HAR_LSTM-MODEL

June 29, 2019

```
In [1]: # Importing Libraries
        import pandas as pd
        import numpy as np
        import os
        import pickle

        # Import Model related packages
        import tensorflow as tf
        from keras import backend as K
        from keras.models import Sequential
        from keras.layers import LSTM
        from keras.layers.core import Dense, Dropout
        from keras.callbacks import EarlyStopping, ModelCheckpoint

        # Model evaluation related packages
        from sklearn.metrics import confusion_matrix
        from sklearn.metrics import precision_recall_fscore_support

        # for one hot encoding of labels
        from sklearn.preprocessing import OneHotEncoder

        # Plot related packages
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set()

        # Presenting the results
        from prettytable import PrettyTable
```

```
Using TensorFlow backend.
```

1 HumanActivityRecognition

This project is to build a model that predicts the human activities such as Walking, Walking_Upstairs, Walking_Downstairs, Sitting, Standing or Laying.

This dataset is collected from 30 persons(referred as subjects in this dataset), performing different activities with a smartphone to their waists. The data is recorded with the help of sensors (accelerometer and Gyroscope) in that smartphone. This experiment was video recorded to label the data manually.

1.1 How data was recorded

By using the sensors(Gyroscope and accelerometer) in a smartphone, they have captured '3-axial linear acceleration'(*tAcc-XYZ*) from accelerometer and '3-axial angular velocity' (*tGyro-XYZ*) from Gyroscope with several variations.

> prefix 't' in those metrics denotes time.

> suffix 'XYZ' represents 3-axial signals in X , Y, and Z directions.

1.1.1 Feature names

1. These sensor signals are preprocessed by applying noise filters and then sampled in fixed-width windows(sliding windows) of 2.56 seconds each with 50% overlap. ie., each window has 128 readings.
2. From Each window, a feature vector was obtianed by calculating variables from the time and frequency domain. > In our dataset, each datapoint represents a window with different readings
3. The accelertion signal was saperated into Body and Gravity acceleration signals(***tBodyAcc-XYZ*** and ***tGravityAcc-XYZ***) using some low pass filter with corner frequecy of 0.3Hz.
4. After that, the body linear acceleration and angular velocity were derived in time to obtian *jerk signals* (***tBodyAccJerk-XYZ*** and ***tBodyGyroJerk-XYZ***).
5. The magnitude of these 3-dimensional signals were calculated using the Euclidian norm. This magnitudes are represented as features with names like *tBodyAccMag*, *tGravityAccMag*, *tBodyAccJerkMag*, *tBodyGyroMag* and *tBodyGyroJerkMag*.
6. Finally, We've got frequency domain signals from some of the available signals by applying a FFT (Fast Fourier Transform). These signals obtained were labeled with ***prefix 'f'*** just like original signals with ***prefix 't'***. These signals are labeled as ***fBodyAcc-XYZ***, ***fBodyGyroMag*** etc.,.
7. These are the signals that we got so far.

    - tBodyAcc-XYZ
    - tGravityAcc-XYZ
    - tBodyAccJerk-XYZ
    - tBodyGyro-XYZ
    - tBodyGyroJerk-XYZ
    - tBodyAccMag
    - tGravityAccMag
    - tBodyAccJerkMag
    - tBodyGyroMag
    - tBodyGyroJerkMag
    - fBodyAcc-XYZ

- fBodyAccJerk-XYZ
- fBodyGyro-XYZ
- fBodyAccMag
- fBodyAccJerkMag
- fBodyGyroMag
- fBodyGyroJerkMag

8. We can esitmate some set of variables from the above signals. ie., We will estimate the following properties on each and every signal that we recoreded so far.

   - ***mean()***: Mean value
   - ***std()***: Standard deviation
   - ***mad()***: Median absolute deviation
   - ***max()***: Largest value in array
   - ***min()***: Smallest value in array
   - ***sma()***: Signal magnitude area
   - ***energy()***: Energy measure. Sum of the squares divided by the number of values.
   - ***iqr()***: Interquartile range
   - ***entropy()***: Signal entropy
   - ***arCoeff()***: Autorregresion coefficients with Burg order equal to 4
   - ***correlation()***: correlation coefficient between two signals
   - ***maxInds()***: index of the frequency component with largest magnitude
   - ***meanFreq()***: Weighted average of the frequency components to obtain a mean frequency
   - ***skewness()***: skewness of the frequency domain signal
   - ***kurtosis()***: kurtosis of the frequency domain signal
   - ***bandsEnergy()***: Energy of a frequency interval within the 64 bins of the FFT of each window.
   - ***angle()***: Angle between to vectors.

9. We can obtain some other vectors by taking the average of signals in a single window sample. These are used on the angle() variable' '

   - gravityMean
   - tBodyAccMean
   - tBodyAccJerkMean
   - tBodyGyroMean
   - tBodyGyroJerkMean

1.1.2 Y_Labels(Encoded)

- In the dataset, Y_labels are represented as numbers from 1 to 6 as their identifiers.

  - WALKING as **1**
  - WALKING_UPSTAIRS as **2**
  - WALKING_DOWNSTAIRS as **3**
  - SITTING as **4**
  - STANDING as **5**
  - LAYING as **6**

1.2 Train and test data were saperated

- The readings from ***70%*** of the volunteers were taken as ***trianing data*** and remaining ***30%*** subjects recordings were taken for ***test data***

1.3 Data

- All the data is present in 'UCI_HAR_dataset/' folder in present working directory.
  - Feature names are present in 'UCI_HAR_dataset/features.txt'
  - ***Train Data***
    * 'UCI_HAR_dataset/train/X_train.txt'
    * 'UCI_HAR_dataset/train/subject_train.txt'
    * 'UCI_HAR_dataset/train/y_train.txt'
  - ***Test Data***
    * 'UCI_HAR_dataset/test/X_test.txt'
    * 'UCI_HAR_dataset/test/subject_test.txt'
    * 'UCI_HAR_dataset/test/y_test.txt'

1.4 Data Size :

27 MB

2 Quick overview of the dataset :

- Accelerometer and Gyroscope readings are taken from 30 volunteers(referred as subjects) while performing the following 6 Activities.

  1. Walking

  2. WalkingUpstairs
  3. WalkingDownstairs
  4. Standing
  5. Sitting
  6. Lying.

- Readings are divided into a window of 2.56 seconds with 50% overlapping.

- Accelerometer readings are divided into gravity acceleration and body acceleration readings, which has x,y and z components each.

- Gyroscope readings are the measure of angular velocities which has x,y and z components.

- Jerk signals are calculated for BodyAcceleration readings.

- Fourier Transforms are made on the above time readings to obtain frequency readings.

- Now, on all the base signal readings., mean, max, mad, sma, arcoefficient, engerybands,entropy etc., are calculated for each window.

- We get a feature vector of 561 features and these features are given in the dataset.
- Each window of readings is a datapoint of 561 features.

2.1 Problem Framework

- 30 subjects(volunteers) data is randomly split to 70%(21) test and 30%(7) train data.
- Each datapoint corresponds one of the 6 Activities.

3 Configs

In [2]:
```
# base directory for dataset
data_base_dir = '/home/nisheel-s/RUN_AMT/DS/CS11_HUMAN_ACTIVITY_RECOGNITION/'

# classification related configs
num_clasess = 6
class_names_list = ['WALKING', 'WALKING_UPSTAIRS', 'WALKING_DOWNSTAIRS',
                    'STANDING', 'SITTING', 'LAYING']
class_labels_list = list(range(1, num_clasess + 1))

# dataset size related configs
dataset_size = -1 # set -1  for using full size
```

4 UTIL functions

In [3]:
```
def get_confusion_matrix(actual_list, predicted_list, title_suffix=str(), plot_fig=True)
    """
    This function plots the confusion matrix given ground truth and predicted
    """

    conf_matrix = confusion_matrix(actual_list, predicted_list,
                                   labels=list(range(0, num_clasess)))

    conf_df = pd.DataFrame(conf_matrix, columns=class_names_list)
    conf_df.index = class_names_list

    # plot confusion matrix
    if plot_fig:
        plt.figure(figsize=(9,6))
        sns.heatmap(conf_df, annot=True, annot_kws={'size': 8}, fmt='g', cmap='YlGnBu',
                    cbar_kws={'label': 'prediction_count', 'format':'%d'})
        plt.yticks(rotation=0)
        plt.xticks(rotation=90)
        plt.xlabel('Predicted')
        plt.ylabel('Actual')
        plt.title('Confusion Matrix -' + title_suffix)
        plt.show()
```

```
    return conf_df
```

In [4]:
```
def get_precision_recall_matrix(conf_matrix, title_suffix=str(), plot_fig=True):

    # compute precision matrix
    precision_matrix = conf_matrix.div(conf_matrix.sum(axis=0), axis=1) * 100.0

    # compute recall matrix
    recall_matrix = conf_matrix.div(conf_matrix.sum(axis=1), axis=0) * 100.0

    # plot both the matrices
    if plot_fig:
        # plot precision matrix
        plt.figure(figsize=(9,6))
        sns.heatmap(precision_matrix, annot=True, annot_kws={'size': 8},
                    fmt='.4f', cmap='YlGnBu',
                    cbar_kws={'label': 'percentage', 'format':'%.2f'})
        plt.yticks(rotation=0)
        plt.xticks(rotation=90)
        plt.xlabel('Predicted')
        plt.ylabel('Actual')
        plt.title('Precision Matrix -' + title_suffix)
        plt.show()

        # plot recall matrix
        plt.figure(figsize=(9,6))
        sns.heatmap(recall_matrix, annot=True, annot_kws={'size': 8},
                    fmt='.4f', cmap='YlGnBu',
                    cbar_kws={'label': 'percentage', 'format':'%.2f'})
        plt.yticks(rotation=0)
        plt.xticks(rotation=90)
        plt.xlabel('Predicted')
        plt.ylabel('Actual')
        plt.title('Recall Matrix -' + title_suffix)
        plt.show()

    # return as a tuple
    return (precision_matrix, recall_matrix,)
```

In [5]:
```
def get_classification_report(actual, predicted, title_suffix=str(), plot_fig=True):

    # compute performance df
    eval_matrix = precision_recall_fscore_support(actual, predicted,
                                                  labels=list(range(0, num_clasess)))

    eval_df = pd.DataFrame(list(eval_matrix), columns=list(range(0, num_clasess)))
    eval_df.index = ['Precision', 'Recall', 'Fscore', 'Support']
```

```
        eval_df.columns = class_names_list


        # normalize the performace df
        eval_df_normed = eval_df * 100.0
        eval_df_normed.loc['Support', class_names_list] /= eval_df_normed.loc['Support',
                                                                              class_names_list].sum()
        eval_df_normed.iloc[3:4, :] *= 100.0

        # plot the classification report
        if plot_fig:
            plt.figure(figsize=(9,6))
            sns.heatmap(eval_df_normed, annot=True, annot_kws={'size': 8},
                        fmt='.4f', cmap='YlGnBu',
                        cbar_kws={'label': 'Percentage', 'format':'%.2f'})
            plt.yticks(rotation=0)
            plt.xticks(rotation=90)

            plt.xlabel('Classes')
            plt.ylabel('Metrics')
            plt.title('Classification Report on ' + title_suffix + ' Data')
            plt.show()

        return eval_df_normed
```

```
In [6]: def plot_loss_curve(hist_obj):
            """
            This function plots the loss curve
            """

            # get train , validation loss information from object
            train_loss_list = list(hist_obj['loss'])
            validation_loss_list = list(hist_obj['val_loss'])

            # get x-label list
            epcoh_list = range(1, len(train_loss_list) + 1 )

            # plot the performace
            # plot both train, validation curve
            plt.plot(epcoh_list, train_loss_list,
                     label='Train Loss', color='r')
            plt.plot(epcoh_list, validation_loss_list,
                     label='Validation Loss', color='b')
            plt.xlabel('Training Epoch')
            plt.ylabel('Multiclass Log Loss')
            plt.title('Training Loss Vs Validation Loss')
            plt.legend()
            plt.show()
```

In [7]:
```
def plot_accuracy_curve(hist_obj):
    """
    This is a helper function for plotting accuracy
    """

    # extract train, validation accuracy metrics
    train_acc_list = list(hist_obj['acc'])
    val_acc_list = list(hist_obj['val_acc'])

    # get x-label list
    epcoh_list = range(1, len(train_acc_list) + 1 )


    # plot both train, validation curve
    plt.plot(epcoh_list, train_acc_list, label='Train Accuracy', color='r')
    plt.plot(epcoh_list, val_acc_list, label='Validation Accuracy', color='b')
    plt.xlabel('Training Epoch')
    plt.ylabel('Accuracy')
    plt.title('Training Accuracy Vs Validation Accuracy')
    plt.legend()
    plt.show()
```

5 Data

In [8]:
```
# declare one hot encoder for label
one_hot_encoder = OneHotEncoder(sparse=False, categories='auto')
one_hot_encoder.fit(np.array(class_labels_list).reshape(num_clasess, 1))
```

Out[8]:
```
OneHotEncoder(categorical_features=None, categories='auto',
       dtype=<class 'numpy.float64'>, handle_unknown='error',
       n_values=None, sparse=False)
```

In [9]:
```
# Utility function to load the features
def load_features(data_base_dir, dataset_type):

    # declare all the signals in a list
    SIGNALS = [
    'body_acc_x',
    'body_acc_y',
    'body_acc_z',
    'body_gyro_x',
    'body_gyro_y',
    'body_gyro_z',
    'total_acc_x',
    'total_acc_y',
    'total_acc_z' ]

    # declare a list for holding the entire data frame
```

```
        signals_data = list()

        # do for all signals in the list
        for signal in SIGNALS:

            # set the file path
            file_path = os.path.join(data_base_dir,
                                     f'{dataset_type}/Inertial Signals/{signal}_{dataset_typ
            # read the file
            tdf = pd.read_csv(file_path, delim_whitespace=True, header=None)
            # update the list
            signals_data.append(tdf.values)

        # Transpose is used to change the dimensionality of the output,
        # aggregating the signals by combination of sample/timestep.
        # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
        signals_data =  np.transpose(signals_data, (1, 2, 0))


        return signals_data
```

```
In [10]: def load_labels(data_base_dir, dataset_type):

             # set the file path
             file_path = os.path.join(data_base_dir, f'{dataset_type}/y_{dataset_type}.txt')
             # read the file
             tdf = pd.read_csv(file_path, delim_whitespace=True, header=None, squeeze=True)

             print('Distribution of labels :\n', tdf.value_counts())

             # get labels in one-hot encoded representation
             labels = one_hot_encoder.transform(tdf.values.reshape(len(tdf), 1)).astype(int)

             return labels
```

5.1 Raw data signals Information

Signals are from Accelerometer and Gyroscope
The signals are in x,y,z directions
Triaxial acceleration from the accelerometer is total acceleration.
Sensor signals are filtered to have only body acceleration
excluding the acceleration due to gravity

```
In [11]: # Load the features
         X_train = load_features(data_base_dir, 'train')
         X_test = load_features(data_base_dir, 'test')
         # Load the labels
         y_train = load_labels(data_base_dir, 'train')
```

```
        y_test = load_labels(data_base_dir, 'test')

        if dataset_size > 0:
            X_train = X_train[0:dataset_size]
            X_test = X_test[0:dataset_size]
            y_train = y_train[0:dataset_size]
            y_test = y_test[0:dataset_size]
```

```
Distribution of labels :
 6    1407
5    1374
4    1286
1    1226
2    1073
3     986
Name: 0, dtype: int64
Distribution of labels :
 6    537
5    532
1    496
4    491
2    471
3    420
Name: 0, dtype: int64
```

```
In [12]: print('Train features shape : ', X_train.shape)
         print('Train labels shape : ', y_train.shape)
         print('Test features shape : ', X_test.shape)
         print('Test labels shape : ', y_test.shape)
```

```
Train features shape :  (7352, 128, 9)
Train labels shape :  (7352, 6)
Test features shape :  (2947, 128, 9)
Test labels shape :  (2947, 6)
```

6 MODEL

```
In [13]: def build_model_a(timesteps, input_dim, h_params):

             # Initiliazing the sequential model
             model = Sequential()

             # extract the hyper params
             n_hidden = h_params[0]
             dr_rate = h_params[1]
```

```
        # Configuring the parameters
        model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))

        # Adding a dropout layer
        model.add(Dropout(dr_rate))

        # Adding a dense output layer with sigmoid activation
        model.add(Dense(num_clasess, activation='sigmoid'))

        print(model.summary())

        return model
```

In [14]:
```
def build_model_b(timesteps, input_dim, h_params):

    # Initiliazing the sequential model
    model = Sequential()

    # Extract Hyperparameters

    # 1 - extract the number of neuorons
    n_hidden_1 = h_params[0]
    n_hidden_2 = h_params[1]

    # 2 - extract dropout rates
    dr_rate_1 = h_params[2]
    dr_rate_2 = h_params[3]

    # Configuring the parameters
    model.add(LSTM(n_hidden_1, input_shape=(timesteps, input_dim),
                   return_sequences=True))
    model.add(Dropout(dr_rate_1))
    model.add(LSTM(n_hidden_2, return_sequences=False))

    # Adding a dropout layer
    model.add(Dropout(dr_rate_2))

    # Adding a dense output layer with sigmoid activation
    model.add(Dense(num_clasess, activation='sigmoid'))

    print(model.summary())

    return model
```

In [15]:
```
def train_model(model, model_name, X_train, y_train, num_epochs):

    # Compiling the model
    model.compile(loss='categorical_crossentropy',
```

```
                optimizer='adam',
                metrics=['accuracy'])


    # monitor the performace of model on  every epoch
    checkpoint = ModelCheckpoint('./model/' + model_name, monitor='val_loss',
                                 verbose=0, save_best_only=True, mode='auto')

     # add early stopping
    early_stop =  EarlyStopping(monitor='val_loss', min_delta=0,
                        patience=5, verbose=0, mode='auto')

    callbacks_list = [checkpoint, early_stop]


    # Train the model
    hist_obj = model.fit(X_train, y_train, epochs=num_epochs, batch_size=batch_size,
                         validation_data=(X_test, y_test),
                         callbacks=callbacks_list, verbose=0)
    hist_obj = hist_obj.history

    # write train history to a file
    hist_path = './results/' + model_name[0:-3] + '_train_history.pkl'
    pickle_out = open(hist_path, 'wb')
    pickle.dump(hist_obj, pickle_out)
    pickle_out.close()

    return hist_obj
```

In [16]:
```
def evaluate_model(model, model_name, X, y, title_suffix=str(), plot_fig=True):

    # load weights from the saved model
    model_path = './model/' + model_name
    model.load_weights(model_path)

    # Compile model (required to make predictions)
    model.compile(loss='categorical_crossentropy', optimizer='adam',
                  metrics=['accuracy'])
    print('Restored best model weights from saved file', model_path)

    # evaluate model
    score = model.evaluate(X, y)

    # predict using model & get the labels
    predicted_labels = model.predict(X)
    predicted_labels_list = predicted_labels.argmax(axis=1)

    # format the actual list
```

```
    y_list = y.argmax(axis=1)


    # 1. Create confusion matrix
    conf_df = get_confusion_matrix(y_list, predicted_labels_list,
                                   title_suffix, plot_fig)
    # 2. Precision, Recall matrix
    pre_matrix, rec_matrix = get_precision_recall_matrix(conf_df,
                                                         title_suffix,
                                                         plot_fig)

    # 3. Evaluation metrics
    eval_df = get_classification_report(y_list, predicted_labels_list,
                                        title_suffix, plot_fig)

    # convert accuracy to percentage
    score[1] *= 100.0

    # extract individual fields
    return score
```

7 Run Models

```
In [17]: # Initializing parameters
         num_epochs = 30
         batch_size = 16

         timesteps = len(X_train[0])
         input_dim = len(X_train[0][0])

         print('Number of clasess :', num_clasess)
         print('Number of timesteps :', timesteps)
         print('Input data dimenion :', input_dim)
```

```
Number of clasess : 6
Number of timesteps : 128
Input data dimenion : 9
```

```
In [18]: # Importing tensorflow
         np.random.seed(42)
         tf.set_random_seed(42)
```

```
In [19]: # Configuring a session
         session_conf = tf.ConfigProto(
             intra_op_parallelism_threads=1,
             inter_op_parallelism_threads=1
         )
```

In [20]:
```
sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)
```

7.1 a) Single-Layered Architecture

7.1.1 Architecture 1

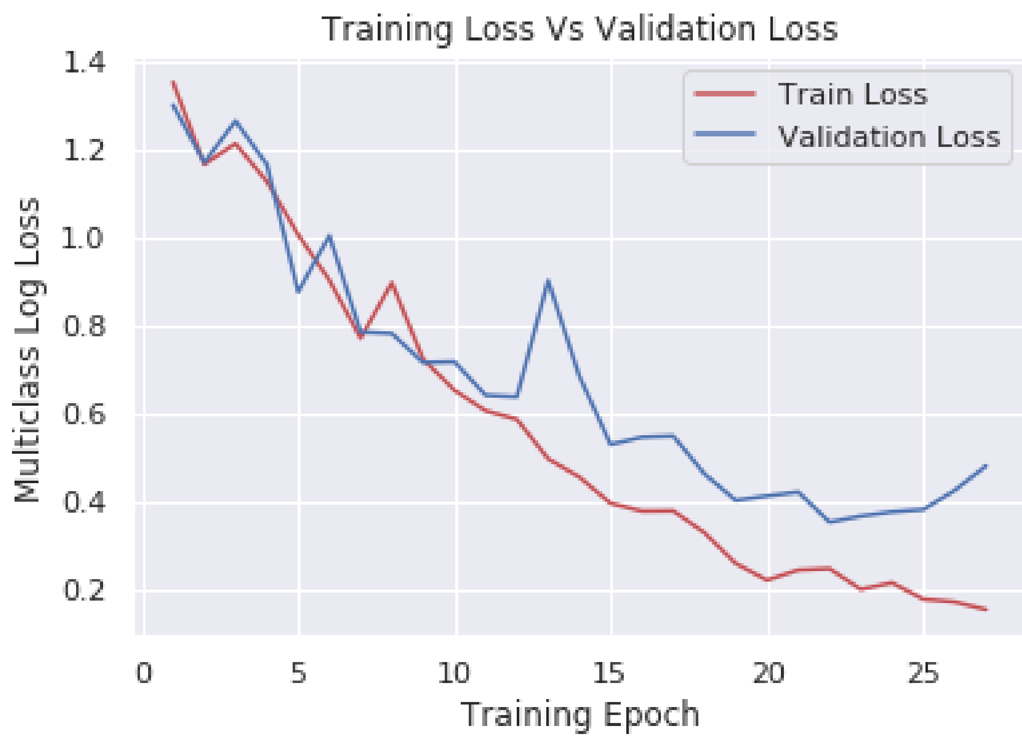
In [21]:
```
# Build the Model
h_params_a1 = (32, 0.32,)
model_a1 = build_model_a(timesteps, input_dim, h_params_a1)
```

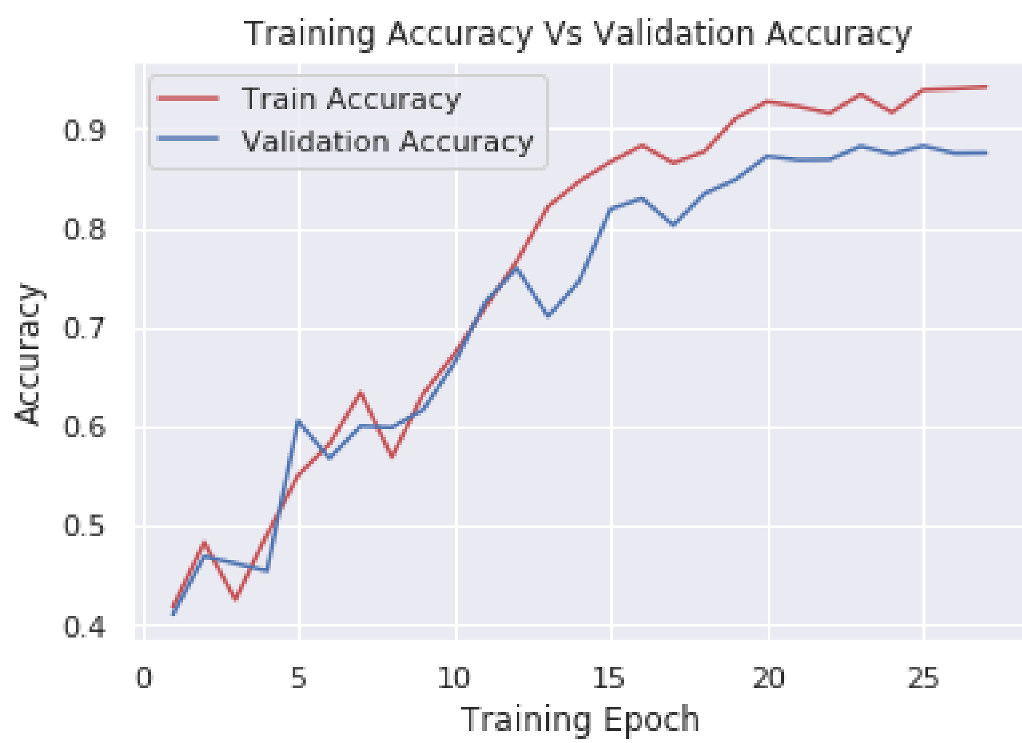
```
WARNING:tensorflow:From /home/nisheel-s/anaconda3/lib/python3.6/site-packages/keras/backend/tens
Instructions for updating:
keep_dims is deprecated, use keepdims instead
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 32)                5376
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 198
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
```

In [22]:
```
# Train the Model
model_a1_name = 'Single_Layered_LSTM_1.h5'
hist_model_a1 = train_model(model_a1, model_a1_name, X_train, y_train, num_epochs)
```

```
WARNING:tensorflow:From /home/nisheel-s/anaconda3/lib/python3.6/site-packages/keras/backend/tens
Instructions for updating:
keep_dims is deprecated, use keepdims instead
```

In [23]:
```
# plot loss, accuracy curves
plot_loss_curve(hist_model_a1)
plot_accuracy_curve(hist_model_a1)
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Multiclass Log Loss
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0
5
10
15
20
25
Training Epoch

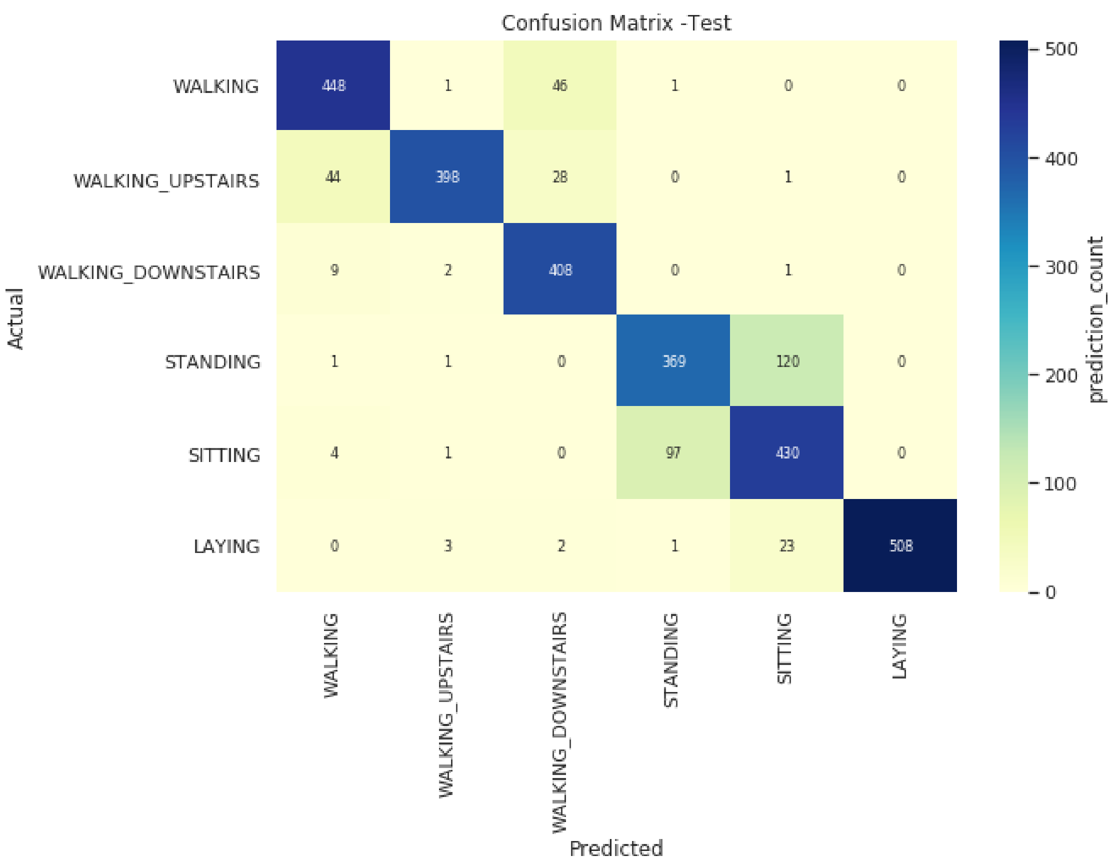

Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
0.9
0.8
0.7
0.6
0.5
0.4
0
5
10
15
20
25
Training Epoch

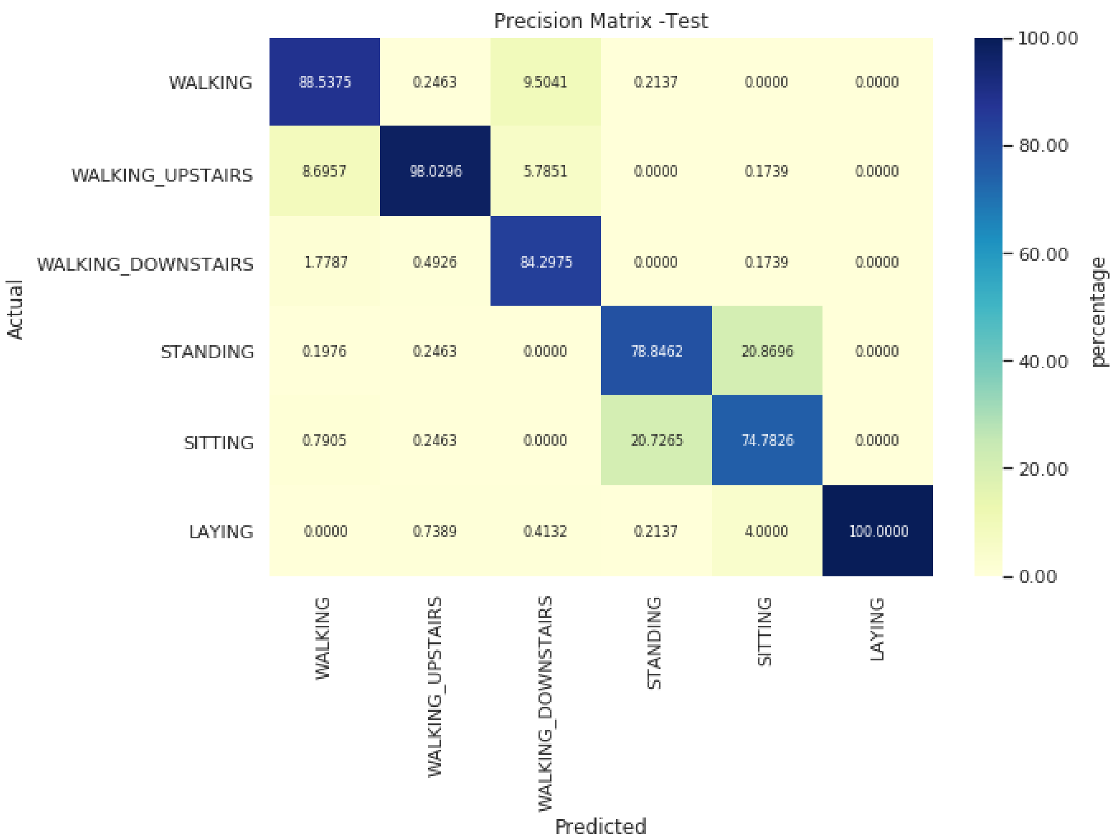
```
In [24]: # Evaluate the model on Test data
         train_score_model_a1 = evaluate_model(model_a1, model_a1_name, X_train, y_train,
                                               title_suffix='Train', plot_fig=False)
         train_score_model_a1 = [round(item, 4) for item in train_score_model_a1]
```

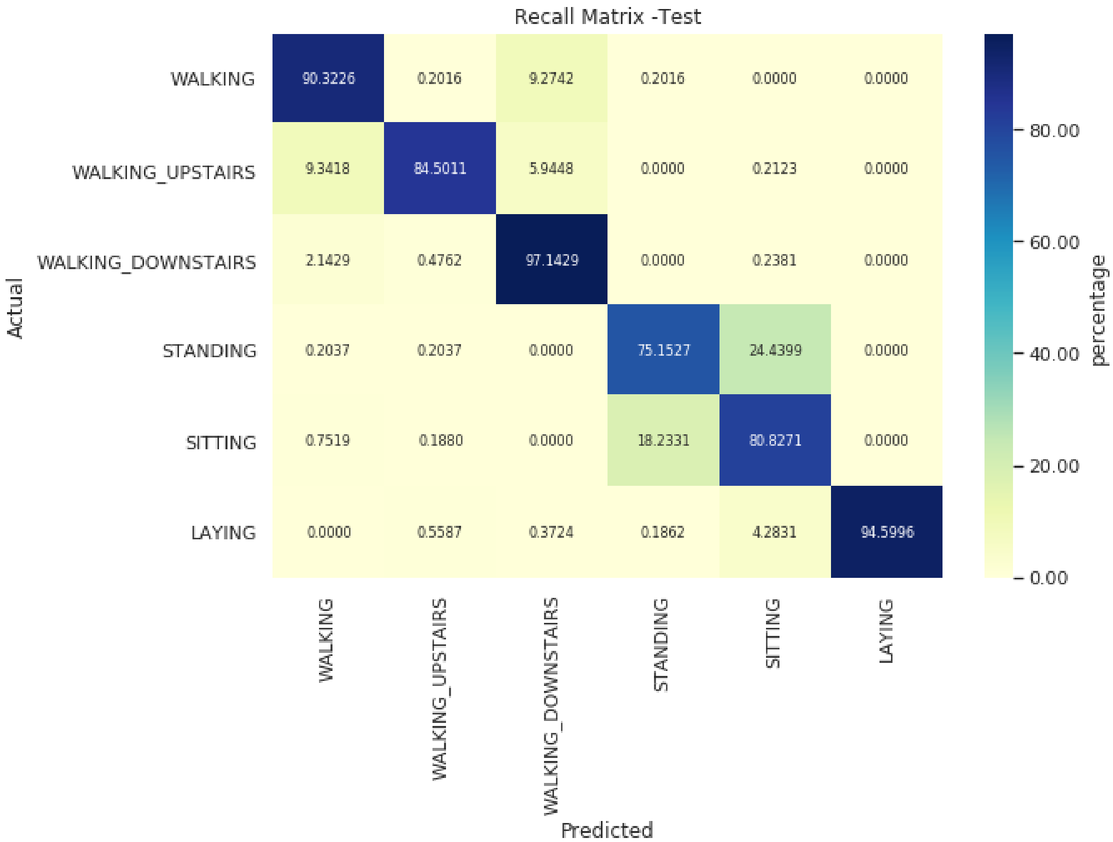
```
Restored best model weights from saved file ./model/Single_Layered_LSTM_1.h5
7352/7352 [==============================] - 2s 304us/step
```

```
In [25]: # Evaluate the model on Test data
         test_score_model_a1 = evaluate_model(model_a1, model_a1_name, X_test, y_test,
                                              title_suffix='Test', plot_fig=True)
         test_score_model_a1 = [round(item, 4) for item in test_score_model_a1]
```

```
Restored best model weights from saved file ./model/Single_Layered_LSTM_1.h5
2947/2947 [==============================] - 1s 351us/step
```




Precision Matrix -Test
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
Actual
Predicted
percentage
100.00
80.00
60.00
40.00
20.00
0.00
88.5375 0.2463 9.5041 0.2137 0.0000 0.0000
8.6957 98.0296 5.7851 0.0000 0.1739 0.0000
1.7787 0.4926 84.2975 0.0000 0.1739 0.0000
0.1976 0.2463 0.0000 78.8462 20.8696 0.0000
0.7905 0.2463 0.0000 20.7265 74.7826 0.0000
0.0000 0.7389 0.4132 0.2137 4.0000 100.0000


Recall Matrix -Test
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
Actual
Predicted
percentage
90.3226
0.2016
9.2742
0.2016
0.0000
0.0000
9.3418
84.5011
5.9448
0.0000
0.2123
0.0000
2.1429
0.4762
97.1429
0.0000
0.2381
0.0000
0.2037
0.2037
0.0000
75.1527
24.4399
0.0000
0.7519
0.1880
0.0000
18.2331
80.8271
0.0000
0.0000
0.5587
0.3724
0.1862
4.2831
94.5996
80.00
60.00
40.00
20.00
0.00


```
In [26]: table_entry_model_a1 = ['1 Layered LSTM(1)', h_params_a1] + train_score_model_a1 + \
                                  test_score_model_a1
```

7.1.2 Architecture 2

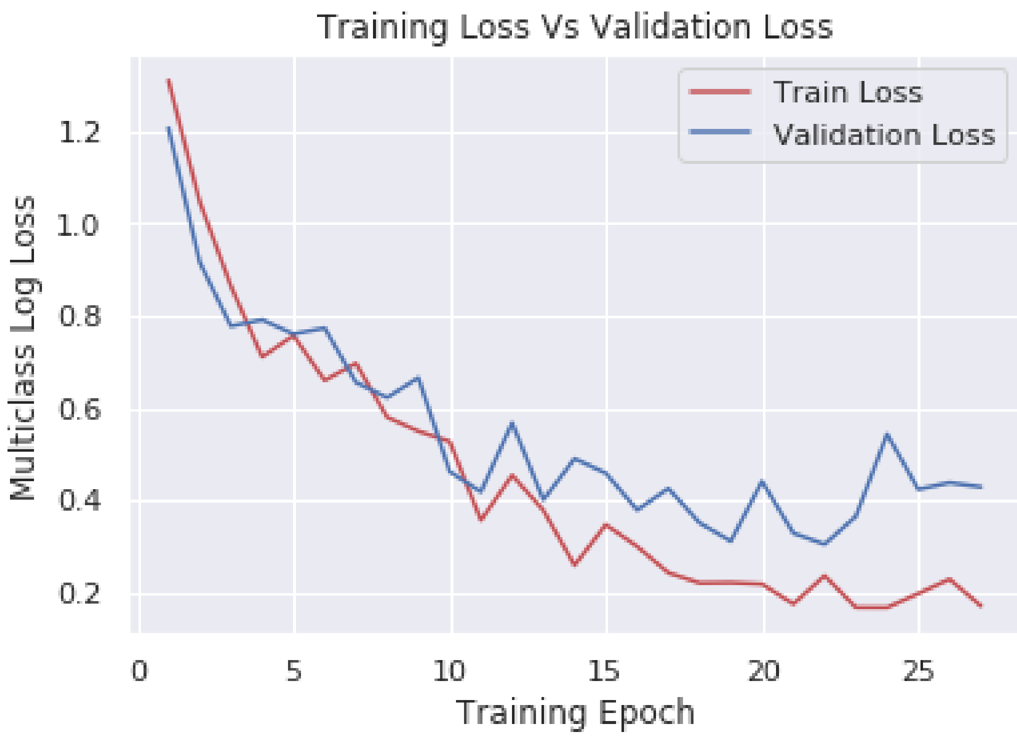
```
In [27]: # Build the Model
         h_params_a2 = (48, 0.40,)
         model_a2 = build_model_a(timesteps, input_dim, h_params_a2)
```

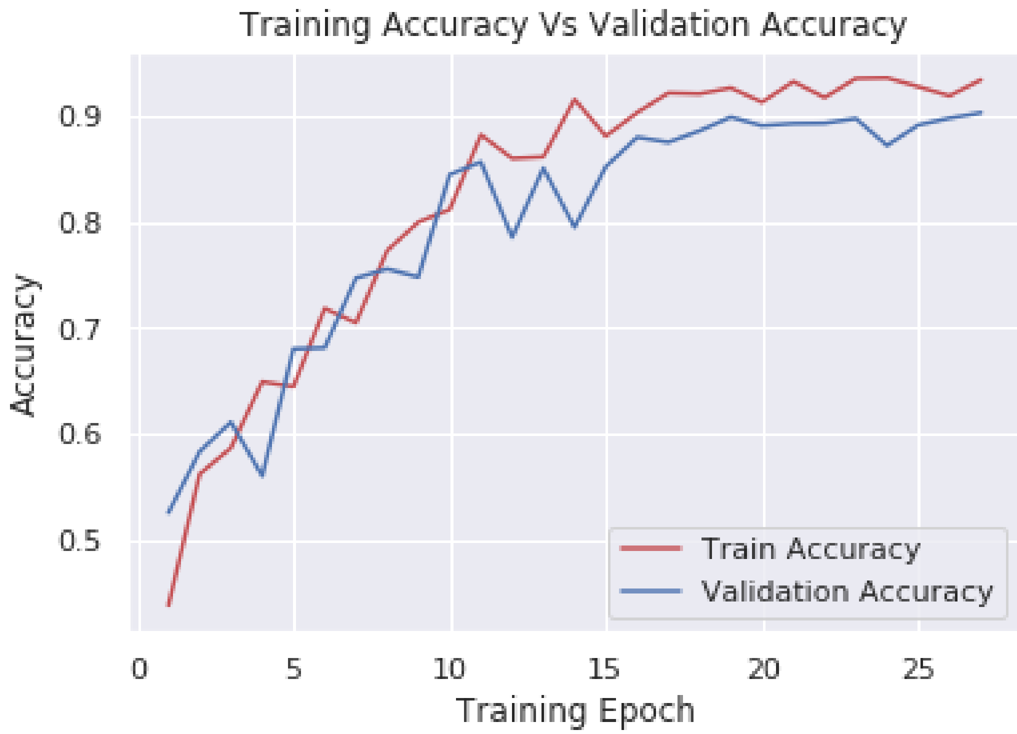
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_2 (LSTM)                (None, 48)                11136
_________________________________________________________________
dropout_2 (Dropout)          (None, 48)                0
_________________________________________________________________
dense_2 (Dense)              (None, 6)                 294
```

```
=================================================================
Total params: 11,430
Trainable params: 11,430
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [28]: # Train the Model
         model_a2_name = 'Single_Layered_LSTM_2.h5'
         hist_model_a2 = train_model(model_a2, model_a2_name, X_train, y_train, num_epochs)
```

```
In [29]: # plot loss, accuracy curves
         plot_loss_curve(hist_model_a2)
         plot_accuracy_curve(hist_model_a2)
```



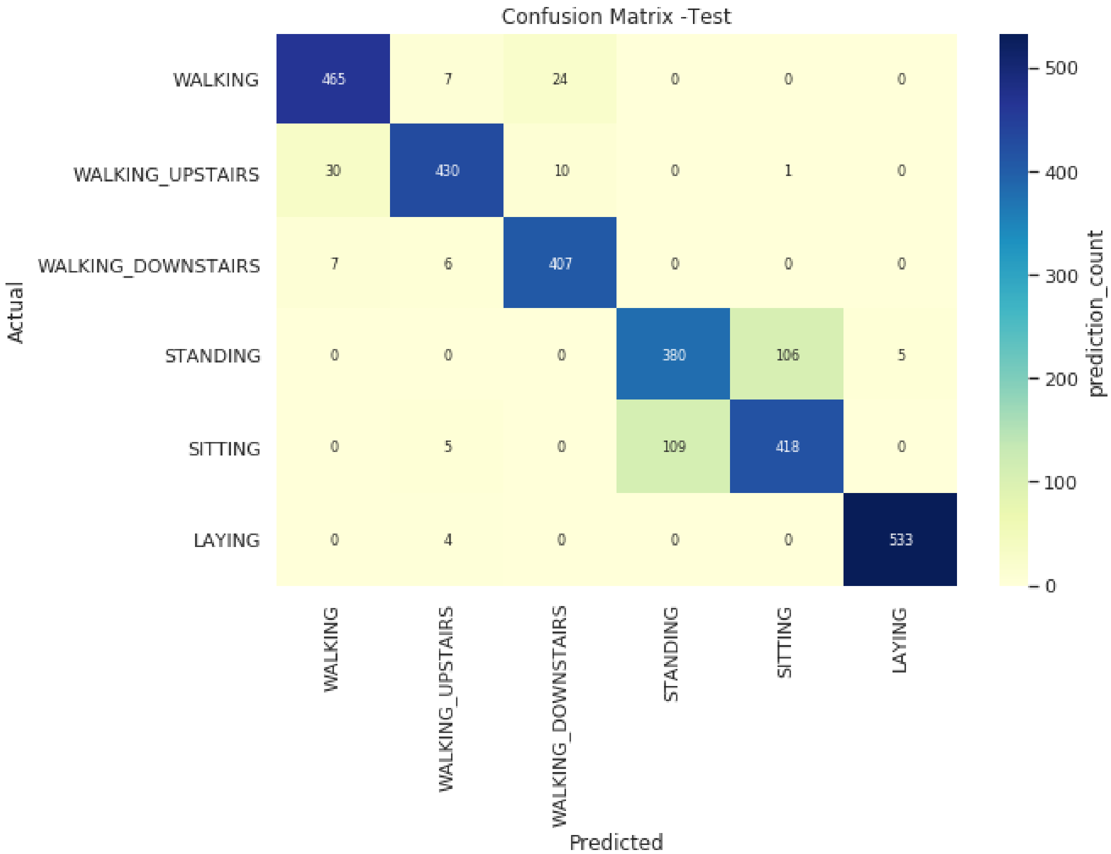


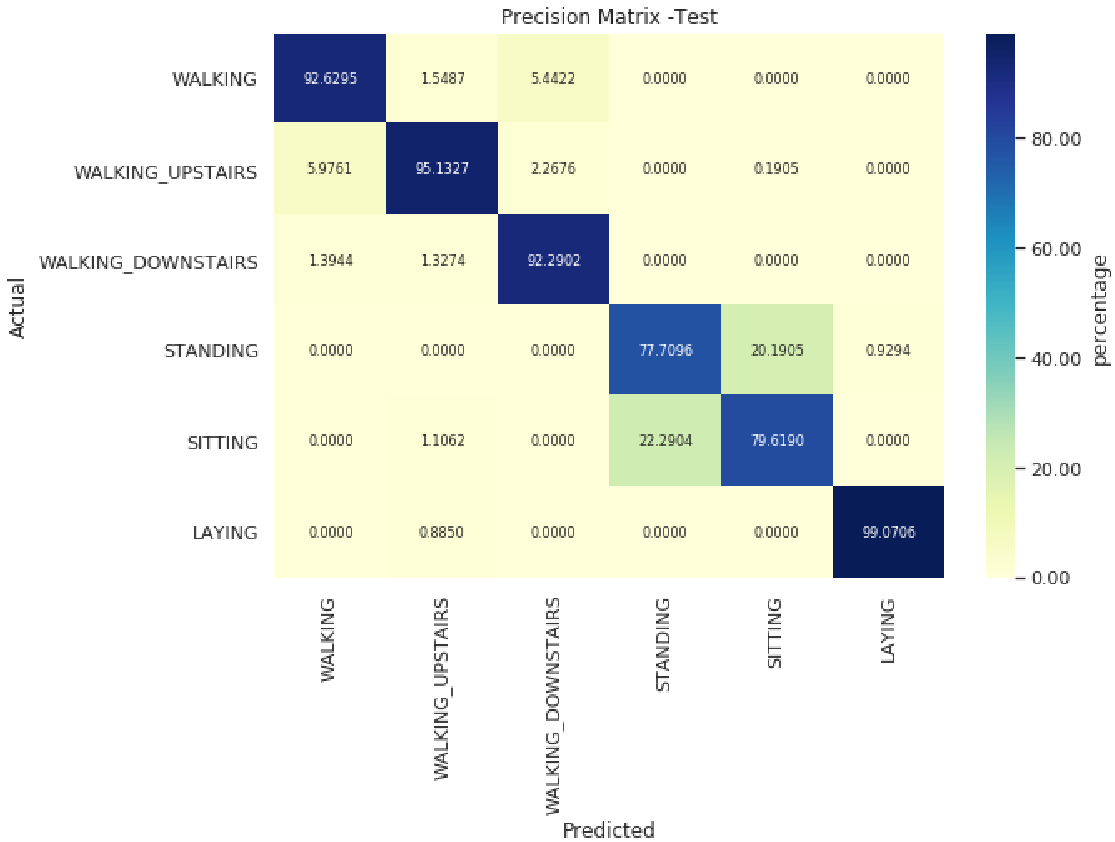

```
In [30]: # Evaluate the model on Test data
         train_score_model_a2 = evaluate_model(model_a2, model_a2_name, X_train, y_train,
                                               title_suffix='Train', plot_fig=False)
         train_score_model_a2 = [round(item, 4) for item in train_score_model_a2]
```

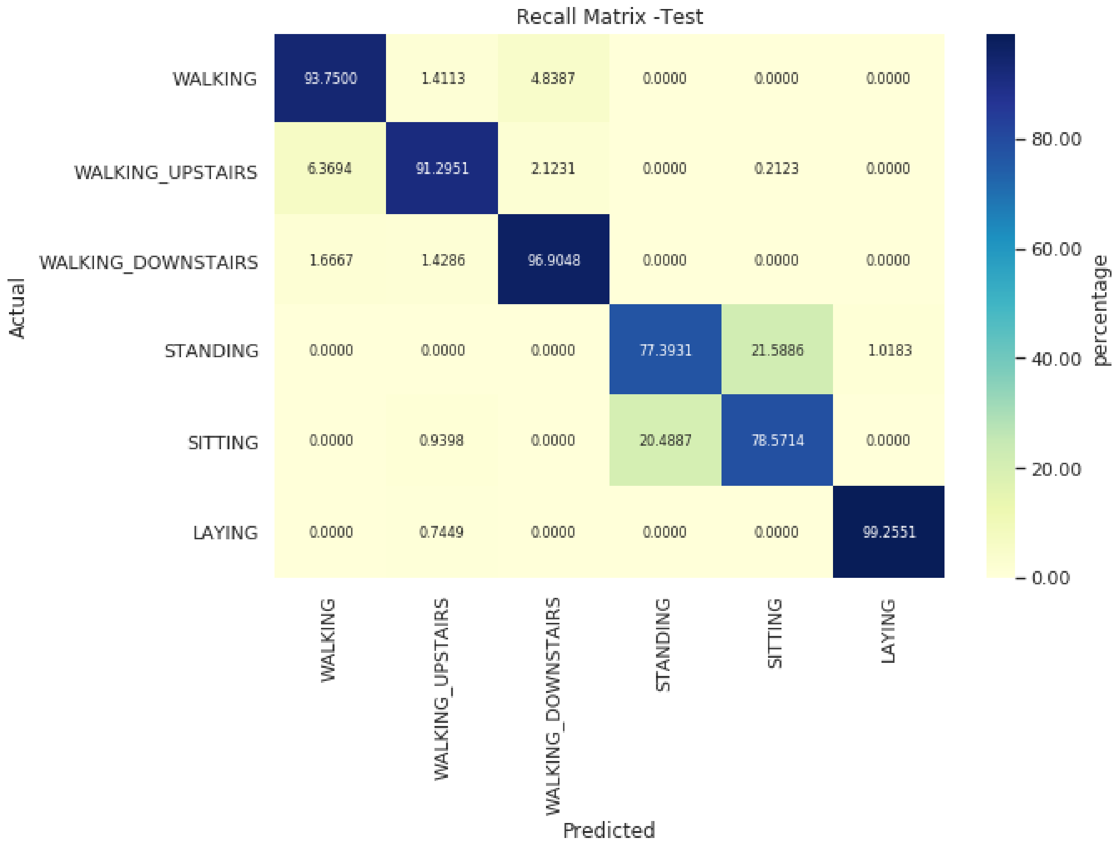
```
Restored best model weights from saved file ./model/Single_Layered_LSTM_2.h5
7352/7352 [==============================] - 2s 293us/step
```

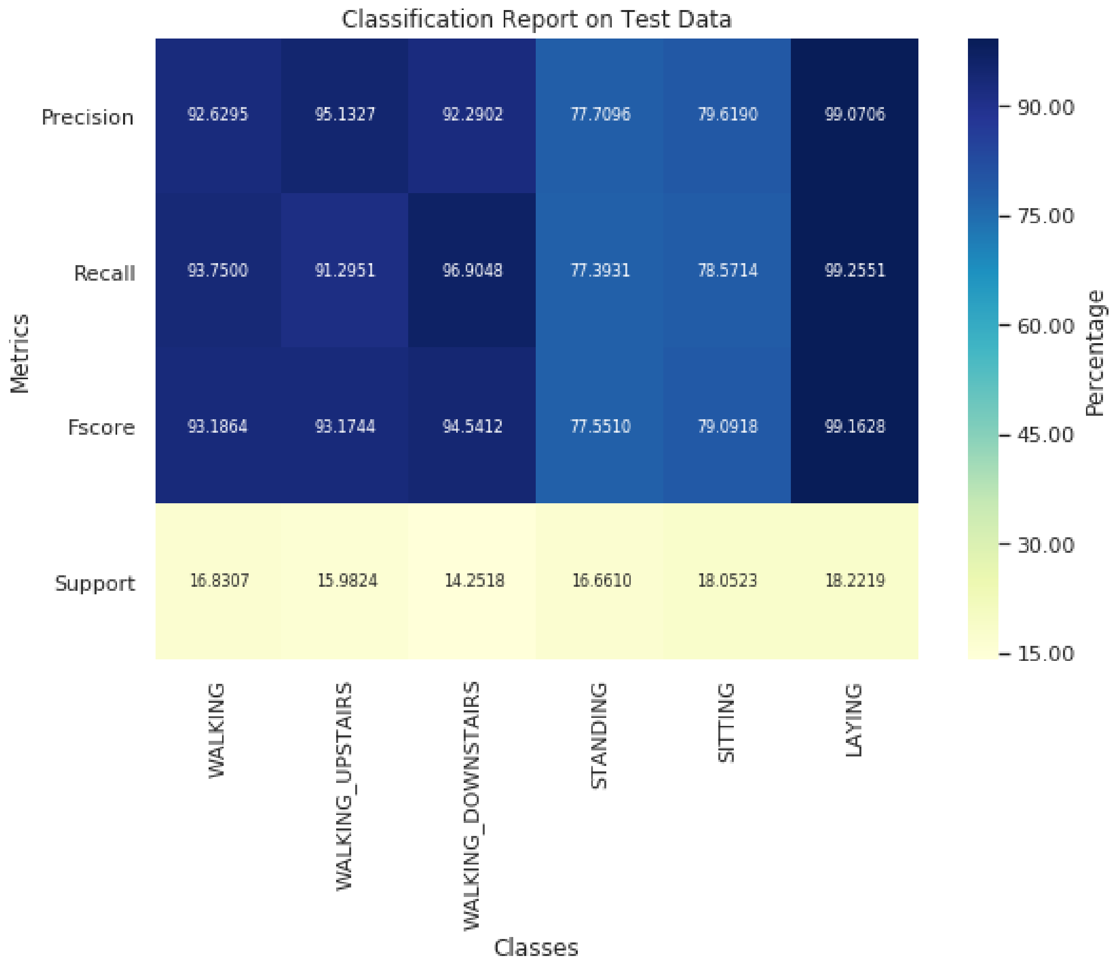
```
In [31]: # Evaluate the model on Test data
         test_score_model_a2 = evaluate_model(model_a2, model_a2_name, X_test, y_test,
                                              title_suffix='Test', plot_fig=True)
         test_score_model_a2 = [round(item, 4) for item in test_score_model_a2]
```

```
Restored best model weights from saved file ./model/Single_Layered_LSTM_2.h5
2947/2947 [==============================] - 1s 338us/step
```


Confusion Matrix -Test
Actual
Predicted
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
465
7
24
0
0
0
30
430
10
0
1
0
7
6
407
0
0
0
0
0
0
380
106
5
0
5
0
109
418
0
0
4
0
0
0
533
prediction_count
500
400
300
200
100
0


Precision Matrix -Test
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
Actual
92.6295
1.5487
5.4422
0.0000
0.0000
0.0000
5.9761
95.1327
2.2676
0.0000
0.1905
0.0000
1.3944
1.3274
92.2902
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
77.7096
20.1905
0.9294
0.0000
1.1062
0.0000
22.2904
79.6190
0.0000
0.0000
0.8850
0.0000
0.0000
0.0000
99.0706
80.00
60.00
40.00
20.00
0.00
percentage
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
Predicted


Recall Matrix -Test
Actual
Predicted
percentage
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
93.7500
1.4113
4.8387
0.0000
0.0000
0.0000
6.3694
91.2951
2.1231
0.0000
0.2123
0.0000
1.6667
1.4286
96.9048
0.0000
0.0000
0.0000
0.0000
0.0000
0.0000
77.3931
21.5886
1.0183
0.0000
0.9398
0.0000
20.4887
78.5714
0.0000
0.0000
0.7449
0.0000
0.0000
0.0000
99.2551
80.00
60.00
40.00
20.00
0.00




```
In [32]: table_entry_model_a2 = ['1 Layered LSTM(2)', h_params_a2] + train_score_model_a2 + \
                                test_score_model_a2
```

7.2 b) 2-Layered Architecture

7.2.1 Architecture 1

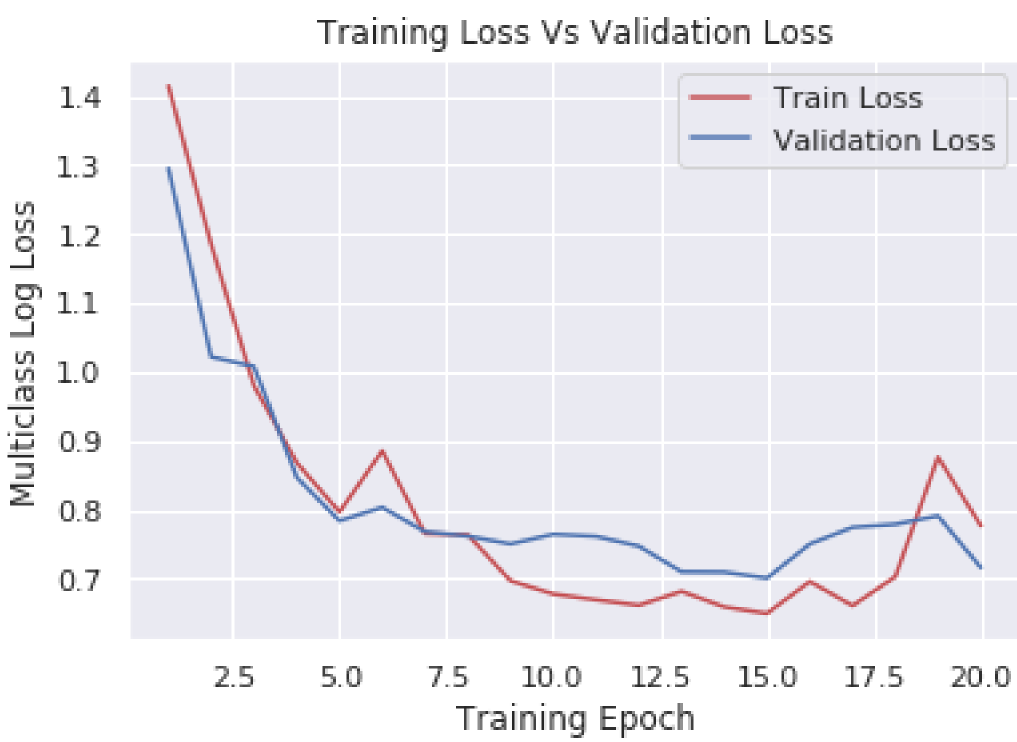
```
In [33]: h_params_b1 = (32, 18, 0.30, 0.45,)
         model_b1 = build_model_b(timesteps, input_dim, h_params_b1)
```

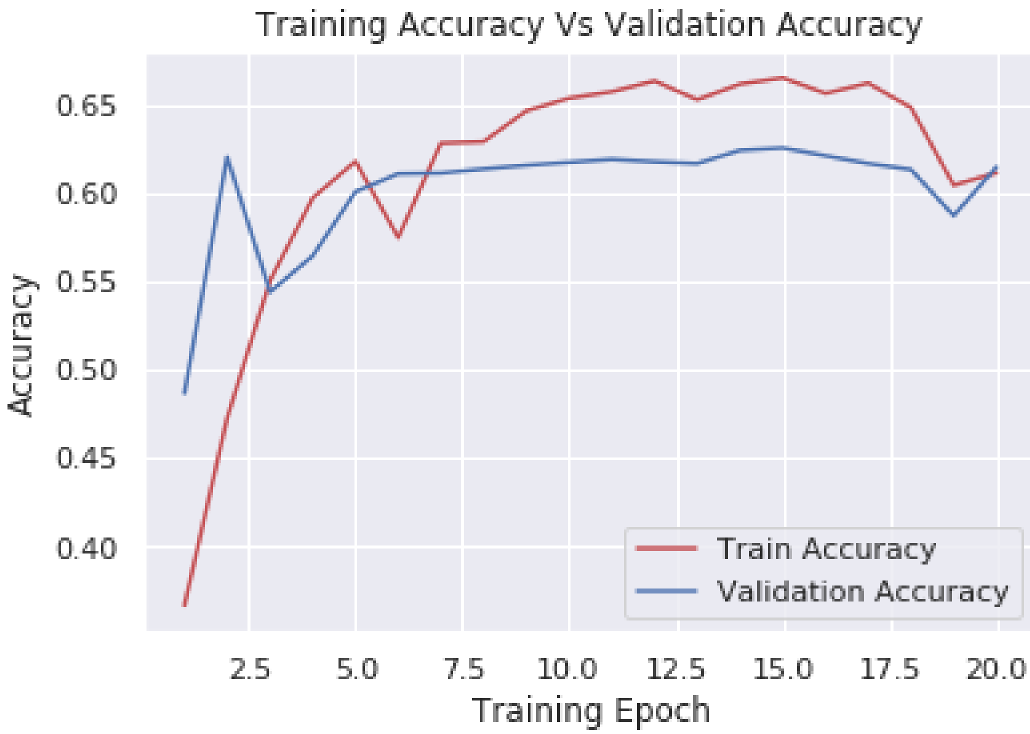
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 128, 32)           5376
_________________________________________________________________
dropout_3 (Dropout)          (None, 128, 32)           0
_________________________________________________________________
lstm_4 (LSTM)                (None, 18)                3672
```

```
_________________________________________________________________
dropout_4 (Dropout)          (None, 18)                0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 114
=================================================================
Total params: 9,162
Trainable params: 9,162
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [34]: # Train the Model
         model_b1_name = 'Two_Layered_LSTM_1.h5'
         hist_model_b1 = train_model(model_b1, model_b1_name, X_train, y_train, num_epochs)
```

```
In [35]: # plot loss, accuracy curves
         plot_loss_curve(hist_model_b1)
         plot_accuracy_curve(hist_model_b1)
```





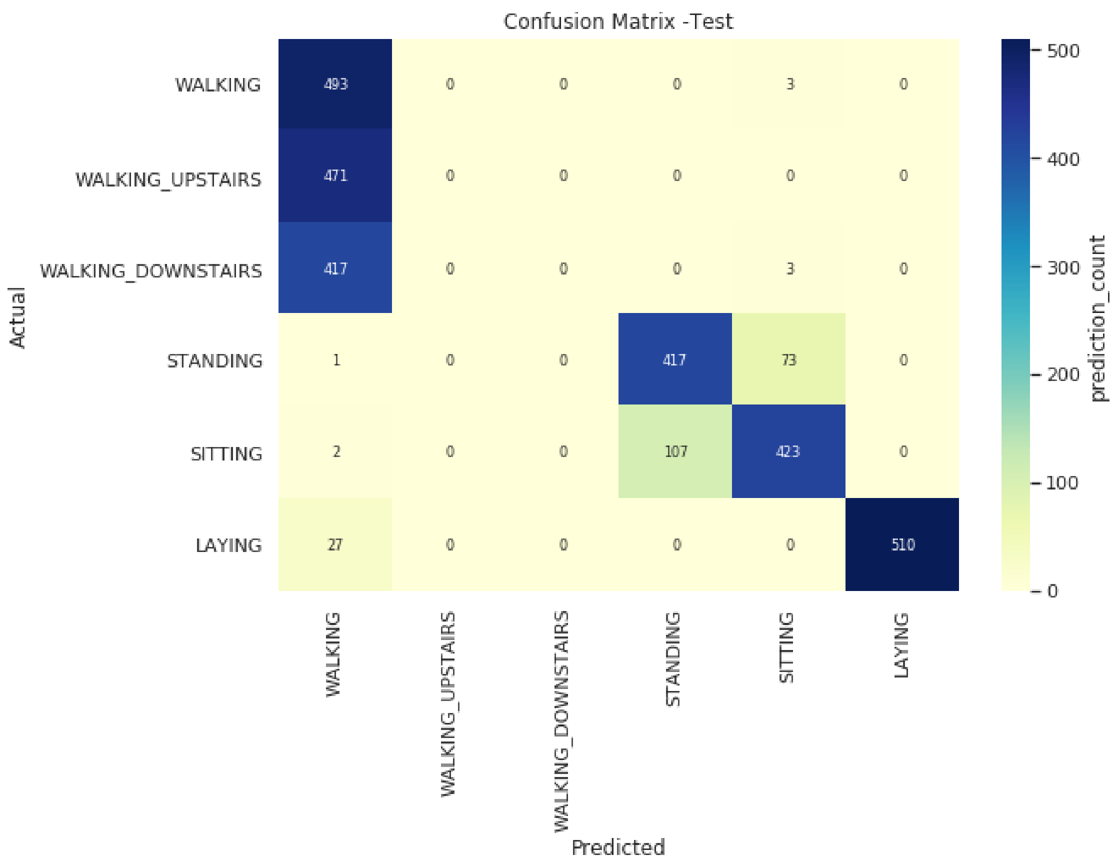

```
In [36]: # Evaluate the model on train data
         train_score_model_b1 = evaluate_model(model_b1, model_b1_name, X_train, y_train,
                                               title_suffix='Train', plot_fig=False)
         train_score_model_b1 = [round(item, 4) for item in train_score_model_b1]
```

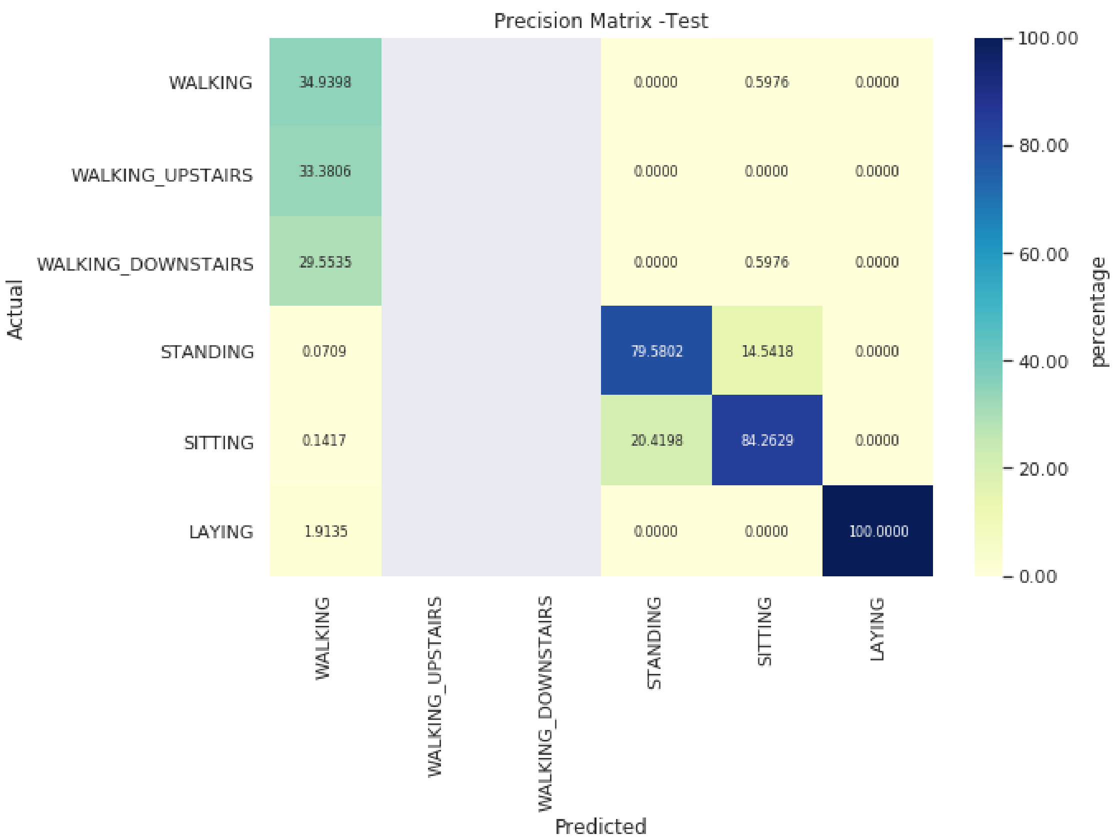
```
Restored best model weights from saved file ./model/Two_Layered_LSTM_1.h5
7352/7352 [==============================] - 4s 575us/step


/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Un
  'precision', 'predicted', average, warn_for)
```

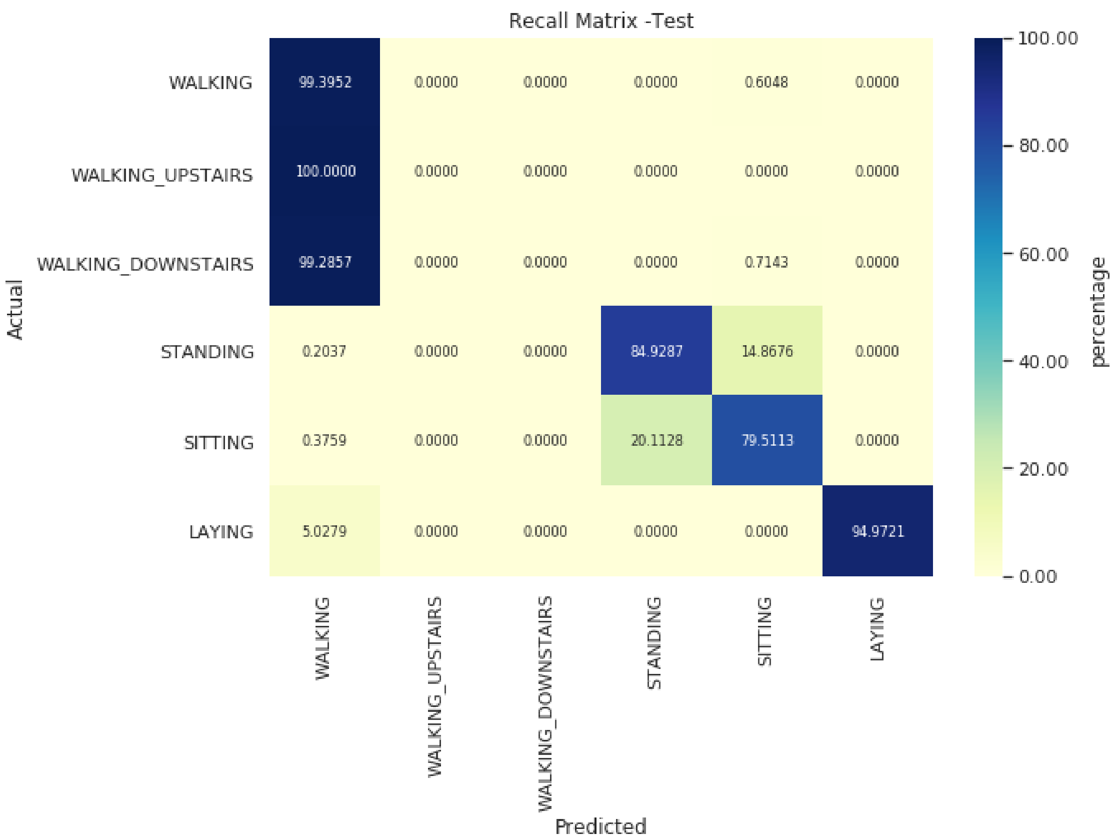
```
In [37]: # Evaluate the model on test data
         test_score_model_b1 = evaluate_model(model_b1, model_b1_name, X_test, y_test,
                                              title_suffix='Test', plot_fig=True)
         test_score_model_b1 = [round(item, 4) for item in test_score_model_b1]
```

```
Restored best model weights from saved file ./model/Two_Layered_LSTM_1.h5
2947/2947 [==============================] - 2s 656us/step
```

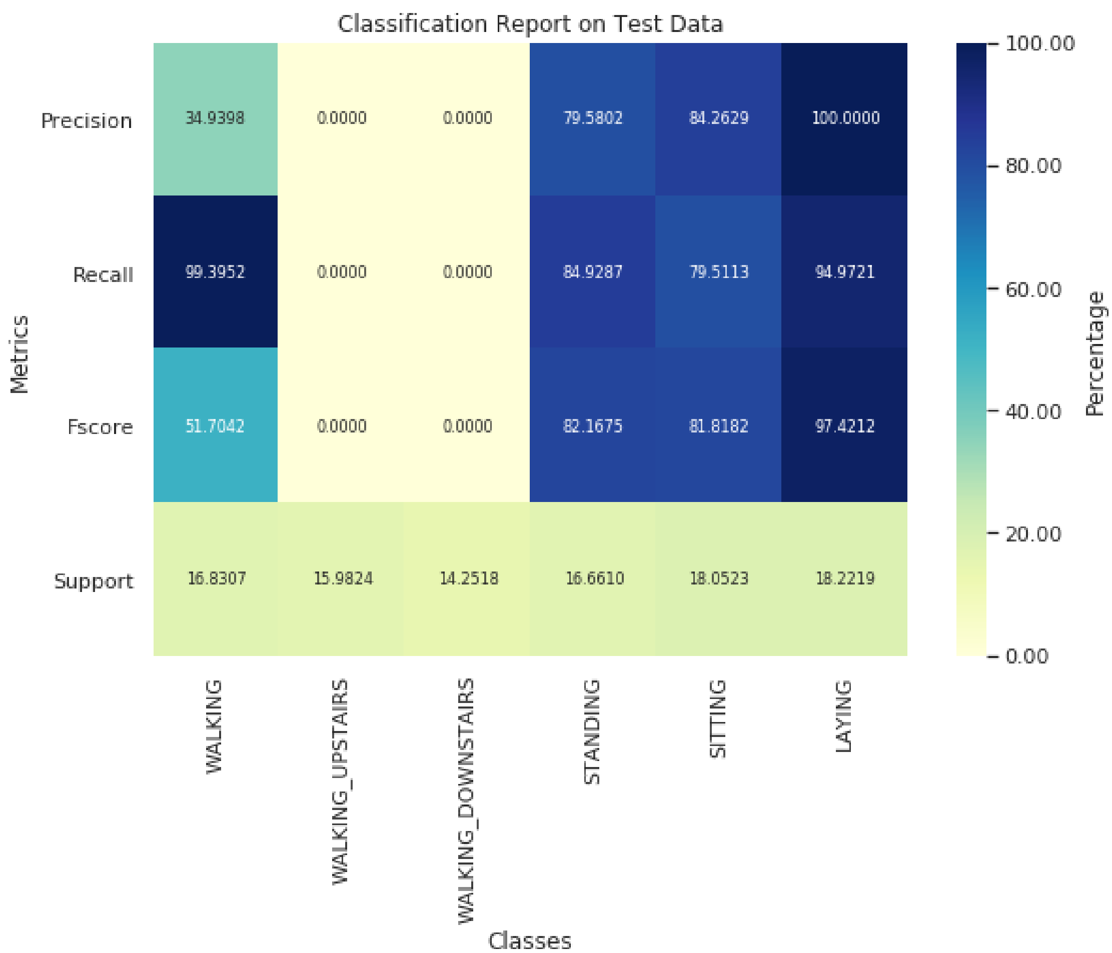

Confusion Matrix -Test
Actual
Predicted
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
493
471
417
1
2
27
107
417
73
423
3
510
prediction_count
500
400
300
200
100
0



Precision Matrix -Test
Actual
Predicted
percentage
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
34.9398
0.0000
0.5976
0.0000
33.3806
0.0000
0.0000
0.0000
29.5535
0.0000
0.5976
0.0000
0.0709
79.5802
14.5418
0.0000
0.1417
20.4198
84.2629
0.0000
1.9135
0.0000
0.0000
100.0000
100.00
80.00
60.00
40.00
20.00
0.00




```
/home/nisheel-s/anaconda3/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143: Un
  'precision', 'predicted', average, warn_for)
```




```
In [38]: table_entry_model_b1 = ['2 Layered LSTM(1)', h_params_b1] + train_score_model_b1 + \
                                 test_score_model_b1
```

7.2.2 Architecture 2

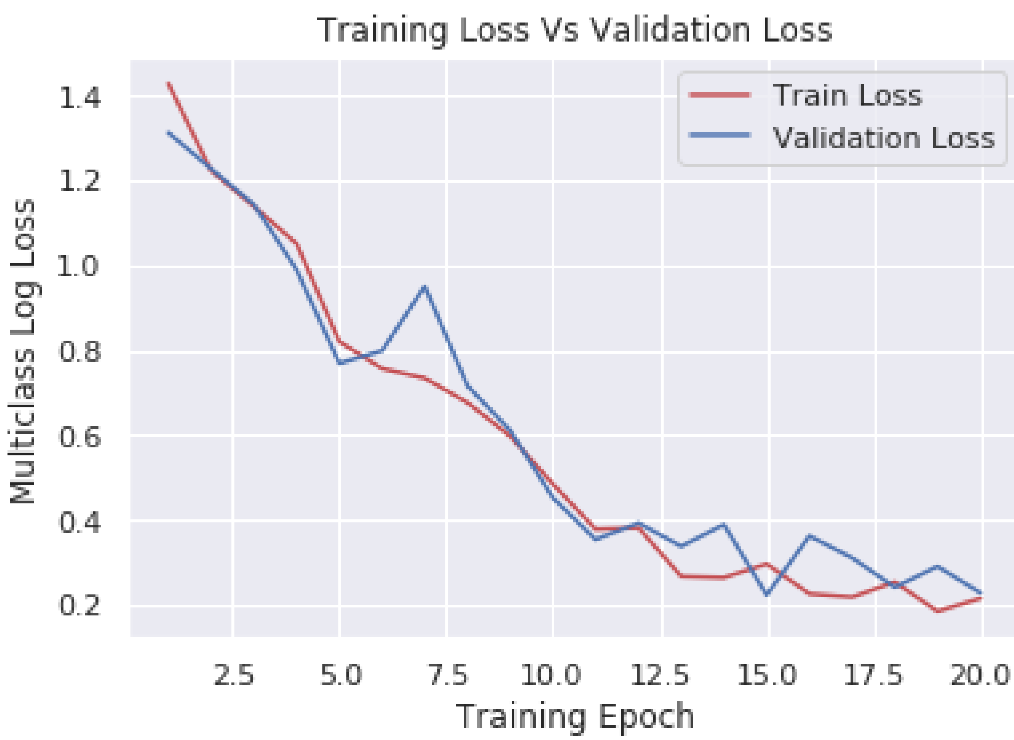
```
In [39]: h_params_b2 = (44, 23, 0.32, 0.48,)
         model_b2 = build_model_b(timesteps, input_dim, h_params_b2)
```

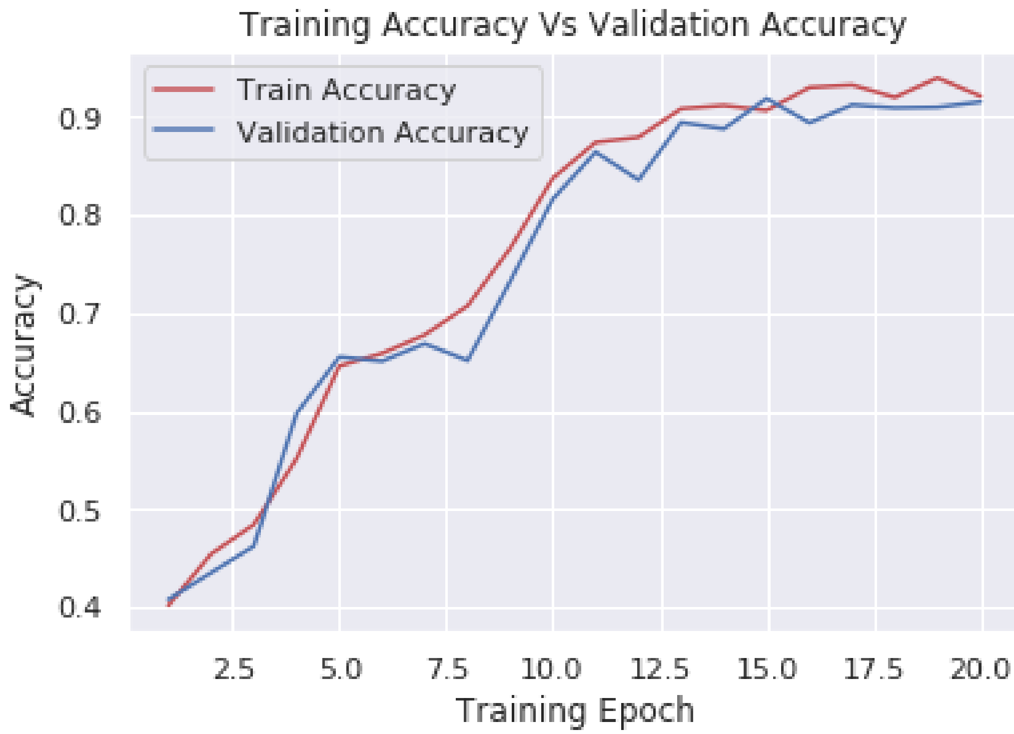
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_5 (LSTM)                (None, 128, 44)           9504
_________________________________________________________________
dropout_5 (Dropout)          (None, 128, 44)           0
_________________________________________________________________
lstm_6 (LSTM)                (None, 23)                6256
_________________________________________________________________
dropout_6 (Dropout)          (None, 23)                0
```

```
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 144
=================================================================
Total params: 15,904
Trainable params: 15,904
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [40]: # Train the Model
         model_b2_name = 'Two_Layered_LSTM_2.h5'
         hist_model_b2 = train_model(model_b2, model_b2_name, X_train, y_train, num_epochs)

In [41]: # plot loss, accuracy curves
         plot_loss_curve(hist_model_b2)
         plot_accuracy_curve(hist_model_b2)
```



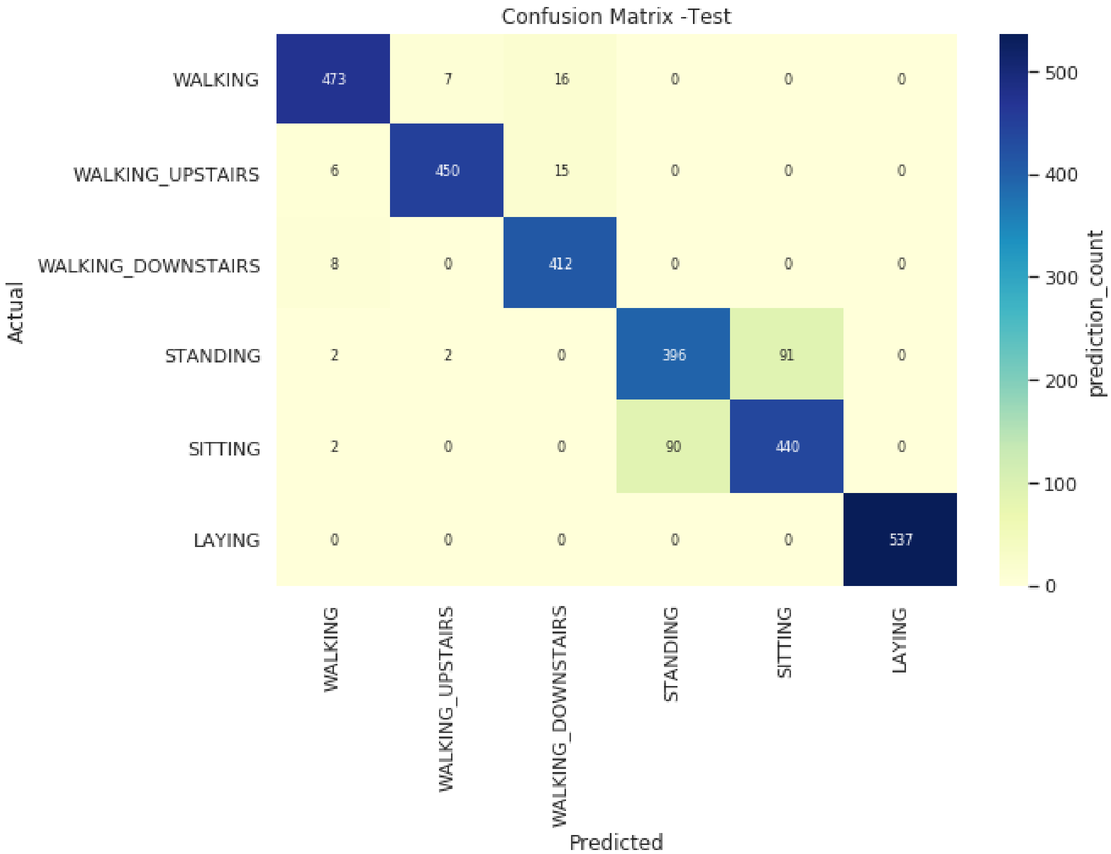



```
In [42]: # Evaluate the model on train data
         train_score_model_b2 = evaluate_model(model_b2, model_b2_name, X_train, y_train,
                                               title_suffix='Train', plot_fig=False)
         train_score_model_b2 = [round(item, 4) for item in train_score_model_b2]
```

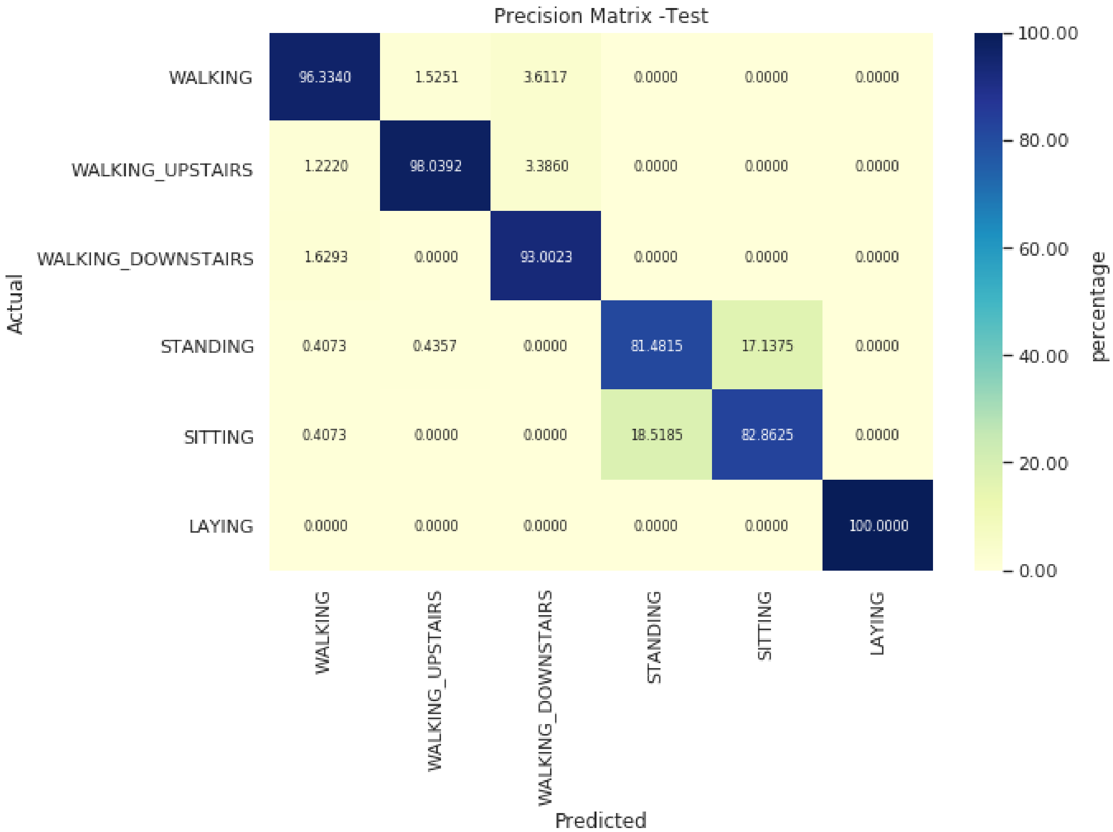
```
Restored best model weights from saved file ./model/Two_Layered_LSTM_2.h5
7352/7352 [==============================] - 5s 687us/step
```

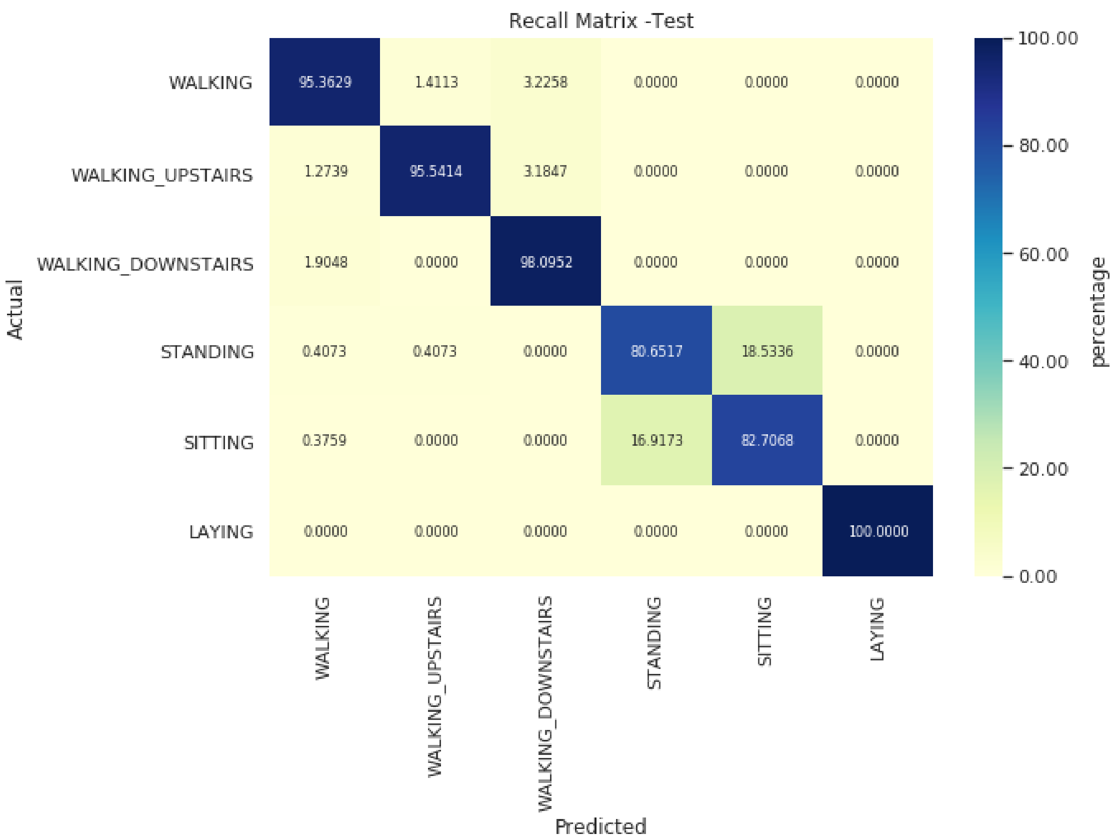
```
In [43]: # Evaluate the model on test data
         test_score_model_b2 = evaluate_model(model_b2, model_b2_name, X_test, y_test,
                                              title_suffix='Test', plot_fig=True)
         test_score_model_b2 = [round(item, 4) for item in test_score_model_b2]
```

```
Restored best model weights from saved file ./model/Two_Layered_LSTM_2.h5
2947/2947 [==============================] - 2s 786us/step
```



Confusion Matrix -Test
Actual
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
473
7
16
0
0
0
6
450
15
0
0
0
8
0
412
0
0
0
2
2
0
396
91
0
2
0
0
90
440
0
0
0
0
0
0
537
Predicted
prediction_count
500
400
300
200
100
0


Precision Matrix -Test
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
Actual
Predicted
percentage
96.3340 1.5251 3.6117 0.0000 0.0000 0.0000
1.2220 98.0392 3.3860 0.0000 0.0000 0.0000
1.6293 0.0000 93.0023 0.0000 0.0000 0.0000
0.4073 0.4357 0.0000 81.4815 17.1375 0.0000
0.4073 0.0000 0.0000 18.5185 82.8625 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000 100.0000
100.00
80.00
60.00
40.00
20.00
0.00



Recall Matrix -Test
Actual
Predicted
percentage
WALKING
WALKING_UPSTAIRS
WALKING_DOWNSTAIRS
STANDING
SITTING
LAYING
95.3629 1.4113 3.2258 0.0000 0.0000 0.0000
1.2739 95.5414 3.1847 0.0000 0.0000 0.0000
1.9048 0.0000 98.0952 0.0000 0.0000 0.0000
0.4073 0.4073 0.0000 80.6517 18.5336 0.0000
0.3759 0.0000 0.0000 16.9173 82.7068 0.0000
0.0000 0.0000 0.0000 0.0000 0.0000 100.0000
100.00
80.00
60.00
40.00
20.00
0.00


```
In [44]: table_entry_model_b2 = ['2-Layered LSTM(2)', h_params_b2] + train_score_model_b2 + \
                                 test_score_model_b2
```

8 Results

```
In [45]: Pret_table = PrettyTable()
         Pret_table.field_names = ['Model', """Hyperparam (#units,dropout)""",
                                   'Train Loss', 'Train Acc (%)', 'Test Loss',
                                   'Test Acc (%)']
         Pret_table.title = 'HAR LSTM Model Performances'

         Pret_table.add_row(table_entry_model_a1)
         Pret_table.add_row(table_entry_model_a2)
         Pret_table.add_row(table_entry_model_b1)
         Pret_table.add_row(table_entry_model_b2)
         print(Pret_table)
```

Model	Hyperparam (#units,dropout)	Train Loss	Train Acc (%)	Test Loss	Tes
1 Layered LSTM(1)	(32, 0.32)	0.1624	93.7432	0.3532	8
1 Layered LSTM(2)	(48, 0.4)	0.1592	94.056	0.3041	8
2 Layered LSTM(1)	(32, 18, 0.3, 0.45)	0.6048	67.519	0.7012	6
2-Layered LSTM(2)	(44, 23, 0.32, 0.48)	0.1456	94.9674	0.2236	9

9 Procedure Summary

The dataset is re-formated to feed into LSTM model

The datset is pattioned based on the number of users , 21 users in train side, 9 in test side (70:30) split

Two versions of single layered LSTM is architecure is desinged

Two versions of two layered LSTM is architecure is desinged

Train vs validation loss plot is made to ealuate performance

10 Conclusion

2-Layered LSTM architecture 2 performed well with 91.89 % accuracy

2-Layered LSTM architecure performace is not good as tbe accuracy is 62% very less compared to other models

Single layered architectue 1 showed 7% deviation between train, test. It shows tendancy to overfit

Hyperparam of 2-layered architecture 2 can be tuned to improve the results further

All models get confused more in classiying between sitting & standing