Proto Assignment 5 - General Adversariel Network (GAN) Monet Painting Style Transfer

Description

This project is a GAN based style transformation. The goal of this project is to develop a GAN model that can accurately transfer the Monet style of paintings to a photograph. The model will train on sample Monet painting images learning the Monet style. It will then reproduce photographs in the Monet style. The data is provided by the Kaggle competition 'I'm Somewhat of a Painter Myself' Competition and located at https://www.kaggle.com/competitions/gan-getting-started.

CycleGAN, a very popular extension of the GAN architecture will be used to develope the model. CycleGan deploys two Generator and Discriminator models to create the style transfer paramters. A more detailed description of the CyclGan architecture is provided in the Model section of the document.

GAN networks are a common tool employed in Generative Artificial Intelligence. Generative AI uses deep learning techniques to produce or replicate new content, such as images, music, and text. Generative models aim to generate outputs based on little or no related inputs. They can work in a purely productive manner where no related inputs are provided or in a replecative manner where related inputs are provided to produce a desired output. In the most simplistic terms, GAN networks can be thought of as a tug-o-war between the generative (generator) and descrimintive (descriminator) components of the network.

The generator produces an output based on some inputs. The descriminator takes the output from the generator as input. The discriminator then makes an assessment of the generator's input as real of fake. The output of the discriminator is then fed back into both genrator and discriminator. The discriminator attempts to fool the generator with feedback while also using its own feedback. The two battle back and forth resulting in both improving their ability to produce and identify the most accurate outputs.

The course material was a very brief and provided only a very high level view of GAN theory. The course material did not cover GAN implmentation. With that in mind, this project will rely heavily on the tutorials in the references for implementation guidance. Custom adaptations will be injected where possible to build a unique project structured around the tutorial's base structures. The course did not offer specifics into the CycleGAN package. For readability and consistency purposes, non-model elements in this project will be pulled from the tutorial where applicable.

Data Summary

In [11]:
```
#File Maintainance
#!pip
import os
# print(os.getcwd())
# print(os.listdir())
# print(os.chdir('/kaggle'))
# print(os.listdir())
# #!mkdir tmp


# #Set Page Width to 100%
from IPython.display import display, HTML
import warnings
warnings.filterwarnings('ignore')
display(HTML("<style>.container { width:100% !important; }</style>"))
```

In [3]:
```
import warnings
warnings.filterwarnings('ignore')

#Load Required Resources
import os
import pandas as pd
import numpy as np
from tensorflow import keras
from tensorflow.keras import layers
#import tensorflow_addons as tfa

import matplotlib.pyplot as plt

import tensorflow as tf

#from Monet CycleGAN Tutorial
#Uncomment for use in Kaggle notebook
from kaggle_datasets import KaggleDatasets
import tensorflow_addons as tfa

try:
    tpu = tf.distribute.cluster_resolver.TPUClusterResolver()
    print('Device:', tpu.master())
    tf.config.experimental_connect_to_cluster(tpu)
    tf.tpu.experimental.initialize_tpu_system(tpu)
    strategy = tf.distribute.experimental.TPUStrategy(tpu)
except:
    strategy = tf.distribute.get_strategy()
print('Number of replicas:', strategy.num_replicas_in_sync)

AUTOTUNE = tf.data.experimental.AUTOTUNE

print(tf.__version__)
```

```
Number of replicas: 1
2.10.1
```

Build Dataset

As loading the data set is beyond the scope of this project the 'Load in the Data' code provided in the Kaggel tutorial will be implemented. The data set consists of 5 TFREC files containing the Monet training images and 20 TFREC files containing the photo images to be transformed into the Monet style. When unpacked there are a total of 300 Monet training images and 7000 photo images. The data set also provides the same quantity of Monet and photo images in JPEG format. The shape of the images is 256 x 256 with the three associated RGB channels.

In [3]:
```
#Kaggle Notebook Data Import
#from Monet CycleGAN Tutorial
#Uncomment for use in Kaggle notebook
GCS_PATH = KaggleDatasets().get_gcs_path()

monet_filename_id = tf.io.gfile.glob(str(GCS_PATH + '/monet_tfrec/*.tfrec'))
print('Count of Monet TF record Files:', len(monet_filename_id))

photo_filename_id = tf.io.gfile.glob(str(GCS_PATH + '/photo_tfrec/*.tfrec'))
print('Count of Photo TF record Files: ', len(photo_filename_id))
```

```
Count of Monet TF record Files: 5
Count of Photo TF record Files:  20
```

In [6]:
```
#Local Data Import
#The .tfrec files from the Kaggle Competition site will be used
#Comment out for use in Kaggle Notebook
monet_filename_id = tf.io.gfile.glob(str('monet_tfrec/*.tfrec'))
print('Count of Monet TF record Files: ', len(monet_filename_id))

photo_filename_id = tf.io.gfile.glob(str('photo_tfrec/*.tfrec'))
print('Count of Photo TF record Files: ', len(photo_filename_id))
```

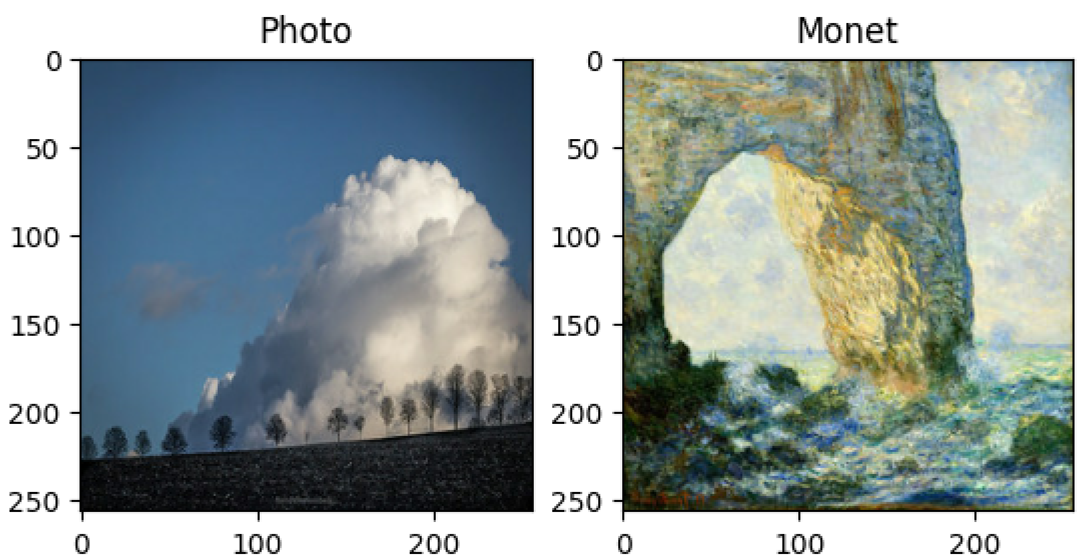
```
Count of Monet TF record Files:  5
Count of Photo TF record Files:  20
```

In [8]:
```
# Scale the images and pull only the image files
IMAGE_SIZE = [256, 256]

def decode_image(image):
    image = tf.image.decode_jpeg(image, channels=3)
    image = (tf.cast(image, tf.float32) / 127.5) - 1
    image = tf.reshape(image, [*IMAGE_SIZE, 3])
    return image

def read_tfrecord(example):
    tfrecord_format = {
        "image_name": tf.io.FixedLenFeature([], tf.string),
        "image": tf.io.FixedLenFeature([], tf.string),
        "target": tf.io.FixedLenFeature([], tf.string)
    }
    example = tf.io.parse_single_example(example, tfrecord_format)
    image = decode_image(example['image'])
    return image

def load_dataset(filenames, labeled=True, ordered=False):
    dataset = tf.data.TFRecordDataset(filenames)
    dataset = dataset.map(read_tfrecord, num_parallel_calls=AUTOTUNE)
    return dataset

#Example and visualize scaled images
```

```
monet_ds = load_dataset(monet_filename_id, labeled=True).batch(1)
photo_ds = load_dataset(photo_filename_id, labeled=True).batch(1)

example_monet = next(iter(monet_ds))
example_photo = next(iter(photo_ds))

plt.subplot(121)
plt.title('Photo')
plt.imshow(example_photo[0] * 0.5 + 0.5)

plt.subplot(122)
plt.title('Monet')
plt.imshow(example_monet[0] * 0.5 + 0.5)
```

Out[8]:

```
<matplotlib.image.AxesImage at 0x7aa22d44c6d0>
```



EDA

EDA will be performed as follows:

```
1. Verify Train Image Counts and Size
2. Verify Test Image Counts and size
3. Provide Sample Monet and photograph images
```

Various random images, and their sizes were reviewed and the Monet images are assessed to be of the Monet style and photo images are photographs. Given that the images and photos are directly from the competition dataset, and the competition dataset is assumed to be in the proper condition, no addtional EDA is requied.

In [9]:

```
# Sample Images and sizes
monet_file_id_df = pd.DataFrame(monet_filename_id)
print('Monet File Summary:')
print(monet_file_id_df.head())
print(monet_file_id_df.info())
```

```
photo_file_id_df = pd.DataFrame(photo_filename_id)
print('Photo FileSummary:')
print(photo_file_id_df.head())
print(photo_file_id_df.info())
```

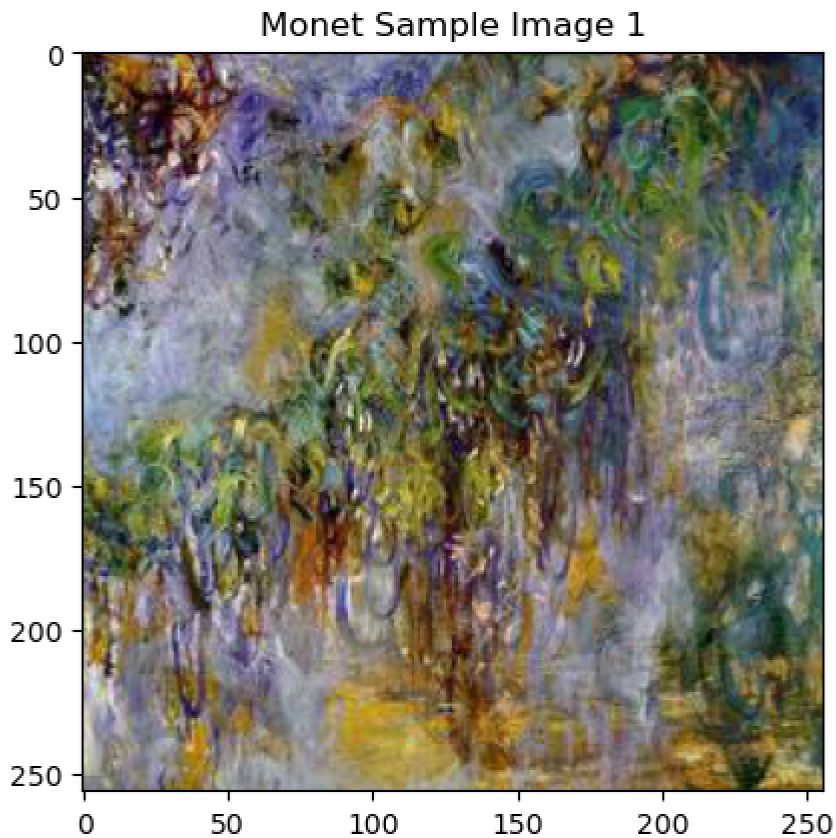
```
Monet File Summary:
                                                   0
0  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
1  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
2  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
3  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
4  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   0       5 non-null      object
dtypes: object(1)
memory usage: 168.0+ bytes
None
Photo FileSummary:
                                                   0
0  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
1  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
2  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
3  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
4  gs://kds-c9c6b95b166162573ee9220e81a91aeba3c26...
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   0       20 non-null     object
dtypes: object(1)
memory usage: 288.0+ bytes
None
```

In [8]:

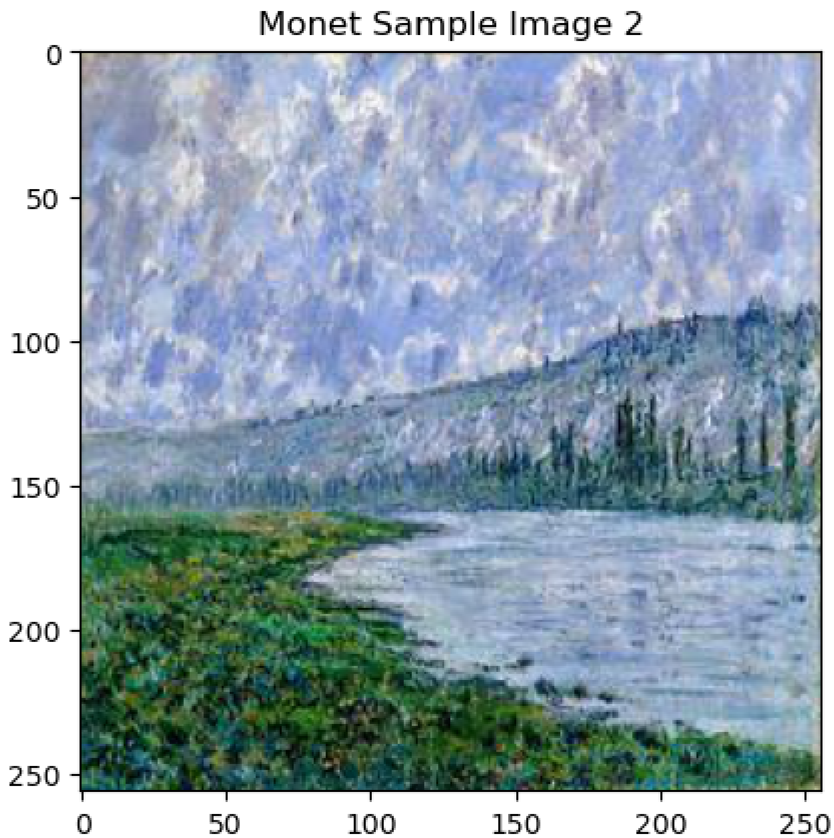
```
# Plot Example Images


monet1 = plt.imread('monet_jpg/0a5075d42a.jpg')
print('Monet Sample Image 1 Shape')
print(monet1.shape)
plt.imshow(monet1)
plt.title('Monet Sample Image 1')
plt.show()

monet2 = plt.imread('monet_jpg/0bd913dbc7.jpg')
print('Monet Sample Image 2 Shape')
print(monet2.shape)
plt.imshow(monet2)
plt.title('Monet Sample Image 2')
plt.show()

photo1 = plt.imread('photo_jpg/0a0c3a6d07.jpg')
print('Photo Sample Image 1 Shape')
print(photo1.shape)
plt.imshow(photo1)
plt.title('Photo Sample Image 1')
```

```
plt.show()

photo2 = plt.imread('photo_jpg/0a0d3e6ea7.jpg')
print('Photo Sample Image 2 Shape')
print(photo2.shape)
plt.imshow(photo2)
plt.title('Photo Sample Image 2')
plt.show()
```

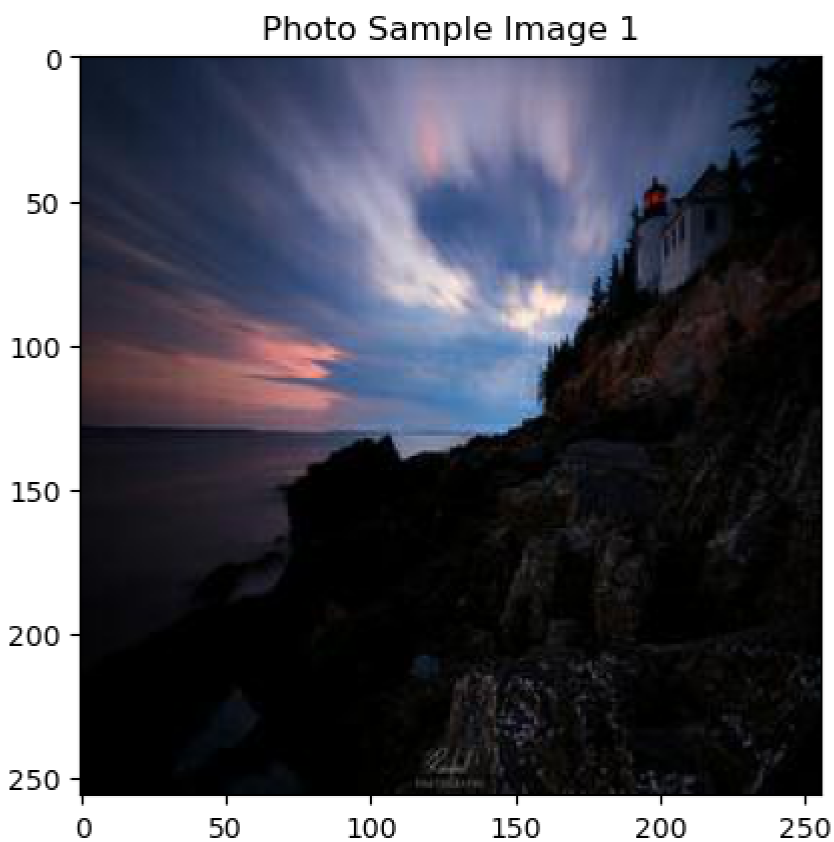
```
Monet Sample Image 1 Shape
(256, 256, 3)
```



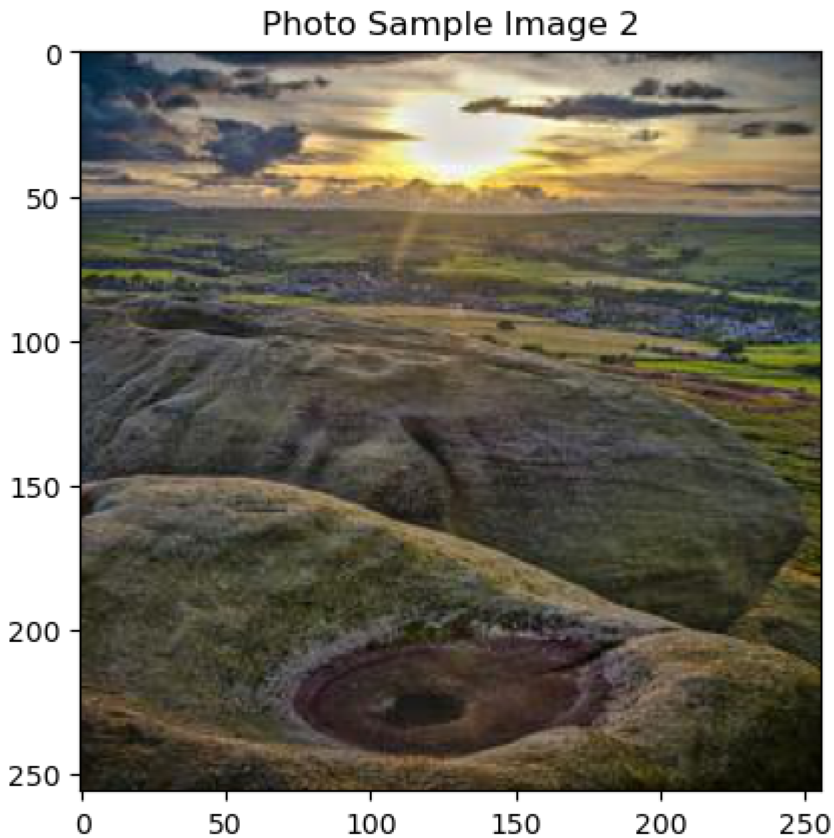

```
Monet Sample Image 2 Shape
(256, 256, 3)
```




```
Photo Sample Image 1 Shape
(256, 256, 3)
```




```
Photo Sample Image 2 Shape
(256, 256, 3)
```



Models

The CycleGAN UNET architecture consists of two generators and two discriminators. The first generator learns image 1 and translates image 1 to image 2. The second generator performs the inverse and learns image 2 and translates image 2 to image 1. The discriminators also come in a pair. The first discriminator learns how to differenciate between images 1 and the generated image 2. The second discriminator, similiar to the second generator's role learns the inverse of discriminator 1 and learns how to differentiate between image2 and the generated image 1.

Based on a review of the literature a good trade off between processing time and accuracy is between 3-6 convolution layers in the generator and discriminator. For this project we'll split the difference and start with 4 layers of each. For the upsampling (encoding) side the generator will have four convolution layers with a stride of 2 and the ReLU activation function. For downsampling (decoding) the generator will have three transpose convolution layers with a stride of 2 and ReLU activation function. The final encoding layer will use the tanh activation function.

For downsampling (decoding) the discriminator will have three transpose convolution layers with a stride of 2 and ReLU activation function. The final encoding layer will use the tanh activation function.

The models will be constructed as follows

1. Build the generator and discrimnator, including both downsampling and upsampling
2. Define the loss functions (per the tutorial using binary cross entroy)

3. Train the models

Import the CycleGAN Class and loss Functions From Kaggle Tutorial

In [10]:
```
# The CycleGAN class has been imported from the Kaggle Tutorial notebook
# Link: https://www.kaggle.com/code/amyjang/monet-cyclegan-tutorial/notebook#Build-the

class CycleGan(keras.Model):
    def __init__(
        self,
        monet_generator,
        photo_generator,
        monet_discriminator,
        photo_discriminator,
        lambda_cycle=10,
    ):
        super(CycleGan, self).__init__()
        self.m_gen = monet_generator
        self.p_gen = photo_generator
        self.m_disc = monet_discriminator
        self.p_disc = photo_discriminator
        self.lambda_cycle = lambda_cycle

    def compile(
        self,
        m_gen_optimizer,
        p_gen_optimizer,
        m_disc_optimizer,
        p_disc_optimizer,
        gen_loss_fn,
        disc_loss_fn,
        cycle_loss_fn,
        identity_loss_fn
    ):
        super(CycleGan, self).compile()
        self.m_gen_optimizer = m_gen_optimizer
        self.p_gen_optimizer = p_gen_optimizer
        self.m_disc_optimizer = m_disc_optimizer
        self.p_disc_optimizer = p_disc_optimizer
        self.gen_loss_fn = gen_loss_fn
        self.disc_loss_fn = disc_loss_fn
        self.cycle_loss_fn = cycle_loss_fn
        self.identity_loss_fn = identity_loss_fn

    def train_step(self, batch_data):
        real_monet, real_photo = batch_data

        with tf.GradientTape(persistent=True) as tape:
            # photo to monet back to photo
            fake_monet = self.m_gen(real_photo, training=True)
            cycled_photo = self.p_gen(fake_monet, training=True)

            # monet to photo back to monet
            fake_photo = self.p_gen(real_monet, training=True)
            cycled_monet = self.m_gen(fake_photo, training=True)

            # generating itself
            same_monet = self.m_gen(real_monet, training=True)
            same_photo = self.p_gen(real_photo, training=True)
```

```
            # discriminator used to check, inputing real images
            disc_real_monet = self.m_disc(real_monet, training=True)
            disc_real_photo = self.p_disc(real_photo, training=True)

            # discriminator used to check, inputing fake images
            disc_fake_monet = self.m_disc(fake_monet, training=True)
            disc_fake_photo = self.p_disc(fake_photo, training=True)

            # evaluates generator loss
            monet_gen_loss = self.gen_loss_fn(disc_fake_monet)
            photo_gen_loss = self.gen_loss_fn(disc_fake_photo)

            # evaluates total cycle consistency loss
            total_cycle_loss = self.cycle_loss_fn(real_monet, cycled_monet, self.lambd

            # evaluates total generator loss
            total_monet_gen_loss = monet_gen_loss + total_cycle_loss + self.identity_l
            total_photo_gen_loss = photo_gen_loss + total_cycle_loss + self.identity_l

            # evaluates discriminator loss
            monet_disc_loss = self.disc_loss_fn(disc_real_monet, disc_fake_monet)
            photo_disc_loss = self.disc_loss_fn(disc_real_photo, disc_fake_photo)

        # Calculate the gradients for generator and discriminator
        monet_generator_gradients = tape.gradient(total_monet_gen_loss,
                                                  self.m_gen.trainable_variables)
        photo_generator_gradients = tape.gradient(total_photo_gen_loss,
                                                  self.p_gen.trainable_variables)

        monet_discriminator_gradients = tape.gradient(monet_disc_loss,
                                                      self.m_disc.trainable_variables)
        photo_discriminator_gradients = tape.gradient(photo_disc_loss,
                                                      self.p_disc.trainable_variables)

        # Apply the gradients to the optimizer
        self.m_gen_optimizer.apply_gradients(zip(monet_generator_gradients,
                                                 self.m_gen.trainable_variables))

        self.p_gen_optimizer.apply_gradients(zip(photo_generator_gradients,
                                                 self.p_gen.trainable_variables))

        self.m_disc_optimizer.apply_gradients(zip(monet_discriminator_gradients,
                                                  self.m_disc.trainable_variables))

        self.p_disc_optimizer.apply_gradients(zip(photo_discriminator_gradients,
                                                  self.p_disc.trainable_variables))

        return {
            "monet_gen_loss": total_monet_gen_loss,
            "photo_gen_loss": total_photo_gen_loss,
            "monet_disc_loss": monet_disc_loss,
            "photo_disc_loss": photo_disc_loss
        }
```

In [11]:

```
#Suppress Warning Messages Code
import warnings
warnings.filterwarnings('ignore')
```

```
with strategy.scope():


    def discriminator_loss(real, generated):
        real_loss = tf.keras.losses.BinaryCrossentropy(from_logits=True, reduction=tf.

        generated_loss = tf.keras.losses.BinaryCrossentropy(from_logits=True, reductic

        total_disc_loss = real_loss + generated_loss

        return total_disc_loss * 0.5

    def generator_loss(generated):
        return tf.keras.losses.BinaryCrossentropy(from_logits=True, reduction=tf.keras

    def calc_cycle_loss(real_image, cycled_image, LAMBDA):
        loss1 = tf.reduce_mean(tf.abs(real_image - cycled_image))
        return LAMBDA * loss1

    def identity_loss(real_image, same_image, LAMBDA):
        loss = tf.reduce_mean(tf.abs(real_image - same_image))
        return LAMBDA * 0.5 * loss

    monet_generator_optimizer = tf.keras.optimizers.Adam(2e-3, beta_1=0.25)
    photo_generator_optimizer = tf.keras.optimizers.Adam(2e-3, beta_1=0.25)

    monet_discriminator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)
    photo_discriminator_optimizer = tf.keras.optimizers.Adam(2e-4, beta_1=0.5)

#     monet_generator_optimizer = tf.keras.optimizers.SGD(learning_rate=0.00001, momer
#     photo_generator_optimizer = tf.keras.optimizers.SGD(learning_rate=0.00001, momer

#     monet_discriminator_optimizer = tf.keras.optimizers.SGD(learning_rate=0.00001, m
#     photo_discriminator_optimizer = tf.keras.optimizers.SGD(learning_rate=0.00001, m
```

Define the generator and discriminator

In [12]:
```
#Use this format for upsample and downsample instead of the def upsample/downsample fr

def generator():

    input_shape = tf.keras.layers.Input(shape=[256, 256, 3])

    # Down Sampling (Encoder)
    downsample_layer_1 = tf.keras.layers.Conv2D(64, (4, 4), strides=2, padding='same',
    downsample_layer_2 = tf.keras.layers.Conv2D(128, (4, 4), strides=2, padding='same'
    downsample_layer_3 = tf.keras.layers.Conv2D(256, (4, 4), strides=2, padding='same'
    downsample_layer_4 = tf.keras.layers.Conv2D(512, (4, 4), strides=2, padding='same'

    # Up Sampling (Decoder)
    upsample_layer_1 = tf.keras.layers.Conv2DTranspose(256, (4, 4), strides=2, padding
    upsample_layer_2 = tf.keras.layers.Conv2DTranspose(128, (4, 4), strides=2, padding
    upsample_layer_3 = tf.keras.layers.Conv2DTranspose(64, (4, 4), strides=2, padding=

    output = tf.keras.layers.Conv2DTranspose(3, (4, 4), strides=2, padding='same', act

    return tf.keras.Model(inputs=input_shape, outputs=output)
```

```python
def discriminator():
    input_shape= tf.keras.layers.Input(shape=[256, 256, 3])

    dis_downsample_layer1 = tf.keras.layers.Conv2D(64, (4, 4), strides=2, padding='sar
    dis_downsample_layer2 = tf.keras.layers.Conv2D(128, (4, 4), strides=2, padding='sa
    dis_downsample_layer3 = tf.keras.layers.Conv2D(256, (4, 4), strides=2, padding='sa

    output = tf.keras.layers.Conv2D(1, (4, 4), padding='same')(dis_downsample_layer3)

    return tf.keras.Model(inputs=input_shape, outputs=output)
```

Training

In [13]:

```python
#from Monet CycleGAN Tutorial
with strategy.scope():
    monet_generator = generator()
    photo_generator = generator()

    monet_discriminator = discriminator()
    photo_discriminator = discriminator()


    cycle_gan_model = CycleGan(
        monet_generator, photo_generator, monet_discriminator, photo_discriminator
    )

    cycle_gan_model.compile(
        m_gen_optimizer = monet_generator_optimizer,
        p_gen_optimizer = photo_generator_optimizer,
        m_disc_optimizer = monet_discriminator_optimizer,
        p_disc_optimizer = photo_discriminator_optimizer,
        gen_loss_fn = generator_loss,
        disc_loss_fn = discriminator_loss,
        cycle_loss_fn = calc_cycle_loss,
        identity_loss_fn = identity_loss
    )
```

Fit the Model

In [14]:

```python
cycle_gan_model.fit(
    tf.data.Dataset.zip((monet_ds, photo_ds)),
    epochs=20
)
```

```
Epoch 1/20
300/300 [==============================] - 42s 70ms/step - monet_gen_loss: 13.1121 -
photo_gen_loss: 13.5328 - monet_disc_loss: 0.5749 - photo_disc_loss: 0.5585
Epoch 2/20
300/300 [==============================] - 22s 69ms/step - monet_gen_loss: 12.2615 -
photo_gen_loss: 13.1294 - monet_disc_loss: 0.6092 - photo_disc_loss: 0.5762
Epoch 3/20
300/300 [==============================] - 22s 70ms/step - monet_gen_loss: 9.2378 - p
hoto_gen_loss: 9.6320 - monet_disc_loss: 0.6217 - photo_disc_loss: 0.6222
Epoch 4/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 7.6281 - p
hoto_gen_loss: 7.6772 - monet_disc_loss: 0.6222 - photo_disc_loss: 0.6261
Epoch 5/20
300/300 [==============================] - 21s 69ms/step - monet_gen_loss: 7.0953 - p
hoto_gen_loss: 7.1713 - monet_disc_loss: 0.6235 - photo_disc_loss: 0.6311
Epoch 6/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 6.8122 - p
hoto_gen_loss: 6.9218 - monet_disc_loss: 0.6498 - photo_disc_loss: 0.6414
Epoch 7/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 6.5642 - p
hoto_gen_loss: 6.6933 - monet_disc_loss: 0.6556 - photo_disc_loss: 0.6433
Epoch 8/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 6.1787 - p
hoto_gen_loss: 6.2656 - monet_disc_loss: 0.6555 - photo_disc_loss: 0.6539
Epoch 9/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.9428 - p
hoto_gen_loss: 5.9947 - monet_disc_loss: 0.6562 - photo_disc_loss: 0.6504
Epoch 10/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.7886 - p
hoto_gen_loss: 5.8553 - monet_disc_loss: 0.6581 - photo_disc_loss: 0.6504
Epoch 11/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.8171 - p
hoto_gen_loss: 5.9113 - monet_disc_loss: 0.6606 - photo_disc_loss: 0.6458
Epoch 12/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.6914 - p
hoto_gen_loss: 5.7546 - monet_disc_loss: 0.6579 - photo_disc_loss: 0.6437
Epoch 13/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.6812 - p
hoto_gen_loss: 5.7742 - monet_disc_loss: 0.6583 - photo_disc_loss: 0.6402
Epoch 14/20
300/300 [==============================] - 22s 69ms/step - monet_gen_loss: 5.4604 - p
hoto_gen_loss: 5.5079 - monet_disc_loss: 0.6573 - photo_disc_loss: 0.6425
Epoch 15/20
300/300 [==============================] - 21s 67ms/step - monet_gen_loss: 5.2340 - p
hoto_gen_loss: 5.2990 - monet_disc_loss: 0.6610 - photo_disc_loss: 0.6486
Epoch 16/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.2857 - p
hoto_gen_loss: 5.3416 - monet_disc_loss: 0.6580 - photo_disc_loss: 0.6519
Epoch 17/20
300/300 [==============================] - 21s 68ms/step - monet_gen_loss: 5.1962 - p
hoto_gen_loss: 5.2357 - monet_disc_loss: 0.6598 - photo_disc_loss: 0.6465
Epoch 18/20
300/300 [==============================] - 22s 69ms/step - monet_gen_loss: 5.1991 - p
hoto_gen_loss: 5.2335 - monet_disc_loss: 0.6571 - photo_disc_loss: 0.6477
Epoch 19/20
300/300 [==============================] - 22s 69ms/step - monet_gen_loss: 5.1366 - p
hoto_gen_loss: 5.1831 - monet_disc_loss: 0.6581 - photo_disc_loss: 0.6514
Epoch 20/20
300/300 [==============================] - 22s 69ms/step - monet_gen_loss: 5.1046 - p
hoto_gen_loss: 5.1471 - monet_disc_loss: 0.6553 - photo_disc_loss: 0.6472
```

Out[14]: <keras.callbacks.History at 0x7aa1ccbceef0>

Various results from different training sessions

Table 2: Epoch Count vs Accuracy

Epoch Count	Optimizer	Monet Generator Loss	Photo Generator Loss	Monet Dicsiminator Loss	Photo Discriminator Loss)
5	Adam	5.00	4.96	0.63	0.62
10	Adam	4.87	4.81	0.62	.61
15	Adam	4.59	4.57	0.62	0.60
20	Adam	4.46	4.44	0.62	0.61
5	SGD	13.91	13.81	0.27	0.29
10	SGD	13.78	13.06	0.19	0.39
15	SGD	7.31	7.44	.51	.52
20	SGD	6.95	7.25	0.58	0.49

Generate Submision File

In [15]:
```
### Sumbit Results, tutorial code modified to accommodate both Kaggel and local direct
import PIL
! mkdir ../images

i = 1
for img in photo_ds:
    prediction = monet_generator(img, training=False)[0].numpy()
    prediction = (prediction * 127.5 + 127.5).astype(np.uint8)
    im = PIL.Image.fromarray(prediction)

    #kaggle Notebook
    im.save("../images/" + str(i) + ".jpg")

    #local Notebook
    #im.save('images/' + str(i) + ".jpg")
    i += 1
```

```
mkdir: cannot create directory '../images': File exists
```

In [16]:
```
import shutil
shutil.make_archive("/kaggle/working/images", 'zip', "/kaggle/images")
```

Out[16]: '/kaggle/working/images.zip'

In [19]:
```
_, ax = plt.subplots(10, 2, figsize=(20, 20))
for i, img in enumerate(photo_ds.take(10)):
    prediction = monet_generator(img, training=False)[0].numpy()
    prediction = (prediction * 127.5 + 127.5).astype(np.uint8)
    img = (img[0] * 127.5 + 127.5).numpy().astype(np.uint8)

    ax[i, 0].imshow(img)
    ax[i, 1].imshow(prediction)
```

```
    ax[i, 0].set_title("Input Photo")
    ax[i, 1].set_title("Monet-Transform")
    ax[i, 0].axis("off")
    ax[i, 1].axis("off")
plt.show()
```

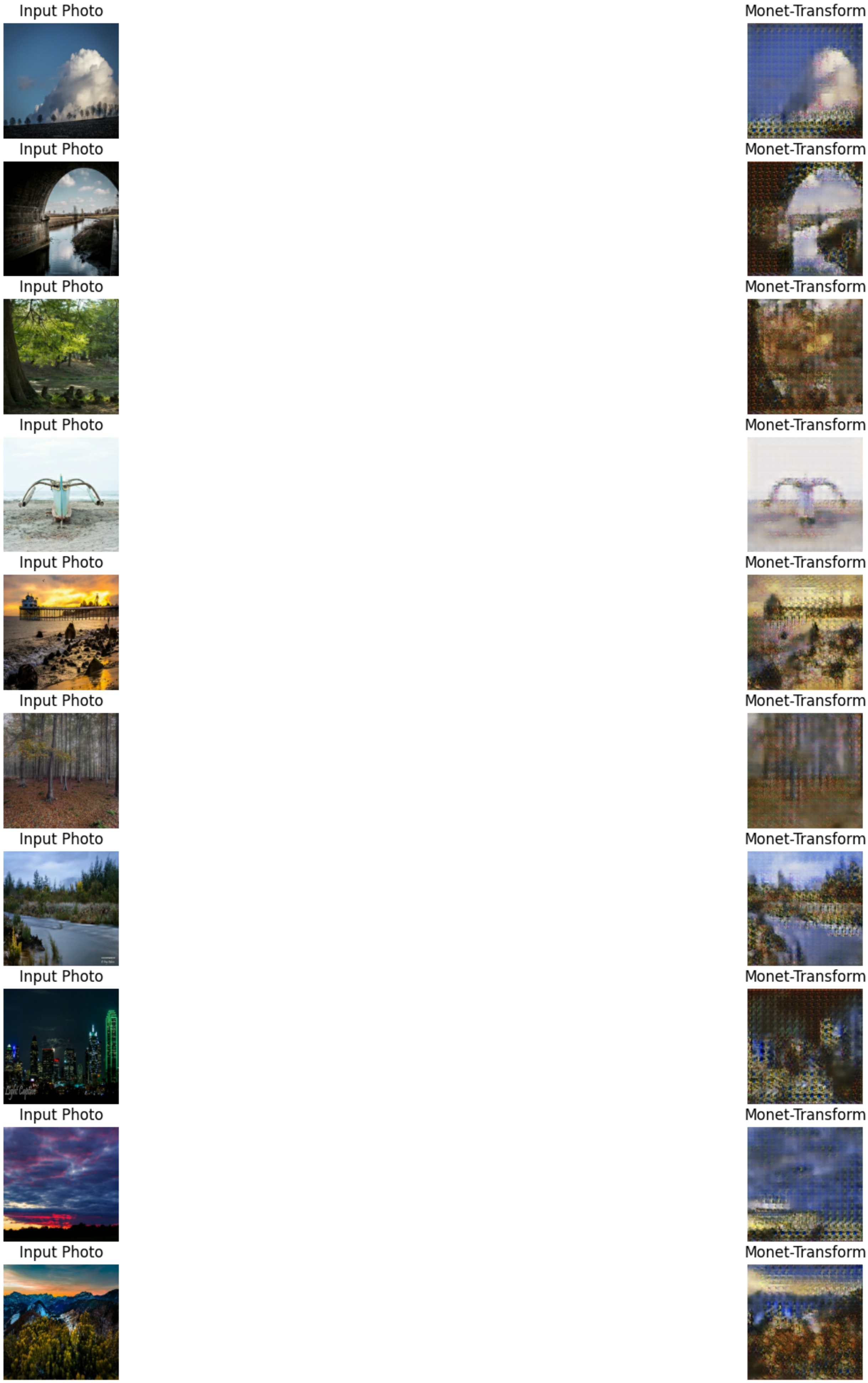

Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform
Input Photo
Monet-Transform

Image Comparison

As can be seen in the samples above, the model provides a reasonable representation of the photographs in the Monet style. However, the representations are quite grainy and unclear. The smoothness that is apparent in the Monet style is clearly not represented by the reproductions. 20 epochs were used to generate the images, addtional epochs may improve image quality.

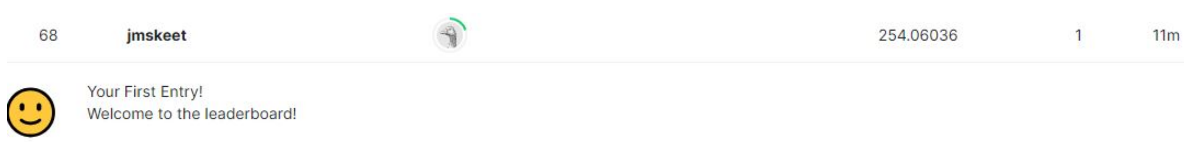
Conclusion

Various models were trained and tested utilizing two different optimizers (Adam and SGD) over four epoch counts (5, 10, 15, 20). As can be seen in Table 1, the Adam optimizer provided superior performance. Increasing epoch count also led the models to increased performance. The SGD model did however, show much greater acceleration with respect to both generator and dicriminator losses. Based on the trend in Table 1, increasing the epoch count using the SDG optimizer may have led to superior perfromance over the Adam optimizer. Addtionally, possibly improving the appearance of the images.

Through the course of model development and testing, batch size, SGD learning rate and SGD momentum were varied to assess the impact on the model's performance and resource consumption. Batch sizes were varied from (4,4) to 8 and to 2. Interestingly enough, the (4,4) configuration provided the most expedient processing. Changing the batch size to 8 or 2 slowed the processing dramatically.

For comparison purposes, the Adam optimization parameters were left defaulted to the tutorial values. Only the SGD parameters were varied. In the intial trial, the learning rate was set to .025 and the momentum to .05. These values were clearly too large and the model produce NaN and infinte loss values. It took walking both values down to .0001 to produce useable results. An extension of this project could be to further tune the SDG learning rate and momentum in order to identify the optimum values.

Submission



References

GAN — CycleGAN (Playing magic with pictures), https://jonathan-hui.medium.com/gan-cyclegan-6a50e7600d7

Monet CycleGAN Tutorial, https://www.kaggle.com/code/amyjang/monet-cyclegan-tutorial

Train your first CycleGAN for Image to Image Translation, https://blog.jaysinha.me/train-your-first-cyclegan-for-image-to-image-translation/

Overview of CycleGAN architecture and training, https://towardsdatascience.com/overview-of-cyclegan-architecture-and-training-afee31612a2f#:~:text=A%20CycleGAN%20is%20composed%20of,other%20transform%20zebras%2(

Tensorflow CycleGan, https://www.tensorflow.org/tutorials/generative/cyclegan

A hands-on guide to TFRecords, https://towardsdatascience.com/a-practical-guide-to-tfrecords-584536bc786c

Kaggle Code Refernces

CycleGAN Monet, https://www.kaggle.com/code/anubhav012/cyclegan-monet

Monet Who?, https://www.kaggle.com/code/nisargbhatt/monet-who

In [ ]:

```
```