EXPLORING DEEP LEARNING IN ART

Team Artificial Impressions

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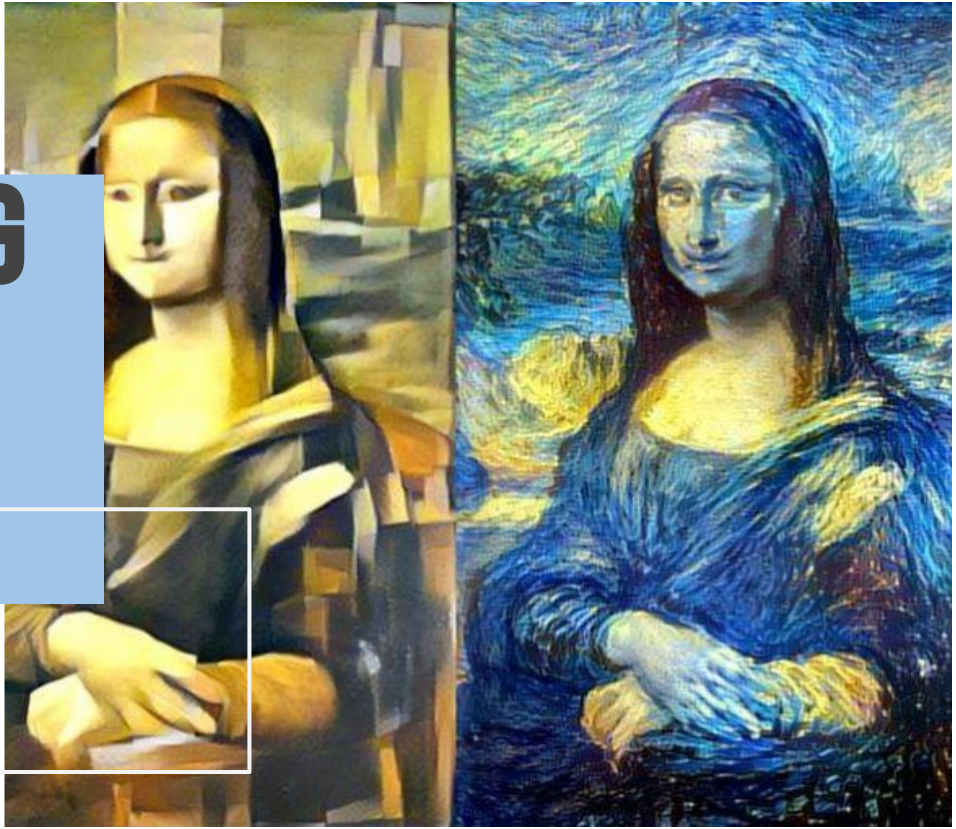

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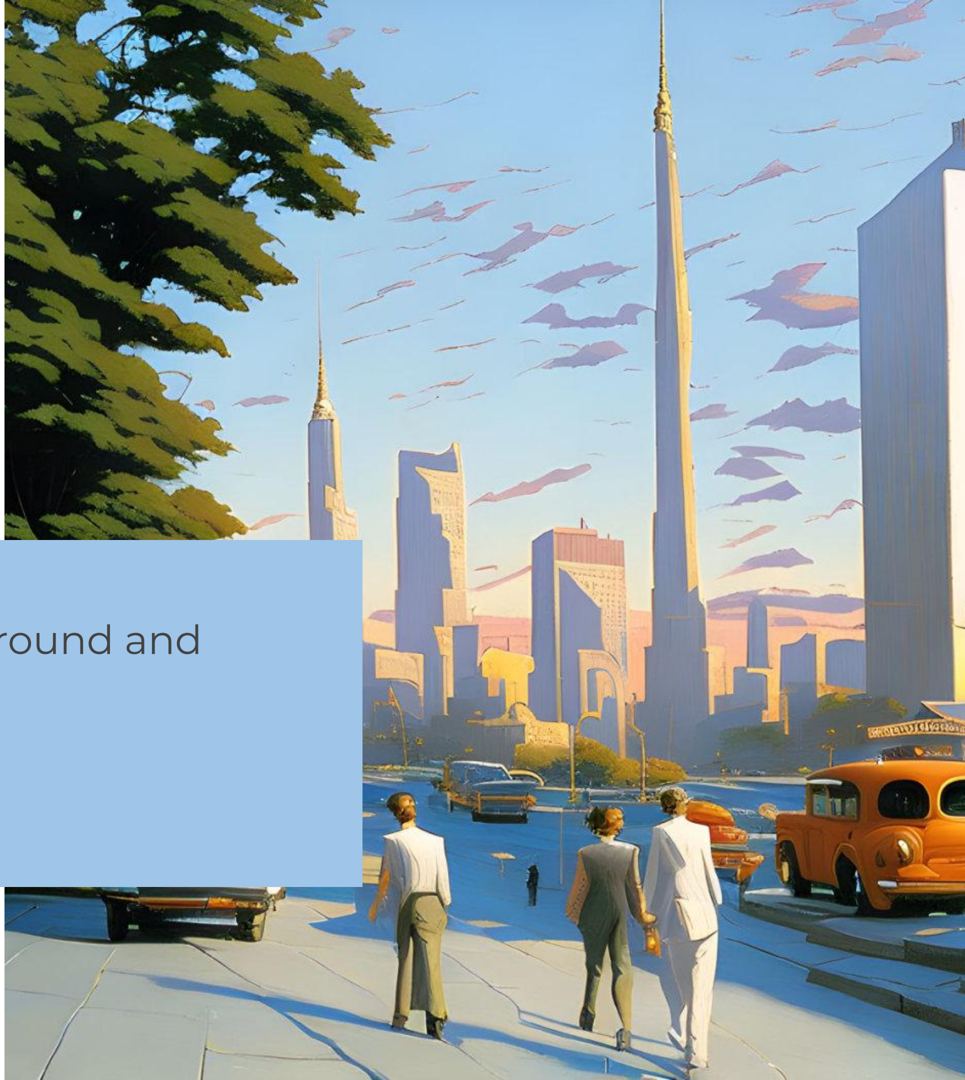
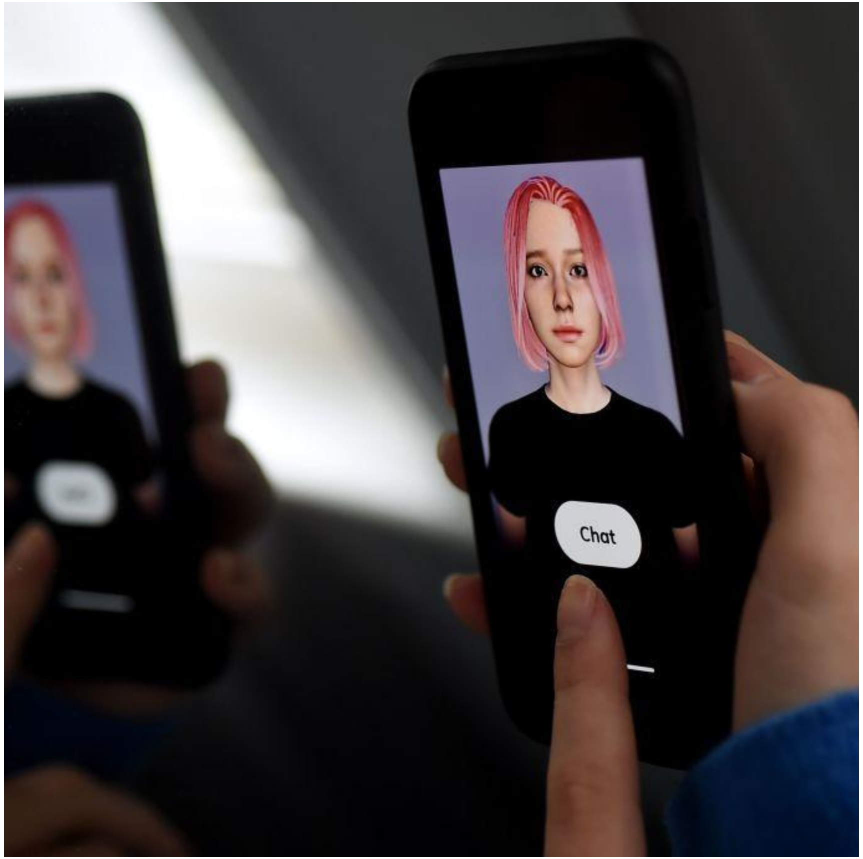
INTRODUCTION

Overview of project background and primary objectives

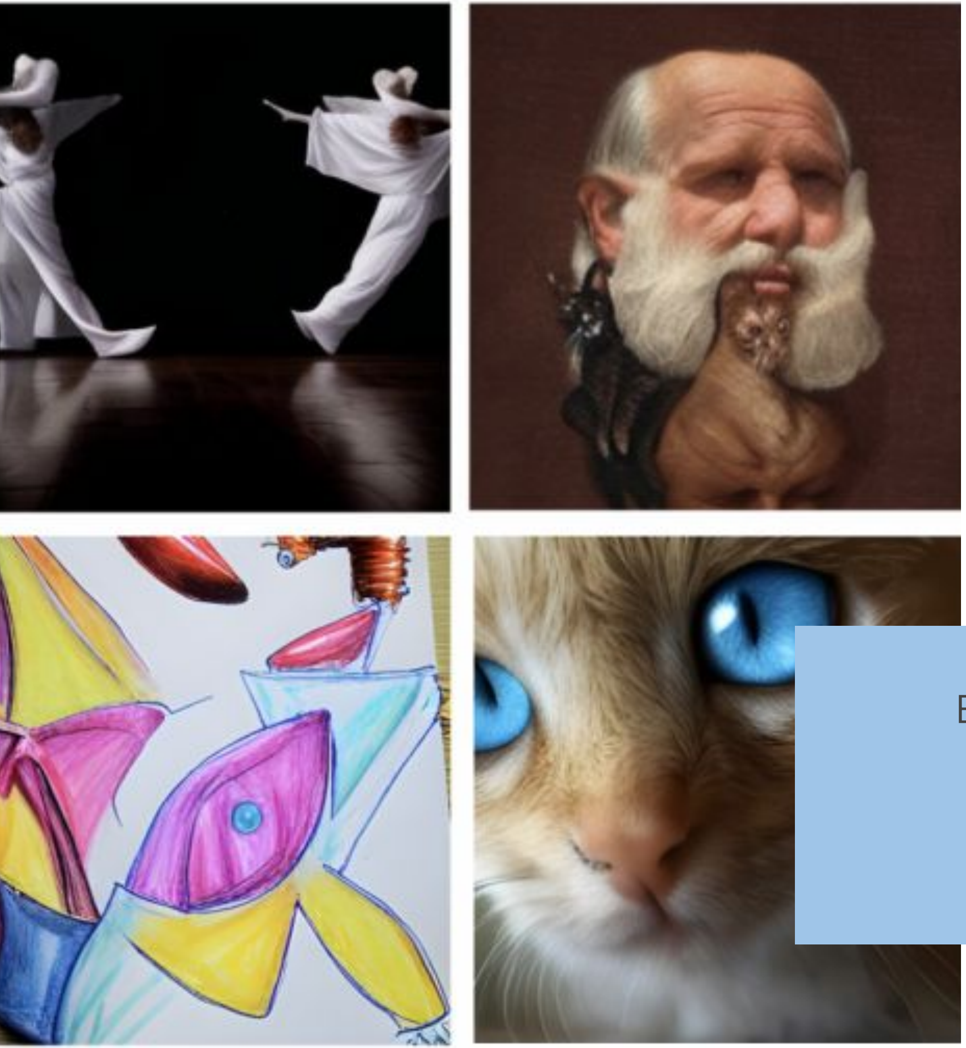




OBJECTIVE

Our objective is to utilize style transfer techniques in the visual arts to inspire emerging artists and innovators. We'll explore existing Deep Learning methods, implement them uniquely for our purpose.

In a business context, we envision that it can be extended to create a versatile tool for use in graphic design, traditional art inspiration, gaming avatars, streaming platforms, printing, and more.



02 LITERATURE REVIEW

Exploring the history and evolution of Artificial Intelligence and Deep Learning methodologies in Art

HOW DID A.I. ART EVOLVE?

3000 BC → **1842** → **1950**

Talking Knots

The ancient Inca used a system called *Quipu*—"talking knots"—to collect data and keep records on everything

Poetical Science

Ada Lovelace, while developing the first algorithm,imagined a machine that could have applications beyond calculation—could computers be used to make art?

The Imitation Game

Alan Turing developed the Turing Test, to test for a machine's ability to exhibit intelligent behavior indistinguishable from a human

HOW DID A.I. ART EVOLVE?

1953 → 1968 → 1973

Reactive Machines

Researchers create a reactive machine that responded to sound input from a human performer to drive an array of lights

Cybernetic Serendipity

Artists were influenced by “cybernetic” creations, and many created “artificial life” artworks that behaved according to biological analogies.

Aaron

Harold Cohen developed ‘Aaron’, which could generate unexpected forms and make artistic decisions beyond his original instructions.

1980S- EARLY 2000S

- 20th century: Personal computers made software and programming accessible, driving rapid field development.
- Researchers shared datasets (e.g., ImageNet) for training algorithms in image cataloging and object identification.
- Accessible computer vision programs (e.g., **Google DeepDream**) enabled exploration of computer-interpreted visual representations.

Anna Ridler, Tulips from *Mosaic Virus* (2018). Image courtesy the artist.

GENERATIVE ART

The most commonly associated with A.I. art today are Generative Adversarial Networks—or GANs.

In the generative part, the algorithm is trained on a dataset to recognize and generate new images based on its learning.

In the adversarial part, the generated images are tested against another algorithm to determine if they can deceive it into thinking they were created by humans.

EVOLUTION OF G.A.N.ISM

Ian Goodfellow coined the term in a 2014 essay theorizing that GANs could be used to produce completely new images.

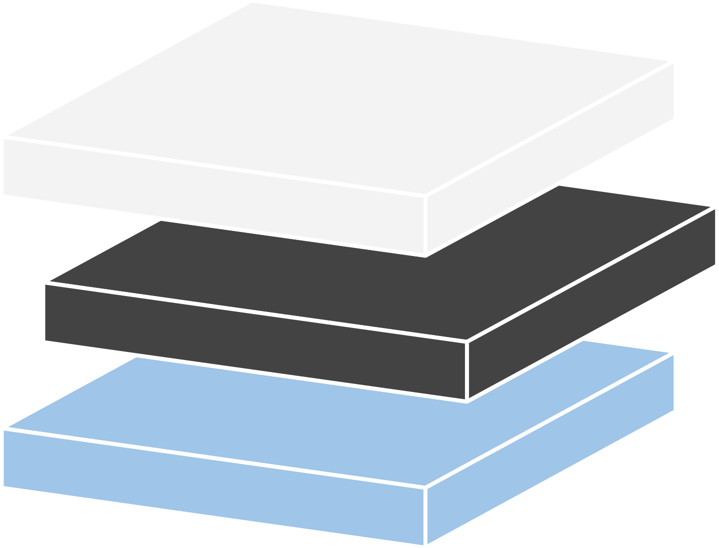
2014

Tech companies open-sourced their raw and untrained GANs, including Google (TensorFlow) and Meta (Torch)

2017

Artists trained a GAN on 15,000 portraits from 14th-20th century, and then asked it generate its own portrait, which sold at Christie's in 2018 for a whopping $432,000

2018



WHERE ARE WE NOW?

CLIP

A powerful model that learns the relationship between images and text, enabling applications such as image classification and text-based image retrieval.

MiDaS

A depth estimation model that predicts the distance of objects in a scene from a 2D image, useful for applications like virtual reality and image editing

WHERE ARE WE NOW?

StyleGAN

A breakthrough algorithm for generating realistic and diverse synthetic images, allowing artists to control the visual style of the generated images

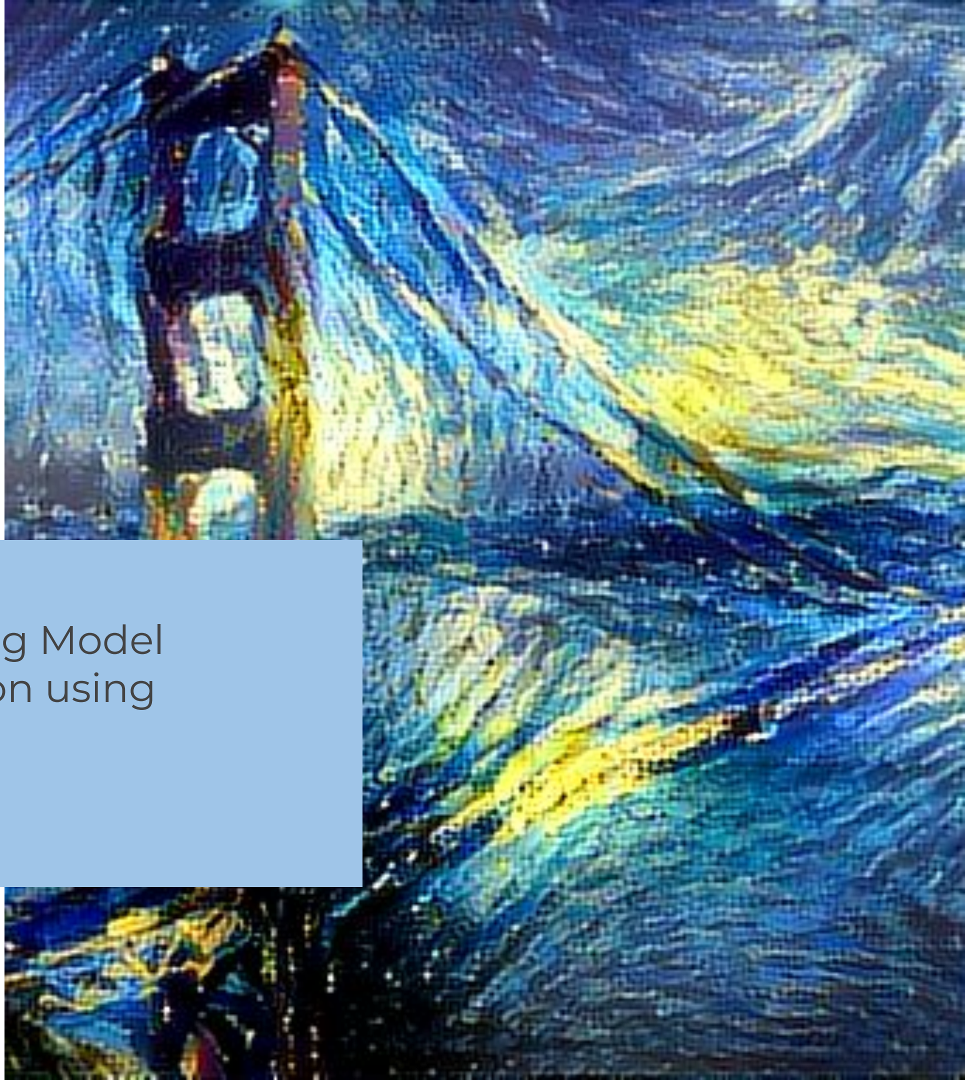
DALL-E

An advanced model that generates images based on textual descriptions, showcasing the potential of AI to create imaginative visual content.

03

METHODS AND MODELING

Our detailed Deep Learning Model framework, implementation using Python and Results



STYLE TRANSFER

Style transfer is a computer vision technique that takes two images—a *content image* and a *style reference image*—and blends them together so that the resulting output image retains the core elements of the content image, but appears to be "painted" in the style of the style reference image.

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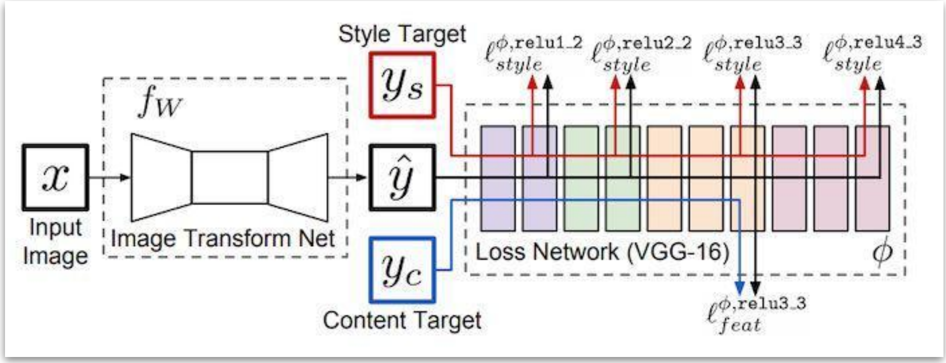
HOW DOES IT WORK?

- Style images go through the feature extractor to save style layer outputs.
- Content images pass through the feature extractor and transfer network to get stylized images, with saved content and style features.
- A custom loss function evaluates the quality of stylized images by comparing content and style.
- Adjusting weights in the loss function controls the level of stylization in the output.

Feature Extractor

Captures image content and style information from pre-trained layers



Transfer Network

Consists of an encoder-decoder architecture, generates the stylized image.

DATASET

ImageNet is a vast dataset of wide ranged labeled images used to train and evaluate computer vision algorithms.

Our implementation utilizes the VGG19 pretrained model for Keras, a 19-layer deep convolutional neural network,which is trained on over a million images from ImageNet.

IMPLEMENTATION

We used Google Colab Pro to train and run our model.

The code can be broken down as follows :

- The **Gram matrix** measures correlations between features of a given layer; reshapes the input tensor and computes the dot product of its flattened versions
- **Style loss** measures the difference between style images and generated images using Gram matrices, while **content loss** measures the difference between content and generated images using feature maps.
- The **VGG19 model** is loaded with **ImageNet** weights, and style layers and content layer are defined.
- **Loss weights** are assigned to balance content and style importance.
- The **Total Loss** and **Gradients of loss** with respect to the combination image are computed.
- The input images are **pre-processed** before and **de-processed** after.
- Model is **trained** and results are stored at pre-defined iteration checkpoints.

MODEL RESULTS

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MODEL RESULTS

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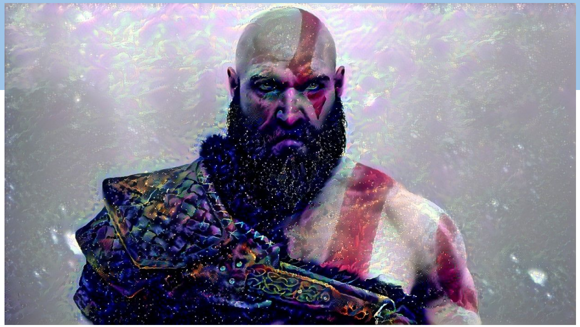

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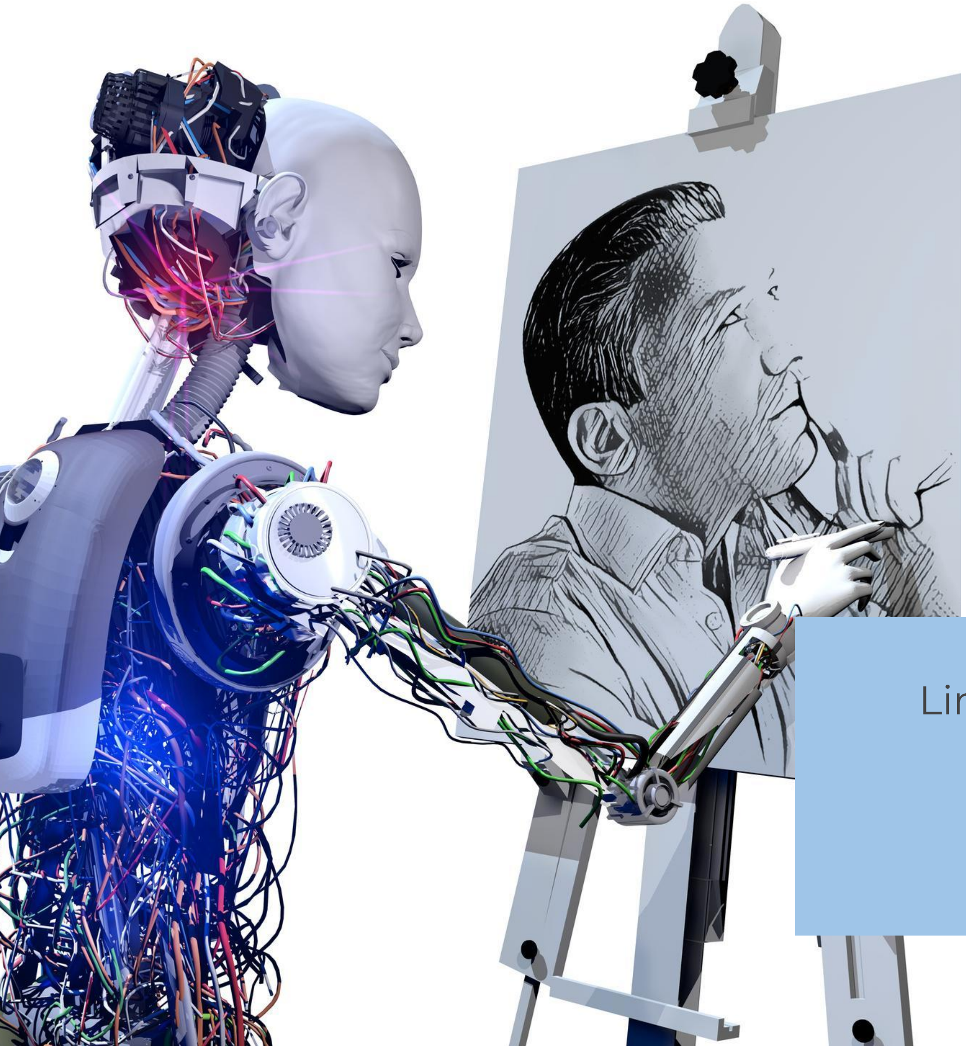

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IMPROVEMENTS & FUTURE SCOPE

Limitations, Improvements, Possible Applications and Future Scope

WHAT CAN WE DO BETTER?

LIMITATIONS

- Lack of flexibility in VGG19
- Trial and error for fine-tuning Style-Content balance
- Requires significant memory and computation resources.
- Expanding scope to multiple style references is limited

IMPROVEMENTS

- Explore more advanced architectures for improved style transfer.
- Utilize perceptual loss functions to enhance visual quality.
- Apply regularization techniques like total variation or style consistency to reduce artifacts.
- Train with increasing resolutions for better convergence and fine detail capture.

APPLICATIONS AND FUTURE SCOPE

Style transfer has practical applications in the commercial art world and enables creative experimentation worldwide.

With advancements in AI-accelerated hardware, it can be applied to :

- Photo and Video editing
- Artist-Community engagement
- Commercial Art
- Gaming
- Virtual Reality

THANK YOU