GALGOTIAS UNIVERSITY

NAAC GRADE A+ Accredited University

Plot No. 2, Sector 17-A, Yamuna Expressway, Greater Noida, Gautam Buddh Nagar, U.P., India

STTP PROJECT REPORT

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

Domain:- Machine Learning, Deep Learning, Generative AI (GANs).

Project Title:- ImageGAN

SUBMITTED BY:

Vayu Nandan Tripathi - 24SCSE1180366

Ratan Shah - 24SCSE1180293

SEM : 3rd (2024-2028)

INDEX

Sr.no	Table of Contents	Page No
1.	Project Domain	1
2.	Project Title	1
3.	Abstract	2
4.	Introduction	3
5.	Literature Survey	4
6.	Problem Statement	5
7.	Objectives	5
8.	Scope of the Project	6
9.	Expected Outcomes	6
10.	Methodology	7
	a. Data Collection	7
	b. Data Preprocessing	7
	c. ML/DL Model Architecture	8
	d. Model Training & Optimization	9
	e. Model Evaluation	10
11.	Results & Discussion	11
	a. Experimental Analysis	11
	b. Graphical representation / Visualization	12
12.	Conclusion	13
13.	References	14

3. Project Domain

Machine Learning, Deep Learning, Generative AI (GANs).

4. Project Title

Synthetic Fashion Image Generation using Generative Adversarial Networks (GANs)

5. Abstract

This project explores **Generative Adversarial Networks (GANs)** for synthetic image generation using the **Fashion MNIST** dataset. A GAN consists of two competing neural networks—a generator and a discriminator—that learn through adversarial training. The project involves setting up the environment, visualizing data, building generator and discriminator models, creating a custom GAN training loop, and evaluating the quality of generated fashion images. The results demonstrate the capability of GANs to learn underlying patterns of real images and produce realistic synthetic outputs.

6. Introduction / Background

Generative modeling has become a crucial technique in modern AI, enabling machines to create new data similar to existing samples. Among these models, **Generative Adversarial Networks (GANs)** are especially powerful for producing synthetic images. This project is based on a demonstration where a GAN is used to build a synthetic fashion line by generating clothing images from random noise. The Fashion MNIST dataset provides grayscale images of clothing items, making it a suitable training ground for understanding adversarial learning. The project aims to replicate, understand, and document the complete GAN workflow from data visualization to model evaluation.

7. Literature Survey

1} Ian Goodfellow et al. (2014) introduced GANs, establishing a min-max game between generator and discriminator networks.

2}**Radford et al. (2015)** proposed DCGANs, demonstrating stable GAN training using convolutional layers.

3}**Fashion MNIST (Xiao et al., 2017)** became a standard benchmark dataset for lightweight deep learning experiments.

4}Prior works show GANs successfully generating images of faces, clothing, artwork, and other structured visual data.

This project follows standard practices derived from GAN literature, including upsampling in the generator, convolutional downsampling in the discriminator, and training stabilization techniques.

8. Problem Statement

To design and train a Generative Adversarial Network capable of generating realistic synthetic images of fashion items using the Fashion MNIST dataset.

9. Objectives

- To understand the fundamental working mechanism of GANs.
- To build generator and discriminator models using deep learning.
- To train GANs using a custom training loop for stable learning.
- To generate and visualize synthetic fashion images.
- To evaluate the quality and progression of generated samples across epochs.

10. Scope of the Project

- Implementation limited to **Fashion MNIST (28×28 grayscale images)**.
- Focus on **basic GAN architecture**, not advanced variants.
- Potential extensions include Conditional GANs, StyleGAN, or training on high-resolution datasets.

11. Expected Outcomes

- A trained GAN model that generates new clothing images resembling Fashion MNIST samples.
- Visual understanding of adversarial learning progression.
- Improved knowledge of model architecture design, loss functions, and training stability techniques.

12. Methodology

a. Data Collection-

- Dataset used: **Fashion MNIST**
- Contains 60,000 training and 10,000 test images of apparel items (shoes, shirts, bags, etc.).
- Loaded directly from TensorFlow/Keras libraries.

b. Data Preprocessing-

- Images normalized to range **[0, 1]**.
- Reshaped to **(28, 28, 1)** for convolutional layers.
- Batched and shuffled for training stability.

c. ML/DL Model Architecture

1. Generator Model-

- Input: Random noise vector (latent dimension).
- Dense layer reshaping to 7×7×128.
- Upsampling layers (Conv2DTranspose) to 14×14 and then 28×28.
- Activation functions: ReLU for hidden layers, Sigmoid for output.
- Output: Synthetic 28×28 grayscale image.

2. Discriminator Model-

- Input: Real or generated image.
- Convolutional layers for downsampling.
- Dropout layers to reduce overfitting.
- Flatten + Dense output (sigmoid) for binary classification.
- Output: Real (1) or Fake (0).

d. Model Training & Optimization

- Loss Functions:
- Generator loss = ability to fool discriminator.
- Discriminator loss = ability to classify real vs fake images.
- Optimizers: Adam with standard GAN parameters.
- Training Loop Steps:

1. Generate noise → produce fake images.
2. Train discriminator on real and fake samples.
3. Train generator through combined model.
4. Introduce **label noise** for stabilizing discriminator learning.
5. Save generated samples per epoch for visualization.

e. Model Evaluation

- Evaluation is qualitative, based on visual inspection of generated images across epochs.
- Improvement measured by:
- Clarity
- Shape accuracy
- Reduction in noise
- Resemblance to real Fashion MNIST samples

13. Results & Discussion

a. Experimental Analysis-

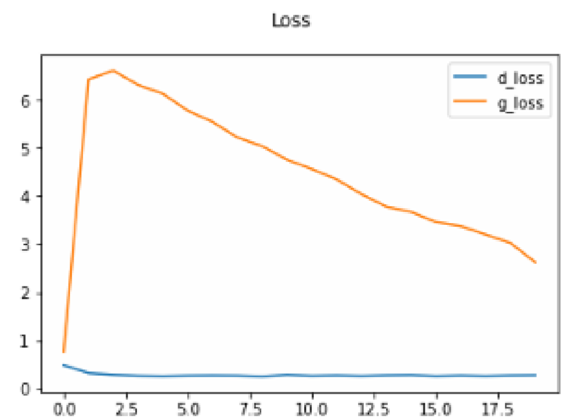
- Initial epochs produce noisy, unclear images.
- Middle epochs begin showing shape outlines (shirts, shoes, trousers).
- Later epochs produce identifiable fashion items.
- Generator gradually learns fashion structure, while discriminator enhances its classification ability.

Training challenges included:-

- Balancing generator-discriminator learning speeds.
- Avoiding mode collapse.
- Maintaining training stability through label smoothing.

b. Graphical Representation / Visualization

12/9/25, 3:02 PM ImageGAN-Project.ipynb - Colab



14. Conclusion

This project successfully demonstrates the implementation of a Generative Adversarial Network for fashion image generation. By training the generator and discriminator together in an adversarial framework, the model learns to produce visually meaningful synthetic clothing images. The experiment validates the effectiveness of GANs and provides foundational understanding for future work in advanced generative modeling, including Conditional GANs, StyleGANs, and domain-specific generation tasks.

1. Import Dependencies and Data

```
!pip install tensorflow tensorflow-gpu matplotlib tensorflow-datasets ipywidgets
```

```
!pip list
```

```
# Bringing in tensorflow
import tensorflow as tf
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
```

```
# Brining in tensorflow datasets for fashion mnist
import tensorflow_datasets as tfds
# Bringing in matplotlib for viz stuff
from matplotlib import pyplot as plt
```

```
# Use the tensorflow datasets api to bring in the data source
ds = tfds.load('fashion_mnist', split='train')
```

```
ds.as_numpy_iterator().next()['label']
```

```
2
```

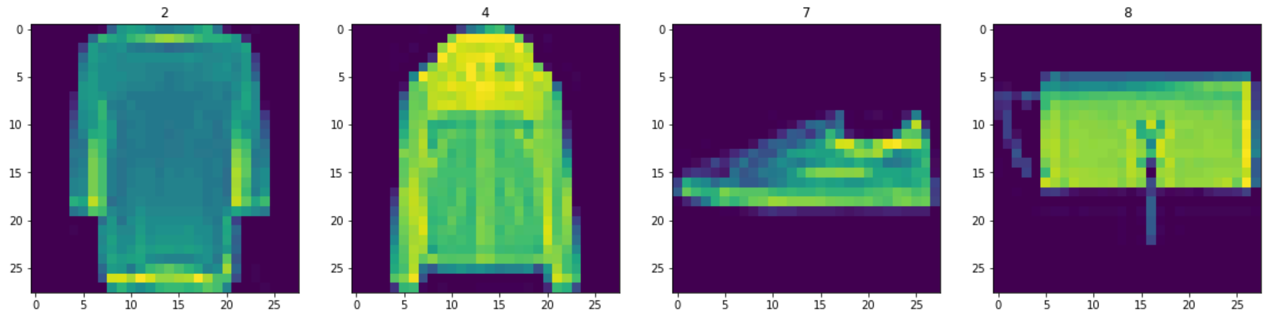
2. Viz Data and Build Dataset

```
# Do some data transformation
import numpy as np
```

```
# Setup connection aka iterator
dataiterator = ds.as_numpy_iterator()
```

```
# Getting data out of the pipeline
dataiterator.next()['image']
```

```
# Setup the subplot formatting
fig, ax = plt.subplots(ncols=4, figsize=(20,20))
# Loop four times and get images
for idx in range(4):
    # Grab an image and label
    sample = dataiterator.next()
    # Plot the image using a specific subplot
    ax[idx].imshow(np.squeeze(sample['image']))
    # Appending the image label as the plot title
    ax[idx].title.set_text(sample['label'])
```




```
# Scale and return images only
def scale_images(data):
    image = data['image']
    return image / 255
```

```
# Reload the dataset
ds = tfds.load('fashion_mnist', split='train')
# Running the dataset through the scale_images preprocessing step
ds = ds.map(scale_images)
# Cache the dataset for that batch
ds = ds.cache()
# Shuffle it up
ds = ds.shuffle(60000)
# Batch into 128 images per sample
ds = ds.batch(128)
# Reduces the likelihood of bottlenecking
ds = ds.prefetch(64)
```

```
ds.as_numpy_iterator().next().shape
```

```
(128, 28, 28, 1)
```

3. Build Neural Network

3.1 Import Modelling Components

```
# Bring in the sequential api for the generator and discriminator
from tensorflow.keras.models import Sequential
# Bring in the layers for the neural network
from tensorflow.keras.layers import Conv2D, Dense, Flatten, Reshape, LeakyReLU, Dropout, UpSampling2D
```

3.2 Build Generator

```
def build_generator():
    model = Sequential()

    # Takes in random values and reshapes it to 7x7x128
    # Beginnings of a generated image
    model.add(Dense(7*7*128, input_dim=128))
    model.add(LeakyReLU(0.2))
    model.add(Reshape((7,7,128)))

    # Upsampling block 1
    model.add(UpSampling2D())
    model.add(Conv2D(128, 5, padding='same'))
    model.add(LeakyReLU(0.2))

    # Upsampling block 2
    model.add(UpSampling2D())
    model.add(Conv2D(128, 5, padding='same'))
    model.add(LeakyReLU(0.2))

    # Convolutional block 1
    model.add(Conv2D(128, 4, padding='same'))
    model.add(LeakyReLU(0.2))

    # Convolutional block 2
    model.add(Conv2D(128, 4, padding='same'))
    model.add(LeakyReLU(0.2))

    # Conv layer to get to one channel
    model.add(Conv2D(1, 4, padding='same', activation='sigmoid'))

    return model
```

```
generator = build_generator()
```

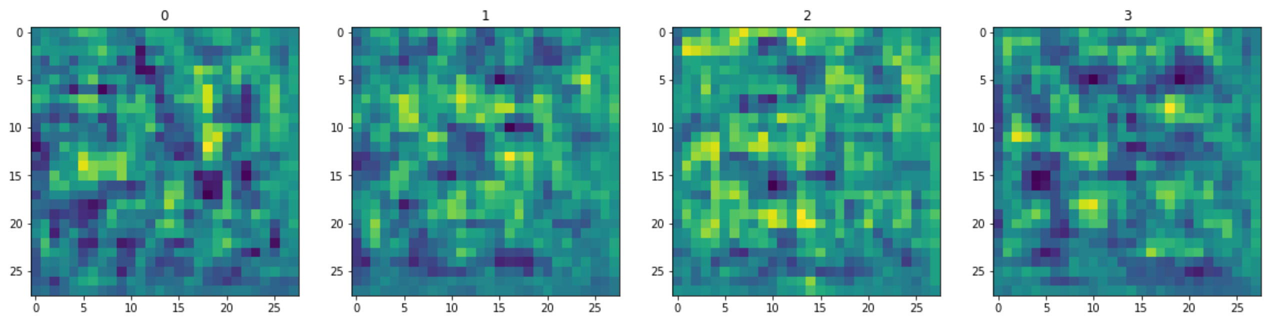
```
generator.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_10 (Dense)            (None, 6272)              809088

 leaky_re_lu_26 (LeakyReLU)  (None, 6272)              0

 reshape_9 (Reshape)         (None, 7, 7, 128)         0

 up_sampling2d_12 (UpSamplin  (None, 14, 14, 128)      0
```

```
 g2D)

 conv2d_19 (Conv2D)          (None, 14, 14, 128)       409728

 leaky_re_lu_27 (LeakyReLU)  (None, 14, 14, 128)       0

 up_sampling2d_13 (UpSamplin  (None, 28, 28, 128)      0
 g2D)

 conv2d_20 (Conv2D)          (None, 28, 28, 128)       409728

 leaky_re_lu_28 (LeakyReLU)  (None, 28, 28, 128)       0

 conv2d_21 (Conv2D)          (None, 28, 28, 128)       262272

 leaky_re_lu_29 (LeakyReLU)  (None, 28, 28, 128)       0

 conv2d_22 (Conv2D)          (None, 28, 28, 128)       262272

 leaky_re_lu_30 (LeakyReLU)  (None, 28, 28, 128)       0

 conv2d_23 (Conv2D)          (None, 28, 28, 1)         2049

=================================================================
Total params: 2,155,137
Trainable params: 2,155,137
Non-trainable params: 0
_________________________________________________________________
```

```
img = generator.predict(np.random.randn(4,128,1))
```

```
# Generate new fashion
img = generator.predict(np.random.randn(4,128,1))
# Setup the subplot formatting
fig, ax = plt.subplots(ncols=4, figsize=(20,20))
# Loop four times and get images
for idx, img in enumerate(img):
    # Plot the image using a specific subplot
    ax[idx].imshow(np.squeeze(img))
    # Appending the image label as the plot title
    ax[idx].title.set_text(idx)
```



3.3 Build Discriminator

```
def build_discriminator():
    model = Sequential()

    # First Conv Block
    model.add(Conv2D(32, 5, input_shape = (28,28,1)))
    model.add(LeakyReLU(0.2))
    model.add(Dropout(0.4))

    # Second Conv Block
    model.add(Conv2D(64, 5))
    model.add(LeakyReLU(0.2))
    model.add(Dropout(0.4))

    # Third Conv Block
    model.add(Conv2D(128, 5))
    model.add(LeakyReLU(0.2))
    model.add(Dropout(0.4))

    # Fourth Conv Block
    model.add(Conv2D(256, 5))
    model.add(LeakyReLU(0.2))
```

```
    model.add(Dropout(0.4))

    # Flatten then pass to dense layer
    model.add(Flatten())
    model.add(Dropout(0.4))
    model.add(Dense(1, activation='sigmoid'))

    return model
```

```
discriminator = build_discriminator()
```

```
discriminator.summary()
```

```
Model: "sequential_15"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_32 (Conv2D)          (None, 24, 24, 32)        832

 leaky_re_lu_39 (LeakyReLU)  (None, 24, 24, 32)        0

 dropout_8 (Dropout)         (None, 24, 24, 32)        0

 conv2d_33 (Conv2D)          (None, 20, 20, 64)        51264

 leaky_re_lu_40 (LeakyReLU)  (None, 20, 20, 64)        0

 dropout_9 (Dropout)         (None, 20, 20, 64)        0

 conv2d_34 (Conv2D)          (None, 16, 16, 128)       204928

 leaky_re_lu_41 (LeakyReLU)  (None, 16, 16, 128)       0

 dropout_10 (Dropout)        (None, 16, 16, 128)       0

 conv2d_35 (Conv2D)          (None, 12, 12, 256)       819456

 leaky_re_lu_42 (LeakyReLU)  (None, 12, 12, 256)       0

 dropout_11 (Dropout)        (None, 12, 12, 256)       0

 flatten (Flatten)           (None, 36864)             0

 dropout_12 (Dropout)        (None, 36864)             0

 dense_11 (Dense)            (None, 1)                 36865

=================================================================
Total params: 1,113,345
Trainable params: 1,113,345
Non-trainable params: 0
_________________________________________________________________
```

```
img = img[0]
```

```
img.shape
```

```
(28, 28, 1)
```

```
discriminator.predict(img)
```

```
array([[0.50057805],
       [0.5006448 ],
       [0.50065   ],
       [0.5005127 ]], dtype=float32)
```

4. Construct Training Loop

4.1 Setup Losses and Optimizers

```
# Adam is going to be the optimizer for both
from tensorflow.keras.optimizers import Adam
# Binary cross entropy is going to be the loss for both
from tensorflow.keras.losses import BinaryCrossentropy
```

```
g_opt = Adam(learning_rate=0.0001)
d_opt = Adam(learning_rate=0.00001)
```

```
g_loss = BinaryCrossentropy()
d_loss = BinaryCrossentropy()
```

4.2 Build Subclassed Model

```
# Importing the base model class to subclass our training step
from tensorflow.keras.models import Model
```

```
class FashionGAN(Model):
    def __init__(self, generator, discriminator, *args, **kwargs):
        # Pass through args and kwargs to base class
        super().__init__(*args, **kwargs)

        # Create attributes for gen and disc
        self.generator = generator
        self.discriminator = discriminator

    def compile(self, g_opt, d_opt, g_loss, d_loss, *args, **kwargs):
        # Compile with base class
        super().compile(*args, **kwargs)

        # Create attributes for losses and optimizers
        self.g_opt = g_opt
        self.d_opt = d_opt
        self.g_loss = g_loss
        self.d_loss = d_loss

    def train_step(self, batch):
        # Get the data
        real_images = batch
        fake_images = self.generator(tf.random.normal((128, 128, 1)), training=False)

        # Train the discriminator
        with tf.GradientTape() as d_tape:
            # Pass the real and fake images to the discriminator model
            yhat_real = self.discriminator(real_images, training=True)
            yhat_fake = self.discriminator(fake_images, training=True)
            yhat_realfake = tf.concat([yhat_real, yhat_fake], axis=0)

            # Create labels for real and fakes images
            y_realfake = tf.concat([tf.zeros_like(yhat_real), tf.ones_like(yhat_fake)], axis=0)

            # Add some noise to the TRUE outputs
            noise_real = 0.15*tf.random.uniform(tf.shape(yhat_real))
            noise_fake = -0.15*tf.random.uniform(tf.shape(yhat_fake))
            y_realfake += tf.concat([noise_real, noise_fake], axis=0)

            # Calculate loss - BINARYCROSS
            total_d_loss = self.d_loss(y_realfake, yhat_realfake)

        # Apply backpropagation - nn learn
        dgrad = d_tape.gradient(total_d_loss, self.discriminator.trainable_variables)
        self.d_opt.apply_gradients(zip(dgrad, self.discriminator.trainable_variables))

        # Train the generator
        with tf.GradientTape() as g_tape:
            # Generate some new images
            gen_images = self.generator(tf.random.normal((128,128,1)), training=True)

            # Create the predicted labels
            predicted_labels = self.discriminator(gen_images, training=False)

            # Calculate loss - trick to training to fake out the discriminator
            total_g_loss = self.g_loss(tf.zeros_like(predicted_labels), predicted_labels)

        # Apply backprop
        ggrad = g_tape.gradient(total_g_loss, self.generator.trainable_variables)
        self.g_opt.apply_gradients(zip(ggrad, self.generator.trainable_variables))

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

```
# Create instance of subclassed model
fashgan = FashionGAN(generator, discriminator)
```

```
# Compile the model
fashgan.compile(g_opt, d_opt, g_loss, d_loss)
```

4.3 Build Callback

```
import os
from tensorflow.keras.preprocessing.image import array_to_img
from tensorflow.keras.callbacks import Callback
```

```
class ModelMonitor(Callback):
    def __init__(self, num_img=3, latent_dim=128):
        self.num_img = num_img
        self.latent_dim = latent_dim

    def on_epoch_end(self, epoch, logs=None):
        random_latent_vectors = tf.random.uniform((self.num_img, self.latent_dim,1))
        generated_images = self.model.generator(random_latent_vectors)
        generated_images *= 255
        generated_images.numpy()
        for i in range(self.num_img):
            img = array_to_img(generated_images[i])
            img.save(os.path.join('images', f'generated_img_{epoch}_{i}.png'))
```

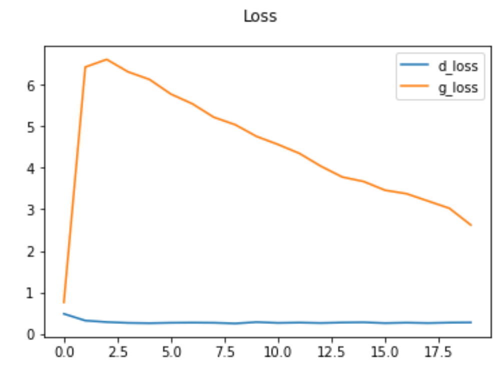
4.3 Train

```
# Recommend 2000 epochs
hist = fashgan.fit(ds, epochs=20, callbacks=[ModelMonitor()])
```

```
Epoch 1/20
469/469 [==============================] - 43s 88ms/step - d_loss: 0.5911 - g_loss: 0.6832
Epoch 2/20
469/469 [==============================] - 41s 88ms/step - d_loss: 0.4158 - g_loss: 3.2742
Epoch 3/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2878 - g_loss: 6.5225
Epoch 4/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2780 - g_loss: 6.5009
Epoch 5/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2755 - g_loss: 6.2294
Epoch 6/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2732 - g_loss: 5.9429
Epoch 7/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2728 - g_loss: 5.6715
Epoch 8/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2708 - g_loss: 5.4097
Epoch 9/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2704 - g_loss: 5.1352
Epoch 10/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2701 - g_loss: 4.8858
Epoch 11/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2694 - g_loss: 4.6344
Epoch 12/20
469/469 [==============================] - 40s 85ms/step - d_loss: 0.2691 - g_loss: 4.3753
Epoch 13/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2694 - g_loss: 4.1332
Epoch 14/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2687 - g_loss: 3.9182
Epoch 15/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2679 - g_loss: 3.7484
Epoch 16/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2681 - g_loss: 3.5493
Epoch 17/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2683 - g_loss: 3.3835
Epoch 18/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2675 - g_loss: 3.2472
Epoch 19/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.2679 - g_loss: 3.1084
Epoch 20/20
469/469 [==============================] - 40s 86ms/step - d_loss: 0.3128 - g_loss: 2.6171
```

4.4 Review Performance

```
plt.suptitle('Loss')
plt.plot(hist.history['d_loss'], label='d_loss')
plt.plot(hist.history['g_loss'], label='g_loss')
plt.legend()
plt.show()
```



5. Test Out the Generator

5.1 Generate Images

↳ 3 cells hidden

5.2 Save the Model

```
generator.save('generator.h5')
discriminator.save('discriminator.h5')
```

```
Start coding or generate with AI.
```

15. References-

- **Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., & Bengio, Y. (2014).** *Generative Adversarial Nets.* Advances in Neural Information Processing Systems (NeurIPS). Available at: https://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf
- **TensorFlow Documentation – Generative Adversarial Networks (GANs).** TensorFlow Official Guide. Available at: https://www.tensorflow.org/tutorials/generative
- **Fashion-MNIST Dataset – Xiao, Liang, and Zhang (2017).** *Fashion-MNIST: A Novel Image Dataset for Benchmarking Machine Learning Algorithms.* Official GitHub Repository: https://github.com/zalandoresearch/fashion-mnist
- **TensorFlow Datasets Documentation – Fashion MNIST.** Available at:

https://www.tensorflow.org/datasets/catalog/fashion_mnist

- **TensorFlow API Reference – tf.keras.datasets.mnist / fashion_mnist.** Available at: https://www.tensorflow.org/api_docs/python/tf/keras/datasets
- **Nicholas Renotte – YouTube Channel.** Creator of machine learning, deep learning, and GAN tutorials. Available at: https://www.youtube.com/c/NicholasRenotte
- **Matplotlib Documentation.** Used for visualization of dataset and generated images. Available at: https://matplotlib.org/stable/contents.html