Image Colorization With GANs

GANs are the state-of-the-art machine learning models which can generate new data instances from existing ones. They use a very interesting technique, inspired from the Game Theory, to generate realistic samples.

In this notebook, we'll use GANs to colorize a grayscale (B/W) image. In addition to that, our generator model will have a structure similar to that of a UNet i.e the one with skip connections.

1. Downloading and Processing the data

A dataset of RGB images to train the GAN model whose images consists of various scenes/places.

- Download the dataset on your machine from here (https://drive.google.com/file/d/1sQ5C8HiKVr2Edp3ojLLNauwRbOLfVn2q/view?usp=sharing).
- Upload the downloaded `.zip` file here on Colab.

In [ ]:
```
#Drive mounting
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [ ]:
```
import os
from os import listdir
#Drive path
path ='/content/drive/MyDrive/Deep Learning/'
```

In [ ]:
```
# Data set checking in Drive
for images in os.listdir(path):
    # check if the image ends with png
    if (images.endswith(".jpg")):
        print(images)
```

```
22903.jpg
22967.jpg
22913.jpg
22953.jpg
22936.jpg
22935.jpg
22963.jpg
22964.jpg
22973.jpg
22899.jpg
22974.jpg
22920.jpg
22951.jpg
22924.jpg
22942.jpg
22954.jpg
22917.jpg
22933.jpg
22969.jpg
```

In [ ]:
```
#Concating the path with files
import glob
for name in glob.glob(path+'*'):
    print(name)
```

```
/content/drive/MyDrive/Deep Learning/22903.jpg
/content/drive/MyDrive/Deep Learning/22967.jpg
/content/drive/MyDrive/Deep Learning/22913.jpg
/content/drive/MyDrive/Deep Learning/22953.jpg
/content/drive/MyDrive/Deep Learning/22936.jpg
/content/drive/MyDrive/Deep Learning/22935.jpg
/content/drive/MyDrive/Deep Learning/22963.jpg
/content/drive/MyDrive/Deep Learning/22964.jpg
/content/drive/MyDrive/Deep Learning/22973.jpg
/content/drive/MyDrive/Deep Learning/22899.jpg
/content/drive/MyDrive/Deep Learning/22974.jpg
/content/drive/MyDrive/Deep Learning/22920.jpg
/content/drive/MyDrive/Deep Learning/22951.jpg
/content/drive/MyDrive/Deep Learning/22924.jpg
/content/drive/MyDrive/Deep Learning/22942.jpg
/content/drive/MyDrive/Deep Learning/22954.jpg
/content/drive/MyDrive/Deep Learning/22917.jpg
/content/drive/MyDrive/Deep Learning/22933.jpg
/content/drive/MyDrive/Deep Learning/22969.jpg
/content/drive/MyDrive/Deep Learning/22965.jpg
```

We are creating a preprocessing model by converting the RGB image to Grey scale image using convert method. The RGB image is kept as the Ground image to make sure we compare the predicted image to the actual image using Deep learing Techniques using GAN

We are spliting the dataset using train_test_split as 2500 images as the train dataset and 500 images as test dataset.

In [ ]:
```
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
import numpy as np
from keras.utils.vis_utils import plot_model
from matplotlib import image
from matplotlib import pyplot as plt
import os
import time
import tensorflow as tf
from tensorflow import keras
tf.config.run_functions_eagerly(True)

# The batch size we'll use for training
batch_size = 64

# Size of the image required to train our model
img_size = 120

# These many images will be used from the data archive
dataset_split = 2500

dir_path = path
x = []
y = []
for image_file in os.listdir( dir_path )[ 0 : dataset_split ]:
    rgb_image = Image.open( os.path.join( dir_path , image_file ) ).re
    # Normalize the RGB image array
    rgb_img_array = (np.asarray( rgb_image ) ) / 255
    gray_image = rgb_image.convert( 'L' )
    # Normalize the grayscale image array
    gray_img_array = ( np.asarray( gray_image ).reshape( ( img_size ,
    # Append both the Grey scale array and the RBG Scale array images
    x.append( gray_img_array )
    y.append( rgb_img_array )

# Train-test splitting
train_x, test_x, train_y, test_y = train_test_split( np.array(x) , np.

# Construct tesnor flow Dataset object for the training
dataset = tf.data.Dataset.from_tensor_slices( ( train_x , train_y ) )
dataset = dataset.batch( batch_size )
```

2. The GAN

The GAN model works on Generator and Discriminator. The data is passed to GAN model step by step and the loss function is checked for both the Generator and the Discriminator.

A. Generator

The Generator function works based on converting the Grey scale images to RGB image.

Using generator we are using the tensor shape by using the batch size $(\ batch\ size\ ,\ 120\ ,\ 120\ ,\ 1\ )$ and the output $G(x)$ will have a shape $(\ batch\ size\ ,\ 120\ ,\ 120\ ,\ 3\ )$

We are using the generator as similar to Encoder-Decoder from the UNet architecture.

In [ ]:
```
def get_generator_model():

    inputs = tf.keras.layers.Input( shape=( img_size , img_size , 1 )

    conv1 = tf.keras.layers.Conv2D( 16 , kernel_size=( 5 , 5 ) , stric
    conv1 = tf.keras.layers.LeakyReLU()( conv1 )
    conv1 = tf.keras.layers.Conv2D( 32 , kernel_size=( 3 , 3 ) , stric
    conv1 = tf.keras.layers.LeakyReLU()( conv1 )
    conv1 = tf.keras.layers.Conv2D( 32 , kernel_size=( 3 , 3 ) , stric
    conv1 = tf.keras.layers.LeakyReLU()( conv1 )

    conv2 = tf.keras.layers.Conv2D( 32 , kernel_size=( 5 , 5 ) , stric
    conv2 = tf.keras.layers.LeakyReLU()( conv2 )
    conv2 = tf.keras.layers.Conv2D( 64 , kernel_size=( 3 , 3 ) , stric
    conv2 = tf.keras.layers.LeakyReLU()( conv2 )
    conv2 = tf.keras.layers.Conv2D( 64 , kernel_size=( 3 , 3 ) , stric
    conv2 = tf.keras.layers.LeakyReLU()( conv2 )

    conv3 = tf.keras.layers.Conv2D( 64 , kernel_size=( 5 , 5 ) , stric
    conv3 = tf.keras.layers.LeakyReLU()( conv3 )
    conv3 = tf.keras.layers.Conv2D( 128 , kernel_size=( 3 , 3 ) , stri
    conv3 = tf.keras.layers.LeakyReLU()( conv3 )
    conv3 = tf.keras.layers.Conv2D( 128 , kernel_size=( 3 , 3 ) , stri
    conv3 = tf.keras.layers.LeakyReLU()( conv3 )

    bottleneck = tf.keras.layers.Conv2D( 128 , kernel_size=( 3 , 3 ) ,

    concat_1 = tf.keras.layers.Concatenate()( [ bottleneck , conv3 ] )
    conv_up_3 = tf.keras.layers.Conv2DTranspose( 128 , kernel_size=( 3
    conv_up_3 = tf.keras.layers.Conv2DTranspose( 128 , kernel_size=( 3
    conv_up_3 = tf.keras.layers.Conv2DTranspose( 64 , kernel_size=( 5

    concat_2 = tf.keras.layers.Concatenate()( [ conv_up_3 , conv2 ] )
    conv_up_2 = tf.keras.layers.Conv2DTranspose( 64 , kernel_size=( 3
    conv_up_2 = tf.keras.layers.Conv2DTranspose( 64 , kernel_size=( 3
    conv_up_2 = tf.keras.layers.Conv2DTranspose( 32 , kernel_size=( 5

    concat_3 = tf.keras.layers.Concatenate()( [ conv_up_2 , conv1 ] )
    conv_up_1 = tf.keras.layers.Conv2DTranspose( 32 , kernel_size=( 3
    conv_up_1 = tf.keras.layers.Conv2DTranspose( 32 , kernel_size=( 3
    conv_up_1 = tf.keras.layers.Conv2DTranspose( 3 , kernel_size=( 5 ,

    model = tf.keras.models.Model( inputs , conv_up_1 )
    return model
```

B. Discriminator

B. Discriminator

The discriminator model, represented as D, will take in the *real image* y (from the training data) and the *generated image* $G(x)$ (from the generator) to output two probabilities.

- We train the discriminator in such a manner that is able to differentiate the *real images* and the generated *images*. So, we train the model such that y produces a output of 1.0 and $G(x)$ produces an output of 0.0.
- Note that instead of using hard labels like 1.0 and 0.0, we use soft labels which are close to 1 and 0. So for a hard label of 1.0, the soft label will be $(1 - \epsilon)$ where ϵ is picked uniformly from $(0, 0.1]$

In [ ]:

```
def get_discriminator_model():
    layers = [
        tf.keras.layers.Conv2D( 32 , kernel_size=( 7 , 7 ) , strides=1
        tf.keras.layers.Conv2D( 32 , kernel_size=( 7, 7 ) , strides=1,
        tf.keras.layers.MaxPooling2D(),
        tf.keras.layers.Conv2D( 64 , kernel_size=( 5 , 5 ) , strides=1
        tf.keras.layers.Conv2D( 64 , kernel_size=( 5 , 5 ) , strides=1
        tf.keras.layers.MaxPooling2D(),
        tf.keras.layers.Conv2D( 128 , kernel_size=( 3 , 3 ) , strides=
        tf.keras.layers.Conv2D( 128 , kernel_size=( 3 , 3 ) , strides=
        tf.keras.layers.MaxPooling2D(),
        tf.keras.layers.Conv2D( 256 , kernel_size=( 3 , 3 ) , strides=
        tf.keras.layers.Conv2D( 256 , kernel_size=( 3 , 3 ) , strides=
        tf.keras.layers.MaxPooling2D(),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense( 512, activation='relu'  )  ,
        tf.keras.layers.Dense( 128 , activation='relu' ) ,
        tf.keras.layers.Dense( 16 , activation='relu' ) ,
        tf.keras.layers.Dense( 1 , activation='sigmoid' )
    ]
    model = tf.keras.models.Sequential( layers )
    return model
```

C. Loss Functions

We are implementing the GAN model using loss functions. we are using L2 loss and MSE loss. We are using the optimizer with the learning rate of 0.0005.

In [ ]:
```
cross_entropy = tf.keras.losses.BinaryCrossentropy()
mse = tf.keras.losses.MeanSquaredError()

def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output) - tf.random.ur
    fake_loss = cross_entropy(tf.zeros_like(fake_output) + tf.random.u
    total_loss = real_loss + fake_loss
    return total_loss

def generator_loss(fake_output , real_y):
    real_y = tf.cast( real_y , 'float32' )
    return mse( fake_output , real_y )

generator_optimizer = tf.keras.optimizers.Adam( 0.0005 )
discriminator_optimizer = tf.keras.optimizers.Adam( 0.0005 )

generator = get_generator_model()
discriminator = get_discriminator_model()
#used Checkpoints to save the model to load it for future model usage
#checkpoint_generator_path = '/content/drive/MyDrive/Training/generato
#checkpoint_discriminator_path = '/content/drive/MyDrive/Training/disc
```

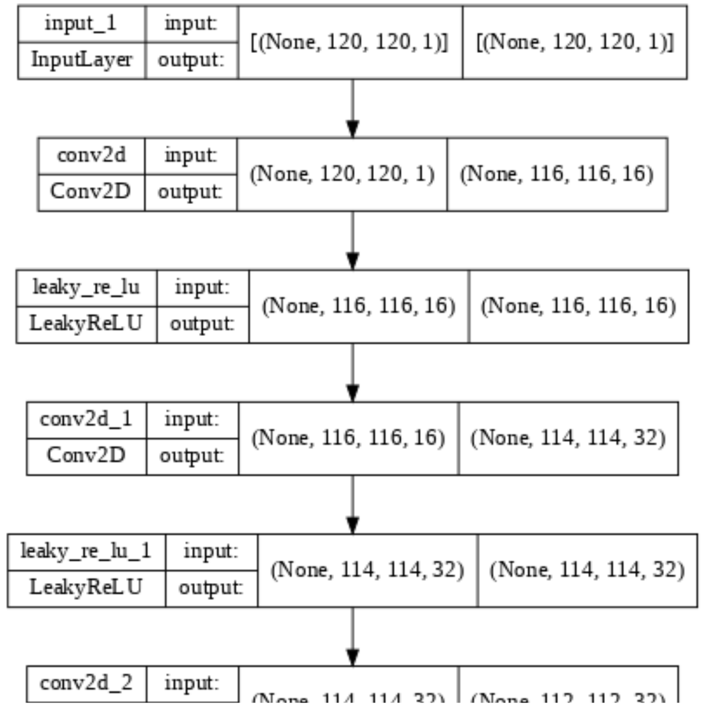
3. Training The GAN

In [ ]:
```
@tf.function
def train_step( input_x , real_y ):

    with tf.GradientTape() as gen_tape, tf.GradientTape() as disc_tape
        # Generate an image -> G( x )
        generated_images = generator( input_x , training=True)
        # Probability that the given image is real -> D( x )
        real_output = discriminator( real_y, training=True)
        # Probability that the given image is the one generated -> D(
        generated_output = discriminator(generated_images, training=Tr

        # L2 Loss -> || y - G(x) ||^2
        gen_loss = generator_loss( generated_images , real_y )
        # Log loss for the discriminator
        disc_loss = discriminator_loss( real_output, generated_output

        losses["D"].append(disc_loss.numpy())
        losses["G"].append(gen_loss.numpy())
    #tf.keras.backend.print_tensor( tf.keras.backend.mean( gen_loss )
    #tf.keras.backend.print_tensor( gen_loss + disc_loss )

    # Compute the gradients
    gradients_of_generator = gen_tape.gradient(gen_loss, generator.tra
    gradients_of_discriminator = disc_tape.gradient(disc_loss, discrim

    # Optimize with Adam
    generator_optimizer.apply_gradients(zip(gradients_of_generator, ge
    discriminator_optimizer.apply_gradients(zip(gradients_of_discrimin

generator.compile(
    optimizer=generator_optimizer,
    loss=generator_loss,
    metrics=['accuracy']
)
#generator.save_weights(checkpoint_generator_path)

discriminator.compile(
    optimizer=discriminator_optimizer,
    loss=discriminator_loss,
    metrics=['accuracy']
)
#discriminator.save_weights(checkpoint_discriminator_path)
```

Visualising the Generator model

In [ ]:
```
plot_model(generator, to_file='generator.png', show_shapes=True, show_
```

Out[10]:



Trainning data

In [ ]:
```
def plot_loss(losses):
    """
    @losses.keys():
        0: loss
        1: accuracy
    """
    g_loss = []
    d_loss = []

    count = 0
    for i in losses['D']:
      count += 1
      if(count == 36):
        d_loss.append(i)
        count = 0

    count = 0
    for i in losses['G']:
      count += 1
      if(count == 36):
        g_loss.append(i)
        count = 0

    plt.figure(figsize=(10,8))
    plt.plot(d_loss, label="Discriminator loss")
    plt.plot(g_loss, label="Generator loss")
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
```

4. Results

We are plotting the image after the model is trained and the prdicted image is obtained. The image is compared with the Ground image and the predicted image.

In [ ]:
```
y = generator( test_x[0 : ] ).numpy()
```

The No.of Epochs are used to train the model

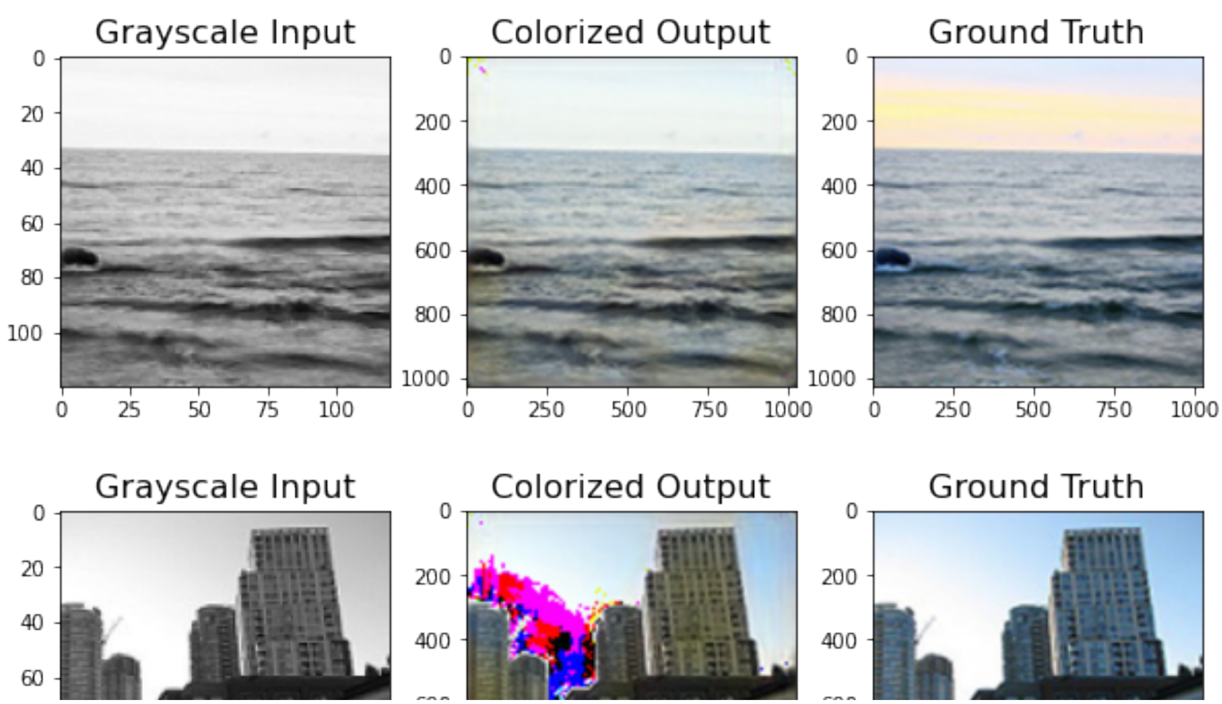
In [ ]:
```
```

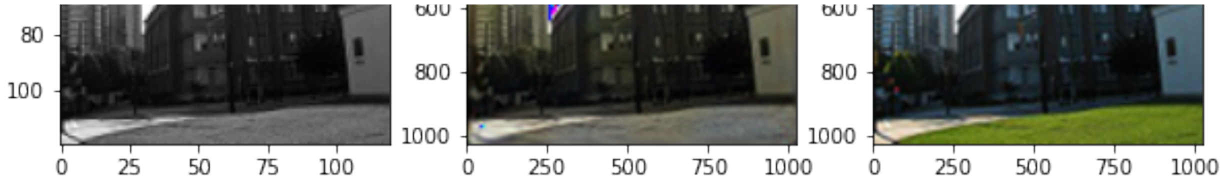
```
# Please have a look at the Notebook in pdf form that was train on 50
num_epochs = 50
losses = {"D":[], "G":[]}
for e in range( num_epochs ):
    print("Running epoch : ", e )
    for ( x , y ) in dataset:
        # Here ( x , y ) represents a batch from our training dataset.
        # print( x.shape )
        train_step( x , y )
```

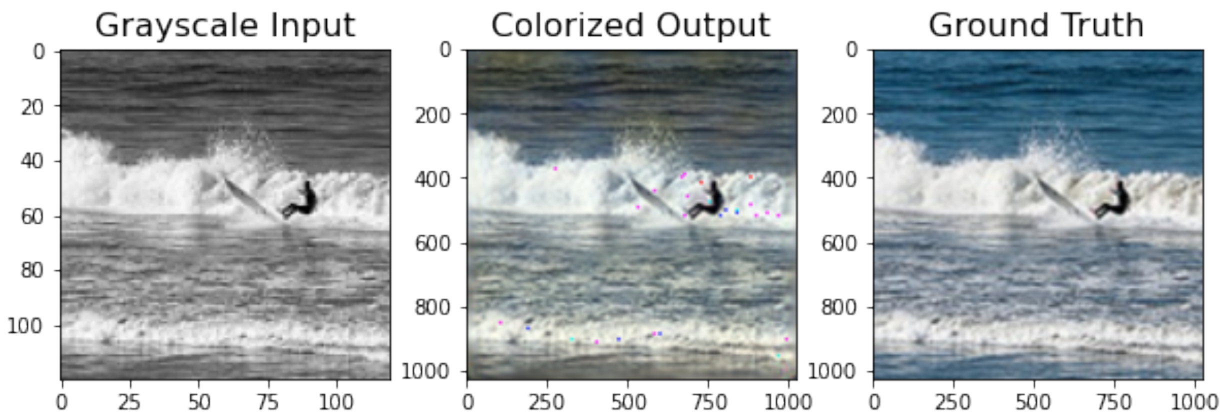
```
Running epoch :  0
Running epoch :  1
Running epoch :  2
Running epoch :  3
Running epoch :  4
Running epoch :  5
Running epoch :  6
Running epoch :  7
Running epoch :  8
Running epoch :  9
Running epoch :  10
Running epoch :  11
Running epoch :  12
Running epoch :  13
Running epoch :  14
Running epoch :  15
Running epoch :  16
Running epoch :  17
Running epoch :  18
Running epoch :  19
Running epoch :  20
Running epoch :  21
Running epoch :  22
Running epoch :  23
Running epoch :  24
Running epoch :  25
Running epoch :  26
Running epoch :  27
Running epoch :  28
Running epoch :  29
Running epoch :  30
Running epoch :  31
Running epoch :  32
Running epoch :  33
Running epoch :  34
Running epoch :  35
Running epoch :  36
Running epoch :  37
Running epoch :  38
Running epoch :  39
```

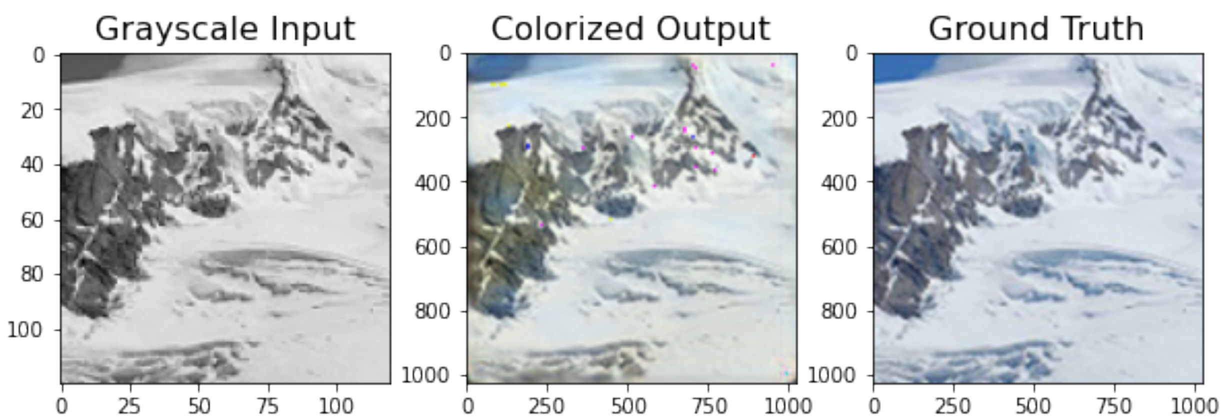
```
Running epoch :  40
Running epoch :  41
Running epoch :  42
Running epoch :  43
Running epoch :  44
Running epoch :  45
Running epoch :  46
Running epoch :  47
Running epoch :  48
Running epoch :  49
```

In [ ]:
```
#printing the image with the results obtained
for i in range(11, 33, 7):
  plt.figure(figsize=(10,10))
  or_image = plt.subplot(3,3,1)
  or_image.set_title('Grayscale Input', fontsize=16)
  plt.imshow( test_x[i].reshape((120,120)) , cmap='gray' )

  in_image = plt.subplot(3,3,2)
  image = Image.fromarray( ( y[i] * 255 ).astype( 'uint8' ) ).resize(
  image = np.asarray( image )
  in_image.set_title('Colorized Output', fontsize=16)
  plt.imshow( image )

  ou_image = plt.subplot(3,3,3)
  image = Image.fromarray( ( test_y[i] * 255 ).astype( 'uint8' ) ).res
  ou_image.set_title('Ground Truth', fontsize=16)
  plt.imshow( image )

  plt.show()
```






Grayscale Input
Colorized Output
Ground Truth


Grayscale Input
Colorized Output
Ground Truth