cycle_gan

December 3, 2025

1 Style transfer with Cycle-GAN

I got introduced to the concept through Kaggles "I'm something of a painter myself" competition. Here's my go at it. The architecture of the generator and the descriminator, and the loss function are inspired by Amy Jang's notebook and this paper by Zhu et al.

[ ]:
```
import tensorflow as tf
!pip install tensorflow_addons
import tensorflow_addons as tfa
from tensorflow import keras
from tensorflow.keras import layers
import tensorflow_datasets as tfds
import os

import matplotlib.pyplot as plt
import numpy as np
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting tensorflow_addons
  Downloading tensorflow_addons-0.19.0-cp38-cp38-manylinux_2_17_x86_64.manylinux
2014_x86_64.whl (1.1 MB)
                            1.1/1.1 MB
14.6 MB/s eta 0:00:00
Requirement already satisfied: typeguard>=2.7 in
/usr/local/lib/python3.8/dist-packages (from tensorflow_addons) (2.7.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.8/dist-
packages (from tensorflow_addons) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/usr/local/lib/python3.8/dist-packages (from packaging->tensorflow_addons)
(3.0.9)
Installing collected packages: tensorflow_addons
Successfully installed tensorflow_addons-0.19.0
```

1.1 Preprocessing the images.

Cast to float32, renormalize to $[-1, 1]$, and reshape to $256 \times 256 \times 3$.

[ ]:
```python
IMAGE_SIZE = [256, 256]

def decode_image(image):
    #image = tf.image.decode_jpeg(image, channels=3)
    image = tf.cast(image, tf.float32)
    image = (image / tf.reduce_max(image))*2 - 1 ## Scale the image between -1␣
 ↪and 1 (divide by half the max and then - 1)
    image = tf.reshape(image, [*IMAGE_SIZE, 3])
    return image
```

1.2 Download the dataset from tfds

[ ]:
```python
tfds_data = tfds.builder('cycle_gan', config='monet2photo')
tfds_data.download_and_prepare()
monet_ds = tfds_data.as_dataset(split='trainA', shuffle_files=True,␣
 ↪batch_size=-1)['image']
photo_ds = tfds_data.as_dataset(split='trainB', shuffle_files=True,␣
 ↪batch_size=-1)['image']
```

```
Downloading and preparing dataset 291.09 MiB (download: 291.09 MiB, generated:
Unknown size, total: 291.09 MiB) to
/root/tensorflow_datasets/cycle_gan/monet2photo/2.0.0…

Dl Completed…: 0 url [00:00, ? url/s]

Dl Size…: 0 MiB [00:00, ? MiB/s]

Extraction completed…: 0 file [00:00, ? file/s]

Generating splits…:   0%|          | 0/4 [00:00<?, ? splits/s]

Generating trainA examples…:   0%|          | 0/1072 [00:00<?, ? examples/s]

Shuffling /root/tensorflow_datasets/cycle_gan/monet2photo/2.0.0.incompletePSK8T8/
 ↪cycle_gan-trainA.tfrecord*……

Generating trainB examples…:   0%|          | 0/6287 [00:00<?, ? examples/s]

Shuffling /root/tensorflow_datasets/cycle_gan/monet2photo/2.0.0.incompletePSK8T8/
 ↪cycle_gan-trainB.tfrecord*……

Generating testA examples…:   0%|          | 0/121 [00:00<?, ? examples/s]

Shuffling /root/tensorflow_datasets/cycle_gan/monet2photo/2.0.0.incompletePSK8T8/
 ↪cycle_gan-testA.tfrecord*…:…

Generating testB examples…:   0%|          | 0/751 [00:00<?, ? examples/s]

Shuffling /root/tensorflow_datasets/cycle_gan/monet2photo/2.0.0.incompletePSK8T8/
 ↪cycle_gan-testB.tfrecord*…:…

Dataset cycle_gan downloaded and prepared to
/root/tensorflow_datasets/cycle_gan/monet2photo/2.0.0. Subsequent calls will
reuse this data.
```

1.3 Setup for TPU usage

I didn't use TPU for training but this should take care of the setup. There might be some changes to the training loop as well since this uses the distributed strategy (`strategy.run` , etc.)

[ ]:
```
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.TPUStrategy(tpu)
except:
    print("TPU setup failed")
    strategy = tf.distribute.get_strategy()
print('Number of replicas:', strategy.num_replicas_in_sync)

AUTOTUNE = tf.data.experimental.AUTOTUNE

print(tf.__version__)
```

```
TPU setup failed
Number of replicas: 1
2.9.2
```

1.4 setup the Dataset objects.

This doesn't have to be done exactly like this but the `drop_remainder=True` setting is necessary for XLA and TPU training. Doesn't matter for my case.

[ ]:
```
with strategy.scope():
  monet_ds = tf.data.Dataset.from_tensor_slices(monet_ds).map(decode_image).
↪batch(1, drop_remainder=True).prefetch(AUTOTUNE)
  photo_ds = tf.data.Dataset.from_tensor_slices(photo_ds).map(decode_image).
↪batch(1, drop_remainder=True).prefetch(AUTOTUNE)
```

take one example of each dataset

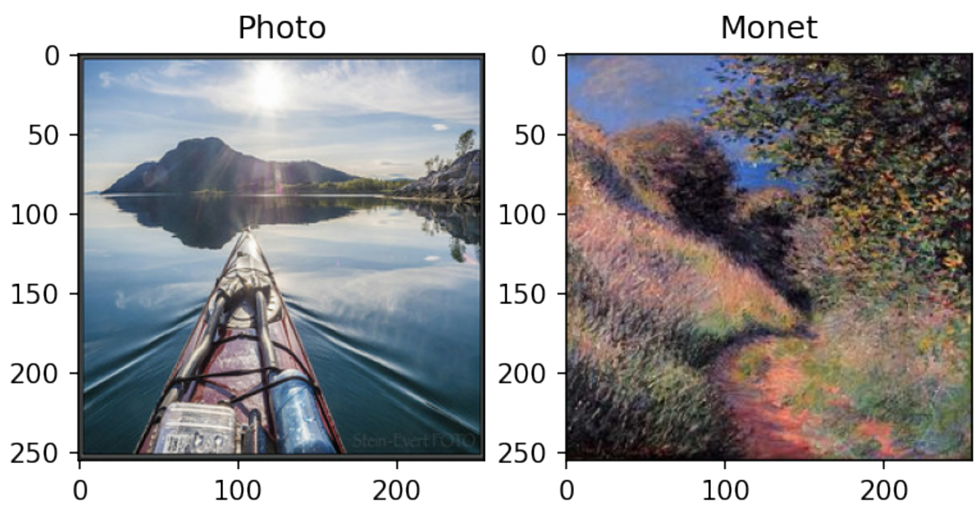
[ ]:
```
example_monet = next(iter(monet_ds))
example_photo = next(iter(photo_ds))
```

have a look at the examples

[ ]:
```
fig, ax = plt.subplots(1, 2, dpi=150)
ax[0].set_title('Photo')
ax[0].imshow(example_photo[0]*0.5 + 0.5)

ax[1].set_title('Monet')
ax[1].imshow(example_monet[0]*0.5 + 0.5)
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7f53ebf80be0>
```



1.5 Downsampling unit

A convolution layer followed by instance normalization and a LeakyReLU activation.

```
[ ]: class Downsample(layers.Layer):
         def __init__(self, filters, apply_InstanceNorm=True, **kwargs):
             super(Downsample, self).__init__(**kwargs)
             self.instance_Norm = apply_InstanceNorm
             self.init = tf.random_normal_initializer(mean=0., stddev=0.02)
             self.init_gamma = keras.initializers.RandomNormal(mean=0., stddev=0.02)
             self.conv = layers.Conv2D(filters, 4, strides=2, padding='same',\
                                       use_bias=False, kernel_initializer=self.init)
             self.insNorm = tfa.layers.InstanceNormalization(gamma_initializer=self.
      ↪init_gamma)
             self.activation = layers.LeakyReLU()

         def call(self, inputs):
             x = self.conv(inputs)
             if self.instance_Norm:
                 x = self.insNorm(x)
             return self.activation(x)
```

1.6 Upsampling unit

A transpose convolution unit followed by instance normalization, dropout, and ReLU activation

```
[ ]: class Upsample(layers.Layer):
         def __init__(self, filters, apply_dropout=False, **kwargs):
             super(Upsample, self).__init__(**kwargs)
             self.apply_dropout = apply_dropout
```

```
        self.init = tf.random_normal_initializer(mean=0., stddev=0.02)
        self.init_gamma = keras.initializers.RandomNormal(mean=0., stddev=0.02)
        self.conv = layers.Conv2DTranspose(filters, 4, strides=2,␣
↪padding='same',\
                                    use_bias=False, kernel_initializer=self.init)
        self.insNorm = tfa.layers.InstanceNormalization(gamma_initializer=self.
↪init_gamma)
        self.dropout = layers.Dropout(0.5)
        self.activation = layers.ReLU()

    def call(self, inputs):
        x = self.conv(inputs)
        x = self.insNorm(x)
        if self.apply_dropout:
            x = self.dropout(x)
        return self.activation(x)
```

1.7 The Generator

The Generator is a U-Net with 8 downsample units (64-128-256-512-512-512-512-512-512) and 7 upsampling units (512-512-512-512-256-128-64) connected to a final Conv2DTranspose layer.

[ ]:

```
class Generator(keras.models.Model):
    def __init__(self, **kwargs):
        super(Generator, self).__init__(**kwargs)
        self.ds1 = Downsample(64, False)
        self.ds2 = Downsample(128)
        self.ds3 = Downsample(256)
        self.ds4 = Downsample(512)
        self.ds5 = Downsample(512)
        self.ds6 = Downsample(512)
        self.ds7 = Downsample(512)
        self.ds8 = Downsample(512)
        self.us1 = Upsample(512, True)
        self.us2 = Upsample(512, True)
        self.us3 = Upsample(512, True)
        self.us4 = Upsample(512)
        self.us5 = Upsample(256)
        self.us6 = Upsample(128)
        self.us7 = Upsample(64)
        self.final = layers.Conv2DTranspose(3, 4, strides=2, padding='same',
                            kernel_initializer = tf.random_normal_initializer(mean=0.,␣
↪stddev=0.02),
                                                activation='tanh')
        self.concat = layers.Concatenate()

    def call(self, inputs):
```

```
        x1  = self.ds1(inputs)
        x2  = self.ds2(x1)
        x3  = self.ds3(x2)
        x4  = self.ds4(x3)
        x5  = self.ds5(x4)
        x6  = self.ds6(x5)
        x7  = self.ds7(x6)
        x8  = self.ds8(x7)
        x9  = self.us1(x8)
        x9  = self.concat([x9, x7])
        x10 = self.us2(x9)
        x10 = self.concat([x10, x6])
        x11 = self.us3(x10)
        x11 = self.concat([x11, x5])
        x12 = self.us4(x11)
        x12 = self.concat([x12, x4])
        x13 = self.us5(x12)
        x13 = self.concat([x13, x3])
        x14 = self.us6(x13)
        x14 = self.concat([x14, x2])
        x15 = self.us7(x14)
        x15 = self.concat([x15, x1])
        out = self.final(x15)
        return out
```

1.8 The Discriminator

Simple Discriminator with 3 downsample units and 2 convolution layers. The output is a $30 \times 30 \times 1$ patch instead of a single number.

[ ]:
```
class Discriminator(keras.models.Model):
    def __init__(self, **kwargs):
        super(Discriminator, self).__init__(**kwargs)
        self.ds1 = Downsample(64, False)
        self.ds2 = Downsample(128)
        self.ds3 = Downsample(256)
        self.zeropad = layers.ZeroPadding2D()
        self.conv = layers.Conv2D(512, 4, strides=1,
                    kernel_initializer = tf.random_normal_initializer(mean=0.,␣
↪stddev=0.02),
                                 use_bias=False)
        self.norm = tfa.layers.InstanceNormalization(
            gamma_initializer = keras.initializers.RandomNormal(mean=0.,␣
↪stddev=0.02))
        self.activation = layers.LeakyReLU()
        self.final = layers.Conv2D(1, 4, strides=1,
```

```
                    kernel_initializer = tf.random_normal_initializer(mean=0.,␣
↪stddev=0.02))

    def call(self, inputs):
        x = self.ds1(inputs)
        x = self.ds2(x)
        x = self.ds3(x)
        x = self.zeropad(x)
        x = self.conv(x)
        x = self.norm(x)
        x = self.activation(x)
        x = self.zeropad(x)
        x = self.final(x)
        return x
```

1.9 Compelete CycleGAN object

There are 2 generators, one for making real photos look like monet and the other for making monet painting look like real photos.

There are 2 discriminators as well, one for each generator.

There are 4 losses defined here: 1. Descriminator loss: Did the discriminator succesfully determined whether the input was fake or real? 2. Generator loss: Did the generator succesfully fool the discriminator into thinking the image it generated was real? 3. Cycle loss:

real → `monet_gen` → fake_monet → `real_gen` → real

and

monet → `real_gen` → fake_real → `real_gen` → monet Basically, an input going around the cycle should come out as itself. 4. Identity loss:

monet → `monet_gen` → monet

real → `real_gen` → real

Overall loss is the sum of these.

[ ]:
```
class CycleGAN(keras.models.Model):
    def __init__(self, **kwargs):
        super(CycleGAN, self).__init__(**kwargs)
        self.monet_gen = Generator()
        self.photo_gen = Generator()
        self.monet_dsc = Discriminator()
        self.photo_dsc = Discriminator()
        self.monet_gen_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
        self.photo_gen_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
        self.monet_dsc_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
        self.photo_dsc_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
```

```
    def dsc_loss(self, real, generated):
        real_loss = keras.losses.BinaryCrossentropy(from_logits=True,
                    reduction=keras.losses.Reduction.NONE)(tf.ones_like(real),␣
↪real)
        fake_loss = keras.losses.BinaryCrossentropy(from_logits=True,
                    reduction=keras.losses.Reduction.NONE)(tf.
↪zeros_like(generated), generated)
        return real_loss + fake_loss

    def gen_loss(self, generated):
        return keras.losses.BinaryCrossentropy(from_logits=True,
               reduction=keras.losses.Reduction.NONE)(tf.ones_like(generated),␣
↪generated)

    def cycle_loss(self, real, cycled, lam=10):
        return lam * tf.reduce_mean(tf.abs(real - cycled))

    def identity_loss(self, real, same, lam=10):
        return lam * 0.5 * tf.reduce_mean(tf.abs(real - same))

    def train_step(self, batch):
        photo, monet = batch
        with tf.GradientTape(persistent=True) as tape:
            fake_monet = self.monet_gen(photo)
            cycled_photo = self.photo_gen(fake_monet)

            fake_photo = self.photo_gen(monet)
            cycled_monet = self.monet_gen(fake_photo)

            same_photo = self.photo_gen(photo)
            same_monet = self.monet_gen(monet)

            disc_real_monet = self.monet_dsc(monet)
            disc_real_photo = self.photo_dsc(photo)

            disc_fake_monet = self.monet_dsc(fake_monet)
            disc_fake_photo = self.photo_dsc(fake_photo)

            monet_dsc_loss = self.dsc_loss(disc_real_monet, disc_fake_monet)
            photo_dsc_loss = self.dsc_loss(disc_real_photo, disc_fake_photo)

            total_cycle_loss = self.cycle_loss(monet, cycled_monet) + self.
↪cycle_loss(photo, cycled_photo)

            monet_gen_loss = self.gen_loss(disc_fake_monet) + total_cycle_loss␣
↪+\
            self.identity_loss(monet, same_monet)
```

```
            photo_gen_loss = self.gen_loss(disc_fake_photo) + total_cycle_loss␣
↪+\
            self.identity_loss(photo, same_photo)

        m_gen_grad = tape.gradient(monet_gen_loss, self.monet_gen.
↪trainable_variables)
        m_dsc_grad = tape.gradient(monet_dsc_loss, self.monet_dsc.
↪trainable_variables)
        p_gen_grad = tape.gradient(photo_gen_loss, self.photo_gen.
↪trainable_variables)
        p_dsc_grad = tape.gradient(photo_dsc_loss, self.photo_dsc.
↪trainable_variables)

        self.monet_gen_optimizer.apply_gradients(zip(m_gen_grad, self.monet_gen.
↪trainable_variables))
        self.monet_dsc_optimizer.apply_gradients(zip(m_dsc_grad, self.monet_dsc.
↪trainable_variables))
        self.photo_gen_optimizer.apply_gradients(zip(p_gen_grad, self.photo_gen.
↪trainable_variables))
        self.photo_dsc_optimizer.apply_gradients(zip(p_dsc_grad, self.photo_dsc.
↪trainable_variables))

        return {
            "m_gen_loss": monet_gen_loss,
            "p_gen_loss": photo_gen_loss,
            "m_dsc_loss": monet_dsc_loss,
            "p_dsc_loss": photo_dsc_loss,
        }

    def train(self, ds, epochs):
        for epoch in range(epochs):
            for data in ds:
                losses = self.train_step(data)
            tf.print(f"""epoch: {epoch},\t m_gen loss: {tf.
↪reduce_mean(losses["m_gen_loss"])},\t p_gen loss: {tf.
↪reduce_mean(losses["p_gen_loss"])}, m_dsc loss: {tf.
↪reduce_mean(losses["m_dsc_loss"])}, p_dsc loss: {tf.
↪reduce_mean(losses["p_dsc_loss"])}""")

        return None
```

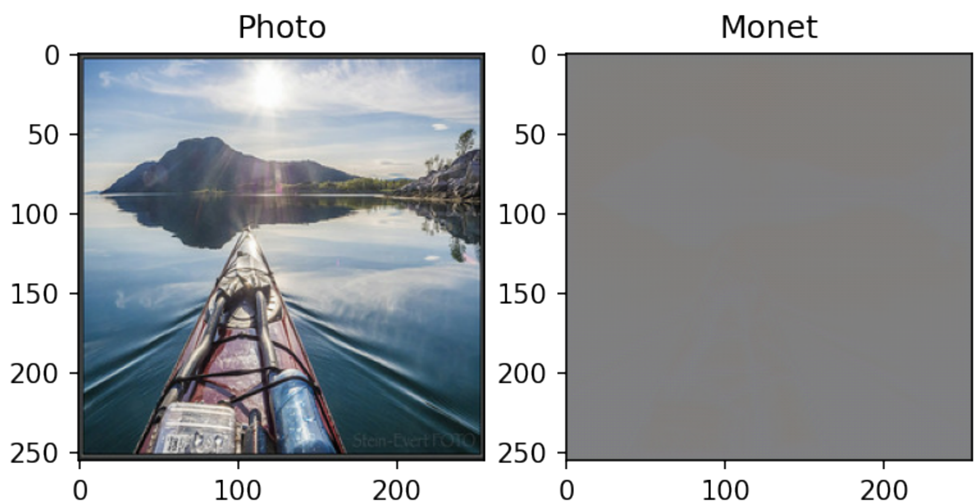
Create the object and test an input

```
[ ]: with strategy.scope():
         cycle_gan_model = CycleGAN()
     test_monet = cycle_gan_model.monet_gen(example_photo)
```

```
[ ]: fig, ax = plt.subplots(1, 2, dpi=150)
     ax[0].set_title('Photo')
     ax[0].imshow(example_photo[0]*0.5 + 0.5)

     ax[1].set_title('Monet')
     ax[1].imshow(test_monet[0]*0.5 + 0.5)
```

```
[ ]: <matplotlib.image.AxesImage at 0x7f53ec208fa0>
```



Outputs noise because it has random weights before training.

1.10 Train

Train CycleGAN for 10 epochs. Notice the two datasets are zipped and passed to the model. It doesn't matter which two pair of photo/monet are passed at each epoch as long as the same ones don't get passed in. Also the batch size for both data sets is 1 so each epoch is just one pair of photos.

```
[ ]: with strategy.scope():
       cycle_gan_model = CycleGAN()
       cycle_gan_model.train(
             tf.data.Dataset.zip((photo_ds, monet_ds)),
             epochs=10
         )
```

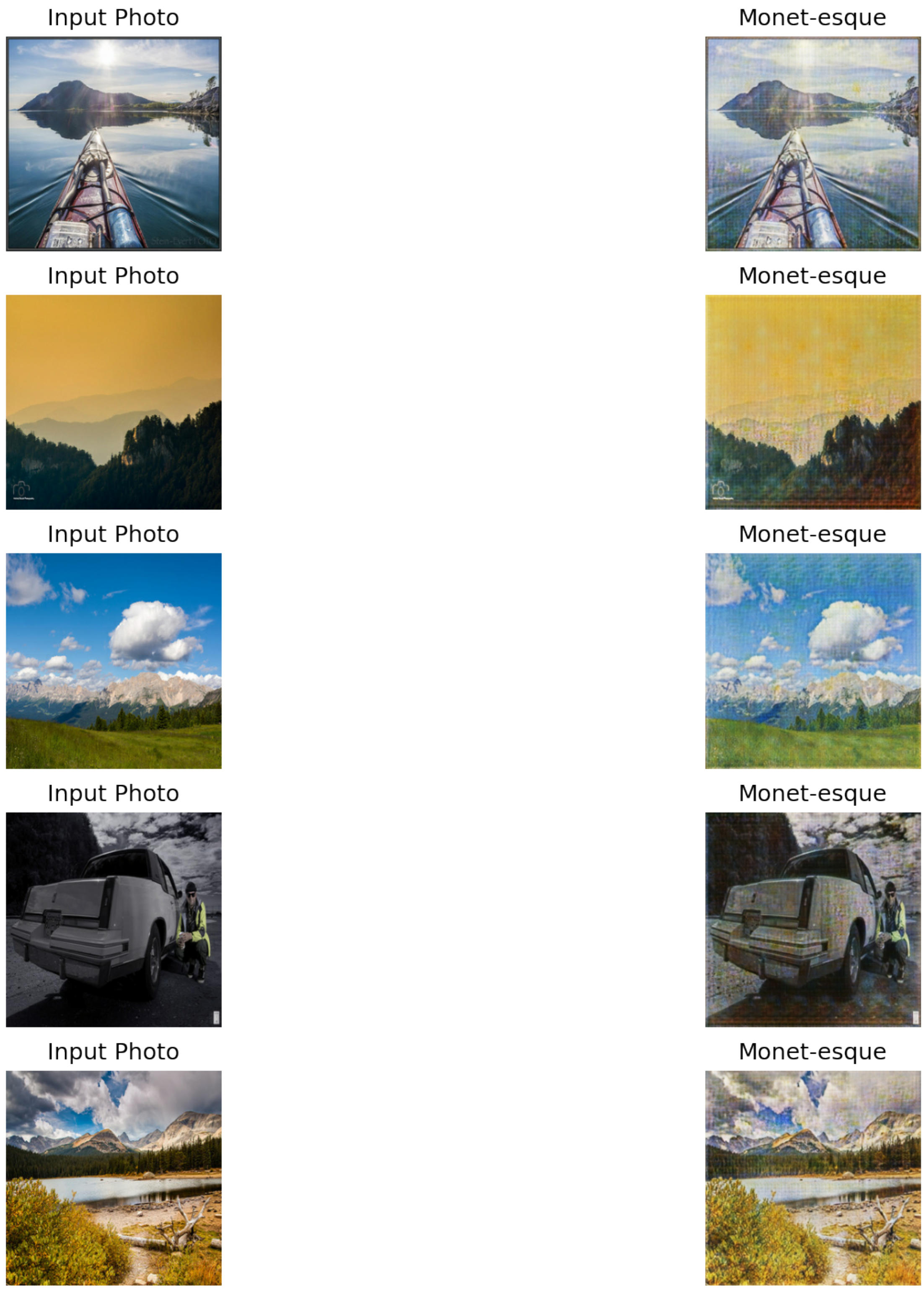
```
epoch: 0,        m_gen loss: 4.036203384399414,  p_gen loss: 5.0994553565979,
m_dsc loss: 1.2989656925201416, p_dsc loss: 0.791059136390686
```

```
epoch: 1,        m_gen loss: 3.5121445655822754,         p_gen loss:
4.297967433929443, m_dsc loss: 1.546463131904602, p_dsc loss: 1.2357348203659058
epoch: 2,        m_gen loss: 3.261470079421997,  p_gen loss: 4.106157302856445,
m_dsc loss: 1.4388259649276733, p_dsc loss: 1.1355243921279907
epoch: 3,        m_gen loss: 3.1116626262664795,         p_gen loss:
3.7555954456329346, m_dsc loss: 1.3309767246246338, p_dsc loss:
1.3365322351455688
epoch: 4,        m_gen loss: 2.8883275985717773,         p_gen loss:
3.7058777809143066, m_dsc loss: 1.2498728036880493, p_dsc loss:
1.317004680633545
epoch: 5,        m_gen loss: 2.8293566703796387,         p_gen loss:
3.718421697616577, m_dsc loss: 1.2094194889068604, p_dsc loss: 1.297163724899292
epoch: 6,        m_gen loss: 2.8371212482452393,         p_gen loss:
3.633399486541748, m_dsc loss: 1.1624222993850708, p_dsc loss: 1.247989535331726
epoch: 7,        m_gen loss: 2.814274311065674,  p_gen loss: 3.5465259552001953,
m_dsc loss: 1.1558595895767212, p_dsc loss: 1.2297011613845825
epoch: 8,        m_gen loss: 2.905796766281128,  p_gen loss: 3.956342935562134,
m_dsc loss: 1.1680665016174316, p_dsc loss: 0.9180918335914612
epoch: 9,        m_gen loss: 2.9855830669403076,         p_gen loss:
3.655225992202759, m_dsc loss: 1.2676938772201538, p_dsc loss:
1.0644094944000244
```

I couldn't afford to train for longer but 10 epochs already shows improvements

[ ]:
```python
_, ax = plt.subplots(5, 2, figsize=(12, 12), dpi=150)
for i, img in enumerate(photo_ds.take(5)):
    prediction = cycle_gan_model.monet_gen(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-esque")
    ax[i, 0].axis("off")
    ax[i, 1].axis("off")
plt.show()
```



You can see the texture added on top of the pictures here to make them look more like a painting!

More training steps should give better results too!

```
[ ]:
```