Experiment No. 7

Design and implement LSTM model for handwriting recognition

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Aim: Design and implement LSTM model for handwriting recognition.

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

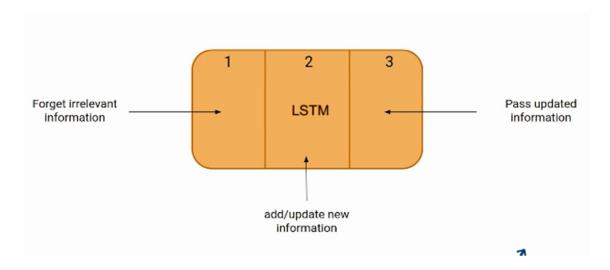
Theory:

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/handwriting-
recognition/written name train v2.csv')
valid = pd.read csv('/kaggle/input/handwriting-
recognition/written name validation v2.csv')
train
plt.figure(figsize=(15, 10))
for i in range(9):
```



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```
ax = plt.subplot(3,3,i+1)
    img dir = '/kaggle/input/handwriting-
recognition/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/handwriting-
recognition/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()
```



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```
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/handwriting-
recognition/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'])
```



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```
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))
```



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```
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')
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/handwriting-
recognition/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/handwriting-
recognition/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):
```



Output:

MNAE

Male

Output:

FROME





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.