

Human Face Generator using GANs

This project implements a Generative Adversarial Network (GAN) to generate realistic human faces. GANs consist of two neural networks, a Generator and a Discriminator, that are trained together to create images that become increasingly realistic over time.

Import Modules

```
import os
import numpy as np
import matplotlib.pyplot as plt
import warnings
from tqdm.notebook import tqdm
from PIL import Image

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.preprocessing.image import load_img,
array_to_img
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras import layers
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy

warnings.filterwarnings('ignore')

2024-06-17 17:52:06.825962: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable
to register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
2024-06-17 17:52:06.826071: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to
register cuFFT factory: Attempting to register factory for plugin
cuFFT when one has already been registered
2024-06-17 17:52:06.959981: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable
to register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
```

Load the files from kaggle 50k-celebrity-faces-image-dataset of 50k human faces

```
BASE_DIR =
'/kaggle/input/50k-celebrity-faces-image-dataset/Celebrity_Faces_Datas
et'
```

```
image_paths = []
for image_name in os.listdir(BASE_DIR):
    image_path = os.path.join(BASE_DIR, image_name)
    image_paths.append(image_path)

len(image_paths)

50000
```

Visualize the Image

```
plt.figure(figsize=(20, 20))
temp_images = image_paths[:49]
index = 1

for image_path in temp_images:
    plt.subplot(7, 7, index)
    img = Image.open(image_path)
    img = img.crop((0, 20, 178, 198))
    img = img.resize((64, 64))
    img = np.array(img)
    plt.imshow(img)
    plt.axis('off')
    index += 1
```



Preprocess Images like loading ,cropping ,normalizing

```
def load_and_preprocess_real_images(image_path, target_size=(64, 64)):
    img = Image.open(image_path)
    img = img.crop((0, 20, 178, 198))
    img = img.resize(target_size)
    img = (np.array(img)-127.5)/127.5
    return img
```

```
train_images = [load_and_preprocess_real_images(path) for path in
tqdm(image_paths)]
train_images = np.array(train_images)
```

```
{"model_id": "2e153a9d949b47b28d1826d6943b4b79", "version_major": 2, "version_minor": 0}
```

Define Constants for Model Configuration

1. **LATENT_DIM:** This constant defines the dimensionality of the latent space, which is set to 200. The latent space is typically used in generative models like GANs (Generative Adversarial Networks)
2. **WEIGHT_INIT:** This constant specifies the weight initialization method for the neural network layers. Here, the weights are initialized using a normal distribution with a mean of 0.0 and a standard deviation of 0.02. This type of initialization is often used to stabilize the training of deep neural networks.
3. **CHANNELS:** This constant defines the number of channels in the input data. For example, in the case of RGB images, the number of channels is 3

```
LATENT_DIM = 200  
  
WEIGHT_INIT = keras.initializers.RandomNormal(mean=0.0, stddev=0.02)  
  
CHANNELS = 3
```

Define the Generator Model

This section defines a generator model using the `Sequential` API from Keras. The model is designed to generate images from random noise.

```
model = Sequential(name='generator1')  
  
model.add(layers.Dense(8 * 8 * 512, input_dim=LATENT_DIM))  
model.add(layers.ReLU())  
  
model.add(layers.Reshape((8, 8, 512)))  
  
model.add(layers.Conv2DTranspose(256, (4, 4), strides=(2, 2),  
padding='same', kernel_initializer=WEIGHT_INIT))  
model.add(layers.ReLU())  
  
model.add(layers.Conv2DTranspose(128, (4, 4), strides=(2, 2),  
padding='same', kernel_initializer=WEIGHT_INIT))  
model.add(layers.ReLU())  
  
model.add(layers.Conv2DTranspose(64, (4, 4), strides=(2, 2),  
padding='same', kernel_initializer=WEIGHT_INIT))  
model.add(layers.ReLU())  
  
model.add(layers.Conv2D(CHANNELS, (4, 4), padding='same',
```

```
activation='tanh'))

generator1 = model
generator1.summary()
```

Model: "generator1"

Layer (type) Param #	Output Shape	
dense (Dense) 6,586,368	(None, 32768)	
re_lu (ReLU) 0	(None, 32768)	
reshape (Reshape) 0	(None, 8, 8, 512)	
conv2d_transpose 2,097,408 (Conv2DTranspose)	(None, 16, 16, 256)	
re_lu_1 (ReLU) 0	(None, 16, 16, 256)	
conv2d_transpose_1 524,416 (Conv2DTranspose)	(None, 32, 32, 128)	
re_lu_2 (ReLU) 0	(None, 32, 32, 128)	
conv2d_transpose_2 131,136 (Conv2DTranspose)	(None, 64, 64, 64)	

0	re_lu_3 (ReLU)	(None, 64, 64, 64)
3,075	conv2d (Conv2D)	(None, 64, 64, 3)

Total params: 9,342,403 (35.64 MB)

Trainable params: 9,342,403 (35.64 MB)

Non-trainable params: 0 (0.00 B)

Define the Discriminator Model

This section defines a discriminator model using the `Sequential` API from Keras. The model is designed to classify images as real or fake.

```
model = Sequential(name='discriminator1')
input_shape = (64, 64, 3)
alpha = 0.2

model.add(layers.Conv2D(64, (4, 4), strides=(2, 2), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Conv2D(128, (4, 4), strides=(2, 2), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Conv2D(128, (4, 4), strides=(2, 2), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Flatten())
model.add(layers.Dropout(0.3))

model.add(layers.Dense(1, activation='sigmoid'))

discriminator1 = model
discriminator1.summary()

Model: "discriminator1"
```

Layer (type)	Output Shape
Param #	
conv2d_1 (Conv2D)	(None, 32, 32, 64)
3,136	
batch_normalization	(None, 32, 32, 64)
256	
(BatchNormalization)	
leaky_re_lu (LeakyReLU)	(None, 32, 32, 64)
0	
conv2d_2 (Conv2D)	(None, 16, 16, 128)
131,200	
batch_normalization_1	(None, 16, 16, 128)
512	
(BatchNormalization)	
leaky_re_lu_1 (LeakyReLU)	(None, 16, 16, 128)
0	
conv2d_3 (Conv2D)	(None, 8, 8, 128)
262,272	
batch_normalization_2	(None, 8, 8, 128)
512	
(BatchNormalization)	
leaky_re_lu_2 (LeakyReLU)	(None, 8, 8, 128)
0	
flatten (Flatten)	(None, 8192)
0	

dropout (Dropout)	(None, 8192)	
0		
dense_1 (Dense)	(None, 1)	
8,193		

Total params: 406,081 (1.55 MB)

Trainable params: 405,441 (1.55 MB)

Non-trainable params: 640 (2.50 KB)

Define the Second Generator Model

This section defines a second generator model using the `Sequential` API from Keras. The model is designed to generate images from random noise, with additional convolutional layers compared to the first generator.

```
model = Sequential(name='generator2')

model.add(layers.Dense(8 * 8 * 512, input_dim=LATENT_DIM))
model.add(layers.ReLU())

model.add(layers.Reshape((8, 8, 512)))

model.add(layers.Conv2DTranspose(256, (4, 4), strides=(2, 2),
padding='same', kernel_initializer=WEIGHT_INIT))
model.add(layers.ReLU())
model.add(layers.Conv2DTranspose(256, (4, 4), strides=(1, 1),
padding='same', kernel_initializer=WEIGHT_INIT))
model.add(layers.ReLU())
model.add(layers.Conv2DTranspose(256, (4, 4), strides=(2, 2),
padding='same', kernel_initializer=WEIGHT_INIT))
model.add(layers.ReLU())
model.add(layers.Conv2DTranspose(156, (4, 4), strides=(1, 1),
padding='same', kernel_initializer=WEIGHT_INIT))
model.add(layers.ReLU())

model.add(layers.Conv2DTranspose(128, (4, 4), strides=(2, 2),
padding='same', kernel_initializer=WEIGHT_INIT))
model.add(layers.ReLU())

model.add(layers.Conv2DTranspose(128, (4, 4), strides=(1, 1),
padding='same', kernel_initializer=WEIGHT_INIT))
```



```
model.add(layers.ReLU())
```

```
model.add(layers.Conv2D(CHANNELS, (4, 4), padding='same',  
activation='tanh'))
```

```
generator2 = model  
generator2.summary()
```

Model: "generator2"

Layer (type) Param #	Output Shape
dense_2 (Dense) 6,586,368	(None, 32768)
re_lu_4 (ReLU) 0	(None, 32768)
reshape_1 (Reshape) 0	(None, 8, 8, 512)
conv2d_transpose_3 2,097,408 (Conv2DTranspose)	(None, 16, 16, 256)
re_lu_5 (ReLU) 0	(None, 16, 16, 256)
conv2d_transpose_4 1,048,832 (Conv2DTranspose)	(None, 16, 16, 256)
re_lu_6 (ReLU) 0	(None, 16, 16, 256)
conv2d_transpose_5 1,048,832	(None, 32, 32, 256)

	(Conv2DTranspose)		
0	re_lu_7 (ReLU)	(None, 32, 32, 256)	
639,132	conv2d_transpose_6	(None, 32, 32, 156)	
	(Conv2DTranspose)		
0	re_lu_8 (ReLU)	(None, 32, 32, 156)	
319,616	conv2d_transpose_7	(None, 64, 64, 128)	
	(Conv2DTranspose)		
0	re_lu_9 (ReLU)	(None, 64, 64, 128)	
262,272	conv2d_transpose_8	(None, 64, 64, 128)	
	(Conv2DTranspose)		
0	re_lu_10 (ReLU)	(None, 64, 64, 128)	
6,147	conv2d_4 (Conv2D)	(None, 64, 64, 3)	

Total params: 12,008,607 (45.81 MB)

Trainable params: 12,008,607 (45.81 MB)

Non-trainable params: 0 (0.00 B)

Define the Second Discriminator Model

This section defines a second discriminator model using the `Sequential` API from Keras. The model is designed to classify images as real or fake, with additional convolutional layers compared to the first discriminator.

```
model = Sequential(name='discriminator2')
input_shape = (64, 64, 3)
alpha = 0.2

model.add(layers.Conv2D(128, (4, 4), strides=(2, 2), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Conv2D(128, (4, 4), strides=(2, 2), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))
model.add(layers.Conv2D(64, (4, 4), strides=(1, 1), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Conv2D(64, (4, 4), strides=(2, 2), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Conv2D(64, (4, 4), strides=(1, 1), padding='same',
input_shape=input_shape))
model.add(layers.BatchNormalization())
model.add(layers.LeakyReLU(alpha=alpha))

model.add(layers.Flatten())
model.add(layers.Dropout(0.3))

model.add(layers.Dense(1, activation='sigmoid'))

discriminator2 = model
discriminator2.summary()

Model: "discriminator2"
```

Layer (type)	Output Shape	
Param #		

conv2d_5 (Conv2D)	(None, 32, 32, 128)	
6,272		
batch_normalization_3	(None, 32, 32, 128)	
512		
(BatchNormalization)		
leaky_re_lu_3 (LeakyReLU)	(None, 32, 32, 128)	
0		
conv2d_6 (Conv2D)	(None, 16, 16, 128)	
262,272		
batch_normalization_4	(None, 16, 16, 128)	
512		
(BatchNormalization)		
leaky_re_lu_4 (LeakyReLU)	(None, 16, 16, 128)	
0		
conv2d_7 (Conv2D)	(None, 16, 16, 64)	
131,136		
batch_normalization_5	(None, 16, 16, 64)	
256		
(BatchNormalization)		
leaky_re_lu_5 (LeakyReLU)	(None, 16, 16, 64)	
0		
conv2d_8 (Conv2D)	(None, 8, 8, 64)	
65,600		
batch_normalization_6	(None, 8, 8, 64)	

256	(BatchNormalization)		
	leaky_re_lu_6 (LeakyReLU)	(None, 8, 8, 64)	
0			
	conv2d_9 (Conv2D)	(None, 8, 8, 64)	
65,600			
	batch_normalization_7	(None, 8, 8, 64)	
256			
	(BatchNormalization)		
	leaky_re_lu_7 (LeakyReLU)	(None, 8, 8, 64)	
0			
	flatten_1 (Flatten)	(None, 4096)	
0			
	dropout_1 (Dropout)	(None, 4096)	
0			
	dense_3 (Dense)	(None, 1)	
4,097			

Total params: 536,769 (2.05 MB)

Trainable params: 535,873 (2.04 MB)

Non-trainable params: 896 (3.50 KB)

Define the DCGAN Model Class

This class implements a DCGAN model, including generator and discriminator models, custom training steps, and loss tracking. It supports compilation with optimizers and a loss function, and uses gradient tapes for backpropagation during training

```

class DCGAN(keras.Model):
    def __init__(self, generator, discriminator, latent_dim):
        super().__init__()
        self.generator = generator
        self.discriminator = discriminator
        self.latent_dim = latent_dim
        self.g_loss_metric = keras.metrics.Mean(name='g_loss')
        self.d_loss_metric = keras.metrics.Mean(name='d_loss')

    @property
    def metrics(self):
        return [self.g_loss_metric, self.d_loss_metric]

    def compile(self, g_optimizer, d_optimizer, loss_fn):
        super(DCGAN, self).compile()
        self.g_optimizer = g_optimizer
        self.d_optimizer = d_optimizer
        self.loss_fn = loss_fn

    def train_step(self, real_images):

        batch_size = tf.shape(real_images)[0]

        random_noise = tf.random.normal(shape=(batch_size,
self.latent_dim))

        with tf.GradientTape() as tape:

            pred_real = self.discriminator(real_images, training=True)
            real_labels = tf.ones((batch_size, 1))
            d_loss_real = self.loss_fn(real_labels, pred_real)

            fake_images = self.generator(random_noise)
            pred_fake = self.discriminator(fake_images, training=True)

            fake_labels = tf.zeros((batch_size, 1))
            d_loss_fake = self.loss_fn(fake_labels, pred_fake)

            d_loss = d_loss_real + d_loss_fake

            gradients = tape.gradient(d_loss,
self.discriminator.trainable_variables)

            self.d_optimizer.apply_gradients(zip(gradients,

```

```

self.discriminator.trainable_variables))

    labels = tf.ones((batch_size, 1))

    with tf.GradientTape() as tape:
        fake_images = self.generator(random_noise, training=True)
        pred_fake = self.discriminator(fake_images, training=True)
        g_loss = self.loss_fn(labels, pred_fake)

        gradients = tape.gradient(g_loss,
self.generator.trainable_variables)

        self.g_optimizer.apply_gradients(zip(gradients,
self.generator.trainable_variables))

        self.d_loss_metric.update_state(d_loss)
        self.g_loss_metric.update_state(g_loss)

    return {'d_loss': self.d_loss_metric.result(), 'g_loss':
self.g_loss_metric.result()}

```

Define the DCGAN Monitor Callback

This callback monitors the training process of the DCGAN model, saving generated images and tracking loss values. It generates images at the end of each epoch and plots the discriminator and generator losses at the end of training.

```

class DCGANMonitor(keras.callbacks.Callback):
    def __init__(self, num_imgs=25, latent_dim=200):
        self.num_imgs = num_imgs
        self.latent_dim = latent_dim

        self.noise = tf.random.normal([25, latent_dim])
        self.d_losses = []
        self.g_losses = []
        self.d_losses_all=[]
        self.g_losses_all=[]
        self.total_loss = []

```

```

def on_epoch_end(self, epoch, logs=None):

    g_img = self.model.generator(self.noise)

    g_img = (g_img * 127.5) + 127.5
    g_img.numpy()
    self.d_losses.append(logs['d_loss'])
    self.g_losses.append(logs['g_loss'])
    self.total_loss.append(logs['d_loss']+logs['g_loss'])

    if (epoch)%10 == 0:
        fig = plt.figure(figsize=(8, 8))
        for i in range(25):
            plt.subplot(5, 5, i+1)
            img = array_to_img(g_img[i])
            plt.imshow(img)
            plt.axis('off')
        plt.show()

def on_train_end(self, logs=None):
    plt.figure(figsize=(10, 5))
    plt.plot(self.d_losses, label='Discriminator Loss')
    plt.plot(self.g_losses, label='Generator Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.title('Discriminator and Generator Losses')
    plt.show()
    print(f"minimum value of d_loss = {min(self.d_losses)} for
epoch {self.d_losses.index(min(self.d_losses))} ")
    print(f"minimum value of g_loss = {min(self.g_losses)} for
epoch {self.g_losses.index(min(self.g_losses))} ")
    print(f"minimum value of total = {min(self.total_loss)} for
epoch {self.total_loss.index(min(self.total_loss))} ")
    self.model.generator.save('generator_final.h5')

```

DCGAN Initialization

The `dcgan` and `dcgan2` model is initialized with `generator1` and `generator2` for image generation, `discriminator1` and `discriminator2` for image classification respectively, and a latent dimension of `LATENT_DIM` for random noise input.

```

dcgan = DCGAN(generator=generator1, discriminator=discriminator1,
latent_dim=LATENT_DIM)

```



```
dcgan2 = DCGAN(generator=generator2, discriminator=discriminator2,
latent_dim=LATENT_DIM)
```

Compile DCGAN Model

The `dcgan` model is compiled with Adam optimizers for the generator and discriminator (`G_LR` and `D_LR` learning rates, `beta_1=0.5`) and BinaryCrossentropy loss function.

```
D_LR = 0.0001
G_LR = 0.0003
dcgan.compile(g_optimizer=Adam(learning_rate=G_LR, beta_1=0.5),
d_optimizer=Adam(learning_rate=D_LR, beta_1=0.5),
loss_fn=BinaryCrossentropy())

D_LR = 0.0001
G_LR = 0.0003
dcgan2.compile(g_optimizer=Adam(learning_rate=G_LR, beta_1=0.5),
d_optimizer=Adam(learning_rate=D_LR, beta_1=0.5),
loss_fn=BinaryCrossentropy())
```

Train DCGAN Model

The `dcgan` model is trained for `N_EPOCHS` epochs using `train_images` data, with `DCGANMonitor` callback to visualize generated images and monitor losses during training.

```
N_EPOCHS = 50
dcgan.fit(train_images, epochs=N_EPOCHS,
callbacks=[DCGANMonitor(DCGAN)])

Epoch 1/50
 5/1563 _____ 47s 30ms/step - d_loss: 2.3296 -
g_loss: 0.6535

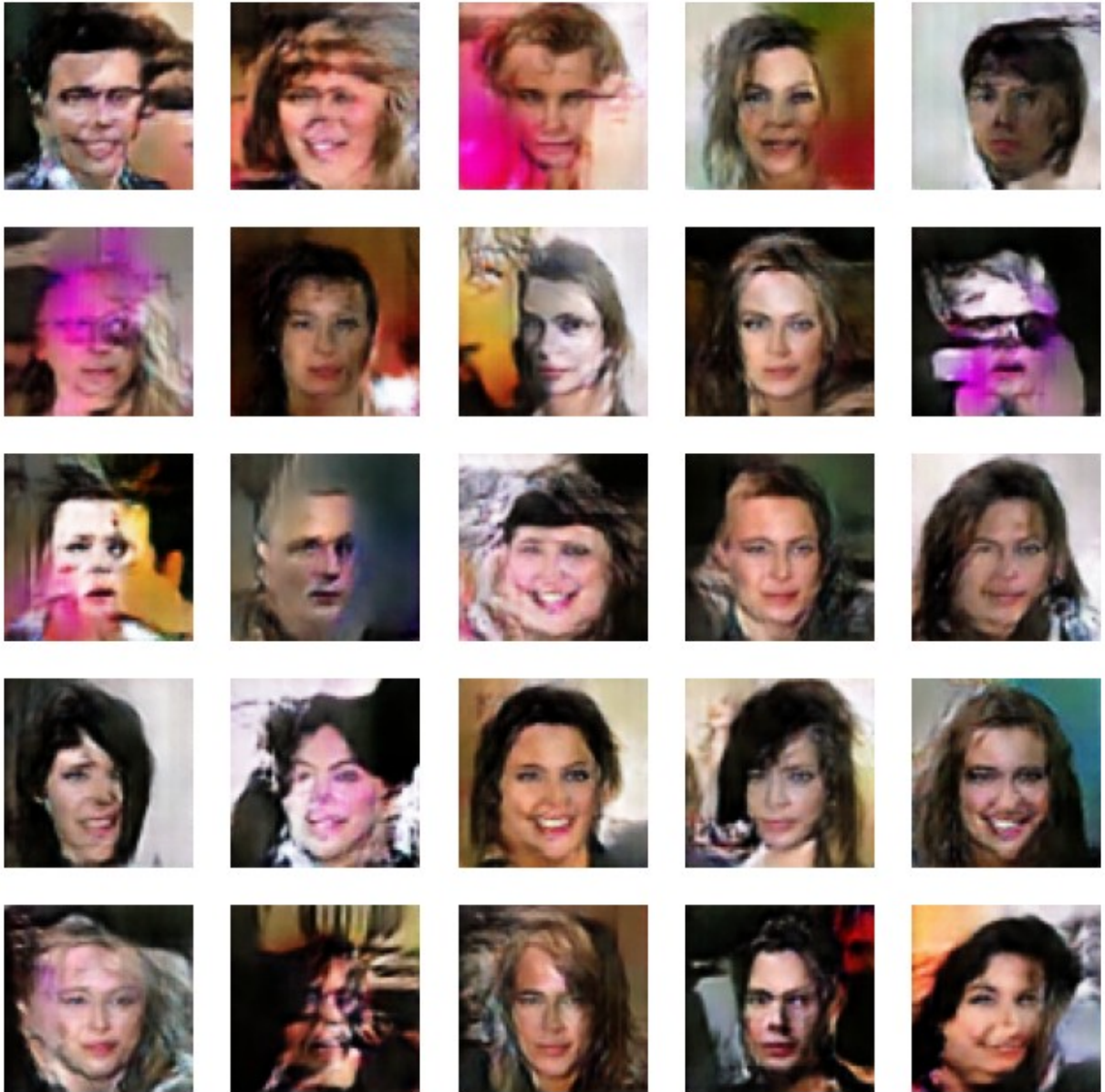
WARNING: All log messages before absl::InitializeLog() is called are
written to STDERR
I0000 00:00:1718647148.171929      74 device_compiler.h:186] Compiled
cluster using XLA! This line is logged at most once for the lifetime
of the process.
W0000 00:00:1718647148.194784      74 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

1563/1563 _____ 0s 37ms/step - d_loss: 1.8600 - g_loss:
2.4383
```



```
1563/1563 ————— 77s 38ms/step - d_loss: 1.8596 -  
g_loss: 2.4383  
Epoch 2/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.1241 -  
g_loss: 1.4399  
Epoch 3/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.2715 -  
g_loss: 1.2816  
Epoch 4/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.4415 -  
g_loss: 0.9326  
Epoch 5/50
```

```
1563/1563 _____ 45s 29ms/step - d_loss: 1.4390 -  
g_loss: 0.8252  
Epoch 6/50  
1563/1563 _____ 46s 29ms/step - d_loss: 1.4216 -  
g_loss: 0.7985  
Epoch 7/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.4193 -  
g_loss: 0.7708  
Epoch 8/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.4158 -  
g_loss: 0.7562  
Epoch 9/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.4110 -  
g_loss: 0.7468  
Epoch 10/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.4062 -  
g_loss: 0.7456  
Epoch 11/50  
1561/1563 _____ 0s 29ms/step - d_loss: 1.4037 - g_loss:  
0.7402
```

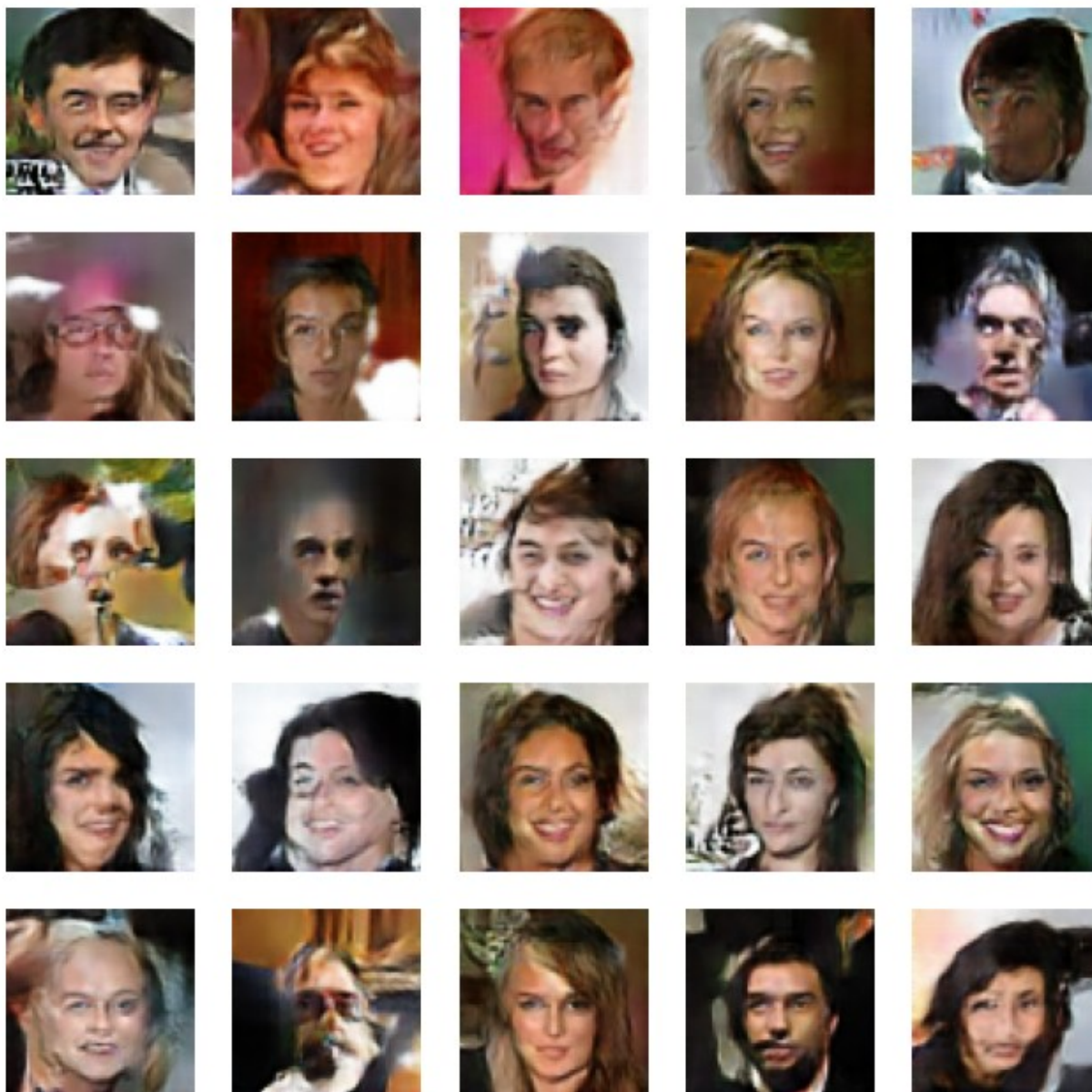


```

1563/1563 _____ 46s 29ms/step - d_loss: 1.4037 -
g_loss: 0.7402
Epoch 12/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.4010 -
g_loss: 0.7371
Epoch 13/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3999 -
g_loss: 0.7364
Epoch 14/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3965 -
g_loss: 0.7374
Epoch 15/50

```

```
1563/1563 _____ 45s 29ms/step - d_loss: 1.3976 -  
g_loss: 0.7364  
Epoch 16/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.3937 -  
g_loss: 0.7403  
Epoch 17/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.3905 -  
g_loss: 0.7423  
Epoch 18/50  
1563/1563 _____ 82s 29ms/step - d_loss: 1.3885 -  
g_loss: 0.7414  
Epoch 19/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.3894 -  
g_loss: 0.7411  
Epoch 20/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.3848 -  
g_loss: 0.7481  
Epoch 21/50  
1561/1563 _____ 0s 29ms/step - d_loss: 1.3855 - g_loss:  
0.7456
```

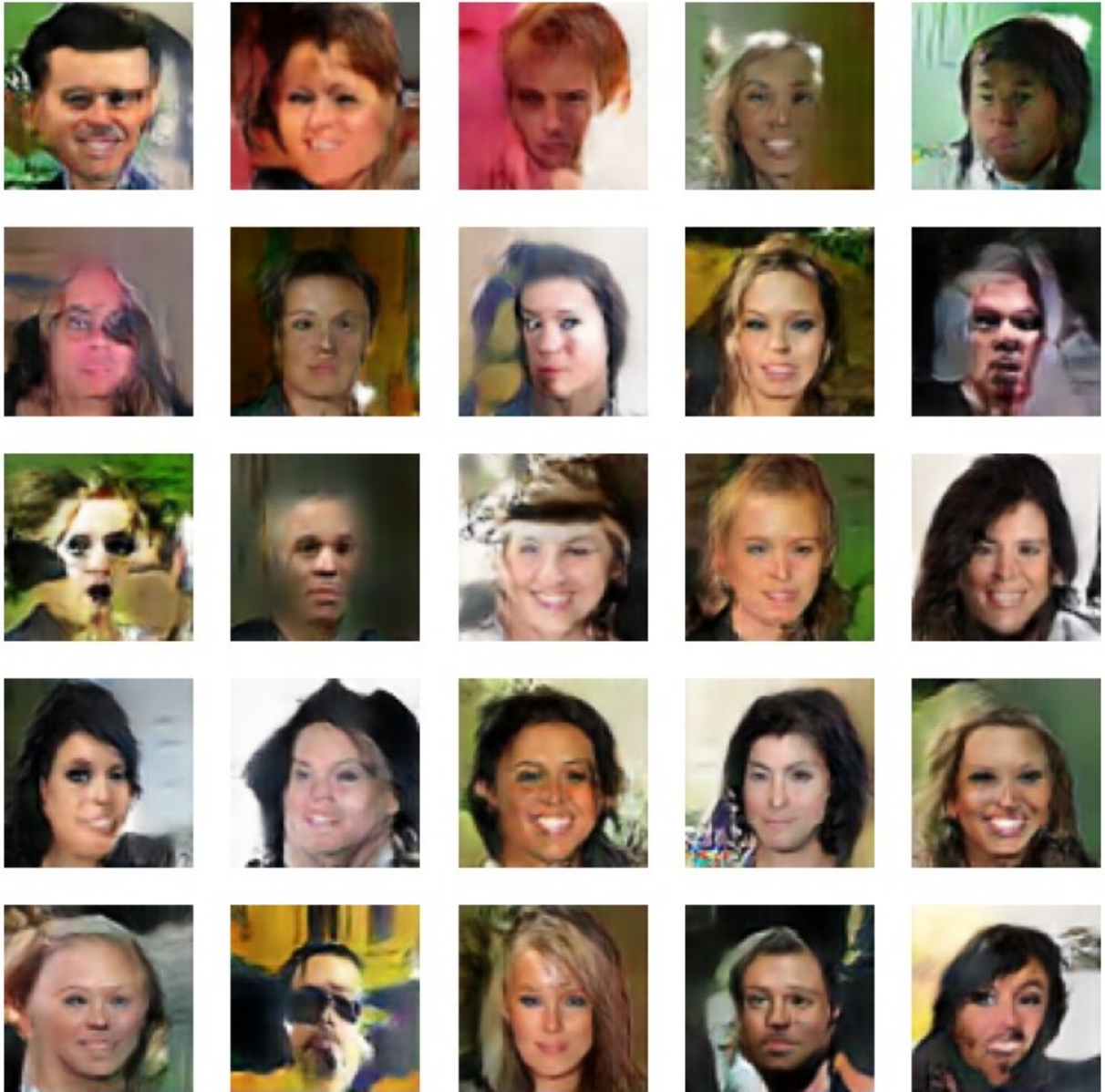



```

1563/1563 _____ 46s 30ms/step - d_loss: 1.3855 -
g_loss: 0.7456
Epoch 22/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3820 -
g_loss: 0.7492
Epoch 23/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3791 -
g_loss: 0.7533
Epoch 24/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3767 -
g_loss: 0.7556
Epoch 25/50

```

```
1563/1563 ————— 45s 29ms/step - d_loss: 1.3739 -  
g_loss: 0.7585  
Epoch 26/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.3741 -  
g_loss: 0.7647  
Epoch 27/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.3668 -  
g_loss: 0.7732  
Epoch 28/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.3625 -  
g_loss: 0.7830  
Epoch 29/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.3586 -  
g_loss: 0.7864  
Epoch 30/50  
1563/1563 ————— 45s 29ms/step - d_loss: 1.3543 -  
g_loss: 0.7996  
Epoch 31/50  
1561/1563 ————— 0s 29ms/step - d_loss: 1.3478 - g_loss:  
0.8095
```



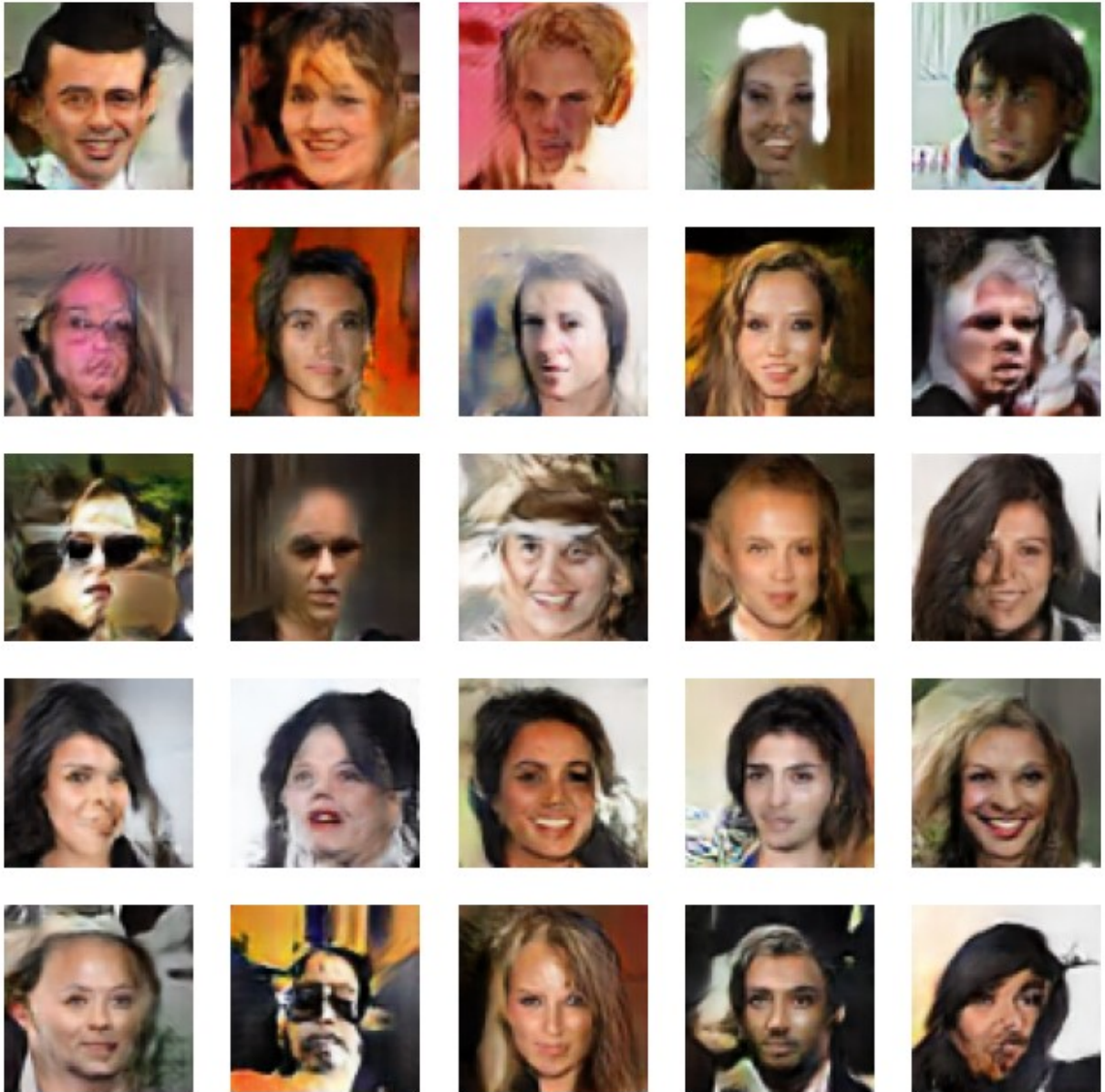
```

1563/1563 _____ 46s 29ms/step - d_loss: 1.3478 -
g_loss: 0.8095
Epoch 32/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3360 -
g_loss: 0.8264
Epoch 33/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3291 -
g_loss: 0.8415
Epoch 34/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.3205 -
g_loss: 0.8585
Epoch 35/50

```



```
1563/1563 _____ 45s 29ms/step - d_loss: 1.3070 -  
g_loss: 0.8756  
Epoch 36/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.2975 -  
g_loss: 0.8965  
Epoch 37/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.2818 -  
g_loss: 0.9226  
Epoch 38/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.2720 -  
g_loss: 0.9516  
Epoch 39/50  
1563/1563 _____ 45s 29ms/step - d_loss: 1.2509 -  
g_loss: 0.9812  
Epoch 40/50  
1563/1563 _____ 82s 29ms/step - d_loss: 1.2326 -  
g_loss: 1.0126  
Epoch 41/50  
1561/1563 _____ 0s 29ms/step - d_loss: 1.2168 - g_loss:  
1.0437
```



```

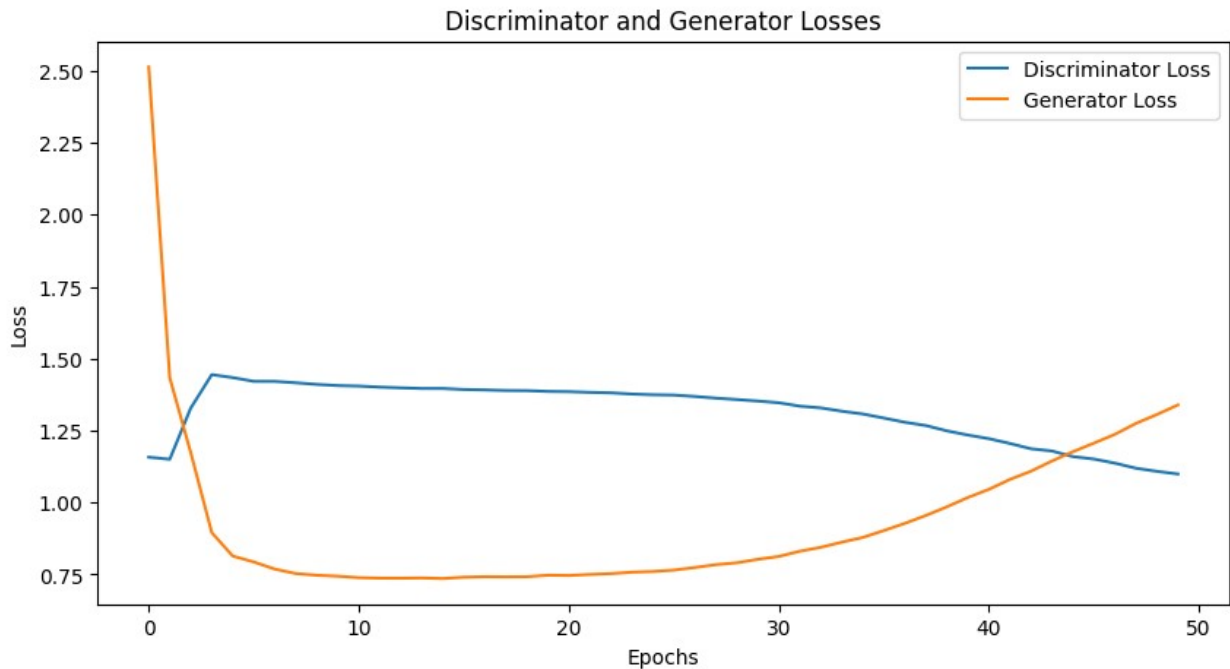
1563/1563 _____ 46s 29ms/step - d_loss: 1.2168 -
g_loss: 1.0437
Epoch 42/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.2070 -
g_loss: 1.0681
Epoch 43/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.1841 -
g_loss: 1.1022
Epoch 44/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.1787 -
g_loss: 1.1412
Epoch 45/50

```

```

1563/1563 _____ 45s 29ms/step - d_loss: 1.1627 -
g_loss: 1.1679
Epoch 46/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.1435 -
g_loss: 1.2033
Epoch 47/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.1371 -
g_loss: 1.2283
Epoch 48/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.1187 -
g_loss: 1.2710
Epoch 49/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.1071 -
g_loss: 1.2996
Epoch 50/50
1563/1563 _____ 45s 29ms/step - d_loss: 1.0970 -
g_loss: 1.3307

```



```

minimum value of d_loss = 1.099036693572998 for epoch 49
minimum value of g_loss = 0.7358095645904541 for epoch 14
minimum value of total = 2.130660891532898 for epoch 17

```

```
<keras.src.callbacks.history.History at 0x7ac52b5dbeb0>
```

```

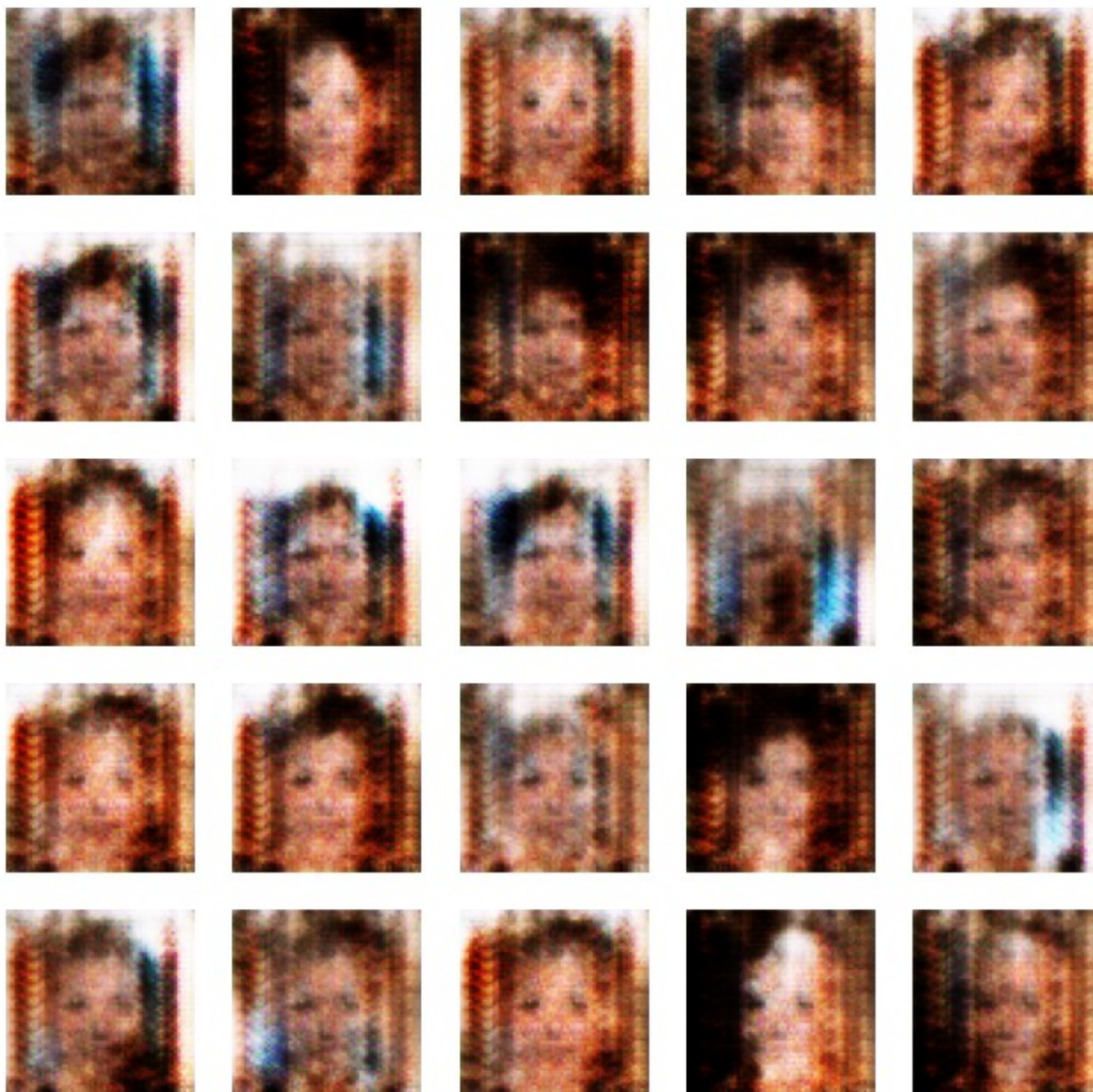
N_EPOCHS = 50
dcgan2.fit(train_images, epochs=N_EPOCHS,
callbacks=[DCGANMonitor(DCGAN)])

```

Epoch 1/50
2/1563 ————— 2:23 92ms/step - d_loss: 2.0665 -
g_loss: 1.0457

W0000 00:00:1718649540.017232 73 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

1563/1563 ————— 0s 101ms/step - d_loss: 2.5843 -
g_loss: 1.1827



1563/1563 ————— 188s 102ms/step - d_loss: 2.5838 -
g_loss: 1.1827

```
Epoch 2/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.4487 -
g_loss: 0.8069
Epoch 3/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.4332 -
g_loss: 0.7721
Epoch 4/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.4249 -
g_loss: 0.7398
Epoch 5/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.4103 -
g_loss: 0.7455
Epoch 6/50
1563/1563 _____ 143s 92ms/step - d_loss: 1.4048 -
g_loss: 0.7436
Epoch 7/50
1563/1563 _____ 143s 92ms/step - d_loss: 1.3998 -
g_loss: 0.7422
Epoch 8/50
1563/1563 _____ 143s 92ms/step - d_loss: 1.3956 -
g_loss: 0.7548
Epoch 9/50
1563/1563 _____ 144s 92ms/step - d_loss: 1.3934 -
g_loss: 0.7503
Epoch 10/50
1563/1563 _____ 143s 92ms/step - d_loss: 1.3861 -
g_loss: 0.7542
Epoch 11/50
1563/1563 _____ 0s 92ms/step - d_loss: 1.3916 - g_loss:
0.7362
```




```

1563/1563 _____ 145s 93ms/step - d_loss: 1.3916 -
g_loss: 0.7363
Epoch 12/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.3833 -
g_loss: 0.7507
Epoch 13/50
1563/1563 _____ 143s 91ms/step - d_loss: 1.3911 -
g_loss: 0.7370
Epoch 14/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.3918 -
g_loss: 0.7308
Epoch 15/50

```

```
1563/1563 _____ 142s 91ms/step - d_loss: 1.3943 -  
g_loss: 0.7246  
Epoch 16/50  
1563/1563 _____ 142s 91ms/step - d_loss: 1.3808 -  
g_loss: 0.7548  
Epoch 17/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3867 -  
g_loss: 0.7374  
Epoch 18/50  
1563/1563 _____ 141s 91ms/step - d_loss: 1.3910 -  
g_loss: 0.7252  
Epoch 19/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3919 -  
g_loss: 0.7213  
Epoch 20/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3894 -  
g_loss: 0.7271  
Epoch 21/50  
1563/1563 _____ 0s 90ms/step - d_loss: 1.3896 - g_loss:  
0.7261
```



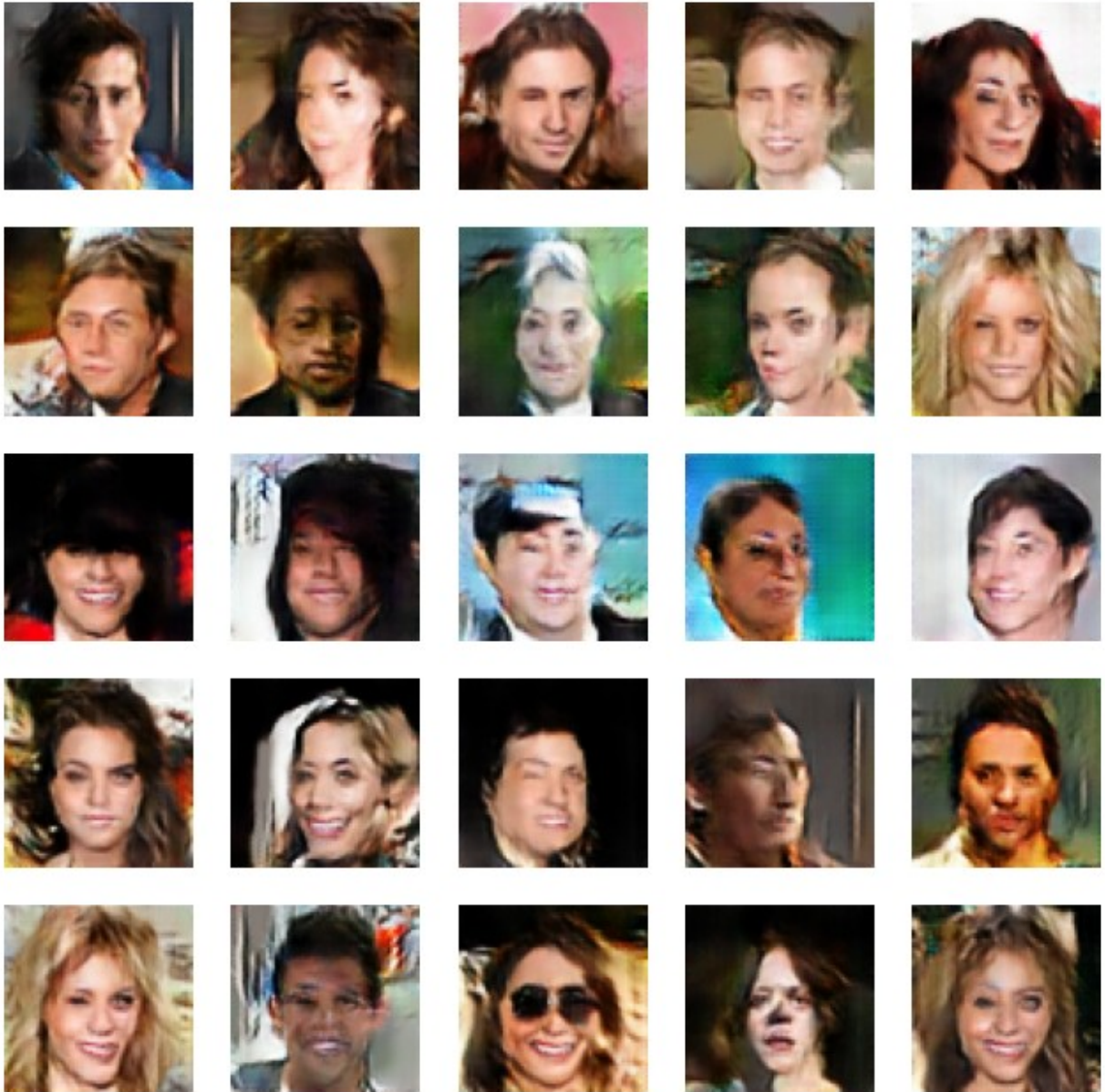
```

1563/1563 _____ 143s 91ms/step - d_loss: 1.3896 -
g_loss: 0.7261
Epoch 22/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.3869 -
g_loss: 0.7302
Epoch 23/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.3851 -
g_loss: 0.7301
Epoch 24/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.3729 -
g_loss: 0.7591
Epoch 25/50

```



```
1563/1563 _____ 141s 90ms/step - d_loss: 1.3809 -  
g_loss: 0.7403  
Epoch 26/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3809 -  
g_loss: 0.7430  
Epoch 27/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3756 -  
g_loss: 0.7530  
Epoch 28/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3806 -  
g_loss: 0.7494  
Epoch 29/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3592 -  
g_loss: 0.7848  
Epoch 30/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3772 -  
g_loss: 0.7596  
Epoch 31/50  
1563/1563 _____ 0s 90ms/step - d_loss: 1.3643 - g_loss:  
0.7760
```

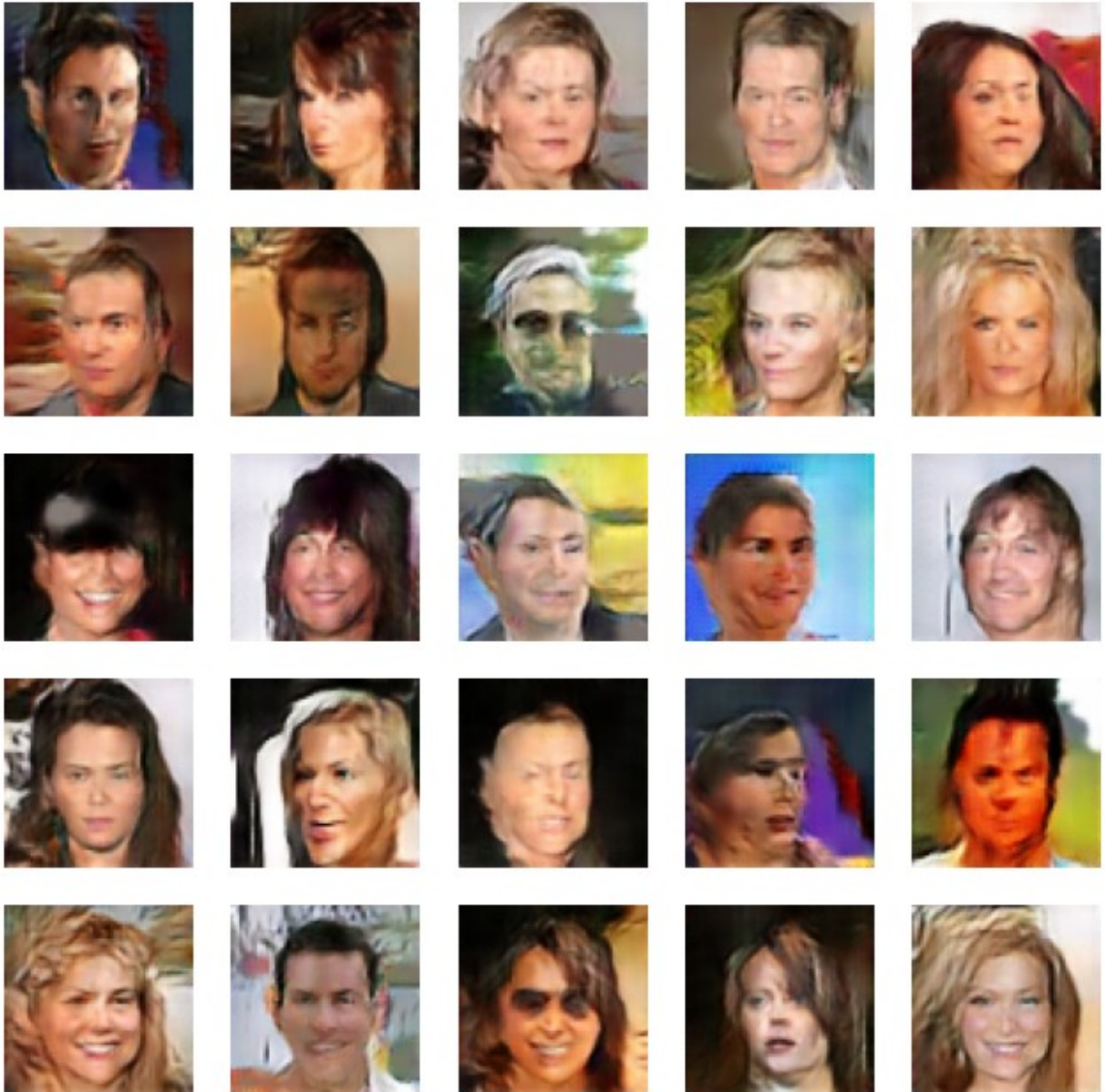


```

1563/1563 _____ 142s 91ms/step - d_loss: 1.3643 -
g_loss: 0.7760
Epoch 32/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.3682 -
g_loss: 0.7668
Epoch 33/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.3728 -
g_loss: 0.7686
Epoch 34/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.3677 -
g_loss: 0.7757
Epoch 35/50

```

```
1563/1563 _____ 141s 90ms/step - d_loss: 1.3633 -  
g_loss: 0.7754  
Epoch 36/50  
1563/1563 _____ 142s 91ms/step - d_loss: 1.3629 -  
g_loss: 0.7823  
Epoch 37/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3641 -  
g_loss: 0.7844  
Epoch 38/50  
1563/1563 _____ 142s 91ms/step - d_loss: 1.3647 -  
g_loss: 0.7857  
Epoch 39/50  
1563/1563 _____ 142s 91ms/step - d_loss: 1.3587 -  
g_loss: 0.7992  
Epoch 40/50  
1563/1563 _____ 142s 91ms/step - d_loss: 1.3531 -  
g_loss: 0.8000  
Epoch 41/50  
1563/1563 _____ 0s 90ms/step - d_loss: 1.3535 - g_loss:  
0.8073
```

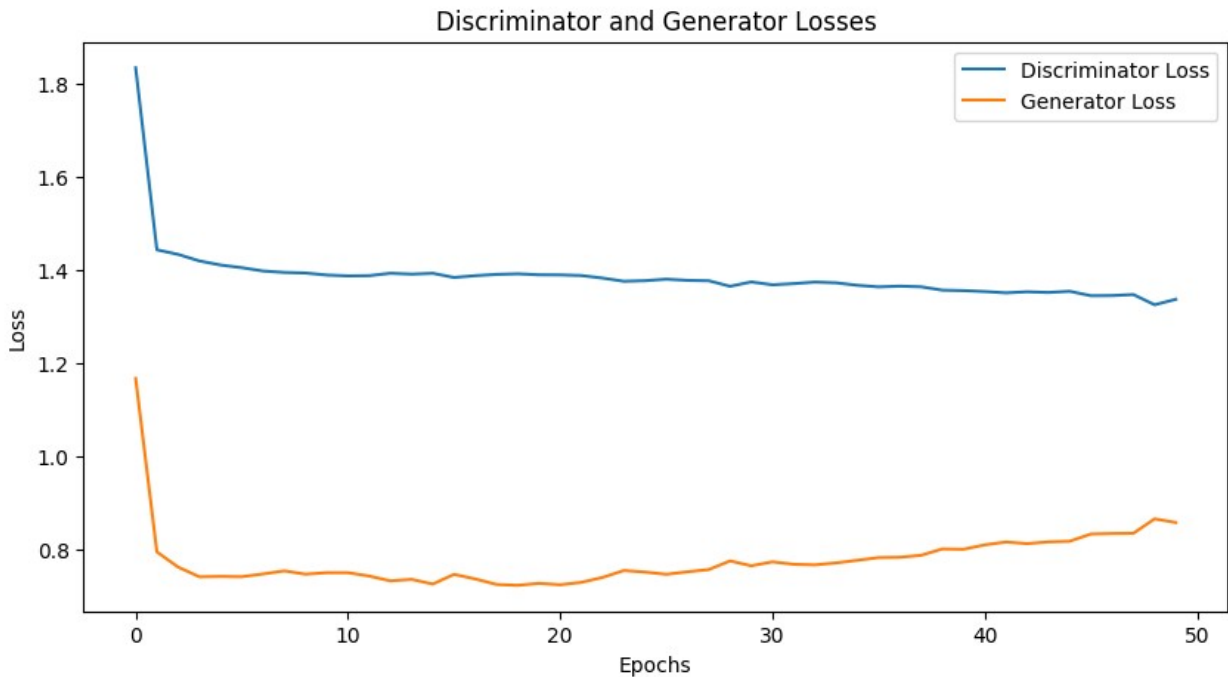


```

1563/1563 _____ 143s 91ms/step - d_loss: 1.3535 -
g_loss: 0.8073
Epoch 42/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.3478 -
g_loss: 0.8172
Epoch 43/50
1563/1563 _____ 142s 91ms/step - d_loss: 1.3559 -
g_loss: 0.8068
Epoch 44/50
1563/1563 _____ 141s 90ms/step - d_loss: 1.3532 -
g_loss: 0.8144
Epoch 45/50

```

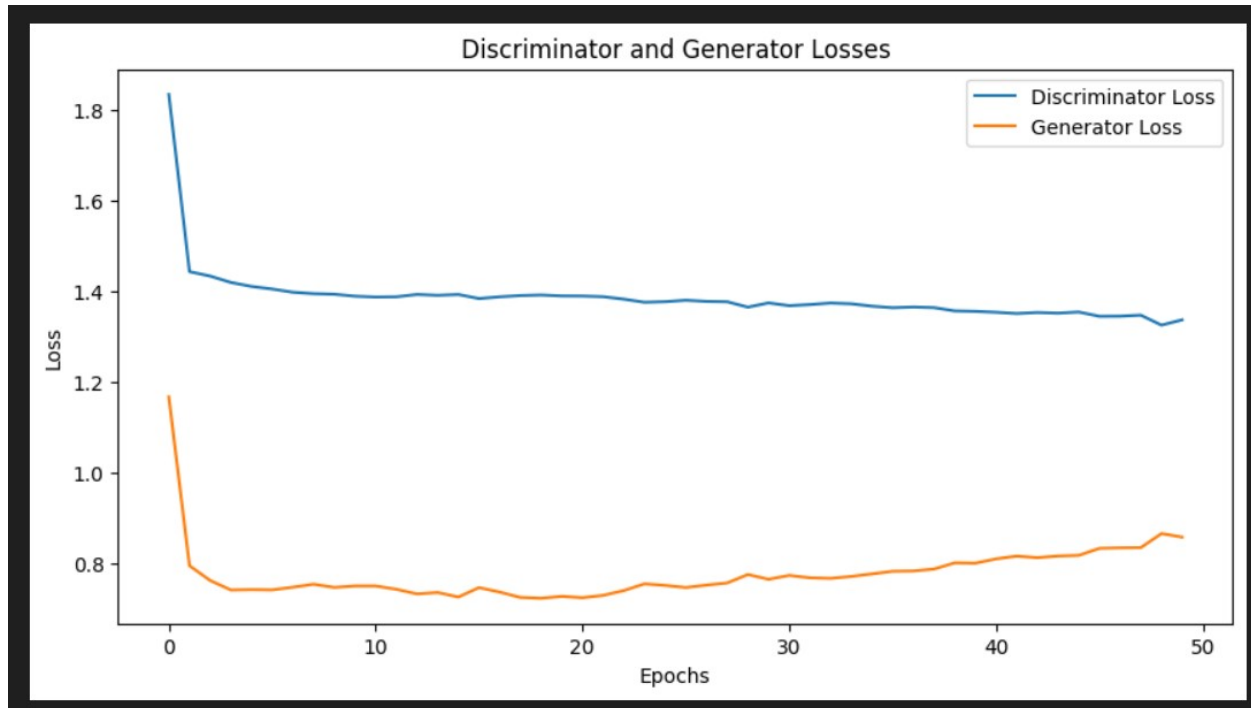
```
1563/1563 _____ 141s 90ms/step - d_loss: 1.3540 -  
g_loss: 0.8220  
Epoch 46/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3406 -  
g_loss: 0.8322  
Epoch 47/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3431 -  
g_loss: 0.8338  
Epoch 48/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3480 -  
g_loss: 0.8351  
Epoch 49/50  
1563/1563 _____ 141s 91ms/step - d_loss: 1.3276 -  
g_loss: 0.8588  
Epoch 50/50  
1563/1563 _____ 141s 90ms/step - d_loss: 1.3334 -  
g_loss: 0.8640
```



```
minimum value of d_loss = 1.325143814086914 for epoch 48  
minimum value of g_loss = 0.7227808833122253 for epoch 18  
minimum value of total = 2.113315999507904 for epoch 20
```

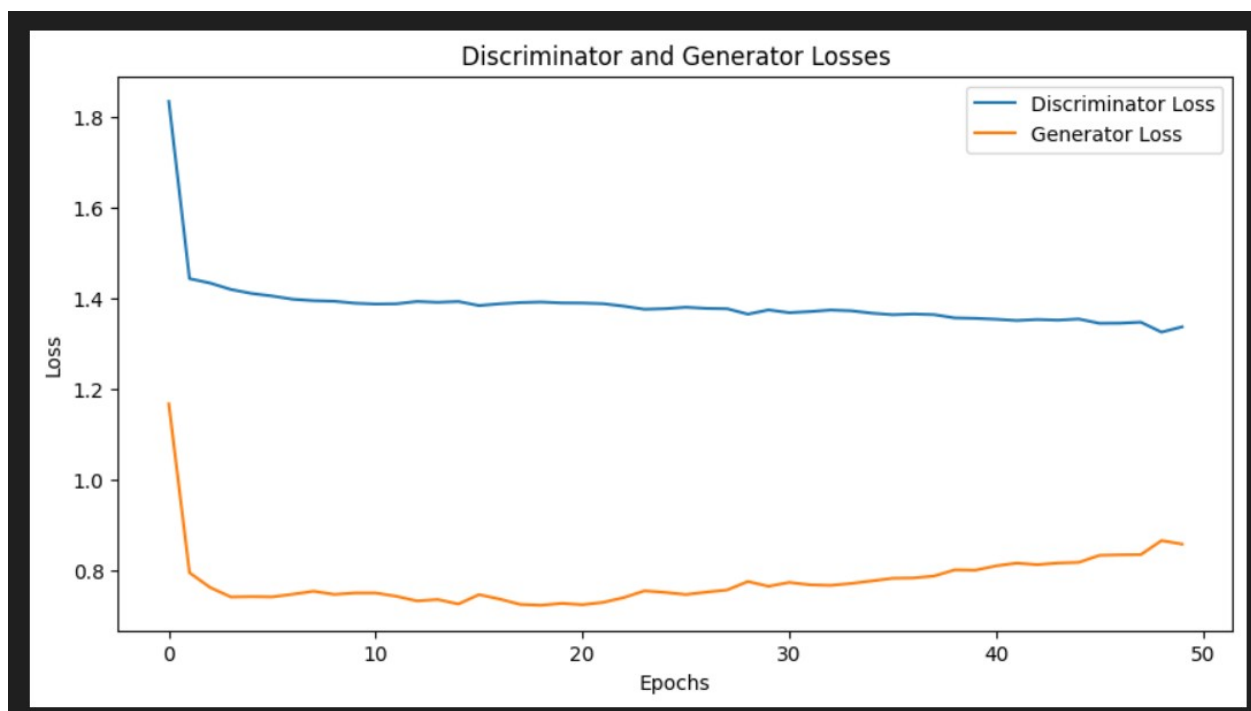
```
<keras.src.callbacks.history.History at 0x7ac3e0ebdbf0>
```

First model graph and error



minimum value of $d_loss = 1.099036693572998$ for epoch 49
minimum value of $g_loss = 0.7358095645904541$ for epoch 14
minimum value of total = 2.130660891532898 for epoch 17

Second model graph and error



minimum value of d_loss = 1.325143814086914 for epoch 48
minimum value of g_loss = 0.7227808833122253 for epoch 18
minimum value of total = 2.113315999507904 for epoch 20

Generate New Human Faces

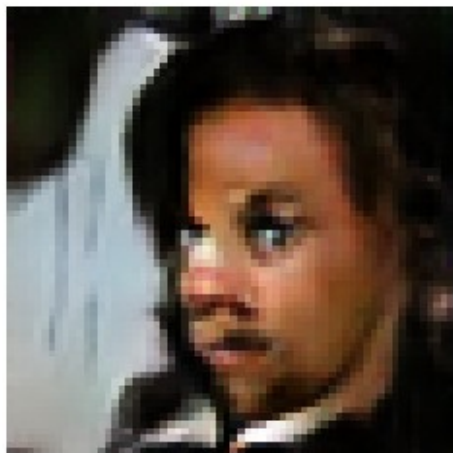
First model image

```
noise = tf.random.normal([1, 200])  
fig = plt.figure(figsize=(3, 3))  
g_img = dcgan.generator(noise)  
g_img = (g_img * 127.5) + 127.5  
g_img.numpy()  
img = array_to_img(g_img[0])  
plt.imshow(img)  
plt.axis('off')  
plt.show()
```



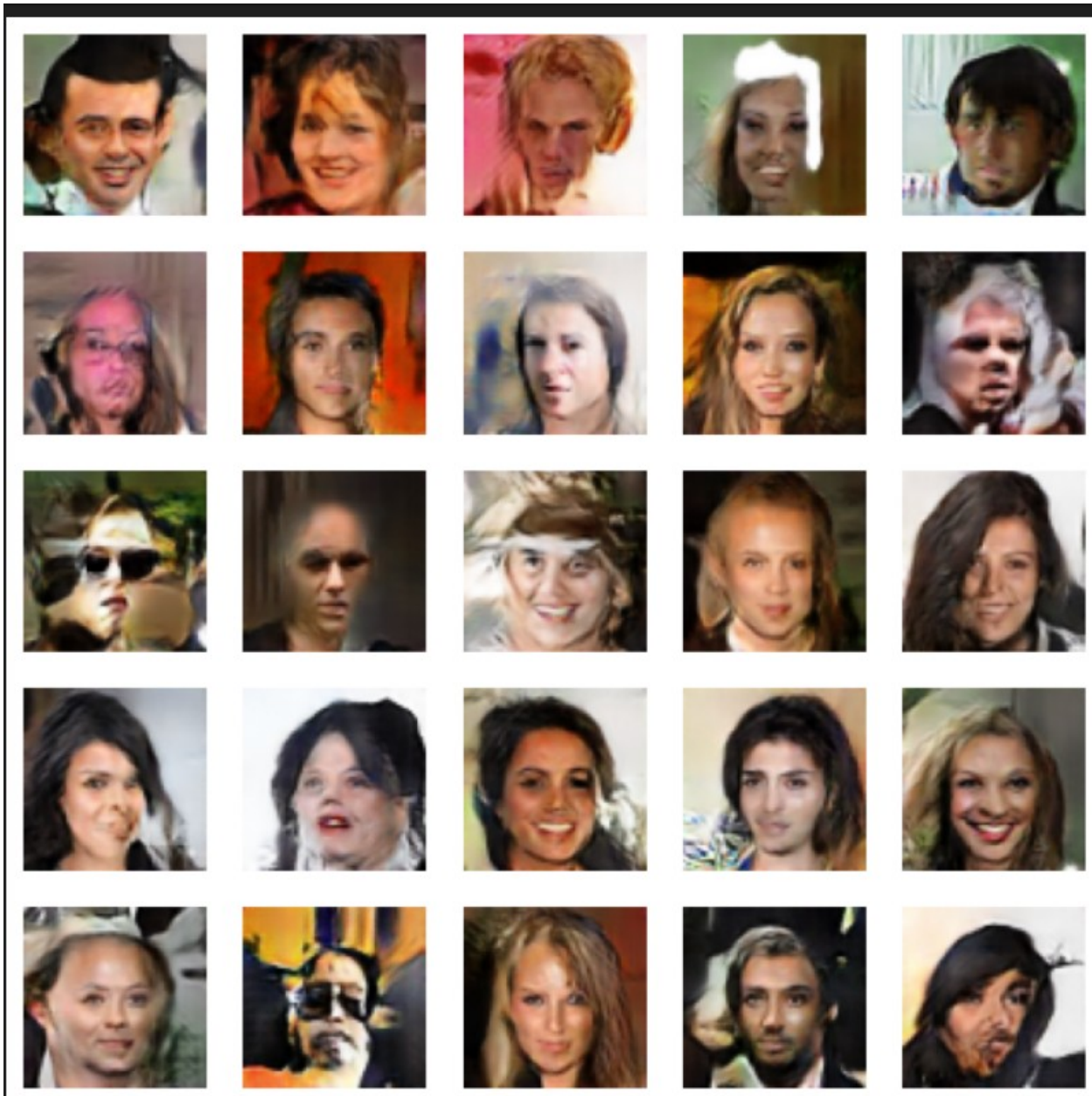
Second model image

```
noise = tf.random.normal([1, 200])  
fig = plt.figure(figsize=(3, 3))  
g_img = dcgan2.generator(noise)  
g_img = (g_img * 127.5) + 127.5  
g_img.numpy()  
img = array_to_img(g_img[0])  
plt.imshow(img)  
plt.axis('off')  
plt.show()
```

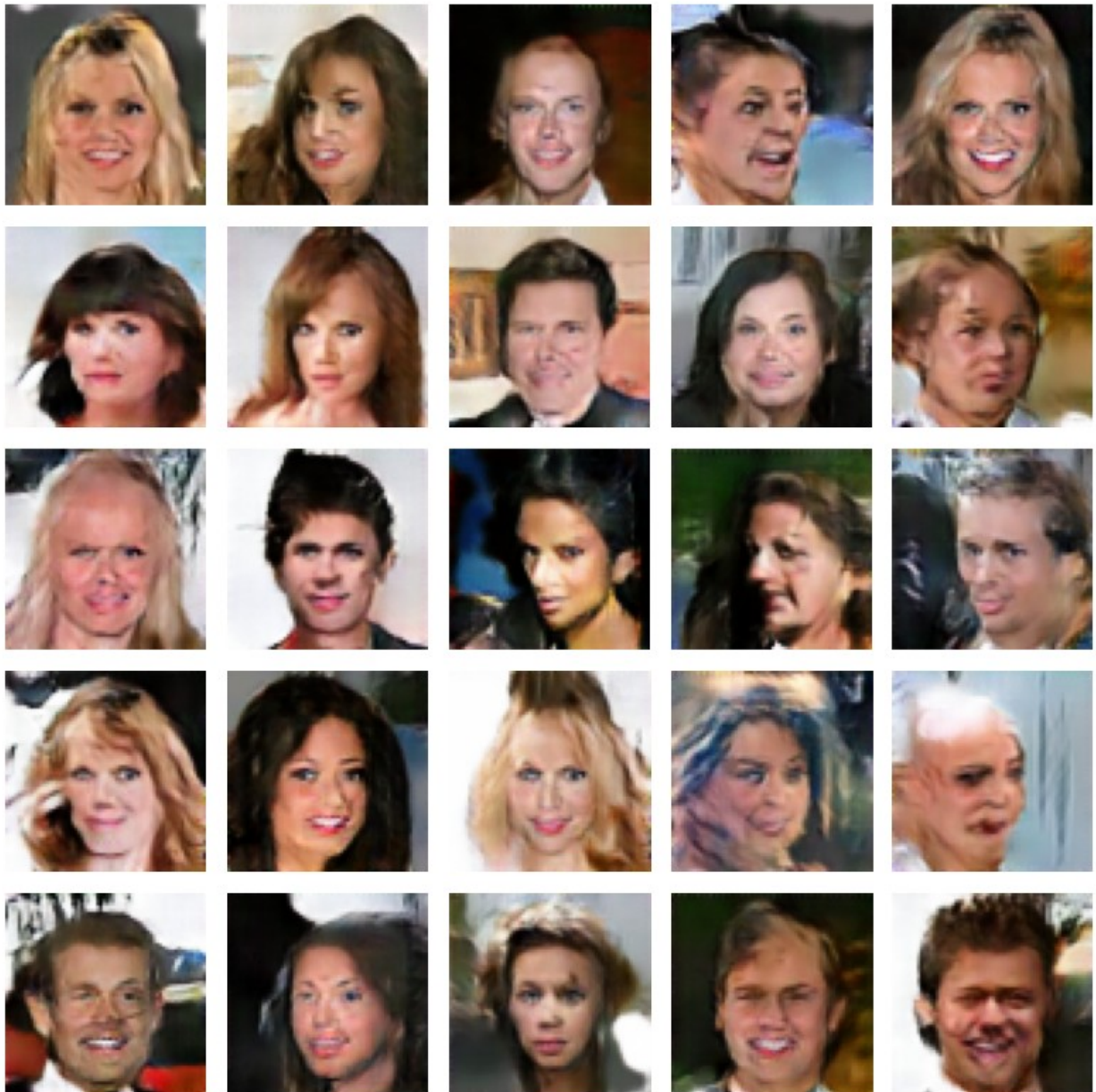



After manually generating outputs by loading the .h5 file into the model, the results were promising and aligned well with our expectations.

First model images



Second model images



The second model's images show slight improvement over the first, as they exhibit less blurriness. Perhaps after 100 or 200 epochs, both models will significantly enhance their image quality.

tilt faces are good in second model

Comment

Despite my efforts, I was unable to reduce the error rate by 5%. However, I did manage to improve it by around 1-2%. Additionally, the image quality appears to have noticeably enhanced. Due to time constraints, I limited training to 50 epochs, as this notebook takes approximately 4 hours to train on a Kaggle GPU.