**Report**

**Neural Style Transfer**

**Name – Adarsh Shukla En No. - 22123001**

**Overview**

Neural Style Transfer is a technique in deep learning that merges the content of one image with the style of another to create a new, aesthetically appealing image. This project implements Neural Style Transfer using TensorFlow and Keras, leveraging a pre-trained VGG19 model for feature extraction.

**Demo Video**

Click on this demo YouTube video for complete procedure of the Model

**https://www.youtube.com/watch?v=7sgF6nAb32E**

**Repository Contents**

The repository includes:

* Code for performing Neural Style Transfer.
* Pre-trained VGG19 model for feature extraction.
* Implementation of content loss, style loss, and total variation loss functions.
* Example images demonstrating the results of style transfer.

**Model Architecture**

The model uses the VGG19 network pretrained on ImageNet. Only the convolutional layers are used, while the fully connected layers are excluded. The key layers for content and style extraction are:

* **Content Layer:** block5\_conv2
* **Style Layers:** block1\_conv1, block2\_conv1, block3\_conv1, block4\_conv1, block5\_conv1

**Loss Functions**

**Content Loss**

The content loss measures the difference in content between the generated image and the content image. It is computed using the mean squared error between the feature representations of the content image and the generated image from the content layer.

python

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def get\_content\_loss(noise, target):

loss = tf.reduce\_mean(tf.square(noise - target))

return loss

**Style Loss**

The style loss measures the difference in style using Gram matrices. The Gram matrix captures the correlations between different filter responses, representing the style of the image. The style loss is computed as the mean squared error between the Gram matrices of the style image and the generated image.

python

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def get\_style\_loss(noise, target):

gram\_noise = gram\_matrix(noise)

loss = tf.reduce\_mean(tf.square(target - gram\_noise))

return loss

**Total Loss**

The total loss is a weighted sum of the content loss and style loss. This combined loss is used as the optimization objective during the training process.

python

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def compute\_loss(model, loss\_weights, image, gram\_style\_features, content\_features):

...

total\_loss = content\_loss \* content\_weight + style\_loss \* style\_weight

return total\_loss, style\_loss, content\_loss

**Usage**

**Running the Code**

1. **Upload Images:** The script prompts you to upload a content image and a style image.
2. **Run Style Transfer:** To run the style transfer, call the run\_style\_transfer function with the appropriate parameters:

python

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best, best\_loss, image = run\_style\_transfer(content\_path, style\_path, epochs=2000)

1. **Display Results:** The script includes functionality to display the content, style, and generated images using Matplotlib.

**Code Execution**

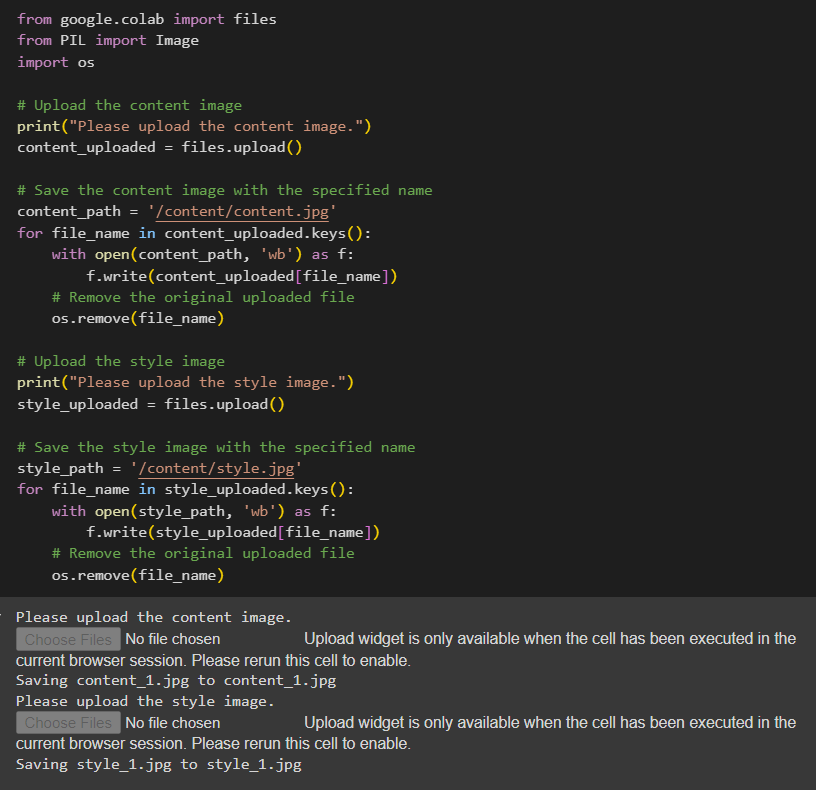
Run each cell in the provided Colab notebook. <https://colab.research.google.com/github/adarshukla3005/neural_style_transfer/blob/main/Neural_Style_Transfer.ipynb>

**Take Input images:**

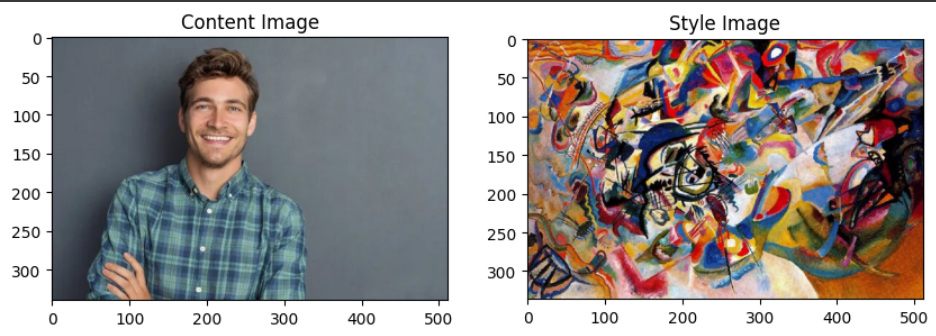
Upload the required content and style image

files. You can download the files from the repository. Make sure to take input content and

Style images.



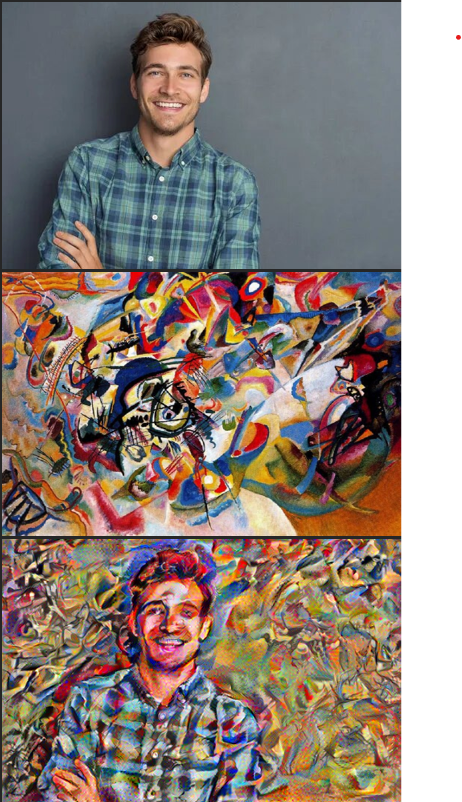
**Preview images**:



**Some Stylized images**



**Transfer Results**



**References**

[A Neural Algorithm of Artistic Style](https://arxiv.org/abs/1508.06576) by Leon A. Gatys, Alexander S. Ecker, Matthias Bethge

[TensorFlow Neural Style Transfer Tutorial](https://www.tensorflow.org/tutorials/generative/style_transfer)

https://hackernoon.com/how-do-neural-style-transfers-work-7bedaee0559a

**Conclusion**

The Neural Style Transfer project demonstrates the power of deep learning in creating visually appealing images by combining the content of one image with the style of another. By leveraging a pre-trained VGG19 model and carefully crafting loss functions, the project achieves impressive results in artistic image generation. This implementation serves as a foundational approach that can be further optimized and extended for various artistic and practical applications.