

CSCE636 – PROJECT REPORT – 8

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NOTE: All sections with changes and new figures are highlighted in yellow and changed text is written in blue.

Abstract

In Submission 8 of my Project Report, I continue to work on detecting ‘dizziness’ using a neural network work. This can be an important addition in a smart home. Detecting dizziness among people with medical conditions can be used to send out alerts to the concerned personnel to take necessary actions. In order to overcome the challenge of having limited data available I make use of data augmentation techniques. This helped in improving accuracy over previously trained model and also similar model when used without using augmented data. The model used in this submission has linearly stacked LSTM layers.

Data Description and Processing

The dataset consists of 160 self-made videos of roughly 5-6 seconds each. The training-validation split was 70-30 that is 112 for training and 48 videos for testing. Labels for each video have been generated framewise. For example, the video starts with a person sitting who gets up and starts feeling dizzy. So, the initial frames would be marked as a negative class whereas only the target part would be marked as positive labels.

The following steps were taken for processing the videos as input to the neural network model:

Step 1: OpenPose script was used to extract body landmarks from the videos for each frame. These were stored in a json format with x and y coordinates.

Step 2: The JSON files were further combined and stored as a .txt file for reading it as a matrix format.

```

def convert_data(start, end, output_json, output_json_key):
    """
        start - Starting video number to be added to text file
        end - Last video number to be added
        output_json - Path of json files for videos
        output_json_key - path of text file where the key-point values are to stored
    """

    with open(output_json_key, "w") as x:
        for i in range(start, end+1):
            json_files = glob.glob(output_json + '/' + str(i) + "/*")
            j=0
            for jfile in json_files:
                if j< 140:
                    j = j + 1
                    with open(jfile) as f:
                        data = json.load(f)
                        if data['people']:
                            kp= data['people'][0]['pose_keypoints_2d']
                            kp = [ str(v) for v in kp]
                            r = ','.join(kp)
                            x.write('{}\n'.format(r))

```

Step 3: Once the files are read, separate training and validation data are created in a 70-30 split for training.

```

##DATA CONVERSION (only required once for generating text files)####

#INITIALIZATION:
#TRAINING:
output_json = '/content/drive/My Drive/CSCE636/JSON_Output'
output_json_key_train = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_train.txt"
start = 1 #training is from video 1 to video 70 --CHANGE
end = 70
Xtrain = convert_data(start, end, output_json, output_json_key_train)

#VALIDATION:
output_json = '/content/drive/My Drive/CSCE636/JSON_Output'
output_json_key_val = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_val.txt"
start = 71 #validation is from video 70 to video 100 --CHANGE
end = 100
Xtrain = convert_data(start, end, output_json, output_json_key_val)
| ##EXTENSION OF DATASET##

#ADDING MORE TRAINING DATA:
output_json = '/content/drive/My Drive/CSCE636/JSON_Output'
output_json_key_train = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_train_new.txt"
start = 119 #training is from video 119 to video 160 --CHANGE
end = 160
Xtrain_new = convert_data(start, end, output_json, output_json_key_train)

#ADDING MORE VALIDATION DATA:
output_json = '/content/drive/My Drive/CSCE636/JSON_Output'
output_json_key_val = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_Val_new.txt"
start = 101 #validation is from video 101 to video 118 --CHANGE
end = 118
Xval_new = convert_data(start, end, output_json, output_json_key_val)

```

Step 4: The read files are reshaped into appropriate tensor dimensions to be used as the final input for the model training.

```
▶ #GENERATING TRAINING AND VALIDATION ARRAYS:  
  
#FOR X-file:  
train = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_train.txt" ##  
X_train = read_data(train)  
  
train2 = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_train_new.txt"  
X_train_new = read_data(train2)  
  
X_train = np.concatenate((X_train, X_train_new), axis=0)  
X_train = X_train.reshape(1568,10,50)  
  
val = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_val.txt" ##CHAN  
X_val = read_data(val)  
val2 = "/content/drive/My Drive/CSCE636/Train_Val_Test/X_val_new.txt" #  
X_val_new = read_data(val2)  
X_val = np.concatenate((X_val, X_val_new), axis=0)  
X_val = X_val.reshape(672,10,50)  
  
#FOR Y-file:  
Y_train,Y_val = generate_label()  
Y_train = Y_train.reshape(1568,10,1)  
Y_val = Y_val.reshape(672,10,1)  
  
print('X_training = ', X_train.shape)  
print('X_validation = ', X_val.shape)  
print('Y_training = ', Y_train.shape)  
print('Y_validation = ', Y_val.shape)  
  
⇒ X_training = (1568, 10, 50)  
X_validation = (672, 10, 50)  
Y_training = (1568, 10, 1)  
Y_validation = (672, 10, 1)
```

Step 5: The training dataset was doubled up using data augmentation techniques. This allowed for better training and improved accuracy.

```

    ###DATA AUGMENTATION###
A = np.random.normal(0.0, 10.0, (1568,10,50) )
Xtrain_noise = np.add(Xtrain , A)
Xtrain = np.concatenate((Xtrain,Xtrain_noise), axis=0)
print('X-training shape after adding noise = ' , Xtrain.shape)

Ytrain = np.concatenate((Ytrain,Ytrain), axis=0)
print('Y-training shape after adding noise = ' , Ytrain.shape)

```

→ X-training shape after adding noise = (3136, 10, 50)
Y-training shape after adding noise = (3136, 10, 1)

Model Architecture and Design

The model used in this submission is a linear stack of sequential layers. It is a 14-layer model. The hidden layer has 8 LSTM layers, 5 time-distributed layers and 1 1D convolutional layer. The model utilizes 3 batchnormalization layers. The output is also a time-distributed layer.

LSTM architecture

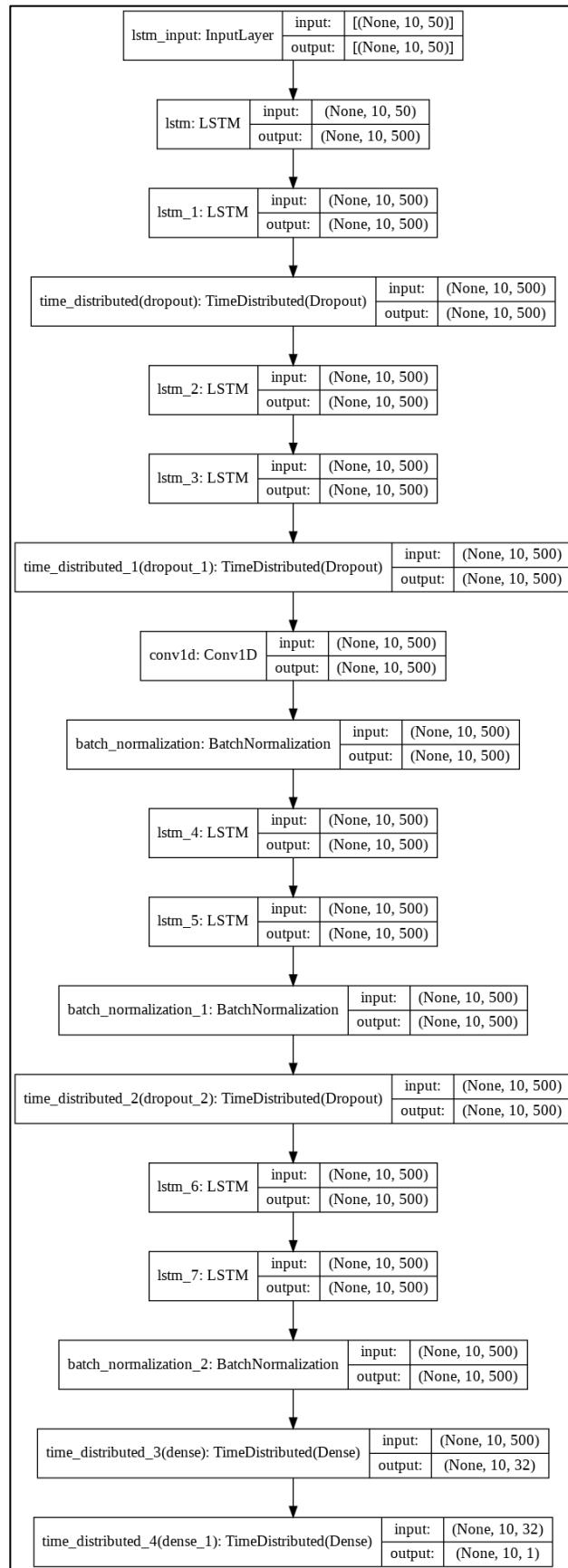
```

model = tf.keras.models.Sequential()
model.add(tf.keras.layers.LSTM(500, input_shape=(10,50), return_sequences=True))
model.add(tf.keras.layers.LSTM(500, input_shape=(10,50), return_sequences=True))
model.add(tf.keras.layers.TimeDistributed(tf.keras.layers.Dropout(0.2)))
model.add(tf.keras.layers.LSTM(500, input_shape=(10,50), return_sequences=True))
model.add(tf.keras.layers.LSTM(500, input_shape=(10,50), return_sequences=True))
model.add(tf.keras.layers.TimeDistributed(tf.keras.layers.Dropout(0.2)))
model.add(tf.keras.layers.Conv1D(500, kernel_size=2, strides=1,activation='relu',input_shape=(10,50), padding='same'))
model.add(BatchNormalization())
model.add(tf.keras.layers.LSTM(500, input_shape=(10,50), return_sequences=True))
model.add(tf.keras.layers.LSTM(500, input_shape=(10,50), return_sequences=True))
model.add(BatchNormalization())
model.add(tf.keras.layers.TimeDistributed(tf.keras.layers.Dropout(0.5)))
model.add(tf.keras.layers.LSTM(500, return_sequences=True))
model.add(tf.keras.layers.LSTM(500, return_sequences=True))
model.add(BatchNormalization())
model.add(tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(32, activation='relu', kernel_regularizer=regularizers.l2(0.01))))
model.add(tf.keras.layers.TimeDistributed(tf.keras.layers.Dense(1, activation='sigmoid')))

adam = tf.keras.optimizers.Adam(lr = 0.0001)
model.compile(loss = 'binary_crossentropy', optimizer=adam ,metrics = ['accuracy'])
print(model.summary())

```

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 10, 500)	1102000
lstm_1 (LSTM)	(None, 10, 500)	2002000
time_distributed (TimeDistri	(None, 10, 500)	0
lstm_2 (LSTM)	(None, 10, 500)	2002000
lstm_3 (LSTM)	(None, 10, 500)	2002000
time_distributed_1 (TimeDist	(None, 10, 500)	0
conv1d (Conv1D)	(None, 10, 500)	500500
batch_normalization (BatchNo	(None, 10, 500)	2000
lstm_4 (LSTM)	(None, 10, 500)	2002000
lstm_5 (LSTM)	(None, 10, 500)	2002000
batch_normalization_1 (Batch	(None, 10, 500)	2000
time_distributed_2 (TimeDist	(None, 10, 500)	0
lstm_6 (LSTM)	(None, 10, 500)	2002000
lstm_7 (LSTM)	(None, 10, 500)	2002000
batch_normalization_2 (Batch	(None, 10, 500)	2000
time_distributed_3 (TimeDist	(None, 10, 32)	16032
time_distributed_4 (TimeDist	(None, 10, 1)	33
Total params:	15,638,565	
Trainable params:	15,635,565	
Non-trainable params:	3,000	



HYPERPARAMETERS

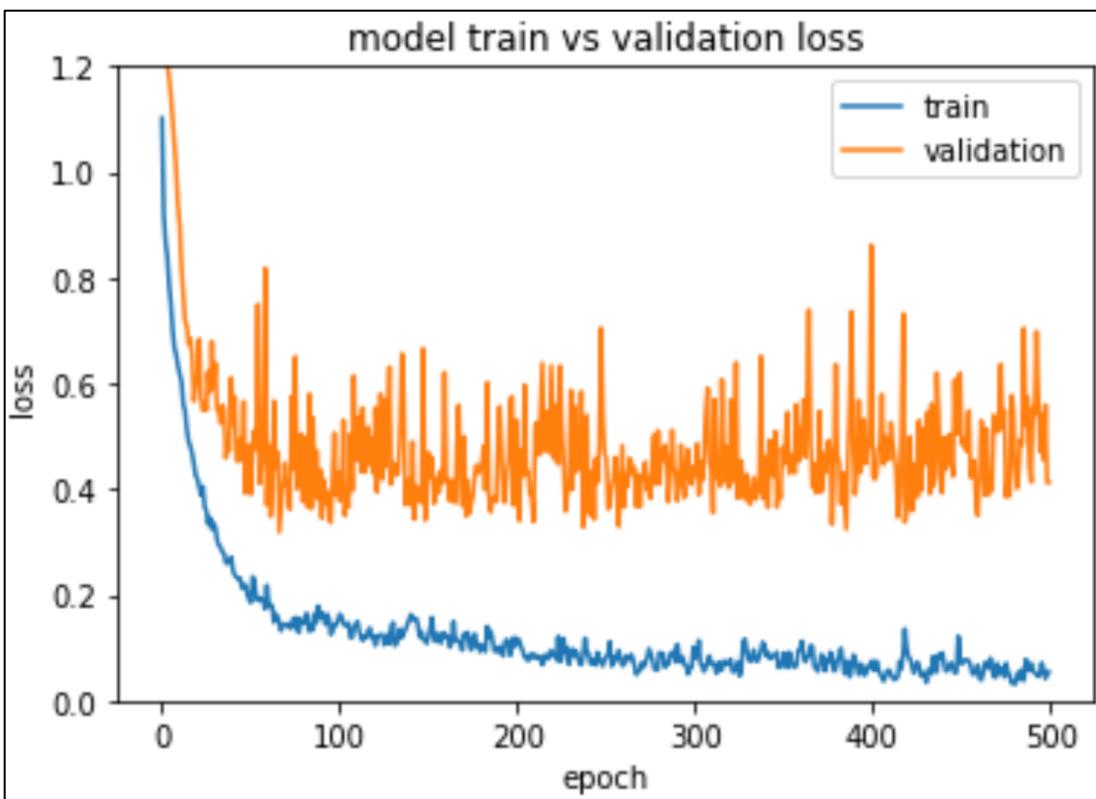
The following hyperparameters were tuned: units, batch_size, epochs, learning rate. The below table summarizes the different values used and the optimal values found.

Hyperparameter	Values Tried	Optimal
Batch Size	50, 100, 200, 300, 400, 500	100
Units	100, 150, 200, 250, 333, 350, 400, 500, 750, 1000	500
Learning rate	0.001, 0.0001, 0.01, 0.000001, 0.00001	0.0001

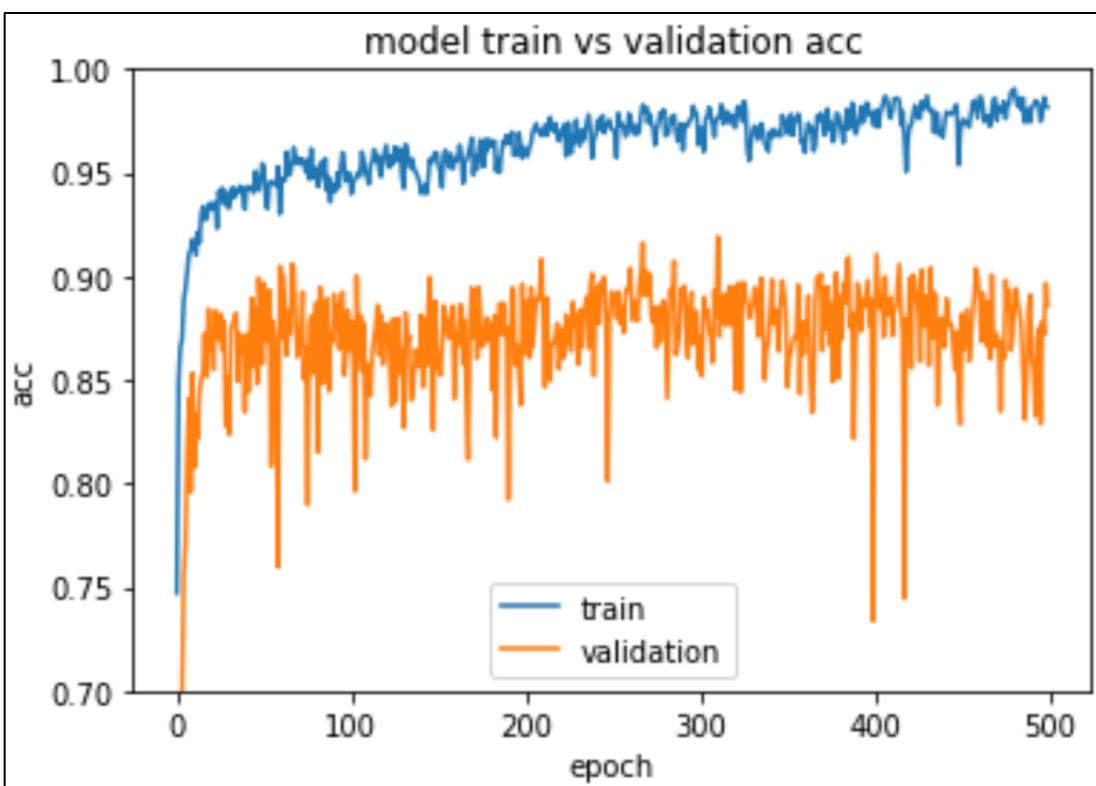
The above 2 hyperparameters were manually tried for various combinations to select the best output. For choosing the optimal epochs, keras features like early stopping and model checkpoint were utilized with 'validation_loss' to be the monitoring metric.

Training and Validation Performance

1. Validation Loss



2. Validation Accuracy



Prediction Results

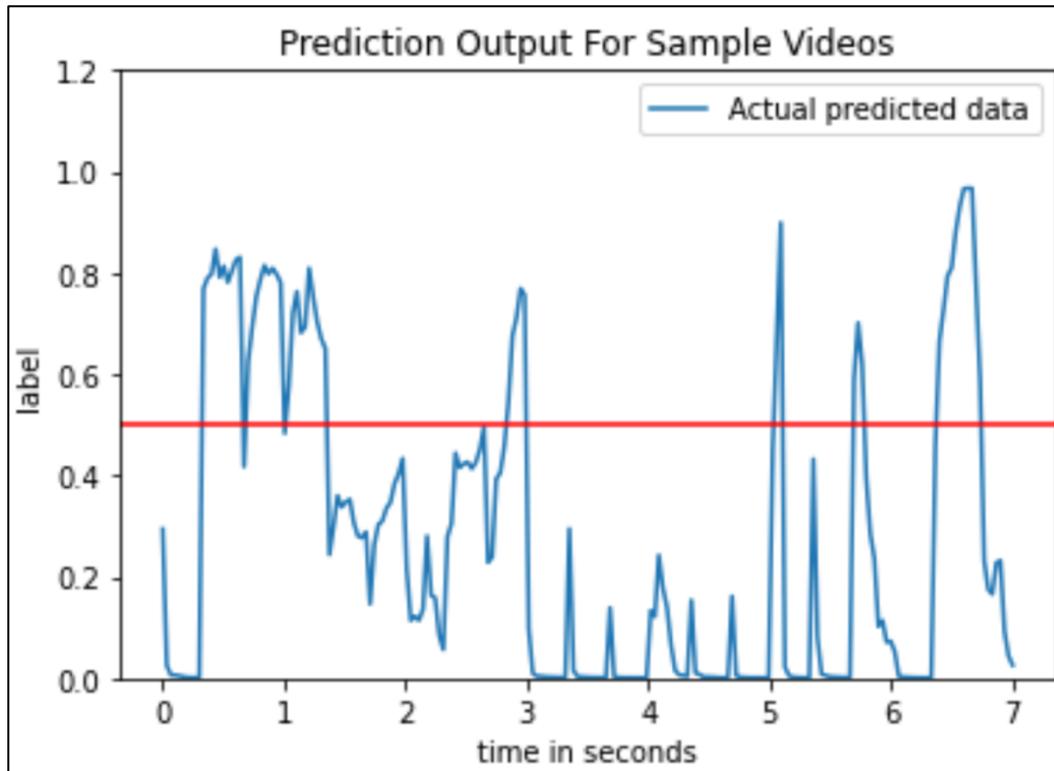
The prediction accuracy on test samples increased substantially in Submission6 with respect to previous submissions and with the test samples being the same. The previous 2 submissions had around 90% accuracy but with batchnormalization added it improved further. In the higher ranges, even a 2% increase can be considered a substantial increase.

```
[29] import sklearn  
      from sklearn.metrics import accuracy_score  
      sklearn.metrics.accuracy_score(predicted_class, true)  
  
0.8858630952380953
```

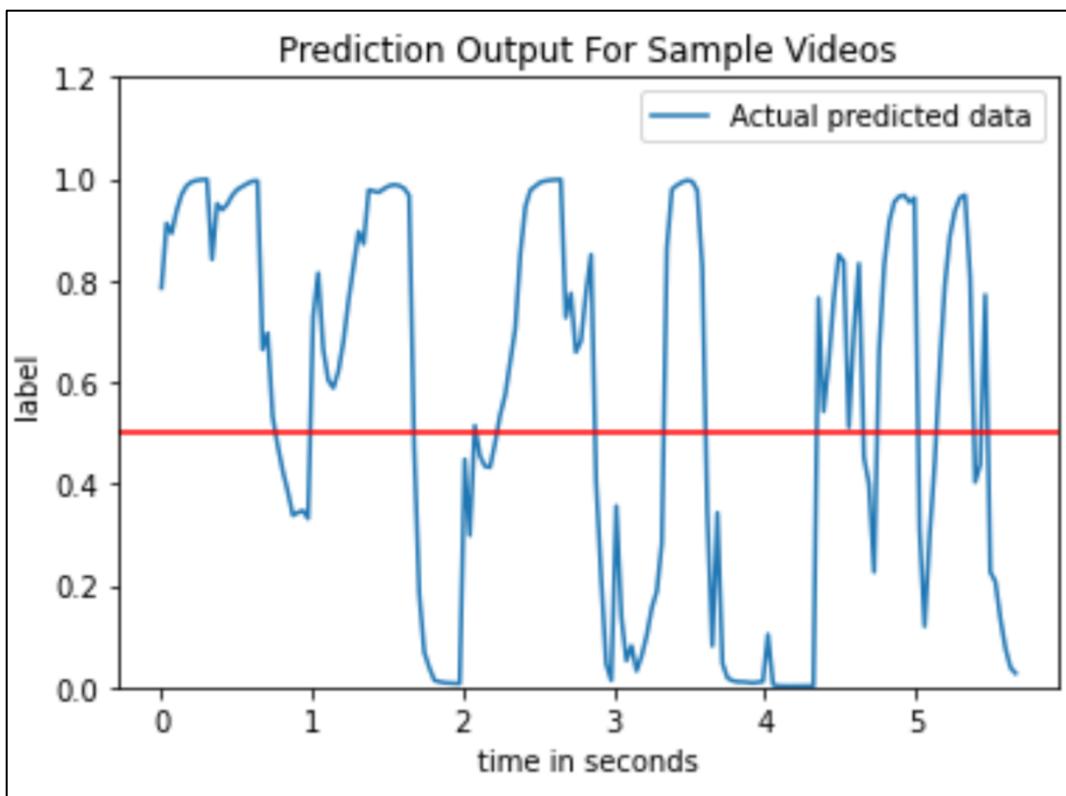
The following are a few sample results for positive (contains target action) and negative classes (does not have target action).

Positive Class

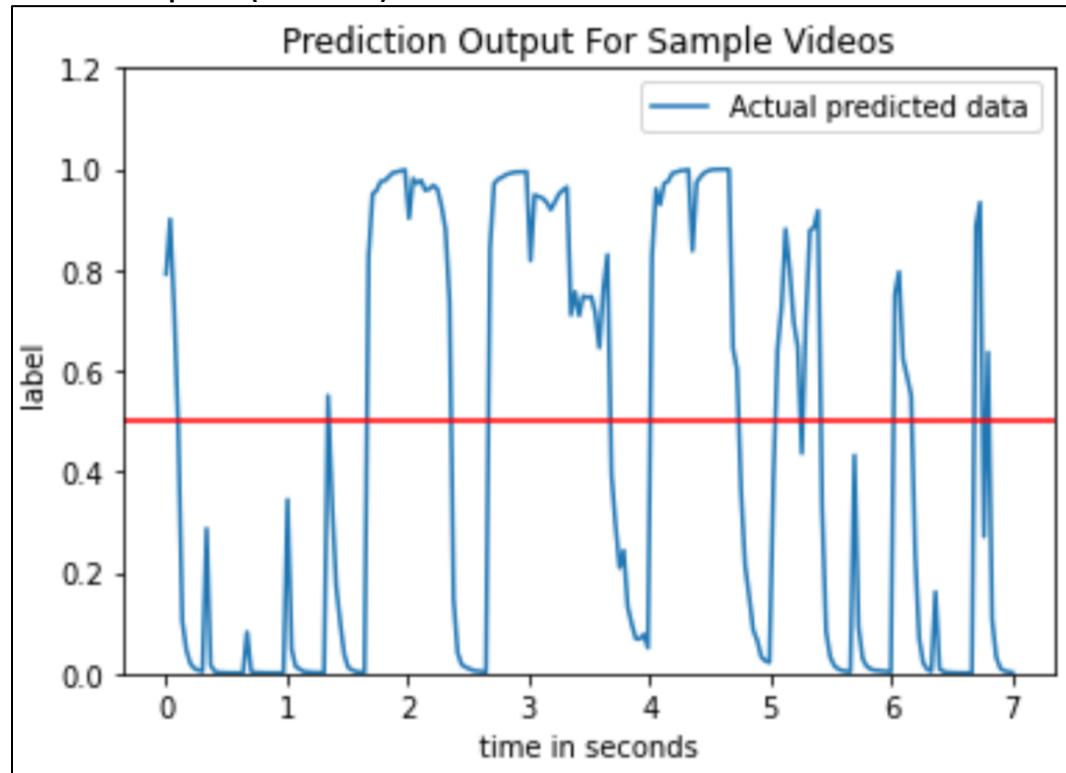
1. Positive Sample – 1 (Video #: 1)



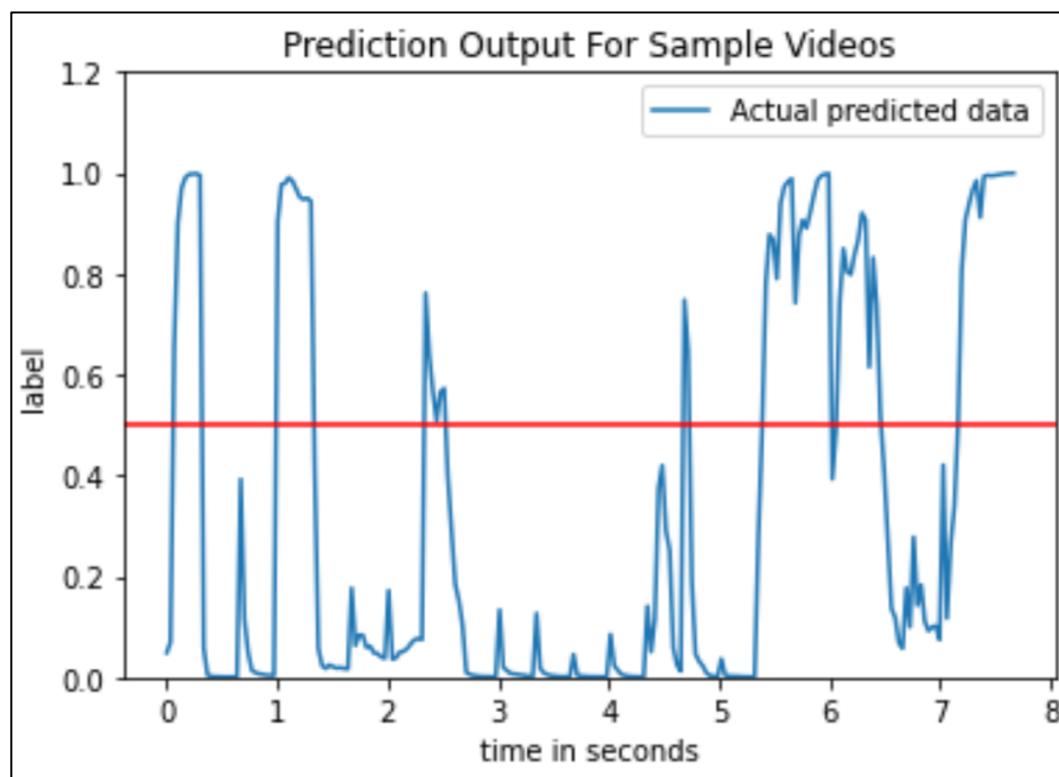
2. Positive Sample – 2 (Video #: 2)



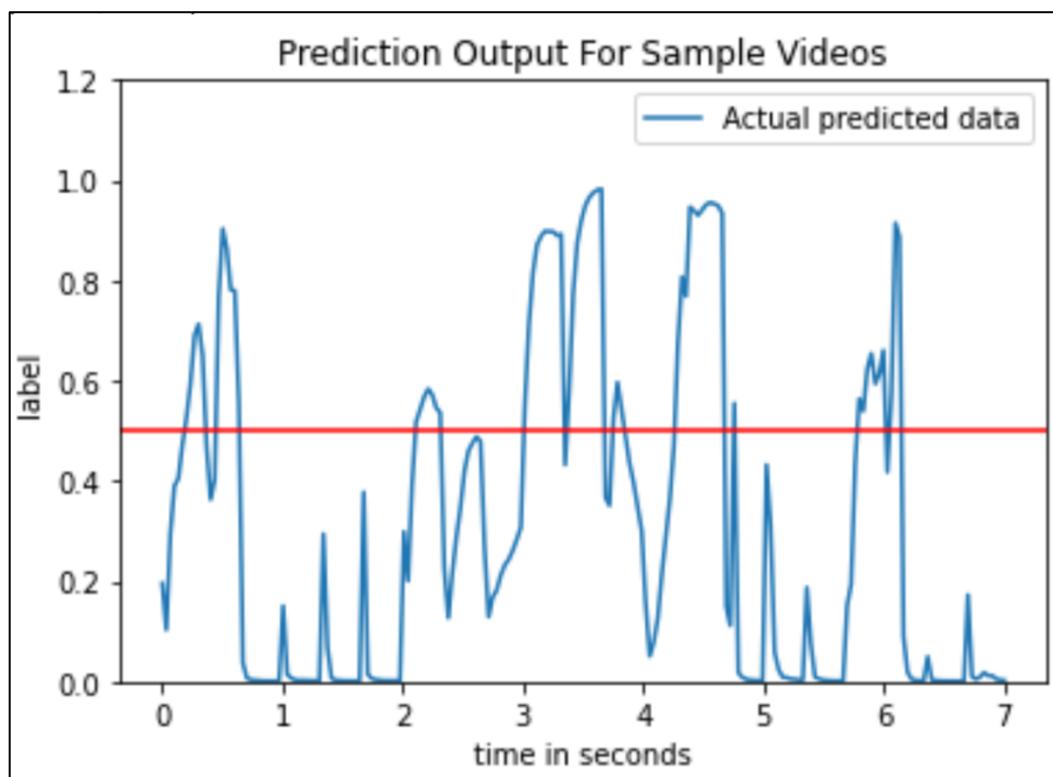
3. Positive Sample - 3 (Video #: 3)



4. Positive Sample - 4 (Video #:4)

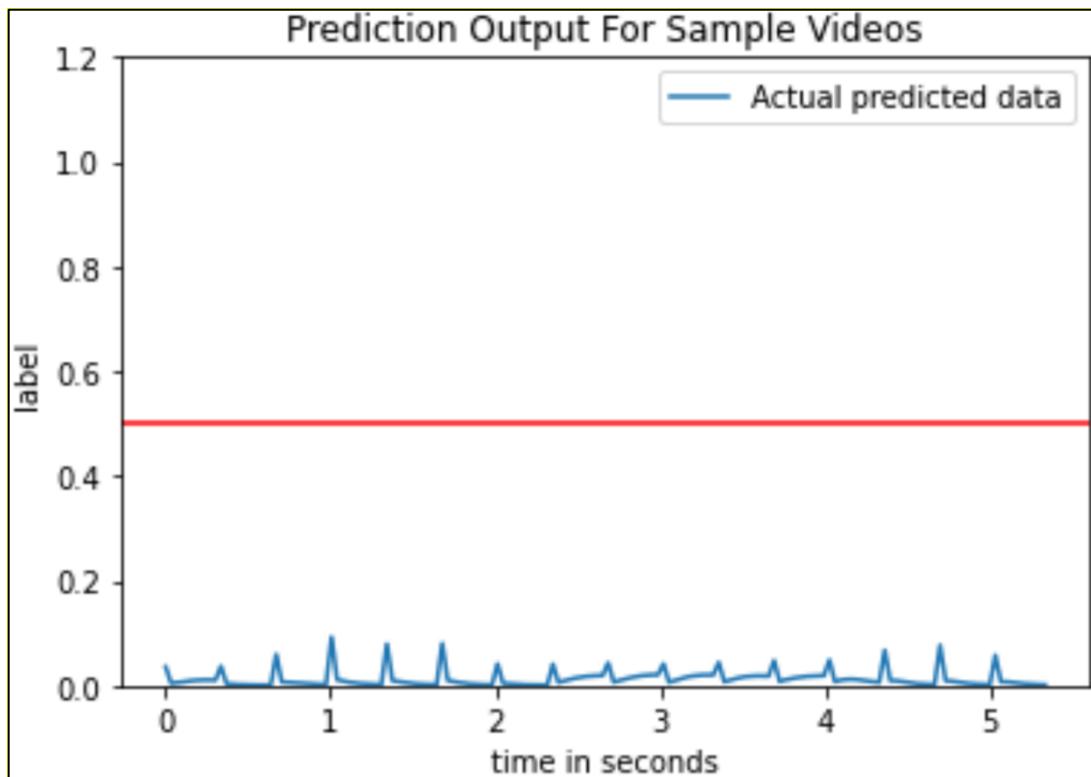


5. Positive Sample - 5 (Video #: 5)

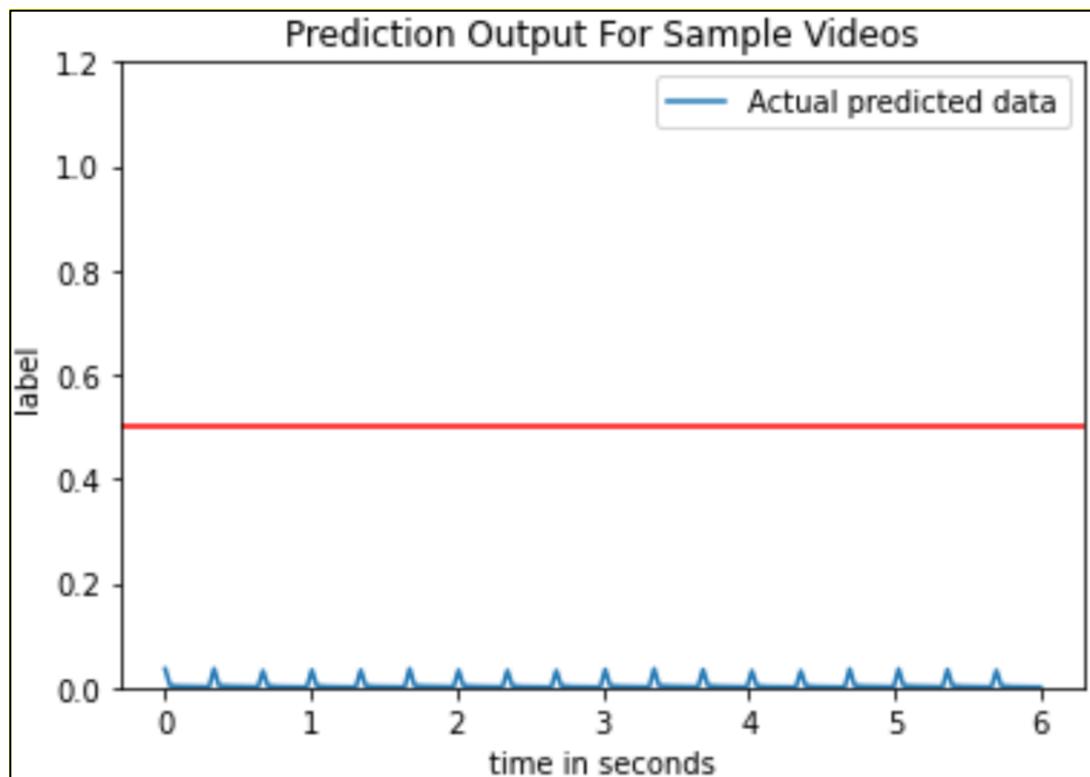


Negative Class

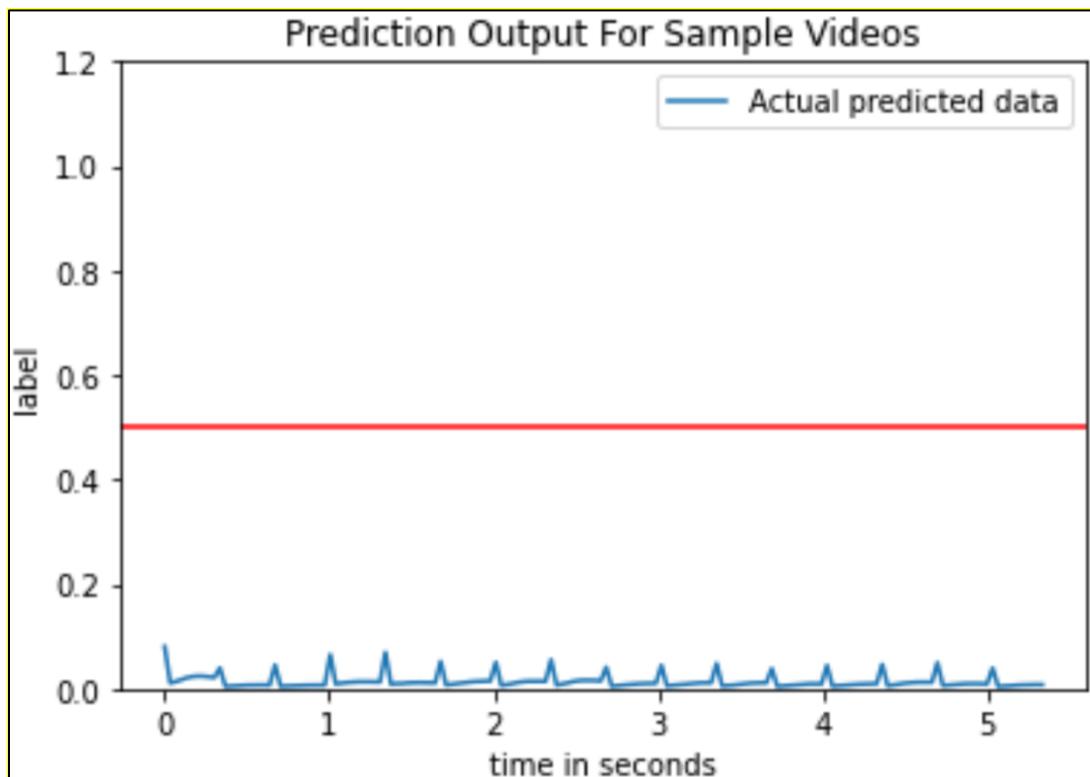
1. Negative Sample – 1 (Video #: 78)



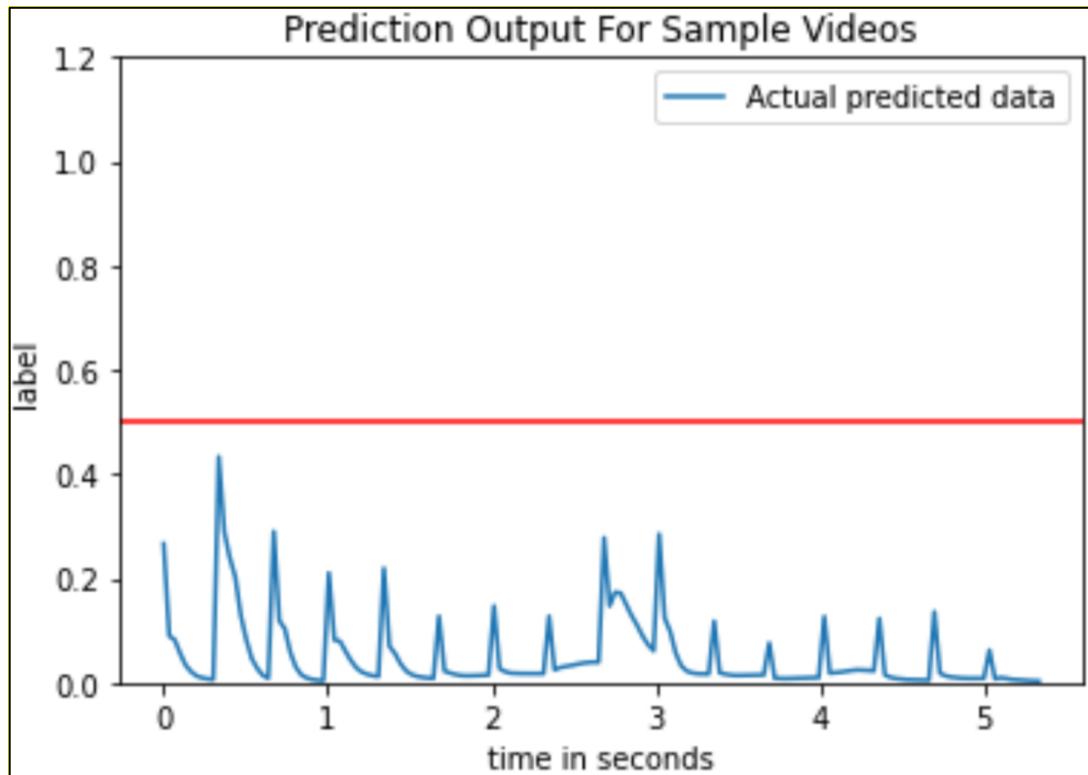
2. Negative Sample – 2 (Video #: 77)



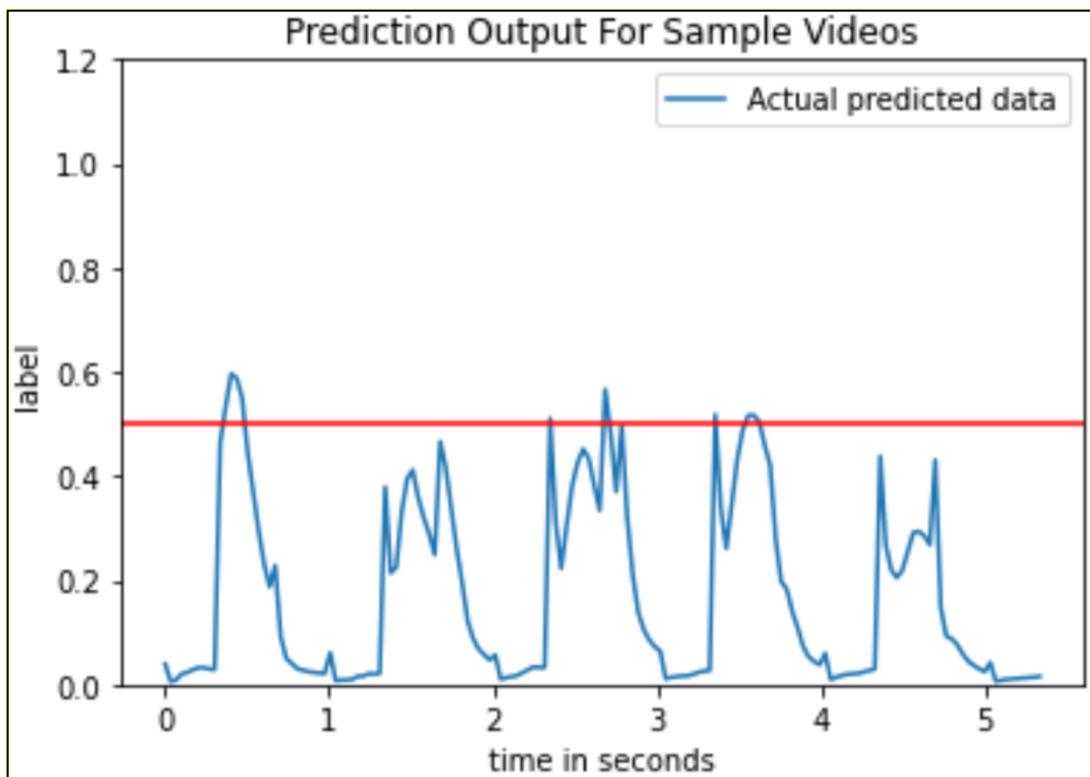
3. Negative Sample – 3 Video #: 75)



4. Negative Sample – 4 (Video #: 73)



5. Negative Sample – 5 (Video #: 71)



IMPORTANT NOTE:

As part of submission 8, I worked on utilizing multi-task learning via the SNORKEL approach. I read through the links provided on the course website and read a few papers on it since I also am trying to implement the same in my research. However, for the purpose of the project, I was unsuccessful in completing a working script and needed to change at the end moment since I also wanted to complete my submission before the deadline. As a result, I have been unable to make major changes to the existing model (previous submission). But, I will try to finish the snorkel approach before the final submission and add it to the report

INSTRUCTION ON HOW TO RUN THE PREDICTION MODEL:

1. Download CSCE636_Submission3_Prediction.ipynb from shared github repository:
<https://github.com/darpitdavetamu/CSCE636-DeepLearning/tree/main/Submission8>.
2. Upload the file to google colab.
3. JSON files and text file required to run the code can also be accessed at
<https://drive.google.com/drive/folders/1Ua297X--JqXMmfB33V4TeSG0rxCbzRZP?usp=sharing>
4. The path written in the code is same as the google drive link shared.

LINK TO DEMO VIDEO:

<https://www.youtube.com/watch?v=cK1aSOpTAn4>