Multi_model_Spoken_and_written_numbers_comparison

May 20, 2019

Recognize whether an image of a hand- written digit and a recording of a spoken digit refer to the same or different number

```
[1]: #Libraries Import
   import numpy as np
   from keras.models import Model
   from keras import layers
   from keras import Input
   import matplotlib.pyplot as plt
   from keras.layers import concatenate
   from keras.layers.core import Dense
   from keras.layers.merge import concatenate
   from sklearn.model_selection import train_test_split
   #For model Visulization
    # import os
    # os.environ["PATH"] += os.pathsep + 'C:/Program Files (x86)/Graphviz2.38/bin/'
   max_len_speak_frames=93
   speak_frame_feature=13
   img_height=img_width=28
```

Using TensorFlow backend.

0.0.1 Data Preprocessing:

Speak data consists of variable length, and is given as an array of shape (N, 13), where N is the number of frames in the recording, and 13 the number of MFCC features. First apply padding operation to make it same length sequence, so that vectorization allows code to efficiently perform the matrix operations on the batch. The pad_sequences() function in the Keras deep learning library can be used to pad variable length sequences.

Pad Spoken data shape: (45000, 93, 13)

0.0.2 Model Building:

We choose multi model approach with lstm and Cnn based models used for speak and image respectively. And concatenated the both model output then apply binary cross entropy loss

```
[5]: # a single input layer
   input1 =Input(shape=(max_len_speak_frames, speak_frame_feature))
    # x1 =layers.LSTM(40, activation="relu", dropout=0.25, recurrent_dropout=0.
    \rightarrow25)(input1)
   x1 =layers.CuDNNLSTM(50)(input1)
   x1=layers.BatchNormalization()(x1)
   x1=layers.Activation('relu')(x1)
   x1 =layers.Dropout(0.2)(x1)
   x1 = layers.Dense(256)(x1)
   x1=layers.BatchNormalization()(x1)
   x1=layers.Activation('relu')(x1)
   x1 =layers.Dropout(0.2)(x1)
   x1 =layers.Dense(128, activation="relu")(x1)
   input2 = Input(shape=(img_height,img_width,1))
   x2 =layers.Conv2D(32, kernel_size=(3, 3))(input2)
   x2=layers.BatchNormalization()(x2)
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x2=layers.Activation('relu')(x2)
x2 =layers.Dropout(0.1)(x2)
x2 =layers.Conv2D(64, kernel_size=(3, 3), activation='relu')(x2)
x2=layers.BatchNormalization()(x2)
x2=layers.Activation('relu')(x2)
x2 =layers.MaxPooling2D(pool_size=(2, 2))(x2)
x2 =layers.Dropout(0.25)(x2)
x2 =layers.Flatten()(x2)
x2=layers.BatchNormalization()(x2)
x2 =layers.Dense(128, activation="relu")(x2)
x2 =layers.Dropout(0.5)(x2)
concatenated = layers.concatenate([x1, x2], axis=-1)
# output layer
predictions = Dense(1, activation='sigmoid')(concatenated)
# At model instantiation, we specify the two inputs and the output:
model = Model([input1, input2], predictions)
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])
model.summary()
```

Layer (type)	Output	Shape		Param #	Connected to
				=======	
<pre>input_2 (InputLayer)</pre>	(None,	28, 28,	1)	0	
conv2d_1 (Conv2D)	(None,	26, 26,	32)	320	input_2[0][0]
batch_normalization_3 (BatchNor	(None,	26, 26,	32)	128	conv2d_1[0][0]
activation_3 (Activation)	(None,	26, 26,	32)	0	
<pre>batch_normalization_3[0][0]</pre>					
input_1 (InputLayer)	(None,	93, 13)		0	

dropout_3 (Dropout) activation_3[0][0]	(None, 26, 26, 32)	0	
cu_dnnlstm_1 (CuDNNLSTM)	(None, 50)	13000	input_1[0][0]
conv2d_2 (Conv2D)	(None, 24, 24, 64)		-
batch_normalization_1 (BatchNor cu_dnnlstm_1[0][0]	(None, 50)	200	
batch_normalization_4 (BatchNor		256	conv2d_2[0][0]
activation_1 (Activation) batch_normalization_1[0][0]	(None, 50)	0	
activation_4 (Activation) batch_normalization_4[0][0]	(None, 24, 24, 64)	0	
dropout_1 (Dropout) activation_1[0][0]	(None, 50)	0	
max_pooling2d_1 (MaxPooling2D) activation_4[0][0]	(None, 12, 12, 64)	0	
dense_1 (Dense)	(None, 256)		_
dropout_4 (Dropout) max_pooling2d_1[0][0]	(None, 12, 12, 64)	0	
batch_normalization_2 (BatchNor	(None, 256)	1024	dense_1[0][0]
flatten_1 (Flatten)	(None, 9216)	0	dropout_4[0][0]
			

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activation_2 (Activation) (None, 256)
  batch_normalization_2[0][0]
                                 36864 flatten_1[0][0]
  batch_normalization_5 (BatchNor (None, 9216)
  dropout_2 (Dropout)
                       (None, 256)
  activation_2[0][0]
  ______
  dense_3 (Dense)
                        (None, 128) 1179776
  batch_normalization_5[0][0]
                       (None, 128) 32896
                                             dropout_2[0][0]
  dense_2 (Dense)
  ______
                  (None, 128) 0
                                              dense_3[0][0]
  dropout_5 (Dropout)
  concatenate_1 (Concatenate) (None, 256) 0
                                              dense_2[0][0]
                                              dropout_5[0][0]
  ______
                       (None, 1)
                                      257
  dense_4 (Dense)
  concatenate_1[0][0]
  ______
  ===========
  Total params: 1,296,273
  Trainable params: 1,277,037
  Non-trainable params: 19,236
  _____
[6]: ## For saving model image but required Graphviz software.
  # from keras.utils import plot model
  # plot_model(model, to_file='modelssss.png',show_layer_names=False)
  0.0.3 Model Training:
[7]: | #class_weight=class_weights,
  val_acc=[]
  acc=[]
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loss=[]
val_loss=[]

```
for i in range(20):
       ## to solve class imbalance problem we choose random almost equal length of the control of the c
  →data. different data sample for every for loop iteration.
       new index=np.unique(np.concatenate(((np.random.randint(0,45000,5000).
  →astype('int')),np.where(match_train0>0)[0].astype('int'))))
       # new data sample train test spliting
   →spoken_train,spoken_test,written_train,written_test,match_train,match_test=train_test_split
   →2,random_state=0)
       hist=model.fit([spoken_train,written_train], match_train,_
   ⇒epochs=20,batch size=1024,
   →validation_data=([spoken_test,written_test],match_test))
       # accuracy and loss saving for all epochs.
       acc=acc+hist.history['acc']
       val_acc=val_acc+hist.history['val_acc']
       loss=loss+hist.history['loss']
       val_loss=val_loss+hist.history['val_loss']
Train on 7026 samples, validate on 1757 samples
Epoch 1/20
0.4994 - val_loss: 0.7714 - val_acc: 0.5145
0.5297 - val_loss: 0.7498 - val_acc: 0.4991
Epoch 3/20
0.5517 - val_loss: 0.7385 - val_acc: 0.4991
Epoch 4/20
0.5642 - val_loss: 0.7445 - val_acc: 0.5088
Epoch 5/20
0.5854 - val_loss: 0.7552 - val_acc: 0.4923
Epoch 6/20
0.5914 - val_loss: 0.7397 - val_acc: 0.4986
Epoch 7/20
0.6107 - val_loss: 0.7416 - val_acc: 0.5026
Epoch 8/20
0.6210 - val_loss: 0.7533 - val_acc: 0.4809
Epoch 9/20
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0.6386 - val_loss: 0.7394 - val_acc: 0.4917
Epoch 10/20
0.6354 - val_loss: 0.7354 - val_acc: 0.4935
Epoch 11/20
0.6674 - val_loss: 0.7327 - val_acc: 0.4986
Epoch 12/20
0.6660 - val_loss: 0.7339 - val_acc: 0.4957
Epoch 13/20
0.6820 - val_loss: 0.7324 - val_acc: 0.5043
Epoch 14/20
0.6971 - val_loss: 0.7360 - val_acc: 0.4986
Epoch 15/20
0.7121 - val_loss: 0.7342 - val_acc: 0.5185
Epoch 16/20
0.7293 - val_loss: 0.7363 - val_acc: 0.5310
Epoch 17/20
0.7269 - val_loss: 0.7479 - val_acc: 0.5202
Epoch 18/20
0.7428 - val_loss: 0.7499 - val_acc: 0.5100
Epoch 19/20
0.7508 - val_loss: 0.7534 - val_acc: 0.5213
Epoch 20/20
0.7612 - val_loss: 0.7587 - val_acc: 0.5162
Train on 7041 samples, validate on 1761 samples
Epoch 1/20
0.6249 - val_loss: 0.6371 - val_acc: 0.6445
Epoch 2/20
0.6496 - val_loss: 0.6530 - val_acc: 0.6059
Epoch 3/20
0.6709 - val_loss: 0.6528 - val_acc: 0.6093
Epoch 4/20
0.6810 - val_loss: 0.6603 - val_acc: 0.6110
Epoch 5/20
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0.7177 - val_loss: 0.6682 - val_acc: 0.6104
Epoch 6/20
0.7232 - val_loss: 0.6722 - val_acc: 0.5957
Epoch 7/20
0.7431 - val_loss: 0.6739 - val_acc: 0.6014
Epoch 8/20
0.7503 - val_loss: 0.6800 - val_acc: 0.5980
0.7780 - val_loss: 0.6994 - val_acc: 0.5758
Epoch 10/20
0.7895 - val_loss: 0.7048 - val_acc: 0.5804
Epoch 11/20
0.8013 - val_loss: 0.7455 - val_acc: 0.5616
Epoch 12/20
0.8046 - val_loss: 0.7068 - val_acc: 0.5906
Epoch 13/20
0.8226 - val_loss: 0.6973 - val_acc: 0.5894
Epoch 14/20
0.8318 - val_loss: 0.7108 - val_acc: 0.5735
Epoch 15/20
0.8421 - val_loss: 0.7166 - val_acc: 0.5764
Epoch 16/20
0.8533 - val loss: 0.7205 - val acc: 0.5747
Epoch 17/20
0.8556 - val_loss: 0.7125 - val_acc: 0.5843
Epoch 18/20
0.8695 - val_loss: 0.7369 - val_acc: 0.5849
Epoch 19/20
0.8723 - val_loss: 0.7309 - val_acc: 0.5758
Epoch 20/20
0.8744 - val_loss: 0.7370 - val_acc: 0.5792
Train on 7068 samples, validate on 1767 samples
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Epoch 1/20
0.7088 - val_loss: 0.5376 - val_acc: 0.7487
Epoch 2/20
0.7473 - val_loss: 0.5671 - val_acc: 0.7051
Epoch 3/20
0.7680 - val_loss: 0.5746 - val_acc: 0.7108
Epoch 4/20
0.7915 - val_loss: 0.5792 - val_acc: 0.7006
Epoch 5/20
0.8155 - val_loss: 0.5802 - val_acc: 0.7051
Epoch 6/20
0.8254 - val_loss: 0.5834 - val_acc: 0.7001
Epoch 7/20
0.8420 - val_loss: 0.5789 - val_acc: 0.7097
Epoch 8/20
0.8461 - val_loss: 0.5847 - val_acc: 0.7040
Epoch 9/20
0.8662 - val_loss: 0.5859 - val_acc: 0.7035
Epoch 10/20
0.8796 - val_loss: 0.5897 - val_acc: 0.6910
Epoch 11/20
0.8864 - val_loss: 0.5981 - val_acc: 0.6853
Epoch 12/20
0.8963 - val_loss: 0.6054 - val_acc: 0.6842
Epoch 13/20
0.8988 - val_loss: 0.6071 - val_acc: 0.6797
Epoch 14/20
0.9121 - val_loss: 0.6113 - val_acc: 0.6729
0.9134 - val_loss: 0.6223 - val_acc: 0.6678
Epoch 16/20
0.9196 - val_loss: 0.6257 - val_acc: 0.6780
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Epoch 17/20
0.9277 - val_loss: 0.6278 - val_acc: 0.6786
Epoch 18/20
0.9269 - val_loss: 0.6330 - val_acc: 0.6763
Epoch 19/20
0.9360 - val_loss: 0.6492 - val_acc: 0.6695
Epoch 20/20
0.9397 - val_loss: 0.6721 - val_acc: 0.6587
Train on 7074 samples, validate on 1769 samples
Epoch 1/20
0.7703 - val_loss: 0.4129 - val_acc: 0.8321
Epoch 2/20
0.8058 - val_loss: 0.5092 - val_acc: 0.7795
Epoch 3/20
0.8199 - val_loss: 0.4853 - val_acc: 0.7965
Epoch 4/20
0.8478 - val_loss: 0.4521 - val_acc: 0.8089
Epoch 5/20
0.8615 - val_loss: 0.4487 - val_acc: 0.8151
0.8822 - val_loss: 0.4619 - val_acc: 0.8095
Epoch 7/20
0.8897 - val_loss: 0.4567 - val_acc: 0.8095
Epoch 8/20
0.8982 - val_loss: 0.4443 - val_acc: 0.8129
Epoch 9/20
0.9061 - val_loss: 0.4484 - val_acc: 0.8044
Epoch 10/20
0.9149 - val_loss: 0.4573 - val_acc: 0.7993
Epoch 11/20
0.9266 - val_loss: 0.4569 - val_acc: 0.8016
Epoch 12/20
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0.9278 - val_loss: 0.4599 - val_acc: 0.7959
Epoch 13/20
0.9358 - val_loss: 0.4732 - val_acc: 0.7925
Epoch 14/20
0.9406 - val_loss: 0.4744 - val_acc: 0.7931
Epoch 15/20
0.9408 - val_loss: 0.4809 - val_acc: 0.7920
Epoch 16/20
0.9474 - val_loss: 0.5000 - val_acc: 0.7846
Epoch 17/20
0.9468 - val_loss: 0.5017 - val_acc: 0.7744
Epoch 18/20
0.9505 - val_loss: 0.5233 - val_acc: 0.7620
Epoch 19/20
0.9518 - val_loss: 0.5185 - val_acc: 0.7603
Epoch 20/20
0.9552 - val_loss: 0.5072 - val_acc: 0.7767
Train on 7024 samples, validate on 1756 samples
Epoch 1/20
0.8172 - val_loss: 0.3319 - val_acc: 0.8867
Epoch 2/20
0.8401 - val_loss: 0.3637 - val_acc: 0.8753
Epoch 3/20
0.8675 - val loss: 0.3556 - val acc: 0.8798
Epoch 4/20
0.8800 - val_loss: 0.3735 - val_acc: 0.8571
Epoch 5/20
0.9002 - val_loss: 0.3400 - val_acc: 0.8696
Epoch 6/20
0.9120 - val_loss: 0.3650 - val_acc: 0.8559
Epoch 7/20
0.9204 - val_loss: 0.3521 - val_acc: 0.8713
Epoch 8/20
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0.9280 - val_loss: 0.3566 - val_acc: 0.8622
Epoch 9/20
0.9348 - val_loss: 0.3581 - val_acc: 0.8622
Epoch 10/20
0.9371 - val_loss: 0.3677 - val_acc: 0.8662
Epoch 11/20
0.9378 - val_loss: 0.3751 - val_acc: 0.8554
Epoch 12/20
0.9466 - val_loss: 0.3693 - val_acc: 0.8605
Epoch 13/20
0.9512 - val_loss: 0.3685 - val_acc: 0.8565
Epoch 14/20
0.9563 - val_loss: 0.3825 - val_acc: 0.8571
Epoch 15/20
0.9554 - val_loss: 0.3946 - val_acc: 0.8468
Epoch 16/20
0.9596 - val_loss: 0.3997 - val_acc: 0.8462
Epoch 17/20
0.9620 - val_loss: 0.4097 - val_acc: 0.8400
Epoch 18/20
0.9590 - val_loss: 0.4164 - val_acc: 0.8366
Epoch 19/20
0.9584 - val loss: 0.4210 - val acc: 0.8371
Epoch 20/20
0.9647 - val_loss: 0.4193 - val_acc: 0.8320
Train on 7059 samples, validate on 1765 samples
Epoch 1/20
0.8491 - val_loss: 0.2383 - val_acc: 0.9320
0.8738 - val_loss: 0.2934 - val_acc: 0.8992
Epoch 3/20
0.8882 - val_loss: 0.2794 - val_acc: 0.9229
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Epoch 4/20
0.9061 - val_loss: 0.2753 - val_acc: 0.9156
0.9194 - val_loss: 0.2619 - val_acc: 0.9190
Epoch 6/20
0.9268 - val_loss: 0.2681 - val_acc: 0.9082
Epoch 7/20
0.9259 - val_loss: 0.2755 - val_acc: 0.9003
Epoch 8/20
0.9377 - val_loss: 0.2746 - val_acc: 0.9054
Epoch 9/20
0.9496 - val_loss: 0.2662 - val_acc: 0.9059
Epoch 10/20
0.9457 - val_loss: 0.2772 - val_acc: 0.9093
Epoch 11/20
0.9482 - val_loss: 0.2758 - val_acc: 0.9020
Epoch 12/20
0.9524 - val_loss: 0.2871 - val_acc: 0.9048
Epoch 13/20
0.9625 - val_loss: 0.2972 - val_acc: 0.8969
Epoch 14/20
0.9601 - val_loss: 0.2946 - val_acc: 0.8980
Epoch 15/20
0.9659 - val_loss: 0.2755 - val_acc: 0.9071
Epoch 16/20
0.9620 - val_loss: 0.2840 - val_acc: 0.9059
Epoch 17/20
0.9653 - val_loss: 0.3094 - val_acc: 0.8969
Epoch 18/20
0.9613 - val_loss: 0.3259 - val_acc: 0.8810
Epoch 19/20
0.9639 - val_loss: 0.2973 - val_acc: 0.8935
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Epoch 20/20
0.9724 - val_loss: 0.3002 - val_acc: 0.8912
Train on 7077 samples, validate on 1770 samples
Epoch 1/20
0.8766 - val_loss: 0.2059 - val_acc: 0.9379
Epoch 2/20
0.8973 - val_loss: 0.2552 - val_acc: 0.9203
Epoch 3/20
0.9077 - val_loss: 0.2350 - val_acc: 0.9452
Epoch 4/20
0.9251 - val_loss: 0.2177 - val_acc: 0.9339
Epoch 5/20
0.9339 - val_loss: 0.2386 - val_acc: 0.9198
Epoch 6/20
0.9419 - val_loss: 0.2148 - val_acc: 0.9328
Epoch 7/20
0.9361 - val_loss: 0.2219 - val_acc: 0.9198
Epoch 8/20
0.9508 - val_loss: 0.2121 - val_acc: 0.9243
0.9527 - val_loss: 0.2198 - val_acc: 0.9186
Epoch 10/20
0.9569 - val_loss: 0.2084 - val_acc: 0.9305
Epoch 11/20
0.9587 - val_loss: 0.2166 - val_acc: 0.9266
Epoch 12/20
0.9551 - val_loss: 0.2331 - val_acc: 0.9153
Epoch 13/20
0.9600 - val_loss: 0.2424 - val_acc: 0.9186
Epoch 14/20
0.9634 - val_loss: 0.2314 - val_acc: 0.9260
Epoch 15/20
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0.9643 - val_loss: 0.2328 - val_acc: 0.9215
Epoch 16/20
0.9648 - val_loss: 0.2352 - val_acc: 0.9198
Epoch 17/20
0.9662 - val_loss: 0.2452 - val_acc: 0.9158
Epoch 18/20
0.9692 - val_loss: 0.2346 - val_acc: 0.9136
Epoch 19/20
0.9715 - val_loss: 0.2408 - val_acc: 0.9147
Epoch 20/20
0.9717 - val_loss: 0.2625 - val_acc: 0.9062
Train on 7030 samples, validate on 1758 samples
Epoch 1/20
0.8910 - val_loss: 0.2096 - val_acc: 0.9408
Epoch 2/20
0.9087 - val_loss: 0.2242 - val_acc: 0.9295
Epoch 3/20
0.9220 - val_loss: 0.1587 - val_acc: 0.9528
Epoch 4/20
0.9334 - val_loss: 0.1556 - val_acc: 0.9482
Epoch 5/20
0.9367 - val_loss: 0.1557 - val_acc: 0.9494
Epoch 6/20
0.9475 - val loss: 0.1636 - val acc: 0.9477
Epoch 7/20
0.9451 - val_loss: 0.1448 - val_acc: 0.9511
Epoch 8/20
0.9491 - val_loss: 0.1421 - val_acc: 0.9522
Epoch 9/20
0.9558 - val_loss: 0.1477 - val_acc: 0.9545
Epoch 10/20
0.9602 - val_loss: 0.1762 - val_acc: 0.9477
Epoch 11/20
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0.9576 - val_loss: 0.1598 - val_acc: 0.9511
Epoch 12/20
0.9603 - val_loss: 0.1686 - val_acc: 0.9460
Epoch 13/20
0.9637 - val_loss: 0.1690 - val_acc: 0.9505
Epoch 14/20
0.9640 - val_loss: 0.1772 - val_acc: 0.9460
Epoch 15/20
0.9667 - val_loss: 0.1588 - val_acc: 0.9477
Epoch 16/20
0.9693 - val_loss: 0.1637 - val_acc: 0.9437
Epoch 17/20
0.9681 - val_loss: 0.1643 - val_acc: 0.9431
Epoch 18/20
0.9681 - val_loss: 0.1858 - val_acc: 0.9374
Epoch 19/20
0.9703 - val_loss: 0.2093 - val_acc: 0.9261
Epoch 20/20
0.9731 - val_loss: 0.1865 - val_acc: 0.9391
Train on 7020 samples, validate on 1755 samples
Epoch 1/20
0.9077 - val_loss: 0.1062 - val_acc: 0.9732
Epoch 2/20
0.9192 - val_loss: 0.1619 - val_acc: 0.9538
Epoch 3/20
0.9326 - val_loss: 0.1238 - val_acc: 0.9715
Epoch 4/20
0.9389 - val_loss: 0.1262 - val_acc: 0.9641
0.9395 - val_loss: 0.1043 - val_acc: 0.9670
Epoch 6/20
0.9528 - val_loss: 0.1074 - val_acc: 0.9692
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Epoch 7/20
0.9526 - val_loss: 0.1214 - val_acc: 0.9624
0.9558 - val_loss: 0.1477 - val_acc: 0.9573
Epoch 9/20
0.9567 - val_loss: 0.1208 - val_acc: 0.9584
Epoch 10/20
0.9614 - val_loss: 0.1226 - val_acc: 0.9556
Epoch 11/20
0.9642 - val_loss: 0.1256 - val_acc: 0.9618
Epoch 12/20
0.9661 - val_loss: 0.1311 - val_acc: 0.9578
Epoch 13/20
0.9684 - val_loss: 0.1316 - val_acc: 0.9527
Epoch 14/20
0.9674 - val_loss: 0.1231 - val_acc: 0.9573
Epoch 15/20
0.9695 - val_loss: 0.1278 - val_acc: 0.9561
Epoch 16/20
0.9744 - val_loss: 0.1238 - val_acc: 0.9567
Epoch 17/20
0.9712 - val_loss: 0.1086 - val_acc: 0.9635
Epoch 18/20
0.9732 - val_loss: 0.1118 - val_acc: 0.9624
Epoch 19/20
0.9754 - val_loss: 0.1391 - val_acc: 0.9521
Epoch 20/20
0.9755 - val_loss: 0.1466 - val_acc: 0.9516
Train on 7037 samples, validate on 1760 samples
Epoch 1/20
0.9237 - val_loss: 0.1282 - val_acc: 0.9665
Epoch 2/20
```

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0.9264 - val_loss: 0.1534 - val_acc: 0.9636
Epoch 3/20
0.9346 - val_loss: 0.1265 - val_acc: 0.9636
Epoch 4/20
0.9466 - val_loss: 0.1514 - val_acc: 0.9602
Epoch 5/20
0.9514 - val_loss: 0.2032 - val_acc: 0.9438
Epoch 6/20
0.9565 - val_loss: 0.1320 - val_acc: 0.9642
Epoch 7/20
0.9558 - val_loss: 0.1012 - val_acc: 0.9699
Epoch 8/20
0.9605 - val_loss: 0.1074 - val_acc: 0.9648
Epoch 9/20
0.9653 - val_loss: 0.1161 - val_acc: 0.9653
Epoch 10/20
0.9642 - val_loss: 0.1475 - val_acc: 0.9540
Epoch 11/20
0.9710 - val_loss: 0.1346 - val_acc: 0.9574
Epoch 12/20
0.9679 - val_loss: 0.1234 - val_acc: 0.9625
Epoch 13/20
0.9682 - val_loss: 0.1199 - val_acc: 0.9597
Epoch 14/20
0.9709 - val_loss: 0.1259 - val_acc: 0.9580
Epoch 15/20
0.9716 - val_loss: 0.1363 - val_acc: 0.9528
Epoch 16/20
0.9737 - val_loss: 0.1294 - val_acc: 0.9574
Epoch 17/20
0.9720 - val_loss: 0.1258 - val_acc: 0.9585
Epoch 18/20
```

```
0.9778 - val_loss: 0.1264 - val_acc: 0.9591
Epoch 19/20
0.9767 - val_loss: 0.1449 - val_acc: 0.9466
Epoch 20/20
0.9773 - val loss: 0.1181 - val acc: 0.9642
Train on 7047 samples, validate on 1762 samples
Epoch 1/20
0.9212 - val_loss: 0.0918 - val_acc: 0.9767
Epoch 2/20
0.9316 - val_loss: 0.1734 - val_acc: 0.9535
0.9414 - val_loss: 0.1569 - val_acc: 0.9557
Epoch 4/20
0.9492 - val_loss: 0.1137 - val_acc: 0.9705
0.9516 - val_loss: 0.1213 - val_acc: 0.9535
Epoch 6/20
0.9542 - val_loss: 0.0984 - val_acc: 0.9665
Epoch 7/20
0.9570 - val_loss: 0.1015 - val_acc: 0.9637
Epoch 8/20
0.9642 - val_loss: 0.1018 - val_acc: 0.9665
Epoch 9/20
0.9610 - val_loss: 0.1037 - val_acc: 0.9659
Epoch 10/20
0.9645 - val_loss: 0.1168 - val_acc: 0.9580
Epoch 11/20
0.9703 - val_loss: 0.0994 - val_acc: 0.9631
Epoch 12/20
0.9701 - val_loss: 0.1070 - val_acc: 0.9608
Epoch 13/20
0.9712 - val_loss: 0.1033 - val_acc: 0.9614
Epoch 14/20
```

```
0.9733 - val_loss: 0.1085 - val_acc: 0.9597
Epoch 15/20
0.9733 - val_loss: 0.1330 - val_acc: 0.9461
Epoch 16/20
0.9760 - val_loss: 0.1222 - val_acc: 0.9535
Epoch 17/20
0.9749 - val_loss: 0.1052 - val_acc: 0.9642
Epoch 18/20
0.9764 - val_loss: 0.1120 - val_acc: 0.9608
Epoch 19/20
0.9776 - val_loss: 0.1046 - val_acc: 0.9620
Epoch 20/20
0.9756 - val loss: 0.1000 - val acc: 0.9682
Train on 7054 samples, validate on 1764 samples
Epoch 1/20
0.9335 - val_loss: 0.0487 - val_acc: 0.9887
Epoch 2/20
0.9436 - val_loss: 0.1079 - val_acc: 0.9677
Epoch 3/20
0.9491 - val_loss: 0.1061 - val_acc: 0.9762
Epoch 4/20
0.9500 - val_loss: 0.0808 - val_acc: 0.9802
Epoch 5/20
0.9579 - val_loss: 0.0810 - val_acc: 0.9762
Epoch 6/20
0.9600 - val_loss: 0.0756 - val_acc: 0.9807
Epoch 7/20
0.9641 - val_loss: 0.0968 - val_acc: 0.9705
0.9654 - val_loss: 0.0823 - val_acc: 0.9739
Epoch 9/20
0.9675 - val_loss: 0.0801 - val_acc: 0.9700
```

```
Epoch 10/20
0.9654 - val_loss: 0.0987 - val_acc: 0.9688
Epoch 11/20
0.9701 - val_loss: 0.1237 - val_acc: 0.9580
Epoch 12/20
0.9714 - val_loss: 0.0977 - val_acc: 0.9694
Epoch 13/20
0.9731 - val_loss: 0.0979 - val_acc: 0.9728
Epoch 14/20
0.9736 - val_loss: 0.0900 - val_acc: 0.9745
Epoch 15/20
0.9731 - val_loss: 0.0863 - val_acc: 0.9779
Epoch 16/20
0.9755 - val_loss: 0.0994 - val_acc: 0.9683
Epoch 17/20
0.9776 - val_loss: 0.0926 - val_acc: 0.9700
Epoch 18/20
0.9787 - val_loss: 0.0858 - val_acc: 0.9745
Epoch 19/20
0.9753 - val_loss: 0.0829 - val_acc: 0.9762
Epoch 20/20
0.9780 - val_loss: 0.0967 - val_acc: 0.9671
Train on 7043 samples, validate on 1761 samples
Epoch 1/20
0.9290 - val_loss: 0.0591 - val_acc: 0.9864
Epoch 2/20
0.9411 - val_loss: 0.1062 - val_acc: 0.9671
Epoch 3/20
0.9477 - val_loss: 0.0582 - val_acc: 0.9858
Epoch 4/20
0.9530 - val_loss: 0.0606 - val_acc: 0.9886
Epoch 5/20
```

```
0.9544 - val_loss: 0.0804 - val_acc: 0.9796
Epoch 6/20
0.9615 - val_loss: 0.0613 - val_acc: 0.9841
Epoch 7/20
0.9631 - val loss: 0.0568 - val acc: 0.9847
Epoch 8/20
0.9634 - val_loss: 0.0728 - val_acc: 0.9761
Epoch 9/20
0.9727 - val_loss: 0.0712 - val_acc: 0.9756
Epoch 10/20
0.9676 - val_loss: 0.0734 - val_acc: 0.9750
Epoch 11/20
0.9703 - val_loss: 0.0871 - val_acc: 0.9710
Epoch 12/20
0.9742 - val_loss: 0.0840 - val_acc: 0.9722
Epoch 13/20
0.9759 - val_loss: 0.0916 - val_acc: 0.9744
Epoch 14/20
0.9749 - val_loss: 0.0736 - val_acc: 0.9773
0.9756 - val_loss: 0.0677 - val_acc: 0.9733
Epoch 16/20
0.9744 - val_loss: 0.0709 - val_acc: 0.9750
Epoch 17/20
0.9754 - val_loss: 0.0995 - val_acc: 0.9654
Epoch 18/20
0.9769 - val_loss: 0.1065 - val_acc: 0.9631
Epoch 19/20
0.9788 - val_loss: 0.0672 - val_acc: 0.9767
Epoch 20/20
0.9790 - val_loss: 0.0646 - val_acc: 0.9761
Train on 7016 samples, validate on 1755 samples
Epoch 1/20
```

```
0.9421 - val_loss: 0.0524 - val_acc: 0.9875
Epoch 2/20
0.9494 - val_loss: 0.1115 - val_acc: 0.9749
Epoch 3/20
0.9493 - val_loss: 0.1160 - val_acc: 0.9681
Epoch 4/20
0.9611 - val_loss: 0.0670 - val_acc: 0.9829
Epoch 5/20
0.9588 - val_loss: 0.0722 - val_acc: 0.9772
0.9607 - val_loss: 0.0618 - val_acc: 0.9812
Epoch 7/20
0.9665 - val_loss: 0.0591 - val_acc: 0.9806
Epoch 8/20
0.9685 - val_loss: 0.0602 - val_acc: 0.9835
Epoch 9/20
0.9704 - val_loss: 0.0724 - val_acc: 0.9749
Epoch 10/20
0.9743 - val_loss: 0.0687 - val_acc: 0.9783
Epoch 11/20
0.9725 - val_loss: 0.0676 - val_acc: 0.9778
Epoch 12/20
0.9736 - val loss: 0.0840 - val acc: 0.9664
Epoch 13/20
0.9762 - val_loss: 0.0757 - val_acc: 0.9732
Epoch 14/20
0.9745 - val_loss: 0.0704 - val_acc: 0.9795
Epoch 15/20
0.9762 - val_loss: 0.0671 - val_acc: 0.9789
Epoch 16/20
0.9758 - val_loss: 0.0698 - val_acc: 0.9766
Epoch 17/20
```

```
0.9765 - val_loss: 0.0702 - val_acc: 0.9778
Epoch 18/20
0.9785 - val_loss: 0.0639 - val_acc: 0.9789
Epoch 19/20
0.9778 - val_loss: 0.0606 - val_acc: 0.9789
Epoch 20/20
0.9815 - val_loss: 0.0696 - val_acc: 0.9749
Train on 7006 samples, validate on 1752 samples
Epoch 1/20
0.9465 - val_loss: 0.0441 - val_acc: 0.9874
Epoch 2/20
0.9506 - val_loss: 0.0547 - val_acc: 0.9852
Epoch 3/20
0.9583 - val_loss: 0.0589 - val_acc: 0.9777
Epoch 4/20
0.9600 - val_loss: 0.0486 - val_acc: 0.9829
Epoch 5/20
0.9625 - val_loss: 0.0482 - val_acc: 0.9852
Epoch 6/20
0.9642 - val_loss: 0.0471 - val_acc: 0.9823
Epoch 7/20
0.9632 - val_loss: 0.0742 - val_acc: 0.9760
Epoch 8/20
0.9692 - val_loss: 0.0794 - val_acc: 0.9749
Epoch 9/20
0.9706 - val_loss: 0.0687 - val_acc: 0.9777
Epoch 10/20
0.9740 - val_loss: 0.0608 - val_acc: 0.9772
7006/7006 [============= ] - 1s 180us/step - loss: 0.0737 - acc:
0.9726 - val_loss: 0.0501 - val_acc: 0.9806
Epoch 12/20
0.9743 - val_loss: 0.0459 - val_acc: 0.9846
```

```
Epoch 13/20
0.9774 - val_loss: 0.0648 - val_acc: 0.9760
Epoch 14/20
0.9745 - val_loss: 0.0740 - val_acc: 0.9755
Epoch 15/20
0.9760 - val_loss: 0.0751 - val_acc: 0.9749
Epoch 16/20
0.9772 - val_loss: 0.0738 - val_acc: 0.9749
Epoch 17/20
0.9770 - val_loss: 0.0797 - val_acc: 0.9715
Epoch 18/20
0.9784 - val_loss: 0.0805 - val_acc: 0.9715
Epoch 19/20
0.9813 - val_loss: 0.0663 - val_acc: 0.9743
Epoch 20/20
0.9817 - val_loss: 0.0721 - val_acc: 0.9737
Train on 7008 samples, validate on 1753 samples
Epoch 1/20
0.9463 - val_loss: 0.0304 - val_acc: 0.9932
0.9513 - val_loss: 0.0488 - val_acc: 0.9869
0.9556 - val_loss: 0.0788 - val_acc: 0.9743
Epoch 4/20
0.9586 - val_loss: 0.0547 - val_acc: 0.9852
Epoch 5/20
0.9599 - val_loss: 0.0545 - val_acc: 0.9857
Epoch 6/20
0.9659 - val_loss: 0.0627 - val_acc: 0.9829
Epoch 7/20
7008/7008 [============ - 1s 179us/step - loss: 0.0863 - acc:
0.9666 - val_loss: 0.0540 - val_acc: 0.9875
Epoch 8/20
```

```
0.9727 - val_loss: 0.0600 - val_acc: 0.9846
Epoch 9/20
0.9697 - val_loss: 0.0661 - val_acc: 0.9829
Epoch 10/20
0.9747 - val_loss: 0.0555 - val_acc: 0.9823
Epoch 11/20
0.9685 - val_loss: 0.0671 - val_acc: 0.9817
Epoch 12/20
0.9737 - val_loss: 0.0643 - val_acc: 0.9806
Epoch 13/20
0.9747 - val_loss: 0.0476 - val_acc: 0.9863
Epoch 14/20
0.9755 - val_loss: 0.0496 - val_acc: 0.9857
Epoch 15/20
0.9726 - val_loss: 0.0665 - val_acc: 0.9772
Epoch 16/20
0.9775 - val_loss: 0.0848 - val_acc: 0.9760
Epoch 17/20
0.9750 - val_loss: 0.0943 - val_acc: 0.9743
Epoch 18/20
0.9810 - val_loss: 0.0734 - val_acc: 0.9795
Epoch 19/20
0.9813 - val_loss: 0.0496 - val_acc: 0.9840
Epoch 20/20
0.9807 - val loss: 0.0539 - val acc: 0.9852
Train on 7036 samples, validate on 1760 samples
Epoch 1/20
0.9515 - val_loss: 0.0254 - val_acc: 0.9932
Epoch 2/20
0.9582 - val_loss: 0.0500 - val_acc: 0.9830
Epoch 3/20
0.9571 - val_loss: 0.0709 - val_acc: 0.9784
Epoch 4/20
```

```
0.9656 - val_loss: 0.0494 - val_acc: 0.9881
Epoch 5/20
0.9626 - val_loss: 0.0448 - val_acc: 0.9881
Epoch 6/20
0.9665 - val_loss: 0.0392 - val_acc: 0.9858
Epoch 7/20
0.9697 - val_loss: 0.0426 - val_acc: 0.9869
Epoch 8/20
0.9679 - val_loss: 0.0433 - val_acc: 0.9852
0.9717 - val_loss: 0.0523 - val_acc: 0.9812
Epoch 10/20
0.9758 - val_loss: 0.0462 - val_acc: 0.9818
Epoch 11/20
0.9785 - val_loss: 0.0442 - val_acc: 0.9835
Epoch 12/20
0.9770 - val_loss: 0.0383 - val_acc: 0.9864
Epoch 13/20
0.9734 - val_loss: 0.0423 - val_acc: 0.9841
Epoch 14/20
0.9780 - val_loss: 0.0407 - val_acc: 0.9864
Epoch 15/20
0.9807 - val loss: 0.0416 - val acc: 0.9847
Epoch 16/20
0.9802 - val_loss: 0.0511 - val_acc: 0.9813
Epoch 17/20
0.9777 - val_loss: 0.0567 - val_acc: 0.9784
Epoch 18/20
0.9811 - val_loss: 0.0545 - val_acc: 0.9790
Epoch 19/20
0.9797 - val_loss: 0.0403 - val_acc: 0.9852
Epoch 20/20
```

```
0.9798 - val_loss: 0.0504 - val_acc: 0.9795
Train on 7028 samples, validate on 1757 samples
Epoch 1/20
0.9523 - val_loss: 0.0319 - val_acc: 0.9932
Epoch 2/20
0.9536 - val_loss: 0.0658 - val_acc: 0.9841
Epoch 3/20
0.9623 - val_loss: 0.0488 - val_acc: 0.9875
Epoch 4/20
0.9654 - val_loss: 0.0342 - val_acc: 0.9903
Epoch 5/20
0.9626 - val_loss: 0.0577 - val_acc: 0.9852
Epoch 6/20
0.9694 - val_loss: 0.0573 - val_acc: 0.9841
Epoch 7/20
0.9654 - val_loss: 0.0387 - val_acc: 0.9898
Epoch 8/20
0.9721 - val_loss: 0.0467 - val_acc: 0.9892
Epoch 9/20
0.9727 - val_loss: 0.0453 - val_acc: 0.9892
Epoch 10/20
0.9744 - val_loss: 0.0309 - val_acc: 0.9898
Epoch 11/20
0.9750 - val_loss: 0.0416 - val_acc: 0.9869
Epoch 12/20
0.9754 - val_loss: 0.0499 - val_acc: 0.9858
Epoch 13/20
0.9762 - val_loss: 0.0576 - val_acc: 0.9858
0.9797 - val_loss: 0.0489 - val_acc: 0.9875
Epoch 15/20
0.9765 - val_loss: 0.0483 - val_acc: 0.9869
```

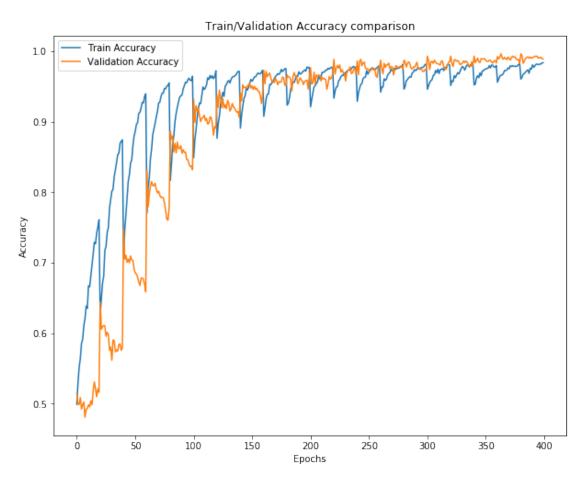
```
Epoch 16/20
0.9808 - val_loss: 0.0581 - val_acc: 0.9846
Epoch 17/20
0.9801 - val_loss: 0.0520 - val_acc: 0.9835
Epoch 18/20
0.9778 - val_loss: 0.0428 - val_acc: 0.9863
Epoch 19/20
0.9775 - val_loss: 0.0486 - val_acc: 0.9869
Epoch 20/20
0.9799 - val_loss: 0.0581 - val_acc: 0.9835
Train on 7056 samples, validate on 1765 samples
Epoch 1/20
0.9562 - val_loss: 0.0313 - val_acc: 0.9926
Epoch 2/20
0.9605 - val_loss: 0.0436 - val_acc: 0.9892
Epoch 3/20
0.9649 - val_loss: 0.0356 - val_acc: 0.9921
Epoch 4/20
0.9663 - val_loss: 0.0218 - val_acc: 0.9966
0.9664 - val_loss: 0.0323 - val_acc: 0.9909
Epoch 6/20
0.9685 - val_loss: 0.0454 - val_acc: 0.9887
Epoch 7/20
0.9728 - val_loss: 0.0369 - val_acc: 0.9915
Epoch 8/20
0.9726 - val_loss: 0.0365 - val_acc: 0.9898
Epoch 9/20
0.9735 - val_loss: 0.0408 - val_acc: 0.9881
Epoch 10/20
0.9765 - val_loss: 0.0490 - val_acc: 0.9921
Epoch 11/20
```

```
0.9753 - val_loss: 0.0454 - val_acc: 0.9898
Epoch 12/20
0.9796 - val_loss: 0.0487 - val_acc: 0.9875
Epoch 13/20
0.9785 - val_loss: 0.0389 - val_acc: 0.9915
Epoch 14/20
0.9797 - val_loss: 0.0321 - val_acc: 0.9932
Epoch 15/20
0.9787 - val_loss: 0.0306 - val_acc: 0.9915
Epoch 16/20
0.9790 - val_loss: 0.0298 - val_acc: 0.9921
Epoch 17/20
0.9785 - val_loss: 0.0375 - val_acc: 0.9892
Epoch 18/20
0.9795 - val_loss: 0.0384 - val_acc: 0.9881
Epoch 19/20
0.9812 - val_loss: 0.0355 - val_acc: 0.9887
Epoch 20/20
0.9831 - val_loss: 0.0480 - val_acc: 0.9824
Train on 7052 samples, validate on 1764 samples
Epoch 1/20
0.9607 - val_loss: 0.0249 - val_acc: 0.9966
Epoch 2/20
0.9633 - val loss: 0.0413 - val acc: 0.9938
Epoch 3/20
0.9678 - val_loss: 0.0853 - val_acc: 0.9830
Epoch 4/20
0.9685 - val_loss: 0.0720 - val_acc: 0.9864
Epoch 5/20
0.9705 - val_loss: 0.0475 - val_acc: 0.9898
Epoch 6/20
0.9725 - val_loss: 0.0345 - val_acc: 0.9915
Epoch 7/20
```

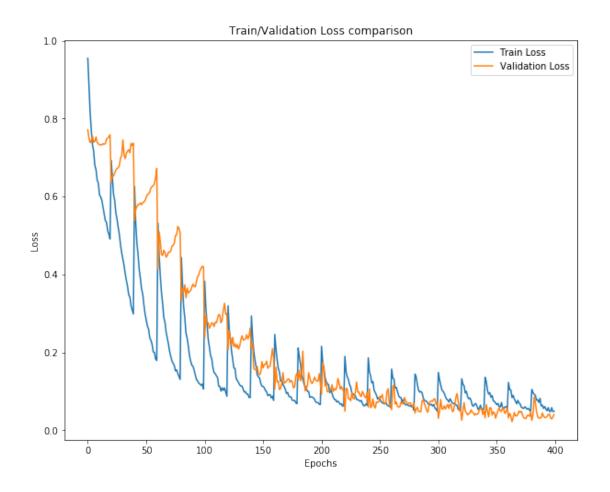
```
0.9736 - val_loss: 0.0309 - val_acc: 0.9921
Epoch 8/20
0.9689 - val_loss: 0.0322 - val_acc: 0.9904
Epoch 9/20
0.9760 - val_loss: 0.0319 - val_acc: 0.9921
Epoch 10/20
0.9748 - val_loss: 0.0443 - val_acc: 0.9904
Epoch 11/20
0.9809 - val_loss: 0.0357 - val_acc: 0.9909
Epoch 12/20
0.9773 - val_loss: 0.0328 - val_acc: 0.9921
Epoch 13/20
0.9796 - val_loss: 0.0323 - val_acc: 0.9932
Epoch 14/20
0.9817 - val_loss: 0.0351 - val_acc: 0.9926
Epoch 15/20
0.9818 - val_loss: 0.0401 - val_acc: 0.9932
Epoch 16/20
0.9811 - val_loss: 0.0414 - val_acc: 0.9904
Epoch 17/20
0.9818 - val_loss: 0.0317 - val_acc: 0.9909
Epoch 18/20
0.9820 - val_loss: 0.0287 - val_acc: 0.9915
Epoch 19/20
0.9834 - val_loss: 0.0340 - val_acc: 0.9898
Epoch 20/20
0.9838 - val_loss: 0.0402 - val_acc: 0.9892
0.0.4 Model Evaluation
```

```
[19]: plt.figure(figsize=[10,8])
   plt.plot(acc,label='Train Accuracy')
   plt.plot(val_acc,label='Validation Accuracy')
```

```
plt.title('Train/Validation Accuracy comparison')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.savefig('Train_Validation_Accuracy_comparison.png')
plt.show()
```



```
[20]: plt.figure(figsize=[10,8])
   plt.plot(loss,label='Train Loss')
   plt.plot(val_loss,label='Validation Loss')
   plt.title('Train/Validation Loss comparison')
   plt.xlabel('Epochs')
   plt.ylabel('Loss')
   plt.legend()
   plt.savefig('Train_Validation_Loss_comparison.png')
   plt.show()
```



```
[11]: print ('Score on last test data [loss,acc]: ', model.
      →evaluate([spoken test, written test], match test))
     ##Confusion matrix prediction on last test Dataset.
    predicted=model.predict([spoken_test,written_test])
    predicted[predicted>0.5]=1
    predicted[predicted<0.51]=0</pre>
    from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(match_test, predicted)
    print ('Confusion Matrix on last test data: ',cm)
    1764/1764 [============ ] - 1s 315us/step
    Score on last test data [loss,acc]: [0.040173865642499966, 0.9892290249433107]
    Confusion Matrix on last test data: [[858 19]
     [ 0 887]]
[14]: import pandas as pd
[16]: pd.DataFrame(cm)
[16]:
         0
              1
       858
             19
    1
         0
           887
[13]: 858+19
[13]: 877
[12]: print ('Prediction on test data and saving output prediction as bolean values
     test_predicted=model.predict([speak_truncated_test,written_test0])
    test_predicted[test_predicted>0.5]=True
    test_predicted[test_predicted<0.51]=False</pre>
    test_predicted=(test_predicted.astype('int')>0).reshape(-1,)
    np.save('result.npy',test_predicted,allow_pickle=True)
    Prediction on test data and saving output prediction as bolean values in
    result.npy file.
```