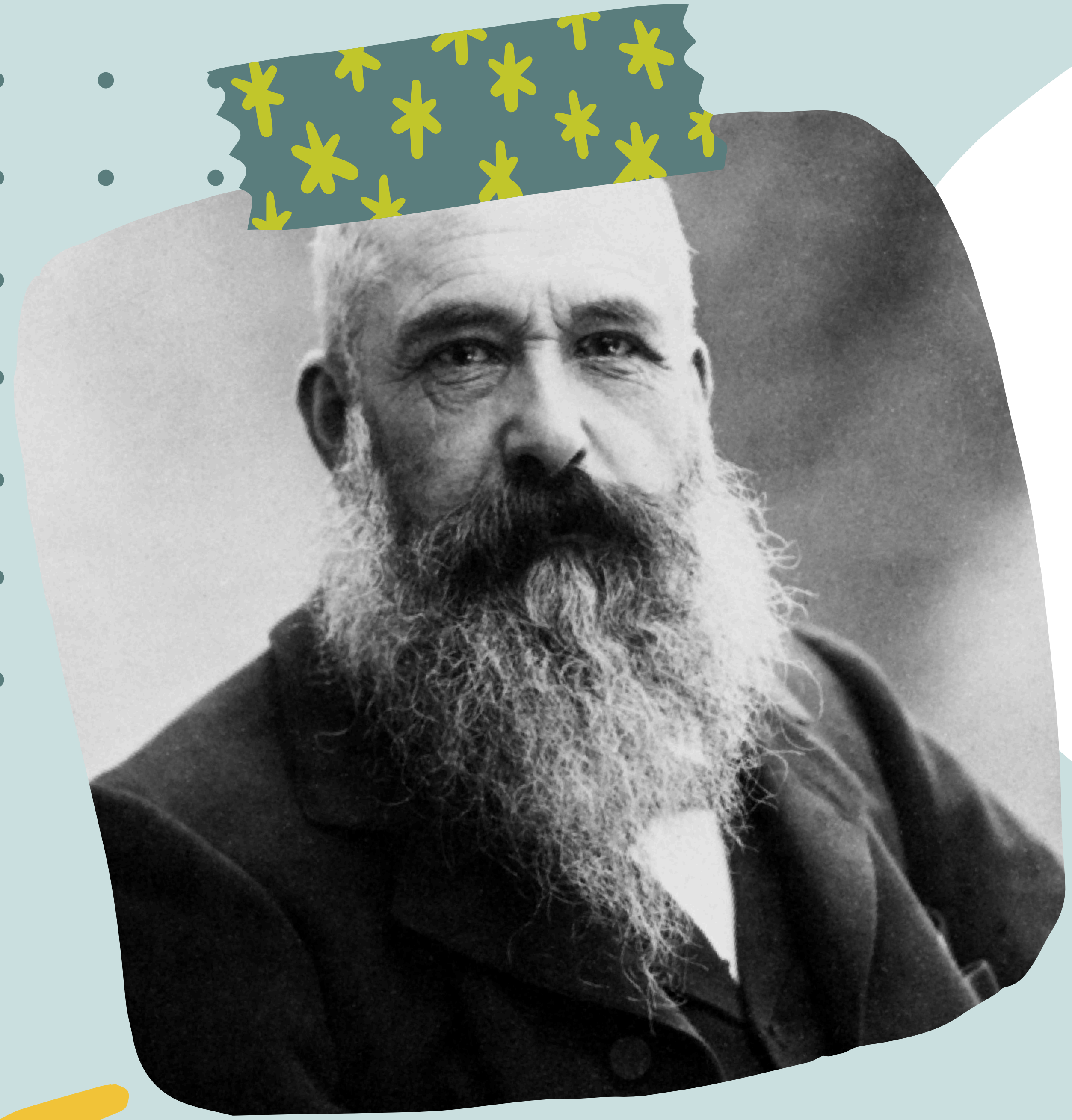
MINI-PROJECT PRESENTATION

Neural Style Transfer with CycleGAN On Monet dataset



GROUP MEMBERS:

- Benghenima Hafsa
- Ghandouz Amina

PLAN

1. Introduction
2. Background and Related Work
3. Dataset
4. Methodology
5. Results & Conclusion

Introduction

Neural style transfer is a technique that generates an image by blending the content of one image with the style of another. It uses deep learning, particularly CNN to extract and recombine features. Unlike traditional style transfer, CycleGAN allows for image transformation without paired datasets.

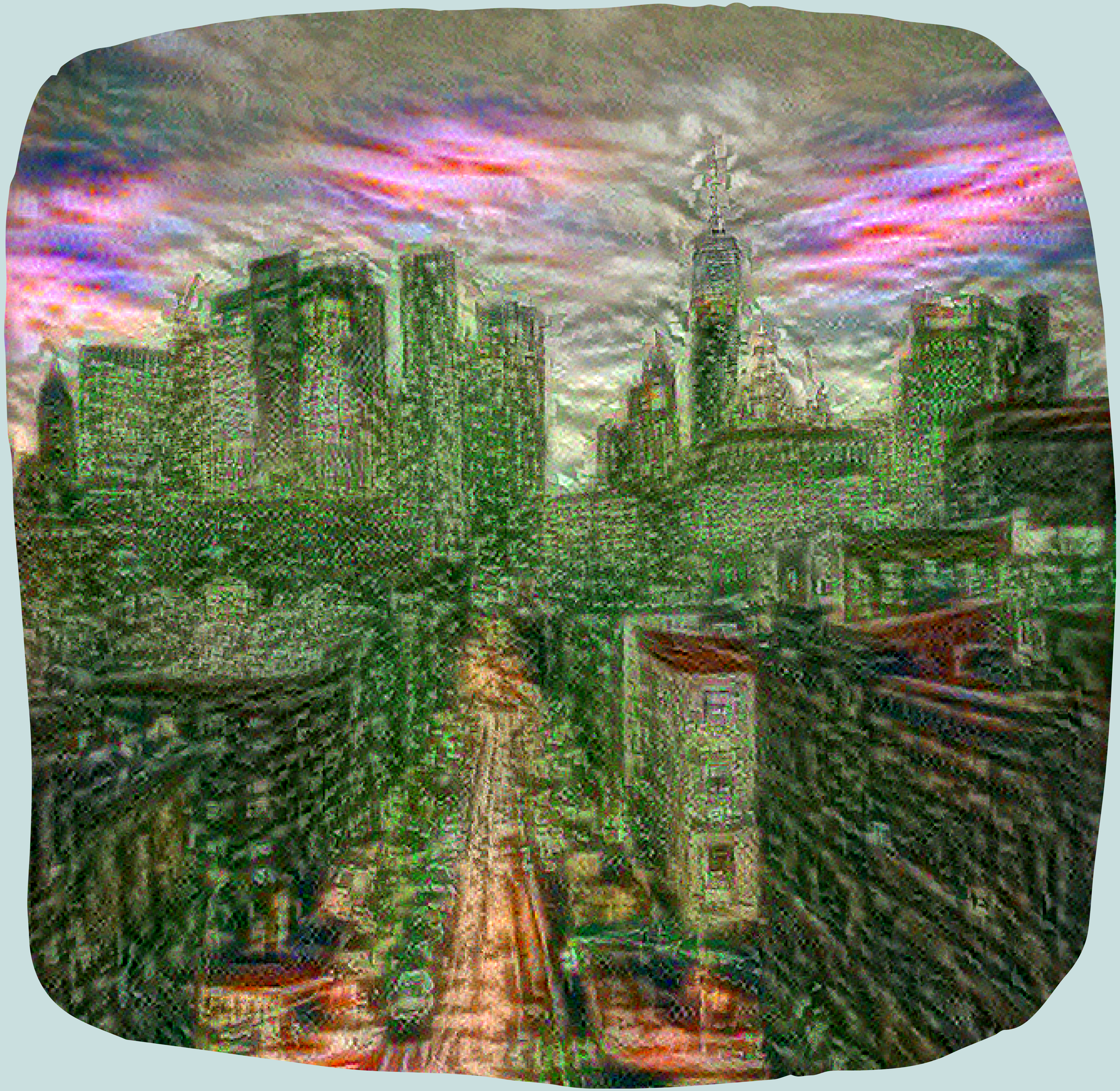
The goal of the project is to transform photographs into artistic paintings painted by monet using CycleGAN.

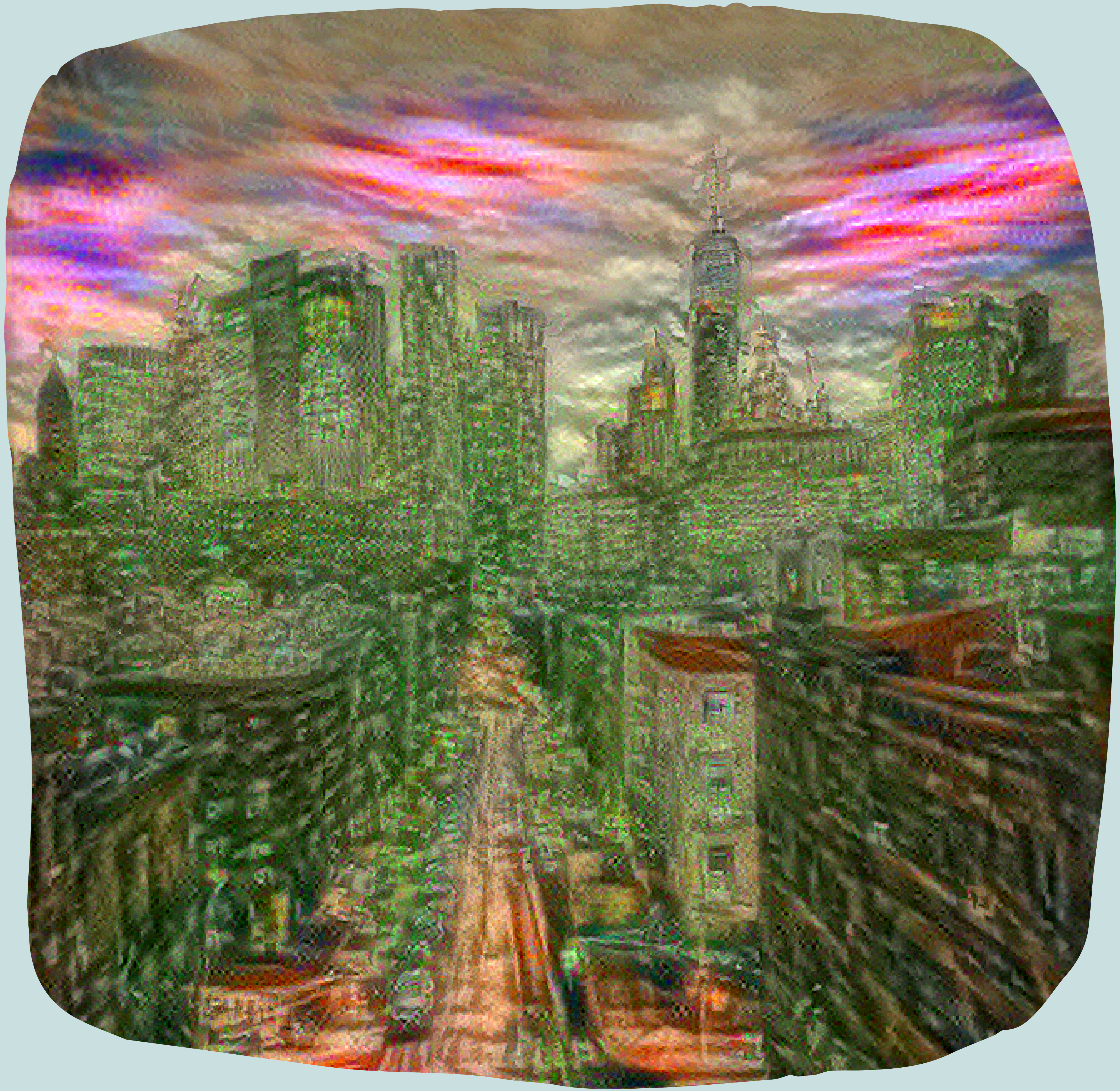
NST

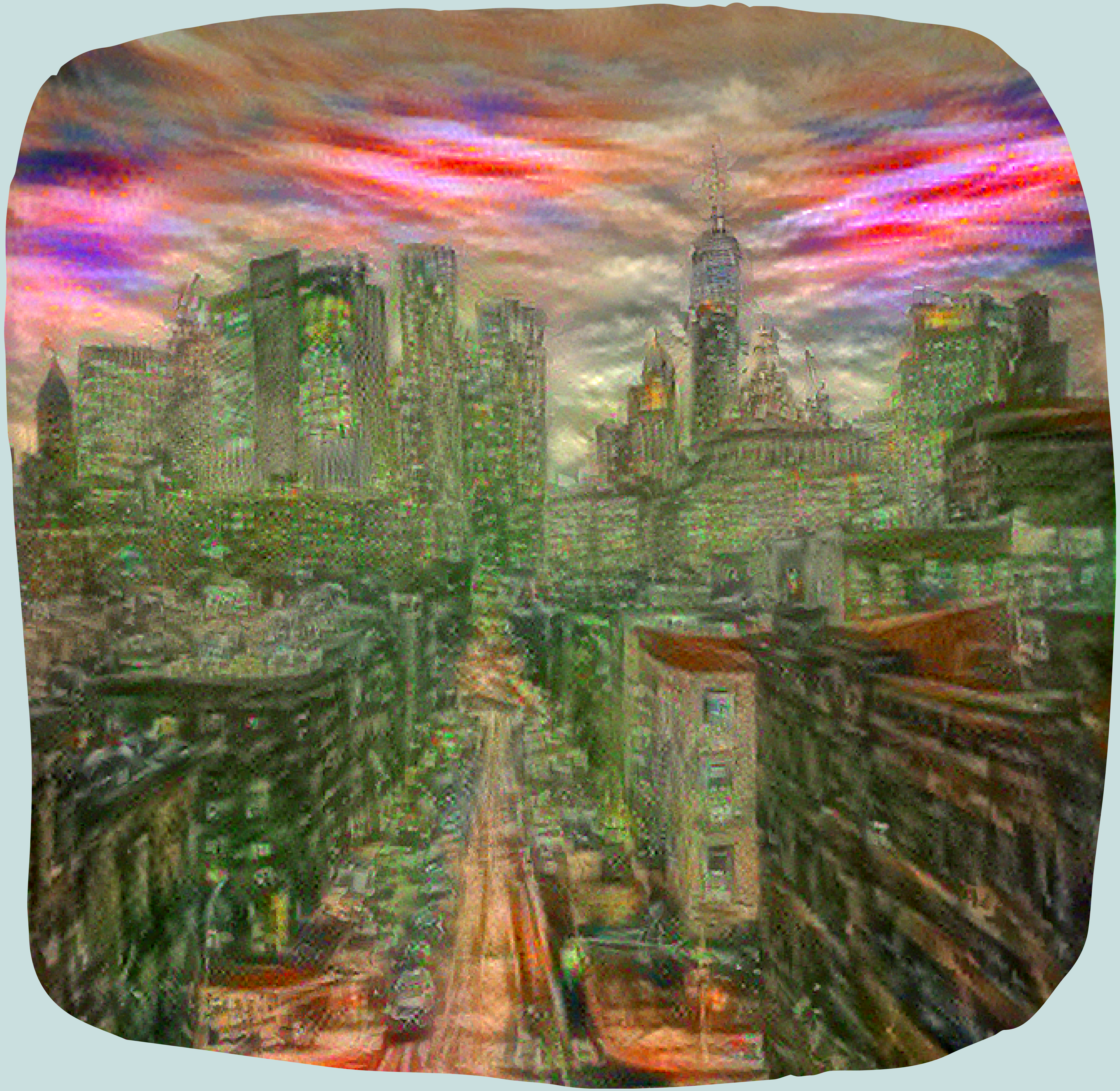
Background and Related Work

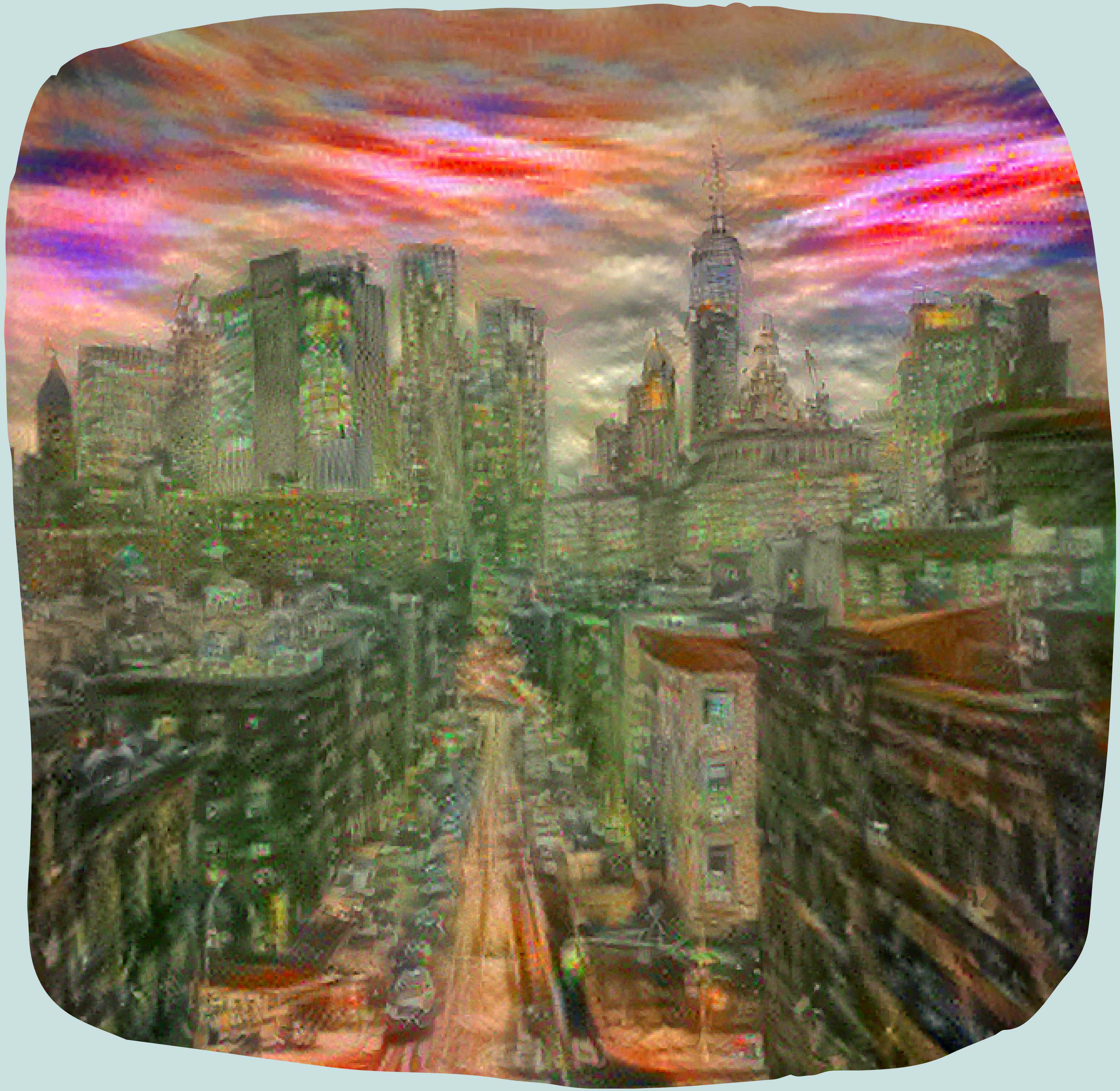
WHAT IS NST!

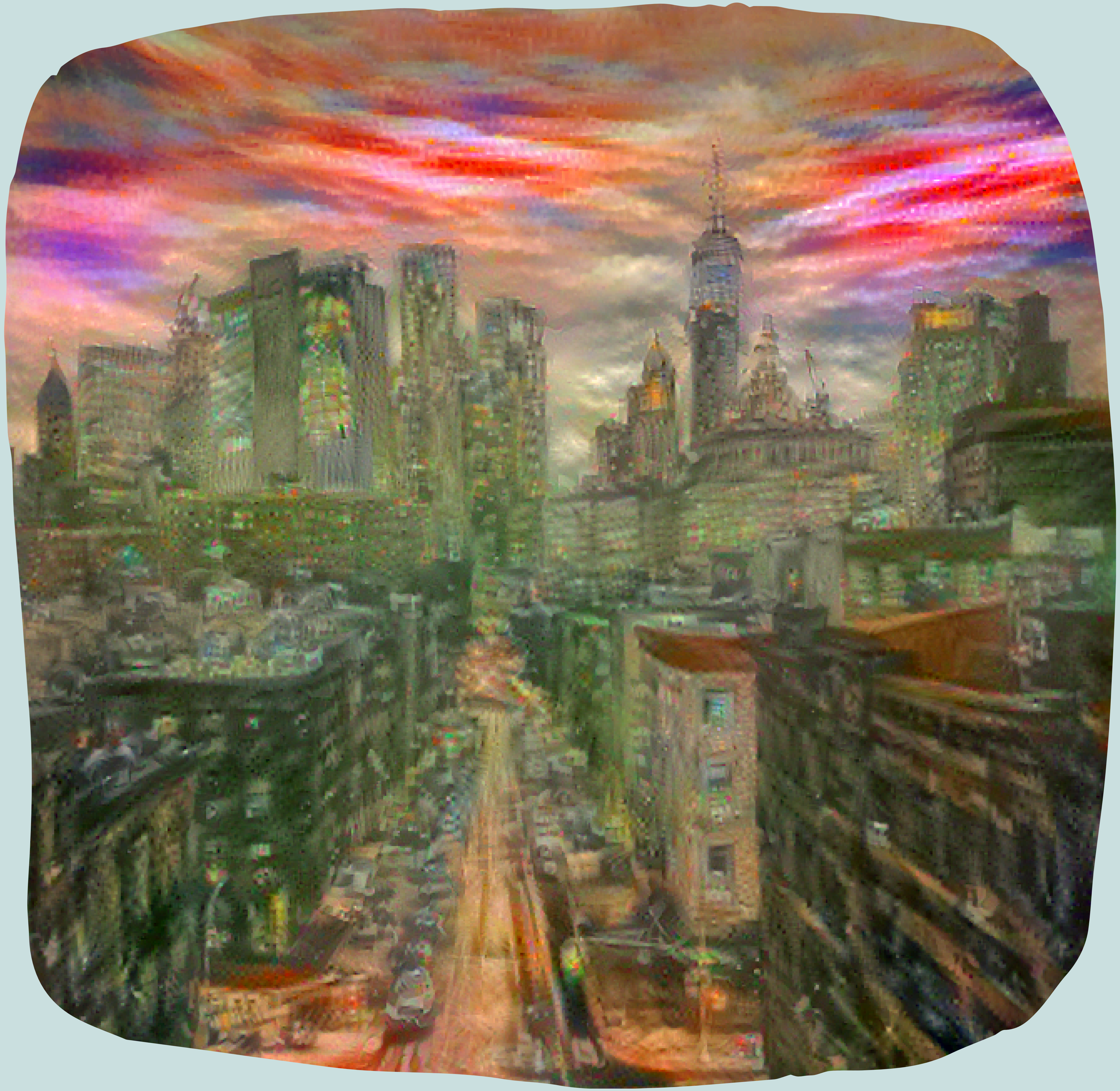
Style transfer merges the content (structure/layout) of one image with the style (textures/colors) of another, creating a new image, it's exactly like telling a machine, "Make this photograph look like it was painted by a known painter". Before the advent of deep learning, style transfer was primarily approached through methods like statistical analysis and patch-based matching while NST leverages CNNs to separate and recombine content/style

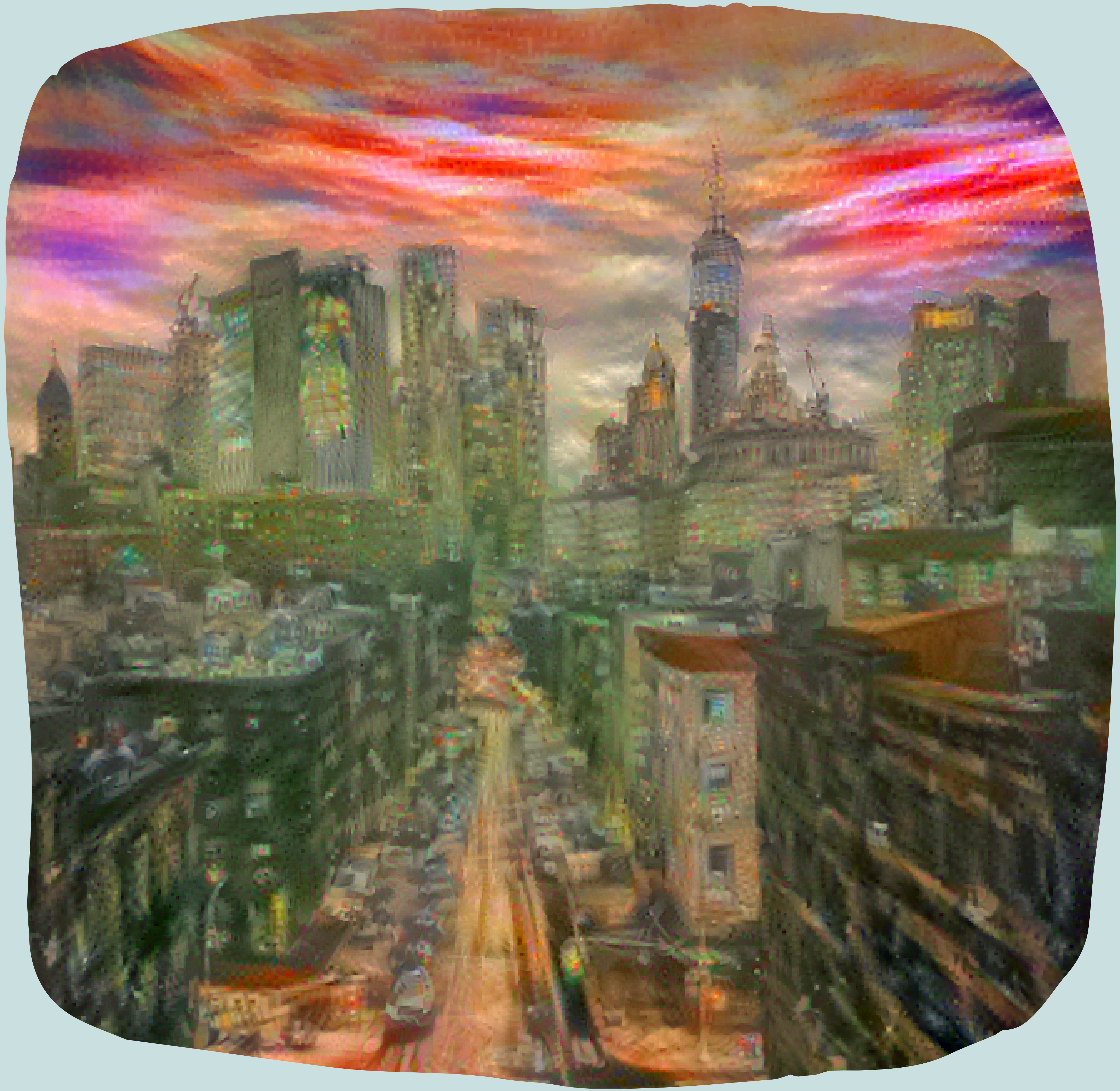


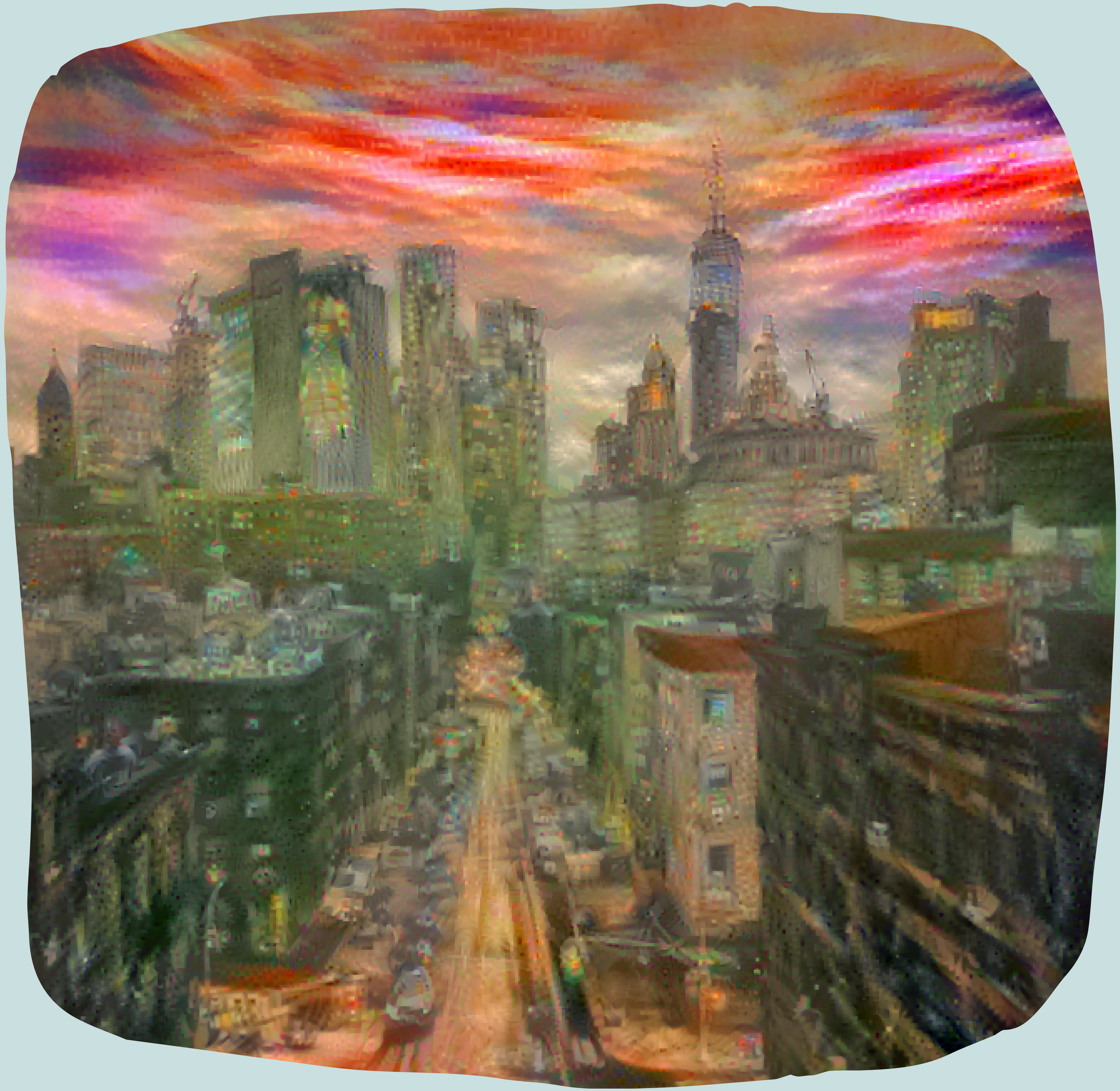


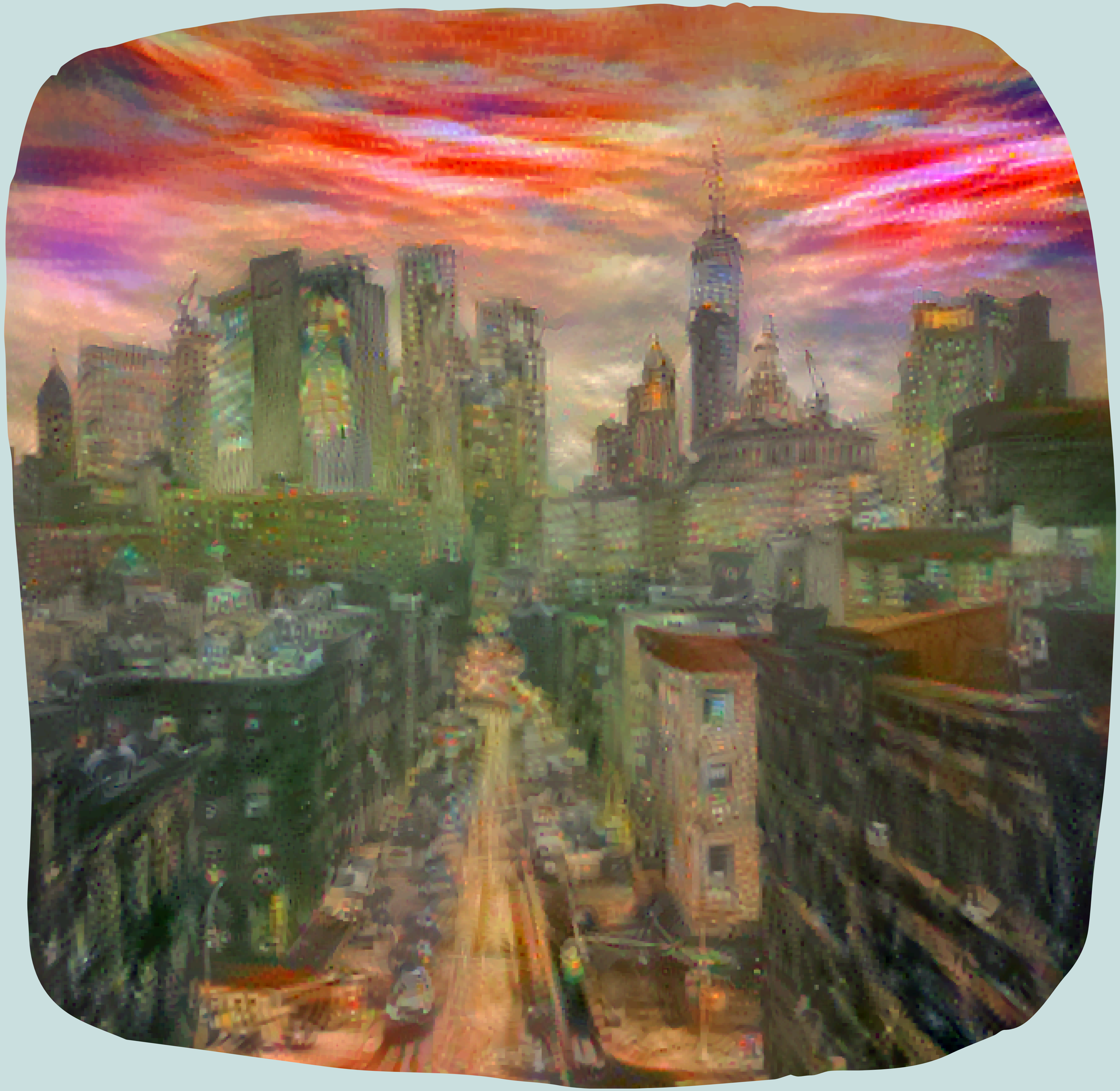


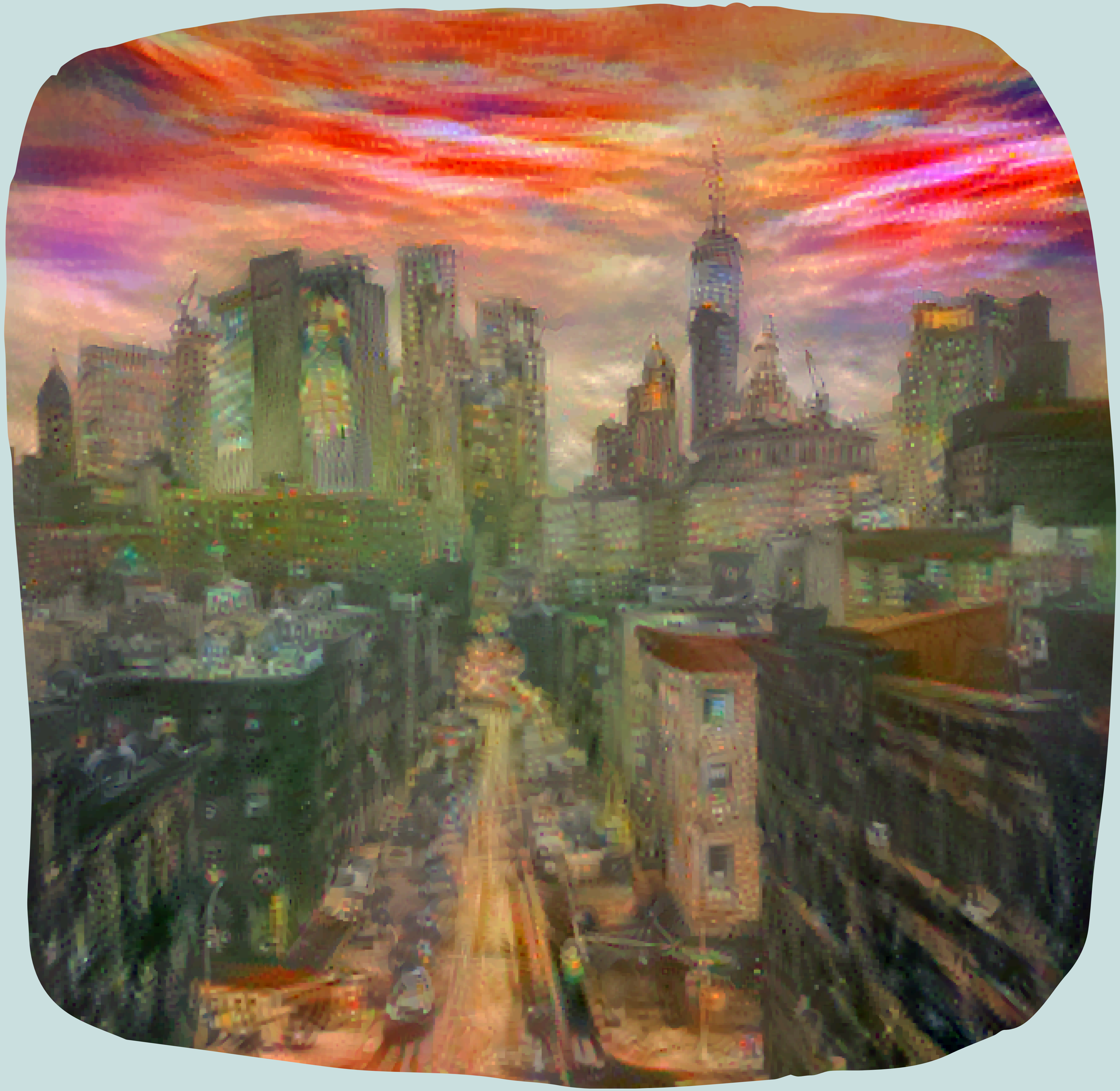


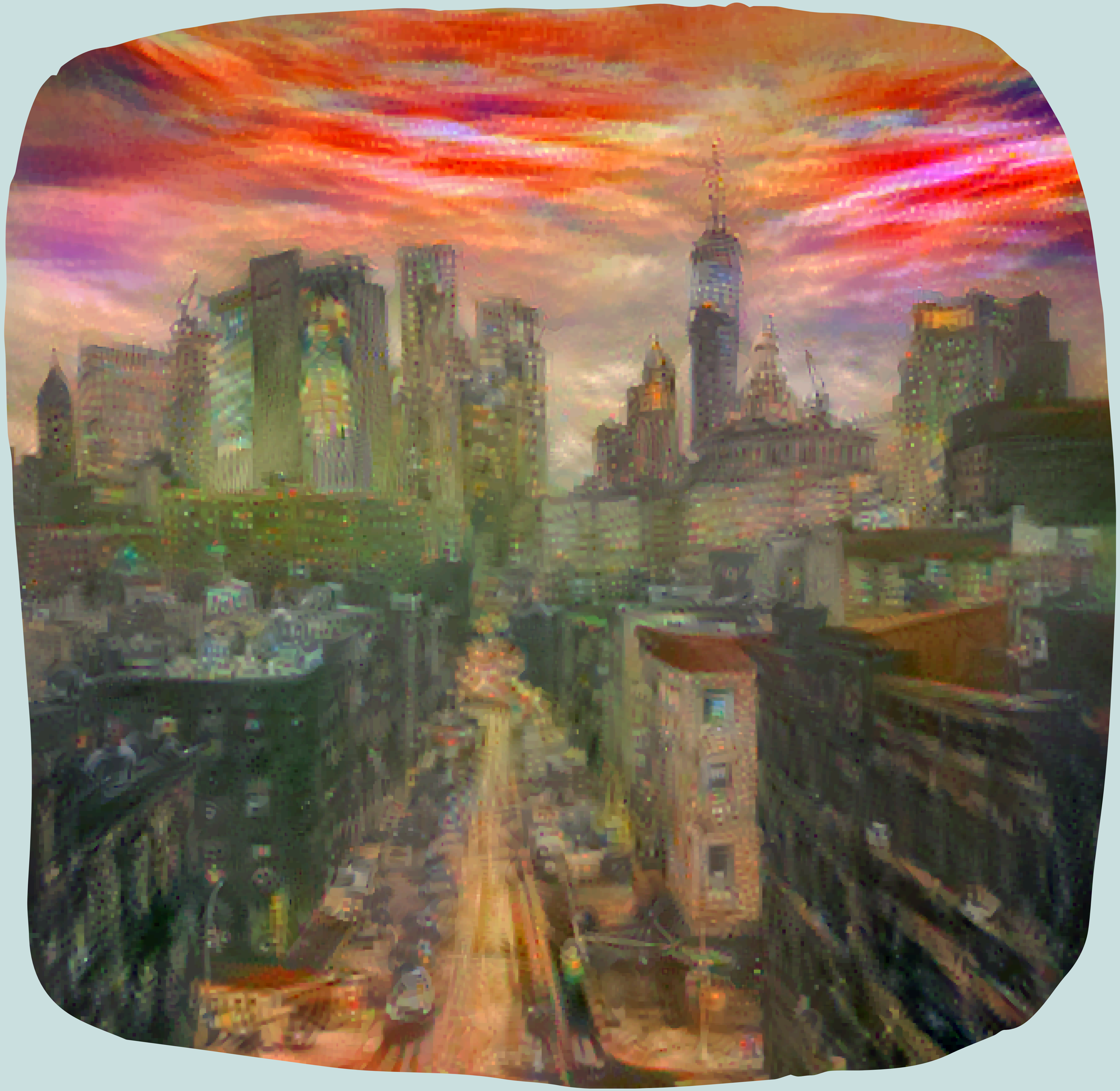












WHAT IS CNN!

Convolutional Neural Networks are a class of deep learning models designed for processing grid-like data (e.g., images). They use convolutional layers (to detect hierarchical patterns and textures in early layers, and complex shapes/objects in deeper layers), pooling layers, fully connected layers ... CNNs excel at tasks like image classification tasks. In NST, they decompose images into content (structural features) and style (textural features) for recombination.

WHAT IS GAN!

Generative Adversarial Networks are deep learning models that pit two neural networks against each other, a generator (which creates fake data) and a discriminator (which tries to detect fakes). Through this adversarial training, the generator learns to produce increasingly realistic outputs (images, paintings). GANs excel at tasks like image synthesis, data augmentation and style transfer using paired dataset.

WHAT IS CYCLEGAN AND WHY!

While traditional GANs require paired datasets for image translation tasks, this limitation inspired the development of CycleGAN, introduced in 2017 in a paper named "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks". CycleGAN solves the paired data problem by employing cycle-consistency loss. It model uses two GANs working in opposite directions with shared constraints, making it ideal for artistic style transfer.

Generator & Discriminator Architectures

G_B2A

D_B

G_A2B

D_A

The Generator architecture in CycleGAN typically uses a ResNet-based design with several residual blocks that help preserve image content while applying the target style. It includes downsampling layers, residual blocks, and upsampling layers to transform input images into styled outputs. The Discriminator architecture uses a PatchGAN.

LOSS FUNCTION

AS IT WAS MENTIONED ON THE PAPER, CYCLEGAN USES THREE KEY LOSSES:

(1) ADVERSARIAL LOSS.
(2) CYCLE-CONSISTENCY LOSS.
(2) IDENTITY LOSS.

OBJECTIVE

HOW WOULD MONET PAINT THIS SCENE?

Dataset

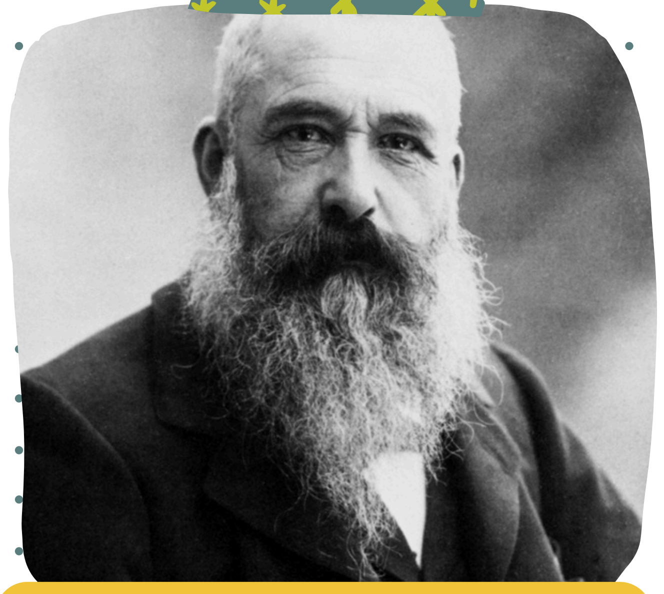
Monet dataset

8,231 IMAGES
- 1,193 MONET PAINTINGS
- 7,038 NATURAL PHOTOS

TWO FOLDERS:
A- MONET IMAGES
B- REAL PHOTOS

MONET2PHOTO DATASET

89% TRAINING SET
11%TEST SET
WITH 256X256 SIZE



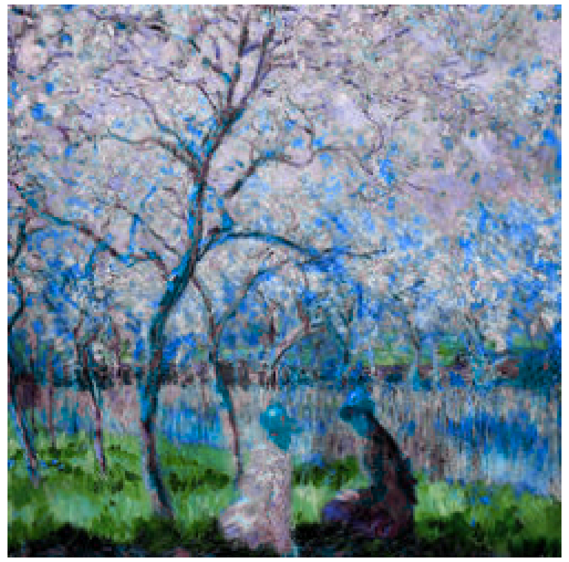
CLAUDE MONET

(1840-1926)

He was was a French painter known for his focus on capturing light and natural scenery, he was interested in painting in the open air

Sample Images

Monet
00651.jpg



Monet
00976.jpg

Monet
00232.jpg

Monet
00985.jpg

Monet
00332.jpg

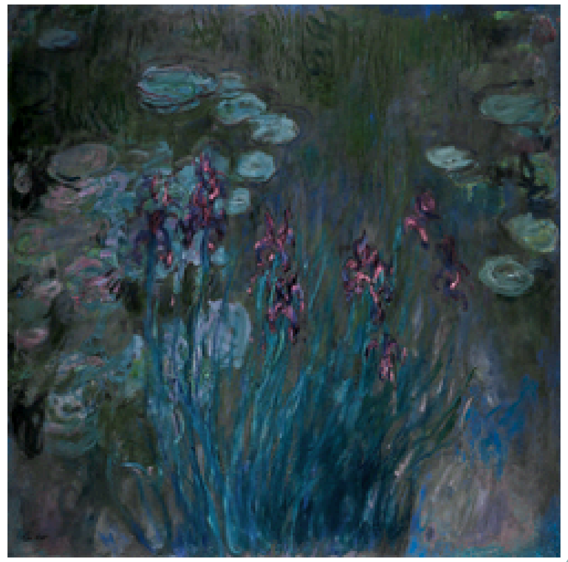


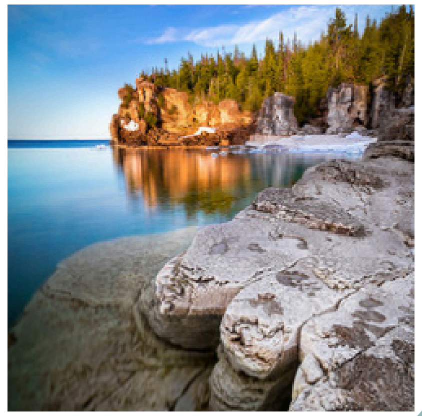
Photo
2016-12-22 15_39_28.jpg

Photo
2015-05-27 09_29_44.jpg

Photo
2014-01-11 15_18_14.jpg

Photo
2013-11-17 18_08_26.jpg

Photo
2016-03-12 09_23_24.jpg



Methodology

Following the architecture that was proposed in the papeR, we used:

1. Two generators, each one attempts to learn the mapping between one image domain and the other (monet painting and real photos):
   - G : P hoto → Monet
   - F : Monet → P hoto
2. Two patch-based (PatchGAN) discriminators to focus on local image details Where:
   - D_{monet}: Distinguishes real Monet paintings from generated ones.
   - D_{photo}: Distinguishes real photographs from generated ones. They are

FOR THE LOSS FUCTION, WE USED THE SUM OF THE THREE LOSSES:

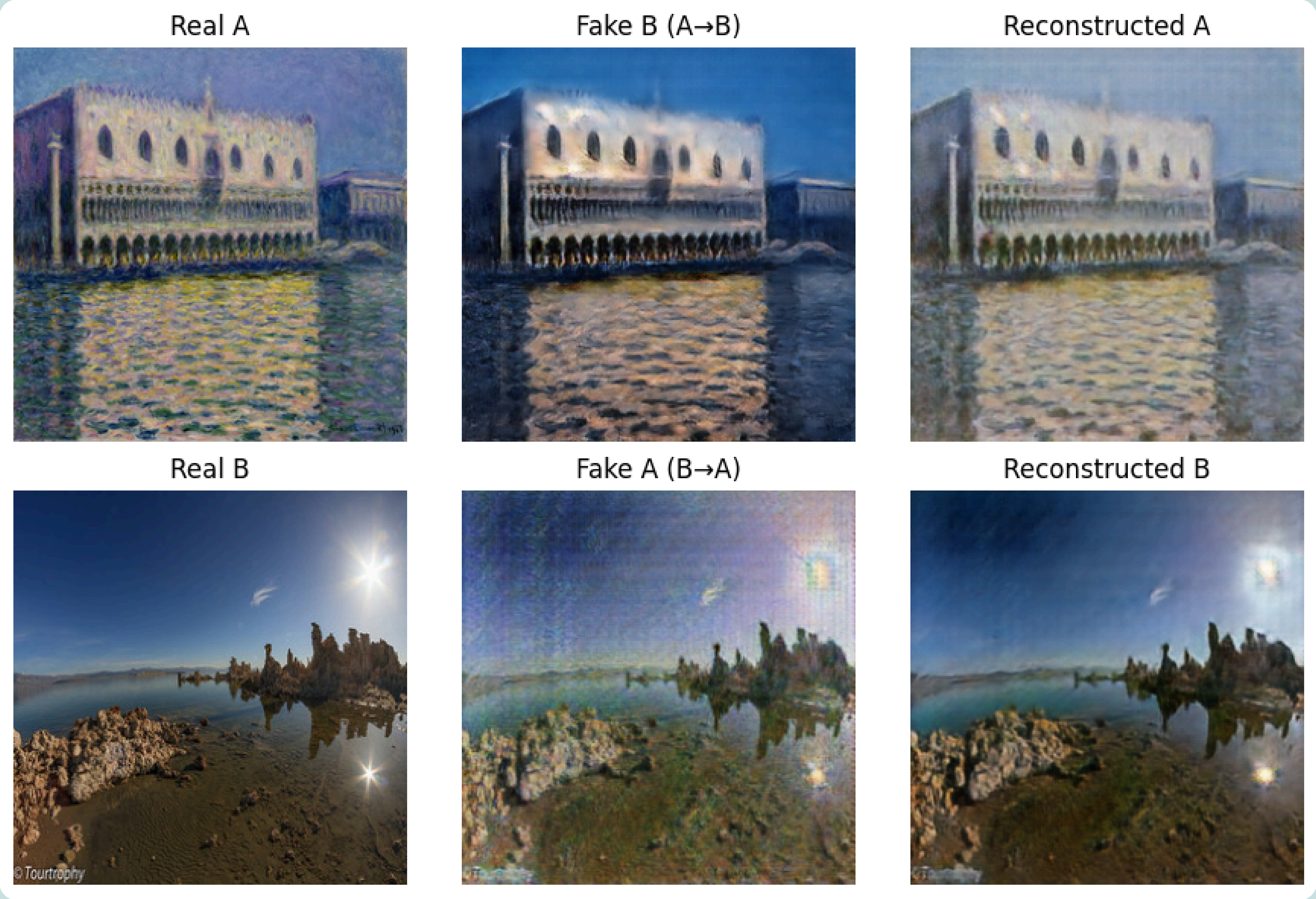
- ADVERSARIAL LOSS
- CYCLE CONSISTENCY LOSS
- IDENTITY LOSS

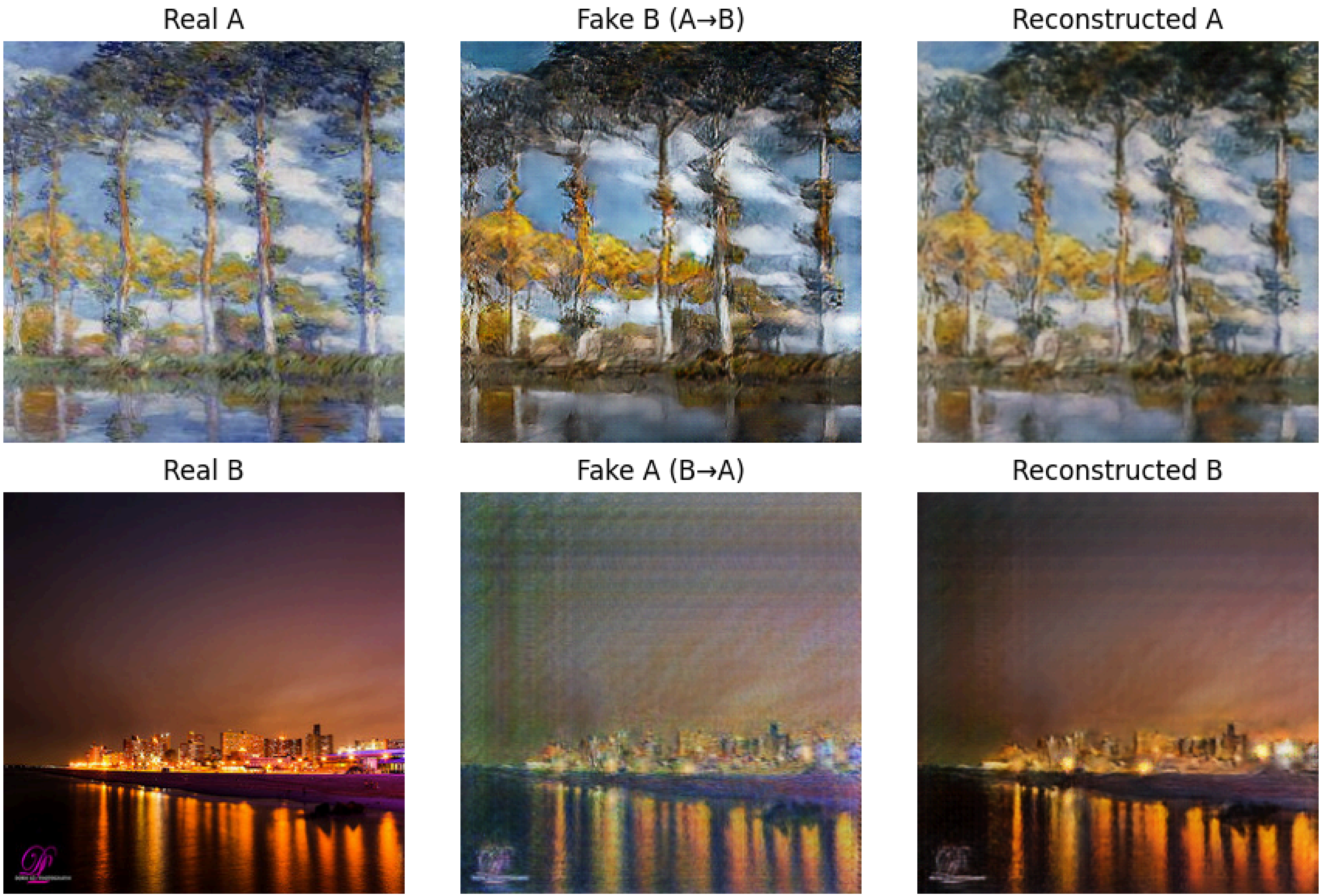
HYPER-PARAMETERS

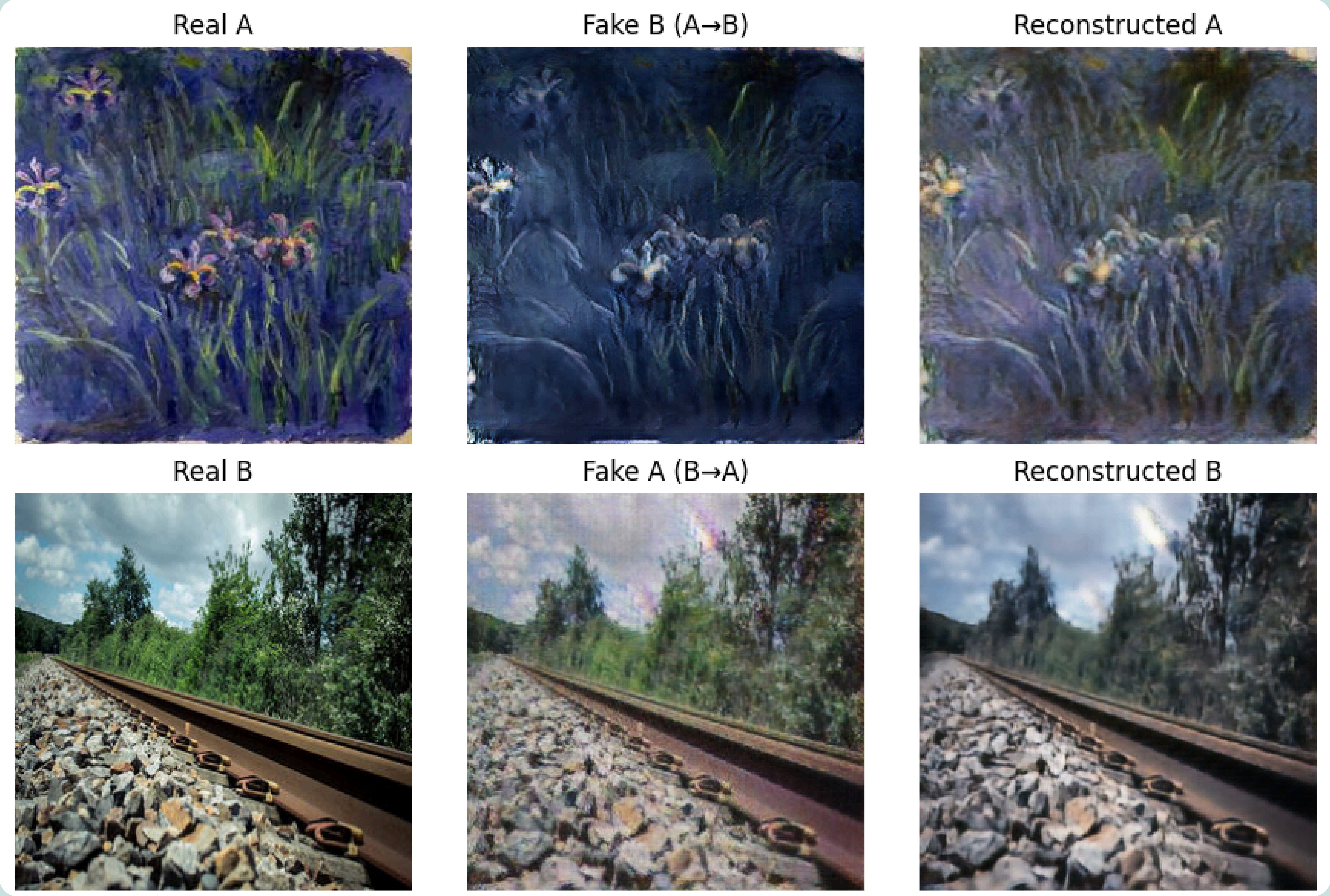
- learning rate = 0.0002
- lambda identity = 5
- lambda cycle = 10
- epochs = 50

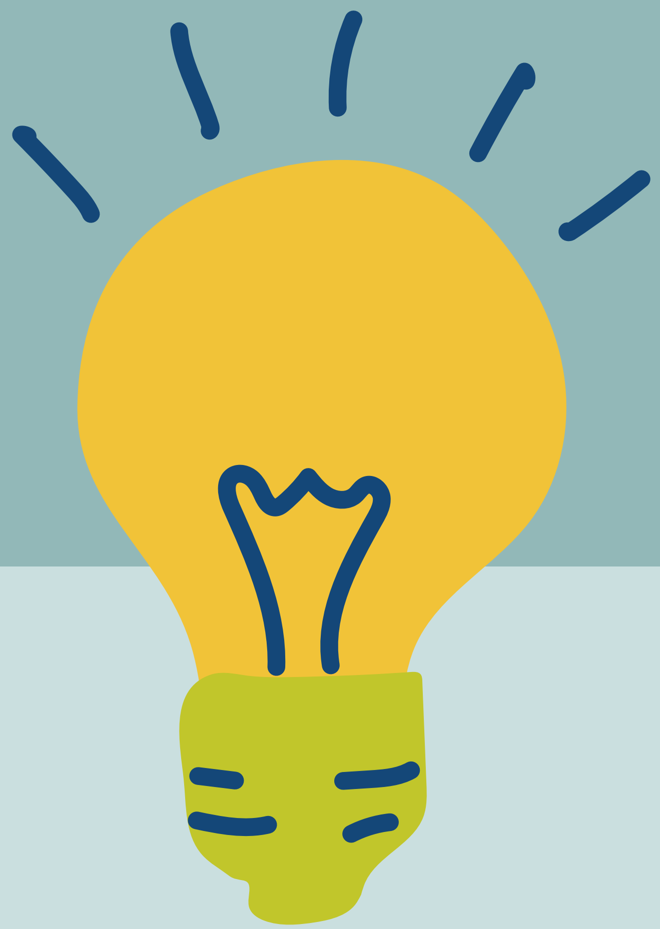
TOTAL RUNNING TIME OF 285.64MIN (4H 46MIN)

Obtained Results


Real A
Fake B (A→B)
Reconstructed A
Real B
Fake A (B→A)
Reconstructed B
© Tourtrophy


Real A
Fake B (A→B)
Reconstructed A
Real B
Fake A (B→A)
Reconstructed B


Real A
Fake B (A→B)
Reconstructed A
Real B
Fake A (B→A)
Reconstructed B



- generator loss ~ 5
- discriminators loss < 0.1
- cycle consistency loss = 0.2965
- LPIPS = 0.3765

Testing the model

REFERENCES

- THE ART STORY
- MEDIUM
- KAGGLE
- THE ORIGINAL PAPER

Merci !