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 generative adversarial neural network model using Keras/TensorFlow.
4. Compile and fit the model.
5. Perform prediction with the test dataset.
6. Calculate performance metrics.

PROGRAM:

```
import numpy as np

import matplotlib.pyplot as plt

import keras

from keras.layers import Input, Dense, Reshape, Flatten, Dropout

from keras.layers import BatchNormalization, Activation, ZeroPadding2D

from tensorflow.keras.layers import LeakyReLU

from tensorflow.keras.layers import UpSampling2D, Conv2D

from keras.models import Sequential, Model

from keras.optimizers import Adam,SGD

#Loading the CIFAR10 data

(X, y), (_, _) = keras.datasets.cifar10.load_data()

#Selecting a single class images

#The number was randomly chosen and any number
```

```
#between 1 to 10 can be chosen
X = X[y.flatten() == 8]
#Defining the Input shape
image_shape = (32, 32, 3)
latent_dimensions = 100
def build_generator():
        model = Sequential()
        #Building the input layer
        model.add(Dense(128 * 8 * 8, activation="relu",
                        input_dim=latent_dimensions))
        model.add(Reshape((8, 8, 128)))
        model.add(UpSampling2D())
        model.add(Conv2D(128, kernel_size=3, padding="same"))
        model.add(BatchNormalization(momentum=0.78))
        model.add(Activation("relu"))
        model.add(UpSampling2D())
        model.add(Conv2D(64, kernel_size=3, padding="same"))
        model.add(BatchNormalization(momentum=0.78))
        model.add(Activation("relu"))
        model.add(Conv2D(3, kernel_size=3, padding="same"))
        model.add(Activation("tanh"))
        #Generating the output image
        noise = Input(shape=(latent_dimensions,))
        image = model(noise)
        return Model(noise, image)
```

```
def build_discriminator():
        #Building the convolutional layers
        #to classify whether an image is real or fake
        model = Sequential()
        model.add(Conv2D(32, kernel_size=3, strides=2,
                        input_shape=image_shape, padding="same"))
        model.add(LeakyReLU(alpha=0.2))
        model.add(Dropout(0.25))

        model.add(Conv2D(64, kernel_size=3, strides=2, padding="same"))
        model.add(ZeroPadding2D(padding=((0,1),(0,1))))
        model.add(BatchNormalization(momentum=0.82))
        model.add(LeakyReLU(alpha=0.25))
        model.add(Dropout(0.25))

        model.add(Conv2D(128, kernel_size=3, strides=2, padding="same"))
        model.add(BatchNormalization(momentum=0.82))
        model.add(LeakyReLU(alpha=0.2))
        model.add(Dropout(0.25))

        model.add(Conv2D(256, kernel_size=3, strides=1, padding="same"))
        model.add(BatchNormalization(momentum=0.8))
        model.add(LeakyReLU(alpha=0.25))
        model.add(Dropout(0.25))
```

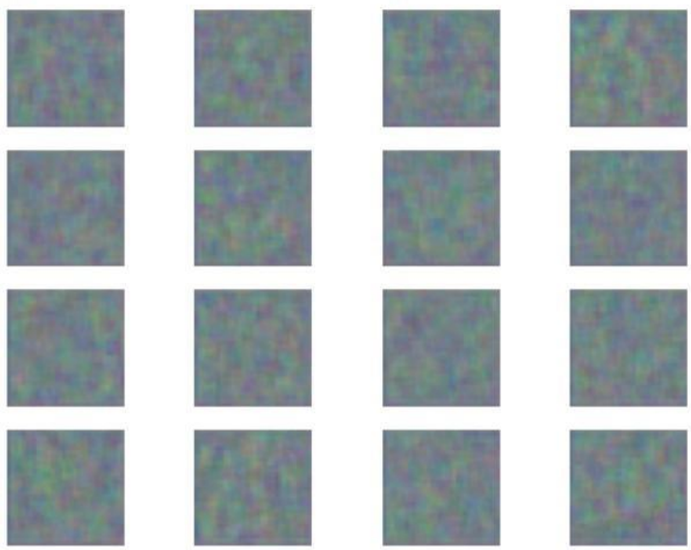
```
        #Building the output layer
        model.add(Flatten())
        model.add(Dense(1, activation='sigmoid'))
        image = Input(shape=image_shape)
        validity = model(image)
        return Model(image, validity)

def display_images():
        r, c = 4,4
        noise = np.random.normal(0, 1, (r * c,latent_dimensions))
        generated_images = generator.predict(noise)
        #Scaling the generated images
        generated_images = 0.5 * generated_images + 0.5
        fig, axs = plt.subplots(r, c)
        count = 0
        for i in range(r):
                for j in range(c):
                        axs[i,j].imshow(generated_images[count, :,:,])
                        axs[i,j].axis('off')
                        count += 1
        plt.show()
        plt.close()

# Building and compiling the discriminator
discriminator = build_discriminator()
```

```
discriminator.compile(loss='binary_crossentropy',
                      optimizer=Adam(0.0002,0.5),
                      metrics=['accuracy'])

#Making the Discriminator untrainable
#so that the generator can learn from fixed gradient
discriminator.trainable = False
# Building the generator
generator = build_generator()

#Defining the input for the generator
#and generating the images
z = Input(shape=(latent_dimensions,))
image = generator(z)
#Checking the validity of the generated image
valid = discriminator(image)

#Defining the combined model of the Generator and the Discriminator
combined_network = Model(z, valid)
combined_network.compile(loss='binary_crossentropy',
                         optimizer=Adam(0.0002,0.5))
num_epochs=10
batch_size=32
display_interval=5
losses=[]
```

```
#Normalizing the input
X = (X / 127.5) - 1.
#Defining the Adversarial ground truths
valid = np.ones((batch_size, 1))

#Adding some noise
valid += 0.05 * np.random.random(valid.shape)
fake = np.zeros((batch_size, 1))
fake += 0.05 * np.random.random(fake.shape)
for epoch in range(num_epochs):
            #Training the Discriminator , Sampling a random half of images
            index = np.random.randint(0, X.shape[0], batch_size)
            images = X[index]
            #Sampling noise and generating a batch of new images
            noise = np.random.normal(0, 1, (batch_size, latent_dimensions))
            generated_images = generator.predict(noise)
            #Training the discriminator to detect more accurately
            #whether a generated image is real or fake
            discm_loss_real = discriminator.train_on_batch(images, valid)
            discm_loss_fake = discriminator.train_on_batch(generated_images, fake)
            discm_loss = 0.5 * np.add(discm_loss_real, discm_loss_fake)
            genr_loss = combined_network.train_on_batch(noise, valid)
            #Tracking the progress
            if epoch % display_interval == 0:
                display_images()
```

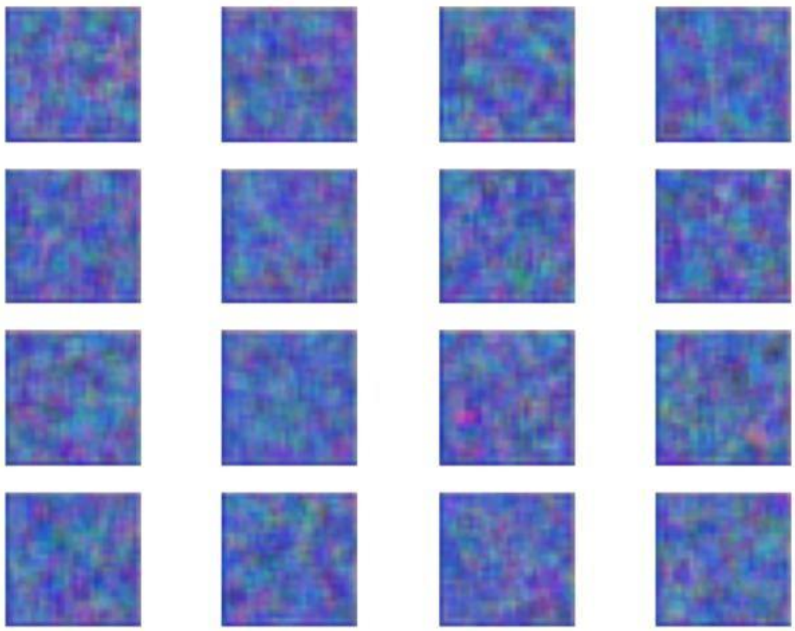
OUTPUT:

```
1/1 [==============================] - 1s 1s/step
WARNING:tensorflow:From C:\Users\Admin\AppData\Roaming\Python\Python311\site-packa
edTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue inst

WARNING:tensorflow:From C:\Users\Admin\AppData\Roaming\Python\Python311\site-packa
ecuting_eagerly_outside_functions is deprecated. Please use tf.compat.v1.executing

1/1 [==============================] - 0s 397ms/step
```



```
1/1 [==============================] - 0s 120ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 167ms/step
1/1 [==============================] - 0s 116ms/step
1/1 [==============================] - 0s 117ms/step
```

```
1/1 [==============================] - 0s 120ms/step
1/1 [==============================] - 0s 130ms/step
1/1 [==============================] - 0s 167ms/step
1/1 [==============================] - 0s 116ms/step
1/1 [==============================] - 0s 117ms/step
1/1 [==============================] - 0s 128ms/step
```



```
1/1 [==============================] - 0s 132ms/step
1/1 [==============================] - 0s 120ms/step
1/1 [==============================] - 0s 119ms/step
1/1 [==============================] - 0s 114ms/step
```

RESULT:

Thus, a generative adversarial neural network using Keras/TensorFlow was successfully implemented.