IARJSET

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Vol. 7, Issue 8, August 2020

DOI 10.17148/IARJSET.2020.7822

# Image Style Transfer using Convolutional Neural Networks

**Miss. Priti K. Mudkanna[1], Miss. Ankita A. Bhabire[2], Miss. Shraddha R. Chougule[3], Miss. Tejaswini D. Pujari[4]**

Student, Computer Science & Engineering Department,

Sharad Institute of Technology College of Engineering, Yadrav – Ichalkaranji (M.S.), India[1,2,3,4]

**Abstract:** The semantic content of an image in different styles has been difficult image processing task. A major limiting factor for previous approaches has been the lack of image representations that explicitly represent semantic in formation and thus, allow separating image content from style. Image representations derived from Convolutional Neural Networks optimized for object recognition, which make high-level image information explicit. Introduce a Neural Algorithm of Artistic Style that can separate and recombine the image content and style of natural images. The algorithm allows producing new images of high perceptual quality that combine the content of an arbitrary photograph with the appearance of numerous well-known artworks. Results provide new insights into the deep image representations learned by Convolutional Neural Networks and demonstrate their potential for high-level image synthesis manipulation.

**Keywords:** Image Reconstruction, Neural Network, Image representation, Visualization, Convolutional Neural Networks, Image Style Transfer, Starry Night Style, Waves Style, La Muse Style, Neural Style Transfer.

## I. INTRODUCTION

There has been lots of progress in the field of image style transfer, a process which aims at redrawing an image in the style of another image. Gatys proposed the first approach using Convolutional Neural Networks, but their iterative algorithm is not efficient. Many others followed and improved their approach in terms of speed. In order to transfer the style of an image to another image, the style and content of these images and the output image must be represented in a suitable way. CNNs are neural networks that can be used for image classification. They have trained on large labelled datasets and learn both feature extraction and classification in an end-to-end manner. Transferring the style from one image into another can be consider a problem of texture transfer. In texture transfer, the goal has to synthesis a texture from a source image while constraining the texture synthesis in order to preserve the semantic content of a target image. For texture synthesis, here exist large ranges of powerful non-parametric algorithms that can synthesize photorealistic natural textures by resampling the pixels of a source texture.

Most previous texture transfer algorithms rely on these nonparametric methods for texture synthesis while using different ways to preserve the structure of the target image. Style transfer is the technique of recomposing images in the style of other images. It has actually possible to transfer artistic style from one painting to another picture using convolutional neural networks. CNN has shown to be able to well replicate and optimize these key steps in a unified framework and learn hierarchical representations directly from raw images. Universal style transfer has been image-editing task that renders an input content image using the visual style of arbitrary reference images, including both artistic and photorealistic stylization. However, due to its optimization-based nature, it suffered from low efficiency. Therefore, developed a fast feed-forward approach that has much faster, but lacks in flexibility. This means, in contrast to the optimization-based approach, it cannot transfer arbitrary styles but must be retrained for every style. The activation values of feature maps in higher layers can be used to roughly reconstruct the content of an image without exactly reconstructing local structures.

## II. NEURAL STYLE TRANSFER ON IMAGES

**A Neural Algorithm of Artistic Style -** Gatys et al proposed the first algorithm that worked really well for the task of neural style transfer. In this algorithm, a VGG-16 architecture pertained on Image Net is used to extract the features that represent semantic content and style.

**Content Representation -** Generally each layer in the network defines a non-linear filter bank whose complexity increases with the position of the layer in the network. Hence a given input image is encoded in each layer of the Convolutional Neural Network by the filter responses to that image.

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**Style Representation -** To obtain a representation of the style of an input image, we use a feature space designed to capture texture information. This feature space can be built on top of the filter responses in any layer of the network. It consists of the correlations between the different filter responses, where the expectation is taken over the spatial extent of the feature maps.

**Style Transfer -** To transfer the style of an artwork onto a photograph we synthesise a new image that simultaneously matches the content representation of and the style representation.

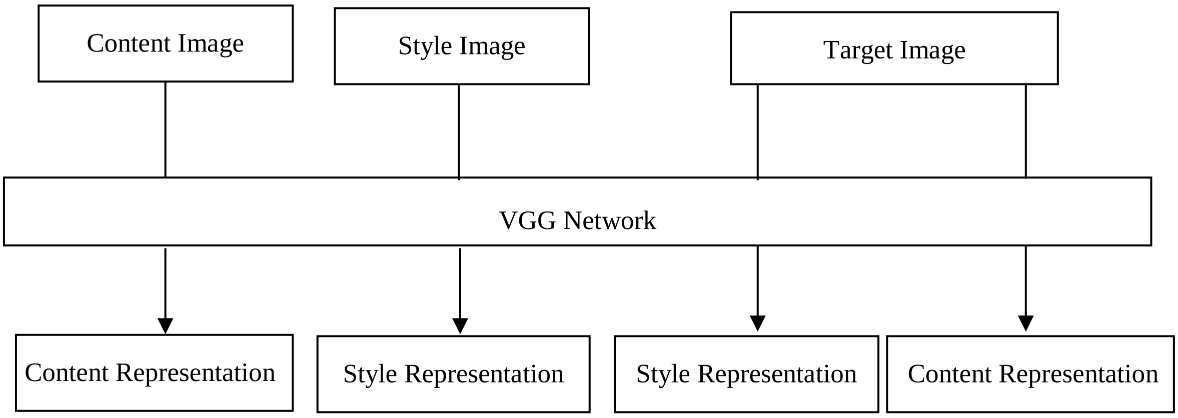


Fig. 1. Image Style Transfer

## III. IMAGES STYLE TRANSFER AFTER APPLYING CNN

The images can transfer in four style namely, Composition vii Style, Starry Night Style, The Waves Style & La Muse Style. Following Fig. 2.1, 2.2, 2.3 & 2.4 shows the style transfer after applying algorithm of Convolutional Neural Networks.

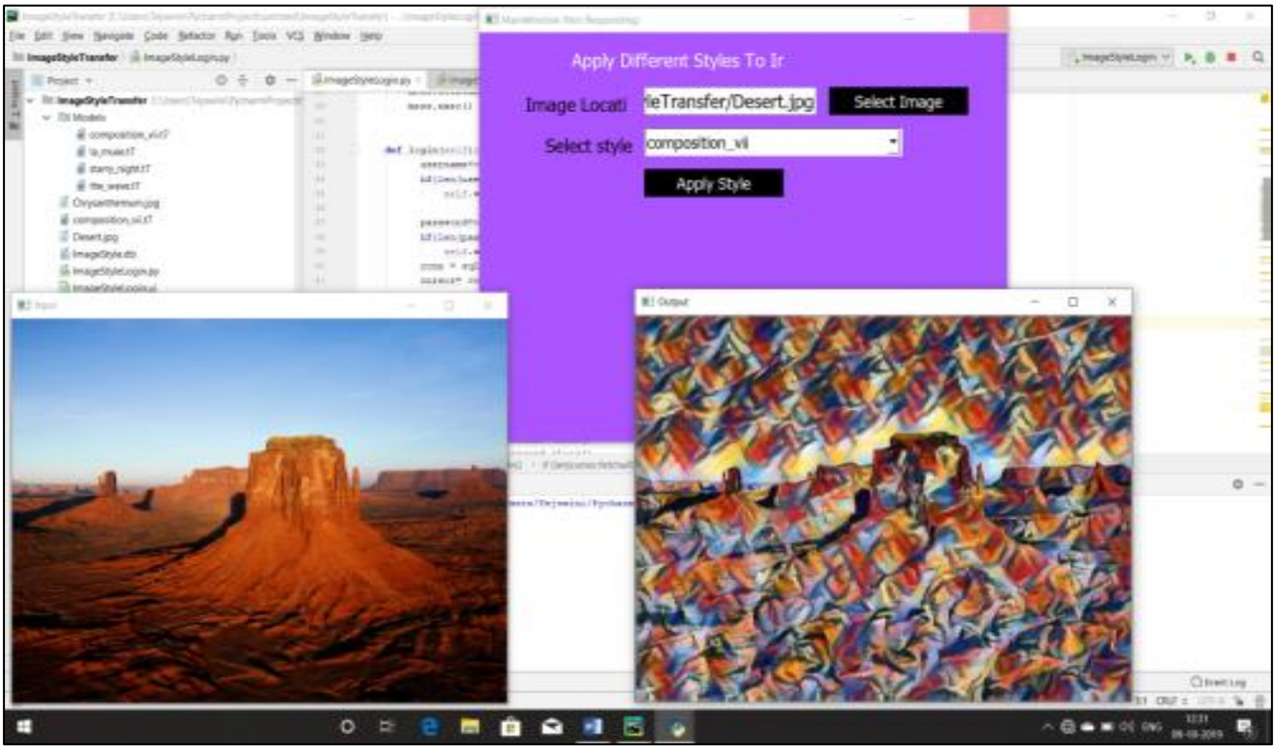


Fig. 2.1. Composition vii Style

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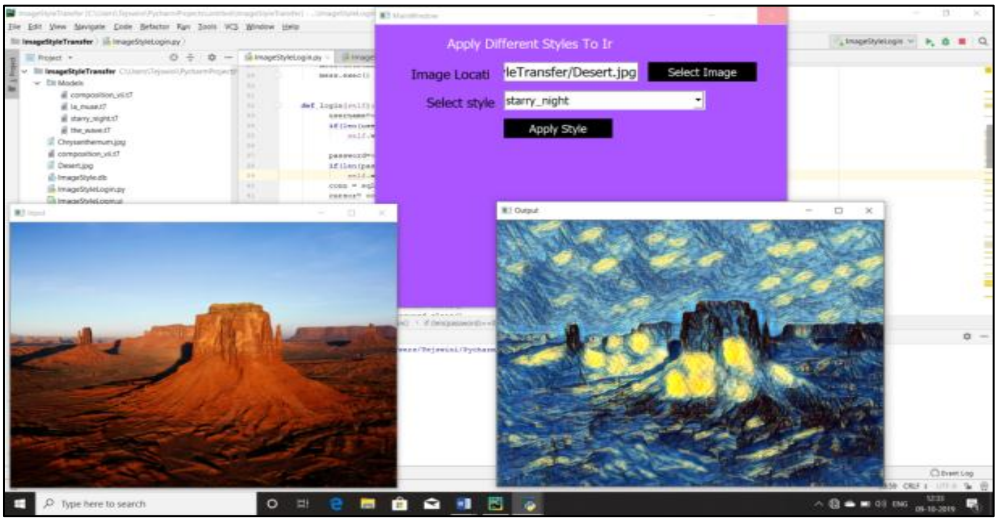


Fig. 2.2. Starry Night Style

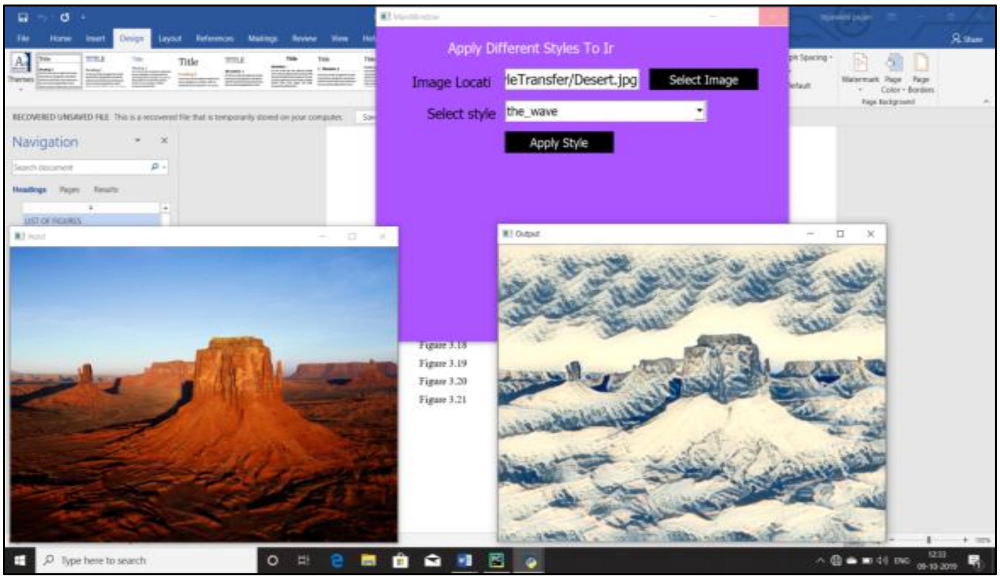


Fig. 2.3. The Waves Style

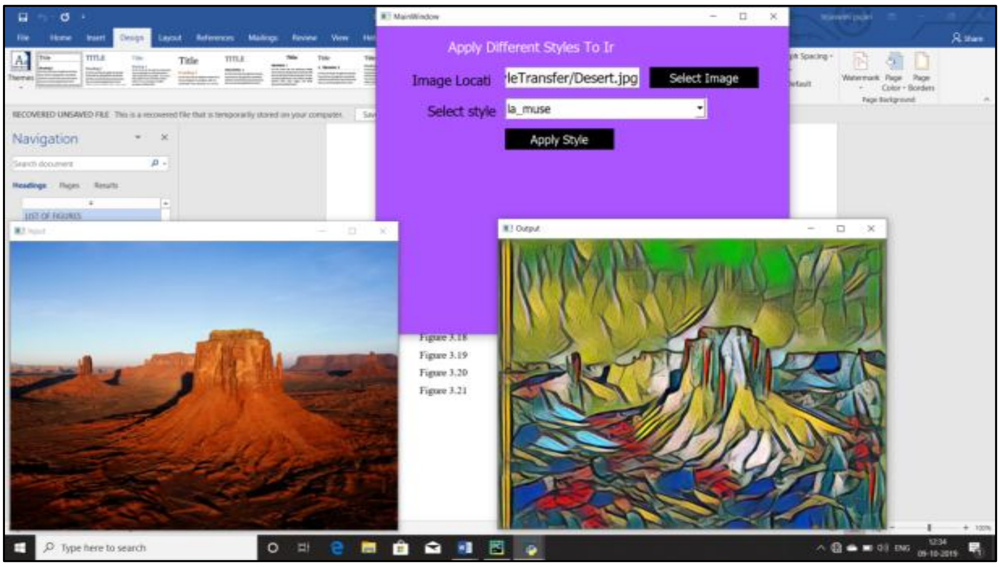


Fig. 2.4. La Muse Style

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**Algorithm -** There are two terms in the loss function, namely Content loss and Style loss. The first is the introduction of a photorealism regularization term into the loss function. The insight is that the input content image is already photorealistic, all we need to do is to ensure that we do not lose the photorealism during the style transfer process. The high-level idea of this loss term is to penalize things that are not well explained by locally affine transformation. Output that is not well explained by locally affine transformation includes things like making a straight edge curvy. A limitation of the style loss in equation is that the Gram matrix is computed over the entire image. By calculating Gram matrix over the entire image, the Gram matrix is limited in terms of its ability to adapt to variations of semantic context.

**Evaluation Metric -** Since determining quality of images is a largely subjective task, most of evaluations of neural style transfer algorithms are qualitative. The most common approach is to qualitatively compare outputs of some current approach with some previous approaches by putting outputs of different algorithms side by side. Another common evaluation method is user study. The typical setup is to recruit some Amazon Mechanical Turk users, show them stylized images output by different algorithms, and ask them which images they prefer. There are also some attempts for quantitative evaluation. The most common approach is to compute the runtime or the convergence speed of different algorithms. Some paper also tries to compare the final values of loss functions of different algorithms. However, the values of loss function do not always correspond precisely to the quality of output images.

## IV. CONCLUSION

Neural Algorithm of Artistic Style that can separate and recombine the image content and style of natural images. The algorithm allows to produce new images of high intuitive quality that combine the content of a masterful photograph with artworks. Results provide new grasp into the deep image representations learned by Convolutional Neural Networks and determine their potential for high level image synthesis and manipulation.

## IV. FUTURE SCOPE

An interesting survey for the future to increasing the number of convolutional layers to extra more high-level features. Also, to improve the quality of the output, two developments can be made.

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