```
import tensorflow as tf
from tensorflow.keras import layers, models
import numpy as np
from sklearn.preprocessing import StandardScaler
import pandas as pd
data=pd.read_csv('/content/creditcard.csv')
print(data)
scaler=StandardScaler()
data_scaled=scaler.fit_transform(data.drop('Class',axis=1))
input dim=data scaled.shape[1]
input_layer=layers.Input(shape=(input_dim,))
encoded=layers.Dense(64,activation='relu')(input_layer)
encoded=layers.Dense(32,activation='relu')(encoded)
decoded=layers.Dense(64,activation='relu')(encoded)
decoded=layers.Dense(input_dim,activation='sigmoid')(decoded)
autocoder=models.Model(input_layer,decoded)
autocoder.compile(optimizer='adam',loss='mean_squared_error')
autocoder.fit(data_scaled,data_scaled,validation_split=0.2,epochs=50,batch_size=256)
reconstructed=autocoder.predict(data_scaled)
mse=np.mean(np.square(data_scaled - reconstructed),axis=1)
threshold=np.percentile(mse,95)
anamolies=mse > threshold
₹
                                                     V3
                 Time
                               V1
                                           V2
                                                                    V27
                                                                               V28 Amount Class
     a
                  0.0 \quad -1.359807 \quad -0.072781 \quad 2.536347 \quad \dots \quad 0.133558 \quad -0.021053 \quad 149.62
                                                                                                a
     1
                  0.0 1.191857
                                   0.266151 0.166480
                                                        ... -0.008983 0.014724
                                                                                      2.69
                                                                                                0
                  1.0 \quad \textbf{-1.358354} \quad \textbf{-1.340163} \quad 1.773209 \quad \dots \quad \textbf{-0.055353} \quad \textbf{-0.059752} \quad 378.66
     2
                                                                                                0
     3
                  1.0 \quad -0.966272 \quad -0.185226 \quad 1.792993 \quad \dots \quad 0.062723 \quad 0.061458 \quad 123.50
                                                                                                a
     4
                  2.0 -1.158233
                                    0.877737 1.548718
                                                              0.219422 0.215153
                                                                                    69.99
                                                                                                0
                                                         . . .
                                                         . . .
                                                         ... 0.943651 0.823731
     284802 172786.0 -11.881118 10.071785 -9.834783
                                                                                      0.77
                                                                                                a
     284803 172787.0
                       -0.732789
                                   -0.055080 2.035030
                                                         . . .
                                                               0.068472 -0.053527
                                                                                     24.79
                                                                                                0
     284804 172788.0 1.919565 -0.301254 -3.249640
                                                        ... 0.004455 -0.026561
                                                                                     67.88
                                                                                                0
                                                        ... 0.108821 0.104533
     284805 172788.0 -0.240440
                                   0.530483 0.702510
                                                                                                a
                                                                                    10.00
     284806 172792.0 -0.533413 -0.189733 0.703337
                                                         ... -0.002415 0.013649 217.00
                                                                                                0
     [284807 rows x 31 columns]
     Epoch 1/50
     891/891 -
                                  - 4s 3ms/step - loss: 0.8881 - val_loss: 0.6803
     Epoch 2/50
     891/891
                                  - 2s 3ms/step - loss: 0.7191 - val_loss: 0.6588
     Epoch 3/50
     891/891
                                  - 2s 2ms/step - loss: 0.7003 - val_loss: 0.6498
     Epoch 4/50
     891/891
                                  - 4s 4ms/step - loss: 0.6943 - val_loss: 0.6470
     Epoch 5/50
     891/891
                                  - 4s 3ms/step - loss: 0.6998 - val_loss: 0.6460
     Epoch 6/50
     891/891
                                  - 2s 3ms/step - loss: 0.6906 - val_loss: 0.6454
     Epoch 7/50
     891/891 -
                                  - 2s 3ms/step - loss: 0.7171 - val loss: 0.6453
     Epoch 8/50
     891/891
                                  - 2s 3ms/step - loss: 0.6868 - val_loss: 0.6451
     Epoch 9/50
                                  - 4s 4ms/step - loss: 0.6960 - val_loss: 0.6455
     891/891
     Epoch 10/50
     891/891
                                  - 3s 3ms/step - loss: 0.6932 - val_loss: 0.6450
     Epoch 11/50
     891/891
                                  - 2s 2ms/step - loss: 0.6870 - val_loss: 0.6450
     Epoch 12/50
     891/891
                                  - 2s 3ms/step - loss: 0.6922 - val_loss: 0.6453
     Epoch 13/50
     891/891
                                  - 2s 3ms/step - loss: 0.6898 - val_loss: 0.6450
     Epoch 14/50
     891/891
                                  - 4s 4ms/step - loss: 0.6984 - val loss: 0.6383
     Epoch 15/50
     891/891
                                 – 3s 3ms/step - loss: 0.7034 - val_loss: 0.6336
```

```
Epoch 16/50
     891/891
                                   - 2s 3ms/step - loss: 0.6892 - val_loss: 0.6327
     Epoch 17/50
     891/891
                                  - 2s 3ms/step - loss: 0.7013 - val_loss: 0.6324
     Epoch 18/50
     891/891 -
                                  - 2s 3ms/step - loss: 0.6673 - val_loss: 0.6326
     Epoch 19/50
                                  - 3s 3ms/step - loss: 0.6740 - val_loss: 0.6326
     891/891
     Epoch 20/50
     891/891
                                   - 4s 3ms/step - loss: 0.6950 - val_loss: 0.6325
     Fnoch 21/50
     891/891
                                  - 2s 3ms/step - loss: 0.6896 - val_loss: 0.6326
     Epoch 22/50
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import skipgrams
import numpy as np
from tensorflow.keras import layers
# a. Data preparation
text = "Your textual document here"
tokenizer = Tokenizer()
tokenizer.fit_on_texts([text])
word_index = tokenizer.word_index
sequences = tokenizer.texts_to_sequences([text])
# b. Generate training data (CBOW)
pairs, labels = skipgrams(sequences[0], vocabulary_size=len(word_index)+1, window_size=2)
# Convert pairs and labels to NumPy arrays
pairs = np.array(pairs)
labels = np.array(labels)
# c. Define the model
vocab_size = len(word_index) + 1 # Vocabulary size
embedding\_dim = 10
# The input is a word, so we use input_length=1
model = tf.keras.Sequential([
    layers.Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=1),
    layers.Flatten(), # Flatten the embedding output
    layers.Dense(10, activation='relu'),
    layers.Dense(vocab_size, activation='softmax')
1)
# Use sparse_categorical_crossentropy to allow integer labels
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy')
# Train the model
model.fit(pairs, labels, epochs=5)
# d. Output predictions
predictions = model.predict(pairs)
     Epoch 1/5
                              - 1s 1s/step - loss: 1.6121
     1/1
     Epoch 2/5
     1/1 -
                              - 0s 48ms/step - loss: 1.6076
     Epoch 3/5
                              - 0s 55ms/step - loss: 1.6031
     1/1 -
     Epoch 4/5
     1/1 -
                               - 0s 48ms/step - loss: 1.5985
     Epoch 5/5
     1/1 -
                              - 0s 42ms/step - loss: 1.5942
     1/1
                              - 0s 96ms/step
from inspect import FullArgSpec
import tensorflow as tf
from tensorflow.keras.applications import VGG16
from tensorflow.keras import layers, models
base_model=VGG16(weights='imagenet',include_top=False,input_shape=(224,224,3))
     Downloading data from <a href="https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16/weights-tf-dim-ordering-tf-kernels-notop.">https://storage.googleapis.com/tensorflow/keras-applications/vgg16/vgg16/weights-tf-dim-ordering-tf-kernels-notop.</a>
     58889256/58889256
                                               0s Ous/step
```

```
import tensorflow as tf
from tensorflow.keras.applications import VGG16
from tensorflow.keras import layers, models
from \ tensorflow. keras. preprocessing. image \ import \ Image Data Generator
# a. Load in a pre-trained CNN model
base_model = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))
# b. Freeze parameters (weights) in model's lower convolutional layers
base model.trainable = False
# c. Add custom classifier
model = models.Sequential([
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(1024, activation='relu'),
    layers.Dense(10, activation='softmax') # Adjust the number of classes
])
# Set up the data generator for training data
train_data_dir = 'path/to/train_data_directory' # Update with the path to your training data
train_datagen = ImageDataGenerator(rescale=1.0/255)
# Load training data
train data = train datagen.flow from directory(
    train_data_dir,
    target_size=(224, 224),
    batch_size=32,
    class_mode='categorical'
)
# d. Train classifier layers on training data
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
model.fit(train_data, epochs=5)
# e. Fine-tune hyperparameters and unfreeze more layers if needed
base model.trainable = True
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
model.fit(train_data, epochs=5)
     FileNotFoundError
                                               Traceback (most recent call last)
     <ipython-input-35-106de7867d4e> in <cell line: 25>()
          23
          24 # Load training data
     ---> 25 train_data = train_datagen.flow_from_directory(
          26
                 train_data_dir,
          27
                 target_size=(224, 224),
                                       🗘 1 frames -
     /usr/local/lib/python3.10/dist-packages/keras/src/legacy/preprocessing/image.py in __init__(self, directory, image_data_generator,
     target_size, color_mode, classes, class_mode, batch_size, shuffle, seed, data_format, save_to_dir, save_prefix, save_format,
     follow_links, subset, interpolation, keep_aspect_ratio, dtype)
         451
                     if not classes:
         452
                        classes = []
                         for subdir in sorted(os.listdir(directory)):
     --> 453
         454
                             if os.path.isdir(os.path.join(directory, subdir)):
         455
                                 classes.append(subdir)
     FileNotEquadEnner: [Fanno 2] No such file on directory: 'nath/to/train data directory'
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
(x_train,y_train),(x_test,y_test)=mnist.load_data()
x train=x train/255
x_test=x_test/255
model=models.Sequential([
   layers.Flatten(input_shape=(28,28)),
   layers.Dense(128,activation='relu'),
   layers.Dropout(0.2),
```

```
layers.Dense(10,activation='softmax')
1)
model.compile(optimizer='sgd',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
history=model.fit(x_train,y_train,epochs=11,validation_data=(x_test,y_test))
test_loss,test_acc=model.evaluate(x_test,y_test)
1875/1875
                                  – 12s 6ms/step - accuracy: 0.6816 - loss: 1.1174 - val_accuracy: 0.9022 - val_loss: 0.3659
     Epoch 2/11
     1875/1875 -
                                  - 15s 3ms/step - accuracy: 0.8813 - loss: 0.4129 - val_accuracy: 0.9174 - val_loss: 0.2937
     Epoch 3/11
     1875/1875 -
                                  – 10s 3ms/step - accuracy: 0.9049 - loss: 0.3280 - val_accuracy: 0.9285 - val_loss: 0.2556
     Epoch 4/11
     1875/1875 -
                                  - 6s 3ms/step - accuracy: 0.9153 - loss: 0.2939 - val_accuracy: 0.9356 - val_loss: 0.2303
     Epoch 5/11
     1875/1875
                                  - 9s 3ms/step - accuracy: 0.9255 - loss: 0.2626 - val_accuracy: 0.9420 - val_loss: 0.2086
     Epoch 6/11
     1875/1875
                                  - 7s 4ms/step - accuracy: 0.9317 - loss: 0.2412 - val_accuracy: 0.9453 - val_loss: 0.1935
     Epoch 7/11
     1875/1875 -
                                  - 8s 2ms/step - accuracy: 0.9351 - loss: 0.2279 - val_accuracy: 0.9483 - val_loss: 0.1826
     Epoch 8/11
     1875/1875
                                  - 7s 4ms/step - accuracy: 0.9411 - loss: 0.2069 - val_accuracy: 0.9512 - val_loss: 0.1702
     Epoch 9/11
     1875/1875 -
                                  – 5s 3ms/step - accuracy: 0.9452 - loss: 0.1958 - val accuracy: 0.9539 - val loss: 0.1617
     Epoch 10/11
     1875/1875
                                  - 6s 3ms/step - accuracy: 0.9460 - loss: 0.1901 - val_accuracy: 0.9561 - val_loss: 0.1528
     Epoch 11/11
     1875/1875
                                  - 6s 3ms/step - accuracy: 0.9486 - loss: 0.1779 - val_accuracy: 0.9574 - val_loss: 0.1463
     Epoch 1/11
                                   - 6s 3ms/step - accuracy: 0.7010 - loss: 1.0778 - val_accuracy: 0.9051 - val_loss: 0.3629
     1875/1875
     Epoch 2/11
     1875/1875
                                  - 9s 2ms/step - accuracy: 0.8868 - loss: 0.4006 - val_accuracy: 0.9215 - val_loss: 0.2895
     Epoch 3/11
     1875/1875 -
                                  - 9s 5ms/step - accuracy: 0.9067 - loss: 0.3280 - val accuracy: 0.9299 - val loss: 0.2527
     Epoch 4/11
     1875/1875 -
                                  - 8s 4ms/step - accuracy: 0.9176 - loss: 0.2918 - val_accuracy: 0.9350 - val_loss: 0.2267
     Epoch 5/11
     1875/1875 -
                                  – 11s 4ms/step - accuracy: 0.9256 - loss: 0.2624 - val_accuracy: 0.9417 - val_loss: 0.2075
     Epoch 6/11
     1875/1875 -
                                  - 11s 4ms/step - accuracy: 0.9332 - loss: 0.2388 - val_accuracy: 0.9446 - val_loss: 0.1917
     Epoch 7/11
                                  - 10s 4ms/step - accuracy: 0.9363 - loss: 0.2235 - val_accuracy: 0.9483 - val_loss: 0.1796
     1875/1875
     Epoch 8/11
     1875/1875
                                  - 7s 4ms/step - accuracy: 0.9411 - loss: 0.2056 - val_accuracy: 0.9509 - val_loss: 0.1687
     Epoch 9/11
     1875/1875
                                  - 13s 5ms/step - accuracy: 0.9445 - loss: 0.1983 - val_accuracy: 0.9532 - val_loss: 0.1603
     Epoch 10/11
     1875/1875 -
                                  - 6s 3ms/step - accuracy: 0.9458 - loss: 0.1895 - val_accuracy: 0.9555 - val_loss: 0.1527
     Epoch 11/11
     1875/1875 -
                                  - 7s 4ms/step - accuracy: 0.9497 - loss: 0.1778 - val_accuracy: 0.9565 - val_loss: 0.1476
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import mnist
(x_train,y_train),(x_test,y_test)=mnist.load_data()
x_train=x_train[...,None]/255
x_test=x_test[...,None]/255
model=models.Sequential([
   layers.Conv2D(32,(3,3),activation='relu',input_shape=(28,28,1)),
   layers.MaxPooling2D((2,2)),
   layers.Conv2D(64,(3,3),activation='relu'),
   layers.MaxPooling2D((2,2)),
    layers.Flatten(),
   lavers.Dense(64.activation='relu').
   layers.Dense(10,activation='softmax')
])
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',metrics=['accuracy'])
history=model.fit(x_train,y_train,epochs=5,validation_data=(x_test,y_test))
test_acc,test_loss=model.evaluate(x_test,y_test)
```

```
🤧 /usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`inpu
       super().__init__(activity_regularizer=activity_regularizer, **kwargs)
     Epoch 1/5
     1875/1875
                                   – 69s 36ms/step - accuracy: 0.9054 - loss: 0.3052 - val_accuracy: 0.9821 - val_loss: 0.0538
     Epoch 2/5
     1875/1875
                                   - 63s 33ms/step - accuracy: 0.9852 - loss: 0.0481 - val_accuracy: 0.9870 - val_loss: 0.0352
     Epoch 3/5
     1875/1875
                                   - 78s 32ms/step - accuracy: 0.9900 - loss: 0.0314 - val_accuracy: 0.9914 - val_loss: 0.0272
     Fnoch 4/5
     1875/1875
                                   - 59s 32ms/step - accuracy: 0.9937 - loss: 0.0206 - val_accuracy: 0.9918 - val_loss: 0.0243
     Epoch 5/5
     1875/1875
                                   - 59s 31ms/step - accuracy: 0.9947 - loss: 0.0177 - val_accuracy: 0.9907 - val_loss: 0.0287
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
# a. Import the necessary packages
from tensorflow.keras.datasets import mnist
# b. Load the training and testing data
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
# c. Define the network architecture using Keras
model = models.Sequential([
    layers.Flatten(input_shape=(28, 28)),
    layers.Dense(128, activation='relu'),
    layers.Dropout(0.2),
    layers.Dense(10, activation='softmax')
# d. Compile the model
model.compile(optimizer='sgd',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
# e. Train the model
history = model.fit(x_train, y_train, epochs=11, validation_data=(x_test, y_test))
# f. Evaluate the network
test_loss, test_acc = model.evaluate(x_test, y_test)
print(f'Test accuracy: {test_acc}')
# Plot the training loss and accuracy
plt.plot(history.history['accuracy'], label='Accuracy')
plt.plot(history.history['loss'], label='Loss')
plt.title('Training Loss and Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Value')
plt.legend()
plt.show()
import tensorflow as tf
from tensorflow.keras import layers, models
from sklearn.preprocessing import StandardScaler
import pandas as pd
import numpy as np
data=pd.read_csv('/content/creditcard.csv')
scaler=StandardScaler()
data scaled=scaler.fit transform(data.drop('Class',axis=1))
input_dim=data_scaled.shape[1]
input layer=layers.Input(shape=(input dim,))
encoded=layers.Dense(64,activation='relu')(input_layer)
encoded=layers.Dense(32,activation='relu')(encoded)
decoded=layers.Dense(64,activation='relu')(encoded)
decoded=layers.Dense(input_dim,activation='relu')(decoded)
```

```
11/7/24, 10:11 PM
    autocoder=models.Model(input layer,decoded)
    autocoder.compile(optimizer='adam',loss='mean_squared_error')
    autocoder.fit(data_scaled,data_scaled,validation_split=0.2,batch_size=256,epochs=50)
    reconstructed=autocoder.predict(data_scaled)
    mse=np.mean(np.square(reconstructed-data_scaled),axis=1)
    threshold=np.percentile(mse,95)
    anamolies=mse>threshold
     \rightarrow
         Epoch 1/50
         891/891
                                      - 4s 3ms/step - loss: 0.7637 - val_loss: 0.5362
         Epoch 2/50
         891/891
                                       2s 2ms/step - loss: 0.5586 - val_loss: 0.5004
         Epoch 3/50
         891/891
                                       3s 2ms/step - loss: 0.5544 - val_loss: 0.4930
         Epoch 4/50
         891/891
                                      - 2s 3ms/step - loss: 0.5457 - val_loss: 0.4907
         Epoch 5/50
         891/891
                                      - 4s 4ms/step - loss: 0.5410 - val_loss: 0.5073
         Epoch 6/50
```

```
891/891
                            - 2s 2ms/step - loss: 0.5443 - val_loss: 0.5042
Epoch 7/50
891/891
                             3s 2ms/step - loss: 0.5497 - val_loss: 0.5058
Epoch 8/50
891/891
                            - 2s 2ms/step - loss: 0.5513 - val_loss: 0.5035
Epoch 9/50
891/891
                             3s 3ms/step - loss: 0.5501 - val_loss: 0.5054
Epoch 10/50
891/891
                            - 4s 5ms/step - loss: 0.5452 - val_loss: 0.5035
Epoch 11/50
891/891
                            - 3s 3ms/step - loss: 0.5516 - val_loss: 0.5041
Epoch 12/50
891/891
                            - 3s 3ms/step - loss: 0.5451 - val_loss: 0.5034
Epoch 13/50
891/891
                            • 2s 3ms/step - loss: 0.5480 - val_loss: 0.4903
Epoch 14/50
891/891
                            2s 2ms/step - loss: 0.5456 - val_loss: 0.5044
Epoch 15/50
                            - 4s 4ms/step - loss: 0.5414 - val_loss: 0.5038
891/891
Epoch 16/50
891/891
                            4s 3ms/step - loss: 0.5342 - val_loss: 0.5034
Epoch 17/50
891/891
                            - 3s 3ms/step - loss: 0.5520 - val_loss: 0.5034
Epoch 18/50
891/891
                            - 6s 3ms/step - loss: 0.5479 - val_loss: 0.5039
Epoch 19/50
891/891
                             3s 4ms/step - loss: 0.5501 - val_loss: 0.5038
Epoch 20/50
                            • 4s 2ms/step - loss: 0.5480 - val_loss: 0.5034
891/891
Epoch 21/50
891/891
                            2s 3ms/step - loss: 0.5454 - val_loss: 0.4906
Epoch 22/50
891/891
                            • 3s 3ms/step - loss: 0.5435 - val_loss: 0.4882
Epoch 23/50
891/891
                             5s 5ms/step - loss: 0.5480 - val loss: 0.4883
Epoch 24/50
891/891
                            • 3s 2ms/step - loss: 0.5485 - val_loss: 0.4882
Epoch 25/50
891/891
                            - 2s 2ms/step - loss: 0.5394 - val_loss: 0.4884
Epoch 26/50
891/891
                             2s 3ms/step - loss: 0.5367 - val_loss: 0.4886
Epoch 27/50
                             2s 3ms/step - loss: 0.5461 - val_loss: 0.4890
891/891
Epoch 28/50
891/891
                            - 4s 4ms/step - loss: 0.5430 - val_loss: 0.4883
Epoch 29/50
891/891
                           - 4s 3ms/step - loss: 0.5455 - val_loss: 0.4882
```

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
tf.__version__
```

img_generator = tf.keras.preprocessing.image.ImageDataGenerator(#rotation_range=90, brightness_range=(0.5,1), #shear range=0.2, #zoom_range=0.2, channel shift range=0.2,

```
horizontal_flip=True,
                                                               vertical_flip=True,
                                                               rescale=1./255,
                                                               validation_split=0.3)
root_dir = '101_ObjectCategories'
img_generator_flow_train = img_generator.flow_from_directory(
    directory=root dir,
    target_size=(224, 224),
    batch_size=32,
    shuffle=True,
    subset="training")
img_generator_flow_valid = img_generator.flow_from_directory(
    directory=root dir,
    target_size=(224, 224),
    batch_size=32,
    shuffle=True,
    subset="validation")
    ______
     FileNotFoundError
                                              Traceback (most recent call last)
     <ipython-input-17-7ac3efe33d85> in <cell line: 16>()
                                                                            validation_split=0.3)
         14
         15 root_dir = '101_ObjectCategories'
     ---> 16 img_generator_flow_train = img_generator.flow_from_directory(
         17
                 directory=root_dir,
          18
                 target_size=(224, 224),
                                    - 💲 1 frames -
     /usr/local/lib/python3.10/dist-packages/keras/src/legacy/preprocessing/image.py in __init__(self, directory, image_data_generator,
     target_size, color_mode, classes, class_mode, batch_size, shuffle, seed, data_format, save_to_dir, save_prefix, save_format,
     follow_links, subset, interpolation, keep_aspect_ratio, dtype)
         451
                    if not classes:
         452
                        classes = []
                        for subdir in sorted(os.listdir(directory)):
     --> 453
         454
                            if os.path.isdir(os.path.join(directory, subdir)):
         455
                                classes.append(subdir)
     FilaNotEquadEngar: [Enga 2] No such file on directory: '101 ObjectCategories
from os import waitpid
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import skipgrams
from tensorflow.keras import layers, models
import numpy as np
text="Your Document is here"
tokenizer=Tokenizer()
tokenizer.fit_on_texts([text])
word_index=tokenizer.word_index
sequences=tokenizer.texts_to_sequences([text])
pairs,labels=skipgrams(sequences[0],vocabulary_size=len(word_index)+1,window_size=2)
pairs=np.array(pairs)
labels=np.array(labels)
vocab_size=len(word_index)+1
embedding_dim=10
model=tf.keras.Sequential([
    layers.Embedding(input_dim=vocab_size,output_dim=embedding_dim),
    layers.Flatten(),
    layers.Dense(10,activation='relu'),
    layers.Dense(vocab_size,activation='softmax')
])
model.compile(optimizer='adam',loss='sparse_categorical_crossentropy')
predictions=model.fit(pairs,labels,epochs=5);
model.predict(pairs)

→ Epoch 1/5

     1/1 -
                            - 2s 2s/step - loss: 1.6290
     Epoch 2/5
     1/1
                           — 0s 59ms/step - loss: 1.6239
```

```
Epoch 3/5
                         - 0s 57ms/step - loss: 1.6194
1/1
Epoch 4/5
1/1
                         - 0s 45ms/step - loss: 1.6152
Epoch 5/5
1/1 -
                         - 0s 56ms/step - loss: 1.6116
1/1 -
                         - 0s 107ms/step
\verb"array" ([[0.20166315, 0.20049031, 0.19866715, 0.1988709 , 0.20030849]",
       [0.20166315, 0.20049031, 0.19866715, 0.1988709 , 0.20030849],
        [0.20124595, 0.2001096 , 0.20187652, 0.19888763, 0.1978803 ],
       [0.20039305, 0.2004738, 0.2010251, 0.1990366, 0.1990715],
       \hbox{\tt [0.19969876, 0.19775316, 0.20183253, 0.20143819, 0.19927734],}\\
       [0.19967465, 0.20048477, 0.20137277, 0.19826165, 0.20020615],
       [0.2041203 , 0.19610062, 0.20568493, 0.19811188, 0.19598228],
       [0.20313333, 0.19869377, 0.2005919, 0.20059021, 0.19699074], [0.19842471, 0.20238212, 0.19592878, 0.20232327, 0.20094106],
       [0.20165712, 0.20060578, 0.20025012, 0.20033959, 0.1971473 ],
        [0.20354581, 0.19725166, 0.20294914, 0.20200284, 0.19425048],
       [0.19969876, 0.19775316, 0.20183253, 0.20143819, 0.19927734],
       \hbox{\tt [0.2041203\ ,\ 0.19610062,\ 0.20568493,\ 0.19811188,\ 0.19598228],}
       [0.19989578, 0.20129879, 0.19853218, 0.19922256, 0.20105058],
       [0.20544447, 0.19847797, 0.19982524, 0.19965297, 0.1965993],
       [0.1989479 , 0.1969421 , 0.20604545, 0.1982765 , 0.19978786],
       [0.20165712, 0.20060578, 0.20025012, 0.20033959, 0.1971473],
       [0.20313333, 0.19869377, 0.2005919 , 0.20059021, 0.19699074],
       [0.19820169, 0.20342936, 0.19372055, 0.2037455, 0.20090288],
       [0.1998958 , 0.2012988 , 0.1985322 , 0.19922258, 0.2010506 ]],
      dtype=float32)
```