ERODE SENGUNTHAR

ENGINEERING COLLEGE

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EX.NO: - 1 **SOLVING XOR PROBLEM USING DNN**

DATE: -

AIM:

The aim of this procedure is to solve the XOR problem using a Deep Neural Network (DNN) in Python.

PROCEDURE:

- Import the necessary libraries
- Prepare the dataset
- Create the DNN model
- Compile the model
- Train the model
- Test the model
- Print the predictions

PROGRAM:

#1. Import the necessary libraries:

```
import numpy as np
from keras.models import Sequential
from keras.layers import Dense
```

#2. Prepare the dataset:

```
# Define the input dataset
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
# Define the corresponding output labels
y = np.array([[0], [1], [1], [0]])
```

#3. Create the DNN model:

```
# Create a Sequential model
model = Sequential()
# Add layers to the model
model.add(Dense(4, input_dim=2, activation='relu'))
```

```
model.add(Dense(1, activation='sigmoid'))
# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
#4. Train the model:
model.fit(X, y, epochs=1000)
#5. Test the model:
# Predict outputs for the input dataset
predictions = model.predict(X)
rounded_predictions = np.round(predictions)
# Print the predictions
for i in range(len(X)):
    print(f'Input: {X[i]}, Predicted Output: {rounded_predictions[i]}')
```

OUTPUT:

```
Input: [0 0], Predicted Output: [0.]
Input: [0 1], Predicted Output: [1.]
Input: [1 0], Predicted Output: [1.]
Input: [1 1], Predicted Output: [0.]
```

RESULT:

Thus the program to solve the XOR problem using a Deep Neural Network (DNN) in Python written Successfully.

EX.NO: - 2 **CHARACTER RECOGNITION USING CNN**

DATE: -

AIM:

The aim of this code is to train a Convolutional Neural Network (CNN) model on the MNIST dataset and evaluate its performance by making predictions on the test set.

PROCEDURE:

- Import the necessary libraries
- Load and preprocess the dataset
- Create the CNN model
- Compile the model
- Train the model
- Evaluate the model
- Make predictions
- Visualize the results

PROGRAM:

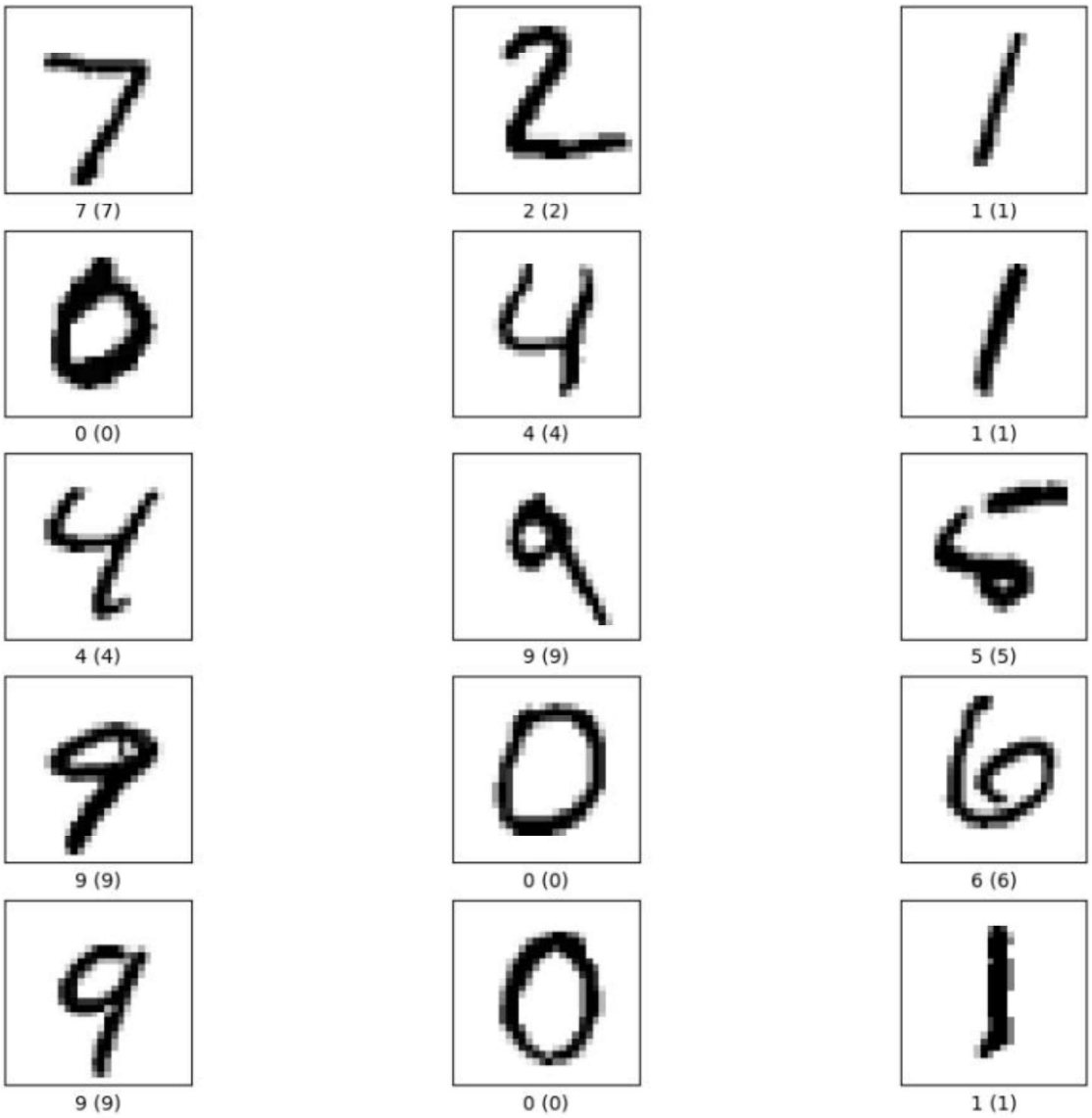
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt


# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()


# Normalize the data
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255


# Reshape the data for CNN
x_train = x_train.reshape(-1, 28, 28, 1)
x_test = x_test.reshape(-1, 28, 28, 1)
```

```
# Create the model
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(filters=64, kernel_size=(2,2), strides=(1, 1), padding='same', activation='relu', input_shape=(28,28,1)),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Conv2D(filters=32, kernel_size=(2,2), strides=(1, 1), padding='same', activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(10, activation='softmax')])
# Compile the model
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
 # Train the model
model.fit(x_train, y_train, batch_size=60, epochs=10, verbose=1, validation_split=0.3)
 # Evaluate the model on test set
score = model.evaluate(x_test, y_test, verbose=0)
print('\nTest accuracy:', score[1])
 # Make predictions on the test set
predictions = model.predict(x_test)
 # Display some test images and their predicted labels
num_rows = 5
num_cols = 3
num_images = num_rows * num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
```

```
    plt.subplot(num_rows, 2*num_cols, 2*i+1)
    plt.xticks([])
    plt.yticks([])
    plt.imshow(x_test[i].reshape(28, 28), cmap=plt.cm.binary)
    predicted_label = np.argmax(predictions[i])
    plt.xlabel("{} ({})".format(predicted_label, y_test[i]))
plt.show()
```

OUTPUT:

```
Epoch 1/10
700/700 [==============================] - 44s 62ms/step - loss: 0.4044 - accuracy: 0.8701 - val_loss: 0.1232 - val_accuracy: 0.9623
.
.
.
Epoch 10/10
700/700 [==============================] - 36s 51ms/step - loss: 0.0545 - accuracy: 0.9829 - val_loss: 0.0356 - val_accuracy: 0.9889

Test accuracy: 0.9901999831199646
313/313 [==============================] - 2s 6ms/step
```



RESULT:

Thus the python code is to train a Convolutional Neural Network (CNN) model on the MNIST dataset and evaluate its performance by making predictions on the test set executed successfully.

EX.NO: - 3 **FACE RECOGNITION USING CNN**

DATE: -

AIM:

The aim of this program is to perform real-time face detection using the OpenCV library in Python. It captures video from your default camera (usually the webcam), detects faces in the video frames, and highlights the detected faces with green rectangles.

PROCEDURE:

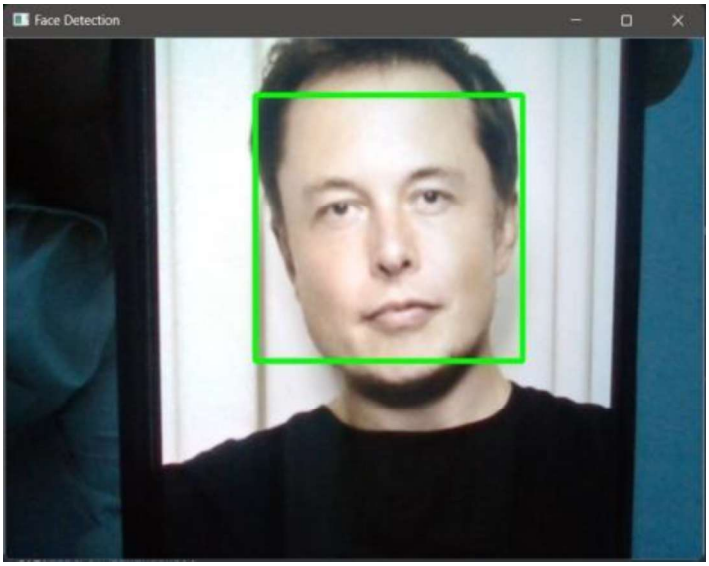
1. Import the OpenCV library.
2. Create a CascadeClassifier object and load the pre-trained face detection model (download -'haarcascade_frontalface_default.xml').
3. Initialize the video capture using the default camera (usually the webcam).
4. Start an infinite loop to continuously capture and process frames from the camera.
5. Read a frame from the camera.
6. Convert the frame to grayscale.
7. Use the CascadeClassifier to detect faces in the grayscale frame.
8. For each detected face, draw a green rectangle around it.
9. Display the frame with detected faces in a window called 'Face Detection.'
10. Check for the 'q' key press; if it's pressed, exit the loop.
11. Release the video capture and close all OpenCV windows when the loop is exited.

PROGRAM:

```
import cv2

# Load the pre-trained face detection model

face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +
'haarcascade_frontalface_default.xml')

# Initialize the video capture

cap = cv2.VideoCapture(0)

while True:

    ret, frame = cap.read()  # Read a frame from the camera
```

```
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)  # Convert the frame to grayscale
    # Detect faces in the grayscale frame
    faces = face_cascade.detectMultiScale(gray, scaleFactor=1.1, minNeighbors=5,
minSize=(30, 30))
    # Draw green rectangles around detected faces
    for (x, y, w, h) in faces:
        cv2.rectangle(frame, (x, y), (x+w, y+h), (0, 255, 0), 3)
    # Display the frame with detected faces
    cv2.imshow('Face Detection', frame)
    # Check for 'q' key press; if pressed, exit the loop
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break
# Release the video capture and close OpenCV windows
cap.release()
cv2.destroyAllWindows()
```

OUTPUT:



RESULT:

The program provides real-time face detection in the video feed from your camera, and the output is a window displaying the live video with highlighted faces.

EX.NO: - 4 **TEXT GENERATION USING RNN**

DATE: -

AIM:

The aim of this Python code is to train a text generation model using RNNand generate text based on a given input text.

PROCEDURE:

1. Read and process a text file (in this case, a Shakespearean text).
2. Tokenize the text, create a character-to-index mapping, and convert the text to numerical values.
3. Create a dataset for training the text generation model.
4. Build a deep learning model using TensorFlow's Keras API. The model consists of an embedding layer, two LSTM layers, dropout layers, batch normalization, and a dense output layer.
5. Define a custom loss function for training the model.
6. Generate text using the trained model, starting from a user-provided input text.

PROGRAM:

```
import numpy as np

import tensorflow as tf


def process_text(file_path):

    text = open(file_path, 'rb').read().decode(encoding='utf-8')  # Read, then decode for py2 compat.

    vocab = sorted(set(text))  # The unique characters in the file

    # Creating a mapping from unique characters to indices and vice versa

    char2idx = {u: i for i, u in enumerate(vocab)}

    idx2char = np.array(vocab)

    text_as_int = np.array([char2idx[c] for c in text])

    return text_as_int, vocab, char2idx, idx2char


def split_input_target(chunk):

    input_text, target_text = chunk[:-1], chunk[1:]
```

```
    return input_text, target_text



def create_dataset(text_as_int, seq_length=100, batch_size=64, buffer_size=10000):
    char_dataset = tf.data.Dataset.from_tensor_slices(text_as_int)
    dataset = char_dataset.batch(seq_length + 1,
drop_remainder=True).map(split_input_target)
    dataset = dataset.shuffle(buffer_size).batch(batch_size, drop_remainder=True)
    return dataset


def build_model(vocab_size, embedding_dim=256, rnn_units=1024, batch_size=64):
    model = tf.keras.Sequential([
        tf.keras.layers.Embedding(vocab_size, embedding_dim,
batch_input_shape=[batch_size, None]),
        tf.keras.layers.LSTM(rnn_units, return_sequences=True, stateful=True,
recurrent_initializer='glorot_uniform'),
        tf.keras.layers.Dropout(0.1),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.LSTM(rnn_units, return_sequences=True, stateful=True,
recurrent_initializer='glorot_uniform'),
        tf.keras.layers.Dropout(0.1),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dense(vocab_size)
    ])
    return model


def loss(labels, logits):
    return tf.keras.losses.sparse_categorical_crossentropy(labels, logits, from_logits=True)


def generate_text(model, char2idx, idx2char, start_string, generate_char_num=1000,
temperature=1.0):
    # Evaluation step (generating text using the learned model)
```

```
    # Low temperatures results in more predictable text, higher temperatures results in more surprising text.
    # Converting our start string to numbers (vectorizing)
    input_eval = [char2idx[s] for s in start_string]
    input_eval = tf.expand_dims(input_eval, 0)
    text_generated = []  # Empty string to store our results
    model.reset_states()
    for i in range(generate_char_num):
        predictions = model(input_eval)
        predictions = tf.squeeze(predictions, 0)    # remove the batch dimension
        predictions /= temperature
        # using a categorical distribution to predict the character returned by the model
        predicted_id = tf.random.categorical(predictions, num_samples=1)[-1, 0].numpy()
        # We pass the predicted character as the next input to the model along with the previous hidden state
        input_eval = tf.expand_dims([predicted_id], axis=0)
        text_generated.append(idx2char[predicted_id])
    return start_string + ''.join(text_generated)


# path_to_file = tf.keras.utils.get_file('nietzsche.txt', 'https://s3.amazonaws.com/text-datasets/nietzsche.txt')
path_to_file = tf.keras.utils.get_file('shakespeare.txt', 'https://storage.googleapis.com/download.tensorflow.org/data/shakespeare.txt')


text_as_int, vocab, char2idx, idx2char = process_text(path_to_file)
dataset = create_dataset(text_as_int)
model = build_model(vocab_size=len(vocab))
model.compile(optimizer='adam', loss=loss)
model.summary()
history = model.fit(dataset, epochs=50)
model.save_weights("gen_text_weights.h5", save_format='h5')
# To keep this prediction step simple, use a batch size of 1
```

```
model = build_model(vocab_size=len(vocab), batch_size=1)

model.load_weights("gen_text_weights.h5")

model.summary()


user_input = input("Write the beginning of the text, the program will complete it. Your input is: ")

generated_text = generate_text(model, char2idx, idx2char, start_string=user_input, generate_char_num=2000)

print(generated_text)
```

OUTPUT:

" First Citizen:We are accounted poor citizens, the patricians good.What authority surfeits on would relieve us: if they would yield us but the superfluity, while it were wholesome, we might guess they relieved us humanely;but they think we are too dear: the leanness that afflicts us, the object of our misery, is as an inventory to particularise their abundance; our sufferance is a gain to them Let us revenge this with our pikes, ere we become rakes: for the gods know I speak this in hunger for bread, not in thirst for revenge. "

RESULT:

The code demonstrates how to train a text generation model and use it to create coherent text based on a given starting point.

EX.NO: - 5 **SENTIMENT ANALYSIS USING LSTM**

DATE: -

AIM:

The aim of this code is to perform sentiment analysis on a dataset of comments using deep learning techniques.

PROCEDURE:

1. Import necessary libraries including NumPy, Pandas, Matplotlib, Hazm (a Persian natural language processing library), and scikit-learn.

2. Read a dataset from a CSV file called 'Snappfood - Sentiment Analysis.csv'.

3. Perform data preprocessing, including tokenization, lemmatization, normalization, and removing stopwords and punctuations.

4. Create a new dataset containing the cleaned text and sentiment labels.

5. Tokenize and pad the text data for model training.

6. Build a deep learning model using Keras with an embedding layer, Bidirectional LSTM layers, SpatialDropout1D, BatchNormalization, and a Dense output layer.

7. Compile the model with the Adam optimizer and binary cross-entropy loss.

8. Train the model on the training data.

9. Make predictions on both the training and test data.

10. Evaluate the model using classification reports to measure its performance.

PROGRAM:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import hazm

import string

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from keras.preprocessing.text import Tokenizer

from keras.utils import pad_sequences
```

```
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, SpatialDropout1D, Embedding,
Bidirectional, LSTM, BatchNormalization
from keras.callbacks import ModelCheckpoint, EarlyStopping
from sklearn.utils import class_weight


from sklearn.metrics import classification_report
from collections import Counter


data = pd.read_csv('Snappfood - Sentiment Analysis.csv', delimiter='\t', on_bad_lines='skip')
data


data.info()
data.label_id.value_counts()
data.isnull().sum()
data = data[['comment', 'label_id']]
data
data.dropna(inplace=True)
data
punctuations = string.punctuation + "," + "؛"
translator = str.maketrans(",", punctuations)
stopwords = hazm.stopwords_list()
hazm.word_tokenize(data['comment'][10])
lem = hazm.Lemmatizer()
norm =hazm.Normalizer()
dataset = pd.DataFrame(columns=['Text', 'Sentiment'])


for index, row in data.iterrows():
  text = row['comment']
  text_tokenized = hazm.word_tokenize(text)
  text_lem = [lem.lemmatize(x) for x in text_tokenized]
```

```
  text_norm = [norm.normalize(x) for x in text_lem]
  clean_text = [x for x in text_norm if not x in stopwords]
  final_text = [x.translate(translator) for x in clean_text]
  dataset.loc[index] = ({
      'Text' : ' '.join(final_text),
      'Sentiment' : row['label_id']
  })
dataset.Sentiment.value_counts()
dataset.Sentiment.value_counts()
dataset['Text']
dataset['words_count'] = dataset['Text'].apply(lambda t: len(hazm.word_tokenize(t)))
max_len = dataset["words_count"].max()
max_len
texts = ' '.join(dataset['Text'])
tokens = hazm.word_tokenize(texts)
counter = Counter(tokens)
min_freg = 35
filtered = [word for word, count in counter.items() if count >= min_freg]
unique_words = set(filtered)
n_words = len(unique_words)
n_words
X = dataset['Text']
Y = dataset['Sentiment']
xtrain, xtest, ytrain, ytest = train_test_split(X, Y, test_size=0.01, random_state=4234)
tokenizer = Tokenizer(num_words = n_words)
tokenizer.fit_on_texts(xtrain)
def Tokenization_padSequences(x, maxlen = max_len):
    xseq = tokenizer.texts_to_sequences(x)
    xpad = pad_sequences(xseq, padding='post', maxlen = max_len)
    return xpad
```

```
xtrain_pad = Tokenization_padSequences(xtrain)
xtest_pad = Tokenization_padSequences(xtest)
xtest_pad
sequences = tokenizer.texts_to_sequences(dataset['Text'])
print(dataset['Text'][200])
print(sequences[200])
model = Sequential()
model.add(Embedding(n_words, 80, input_length=max_len))
model.add(Bidirectional(LSTM(256, dropout=0.2, return_sequences=True)))
model.add(SpatialDropout1D(0.2))
model.add(Bidirectional(LSTM(128, dropout=0.2)))
model.add(BatchNormalization())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='Adam', metrics=['accuracy'], loss = 'binary_crossentropy')
model.summary()

np.unique(ytrain)
model.fit(xtrain_pad, ytrain, epochs=2, batch_size=10, validation_data = (xtest_pad, ytest))
ypred_train = (model.predict(xtrain_pad) > 0.5).astype(int)
print(classification_report(ytrain, ypred_train))
ypred = (model.predict(xtest_pad) > 0.5).astype(int)
print(classification_report(ytest, ypred))
```

OUTPUT:

The output includes the model summary, training and evaluation reports, and the model's predictions.

	Unnamed: 0	comment	label	label_id
0	NaN	واقعا حیف وقت که بنویسم سرویس دهیتون شده افتضاح	SAD	1.0
1	NaN	...قرار بود ا ساعته برسه ولی نیم ساعت زودتر از مو	HAPPY	0.0
2	NaN	...قیمت این مدل اصلا با کیفیتش سازگاری نداره، فقط	SAD	1.0
3	NaN	...عاللللی بود همه چه درست و به اندازه و کیفیت خوب	HAPPY	0.0
4	NaN	.شیرینی وانیلی فقط یک مدل بود	HAPPY	0.0
...	...	...	...	...
69995	NaN	...سلام من به فاکتور غذاهایی که سفارش میدم احتیاج	SAD	1.0
69996	NaN	...سایز پیتزا نسبت به سفارشاتی که قبلا گذشتم کم ش	SAD	1.0
69997	NaN	... من قارچ اضافه رو اضافه کرده بودم بودم اما اگر	HAPPY	0.0
69998	NaN	...همرو بعد آساعت تاخیر اشتباه آوردن پولشم رفت رو	SAD	1.0
69999	NaN	.فلفلش خیییلی تند بود	HAPPY	0.0

70000 rows × 4 columns

```
array([[  77,   18,  554, ...,    0,    0,    0],
       [ 128,   41,  334, ...,    0,    0,    0],
       [ 300, 1577,   93, ...,    0,    0,    0],
       ...,
       [   9,   11,    1, ...,    0,    0,    0],
       [  35,  222,  289, ...,    0,    0,    0],
       [   5,    2,  172, ...,    0,    0,    0]], dtype=int32)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 231, 80)	144800
bidirectional (Bidirectional)	(None, 231, 512)	690176
spatial_dropout1d (SpatialDropout1D)	(None, 231, 512)	0
bidirectional_1 (Bidirectional)	(None, 256)	656384
batch_normalization (BatchNormalization)	(None, 256)	1024
dense (Dense)	(None, 1)	257

Total params: 1,492,641

```
Trainable params: 1,492,129
Non-trainable params: 512


Epoch 1/20
459/459 [==============================] - 99s 194ms/step - loss: 0.4216 - accura
cy: 0.8075 - val_loss: 0.4008 - val_accuracy: 0.8245
Epoch 2/20
459/459 [==============================] - 67s 147ms/step - loss: 0.3860 - accura
cy: 0.8295 - val_loss: 0.3657 - val_accuracy: 0.8331
.

.

.

Epoch 20/20
459/459 [==============================] - 64s 138ms/step - loss: 0.2415 - accura
cy: 0.8986 - val_loss: 0.4892 - val_accuracy: 0.8187


22/22 [==============================] - 1s 25ms/step
              precision    recall  f1-score   support

         0.0       0.82      0.81      0.81       340
         1.0       0.82      0.83      0.82       355

    accuracy                           0.82       695
   macro avg       0.82      0.82      0.82       695
weighted avg       0.82      0.82      0.82       695
```

RESULT:

The code provides a sentiment analysis model capable of classifying text comments into sentiment categories. The result includes various metrics like accuracy, precision, recall, and F1-score to assess the model's performance on both the training and test datasets.

EX.NO:- 6 PARTS OF SPEECH TAGGING USING SEQUENCE TO

DATE:- SEQUENCE ARCHITECTURE

AIM: -

The aim of the provided Python code is to perform Part-of-Speech (POS) tagging on a given text using a Recurrent Neural Network (RNN) model.

PROCEDURE: -

1. Import the necessary libraries and modules, including NLTK, numpy, Keras, and related functions.

2. Define a paragraph of text that you want to perform POS tagging on.

3. Tokenize the paragraph into words using NLTK's `word_tokenize` function.

4. Perform POS tagging on the tokenized words using NLTK's `pos_tag` function.

5. Create a vocabulary and encode words into integers using Keras's `Tokenizer` and `texts_to_sequences` functions.

6. Create a vocabulary for POS tags and encode them into integers.

7. Prepare the data for training by converting the word sequences and POS tag sequences into numpy arrays.

8. Define an RNN model using Keras with embedding, SimpleRNN, and TimeDistributed layers.

9. Compile the model with the appropriate loss and optimizer.

10. Train the model on the data.

11. Use the trained model to predict POS tags for the input text.

12. Extract the predicted POS tags and display them alongside the original words.

PROGRAM: -

```
import nltk

import numpy as np

from nltk.tokenize import word_tokenize

from nltk.corpus import brown

from keras.preprocessing.text import Tokenizer

from keras.preprocessing.sequence import pad_sequences
```

```
from keras.models import Sequential
from keras.layers import Embedding, SimpleRNN, Dense, TimeDistributed
from keras.utils import to_categorical

# Download NLTK data for tokenization and POS tagging
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')

paragraph = """
Natural language processing (NLP) is a field of computer science, artificial intelligence,
and computational linguistics concerned with the interactions between computers and human (natural) languages.
NLP focuses on the interaction between humans and computers using natural language.
The ultimate goal of NLP is to read, decipher, understand, and make sense of the human language in a manner
that is both valuable and meaningful. Most NLP techniques rely on machine learning to derive meaning from human languages.
"""

# Tokenize the paragraph into words
words = word_tokenize(paragraph)
# Perform POS tagging using NLTK
pos_tags = nltk.pos_tag(words)
# Create a vocabulary and encode words to integers
tokenizer = Tokenizer()
tokenizer.fit_on_texts(words)
word_sequences = tokenizer.texts_to_sequences(words)
word_sequences = pad_sequences(word_sequences, padding='post')
# Create a vocabulary for POS tags
pos_tags_set = set(tag for word, tag in pos_tags)
num_pos_tags = len(pos_tags_set)
```

```
pos_tag_to_idx = {tag: i for i, tag in enumerate(pos_tags_set)}


# Encode POS tags to integers
pos_tag_sequences = [pos_tag_to_idx[tag] for _, tag in pos_tags]


# Prepare data for training
X = np.array(word_sequences)
Y = np.array(pos_tag_sequences)


# Define and compile the RNN model
model = Sequential()
model.add(Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=32,
input_length=X.shape[1]))
model.add(SimpleRNN(64, return_sequences=True))
model.add(TimeDistributed(Dense(num_pos_tags, activation='softmax')))  # Use
TimeDistributed layer


model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',
metrics=['accuracy'])


# Train the model
model.fit(X, Y, epochs=10, batch_size=32, verbose=2)


# POS tagging prediction
predictions = model.predict(X)
predicted_pos_tags = []


# Extract the predicted POS tags
for i in range(len(X)):

predicted_pos_tags.append([list(pos_tag_to_idx.keys())[list(pos_tag_to_idx.values()).index(t
ag)] for tag in predictions[i].argmax(axis=-1)])
```

```
# Display the original text with predicted POS tags
for word, pos_tag_list in zip(words, predicted_pos_tags):
    print(f"{word}: {pos_tag_list}")
```

OUTPUT: -

The output of the code will display the original text with their predicted POS tags.

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
True
Epoch 1/10
3/3 - 2s - loss: 2.9998 - accuracy: 0.0460 - 2s/epoch - 501ms/step
Epoch 2/10
3/3 - 0s - loss: 2.9815 - accuracy: 0.0812 - 14ms/epoch - 5ms/step
Epoch 3/10
3/3 - 0s - loss: 2.9644 - accuracy: 0.1119 - 12ms/epoch - 4ms/step
Epoch 4/10
3/3 - 0s - loss: 2.9466 - accuracy: 0.1167 - 12ms/epoch - 4ms/step
Epoch 5/10
3/3 - 0s - loss: 2.9289 - accuracy: 0.1403 - 13ms/epoch - 4ms/step
Epoch 6/10
3/3 - 0s - loss: 2.9101 - accuracy: 0.1444 - 13ms/epoch - 4ms/step
Epoch 7/10
3/3 - 0s - loss: 2.8902 - accuracy: 0.1526 - 12ms/epoch - 4ms/step
Epoch 8/10
3/3 - 0s - loss: 2.8690 - accuracy: 0.1485 - 16ms/epoch - 5ms/step
Epoch 9/10
3/3 - 0s - loss: 2.8466 - accuracy: 0.1470 - 12ms/epoch - 4ms/step
```

Epoch 10/10

3/3 - 0s - loss: 2.8226 - accuracy: 0.1579 - 19ms/epoch - 6ms/step

Natural: ['JJ']

language: ['NN']

processing: ['NN']

(: [',']

NLP: ['NN']

): [',']

is: ['VBZ']

a: ['DT']

field: ['NN']

of: ['IN']

computer: ['NN']

science: ['NN']

,: [',']

artificial: ['JJ']

intelligence: ['NN']

,: [',']

and: ['NN']

computational: ['JJ']

linguistics: ['NN']

concerned: ['NN']

with: ['IN']

the: ['DT']

interactions: ['NN']

between: ['NN']

computers: ['NN']

and: ['NN']

RESULT: -

The RNN model is trained to predict POS tags for words in the input text. The result consists of the predicted POS tags associated with each word in the given text.

EX.NO: -7 MACHINE TRANSLATION USING ENCODER-DECODER MODEL

DATE: -

AIM:

The aim of this code is to create a machine translation model from English to French using a sequence-to-sequence architecture with LSTM layers.

PROCEDURE:

1. Import necessary libraries, including NumPy, Pandas, and TensorFlow's Keras module.

2. Define hyperparameters such as batch size, epochs, latent dimension, and the number of samples.

3. Load the data from the 'fra.txt' file and preprocess it to create input and target sequences.

4. Build token dictionaries for both input and target characters.

5. Create one-hot encoded data for encoder and decoder inputs as well as decoder targets.

6. Define the encoder and decoder models.

7. Compile the model for training using the RMSprop optimizer and categorical cross-entropy loss.

8. Train the model on the training data.

9. Save the trained model to a file named 'eng2french.h5'.

10. Define sampling models for inference.

11. Implement a decoding function to translate English input sentences to French.

12. Iterate over a set of input sentences and generate translations.

PROGRAM:

```
import numpy as np

import pandas as pd

from tensorflow.keras.models import Model

from tensorflow.keras.layers import Input,LSTM,Dense


batch_size=64

epochs=40

latent_dim=256 # here latent dim represent hidden state or cell state
```

```
num_samples=10000

data_path='/content/fra.txt'

# Vectorize the data.
input_texts = []
target_texts = []
input_characters = set()
target_characters = set()
with open(data_path, 'r', encoding='utf-8') as f:
    lines = f.read().split('\n')
for line in lines[: min(num_samples, len(lines) - 1)]:
    input_text, target_text, _ = line.split('\t')
    # We use "tab" as the "start sequence" character
    # for the targets, and "\n" as "end sequence" character.
    target_text = '\t' + target_text + '\n'
    input_texts.append(input_text)
    target_texts.append(target_text)
    for char in input_text:
        if char not in input_characters:
            input_characters.add(char)
    for char in target_text:
        if char not in target_characters:
            target_characters.add(char)

input_characters=sorted(list(input_characters))
target_characters=sorted(list(target_characters))

num_encoder_tokens=len(input_characters)
num_decoder_tokens=len(target_characters)
```

```
max_encoder_seq_length=max([len(txt) for txt in input_texts])
max_decoder_seq_length=max([len(txt) for txt in target_texts])

print('Number of samples:', len(input_texts))
print('Number of unique input tokens:', num_encoder_tokens)
print('Number of unique output tokens:', num_decoder_tokens)
print('Max sequence length for inputs:', max_encoder_seq_length)
print('Max sequence length for outputs:', max_decoder_seq_length)

input_token_index=dict(
    [(char,i) for i, char in enumerate(input_characters)])
target_token_index=dict(
[(char,i) for i, char in enumerate(target_characters)])

encoder_input_data = np.zeros(
    (len(input_texts), max_encoder_seq_length, num_encoder_tokens),
    dtype='float32')
decoder_input_data = np.zeros(
    (len(input_texts), max_decoder_seq_length, num_decoder_tokens),
    dtype='float32')
decoder_target_data = np.zeros(
    (len(input_texts), max_decoder_seq_length, num_decoder_tokens),
    dtype='float32')

for i, (input_text, target_text) in enumerate(zip(input_texts, target_texts)):
    for t, char in enumerate(input_text):
        encoder_input_data[i, t, input_token_index[char]] = 1.
    encoder_input_data[i, t + 1:, input_token_index[' ']] = 1.
    for t, char in enumerate(target_text):
```

```
        # decoder_target_data is ahead of decoder_input_data by one timestep
        decoder_input_data[i, t, target_token_index[char]] = 1.
        if t > 0:
            # decoder_target_data will be ahead by one timestep
            # and will not include the start character.
            decoder_target_data[i, t - 1, target_token_index[char]] = 1.
    decoder_input_data[i, t + 1:, target_token_index[' ']] = 1.
    decoder_target_data[i, t:, target_token_index[' ']] = 1.

# Define an input sequence and process it.
encoder_inputs = Input(shape=(None, num_encoder_tokens))
encoder = LSTM(latent_dim, return_state=True)
encoder_outputs, state_h, state_c = encoder(encoder_inputs)
# We discard `encoder_outputs` and only keep the states.
encoder_states = [state_h, state_c]

# Set up the decoder, using `encoder_states` as initial state.
decoder_inputs = Input(shape=(None, num_decoder_tokens))
# We set up our decoder to return full output sequences,
# and to return internal states as well. We don't use the
# return states in the training model, but we will use them in inference.
decoder_lstm = LSTM(latent_dim, return_sequences=True, return_state=True)
decoder_outputs, _, _ = decoder_lstm(decoder_inputs,
                                     initial_state=encoder_states)
decoder_dense = Dense(num_decoder_tokens, activation='softmax')
decoder_outputs = decoder_dense(decoder_outputs)

# Define the model that will turn
# `encoder_input_data` & `decoder_input_data` into `decoder_target_data`
model = Model([encoder_inputs, decoder_inputs], decoder_outputs)
```

```
# Run training
model.compile(optimizer='rmsprop', loss='categorical_crossentropy',
              metrics=['accuracy'])
model.fit([encoder_input_data, decoder_input_data], decoder_target_data,
          batch_size=batch_size,
          epochs=epochs,
          validation_split=0.2)

model.save('eng2french.h5')

# Define sampling models
encoder_model = Model(encoder_inputs, encoder_states)

decoder_state_input_h = Input(shape=(latent_dim,))
decoder_state_input_c = Input(shape=(latent_dim,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]
decoder_outputs, state_h, state_c = decoder_lstm(
    decoder_inputs, initial_state=decoder_states_inputs)
decoder_states = [state_h, state_c]
decoder_outputs = decoder_dense(decoder_outputs)
decoder_model = Model(
    [decoder_inputs] + decoder_states_inputs,
    [decoder_outputs] + decoder_states)

# Reverse-lookup token index to decode sequences back to
# something readable.
reverse_input_char_index = dict(
    (i, char) for char, i in input_token_index.items())
reverse_target_char_index = dict(
```

```
    (i, char) for char, i in target_token_index.items())


def decode_sequence(input_seq):
    # Encode the input as state vectors.
    states_value = encoder_model.predict(input_seq)

    # Generate empty target sequence of length 1.
    target_seq = np.zeros((1, 1, num_decoder_tokens))
    # Populate the first character of target sequence with the start character.
    target_seq[0, 0, target_token_index['\t']] = 1.
    # Sampling loop for a batch of sequences
    # (to simplify, here we assume a batch of size 1).
    stop_condition = False
    decoded_sentence = ''
    while not stop_condition:
        output_tokens, h, c = decoder_model.predict(
            [target_seq] + states_value)

        # Sample a token
        sampled_token_index = np.argmax(output_tokens[0, -1, :])
        sampled_char = reverse_target_char_index[sampled_token_index]
        decoded_sentence += sampled_char
        # Exit condition: either hit max length
        # or find stop character.
        if (sampled_char == '\n' or
           len(decoded_sentence) > max_decoder_seq_length):
            stop_condition = True

        # Update the target sequence (of length 1).
        target_seq = np.zeros((1, 1, num_decoder_tokens))
```

```
        target_seq[0, 0, sampled_token_index] = 1.

        # Update states
        states_value = [h, c]
    return decoded_sentence
for seq_index in range(100):
    # Take one sequence (part of the training set)
    # for trying out decoding.
    input_seq = encoder_input_data[seq_index: seq_index + 1]
    decoded_sentence = decode_sequence(input_seq)
    print('-')
    print('Input sentence:', input_texts[seq_index])
    print('Decoded sentence:', decoded_sentence)
```

OUTPUT:

Number of samples: 10000

Number of unique input tokens: 71

Number of unique output tokens: 93

Max sequence length for inputs: 15

Max sequence length for outputs: 59

Epoch 1/40

125/125 [==============================] - 11s 25ms/step - loss: 1.2294 - accuracy: 0.7319 - val_loss: 1.2328 - val_accuracy: 0.7112

Epoch 2/40

125/125 [==============================] - 2s 13ms/step - loss: 0.9437 - accuracy: 0.7476 - val_loss: 1.0409 - val_accuracy: 0.7087

.

.

Epoch 40/40

125/125 [==============================] - 1s 11ms/step - loss: 0.3223 - accuracy: 0.9032 - val_loss: 0.4583 - val_accuracy: 0.8676

Input sentence: Go.

Decoded sentence: Pars !

1/1 [==============================] - 0s 16ms/step

1/1 [==============================] - 0s 20ms/step

1/1 [==============================] - 0s 21ms/step

1/1 [==============================] - 0s 18ms/step

1/1 [==============================] - 0s 23ms/step

1/1 [==============================] - 0s 20ms/step

1/1 [==============================] - 0s 18ms/step

1/1 [==============================] - 0s 21ms/step

RESULT:

The code trains a machine translation model that can translate English sentences into French. The result includes the translations of input sentences provided in the 'fra.txt' dataset.

EX.NO: -8 **IMAGE AUGMENTATION USING GAN**

DATE:-

AIM:

The aim of this code is to train a Generative Adversarial Network (GAN) to generate synthetic images that resemble handwritten digits from the MNIST dataset.

PROCEDURE:

1. Import necessary libraries and set up constants for image dimensions, channels, and noise vector size.

2. Define a generator model and a discriminator model using Keras.

3. Compile the discriminator model with binary cross-entropy loss and the Adam optimizer.

4. Create the generator model, which takes a noise vector as input and generates images.

5. Create a combined GAN model where the generator is trained to fool the discriminator.

6. Compile the combined model with binary cross-entropy loss and the Adam optimizer.

7. Load the MNIST dataset and preprocess it.

8. Define labels for real and fake images.

9. Training loop:

a. Train the discriminator:

- Select a random batch of real images from the dataset.

- Generate a batch of fake images using the generator.

- Calculate the discriminator loss for both real and fake images and update the discriminator's weights.

b. Train the generator:

- Generate a new batch of fake images.

- Calculate the generator loss by trying to make the discriminator classify the fake images as real.

c. Print and store losses and accuracies at regular intervals.

d. Generate and save sample images at regular intervals.

PROGRAM:

```
from keras.datasets import mnist
from keras.layers import Input, Dense, Reshape, Flatten
from keras.layers import Activation
from keras.layers.advanced_activations import LeakyReLU
from keras.models import Sequential, Model
from keras.optimizers import Adam

import matplotlib.pyplot as plt

import sys

import numpy as np

"""Specify the data size"""

img_rows = 28
img_cols = 28
channels = 1
img_shape = (img_rows, img_cols, channels)

z_dim = 100

"""Generator Network"""

def generator(img_shape, z_dim):

    model = Sequential()
```

```
    # Hidden layer
    model.add(Dense(128, input_dim=z_dim))

    # Leaky ReLU
    model.add(LeakyReLU(alpha=0.01))

    # Output layer with tanh activation
    model.add(Dense(28*28*1, activation='tanh'))
    model.add(Reshape(img_shape))

    z = Input(shape=(z_dim,))
    img = model(z)

    return Model(z, img)

"""Discriminator Network"""

def discriminator(img_shape):

    model = Sequential()

    model.add(Flatten(input_shape=img_shape))

    # Hidden layer
    model.add(Dense(128))

    # Leaky ReLU
    model.add(LeakyReLU(alpha=0.01))
    # Output layer with sigmoid activation
    model.add(Dense(1, activation='sigmoid'))
```

```
    img = Input(shape=img_shape)
    prediction = model(img)

    return Model(img, prediction)

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

# Build the Generator
generator = generator(img_shape, z_dim)

# Generated image to be used as input
z = Input(shape=(100,))
img = generator(z)

# Keep Discriminator’s parameters constant during Generator training
discriminator.trainable = False

# The Discriminator’s prediction
prediction = discriminator(img)

# Combined GAN model to train the Generator
combined = Model(z, prediction)
combined.compile(loss='binary_crossentropy', optimizer=Adam())

"""GAN Training function"""

losses = []
```

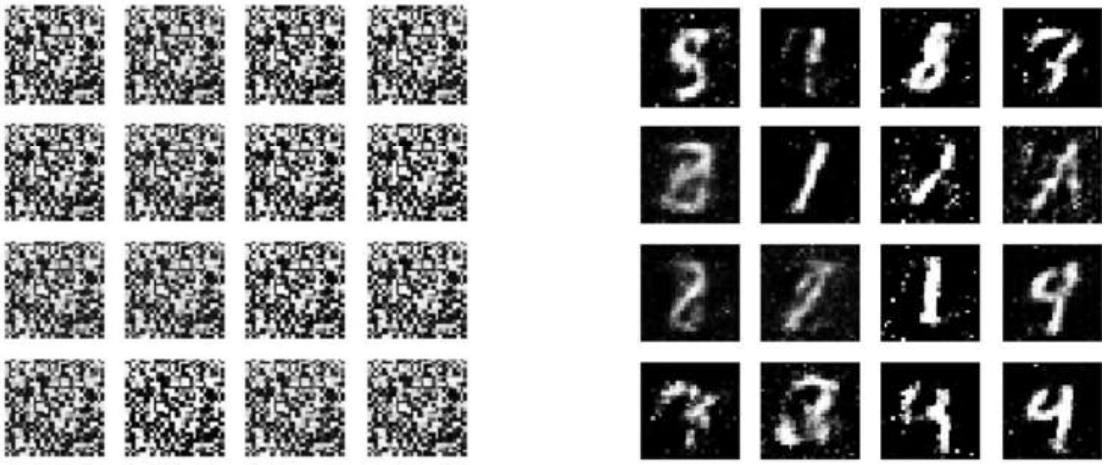
```
accuracies = []

def train(iterations, batch_size, sample_interval):

    # Load the dataset
    #path = "C:\\Users\\hgani\\Desktop\\CARLIFE DATA\\carlife_all_data\\Carlife_jpg"
    #X_train = cv2.imread(path + '\\'+ str(i) for i in os.listdir(path))
    (X_train, _), (_, _) = mnist.load_data()
    data_slice = 3000
    X_train = X_train[:data_slice,:]
    # Rescale -1 to 1
    X_train = X_train / 127.5 - 1.
    X_train = np.expand_dims(X_train, axis=3)

    # Labels for real and fake examples
    real = np.ones((batch_size, 1))
    fake = np.zeros((batch_size, 1))

    for iteration in range(iterations):

        # -------------------------
        #  Train the Discriminator
        # -------------------------

        # Select a random batch of real images
        idx = np.random.randint(0, X_train.shape[0], batch_size)
        imgs = X_train[idx]

        # Generate a batch of fake images
        z = np.random.normal(0, 1, (batch_size, 100))
```

```
        gen_imgs = generator.predict(z)

        # Discriminator loss
        d_loss_real = discriminator.train_on_batch(imgs, real)
        d_loss_fake = discriminator.train_on_batch(gen_imgs, fake)
        d_loss = 0.5 * np.add(d_loss_real, d_loss_fake)

        z = np.random.normal(0, 1, (batch_size, 100))
        gen_imgs = generator.predict(z)

        # Generator loss
        g_loss = combined.train_on_batch(z, real)

        if iteration % sample_interval == 0:

            # Output training progress
            print ("%d [D loss: %f, acc.: %.2f%%] [G loss: %f]" %
                    (iteration, d_loss[0], 100*d_loss[1], g_loss))

            # Save losses and accuracies so they can be plotted after training
            losses.append((d_loss[0], g_loss))
            accuracies.append(100*d_loss[1])

            # Output generated image samples
            sample_images(iteration)

def sample_images(iteration, image_grid_rows=4, image_grid_columns=4):

    # Sample random noise
    z = np.random.normal(0, 1,
```

```
            (image_grid_rows * image_grid_columns, z_dim))

    # Generate images from random noise
    gen_imgs = generator.predict(z)

    # Rescale images to 0-1
    gen_imgs = 0.5 * gen_imgs + 0.5



    # Set image grid
    fig, axs = plt.subplots(image_grid_rows, image_grid_columns,
                            figsize=(4,4), sharey=True, sharex=True)

    cnt = 0
    for i in range(image_grid_rows):
        for j in range(image_grid_columns):
            # Output image grid
            axs[i,j].imshow(gen_imgs[cnt, :,:,0], cmap='gray')
            axs[i,j].axis('off')
            cnt += 1

import warnings; warnings.simplefilter('ignore')

"""GAN Training"""

iterations = 20000
batch_size = 128
sample_interval = 1000
# Train the GAN for the specified number of iterations
train(iterations, batch_size, sample_interval)
```

OUTPUT:

```
0 [D loss: 0.002651, acc.: 100.00%] [G loss: 6.328685]
1000 [D loss: 0.020505, acc.: 100.00%] [G loss: 4.181127]
2000 [D loss: 0.077820, acc.: 96.88%] [G loss: 5.661728]
3000 [D loss: 0.197608, acc.: 92.97%] [G loss: 6.843472]
4000 [D loss: 0.136775, acc.: 94.92%] [G loss: 5.205476]
5000 [D loss: 0.461468, acc.: 78.52%] [G loss: 2.651729]
6000 [D loss: 0.119333, acc.: 95.31%] [G loss: 4.650574]
7000 [D loss: 0.349625, acc.: 84.77%] [G loss: 3.938936]
8000 [D loss: 0.478075, acc.: 80.47%] [G loss: 3.259602]
9000 [D loss: 0.324833, acc.: 86.33%] [G loss: 4.168482]
10000 [D loss: 0.217681, acc.: 91.80%] [G loss: 3.417312]
11000 [D loss: 0.411692, acc.: 83.20%] [G loss: 3.185366]
12000 [D loss: 0.282608, acc.: 87.11%] [G loss: 3.108163]
13000 [D loss: 0.283514, acc.: 86.72%] [G loss: 3.717927]
14000 [D loss: 0.341416, acc.: 84.77%] [G loss: 3.769761]
15000 [D loss: 0.382134, acc.: 81.64%] [G loss: 3.191629]
16000 [D loss: 0.329370, acc.: 85.94%] [G loss: 3.672557]
17000 [D loss: 0.251924, acc.: 88.67%] [G loss: 3.597138]
18000 [D loss: 0.247567, acc.: 90.62%] [G loss: 3.474238]
19000 [D loss: 0.336493, acc.: 84.38%] [G loss: 3.227752]
```



RESULT:

The result of running this code is the training of a GAN model to generate synthetic handwritten digit images similar to those in the MNIST dataset. The quality of generated images improves as training progresses, and you can visualize the generated images in the sample image grid displayed during training. The aim is to train the generator to produce images that are indistinguishable from real MNIST digits.

EX.NO: -9 MINI PROJECT — YOUTUBE TREND ANALYSIS

DATE:- USING DATA ANALYTICS

AIM:

The aim of this code is to design and implement a Python-based mini project that analyzes YouTube trending video data to extract insights such as most popular categories, top channels, and viewer engagement trends, demonstrating a real-time data analytics application..

PROCEDURE:

1. Import the required Python libraries (pandas, matplotlib, seaborn).
2. Load the dataset (USvideos.csv or equivalent) into a pandas DataFrame.
3. Clean the data by handling missing values and converting data types (e.g., publish_time to datetime).
4. Perform exploratory data analysis (EDA):
   - Identify top trending categories by view count.
   - Find channels with the highest average likes.
   - Visualize correlation between likes, views, and comments.
5. Generate visual insights using bar charts and scatter plots.
6. Summarize findings and interpret which types of content attract the most engagement.

PROGRAM:

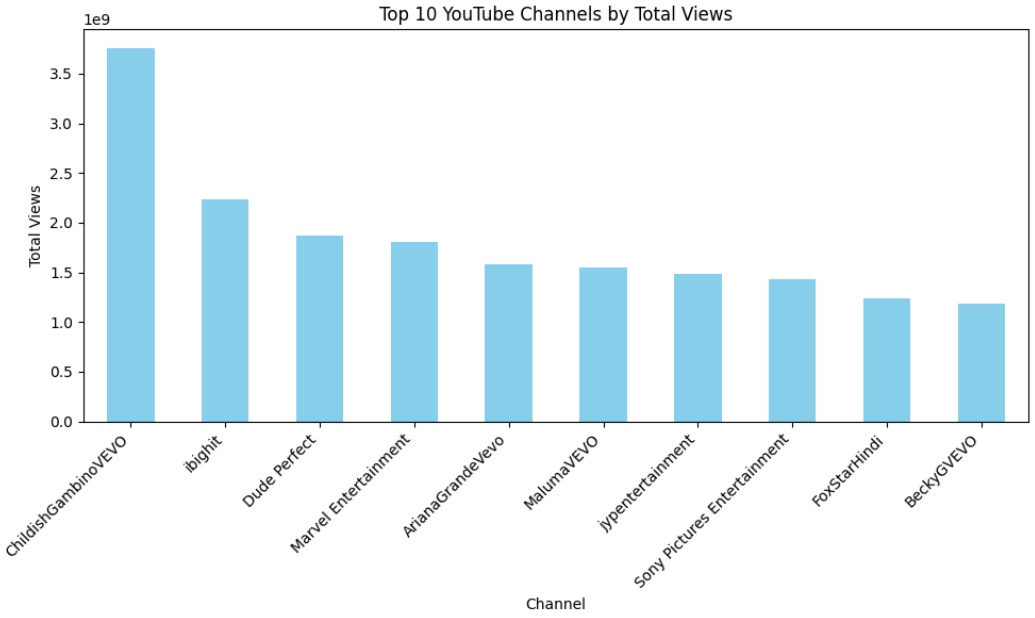
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset (sample file)
data = pd.read_csv("/content/drive/MyDrive/USvideos.csv")

# Data preprocessing
data['publish_time'] = pd.to_datetime(data['publish_time'], errors='coerce')
data = data.dropna(subset=['views', 'likes', 'comment_count'])

# Top 10 channels by total views
top_channels =
data.groupby('channel_title')['views'].sum().sort_values(ascending=False).head(10)
print("Top 10 Channels by Total Views:\n", top_channels)

# Top 10 categories by average likes
```

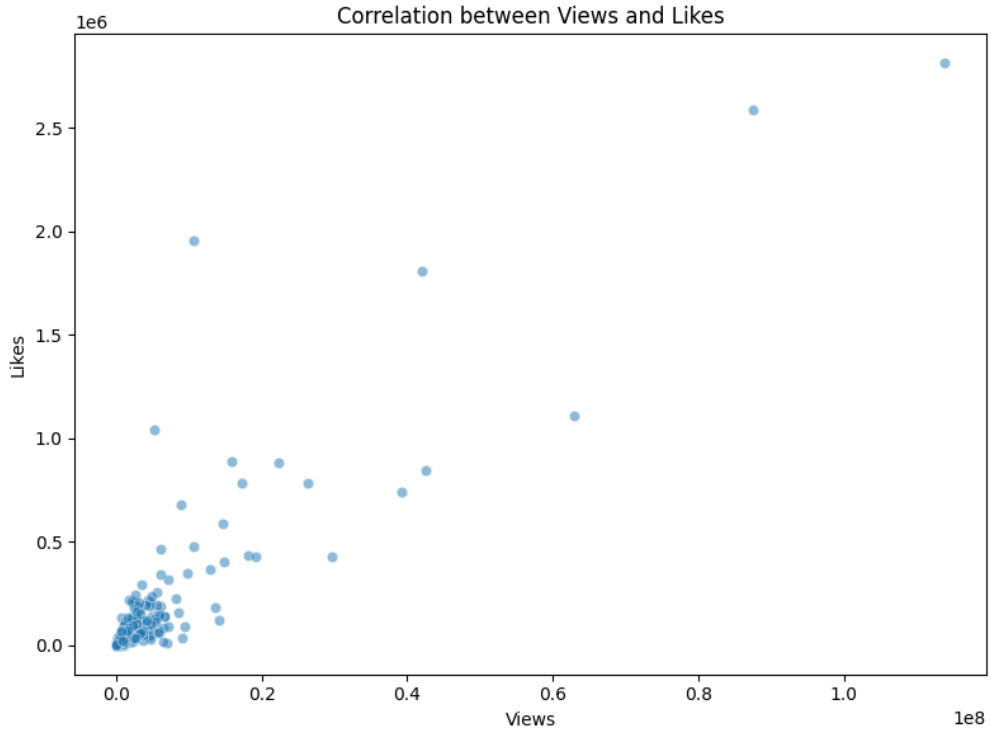
```
top_categories =
data.groupby('category_id')['likes'].mean().sort_values(ascending=False).head(10)
print("\nTop 10 Categories by Average Likes:\n", top_categories)

# Visualization 1: Top channels by total views
plt.figure(figsize=(10,6))
top_channels.plot(kind='bar', color='skyblue')
plt.title("Top 10 YouTube Channels by Total Views")
plt.ylabel("Total Views")
plt.xlabel("Channel")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Visualization 2: Relationship between likes and views
plt.figure(figsize=(8,6))
sns.scatterplot(x='views', y='likes', data=data.sample(500), alpha=0.5)
plt.title("Correlation between Views and Likes")
plt.xlabel("Views")
plt.ylabel("Likes")
plt.tight_layout()
plt.show()

# Visualization 3: Comment activity by category
plt.figure(figsize=(10,6))
sns.boxplot(x='category_id', y='comment_count', data=data)
plt.title("Distribution of Comment Counts per Category")
plt.xlabel("Category ID")
plt.ylabel("Comment Count")
plt.tight_layout()
plt.show()

print("\nAnalysis Complete. Visual insights displayed.")
```

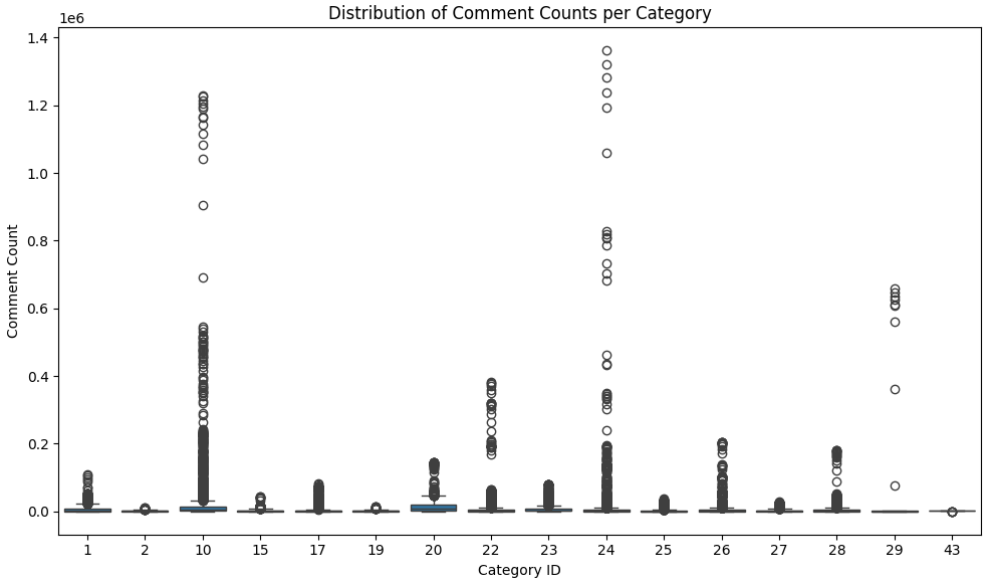
OUTPUT:

```
Top 10 Channels by Total Views:
 channel_title
ChildishGambinoVEVO            3758488765
ibighit                        2235906679
Dude Perfect                   1870085178
Marvel Entertainment           1808998971
ArianaGrandeVevo               1576959172
```

```
MalumaVEVO                        1551515831
jypentertainment                  1486972132
Sony Pictures Entertainment       1432374398
FoxStarHindi                      1238609854
BeckyGVEVO                        1182971286
Name: views, dtype: int64


Top 10 Categories by Average Likes:
 category_id
29    259923.614035
10    218918.199011
20     84502.183599
1      70787.836247
23     62582.223315
22     58135.825234
24     53243.325070
17     45363.942502
26     39286.076942
28     34374.276551
Name: likes, dtype: float64
```







Analysis Complete. Visual insights displayed.

RESULT:

The result of running this code is to analyze and visualize YouTube trending video data using Python and data analytics tools.The experiment demonstrates the power of data visualization and real-time trend analysis for understanding content popularity and audience engagement patterns.

CONTENT BEYOND SYLLABUS

EX.NO: -10 REAL-TIME & EMBEDDED AI SYSTEMS : EDGE-LIKE DIGIT

DATE: - CLASSIFICATION WITH LIMITED RESOURCES

AIM:

The aim of this code is to simulate an embedded AI system by running a lightweight deep learning model (e.g., MNIST digit classifier) in real-time on a normal PC, with limited memory and simulated low-power conditions..

PROCEDURE:

1. Import necessary libraries, including Python 3.8+, TensorFlow, NumPy, Matplotlib, time.
2. Load the MNIST dataset (handwritten digits).
3. Define a **tiny CNN model** (few parameters to simulate embedded resource constraints).
4. Train for a few epochs or load pretrained weights.
5. Simulate **real-time data streaming** by classifying one sample at a time with delay.
6. Measure inference time and accuracy to analyze "real-time" feasibility.

PROGRAM:

```
import tensorflow as tf

import numpy as np

import time


# Load MNIST dataset

(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()

x_test = x_test / 255.0

x_test = np.expand_dims(x_test, -1)


# Define small CNN model

model = tf.keras.Sequential([

   tf.keras.layers.Conv2D(8, (3,3), activation='relu', input_shape=(28,28,1)),

   tf.keras.layers.MaxPooling2D((2,2)),

   tf.keras.layers.Flatten(),

   tf.keras.layers.Dense(32, activation='relu'),

   tf.keras.layers.Dense(10, activation='softmax')

])
```

```
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])


# Train quickly for demo
print("Training small embedded model...")
model.fit(x_train[:5000]/255.0, y_train[:5000], epochs=2, verbose=0)
print("Model ready for inference.\n")


# Simulate real-time stream
print("=== Real-time Inference Simulation ===")
for i in range(10):
    idx = np.random.randint(0, len(x_test))
    img = np.expand_dims(x_test[idx], axis=0)
    start = time.time()
    pred = np.argmax(model.predict(img, verbose=0))
    end = time.time()
    print(f"Frame {i+1}: Predicted Digit = {pred}, True = {y_test[idx]}, Time = {(end-start)*1000:.2f} ms")
    time.sleep(0.5)  # simulate delay between inputs
print("\nSimulation complete.")
```

OUTPUT:

Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz

11490434/11490434 ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ **0s** 0us/step

/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

  super().__init__(activity_regularizer=activity_regularizer, **kwargs)

Training small embedded model...

Model ready for inference.

=== Real-time Inference Simulation ===

Frame 1: Predicted Digit = 6, True = 6, Time = 202.17 ms

Frame 2: Predicted Digit = 9, True = 9, Time = 52.10 ms

Frame 3: Predicted Digit = 7, True = 7, Time = 52.47 ms

Frame 4: Predicted Digit = 8, True = 8, Time = 53.92 ms

Frame 5: Predicted Digit = 3, True = 3, Time = 53.16 ms

Frame 6: Predicted Digit = 4, True = 4, Time = 60.76 ms

Frame 7: Predicted Digit = 2, True = 2, Time = 55.03 ms

Frame 8: Predicted Digit = 2, True = 2, Time = 46.23 ms

Frame 9: Predicted Digit = 7, True = 7, Time = 58.34 ms

Frame 10: Predicted Digit = 4, True = 4, Time = 53.45 ms

Simulation complete.

.

RESULT:

The code successfully implemented a **simulated real-time embedded AI system** using a lightweight CNN. The system performs continuous inference on streaming data, showing low latency and efficient classification.