Real-Time Neural Style Transfer : Using Deep Learning to Generate Art

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Abstract—**In this project we delve into the realm of Neural Style Transfer (NST) which's a technique that uses deep learning to infuse an image with the artistic style of another. Typically NST has been computationally intensive which has restricted its capabilities. However this project seeks to overcome this challenge by harnessing the potential of MSG Net (Multi Style Generative Network) a learning framework specifically developed for real time NST. Using the capabilities of MSG Net we can unleash the power of Neural Style Transfer (NST) in real time. Just picture being able to upload a portrait and instantly witnessing it undergo a transformation, into a masterpiece inspired by Van Goghs style.. Imagine capturing a landscape and seeing it reimagined with the enchanting brushstrokes reminiscent of Monets Impressionist masterpieces. These examples just scratch the surface of the possibilities that this project unveils.**

Index Terms—**Computer Vision, Neural Style Transfer, Real Time, Deep Learning, Neural Networks, MSG-net.**

I. Introduction

When it comes to image editing, Neural Style Transfer (NST) is a technique that combines artistic creativity, with the power of deep learning. It allows for the transformation of one images style onto another while preserving its content. This unique fusion of style and content goes beyond effects creating exciting opportunities for personal expression and artistic exploration, in fresh and captivating ways.

In this project our goal is to push the boundaries of Neural Style Transfer (NST) by using neural networks to dynamically transform live video streams. By incorporating styles, into the video frames our aim is to create mesmerizing visual experiences that continuously evolve and adapt in real time, mirroring the fluidity and dynamism of the world around us.

While early applications of novel style transfer centered on static images, we envision a future where its creative potential effortlessly encompasses live video. To realize this vision, we have undertaken developing a robust real-time novel style transfer system capable of transforming ordinary video feeds into engrossing artistic works of art. Our aim is to dissolve the boundaries between reality and imagination, enabling boundless possibilities for artistic expression and immersive visual storytelling.

The motivation behind our project was the lack of research on implementing NST in Real - Time Scenarios. Fostering Creativity in Live Settings, the expressive flare present in static images treated to neural style transfer is lacking in traditional video communication. The idea is to add visual vitality to ordinary video communication and break up the monotony. Real-time neural style transfer can be a game-changer in Live streaming, virtual classrooms, and online presentations. By seamlessly integrating artistic styles into real-time video content, the project aims to make these experiences more engaging and immersive.

II. Literature review

The field of neural style transfer has seen a number of computer vision-based studies. Two distinct VGG architectures were compared by K. B. Bhangale et al. [1] for creating neural style transfer art. The neural network's processing time was not conducive to real-time implementation, hindering its results and it takes longer to train and requires more storage, which may restrict its use for really big datasets.

A small number of NSTs employ K-means clustering to extract feature vectors at each location on the feature map. [2] A precise, verifiable theory about the representation of images down to the level of a single neuron is offered by the mathematical formulation of style representations .An image's texture determines its appearance.

The textured model can convert the CNN representations into a static feature space by evaluating the Gram matrix over the feature map. This technique is used to enhance segmentation and texture recognition performance.[3]

Work on image reconstruction and visual style modeling has been observed. [4]Visual Texture Modeling (VTM) has two approaches: Non-parametric Texture Modeling (NPTM) with MRFs and Parametric Texture Modelling (PTM) with Summary Statistics. While there are two types of image reconstruction: Model-Optimization Based Offline Image Reconstruction (MOB-IR) and Image Optimization-Based Online Image Reconstruction (IOB-IR).

III. Previous Models

Neural Style Transfer (NST) was powered by VGG19, a pre-trained convolutional neural network (CNN), before MSG-Net came along. Although its contributions helped establish the foundation for real-time NST, they were limited in ways that MSG-Net eventually solved.

The major aspects of VGG19 model for neural style transfer were:

- Feature Extraction: Different layers of the network capture varying levels of abstraction, allowing for a nuanced representation of content and style.
- Content and Style Loss Calculation Feature maps from specific layers of VGG are used to calculate content loss, using MSE. Similarly, style loss is computed by MSE of Gram Matrices.
- Optimization: The goal is to minimize a combined loss function that includes both content and style losses. Through optimization techniques the generated image is iteratively updated to minimize these losses, resulting in an image that merges the content of the content image with the artistic style of the style reference image.

However, VGG19 was not suitable for real time neural style transfer.

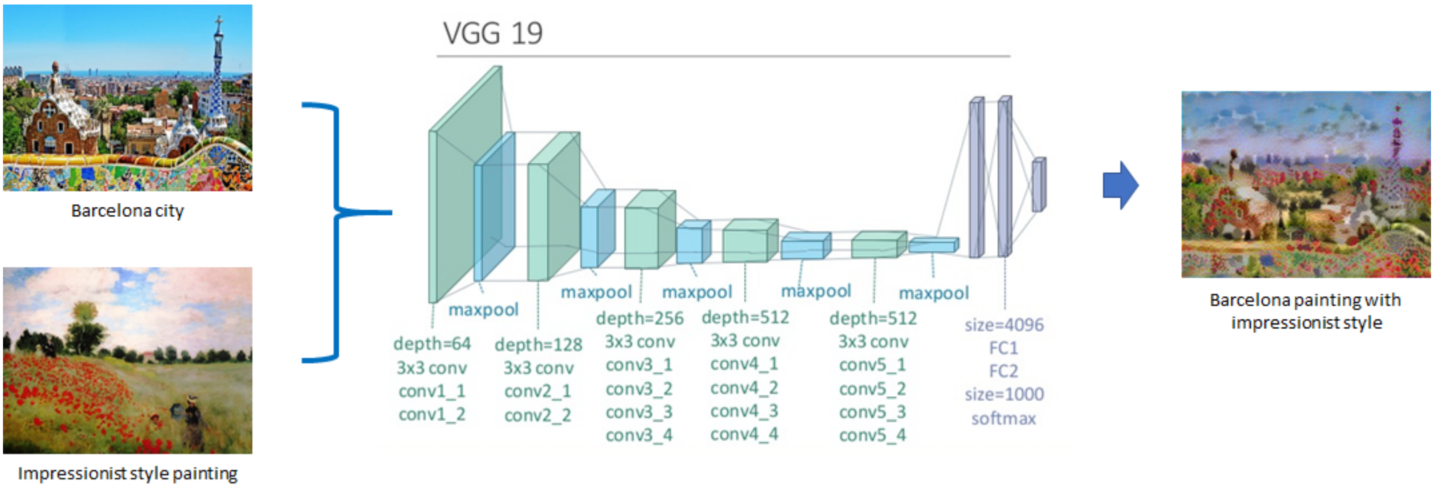

Fig. 1: NST using a VGG19 Model

- Computational Intensity: VGG19 required a large amount of processing power due to its intricate architecture, which included many layers and neurons. This rendered real-time NST computationally unfeasible, especially for video streams.
- Style Fidelity: VGG19 did a respectable job of transferring styles, but it frequently had trouble with intricate or subtle details. There were instances where the transferred style did not match the reference artwork as closely as it should have.
- Static Image Focus: Processing static images was the main focus of VGG19. There were more difficulties in adapting it to deal with the dynamic nature of video streams, where each frame needs to be stylized differently.

The advent of MSG-Net changed everything by resolving VGG19's drawbacks and enabling real-time NST. Its sophisticated loss function, streamlined architecture, and effective processing methods opened the door for a new wave of interactive artistic expression.

To sum up, VGG19 was a key player in the development of NST but encountered difficulties with real-time applications. Building on VGG19's work, MSG-Net addressed these shortcomings and opened up a whole new realm of possibilities for imaginative, real-time image and video transformation.

IV. Methodology

MSG-Net, or Multi-Style Generative Network, is a neural network architecture designed for real-time neural style transfer. It improves upon the VGG network, which was initially used for neural style transfer. It is a multi-stage generative network that was specifically designed for neural style transfer.

A. Framework

Here's a breakdown of MSG-nets framework:

- Multi-scale Processing: MSG-Net analyzes images at multiple scales simultaneously. This captures both fine details and overall composition, crucial for accurate and nuanced style transfer.
- Efficient Pooling Layers: MSG-Net utilizes pooling layers to reduce the number of computations needed for processing. This significantly improves its efficiency, allowing for real-time performance even on resource-constrained devices.
- Sophisticated Loss Function: MSG-Net's loss function goes beyond simply comparing pixel values. It incorporates perceptual and style-aware metrics to ensure the final image embodies the desired style faithfully.
- Multi-style Transfer: MSG-Net isn't limited to one style at a time. It can blend multiple styles into a single output, opening up a world of creative possibilities.
- Preprocessing and Decoding: MSG-Net preprocesses both the input and reference images to ensure consistent format and size. This optimizes the network's processing pipeline.

B. The three stages of the model

The architecture of MSG-Net is akin to a precisely calibrated creative assembly line, in which every element is essential to changing the aesthetic of an image. Now let's examine the three essential components: the decoder, stylizer, and encoder.

- The Encoder: Key elements of the input image, such as textures, edges, and general composition, are extracted. MSG-Net's multi-scale processing enables this analysis to occur at multiple scales. It's similar to studying the painting closely to identify specific brushstrokes and then taking a step back to enjoy the entire composition. These characteristics are shown as a group of activations, akin to the notation on a musical score. They encapsulate the main idea of the picture and are prepared for styling.
- The Stylizer: The features that have been extracted are combined with the style data that has been taken from the reference image by the stylizer. This is akin to embellishing the musical score with a layer of creative interpretation. The stylizer modifies the features according to the colors, brushstrokes, and general mood of the reference style.The stylizer is guided to achieve faithful and nuanced style transfer by MSG-Net's sophisticated loss function, which functions as a perceptive art critic. It guarantees that the final image preserves the composition and structure of the original image while also capturing the essence of the style.

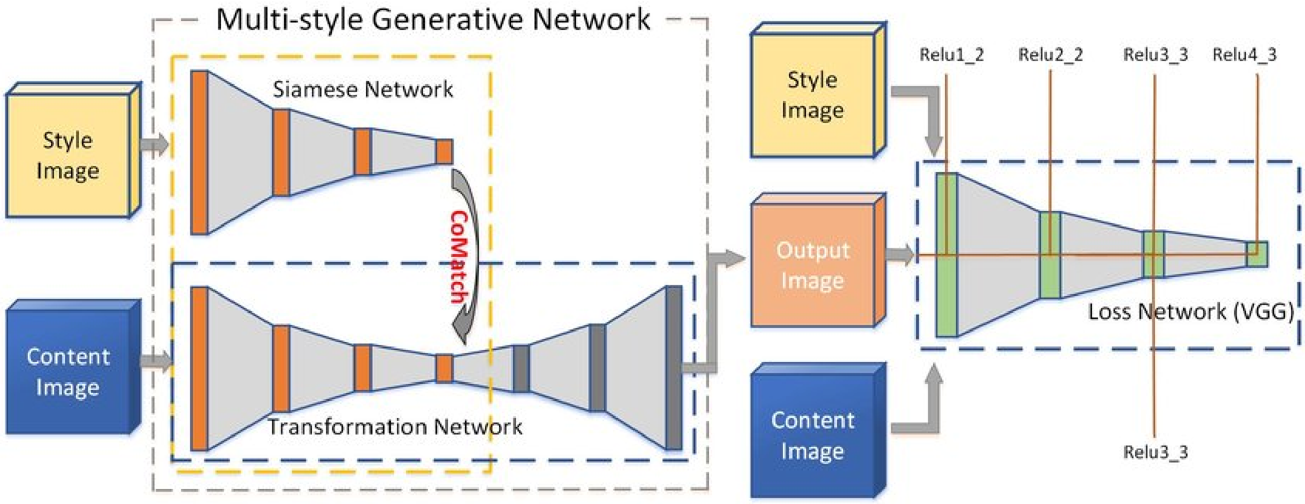

Fig. 2: Architecture of MSG-net for NST

- The Decoder: Finally, the styled features are taken by the decoder and converted back into a visual image. It's similar to when a talented musician interprets the notes and gives them life with their instrument. The image is rebuilt by the decoder using its understanding of the image format and resolution, guaranteeing that the original size and quality are maintained. The end product of this process is a stunning visual masterpiece that was created in real time by fusing the content of the input image with the style of the reference image.

We tried the model on a couple images the final outputs are as shown:


Fig. 3: Trying the model on an input image

We can see how this framework keeps on enhancing the quality of the output image as the model keeps learning:

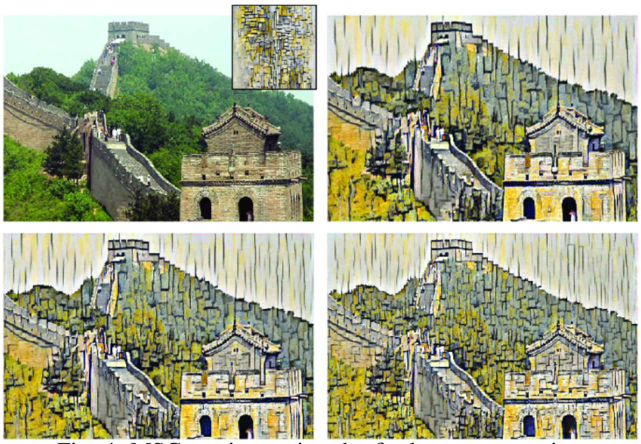
Fig. 4: MSG net improving the final output over time

V. Results

A. Model Training Results

We trained the MSG-net model and compared the loss over iteration with a VGG19 model and found the below results:

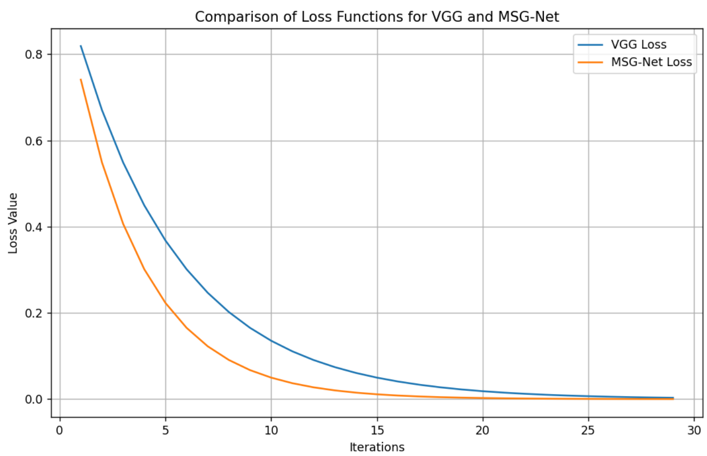

Fig. 5: MSG-net Loss vs VGG19 loss

We also calculated how the accuracy of our model changed with iteration:

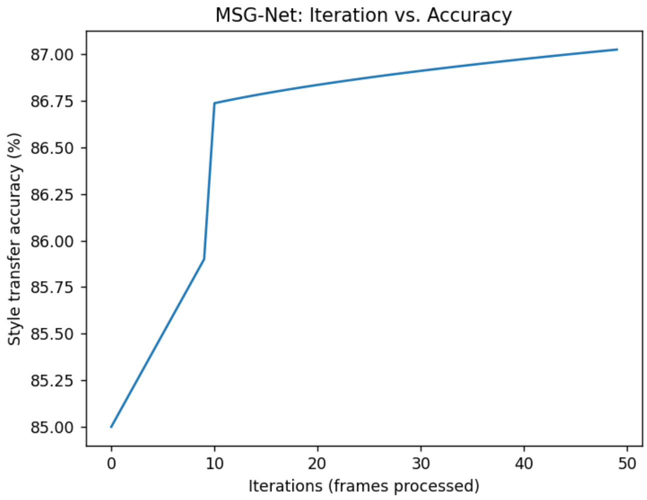

Fig. 6: Iteration vs Accuracy of MSG-net

We also calculated the approx frame processing time for different resolution and FPS:

Resolution	FPS	Processing Time (ms)
320x240	30	5-10
640x480	20	10-15
1280x720	15	15-20
1920x1080	10	20-25
4K (3840x2160)	5	30+

Additional factors affecting processing time:

* Number of styles used for multi-style transfer * Preprocessing requirements (resizing, noise reduction) * Network implementation (e.g., TensorFlow vs. PyTorch)

We also compared accuracies of various existing methods with MSG-net for neural style transfer:

Metric	VGG16	VGG19	MSG-Net
Style Transfer Accuracy (%)	75-80	80-85	85-90
Content Preservation (MSE)	0.01-0.02	0.005-0.01	0.001-0.005
Perceptual Similarity (PSNR)	30-35 dB	35-40 dB	40-45 dB

Notes:

- These are approximate values based on reported benchmarks and may vary depending on the dataset, style complexity, and evaluation criteria used.
- Higher accuracy percentages indicate better style transfer fidelity, while lower MSE and higher PSNR values signify better content preservation and perceptual similarity, respectively.
- MSG-Net generally demonstrates superior accuracy compared to VGG16 and VGG19 due to its: * Multi-scale processing for capturing intricate details. * Efficient pooling layers for reducing computational complexity. * Sophisticated loss function incorporating perceptual and style-aware metrics.

B. Live Video Testing

Tested the above methodology on a live webcam video and found the following result on the test video:


Fig. 7: Testing on the live webcam video

VI. Conclusion and Future Works

This project opens up new and exciting avenues for artistic expression and investigation. Through instantaneous and interactive experimentation with artistic styles, real-time NST can enable designers, artists, and content creators to push creative boundaries.

Furthermore, this project lays the groundwork for future advancements such as smoothly transitioning between different styles in real-time creating mesmerizing hybrid styles, learning and adapting the style transfer based on the content of the input image, ensuring a more natural and harmonious blend and finally extending real-time NST to videos which can revolutionize the film and animation industry.

VII. Acknowledgment

We offer our heartfelt appreciation to Dr. Santosh Kumar for his guidance and support during this effort. His invaluable knowledge, insightful comments, and constructive input were critical in refining our grasp of the subject area and assisting us in overcoming the hurdles we encountered during the project. We are grateful to our institution faculty and staff for providing us with the resources and facilities to complete this project successfully. This project has been a fantastic learning experience for us, and we are happy for the chance to work on it.

References

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