BIVE, VINCE EMMANUEL C. **MIDTERM EXAM**

COE005 – PREDICTION AND MACHINE LEARNING

In this activity, the goal is to apply Generative Adversarial Networks (GANs) in creating images that are in the style of Monet.

Simulations:

The program consist of libraries such tensorflow for the GAN model, matplotlib for visualization of the results, os and google.colab for the data gathering, and zipfile for unzipping the dataset. These libraries were imported following their respective codes to perform the data gathering.

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import matplotlib.pyplot as plt
import os
import time
from IPython.display import clear_output
```

```
[3] from google.colab import drive
    drive.mount('/content/drive', force_remount=True)

    Mounted at /content/drive
```

```
[4] from zipfile import ZipFile
    dataset = '/content/drive/MyDrive/4th Year/gan-getting-started.zip'

    with ZipFile(dataset, 'r') as zpr:
        zpr.extractall()
        print('Na-extract na Lods')

    Na-extract na Lods
```

This is followed by the class called data_pipeline. This class offers a number of functions that sets up the images for training. Aside from the functions that involves dataset calling and plotting, it also showcases a decoder, which allows convolutional filters to be used to adjust data resolution and feature size.

```python
class dataset_pipeline():
    def __init__(self) -> None:
        self.image_feature_description = {
            'image_name': tf.io.FixedLenFeature([], tf.string),
            'image': tf.io.FixedLenFeature([], tf.string),
            'target' : tf.io.FixedLenFeature([], tf.string)
        }
        self.IMAGE_SIZE= [256,256]
        self.IMG_HEIGHT = 256
        self.IMG_WIDTH = 256

    def decode_image(self, image):
        """Decoding image from tf.string form representation from tfrecord"""
        image = tf.image.decode_jpeg(image, channels=3)
        image = (tf.cast(image, tf.float32)/127.5) -1
        image = tf.reshape(image, [*self.IMAGE_SIZE,3])
        return image

    def random_augment(self, image):
        image = tf.image.resize(image, [286,286], method= tf.image.ResizeMethod.NEAREST_NEIGHBOR)
        image = tf.image.random_crop(image, size=[self.IMG_HEIGHT, self.IMG_WIDTH,3])
        image = tf.image.random_flip_left_right(image)
        return image

    def parse_image(self, example):
        parsed_example = tf.io.parse_single_example(example, self.image_feature_description)
        image = self.decode_image(parsed_example["image"])
        image = self.random_augment(image)
        return image
```

```python
    def get_paths(self, directory_path):
        """directory_path : path to the directory containing all tfrecords
        returns the list of all tfrecords"""
        path_list = []
        for path in os.listdir(directory_path):
            path_list.append(os.path.join(directory_path, path))
        return path_list

    def load_tfrecord_dataset(self, directory_path):
        """directory_path : list of paths of all tfrecords."""
        paths =  self.get_paths(directory_path)
        dataset = tf.data.TFRecordDataset(paths)
        dataset = dataset.map(self.parse_image, num_parallel_calls= tf.data.AUTOTUNE)
        dataset = dataset.map(self.random_augment, num_parallel_calls= tf.data.AUTOTUNE)
        return dataset

    def plot_sample(self, dataset):
        sample= next(iter(dataset))
        plt.imshow(sample[0]*0.5+0.3)
        plt.axis('off')
        plt.show()
```

Now, these functions under the said class will be used to set up the Monet Dataset and Photo Dataset. The following code also includes the sample images from the photo and monet dataset.

```python
[9] data_pipe = dataset_pipeline()
    MONET_DS = data_pipe.load_tfrecord_dataset(monet_tf).batch(8)
    data_pipe.plot_sample(MONET_DS)
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

```
[10] PHOTO_DS = data_pipe.load_tfrecord_dataset(photo_tf).batch(10)
     data_pipe.plot_sample(PHOTO_DS)

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

After checking the monet style and the image, some classes are needed to be identified. One of it is the Instance Normalization. This allows all the features of the input input image to be normalized in one channel. This class will help make the image translation much efficient.

```
[11] class InstanceNormalization(layers.Layer):
         """Instance Normalization layer"""
         def __init__(self, epsilon= 1e-5):
             super(InstanceNormalization, self).__init__()
             self.epsilon= epsilon

         def build(self, input_shape):
             self.scale = self.add_weight(name= 'scale', shape= input_shape[-1:], initializer= tf.random_normal_initializer(1, 0.02), trainable= True)
             self.offset = self.add_weight(name='offset', shape= input_shape[-1:], initializer= 'zeros', trainable= True)

         def call(self, x):
             mean, variance = tf.nn.moments(x, axes=[1,2], keepdims=True)
             inv = tf.math.rsqrt(variance + self.epsilon)
             normalized= (x-mean)*inv
             return self.scale*normalized + self.offset
```

The next set of code will be the main code for the training. This is the GAN model which will be implemented. The model consists of a generator, discriminator, and loss functions. The generator is in charge of producing photographs from a particular domain. In this model, the generator gets an image from the photo dataset and will generate it as a monet painting. The discriminator functions to differentiate actual images and those that were produced by the generator.

```
class Model:

    def __init__(self, output_channels=3):
        self.cross_entropy_loss = keras.losses.BinaryCrossentropy(from_logits=True)

        self.OUTPUT_CHANNELS= output_channels
        self.LAMBDA = 30

        self.generator_g = self.Generator()
        self.generator_f = self.Generator()

        self.discriminator_x = self.Discriminator(target= False)
        self.discriminator_y = self.Discriminator(target= False)

        self.generator_g_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
        self.generator_f_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
        self.discriminator_x_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
        self.discriminator_y_optimizer = keras.optimizers.Adam(2e-4, beta_1=0.5)
```

```
[12]
def upsample(self, filters, size, apply_dropout=False):
    initializer = tf.random_normal_initializer(0., 0.02)
    result = keras.Sequential()
    result.add(layers.Conv2DTranspose(filters, size, strides=2, padding='same',
                                      kernel_initializer= initializer, use_bias= False))

    if apply_dropout:
        result.add(layers.Dropout(0.5))

    result.add(layers.LeakyReLU())
    return result


def downsample(self, filters, size, apply_norm = True):
    initializer = tf.random_normal_initializer(0., 0.02)
    result = keras.Sequential()
    result.add(layers.Conv2D(filters, size, strides=2, padding='same', kernel_initializer= initializer, use_bias= False))

    if apply_norm:
        result.add(InstanceNormalization())
    result.add(layers.LeakyReLU())
    return result

def discriminator_loss(self, real, generated):
    real_loss = self.cross_entropy_loss(tf.ones_like(real), real)
    gen_loss = self.cross_entropy_loss(tf.zeros_like(generated), generated)
    total_loss = real_loss + gen_loss
    return total_loss*0.5
```

```
def generator_loss(self, preds_generated):
    return self.cross_entropy_loss(tf.ones_like(preds_generated), preds_generated)

def cycle_loss(self, real_image, cycled_image):
    loss = tf.reduce_mean(tf.abs(real_image-cycled_image))
    return loss*self.LAMBDA

def identity_loss(self, real_image, same_image):

    loss = tf.reduce_mean(tf.abs(real_image - same_image))
    return loss*self.LAMBDA*0.5
```

```
[12]
def Generator(self):

    down_stack=[
      self.downsample(64,4, apply_norm=False),
      self.downsample(128,4),
      self.downsample(256,4),
      self.downsample(512,4),
      self.downsample(512,4),
      self.downsample(512,4),
      self.downsample(512,4),
      self.downsample(512,4),
      ]

    up_stack = [
      self.upsample(512, 4, apply_dropout=True),
      self.upsample(512, 4, apply_dropout=True),
      self.upsample(512, 4, apply_dropout=True),
      self.upsample(512, 4),
      self.upsample(256, 4),
      self.upsample(128, 4),
      self.upsample(64, 4),
      ]

    initializer = tf.random_normal_initializer(0., 0.02)
    last = layers.Conv2DTranspose(self.OUTPUT_CHANNELS, 4, strides=2, padding='same', kernel_initializer= initializer, activation= 'tanh')

    concat = layers.Concatenate()
    inputs= layers.Input(shape=[None, None, 3])
```

```python
        x= inputs

        skips= []

        for down in down_stack:
            x = down(x)
            skips.append(x)

        skips = reversed(skips[:-1])

        for up,skip in zip(up_stack, skips):
            x= up(x)
            x= concat([x, skip])

        x= last(x)
        return keras.Model(inputs= inputs, outputs= x)

    def Discriminator(self, target=True):

        initializer = tf.random_normal_initializer(0., 0.02)
        inp= layers.Input(shape=[None, None, 3], name='input_image')
        x= inp

        if target:
            tar = layers.Input(shape=[None, None, 3], name='target_image')
            x = layers.Concatenate([inp,tar])
```

```python
        down1= self.downsample(64,4, apply_norm=False)(x)
        down2= self.downsample(128,4)(down1)
        down3= self.downsample(256, 4)(down2)

        zero_pad1= layers.ZeroPadding2D()(down3)
        conv= layers.Conv2D(512, 4, strides=1, kernel_initializer=initializer, use_bias=False)(zero_pad1)
        norm1= InstanceNormalization()(conv)
        leaky_relu= layers.LeakyReLU()(norm1)
        zero_pad2= layers.ZeroPadding2D()(leaky_relu)
        last = layers.Conv2D(1, 4, strides= 1, kernel_initializer=initializer)(zero_pad2)

        if target:
            return keras.Model(inputs= [inp, last], outputs= last)
        else:
            return keras.Model(inputs= inp, outputs= last)


    @tf.function
    def train_step(self, real_x, real_y):
```

```python
    @tf.function
    def train_step(self, real_x, real_y):


        with tf.GradientTape(persistent=True) as tape:

            # Cycled predictions, output of cycle should be same as input provided
            # Let generator_g transform x->y , and generator_f transform y->x
            # discriminator_x takes x and classify, and discriminator_y takes y and classify

            # 1. generator_g takes x, generate fake_y, then generator_f takes fake_y and generated, cycle_x (x,cycle_x should be similar)

            fake_y = self.generator_g(real_x, training=True)
            cycled_x = self.generator_f(fake_y, training= True)

            # 2. Same cycle but starting from generator_f

            fake_x = self.generator_f(real_y, training=True)
            cycled_y = self.generator_g(fake_x, training= True)

            # 3. Case when input given to generator is same as expected output

            same_y = self.generator_g(real_y, training=True)
            same_x = self.generator_f(real_x, training= True)
```

```
            disc_pred_real_x = self.discriminator_x(real_x, training=True)
            disc_pred_fake_x = self.discriminator_x(fake_x, training=True)

            disc_pred_real_y = self.discriminator_y(real_y, training=True)
            disc_pred_fake_y = self.discriminator_y(fake_y, training=True)

            # All outputs generated, calculating lossess from these
            total_cycle_loss = self.cycle_loss(real_x, cycled_x) + self.cycle_loss(real_y, cycled_y)

            gen_g_identity_loss = self.identity_loss(real_y, same_y)
            gen_f_identity_loss = self.identity_loss(real_x, same_x)

            gen_g_loss = self.generator_loss(disc_pred_fake_y)
            gen_f_loss = self.generator_loss(disc_pred_fake_x)

            total_gen_g_loss = gen_g_loss + gen_g_identity_loss + total_cycle_loss
            total_gen_f_loss = gen_f_loss + gen_f_identity_loss + total_cycle_loss

            disc_x_loss = self.discriminator_loss(disc_pred_real_x, disc_pred_fake_x)
            disc_y_loss = self.discriminator_loss(disc_pred_real_y, disc_pred_fake_y)

        gen_g_grads = tape.gradient(total_gen_g_loss, self.generator_g.trainable_variables)
        gen_f_grads = tape.gradient(total_gen_f_loss, self.generator_f.trainable_variables)

        disc_x_grads = tape.gradient(disc_x_loss, self.discriminator_x.trainable_variables)
        disc_y_grads = tape.gradient(disc_y_loss, self.discriminator_y.trainable_variables)
```

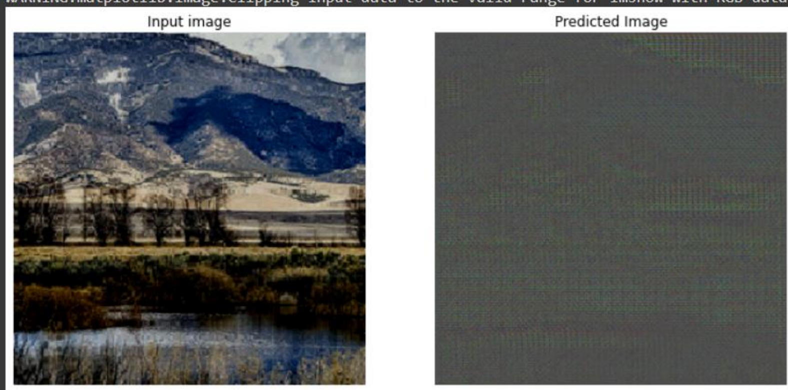
In this part of the code, it shows the portion that processes the training and generating the output images that includes parameters that are involved in the said event. For this activity, the epoch is set at 100.

```
        self.generator_g_optimizer.apply_gradients(zip(gen_g_grads, self.generator_g.trainable_variables ))
        self.generator_f_optimizer.apply_gradients(zip(gen_f_grads, self.generator_f.trainable_variables ))

        self.discriminator_x_optimizer.apply_gradients(zip(disc_x_grads, self.discriminator_x.trainable_variables ))
        self.discriminator_y_optimizer.apply_gradients(zip(disc_y_grads, self.discriminator_y.trainable_variables ))


    def train_image(self, photo, gen_model,fig_size=(12,12)):
        """Plotting image and prediction during training"""
        predicted_image = gen_model(photo)
        titles = ["Input image", "Predicted Image"]
        Images = [photo[0], predicted_image[0]]
        plt.figure(figsize=fig_size)

        for i in range(2):
            plt.subplot(1,2,i+1)
            plt.title(titles[i])
            plt.imshow(Images[i]*0.5 + 0.3)
            plt.axis('off')
        plt.show()

    def generate_images(self, dataset, gen_model, fig_size=(15,15),num=3):
        """saving and plotting predictions in bulk after training"""
        plt.figure(figsize=fig_size)
        for img in dataset.take(num):
            self.train_image(img,gen_model)
```

```
[12]
    def train(self, train_x, train_y, vis="g", epochs=100):
        if(vis.lower() == "g"):
            photo = next(iter(train_x))
            gen_model = self.generator_g
        elif(vis.lower()=="f"):
            photo = next(iter(train_y))
            gen_model = self.generator_f

        print("Before Training")
        self.train_image(photo, gen_model)
        for epoch in range(epochs):
            start = time.time()
            for image_x, image_y in tf.data.Dataset.zip((train_x, train_y)):
                self.train_step(image_x, image_y)
            clear_output(wait=True)
            self.train_image(photo,gen_model)
            print(f"Time for epoch {epoch+1} is : {time.time()- start}")
```

Finally, this model will be imported and used to train the Photo Dataset and the Monet Style Dataset.

```
[13] model = Model()
     sample = next(iter(PHOTO_DS))
     model.train_image(sample, model.generator_g)

     WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```



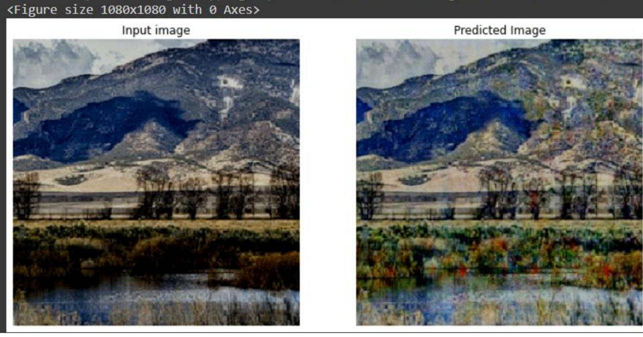
For the part of the code that takes time, the training part, this is where the application of monet style will take place.

```
[14] model.train(PHOTO_DS, MONET_DS)

     WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
     WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

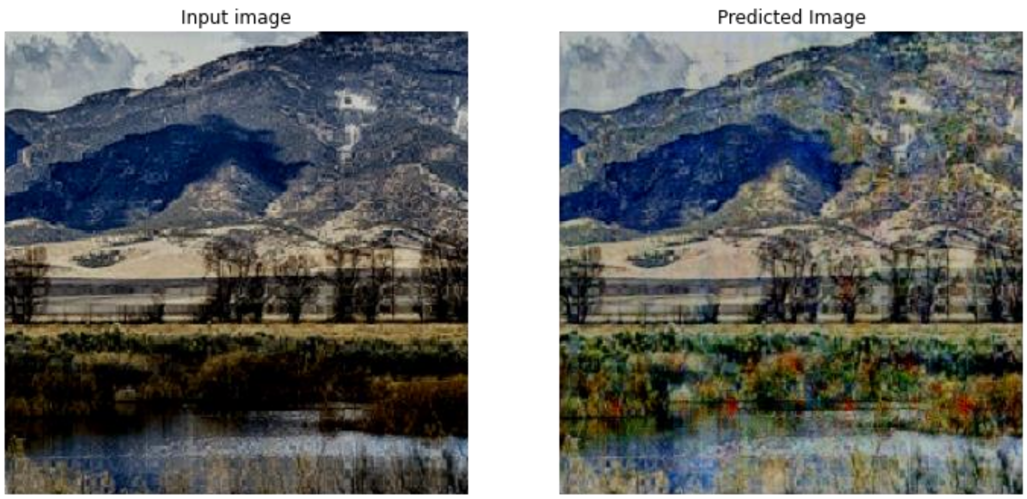

```
     Time for epoch 100 is : 56.75897979736328
```

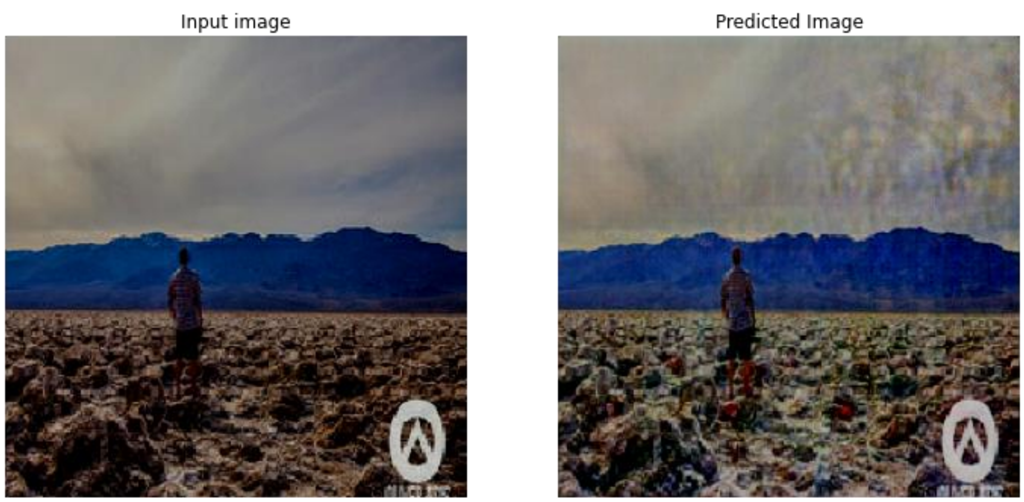
After training, generating the monet versions of the image can be done.

```
model.generate_images(PHOTO_DS, model.generator_g)

WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
<Figure size 1080x1080 with 0 Axes>
```



Output:


Input image
Predicted Image


Input image
Predicted Image


Input image
Predicted Image

Discussion:

The model applied in this activity is called the CycleGAN (Cycle Generative Adversarial Network). As the objective in this activity is to translate images, CycleGAN model could be a great use in the program. This is a technique for deep convolutional neural network training for image-to-image translation challenges. Using an unpaired dataset, the network learns the mapping between the input and output images. As the CycleGAN is applied for training and producing the image-to-image translation, it was able to effectively produce a monet version of the input image.

References:

[1] "How CycleGAN works?," *ArcGIS API for Python*. [Online]. Available: https://developers.arcgis.com/python/guide/how-cyclegan works/#:~:text=The%20Cycle%20Generative%20Adversarial%20Network,output%20images%20using%20unpaired%20dataset. [Accessed: 22-Oct-2022].

[2] S. Wolf, "Cyclegan: Learning to translate images (without paired training data)," *Medium*, 20-Nov-2018. [Online]. Available: https://towardsdatascience.com/cyclegan-learning-to-translate-images-without-paired-training-data-5b4e93862c8d. [Accessed: 22-Oct-2022].