GAN Project with Keras and MNIST Dataset

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Project Overview

I built a Generative Adversarial Network (GAN) on the MNIST dataset (handwritten digits).

Environment Setup

My machine lacked CUDA support, but I found an alternative: OpenVINO — an open-source toolkit optimized for Intel processors. I installed it through my Conda environment.

Installed libraries:

- TensorFlow
- TensorFlow-CPU
- Matplotlib
- TensorFlow-Datasets
- Ipywidgets

Importing Modules

```
import tensorflow as tf

import matplotlib.pyplot as plt

import numpy as np

from tensorflow import keras

from tensorflow.keras import layers
```

```
from tensorflow import keras
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Sequential
```

Data Preparation

Load the Dataset

I prepared the training images by splitting the dataset into:

```
(mnist_train_images,_), (mnist_test_images,_) = keras.datasets.mnist.load_data()
```

Checked the data using matplotlib to ensure images loaded correctly.

Reshaping the Data

Reshaped to (60000, 28, 28) and converted to 32-bit floats:

```
mnist_train_images =  mnist_train_images.reshape(mnist_train_images.shape[0], 28, 28,
1).astype('float32')
```

Normalization

Pixel values (0 to 255) scaled to [-1, 1]:

```
mnist_train_images= (mnist_train_images - 127.5) / 127.5
```

This makes training faster and more stable.

Shuffling and Batching

- **BUFFER_SIZE = 60,000:** Ensures full dataset shuffling to prevent mode collapse.
- **BATCH_SIZE = 256:** Balanced between memory efficiency and training stability.

Converted to a TensorFlow dataset:

```
train_dataset =
tf.data.Dataset.from_tensor_slices(mnist_train_images).shuffle(BUFFER_SIZE).batch(BATC
H_SIZE)
```

Latent Dimensions and Weight Initialization

- **LATENT_DIM = 100:** Ensures the generator learns rich variations while maintaining stability.
- **Weight Initialization:** I used:

```
WEIGHT_UNIT= keras.initializers.RandomNormal(mean=0.01, stddev=0.02)
```

This shifts the mean slightly, giving the generator a head start to produce non-zero outputs.

Building the Generator

I used the DCGAN approach with 12 layers:

1. **Dense Layer:** Projects latent_dim into (7x7x256), no bias (BatchNorm handles it).
2. **Reshape Layer:** Converts to 3D tensor.

3. **3 Conv2DTranspose Layers:** Upscales feature maps.
4. **3 BatchNormalization Layers:** Normalizes activations.
5. **3 LeakyReLU Layers:** Avoids dead neurons with a slope of 0.2.
6. **Output Layer:** Conv2DTranspose with tanh activation.

Layer flow:

- **Input:** Takes random noise. Output: 1D vector (12544 neurons).
- **Reshape:** Converts 1D vector to (7, 7, 256).
- **Upsampling Block:** Output (7, 7, 128).
- **Second Upsampling Block:** Output (14, 14, 128).
- **Final Upsampling Block:** Output (28, 28, 1) grayscale MNIST digit

```
def build_generator():
  model = keras.Sequential([
    layers.Dense(7*7*256, use_bias=False, input_shape=(LATENT_DIM,)),
    layers.BatchNormalization(), # normalize the activation of the previous layer
    layers.LeakyReLU(),

    layers.Reshape((7, 7, 256)),

    layers.Conv2DTranspose(128, (5, 5), strides=(1, 1), padding='same',
use_bias=False),
    layers.BatchNormalization(),
    layers.LeakyReLU(0.2),

    layers.Conv2DTranspose(128, (5, 5), strides=(2, 2), padding='same',
use_bias=False),
    layers.BatchNormalization(),
    layers.LeakyReLU(0.2),

    layers.Conv2DTranspose(1, (5, 5), strides=(2, 2), padding='same', use_bias=False,
activation='tanh')
  ])
  return model
```

Building the Discriminator

The discriminator acts as a binary classifier that classifies input as real (1) or fake (0):

1. **Conv2D Layer:** Downsamples (28x28) to (14x14). Output: (14, 14, 64).
2. **LeakyReLU:** Prevents dead neurons.
3. **Dropout Layer:** Drops 30% of neurons to prevent overfitting.

4. **Second Conv2D Layer:** Learns higher-level features. Output: (7, 7, 128).
5. **Flatten Layer:** Flattens output to 1D vector (6272).
6. **Output Layer:** Dense with a single neuron — outputs probability.

```
def build_discriminator():

  model = keras.Sequential([

      # First COnv2d layer: Detect low level features in the images (edges, textures,
...)

      layers.Conv2D(64, (5,5), strides=(2,2), padding='same', input_shape=[28,28,1]),



      # LeakyRelu activation function to avoid dead neurons and allow negative
gradients

      layers.LeakyReLU(0.2),

      # dropout to prevent overfitting and improve generalization

      layers.Dropout(0.3),



      # First COnv2d layer: learn more complex feature from the images

      layers.Conv2D(128, (5,5), strides=(2,2), padding='same'),

      layers.LeakyReLU(0.2),

      layers.Dropout(0.3),



      # Flatten the 2D feature maps into a 1D vector for the Dense layer

      layers.Flatten(),



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



  ])
```

```
  return model
```

Loss Functions

Used **Binary Cross-Entropy Loss**:

```
cross_entropy = keras.losses.BinaryCrossentropy()
```

real_loss = tf.keras.losses.binary_crossentropy(tf.ones_like(real_output), real_output)
fake_loss = tf.keras.losses.binary_crossentropy(tf.zeros_like(fake_output), fake_output)
total_loss = real_loss + fake_loss

```
def discriminator_loss(real_output, fake_output):
    real_loss = cross_entropy(tf.ones_like(real_output), real_output)
    fake_loss = cross_entropy(tf.zeros_like(fake_output), fake_output)
    total_loss = real_loss + fake_loss

    return total_loss
```

Optimizers

I used two separate Adam optimizers:

generator_optimizer = tf.keras.optimizers.Adam(1e-4, beta_1=0.5)
discriminator_optimizer = tf.keras.optimizers.Adam(1e-4, beta_1=0.5)

```
generator_optimizer = keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.5)
discriminator_optimizer = keras.optimizers.Adam(learning_rate=0.0002, beta_1=0.05)
```

The lowered momentum helps stabilize training.

Custom Training Loop

I built a custom loop to track progress and handle both networks:

- **compile():** Stores optimizers and losses.
- **train_step():** Handles generator/discriminator updates with gradients.

```
# Building our sub ckass model

class GAN(keras.Model):

  def __init__(self, generator, discriminator):

    # initilize the GAN model  with the generator and discriminator

    super(GAN, self).__init__()

    self.generator = generator #set genrator model

    self.discriminator = discriminator # set discriminator moel




  def compile(self, g_optimizer, d_optimizer, g_loss, d_loss):

    super(GAN, self).compile()

    self.g_optimizer = g_optimizer # set the generator optimizer

    self.d_optimizer = d_optimizer # set the discriminator optimizer

    self.g_loss = g_loss # set the generator loss

    self.d_loss = d_loss # set the discriminator loss




  def train_step(self, real_images):

    # Training logic

    batch_size = tf.shape(real_images)[0]


    # Train discriminator

    noise = tf.random.normal([batch_size, LATENT_DIM])
```

```
    with tf.GradientTape() as d_tape:
        generated_images = self.generator(noise)
        real_output = self.discriminator(real_images)
        fake_output = self.discriminator(generated_images)
        d_loss = self.d_loss(real_output, fake_output)

    # Cimputing the gradients for the discriminator based in its loss
    d_gradients = d_tape.gradient(d_loss, self.discriminator.trainable_variables)
    self.d_optimizer.apply_gradients(zip(d_gradients,
self.discriminator.trainable_variables))


    # Train generator
    noise = tf.random.normal([batch_size, LATENT_DIM])
    with tf.GradientTape() as g_tape:
        generated_images = self.generator(noise)
        fake_output = self.discriminator(generated_images)
        g_loss = self.g_loss(fake_output)

    g_gradients = g_tape.gradient(g_loss, self.generator.trainable_variables)
    self.g_optimizer.apply_gradients(zip(g_gradients,
self.generator.trainable_variables))


    return {"d_loss": d_loss, "g_loss": g_loss}
```

Callback for Image Generation

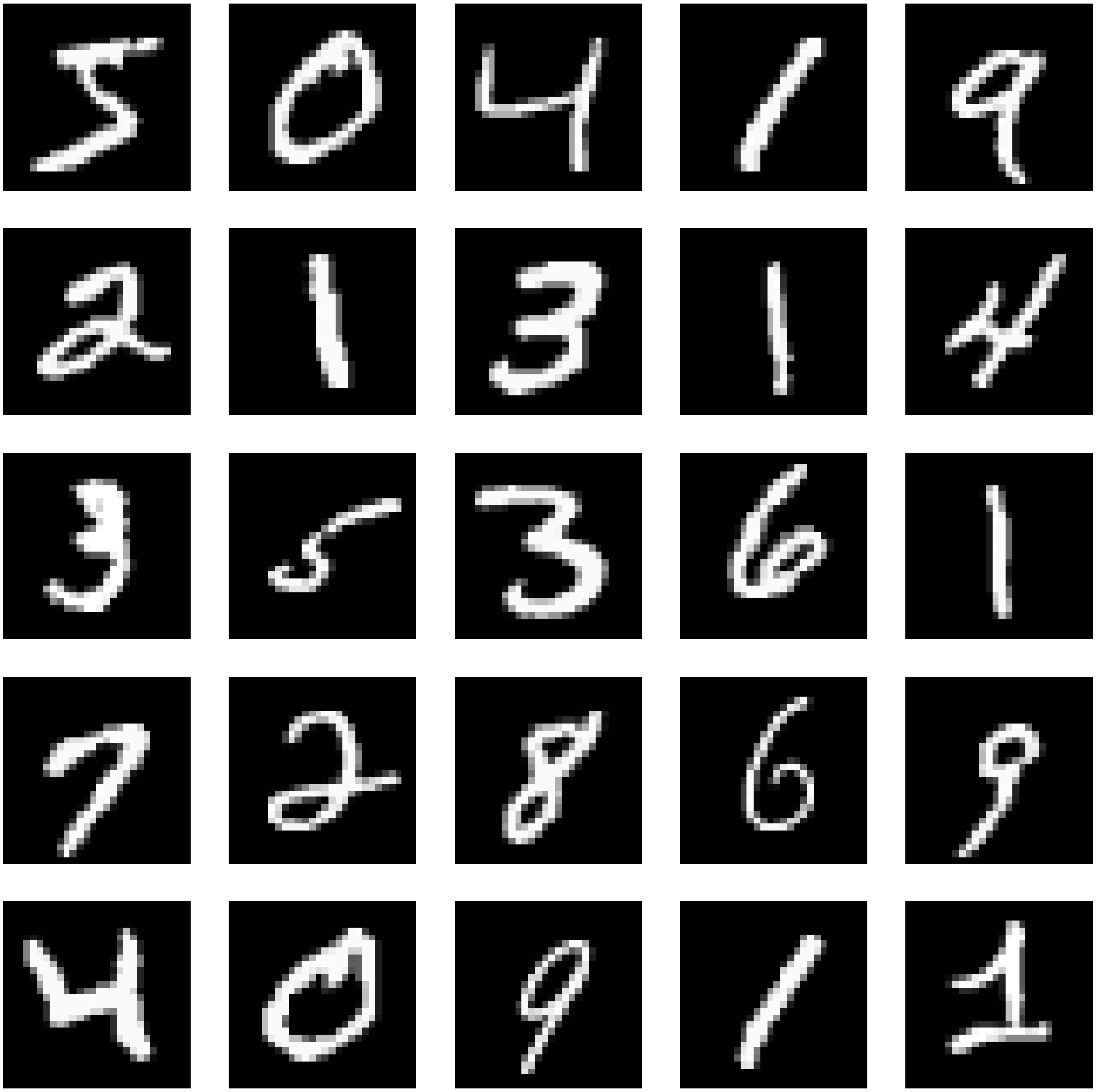
Generated images displayed every 5 epochs:

```
class ImageCallback(keras.callbacks.Callback):
    def __init__(self, num_images=16, latent_dim=100):
        self.num_images = num_images
        self.latent_dim = latent_dim
        self.seed = tf.random.normal([num_images, latent_dim])

    def on_epoch_end(self, epoch, logs=None):
        if epoch % 5 == 0:
            generated_images = self.model.generator(self.seed)
            generated_images = (generated_images * 127.5) + 127.5

            plt.figure(figsize=(10,10))
            for i in range(self.num_images):
                plt.subplot(4, 4, i+1)
                plt.imshow(generated_images[i].numpy().astype("uint8"), cmap="gray")
                plt.axis("off")
            plt.show()
```

```
class ImageCallback(keras.callbacks.Callback):

  def __init__(self, num_images=16, latent_dim=100):

    self.num_images = num_images

    self.latent_dim = latent_dim

    self.seed = tf.random.normal([num_images, latent_dim])



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

    if epoch % 5 == 0:

      generated_images = self.model.generator(self.seed)

      generated_images = (generated_images * 127.5) + 127.5 #rescaleto range [0, 233]



      plt.figure(figsize=(10,10))

      for i in range(self.num_images):
```

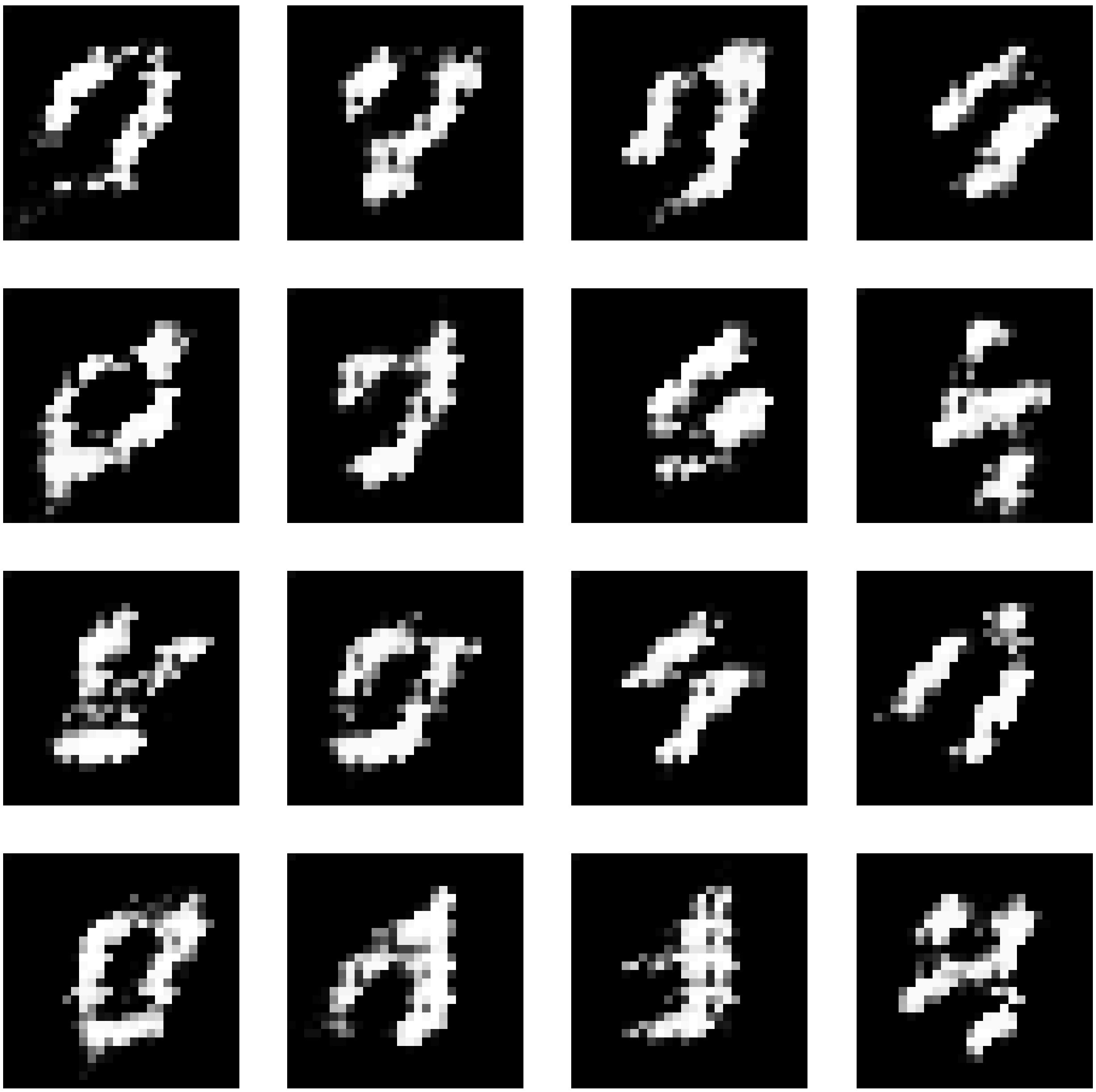
```
    plt.subplot(4, 4, i+1)

    plt.imshow(generated_images[i].numpy().astype("uint8"), cmap="gray")

    plt.axis("off")

  plt.show()
```

Initial dataset:



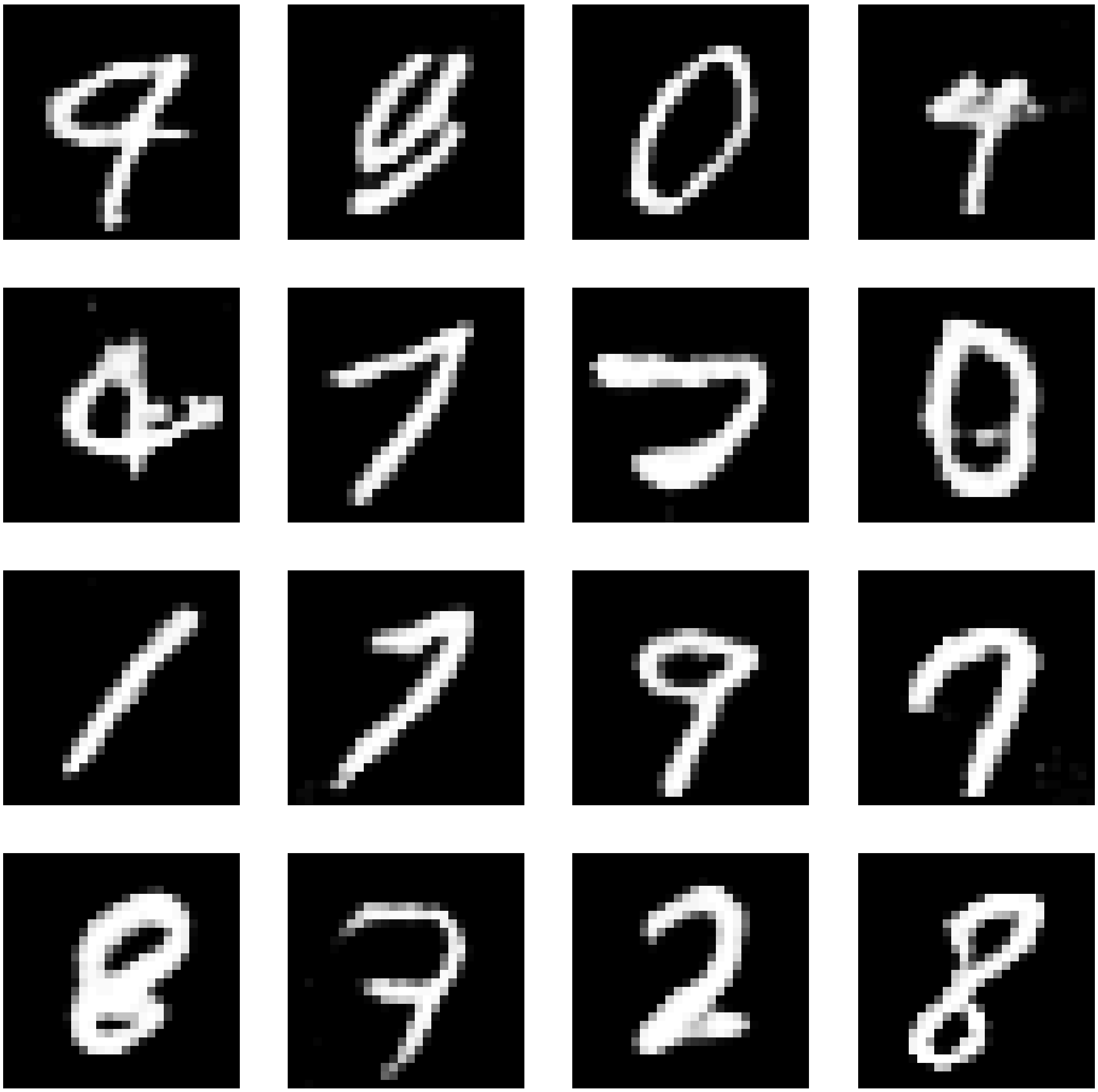
Epoch 1/100

[1m235/235[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2s/step - d_loss: 1.1056 - g_loss: 0.9011

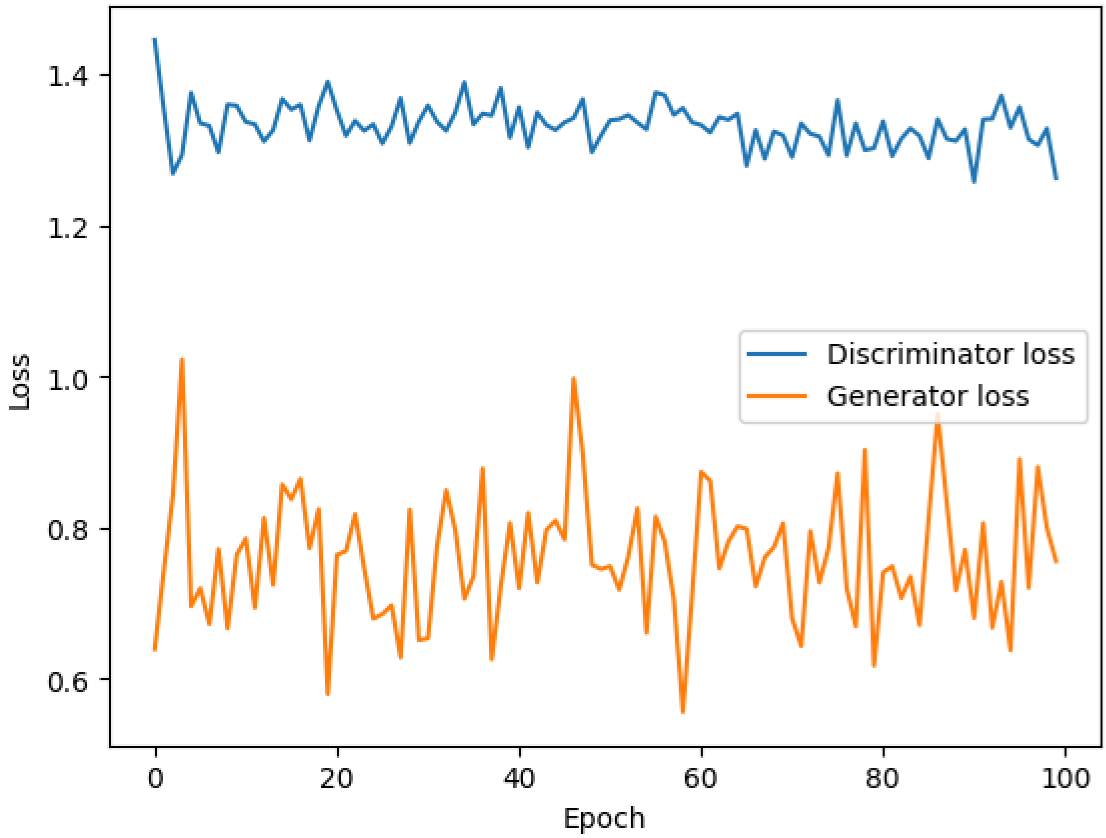


51st Epoch

Epoch 51/100
[1m235/235[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 2s/step - d_loss: 1.3191 - g_loss: 0.7876



The model took around 16hours to train
Averagely an epoch took 400s



Final Thoughts

This project taught me the importance of balancing generator-discriminator power and how hyperparameters like batch size, latent dim, and weight initialization affect performance.