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Neural Style Transfer

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Abstract: The Basically [NST] means a Neural Style Transfer is one Model for changing the whole behaviour of the images. Through the NST we can create a multiple new images using a multiple content image and multiple style images, through this model we can change the all internal structure & Environment of the images, and also in some images the model can transform the style or change a style. Neural style transfer is a machine learning, deep learning and artificial intelligence related one technique thatcombines the features of a content images and style images. Under the content images the all content are present and under the style images all style related images are present are over here. This technique combines the contents imageswith the style of another image creating visually captivatingart works that bridge the gap between human creativity andcomputational process. Introducing the neural network architecture that enables the extraction of content and style features from images.
Keywords: Neural Style Transfer (NST), Deep Learning, Artificial intelligence, Convolutional Neural Network (CNN), Image Processing, Content images, Style images, Content style separation, Style transfer network, Image analysis.

I. INTRODUCTION

Transferring the style from one image into another can be considered a mystery of texture transfer. In texture transfer the goal is to synthesise a texture from a source image whileconstraining the texture synthesis in order to preserve the semantic content of a target image. For texture synthesis there exist a large range of powerful semi-parametric algorithms that can synthesise photorealistic natural textures by resampling the pixels of a given 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 goal image. For instance, introduce a correspondence map that includes features of the target image such as image intensity to constrain the texture synthesis procedure. Here use image analogies to transfer the texture from an already stylised image into a goal image. Focuses on transferring the high texture information while preserving the coarse scale of the target image. Enhance this algorithm by additionally informing the texture transfer with edge orientation Information. Although these algorithms achieve remarkable results, they all suffer from the same fundamental limitation: they use only lower image features of the goal image to. Ideally, however, a style transfer algorithm should be able to extract the semantic image content from the goal image (e.g. the objects and thegeneral scenery) and then inform a texture transfer procedure to render the semantic content of the goal imagein the style of the source image. Therefore, a fundamental prerequisite is to find image representations that independently model variations in the semantic image, content and style images in which generated in a new image. The use of image style migration technology has become extra and more extensive, usually to migrate the artistic style of one picture to another picture, is the imageto ensure that the content characteristics do not change significantly without major changes in the art style. With the rise of deep learning with the help convolutional neuralnetwork models to achieve image style migration, which attracted wide attention. NST has been an important research direction for both decades. Firstly the emergence of neural networks, style migration was a field of non- photorealistic rendering, and then, the neural network-based texture synthesis technology provided new ideas forstyle migration. Although style migration has a nice visualeffect, there are still few problems to be solved. How to better the efficiency of the algorithm under the premise of ensuring the quality of stylized images is the direction thatneeds to be studied at real-time. Here we will provide an overview of the few year's developments in NST.

Input Content Input Style. Output
Fig.1.Example of NST algorithm to transfer a style of a Chinese painting onto a given photograph.

II. LITERATURE SURVEY

In [1] Progress in electron microscopy-based high- resolution connectomes is limited by data analysis throughput. Here, they present SegEM, a toolset for efficient semi-automated analysis of large scale fully Stained 3D-EM datasets for the reconstruction of neuronal circuits. By combining skeleton reconstructions of neurons with automated volume segmentations, SegEM allows the reconstruction of neuronal circuits at a work hour consumption rate of about 100-fold less than manual analysis and about 10-fold less than existing segmentation tools.

In [2] the primate visual system achieves remarkable visual object recognition performance even in brief presentations, and under changes to object exemplar, geometric transformations, and background variation (a.k.a. core visual object recognition). This remarkable performance is mediated by the representation formed in inferior temporal (IT) cortex. In parallel, recent advances in machine learning have led to ever higher performing models of object recognition using artificial deep neural networks (DNNs).

In [8] recently, methods have been proposed that perform texture synthesis and style transfer by using convolutional neural networks (e.g. Gatys et al. [2015, 2016]). These methods are exciting because they can in some cases create results with state-of-the-art quality. However, in this paper, show these methods also have limitations in texture quality, stability, requisite parameter tuning, and lack of user controls. This paper presents a multiscale synthesis pipelinebased on convolutional neural networks that amelioratesthese issues.

III. DEEP IMAGE REPRESENTATION

The results presented under were generated on the common of the VGG network, which was trained to perform object recognition and localisation and is described extensively in the real work. We normalized the network by scaling the weights some that the mean activation of each convolutionalfilter over images and positions is equal to one. Such re- scaling can be done for the VGG network without changing its result, because it contains rectifying linear activation functions and no normalization or pooling over feature maps.We do not use any of the totally connected layers.

A. Content Representation

Generally all 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 ~x isencoded in each layer of the Convolutional Neural Networkby the sort responses to that image. We then define the squared-error loss between the both feature representations.

$$\mathcal{L}_{\text{content}}(\vec{p},\vec{x},l) = \frac{1}{2}\sum_{i,j}\left(F_{ij}^l - P_{ij}^l\right)^2 . \qquad (1)$$

The derivative of this loss with respect to the activations in layer l equal

$$\frac{\partial \mathcal{L}_{\text{content}}}{\partial F_{ij}^l} = \begin{cases} \left(F^l - P^l\right)_{ij} & \text{if } F_{ij}^l > 0 \\ 0 & \text{if } F_{ij}^l < 0 , \end{cases} \qquad (2)$$

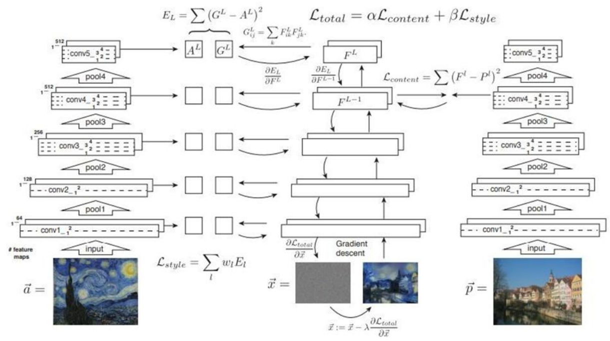
From which the gradient with respect to the image ~x can be computed using standard error back-propagation (Fig 2,right). Thus we can change the initially random image ~x until it generates the same response in a certain layer of theConvolutional Neural Network as the real image ~.

B. Style Representation

To obtain a representation of the style of an input image, we use a feature space designed to save texture information. This feature space can be built on top of the filter feedback in any layer of the network. It consists of the correlations between the different sort responses, where the expectation is taken over the spatial extent of the feature maps. These feature correlations are given by the Gram matrix Gl ∈ RNl×Nl, where Gl ij is the inner productbetween the vectorised feature maps i and j in layer

$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l .$$

By including the feature correlations of multiple layers, weobtain a stationary, more-scale representation of the input image, which captures its texture information but not the global arrangement. Reapeatly, we can visualise the information captured by these style feature spaces built ondifferent.



Style transfer algorithm. Before content and style featuresare extracted and stored. The style image ~a is passed through the network and its style representation on all layers included are computed and stored (left). The contentimage ~p is passed through the network and the content representation P l in one layer is stored (right).

C. Style Transfer

To transfer the style of an artwork ~a onto a photograph ~p we synthesise a new image that simultaneously matches the content representation of ~p and the style representation of ~a. Thus we jointly minimise the distance of the feature representations of a white noise.

Image from the content representation of the photograph in one layer and the style. Representation of the painting defined on a number of layers of the Convolutional Neural Network. The loss function we minimise

Images that mix the content of a photos with the style of several well-study artworks. The images were created by simultanee content representation of the photograph and thestyle representation of the artwork.

IV. GENERATIVE ADVERSARIAL NETWORK OVERVIEW

The first part deal that define the basics of most GANs. These papers are essentially the backbone, as most other follow their pathway by improving upon or making amends to them. GANs generate data based on previously learned patterns and regularities as the model finds these patterns. Deep learning suits generative models as they can effectively recognize patterns in input data.

A. Generative Adversarial Networks

Explores the framework, which was new around then for making generative models in a loosely organized cycle, wherein training two models: a generative model G which gets the details, and a discriminative model D that calculatesthe likelihood that an image comes from training examples instead of G. The arrangement technique of G would be to raise the likelihood of D creation a mistake. This arrangement resembles a more modest than usual max two- player game. The technique used here is to get the most

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extreme probability of doling out the correct mark to both preparing models and tests from G and at the same time preparing G to limit log(1-D(G(z))).

$$\min_{G}\max_{D} V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}\left[\log D(x)\right] + \mathbb{E}_{z\sim p_z(z)}\left[\log(1-D(G(z)))\right] \quad (1)$$

B. Style Based Generator AdversarialNetworks

Generator improvement has seen less attention and improvement compared to Discriminator. To enhance the Picture quality produced by the Generator, introduced a Style transfer literature-based generator.

1) Traditionally the created is provided with a latent code through the input of the first layer of the feed-forward network. At the same time, in the new approach, it is omitted altogether and is started with a learned constant.
2) Provided a latent code z in the non-linear mapping network and latent input space Z, f: Z → W first generatesw ∈ W
3) After the mapping is done, learned affine transformation specializes w to styles: y = (ys, yb) which operates after each convolution layer of the generative network and controls the normalization of the generative network G.
4) The normal technique used is adaptive instance normalization (AdaIN), the (2) for the same is:

$$\text{AdaIN}(\mathbf{x}_i, \mathbf{y}) = \mathbf{y}_{s,i}\frac{\mathbf{x}_i - \mu(\mathbf{x}_i)}{\sigma(\mathbf{x}_i)} + \mathbf{y}_{b,i} \qquad (2)$$

Over here to get the AdaIN between xi and firstly finding the distance between xi and the mean of xi (μ(xi)) further dividing it by standard deviation of xi (σ (xi)), then to scale,the value is multiplied it by ys,i and bias it by yb,i .

a) The Generator is then given direct noise input, which allows it to generate stochastically. The noise input isuncorrelated noise input generated via a single channel of images. Dedicated noise input is given into each layer of the synthesis layer.
b) Using the learned pre-feature scaling factor, the noise image is first transmitted on all feature maps, and then thecorresponding convolution layer output is applied. Generator improvement has been less attention.

V. GENERATIVE ADVERSARIAL NETWORK IN STYLETRANSFER

Now architectures prevalent and in use concerning NeuralStyle Transfer (NST) are discussed. These in this Wes lookat proposing a new architecture and employing unique methods.

A. Conditional Adversarial Networks For Style Transfer

Conditional GANs (cGANs) introduce photos-to-photos translation and a loss function to allow the models' training. It removes the usage of hand-engineered loss functions or mapping functions. Optimizing this loss function allows the generated images to be structurally related or ''conditioned'' as per the input image. TheGenerator has an to solve the limitation of using only low-level image characteristics of the goal photos.

Architecture based on U-Net, whereas the Discriminator has aPatch GAN based architecture. The Patch GAN architecture isshown to be useful as it penalizes local structural differences. The effect of locality or ''patch size'' is also studied. The loss function is given as:

$$L_{cGAN} = E_{x,y}(log(D(x,y))) + E_{x,z}(log(1 - D(x, G(x,z))))$$

Where G and D are the Generator and Discriminator networks,x and y are content and style images, respectively, and z is a random noise vector that gets learned to produce the mappingG: {x, z} → y. The Discriminator is now fed ''x'' or feed in image as an feed in. In addition, an L1 distance term is added to make the generated images closer to ground truth and avoidblurred images:

$$L_{L1}(G) = E_{x,y,z}[||y - G(x,z)||]$$

Thus, the final objective is given as:

$$L_t = L_{cGAN}(G, D) + \lambda . L_{L1}(G)$$

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where G and D are the Generator and Discriminator networks,LcGAN is the conditional loss given in (7) and LL1(G) is the L1 loss of the generator as given the total loss is Lt.

B. Image Style Transfer Using CNN

It is difficult to render a photo's semantic content differently since it lacks representations that explicitly provide semantic information. To solve the limitation of using only low-level image Style neural algorithm that can isolate and recombine the content of images (style texture) and generate the images using those Styles.

The method used is:

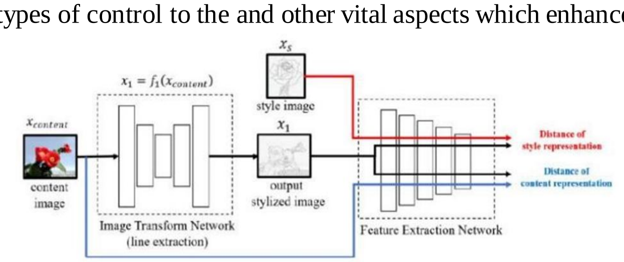
1) The standardized version of the 19-layer VGG networkincludes 16 convolutional and five pooling layers.
2) By scaling weights, the network was normalized such that the mean activation of each convolutional filter over images and positions was equivalent to one.
3) Image synthesis was done by using average pooling as it wasseen that it provided a better result.
4) For Content representation: ◦ One can perform gradientdescent to display image data on several levels of a white noisepicture to locate another image that fits the feature responses of the content image.

VI. ADVANCEMENT PAPER

This set of present advancements to current architectures. These advancements allow different types of control to theStyle Transfer by improving Colour control, Stability, Spatial Control, and other vital aspects which enhance thequality of generated images.

A. Perceptual Factor Control In Neural Style Transfer

Represents an extension to the existing methods by proposing spatial, colour, and scale control over a generated image's features. By breaking down the perceptual factors into these features, more appealing images can be generated that avoid common pitfalls. Theseadvancements allow different types of control to the and other vital aspects which enhance the quality of a generatedimages.



Spatial control implies controlling which region of the style image is applied to each region of the content image. The first method to do this uses Guidance-based Gram Matrices, where each image is provided with a spatial guidance channel indicating which region should be applied to what Style.

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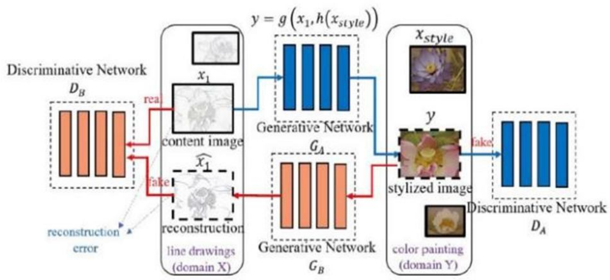
This involves computing a SpatiallyGuided Feature Map for R regions and L layers as:
F r l (x)[:,i] = T r 1 ◦ F1(x)[:,i]



As seen in Fig, the method works well to get a high- resolution image like the one that does not use it. However,the ‘‘CTF’’ model requires fewer iterations and is seen to have less noise.

B. Stability Improvements In Neural Style Transfer

The latest image style transfer methods can be grouped intotwo groups. The first one is the optimization approach that solves a particular optimization problem for the generated image. These results are outstanding but take some time to develop each picture. The combined loss is defined

$$L(W, c_{1:T}, s) = \sum_{t=1}^{T} (\lambda_c L_C(p_t, c_t) + \lambda_s L_s(p_t, s) + \lambda_t L_t(p_{t-1}, p_t))$$

Here λc, λs , and λt areused to assign importance to loss term.The three losses are as follows:
Content style loss Lc which is defined:

- The Fréchet Inception Distance (FID) approximates the real and fake feature distributions with two Gaussian distributions. They then compute the Fréchet distance (Wasserstein-2 distance) between two Gaussian distributions and use the findings to determine the model’squality.
- Few papers use the Intersection-over-Union (IOU) metric to determine the accuracy of segmentation and detection in object classification and localization.
- The perceptual path length quantifies the difference between consecutive images (VGG16 embeddings). It determines if the image changes along the shortestperceptual path in the latent space where fake images are introduced.
- The warping error is the difference between the warped and real subsequent frames. The warping error thesmoothness of video since it is an efficient technique to monitor video stability with many frames.

VII. RESEARCH GAPS

The research gaps observed can be grouped into three basic categories, namely architecture-related, platform- related, and dataset related

A. Platform-related

1) *Native Mobile NST:* Implementing real-time video neural style transfer directly on mobiles. This is primarilydue to mobiles having relatively new software and low- power hardware.
2) *Use of Federated Learning:* Federated learning is another gap observed while looking at Mobile NST. It is a recent idea and has been used to overcome low power device limitations.

B. Dataset Related

$$L_c(p, c) = \sum_{j \in C} \frac{1}{c_j H_j W_j} \left\| \phi_j(p) - \phi_j(c) \right\|_2^2 \quad (33)$$

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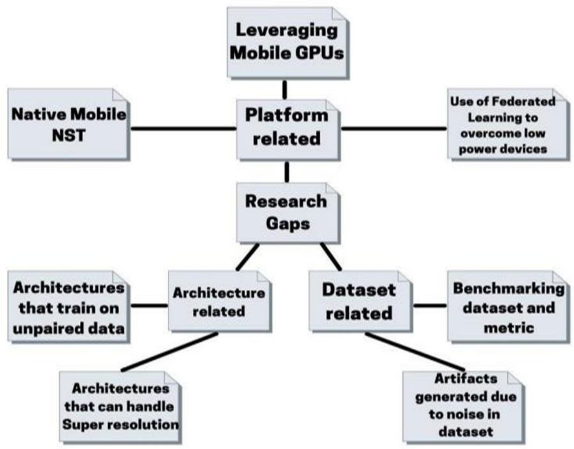
VIII. NST EVALUATION METRICS

Evaluation metrics for NST could be challenging because of the variety in GANs models. However, accuracy, Fréchet Inception Distance (FID), Intersection-over-Union(IOU), time, perceptual path lengths, and warping error arethe most often utilized metrics for the models constructed in the publications evaluated.

The accuracy was used to measure the relative depth of the predicted images. It was also used to predict feature maps, where the higher the accuracy, the more accurate thefeature maps indicated.

Lack of benchmark datasets: A benchmark dataset could make testing, evaluating, and understanding the model's performance standardized. Another point observed is that some create their datasets and apply different transforms todata, which can distort the image's structure, leading to thegeneration of artefacts.



M-Turks (a service that offers manual labour) to inspect the quality of the images generated. Photorealism is usually inspected manually and thus could be a place to add a metric. However, this can be difficult as photorealism is subjective and might change depending on context.

IX. MODELS

A. Convolutional Neural Network (CNNs)

CNNs are the fundamental building blocks used in neural style transfer. CNNs are used to extract features from both the content and style images. Popular pre-trained CNNarchitectures like VGG and ResNet are commonly used. A CNN can have many layers, each of which learn to detect the different features of an input image. A filter or kernel isapplied to each one image to generate that gets progressively better and more detailed after each layer. In the lower layers, the filters can start as easy features.

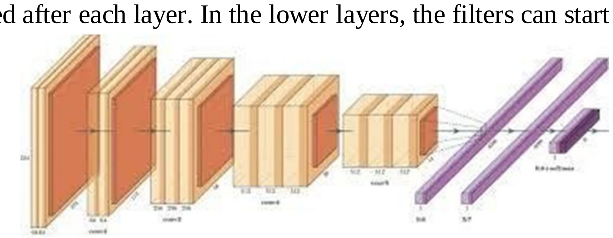


Fig: Convolutional Neural Networks

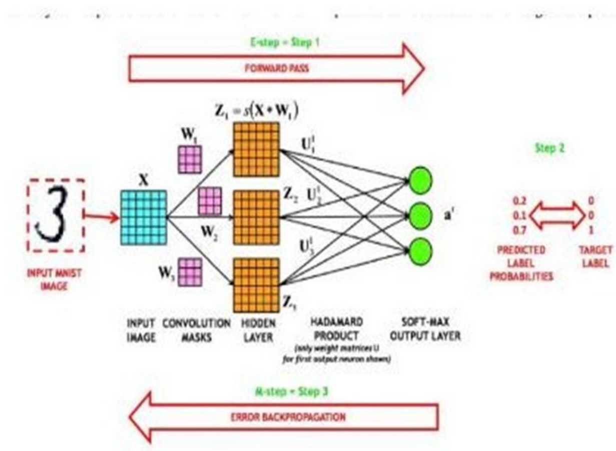
(CNNs):

Similar structures and objects as the content image. Mathematically, the content loss can be expressed as**:**

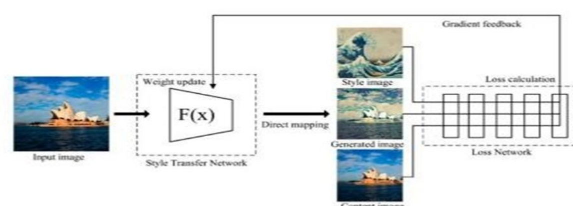
Content Loss = 0.5 * Σ (F_content - F_generated)^2

1) *Style Loss Function:* The style loss function quantifies how well the generated image captures the artistic style ofthe reference style image. It is computed by comparing the statistics of feature maps (mean and covariance) at multiple layers of the neural network. The style loss encourages the generated image to have similar textures, colours, and patterns as the style image. Mathematically, the style loss can be expressed as: Style Loss = Σ (G_style -G_generated)^2 Total Loss: The total loss, which is usedfor optimization, is a combination of the content loss and the style loss, each weighted by a coefficient. The total loss guides the neural network to find an output image that balances content and style, as well as maintains other image properties. Total Loss = α * Content Loss + β * Style Loss.

2) *Backpropagation and Gradient Descent:* To generate the final stylized image, an optimization algorithm (usually gradient descent) is employed to minimize the combined content and style loss. The gradient of the loss with respect to the generated imageis computed, and the image is updated iteratively to minimize this loss.
3) *Backpropagation:* Backpropagation, short for "backward propagation of errors," is a supervised learning algorithm used for training artificial neural networks, including deepneural networks. It is a crucial component of the training process because it allows the network to adjust its weightsand biases in order to minimize the error in its predictions.Here's how backpropagation works:



4) *Content and Style Loss Functions:* Neural style transfer uses loss functions to quantify the difference between the content and style of the input images and the generated image.
5) *Content Loss Function:* The content loss function quantifies how well the content of the generated image matches the content of the reference content image. It is typically computed as the mean squared error (MSE)
6) *Gradient Descent:* Gradient Descent is an optimization algorithm used to minimize a loss function by adjusting the parameters of a model (such as neural network weights) iteratively. It works by following the direction of the steepest descent of the loss function.



7) *Image Pre-processing and Post processing:* Image pre- processing and post processing techniques are used toprepare the input images and render the final stylizedoutput. This may include resizing, normalization, and DE normalization of images to fit the model's requirements andto ensure the output image is visually appealing.

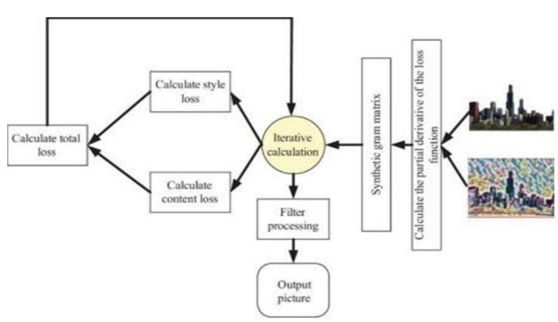


Fig. Flowchart of Neural style Transfer

X. ALGORITHMS

Here are the key algorithms & Technique used in a typicalNST:

1) *Pre-trained CNNs:* Convolutional Neural Networks, suchas VGG-16 or VGG-19, are often used as the backbone forNST. These networks are pre-trained on large image datasets (e.g., ImageNet) and serve as feature extractors for both content and style information.
2) *Content Loss Function:* The content loss is calculated bymeasuring the difference between the feature representations of the generated image and the content image. It is typically based on the mean squared error (MSE) between the feature maps.
3) *Style Loss Function:* The style loss is computed by comparing the statistics of feature maps from the generated Image and the style image. This involves calculating the Gram matrix and evaluating the mean squared error between the Gram matrices of feature maps from the styleand generated images.
4) *Total Variation Regularization:* To promote spatial coherence and reduce artifacts in the generated image, total variation (TV) regularization is often used. TVregularization penalizes rapid changes in pixel values.
5) *Optimization Algorithm:* Gradient Descent or its variants, such as L-BFGS (Limited-memory Broyden- Fletcher-Goldfarb-Shanno) or Adam, is employed to iteratively adjust the pixel values of the generated image tominimize the combined content and style loss.
6) *Hyper Parameters:* Tuning hyper parameters, including the weights for content and style losses, the learning rate, and the number of iterations, is essential to achieving the desired balance between content and style.
7) *Initialization:* Initialization of the generated image, also known as the starting point, can influence the final result. Common initializations include using the content image, random noise, or a combination of both.
8) *Multi-Style Transfer:* Extending NST to incorporate multiple style references, allowing for the creation of images that combine the styles of multiple artists or artworks

XI. TOOLS

1) *Tensor Flow:* Tensor Flow is a mostly-used open-source deep learning framework developed by Google. It providesa high-level API for building neural networks, making it popular for implementing NST.
2) *PyTorch:* PyTorch is a multiplatform deep learning framework prosper by Facebook's AI Research lab. It is known for its flexibility and dynamic computation graph, which makes it a popular choice for many research projects, including NST.
3) *Keras:* Keras is an open-source high-level neural networks API that runs on top of other deep learning frameworks like Tensor Flow and Theano. It simplifies the implementationof neural networks, making it accessible for NST projects.
4) *Fast Neural Style Transfer (NST) Tools:* Various prebuilt NST tools and implementations are available, which allow users to apply NST without extensive coding.Examples include Fast Neural Style Transfer in Tensor Flow, Artistic Style Transfer with Keras, and more.
5) *Adobe Photoshop and Other Image Editing Software:* Traditional image editing software like Adobe Photoshop adjusting the appearance of images.
6) *Jupyter Notebooks:* Jupyter notebooks are often used for experimenting with NST and visualizing the results. Theyprovide an interactive and visually rich environment for exploring the code and its effects.
7) *Online NST Services:* There are various online platformsand services that offer NST as a service. Users can uploadtheir content and style images, and the service will generatethe stylized image. These platforms often use their own implementations of NST.

XII. ADVANTAGES

1) *Artistic Creativity:* NST allows artists and designers to create unique, artistic images by blending the content of one image with the style of another.
2) *Automation:* NST automates the process of applying a specific artistic style to an image, saving time and effort compared to manual artistic rendering. It can generatestylized images relatively quickly, making it suitable for real-time. Applications like photo and video filtering.
3) *Educational Tool:* It can be used in educational contexts to help students understand the relationship between content and style in visual art. NST is a subject of ongoingresearch, and it provides an avenue for experimenting withdeep learning and image processing techniques.

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XIII. IMPLEMENTATION

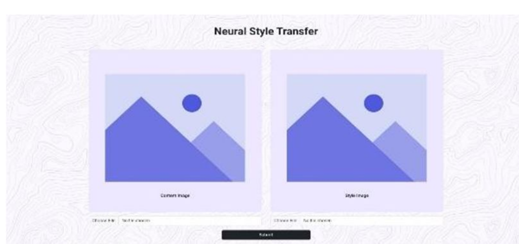
1) Input

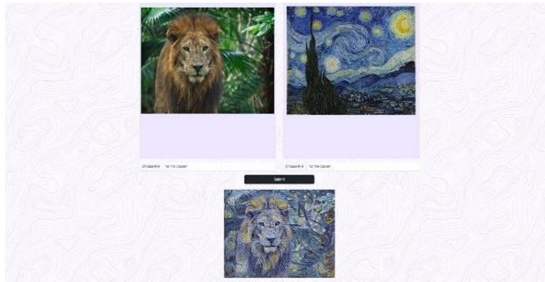
2) Output

XIV. TECHNOLOGY USED

1) JavaScript
2) Python
3) Artificial Intelligence
4) Deep Learning
5) CNN algorithm
6) Style Image
7) Content Image
8) Generated Image

XV. MORE PROJECT WORK





XVI. APPLICATIONS

1) *Artistic Image Generation:* NST allows artists and designers to create unique and visually appealing artworks by combining the content of one image with the style of another. This technique can produce stunning paintings, illustrations, and digital art.
2) *Photo Enhancement:* NST can be used to enhance and stylize photographs. It's a popular choice for making photos look like famous art pieces or applying different artistic styles to personal photos. Graphic designers use NST to apply specific styles to logos, branding materials, and othervisual assets. It can be employed to give a consistent and unique look to a company's visual identity.
3) *Fashion and Textile Design:* NST is used in the fashion industry to create unique patterns, textures, and designs for clothing, accessories, and textiles. It helps designers experiment with different styles and combination. Interior colour schemes would look in a room. It can assist in the creative process of decorating living spaces.
4) *Education and Learning:* NST can be used in educational settings to teach about art, art history, and theconcept of artistic styles. It can help students understandand appreciate the work of famous artists.

XVII. RESULT

Sr.No	Image Type	Time For Execution	Accuracy Percentage
1	JPG	30sec	Above65%
2	PNG	10sec	Above70%
4	JPEG	1min	Above60%

1) Taking 100% Effect of Style image

2) Here Taking 60%,70%,80% effect of styleimage:

3) Taking a colourful images for this project if wetake a black-white images so it's give a very bas effect on a generated image.
4) Using style and content images this projecttaking some second to execute & generate a newimage.
5) If we control a loss and effect of an image so it'screated a fabulous image.

XVIII. CONCLUSION

We concluded that, neural style transfer (NST) is a powerful and versatile technique that offers numerous advantages for a wide range of creative and practical applications. It combines the content of one image with the artistic style of another, enabling the generation of unique and visually appealing artwork.Whether you're an artist, a designer, a researcher, or a hobbyist, NST can be a valuable tool to enhance your projects. The GANs improvement style, explaining how Spatial, Colour, and Scale control can allow better image generation. Lastly, how NST can be applied over mobiledevices in real-time using GANs has been explained. . Inshort, image style migration based on deep learning not only promotes the development of computer field, but also receives wide attention in other fields, so the development of NST has important research significanceand broad application scenarios.

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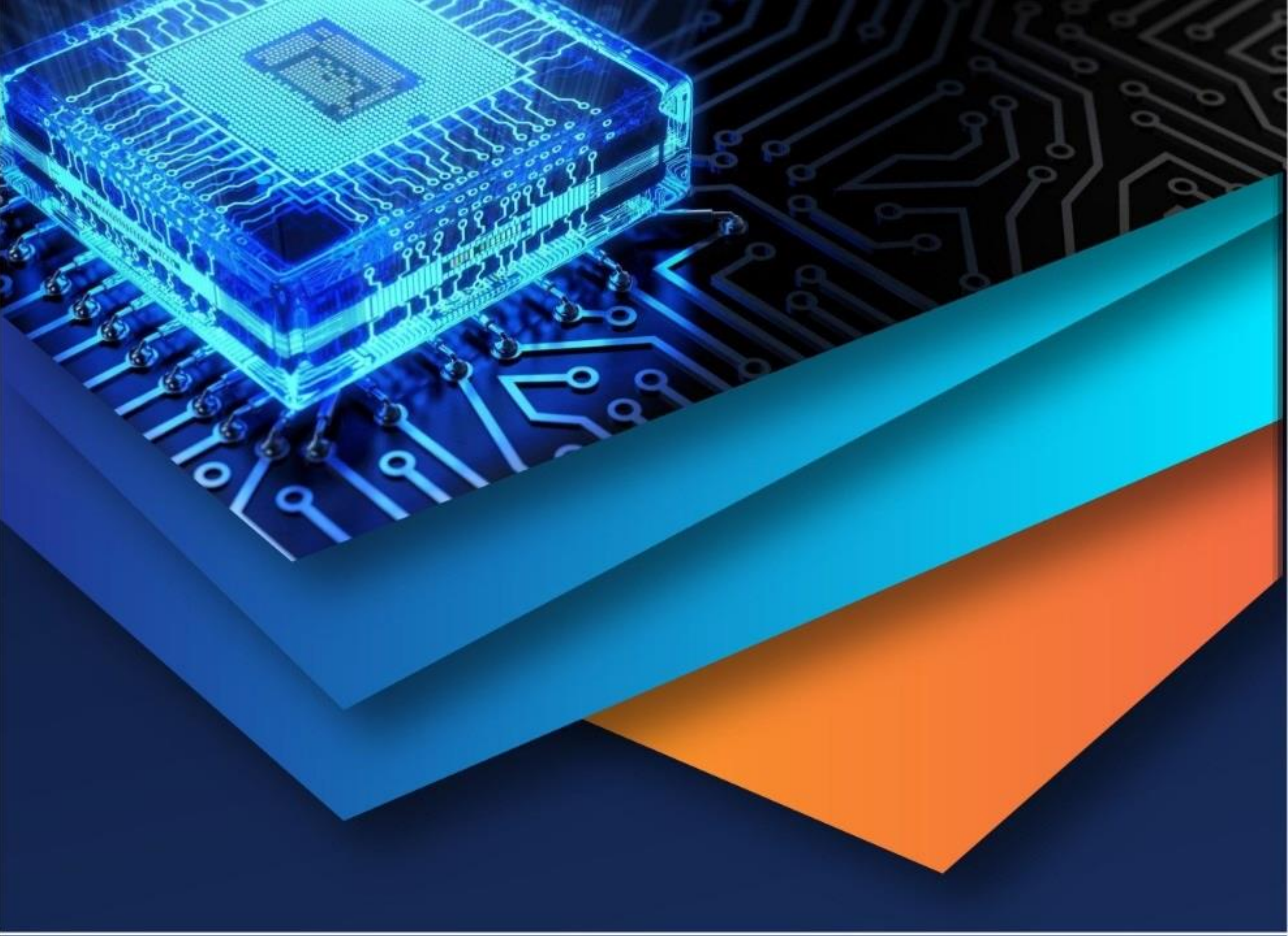

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