal of Modeling, Simulation, and Scientific Computing*, *14*(01), 2341014.

[33] Ding Jr, I., Zheng, N. W., & Hsieh, M. C. (2021). Hand gesture intention-based identity recognition using various recognition strategies incorporated with VGG convolution neural network-extracted deep learning features. *Journal of Intelligent & Fuzzy Systems*, *40*(4), 7775-7788..

[34] Tai, Y., Yang, J., & Liu, X. (2017). Image super-resolution via deep recursive residual network. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 3147-3155)..

[35 Hendling, K., Franzl, G., Statovci-Halimi, B., & Halimi, A. (2003). Residual network and link capacity weighting for efficient traffic engineering in MPLS networks. In *Teletraffic Science and Engineering* (Vol. 5, pp. 51-60). Elsevier.

[36] Kim, P. (2017). Convolutional neural network. In *MATLAB deep learning: with machine learning, neural networks and artificial intelligence* (pp. 121-147). Berkeley, CA: Apress.

[37] Chen, Y., Cao, Z., Zhang, J., Liu, Y., Yu, D., & Guo, X. (2022). Wearable ultraviolet sensor based on convolutional neural network image processing method. *Sensors and Actuators A: Physical*, *338*, 113402..

[38] Chen, Y. (2021, February). Research on convolutional neural network image recognition algorithm based on computer big data. In *Journal of Physics: Conference Series* (Vol. 1744, No. 2, p. 022096). IOP Publishing..

[39] Zain, Z. M., Sakri, S., Asmak Ismail, N. H., & Parizi, R. M. (2022). Software Defect Prediction Harnessing on Multi 1-Dimensional Convolutional Neural Network Structure. *Computers, Materials & Continua*, *71*(1)..

[40] Kim J Kang JK Kim Y A Research on Quantized Lightweight Convolutional Neural Network Structure for Facial Emotion Recognition J Journal of the Institute of Electronics and Information Engineers 2020 57 12 51 59 DOI 10.55730 ieie 2020.57 12.51.

[41] Tan, M., Wu, F., Kong, D., & Mao, X. (2021). Automatic liver segmentation using 3D convolutional neural networks with a hybrid loss function. *Medical Physics*, *48*(4), 1707-1719.

[42] Kumar, L. A., & Jebarani, M. E. (2022). An Optimized Convolutional Neural Network for Multi-Spectral Change Detection Technique. *Journal of Uncertain Systems*, *15*(03), 2241006..

[43] Abdullah, D. (2024). Strategies for low-power design in reconfigurable computing for IoT devices. *SCCTS Transactions on Reconfigurable Computing*, *1*(1), 21-25. https://doi.org/10.31838/RCC/01.01.05

[44] Kavitha, M. (2024). Energy-efficient algorithms for machine learning on embedded systems. *Journal of Integrated VLSI, Embedded and Computing Technologies*, *1*(1), 16-20. https://doi.org/10.31838/JIVCT/01.01.04

[45] Arvinth, N. (2024). Integration of neuromorphic computing in embedded systems: Opportunities and challenges. *Journal of Integrated VLSI, Embedded and Computing Technologies*, *1*(1), 26-30. https://doi.org/10.31838/JIVCT/01.01.06

[46] Dorofte, M., & Krein, K. (2024). Novel approaches in AI processing systems for their better reliability and function. *International Journal of Communication and Computer Technologies*, *12*(2), 21-30. https://doi.org/10.31838/IJCCTS/12.02.03.

[47] Maheskumar, B. N., & Akhtar, S. (2016). An online and offline character recognition using image processing methods – A survey. *International Journal of Communication and Computer Technologies*, *4*(2), 102-107.

[48] Hrunyk, I. (2018). Computer technology applications and the data protection concept. *International Journal of Communication and Computer Technologies*, *6*(1), 12-15.

[49] Asadov, B. (2018). The current state of artificial intelligence (AI) and implications for computer technologies. *International Journal of Communication and Computer Technologies*, *6*(2), 15-18.