Ex No: 9 **BUILD GENERATIVE ADVERSARIAL NEURAL NETWORK**

AIM:

To build a generative adversarial neural network using Keras/TensorFlow.

PROCEDURE:

1. Download and load the dataset.
2. Perform analysis and preprocessing of the dataset.
3. Build a simple neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

PROGRAM:

```
!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']

# Do some data transformation
import numpy as np
# Setup connection aka iterator
dataiterator = ds.as_numpy_iterator()
# Getting data out of the pipeline
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```
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

# 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

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()

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)

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()

img = img[0]
img.shape

discriminator.predict(img)

# 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()

# 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)

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'))

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

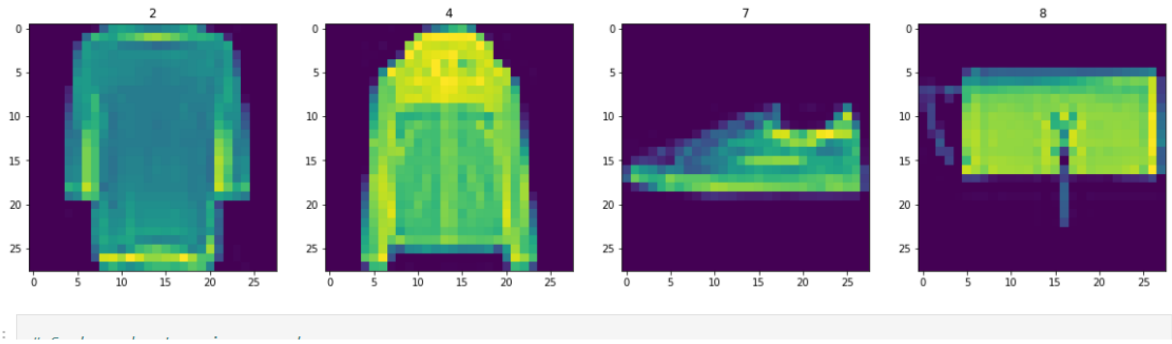
plt.suptitle('Loss')
plt.plot(hist.history['d_loss'], label='d_loss')
plt.plot(hist.history['g_loss'], label='g_loss')
plt.legend()
plt.show()

generator.load_weights(os.path.join('archive', 'generatormodel.h5'))
imgs = generator.predict(tf.random.normal((16, 128, 1)))
```

```
fig, ax = plt.subplots(ncols=4, nrows=4, figsize=(10,10))
for r in range(4):
    for c in range(4):
        ax[r][c].imshow(imgs[(r+1)*(c+1)-1])


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

OUTPUT:



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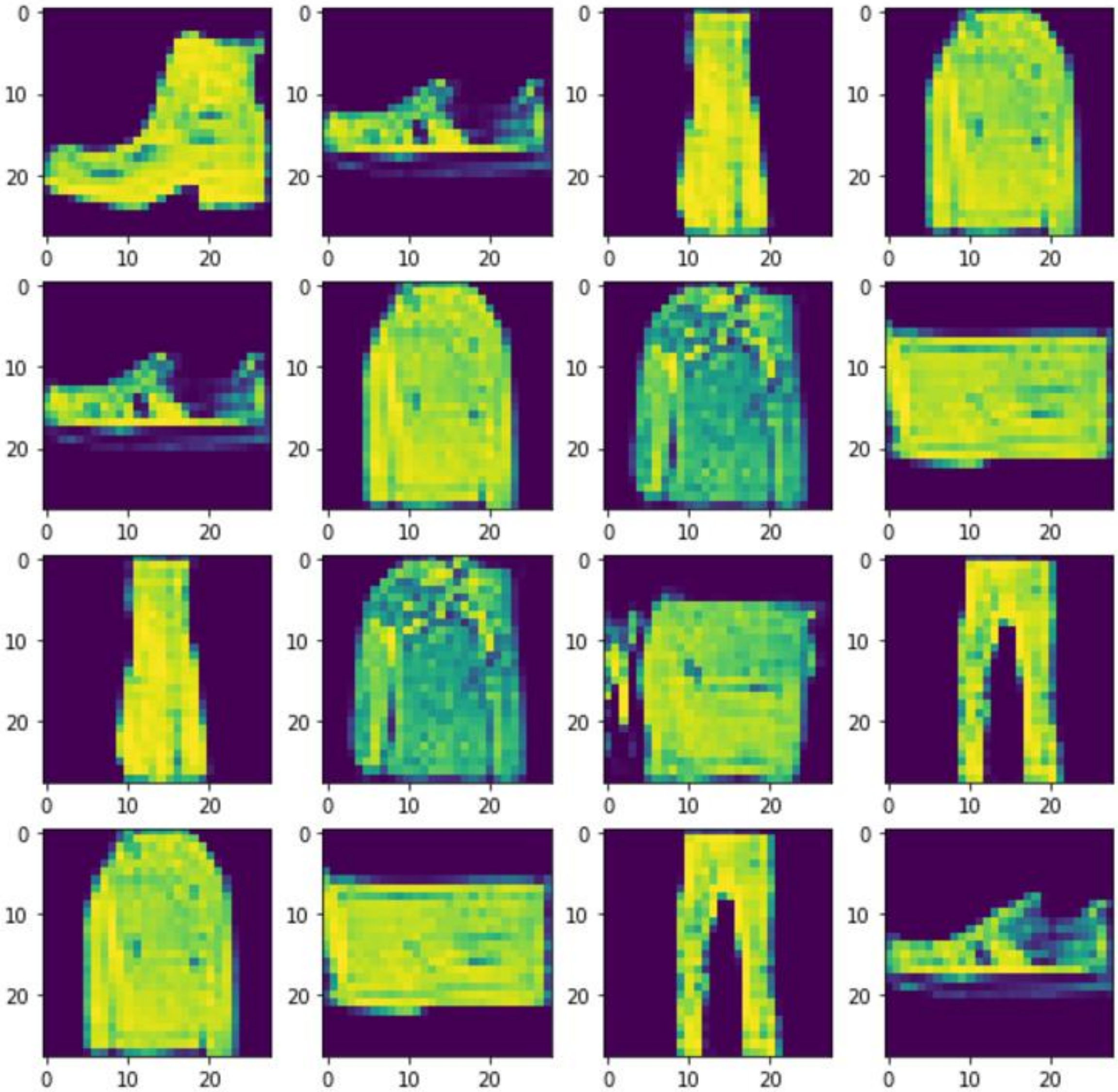

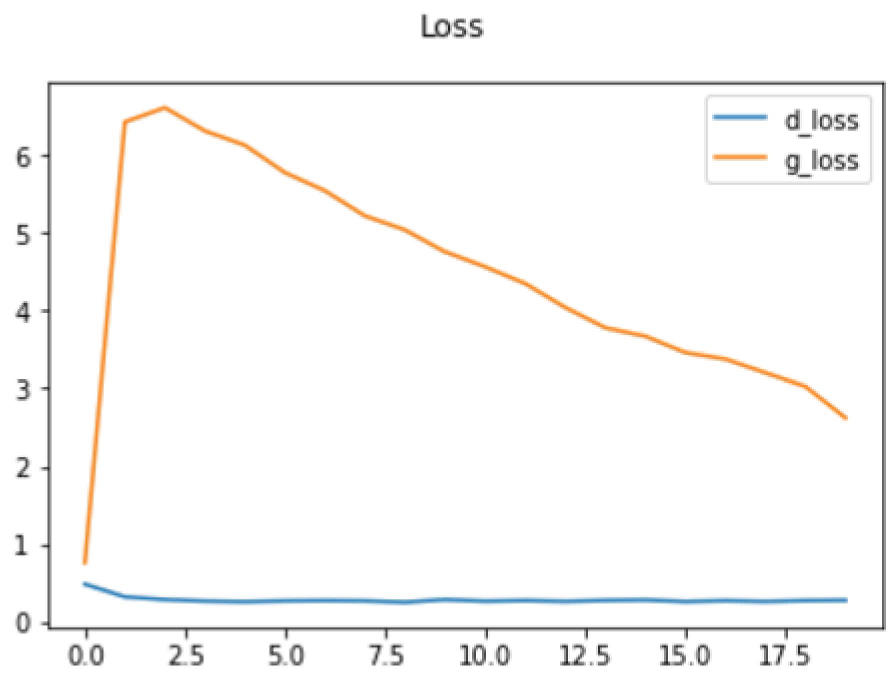

RESULT:

Thus a generative adversarial neural network using Keras/TensorFlow is built.