Experiment No. 7
Design and implement LSTM model for handwriting recognition
Date of Performance: 26/09/23
Date of Submission: 10/10/23

Aim: Design and implement LSTM model for handwriting recognition.

Objective: Ability to design a LSTM network to solve the given problem.

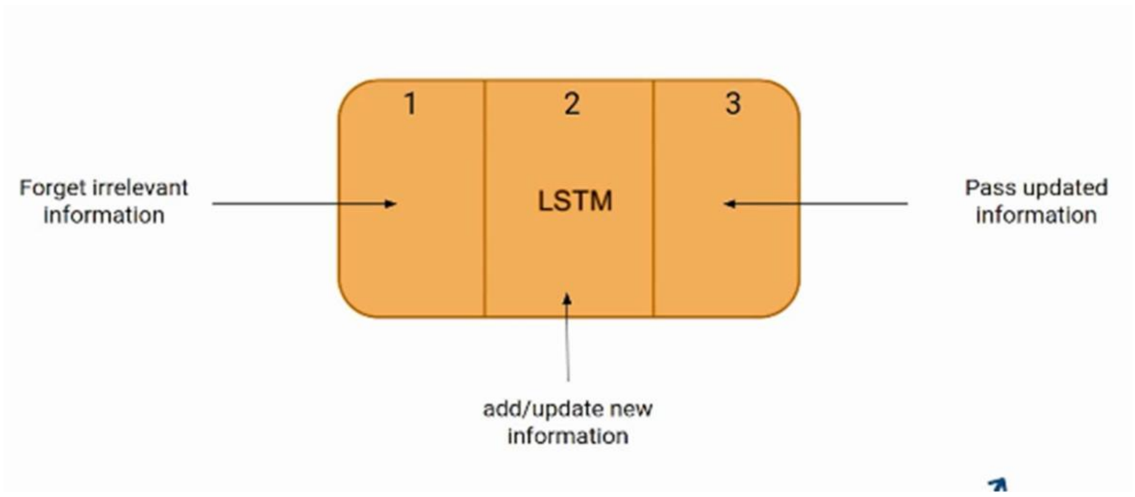
Theory:

LSTM (Long Short-Term Memory) is a recurrent neural network (RNN) architecture widely used in Deep Learning. It excels at capturing long-term dependencies, making it ideal for sequence prediction tasks.

Unlike traditional neural networks, LSTM incorporates feedback connections, allowing it to process entire sequences of data, not just individual data points. This makes it highly effective in understanding and predicting patterns in sequential data like time series, text, and speech.

LSTM Architecture

In the introduction to long short-term memory, we learned that it resolves the vanishing gradient problem faced by RNN, so now, in this section, we will see how it resolves this problem by learning the architecture of the LSTM. At a high level, LSTM works very much like an RNN cell. Here is the internal functioning of the LSTM network. The LSTM network architecture consists of three parts, as shown in the image below, and each part performs an individual function.



The Logic Behind LSTM

The first part chooses whether the information coming from the previous timestamp is to be remembered or is irrelevant and can be forgotten. In the second part, the cell tries to learn new information from the input to this cell. At last, in the third part, the cell passes the updated information from the current timestamp to the next timestamp. This one cycle of LSTM is considered a single-time step.

These three parts of an LSTM unit are known as gates. They control the flow of information in and out of the memory cell or lstm cell. The first gate is called Forget gate, the second gate is known as the Input gate, and the last one is the Output gate. An LSTM unit that consists of these three gates and a memory cell or lstm cell can be considered as a layer of neurons in traditional feedforward neural network, with each neuron having a hidden layer and a current state.

Code:

```
import os import cv2 import random import
numpy as np import pandas as pd import
matplotlib.pyplot as plt
 import tensorflow as tf from keras import backend as K from keras.models import Model
from tensorflow.keras.callbacks import ModelCheckpoint from keras.layers import Input,
Conv2D, MaxPooling2D, Reshape,
Bidirectional, LSTM, Dense, Lambda, Activation, BatchNormalization, Dropout from
keras.optimizers import Adam
 train =
pd.read_csv('/kaggle/input/handwritingrecognition/written_name_trai
n_v2.csv') valid =
pd.read_csv('/kaggle/input/handwritingrecognition/written_name_val
idation_v2.csv') train
plt.figure(figsize=(15, 10))
 for i in range(9):
```

```
    ax = plt.subplot(3,3,i+1)     img_dir = 
'/kaggle/input/handwritingrecognition/train_v2/train/'+train.loc[i, 
'FILENAME']     image = cv2.imread(img_dir, cv2.IMREAD_GRAYSCALE) 
plt.imshow(image, cmap = 'gray')     plt.title(train.loc[i, 'IDENTITY'], 
fontsize=12)     plt.axis('off')

plt.subplots_adjust(wspace=0.2, hspace=-0.8) print("Number of 
NaNs in train set      : ", train['IDENTITY'].isnull().sum()) 
print("Number of NaNs in validation set : ", 
valid['IDENTITY'].isnull().sum())
 print("Number of NaNs in train set      : ", 
train['IDENTITY'].isnull().sum()) print("Number of NaNs in 
validation set : ", valid['IDENTITY'].isnull().sum())
 train.dropna(axis=0, inplace=True)#axis =0, removing rows otherwisw axis =1. removing 
columns valid.dropna(axis=0, inplace=True) #true means dropping
 unreadable = train[train['IDENTITY'] == 'UNREADABLE'] 
unreadable.reset_index(inplace = True, drop=True)
 plt.figure(figsize=(15, 10))
 for i in range(9):
    ax = plt.subplot(3, 3, i+1)     img_dir = 
'/kaggle/input/handwritingrecognition/train_v2/train/'+unreadable.loc[i, 
'FILENAME']     image = cv2.imread(img_dir, cv2.IMREAD_GRAYSCALE) 
plt.imshow(image, cmap = 'gray')     plt.title(unreadable.loc[i, 'IDENTITY'], 
fontsize=12)     plt.axis('off')
 plt.subplots_adjust(wspace=0.2, hspace=-0.8)
 train = train[train['IDENTITY'] != 'UNREADABLE'] valid = 
valid[valid['IDENTITY'] != 'UNREADABLE'] valid 
train['IDENTITY'] = train['IDENTITY'].str.upper()
```

```
valid['IDENTITY'] = valid['IDENTITY'].str.upper()
 train.reset_index(inplace = True, drop=True)
valid.reset_index(inplace = True, drop=True)
 def preprocess(img):
    (h, w) = img.shape

    final_img = np.ones([64, 256])*255 # black white image
        # crop     if w >
256:
        img = img[:, :256]
            if h > 64:
        img = img[:64, :]
            final_img[:h, :w] = img     return cv2.rotate(final_img,
cv2.ROTATE_90_CLOCKWISE)
 train_size = 30000
valid_size= 3000
 train_x = []
 for i in range(train_size):
    img_dir = '/kaggle/input/handwritingrecognition/train_v2/train/'+train.loc[i,
'FILENAME']     image = cv2.imread(img_dir, cv2.IMREAD_GRAYSCALE)
image = preprocess(image)     image = image/255     train_x.append(image)

valid_x = []
 for i in range(valid_size):
    img_dir = '/kaggle/input/handwriting-
recognition/validation_v2/validation/'+valid.loc[i, 'FILENAME']     image =
cv2.imread(img_dir, cv2.IMREAD_GRAYSCALE)     image = preprocess(image)     image
= image/255     valid_x.append(image)
```

```
train_x = np.array(train_x).reshape(-1, 256, 64, 1)#array will get reshaped in such a way that the
resulting array has only 1 column valid_x = np.array(valid_x).reshape(-1, 256, 64, 1) #(16384,1)
```

```
alphabets = u"!\"#&'()*+,-
./0123456789:;?ABCDEFGHIJKLMNOPQRSTUVWXYZabcdefghijklmnopqrstuvwxyz "
max_str_len = 24 # max length of input labels num_of_characters = len(alphabets) + 1 # +1 for ctc
pseudo blank(epsilon)
num_of_timestamps = 64 # max length of predicted labels


def label_to_num(label):
   label_num = []     for ch in
label:
       label_num.append(alphabets.find(ch))
       #find() method returns the lowest index of the substring if it is found in given string otherwise -1
           return np.array(label_num)
 def num_to_label(num):
   ret = ""     for ch in num:        if ch == -1:  #
CTC Blank             break        else:
ret+=alphabets[ch]     return ret
```

```
name = 'JEBASTIN'
print(name, '\n',label_to_num(name))
```

```
train_y = np.ones([train_size, max_str_len]) * -1 train_label_len = np.zeros([train_size, 1])
train_input_len = np.ones([train_size, 1]) * (num_of_timestamps-2) train_output = np.zeros([train_size])
 for i in range(train_size):
   train_label_len[i] = len(train.loc[i, 'IDENTITY'])



   train_y[i, 0:len(train.loc[i, 'IDENTITY'])]=
label_to_num(train.loc[i, 'IDENTITY'])
```

```
valid_y = np.ones([valid_size, max_str_len]) * -1 valid_label_len = np.zeros([valid_size, 1])
valid_input_len = np.ones([valid_size, 1]) * (num_of_timestamps-2) valid_output =
np.zeros([valid_size])
 for i in range(valid_size):
    valid_label_len[i] = len(valid.loc[i, 'IDENTITY'])     valid_y[i, 0:len(valid.loc[i,
'IDENTITY'])]= label_to_num(valid.loc[i, 'IDENTITY'])
```

```
print('True label : ',train.loc[100, 'IDENTITY'] , '\ntrain_y :
',train_y[100],'\ntrain_label_len : ',train_label_len[100],
     '\ntrain_input_len : ', train_input_len[100])
```

```
input_data = Input(shape=(256, 64, 1), name='input')
 inner = Conv2D(32, (3, 3), padding='same', name='conv1',
kernel_initializer='he_normal')(input_data)   inner = BatchNormalization()(inner)
inner = Activation('relu')(inner) inner = MaxPooling2D(pool_size=(2, 2),
name='max1')(inner)

inner = Conv2D(64, (3, 3), padding='same', name='conv2',
kernel_initializer='he_normal')(inner) inner = BatchNormalization()(inner) inner =
Activation('relu')(inner) inner = MaxPooling2D(pool_size=(2, 2),
name='max2')(inner) inner = Dropout(0.3)(inner)

inner = Conv2D(128, (3, 3), padding='same', name='conv3',
kernel_initializer='he_normal')(inner) inner = BatchNormalization()(inner) inner =
Activation('relu')(inner) inner = MaxPooling2D(pool_size=(1, 2),
name='max3')(inner) inner = Dropout(0.3)(inner)

# CNN to RNN inner = Reshape(target_shape=((64, 1024)), name='reshape')(inner)
```

```
inner = Dense(64, activation='relu', kernel_initializer='he_normal',
name='dense1')(inner)
 ## RNN inner = Bidirectional(LSTM(256, return_sequences=True), name =
'lstm1')(inner) inner = Bidirectional(LSTM(256, return_sequences=True), name =
'lstm2')(inner)

## OUTPUT inner = Dense(num_of_characters,
kernel_initializer='he_normal',name='dense2')(inner) y_pred =
Activation('softmax', name='softmax')(inner)
 model = Model(inputs=input_data, outputs=y_pred)
model.summary()
```

```
# the ctc loss function def
ctc_lambda_func(args):
    y_pred, labels, input_length, label_length = args
    # the 2 is critical here since the first couple outputs of the RNN
    # tend to be garbage      y_pred = y_pred[:, 2:, :]      return K.ctc_batch_cost(labels, y_pred,
input_length, label_length)
```

```
labels = Input(name='gtruth_labels', shape=[max_str_len], dtype='float32') input_length =
Input(name='input_length', shape=[1], dtype='int64') label_length = Input(name='label_length',
shape=[1], dtype='int64')

ctc_loss = Lambda(ctc_lambda_func, output_shape=(1,), name='ctc')([y_pred, labels, input_length,
label_length]) model_final = Model(inputs=[input_data, labels, input_length, label_length],
outputs=ctc_loss)
```

```
# the loss calculation occurs elsewhere, so we use a dummy lambda function for the loss
file_path_best = "C_LSTM_best.hdf5"
 model_final.compile(loss={'ctc': lambda y_true, y_pred: y_pred}, optimizer=Adam(lr =
0.0001))
```

```
checkpoint = ModelCheckpoint(filepath=file_path_best,
monitor='val_loss',                          verbose=1,
save_best_only=True,                           mode='min')
 callbacks_list = [checkpoint]
```

```
history = model_final.fit(x=[train_x, train_y, train_input_len, train_label_len],
y=train_output,validation_data=([valid_x, valid_y, valid_input_len, valid_label_len],
valid_output),callbacks=callbacks_list,verbose=1,epochs=60, batch_size=128,shuffle=True)
```

```
plt.plot(history.history['loss']) plt.plot(history.history['val_loss'])
plt.title('model loss') plt.ylabel('loss') plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left') plt.show()
```

```
model.load_weights('/kaggle/working/C_LSTM_best.hdf5')
```

```
preds = model.predict(valid_x)
decoded = K.get_value(K.ctc_decode(preds,
input_length=np.ones(preds.shape[0])*preds.shape[1],                          greedy=True)[0][0])

prediction = [] for i in
range(valid_size):
    prediction.append(num_to_label(decoded[i]))
```

```
y_true = valid.loc[0:valid_size, 'IDENTITY'] correct_char = 0
total_char = 0 correct = 0
```

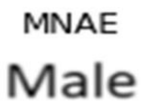
```
 for i in range(valid_size):
    pr = prediction[i]      tr = y_true[i]
total_char += len(tr)
        for j in range(min(len(tr), len(pr))):
       if tr[j] == pr[j]:            correct_char += 1
              if pr == tr :
       correct += 1
    print('Correct characters predicted : %.2f%%'
%(correct_char*100/total_char)) print('Correct words predicted      :
%.2f%%'
%(correct*100/valid_size))
```

```
test = pd.read_csv('/kaggle/input/handwritingrecognition/written_name_validation_v2.csv')
 plt.figure(figsize=(15, 10)) for i in
range(16):
    ax = plt.subplot(4, 4, i+1)     img_dir =
'/kaggle/input/handwritingrecognition/validation_v2/validation/'+test.loc[i, 'FILENAME']
image = cv2.imread(img_dir, cv2.IMREAD_GRAYSCALE)     plt.imshow(image,
cmap='gray')

    image = preprocess(image)     image =
image/255.
    pred = model.predict(image.reshape(1, 256, 64, 1))     decoded =
K.get_value(K.ctc_decode(pred, input_length=np.ones(pred.shape[0])*pred.shape[1],
greedy=True)[0][0])     plt.title(num_to_label(decoded[0]), fontsize=12)     plt.axis('off')
     plt.subplots_adjust(wspace=0.2, hspace=-0.8)
```

```
plt.figure(figsize=(1, 1)) for i in range(1):
    ax = plt.subplot(1, 1, i+1)     img_dir = "/kaggle/input/test123/tr.PNG"
image = cv2.imread(img_dir, cv2.IMREAD_GRAYSCALE)
plt.imshow(image, cmap='gray')
        image = preprocess(image)     image = image/255     pred =
model.predict(image.reshape(1, 256, 64, 1))     decoded =
K.get_value(K.ctc_decode(pred, input_length=np.ones(pred.shape[0])*pred.shape[1],
greedy=True)[0][0])     plt.title(num_to_label(decoded[0]), fontsize=12)
plt.axis('off')
```

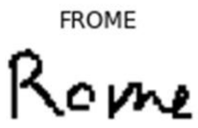
Output:



```
plt.figure(figsize=(3, 1)) for i in range(1):
    ax = plt.subplot(1, 1, i+1)     img_dir =
"/kaggle/input/test234567575/test2.PNG"     image = cv2.imread(img_dir,
cv2.IMREAD_GRAYSCALE)     plt.imshow(image, cmap='gray')

    image = preprocess(image)     image = image/255     pred =
model.predict(image.reshape(1, 256, 64, 1))     decoded =
K.get_value(K.ctc_decode(pred, input_length=np.ones(pred.shape[0])*pred.shape[1],
greedy=True)[0][0])     plt.title(num_to_label(decoded[0]), fontsize=12)
plt.axis('off')
```

Output:



Conclusion:

Designing and implementing an LSTM (Long Short-Term Memory) model for handwriting recognition involves creating a recurrent neural network that can effectively capture sequential information from handwritten data. The architecture typically consists of input layers to process the image data, LSTM layers to analyze the sequential information in the handwriting, and output layers for character or word recognition. The LSTM cells are crucial for maintaining context and handling variable-length sequences. The model is trained on a dataset of handwritten samples, often preprocessed using techniques like image normalization and feature extraction. The results of this approach often yield impressive accuracy in recognizing handwritten characters or words, making it a valuable tool for applications such as digit recognition, signature verification, and text transcription. The performance may vary based on the dataset and the complexity of the handwriting styles, but LSTM models have proven to be effective in this domain.