

# Section 1: Importing libraries and loading data

```
In [0]: 1 import pandas as pd
        2 import numpy as np
        3 import matplotlib.pyplot as plt
```

```
In [0]: 1 from google.colab import drive
        2 drive.mount('/content/drive')
```

Go to this URL in a browser: [https://accounts.google.com/o/oauth2/auth?client\\_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect\\_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aob&response\\_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly](https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aob&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly) (https://accounts.google.com/o/oauth2/auth?client\_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect\_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aob&response\_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly)

Enter your authorization code:

.....

Mounted at /content/drive

## 1.1 Loading data and specifying label names

```

In [0]: 1 # Activities are the class labels
2 # It is a 6 class classification
3 ACTIVITIES = {
4     0: 'WALKING',
5     1: 'WALKING_UPSTAIRS',
6     2: 'WALKING_DOWNSTAIRS',
7     3: 'SITTING',
8     4: 'STANDING',
9     5: 'LAYING',
10 }
11
12 # Data directory
13 DATADIR = 'UCI_HAR_Dataset'
14
15
16 # Raw data signals
17 # Signals are from Accelerometer and Gyroscope
18 # The signals are in x,y,z directions
19 # Sensor signals are filtered to have only body acceleration
20 # excluding the acceleration due to gravity
21 # Triaxial acceleration from the accelerometer is total acceleration
22 SIGNALS = [
23     "body_acc_x",
24     "body_acc_y",
25     "body_acc_z",
26     "body_gyro_x",
27     "body_gyro_y",
28     "body_gyro_z",
29     "total_acc_x",
30     "total_acc_y",
31     "total_acc_z"
32 ]
33
34 # Utility function to read the data from csv file
35 def _read_csv(filename):
36     return pd.read_csv(filename, delim_whitespace=True, header=None)
37
38 # Utility function to load the Load
39 def load_signals(subset):
40     signals_data = []
41
42     for signal in SIGNALS:
43         filename = f'drive/My Drive/UCI_HAR_Dataset/{subset}/Inertial Signals
44         signals_data.append(
45             _read_csv(filename).as_matrix()
46         )
47
48     # Transpose is used to change the dimensionality of the output,
49     # aggregating the signals by combination of sample/timestep.
50     # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 sign
51     return np.transpose(signals_data, (1, 2, 0))
52 # Utility function to print the confusion matrix

```

## 1.2 Reading Data

```

In [0]: 1
2 def load_y(subset):
3     """
4     The objective that we are trying to predict is a integer, from 1 to 6,
5     that represents a human activity. We return a binary representation of
6     every sample objective as a 6 bits vector using One Hot Encoding
7     (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
8     """
9     filename = f'drive/My Drive/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
10    y = _read_csv(filename)[0]
11
12    return pd.get_dummies(y).as_matrix()
13
14    #=====
15
16    def load_data():
17        """
18        Obtain the dataset from multiple files.
19        Returns: X_train, X_test, y_train, y_test
20        """
21        X_train, X_test = load_signals('train'), load_signals('test')
22        y_train, y_test = load_y('train'), load_y('test')
23
24        return X_train, X_test, y_train, y_test

```

```

In [0]: 1 # Loading the train and test data
2 X_train, X_test, Y_train, Y_test = load_data()

```

## Section 2: Tensorflow backend and utility functions

```

In [0]: 1 # Importing tensorflow
2 np.random.seed(42)
3 import tensorflow as tf
4 tf.set_random_seed(42)

```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x. We recommend you [upgrade](https://www.tensorflow.org/guide/migrate) (https://www.tensorflow.org/guide/migrate) now or ensure your notebook will continue to use TensorFlow 1.x via the %tensorflow\_version 1.x magic: [more info](https://colab.research.google.com/notebooks/tensorflow_version.ipynb) (https://colab.research.google.com/notebooks/tensorflow\_version.ipynb).

```

In [0]: 1 # Configuring a session
2 session_conf = tf.ConfigProto(
3     intra_op_parallelism_threads=1,
4     inter_op_parallelism_threads=1
5 )

```

```
In [0]: 1 # Importing libraries
2 # Import Keras
3 from keras import backend as K
4 sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
5 K.set_session(sess)
6 from keras.models import Sequential
7 from keras.layers import LSTM
8 from keras.layers.core import Dense, Dropout
9 from keras.layers import BatchNormalization
```

Using TensorFlow backend.

```
In [0]: 1 # Utility function to count the number of classes
2 def _count_classes(y):
3     return len(set([tuple(category) for category in y]))
```

```
In [0]: 1 timesteps = len(X_train[0])
2 input_dim = len(X_train[0][0])
3 n_classes = _count_classes(Y_train)
4
5 print('Number of timesteps are for each of the input dimensions',timesteps)
6 print('the input dimensions are ',input_dim)
7 print('size of training data is:',len(X_train))
```

Number of timesteps are for each of the input dimensions 128  
the input dimensions are 9  
size of training data is: 7352

```
In [0]: 1 import warnings
2 warnings.filterwarnings('ignore')
3
4
5 #function for saving and opening the file
6 import pickle
7 def savetofile(obj,filename):
8     pickle.dump(obj,open(filename+".p",'wb'))
9
10 def openfromfile(filename):
11     temp = pickle.load(open(filename+".p",'rb'))
12     return temp
```

```
In [0]: 1 # Initializing batch size and number of epochs for all the models
2 epochs = 30
3 batch_size = 16
4
```

```
In [0]: 1 #functions to plot confusion matrix
2 import itertools
3 import numpy as np
4 import matplotlib.pyplot as plt
5 from sklearn.metrics import confusion_matrix
6 from sklearn.metrics import classification_report, accuracy_score
7 plt.rcParams["font.family"] = 'DejaVu Sans'
8
9 def plt_confusion_matrix(cm, classes,
10                          normalize=False,
11                          title='Confusion matrix',
12                          cmap=plt.cm.Blues):
13     if normalize:
14         cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
15
16     plt.imshow(cm, interpolation='nearest', cmap=cmap)
17     plt.title(title)
18     plt.colorbar()
19     tick_marks = np.arange(len(classes))
20     plt.xticks(tick_marks, classes, rotation=90)
21     plt.yticks(tick_marks, classes)
22
23     fmt = '.2f' if normalize else 'd'
24     thresh = cm.max() / 2.
25     for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
26         plt.text(j, i, format(cm[i, j], fmt),
27                  horizontalalignment="center",
28                  color="white" if cm[i, j] > thresh else "black")
29
30     plt.tight_layout()
31     plt.ylabel('True label')
32     plt.xlabel('Predicted label')
```

```

In [0]: 1 #plotting the accuracy and classification report
2
3 from datetime import datetime
4 def perform_model(y_test,y_pred, class_labels, cm_normalize=True, \
5                 print_cm=True, cm_cmap=plt.cm.Greens):
6
7     results = dict()
8     Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
9     Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(y_pred, axis=1)])
10    # calculate overall accuracy of the model
11    accuracy = accuracy_score(y_true=Y_true, y_pred=Y_pred)
12    # store accuracy in results
13    results['accuracy'] = accuracy
14    print('For test data')
15    print('-----')
16    print('|          Accuracy          |')
17    print('-----')
18    print('\n    {}\n\n'.format(accuracy))
19
20
21    # confusion matrix
22    cm = confusion_matrix(y_test,y_pred)
23    results['confusion_matrix'] = cm
24    if print_cm:
25        print('-----')
26        print('| Confusion Matrix |')
27        print('-----')
28        print('\n {}'.format(cm))
29
30    # plot confusion matrix
31    #plt.figure(figsize=(8,8))
32    #plt.grid(b=False)
33    #plot_confusion_matrix(cm, classes=class_labels, normalize=True, title='N
34    #plt.show()
35
36    # get classification report
37    print('-----')
38    print('| Classification Report |')
39    print('-----')
40    class_report = classification_report(Y_true, Y_pred)
41    # store report in results
42    results['class_report'] = class_report
43    print(class_report)
44
45    # add the trained model to the results
46    #results['model'] = model
47
48    return results,cm
49
50
51

```

## Section 3: Deep learning Architecture and Models

so we will be implementing 4 different architectures here with different batchnormalization layers and dropout rates, and optimizers

### **3.1 Model 1: LSTM(32) + Batchnormalization + Dropout(0.3) + RmsProp**

```
In [0]: 1 # Initiliazing the sequential model
2 n_hidden = 32
3 model = Sequential()
4 # Configuring the parameters
5 model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
6
7
8 # Adding a BatchNormalization Layer
9 model.add(BatchNormalization())
10
11 #adding a dropout layer
12 model.add(Dropout(0.3))
13
14 # Adding a dense output layer with sigmoid activation
15 model.add(Dense(n_classes, activation='sigmoid'))
16 model.summary()
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:541: The name tf.placeholder is deprecated. Please use tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:4432: The name tf.random\_uniform is deprecated. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:148: The name tf.placeholder\_with\_default is deprecated. Please use tf.compat.v1.placeholder\_with\_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:3733: calling dropout (from tensorflow.python.ops.nn\_ops) with keep\_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep\_prob`. Rate should be set to `rate = 1 - keep\_prob`.

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
=====		
lstm_1 (LSTM)	(None, 32)	5376
-----		
batch_normalization_1 (Batch Normalization)	(None, 32)	128
-----		
dropout_1 (Dropout)	(None, 32)	0
-----		
dense_1 (Dense)	(None, 6)	198
=====		
Total params: 5,702		
Trainable params: 5,638		
Non-trainable params: 64		
-----		



```
In [0]: 1 # Compiling the model
2 model.compile(loss='categorical_crossentropy',
3               optimizer='rmsprop',
4               metrics=['accuracy'])
5
6
7 # Training the model
8 history_1 = model.fit(X_train,
9                       Y_train,
10                      batch_size=batch_size,
11                      validation_data=(X_test, Y_test),
12                      epochs=epochs)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizer\_s.py:793: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:3576: The name tf.log is deprecated. Please use tf.math.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow\_core/python/ops/math\_grad.py:1424: where (from tensorflow.python.ops.array\_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:1033: The name tf.assign\_add is deprecated. Please use tf.compat.v1.assign\_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

Train on 7352 samples, validate on 2947 samples

Epoch 1/30

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:190: The name tf.get\_default\_session is deprecated. Please use tf.compat.v1.get\_default\_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:207: The name tf.global\_variables is deprecated. Please use tf.compat.v1.global\_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:216: The name tf.is\_variable\_initialized is deprecated. Please use tf.compat.v1.is\_variable\_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:223: The name tf.variables\_initializer is deprecated. Please use tf.compat.v1.variables\_initializer instead.

7352/7352 [=====] - 119s 16ms/step - loss: 1.0557 - acc: 0.5335 - val\_loss: 0.8607 - val\_acc: 0.5881

Epoch 2/30

7352/7352 [=====] - 102s 14ms/step - loss: 0.7560 - acc:

c: 0.5817 - val\_loss: 0.7688 - val\_acc: 0.6098  
Epoch 3/30  
7352/7352 [=====] - 99s 13ms/step - loss: 0.6784 - acc: 0.6178 - val\_loss: 0.6830 - val\_acc: 0.6485  
Epoch 4/30  
7352/7352 [=====] - 98s 13ms/step - loss: 0.5846 - acc: 0.7167 - val\_loss: 0.6987 - val\_acc: 0.6980  
Epoch 5/30  
7352/7352 [=====] - 106s 14ms/step - loss: 0.3940 - acc: 0.8414 - val\_loss: 0.4036 - val\_acc: 0.8521  
Epoch 6/30  
7352/7352 [=====] - 107s 15ms/step - loss: 0.2726 - acc: 0.9132 - val\_loss: 0.4896 - val\_acc: 0.8578  
Epoch 7/30  
7352/7352 [=====] - 102s 14ms/step - loss: 0.2279 - acc: 0.9203 - val\_loss: 0.3373 - val\_acc: 0.8850  
Epoch 8/30  
7352/7352 [=====] - 102s 14ms/step - loss: 0.2101 - acc: 0.9275 - val\_loss: 0.3588 - val\_acc: 0.8914  
Epoch 9/30  
7352/7352 [=====] - 102s 14ms/step - loss: 0.1973 - acc: 0.9248 - val\_loss: 0.4287 - val\_acc: 0.8918  
Epoch 10/30  
7352/7352 [=====] - 103s 14ms/step - loss: 0.2004 - acc: 0.9286 - val\_loss: 0.5229 - val\_acc: 0.8649  
Epoch 11/30  
7352/7352 [=====] - 104s 14ms/step - loss: 0.1723 - acc: 0.9372 - val\_loss: 0.3266 - val\_acc: 0.9033  
Epoch 12/30  
7352/7352 [=====] - 105s 14ms/step - loss: 0.1780 - acc: 0.9370 - val\_loss: 0.3539 - val\_acc: 0.8951  
Epoch 13/30  
7352/7352 [=====] - 102s 14ms/step - loss: 0.1753 - acc: 0.9359 - val\_loss: 0.3288 - val\_acc: 0.9138  
Epoch 14/30  
7352/7352 [=====] - 107s 15ms/step - loss: 0.1772 - acc: 0.9380 - val\_loss: 0.3317 - val\_acc: 0.9152  
Epoch 15/30  
7352/7352 [=====] - 103s 14ms/step - loss: 0.1775 - acc: 0.9378 - val\_loss: 0.4120 - val\_acc: 0.9026  
Epoch 16/30  
7352/7352 [=====] - 104s 14ms/step - loss: 0.1622 - acc: 0.9402 - val\_loss: 0.3215 - val\_acc: 0.9162  
Epoch 17/30  
7352/7352 [=====] - 110s 15ms/step - loss: 0.1615 - acc: 0.9415 - val\_loss: 0.5116 - val\_acc: 0.8833  
Epoch 18/30  
7352/7352 [=====] - 109s 15ms/step - loss: 0.1731 - acc: 0.9429 - val\_loss: 0.3719 - val\_acc: 0.9118  
Epoch 19/30  
7352/7352 [=====] - 107s 15ms/step - loss: 0.1662 - acc: 0.9423 - val\_loss: 0.4025 - val\_acc: 0.9114  
Epoch 20/30  
7352/7352 [=====] - 104s 14ms/step - loss: 0.1660 - acc: 0.9438 - val\_loss: 0.3589 - val\_acc: 0.9026  
Epoch 21/30  
7352/7352 [=====] - 112s 15ms/step - loss: 0.1589 - acc:

```

c: 0.9415 - val_loss: 0.3407 - val_acc: 0.9060
Epoch 22/30
7352/7352 [=====] - 107s 15ms/step - loss: 0.1512 - ac
c: 0.9430 - val_loss: 0.3713 - val_acc: 0.9138
Epoch 23/30
7352/7352 [=====] - 109s 15ms/step - loss: 0.1483 - ac
c: 0.9431 - val_loss: 0.4803 - val_acc: 0.9087
Epoch 24/30
7352/7352 [=====] - 108s 15ms/step - loss: 0.1438 - ac
c: 0.9433 - val_loss: 0.4046 - val_acc: 0.9104
Epoch 25/30
7352/7352 [=====] - 107s 15ms/step - loss: 0.1795 - ac
c: 0.9408 - val_loss: 0.5475 - val_acc: 0.8989
Epoch 26/30
7352/7352 [=====] - 108s 15ms/step - loss: 0.1472 - ac
c: 0.9471 - val_loss: 0.5127 - val_acc: 0.9023
Epoch 27/30
7352/7352 [=====] - 110s 15ms/step - loss: 0.1427 - ac
c: 0.9460 - val_loss: 0.5528 - val_acc: 0.8968
Epoch 28/30
7352/7352 [=====] - 109s 15ms/step - loss: 0.1526 - ac
c: 0.9489 - val_loss: 0.5177 - val_acc: 0.9026
Epoch 29/30
7352/7352 [=====] - 101s 14ms/step - loss: 0.1452 - ac
c: 0.9448 - val_loss: 0.6232 - val_acc: 0.8931
Epoch 30/30
7352/7352 [=====] - 104s 14ms/step - loss: 0.1468 - ac
c: 0.9455 - val_loss: 0.4055 - val_acc: 0.9189

```

```

In [0]: 1 score = model_1.evaluate(X_test,Y_test)
        2 print('loss on test data is',score[0])
        3 print('Accuracy on test data is:',score[1])
        4

```

```

2947/2947 [=====] - 2s 776us/step
loss on test data is 0.409051617424
Accuracy on test data is: 0.905666779776

```

```

In [0]: 1 model_1 = openfromfile('model_lstm1')#getting the saved model

```

```

In [0]: 1 labels=['LAYING', 'SITTING', 'STANDING', 'WALKING', 'WALKING_DOWNSTAIRS', 'WALKING_UPSTAIRS']
2 y_pred=model_1.predict(X_test)
3 results_mod_1,cm_1 = perform_model(Y_test,y_pred,labels, cm_normalize=True,
4                                     print_cm=True, cm_cmap=plt.cm.Greens)
5
6
7 #Get the confusion matrix
8
9 cm_df=confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using
10 classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df
11
12 #Plot a Non-Normalized confusion matrix
13 #plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED CONFUSION MATRIX")
14
15 #Plot a Normalized confusion matrix
16 plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFUSION MATRIX")

```

For test data

```

-----
| Accuracy |
-----

```

0.9056667797760435

```

-----
| Confusion Matrix |
-----

```

Pred \ True	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
LAYING	509	1	27	0	0	0
SITTING	0	418	72	1	0	0
STANDING	0	114	417	1	0	0
WALKING	0	0	0	466	0	0
WALKING_DOWNSTAIRS	0	0	0	0	401	0
WALKING_UPSTAIRS	0	4	0	8	0	1

Pred \ True	WALKING_UPSTAIRS
LAYING	0
SITTING	0
STANDING	0
WALKING	30
WALKING_DOWNSTAIRS	19
WALKING_UPSTAIRS	458

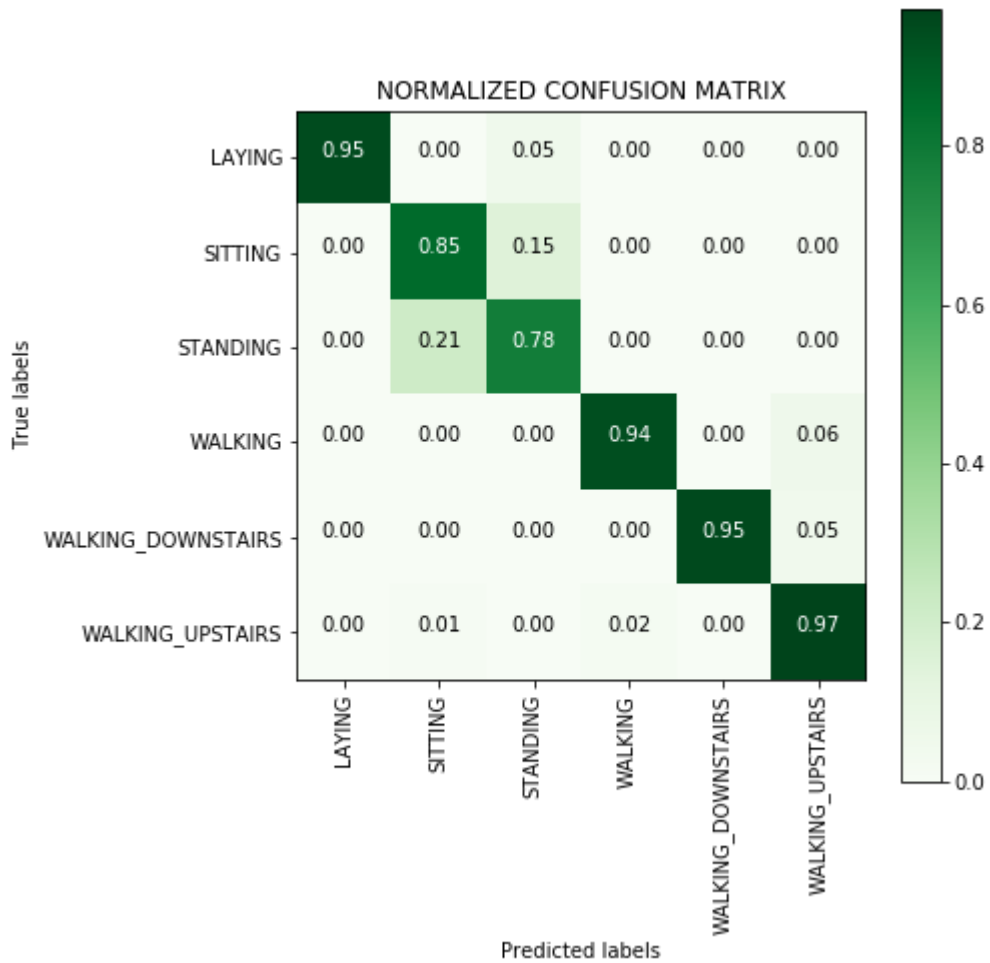
```

-----
| Classification Report |
-----

```

	precision	recall	f1-score	support
LAYING	1.00	0.95	0.97	537
SITTING	0.78	0.85	0.81	491
STANDING	0.81	0.78	0.80	532
WALKING	0.98	0.94	0.96	496

	HAR_LSTM			
WALKING_DOWNSTAIRS	1.00	0.95	0.98	420
WALKING_UPSTAIRS	0.90	0.97	0.94	471
avg / total	0.91	0.91	0.91	2947



**3.2 : LSTM(80 cells) + LSTM (35 cells) + Dropout(0.4) + Dropout(0.2) + 1 BatchNormalization layers + Adam Optimizer**

```

In [0]: 1 from keras.layers import BatchNormalization
        2
        3 model = Sequential()
        4
        5 model.add(LSTM(80,input_shape =(timesteps,input_dim),return_sequences = True
        6 model.add(BatchNormalization())
        7 model.add(Dropout(0.4))
        8
        9
        10 model.add(LSTM(35))
        11 model.add(Dropout(0.2))
        12
        13 model.add(Dense(n_classes,activation = 'sigmoid'))#adding the output layer
        14 print(model.summary())
        15

```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
=====		
lstm_2 (LSTM)	(None, 128, 80)	28800
-----		
batch_normalization_2 (Batch Normalization)	(None, 128, 80)	320
-----		
dropout_2 (Dropout)	(None, 128, 80)	0
-----		
lstm_3 (LSTM)	(None, 35)	16240
-----		
dropout_3 (Dropout)	(None, 35)	0
-----		
dense_2 (Dense)	(None, 6)	216
=====		
Total params: 45,576		
Trainable params: 45,416		
Non-trainable params: 160		
-----		
None		

```
In [0]: 1 model.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics =
2 history = model.fit(X_train,Y_train,batch_size = batch_size,validation_data =
3 epochs = epochs)
```

Train on 7352 samples, validate on 2947 samples

Epoch 1/30

7352/7352 [=====] - 208s 28ms/step - loss: 0.9093 - acc: 0.7252 - val\_loss: 0.5509 - val\_acc: 0.8582

Epoch 2/30

7352/7352 [=====] - 203s 28ms/step - loss: 0.3749 - acc: 0.8898 - val\_loss: 0.9213 - val\_acc: 0.6827

Epoch 3/30

7352/7352 [=====] - 208s 28ms/step - loss: 0.2522 - acc: 0.9208 - val\_loss: 0.3453 - val\_acc: 0.8884

Epoch 4/30

7352/7352 [=====] - 209s 28ms/step - loss: 0.2355 - acc: 0.9223 - val\_loss: 0.2817 - val\_acc: 0.9094

Epoch 5/30

7352/7352 [=====] - 211s 29ms/step - loss: 0.2029 - acc: 0.9285 - val\_loss: 0.3546 - val\_acc: 0.8809

Epoch 6/30

7352/7352 [=====] - 210s 29ms/step - loss: 0.1750 - acc: 0.9357 - val\_loss: 0.3565 - val\_acc: 0.8968

Epoch 7/30

7352/7352 [=====] - 209s 28ms/step - loss: 0.1619 - acc: 0.9404 - val\_loss: 0.2893 - val\_acc: 0.9067

Epoch 8/30

7352/7352 [=====] - 210s 29ms/step - loss: 0.1537 - acc: 0.9433 - val\_loss: 0.2291 - val\_acc: 0.9121

Epoch 9/30

7352/7352 [=====] - 195s 27ms/step - loss: 0.1653 - acc: 0.9363 - val\_loss: 0.3283 - val\_acc: 0.9019

Epoch 10/30

7352/7352 [=====] - 201s 27ms/step - loss: 0.1395 - acc: 0.9468 - val\_loss: 0.2660 - val\_acc: 0.9145

Epoch 11/30

7352/7352 [=====] - 201s 27ms/step - loss: 0.1305 - acc: 0.9476 - val\_loss: 0.2538 - val\_acc: 0.9135

Epoch 12/30

7352/7352 [=====] - 196s 27ms/step - loss: 0.1824 - acc: 0.9300 - val\_loss: 0.4976 - val\_acc: 0.8069

Epoch 13/30

7352/7352 [=====] - 194s 26ms/step - loss: 0.1628 - acc: 0.9382 - val\_loss: 0.2509 - val\_acc: 0.9179

Epoch 14/30

7352/7352 [=====] - 204s 28ms/step - loss: 0.1564 - acc: 0.9373 - val\_loss: 0.2320 - val\_acc: 0.9189

Epoch 15/30

7352/7352 [=====] - 197s 27ms/step - loss: 0.1537 - acc: 0.9422 - val\_loss: 0.2283 - val\_acc: 0.9213

Epoch 16/30

7352/7352 [=====] - 204s 28ms/step - loss: 0.1347 - acc: 0.9471 - val\_loss: 0.2534 - val\_acc: 0.9189

Epoch 17/30

7352/7352 [=====] - 199s 27ms/step - loss: 0.1292 - acc: 0.9487 - val\_loss: 0.2549 - val\_acc: 0.9226

```

Epoch 18/30
7352/7352 [=====] - 204s 28ms/step - loss: 0.1252 - ac
c: 0.9479 - val_loss: 0.2785 - val_acc: 0.9158
Epoch 19/30
7352/7352 [=====] - 207s 28ms/step - loss: 0.1290 - ac
c: 0.9471 - val_loss: 0.2822 - val_acc: 0.9220
Epoch 20/30
7352/7352 [=====] - 210s 29ms/step - loss: 0.1272 - ac
c: 0.9516 - val_loss: 0.2545 - val_acc: 0.9128
Epoch 21/30
7352/7352 [=====] - 208s 28ms/step - loss: 0.1292 - ac
c: 0.9491 - val_loss: 0.2950 - val_acc: 0.9101
Epoch 22/30
7352/7352 [=====] - 212s 29ms/step - loss: 0.1397 - ac
c: 0.9455 - val_loss: 0.2285 - val_acc: 0.9237
Epoch 23/30
7352/7352 [=====] - 196s 27ms/step - loss: 0.1251 - ac
c: 0.9527 - val_loss: 0.2074 - val_acc: 0.9108
Epoch 24/30
7352/7352 [=====] - 197s 27ms/step - loss: 0.1215 - ac
c: 0.9493 - val_loss: 0.2607 - val_acc: 0.9155
Epoch 25/30
7352/7352 [=====] - 199s 27ms/step - loss: 0.1208 - ac
c: 0.9508 - val_loss: 0.2148 - val_acc: 0.9220
Epoch 26/30
7352/7352 [=====] - 194s 26ms/step - loss: 0.1205 - ac
c: 0.9512 - val_loss: 0.2908 - val_acc: 0.9040
Epoch 27/30
7352/7352 [=====] - 194s 26ms/step - loss: 0.1197 - ac
c: 0.9521 - val_loss: 0.2617 - val_acc: 0.9104
Epoch 28/30
7352/7352 [=====] - 193s 26ms/step - loss: 0.1305 - ac
c: 0.9483 - val_loss: 0.2899 - val_acc: 0.9162
Epoch 29/30
7352/7352 [=====] - 189s 26ms/step - loss: 0.1221 - ac
c: 0.9508 - val_loss: 0.3288 - val_acc: 0.9114
Epoch 30/30
7352/7352 [=====] - 185s 25ms/step - loss: 0.1298 - ac
c: 0.9499 - val_loss: 0.2430 - val_acc: 0.9121

```

In [0]:

```

1 score = model.evaluate(X_test,Y_test)
2 print('loss on test data is',score[0])
3 print('Accuracy on test data is:',score[1])
4
5
6 history_lstm2 = savetofile(history,'history_lstm2')
7 model_lstm2 = savetofile(model,'model_lstm2')

```

```

2947/2947 [=====] - 12s 4ms/step
loss on test data is 0.24302211337054586
Accuracy on test data is: 0.9121140142517815

```

In [0]:

```

1 model_2 = openfromfile('model_lstm2')
2 #history_2 = openfromfile('history_lstm2')
3

```



```

In [0]: 1 y_pred=model_2.predict(X_test)
2 results_mod_2,cm_2 = perform_model(Y_test,y_pred,labels, cm_normalize=True,
3                                     print_cm=True, cm_cmap=plt.cm.Greens)
4
5
6 #Get the confusion matrix
7
8 cm_df=confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using
9 classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df
10
11 #Plot a Non-Normalized confusion matrix
12 #plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED
13
14 #Plot a Normalized confusion matrix
15 plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFU

```

For test data

-----  
Accuracy

0.9121140142517815

-----  
Confusion Matrix

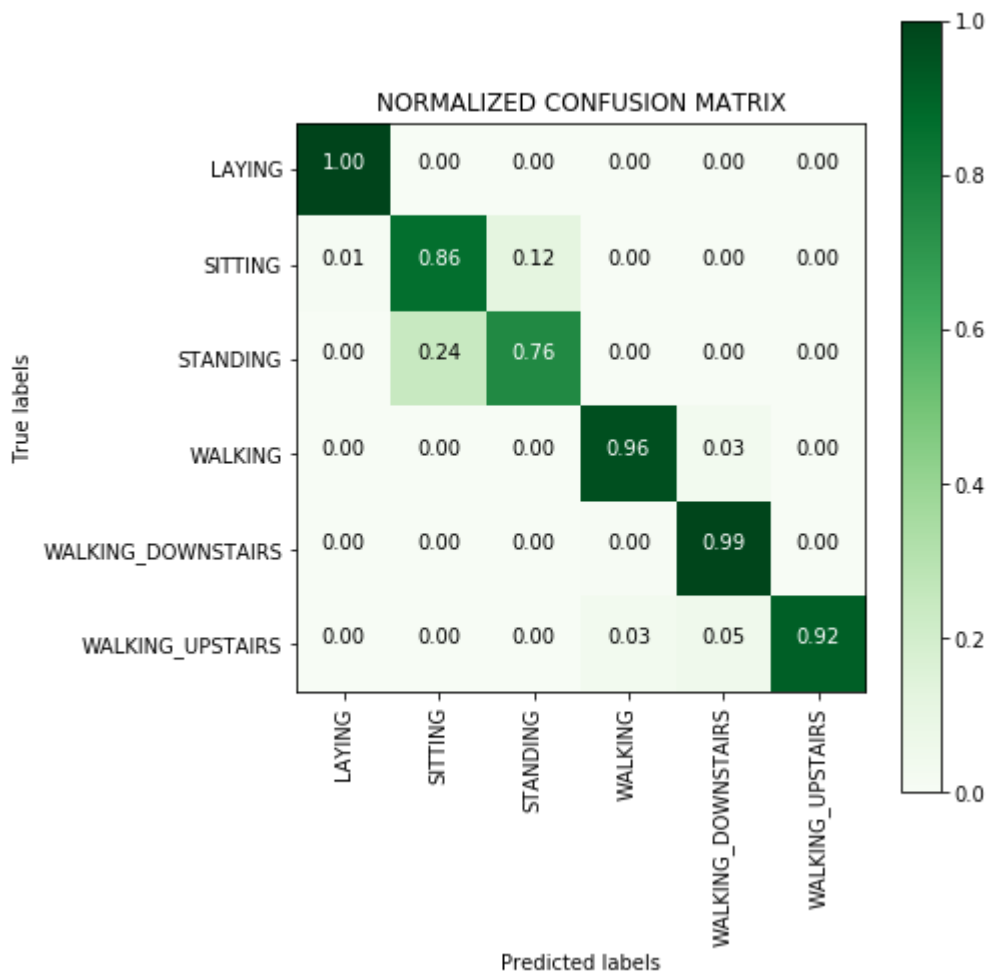
Pred \ True	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS
LAYING	537	0	0	0	0
SITTING	6	423	61	0	0
STANDING	0	129	402	1	0
WALKING	0	0	0	478	17
WALKING_DOWNSTAIRS	0	0	0	2	417
WALKING_UPSTAIRS	0	0	0	15	25

Pred \ True	WALKING_UPSTAIRS
LAYING	0
SITTING	1
STANDING	0
WALKING	1
WALKING_DOWNSTAIRS	1
WALKING_UPSTAIRS	431

-----  
Classification Report

	precision	recall	f1-score	support
LAYING	0.99	1.00	0.99	537
SITTING	0.77	0.86	0.81	491
STANDING	0.87	0.76	0.81	532
WALKING	0.96	0.96	0.96	496
WALKING_DOWNSTAIRS	0.91	0.99	0.95	420

	HAR_LSTM			
WALKING_UPSTAIRS	0.99	0.92	0.95	471
avg / total	0.92	0.91	0.91	2947



### 3.3: Conv1d(64) +Conv1d(48) +Maxpooling(2) + Batchnormalization + Dropout(0.5) +Dense(100)

```
In [0]: 1 #implementing 1 dimensional convnet with 3d tensor as input
2 from keras.layers import Flatten
3 from keras.layers.convolutional import Conv1D
4 from keras.layers.convolutional import MaxPooling1D
5 from keras.initializers import he_normal
6 from keras.layers import BatchNormalization
7
```

```
In [0]: 1 import warnings
2 warnings.filterwarnings('ignore')
```

```

In [0]: 1 #defining the model
2 # we will be tuning the model with different number of filters and different
3
4 model = Sequential()
5 model.add(Conv1D(filters = 64,kernel_size = 3,activation = 'relu',kernel_init
6 model.add(Conv1D(filters = 48,kernel_size = 3,activation = 'relu',kernel_init
7 model.add(MaxPooling1D(pool_size = 2))
8 model.add(BatchNormalization())
9
10 #adding the dropout layer
11 model.add(Dropout(0.5))
12
13 model.add(Flatten())
14 model.add(Dense(100,activation = 'relu',kernel_initializer = he_normal(seed =
15 model.add(BatchNormalization())
16 model.add(Dropout(0.5))
17 model.add(Dense(n_classes,activation = 'softmax'))
18
19 print(model.summary())
20
21 #compiling with adam optimizer
22
23 model.compile(loss = 'categorical_crossentropy',optimizer = 'adam',metrics =
24 history = model.fit(X_train,Y_train,batch_size = batch_size,epochs = epochs,v

```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:4479: The name tf.truncated\_normal is deprecated. Please use tf.random.truncated\_normal instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow\_backend.py:4267: The name tf.nn.max\_pool is deprecated. Please use tf.nn.max\_pool2d instead.

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
=====		
conv1d_1 (Conv1D)	(None, 126, 64)	1792
conv1d_2 (Conv1D)	(None, 124, 48)	9264
max_pooling1d_1 (MaxPooling1D)	(None, 62, 48)	0
batch_normalization_2 (Batch Normalization)	(None, 62, 48)	192
dropout_2 (Dropout)	(None, 62, 48)	0
flatten_1 (Flatten)	(None, 2976)	0
dense_2 (Dense)	(None, 100)	297700
batch_normalization_3 (Batch Normalization)	(None, 100)	400
dropout_3 (Dropout)	(None, 100)	0

dense_3 (Dense)	(None, 6)	606
-----------------	-----------	-----

=====

Total params: 309,954  
Trainable params: 309,658  
Non-trainable params: 296

---

None

Train on 7352 samples, validate on 2947 samples

Epoch 1/30

7352/7352 [=====] - 11s 2ms/step - loss: 0.5626 - acc: 0.7969 - val\_loss: 0.3584 - val\_acc: 0.8728

Epoch 2/30

7352/7352 [=====] - 5s 621us/step - loss: 0.2560 - acc: 0.9013 - val\_loss: 0.5298 - val\_acc: 0.8334

Epoch 3/30

7352/7352 [=====] - 5s 634us/step - loss: 0.2091 - acc: 0.9222 - val\_loss: 0.3970 - val\_acc: 0.8846

Epoch 4/30

7352/7352 [=====] - 5s 625us/step - loss: 0.1758 - acc: 0.9302 - val\_loss: 0.5070 - val\_acc: 0.8490

Epoch 5/30

7352/7352 [=====] - 4s 595us/step - loss: 0.1681 - acc: 0.9362 - val\_loss: 0.3683 - val\_acc: 0.8897

Epoch 6/30

7352/7352 [=====] - 4s 611us/step - loss: 0.1576 - acc: 0.9378 - val\_loss: 0.3331 - val\_acc: 0.9169

Epoch 7/30

7352/7352 [=====] - 5s 623us/step - loss: 0.1458 - acc: 0.9429 - val\_loss: 0.3711 - val\_acc: 0.9080

Epoch 8/30

7352/7352 [=====] - 4s 608us/step - loss: 0.1390 - acc: 0.9437 - val\_loss: 0.3642 - val\_acc: 0.8985

Epoch 9/30

7352/7352 [=====] - 5s 620us/step - loss: 0.1341 - acc: 0.9437 - val\_loss: 0.3172 - val\_acc: 0.9169

Epoch 10/30

7352/7352 [=====] - 4s 590us/step - loss: 0.1328 - acc: 0.9457 - val\_loss: 0.3769 - val\_acc: 0.9040

Epoch 11/30

7352/7352 [=====] - 4s 602us/step - loss: 0.1248 - acc: 0.9505 - val\_loss: 0.3528 - val\_acc: 0.9158

Epoch 12/30

7352/7352 [=====] - 5s 649us/step - loss: 0.1213 - acc: 0.9480 - val\_loss: 0.3666 - val\_acc: 0.9080

Epoch 13/30

7352/7352 [=====] - 4s 608us/step - loss: 0.1278 - acc: 0.9456 - val\_loss: 0.3829 - val\_acc: 0.9040

Epoch 14/30

7352/7352 [=====] - 5s 634us/step - loss: 0.1251 - acc: 0.9504 - val\_loss: 0.3763 - val\_acc: 0.9128

Epoch 15/30

7352/7352 [=====] - 5s 620us/step - loss: 0.1154 - acc: 0.9525 - val\_loss: 0.3565 - val\_acc: 0.9131

Epoch 16/30

7352/7352 [=====] - 4s 592us/step - loss: 0.1133 - acc: 0.9531 - val\_loss: 0.3323 - val\_acc: 0.9206

Epoch 17/30

```

7352/7352 [=====] - 4s 610us/step - loss: 0.1072 - ac
c: 0.9546 - val_loss: 0.3604 - val_acc: 0.9172
Epoch 18/30
7352/7352 [=====] - 4s 567us/step - loss: 0.1032 - ac
c: 0.9587 - val_loss: 0.4090 - val_acc: 0.8751
Epoch 19/30
7352/7352 [=====] - 4s 534us/step - loss: 0.1017 - ac
c: 0.9576 - val_loss: 0.3916 - val_acc: 0.9179
Epoch 20/30
7352/7352 [=====] - 4s 573us/step - loss: 0.1054 - ac
c: 0.9547 - val_loss: 0.3769 - val_acc: 0.9053
Epoch 21/30
7352/7352 [=====] - 4s 550us/step - loss: 0.1063 - ac
c: 0.9547 - val_loss: 0.3801 - val_acc: 0.9203
Epoch 22/30
7352/7352 [=====] - 4s 560us/step - loss: 0.0979 - ac
c: 0.9589 - val_loss: 0.3861 - val_acc: 0.9097
Epoch 23/30
7352/7352 [=====] - 4s 558us/step - loss: 0.0957 - ac
c: 0.9581 - val_loss: 0.3184 - val_acc: 0.9253
Epoch 24/30
7352/7352 [=====] - 4s 537us/step - loss: 0.0931 - ac
c: 0.9614 - val_loss: 0.3612 - val_acc: 0.9084
Epoch 25/30
7352/7352 [=====] - 4s 560us/step - loss: 0.0977 - ac
c: 0.9592 - val_loss: 0.3736 - val_acc: 0.9223
Epoch 26/30
7352/7352 [=====] - 4s 578us/step - loss: 0.0941 - ac
c: 0.9584 - val_loss: 0.4046 - val_acc: 0.9186
Epoch 27/30
7352/7352 [=====] - 4s 545us/step - loss: 0.1000 - ac
c: 0.9591 - val_loss: 0.3557 - val_acc: 0.9019
Epoch 28/30
7352/7352 [=====] - 4s 602us/step - loss: 0.0870 - ac
c: 0.9645 - val_loss: 0.3838 - val_acc: 0.9203
Epoch 29/30
7352/7352 [=====] - 4s 542us/step - loss: 0.0909 - ac
c: 0.9608 - val_loss: 0.3836 - val_acc: 0.9070
Epoch 30/30
7352/7352 [=====] - 4s 525us/step - loss: 0.0835 - ac
c: 0.9645 - val_loss: 0.3845 - val_acc: 0.9091

```

Type *Markdown* and LaTeX:  $\alpha^2$

```

In [0]: 1 score = model.evaluate(X_test,Y_test)
        2 print('Loss on test data is:',score[0])
        3 print('accuracy on test data is:',score[1])

```

```

2947/2947 [=====] - 0s 117us/step
Loss on test data is: 0.3845438683092381
accuracy on test data is: 0.9090600610790635

```

```

In [0]: 1 history_cnn = savetofile(history,'history_cnn')
        2 model_cnn = savetofile(model,'model_cnn')

```

```
In [0]: 1 model_3 = openfromfile('model_cnn')  
        2 #history_3 = openfromfile('history_cnn')
```

```
In [0]: 1 y_pred=model_3.predict(X_test)
2 results_mod_3,cm_3 = perform_model(Y_test,y_pred,labels, cm_normalize=True,
3                                     print_cm=True, cm_cmap=plt.cm.Greens)
4
5
6 #Get the confusion matrix
7
8 cm_df=confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using
9 classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df
10
11 #Plot a Non-Normalized confusion matrix
12 #plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED
13
14 #Plot a Normalized confusion matrix
15 plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFU
```

For test data

-----  
Accuracy

0.9090600610790635

-----  
Confusion Matrix

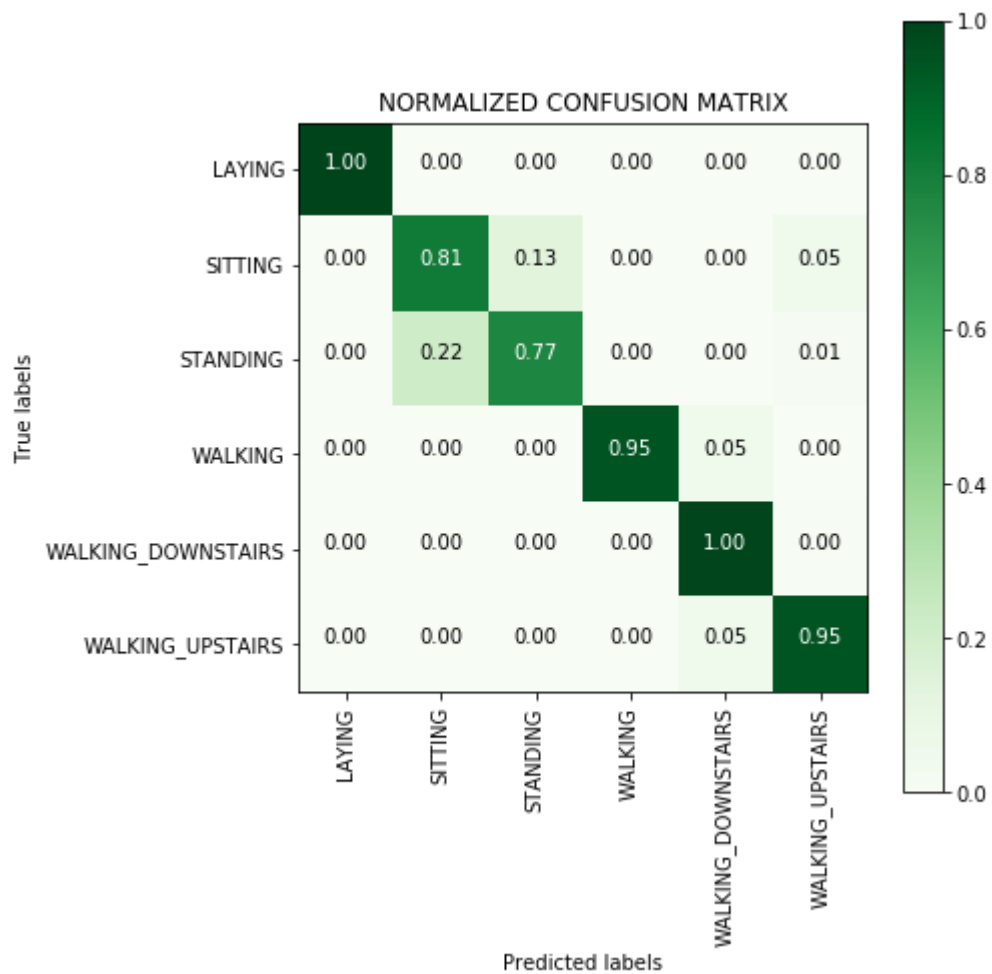
Pred \ True	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS
LAYING	537	0	0	0	0
SITTING	0	399	66	0	0
STANDING	0	115	409	1	0
WALKING	0	0	0	469	26
WALKING_DOWNSTAIRS	0	0	0	0	418
WALKING_UPSTAIRS	0	0	0	0	24

Pred \ True	WALKING_UPSTAIRS
LAYING	0
SITTING	26
STANDING	7
WALKING	1
WALKING_DOWNSTAIRS	2
WALKING_UPSTAIRS	447

-----  
Classification Report

	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	537
SITTING	0.78	0.81	0.79	491
STANDING	0.86	0.77	0.81	532
WALKING	1.00	0.95	0.97	496
WALKING_DOWNSTAIRS	0.89	1.00	0.94	420

	HAR_LSTM			
WALKING_UPSTAIRS	0.93	0.95	0.94	471
avg / total	0.91	0.91	0.91	2947



### 3.4 LSTM(100) + Dropout(0.7) + LSTM(50) + Dropout(0.7) + RmsProp

```
In [0]: 1 from keras.regularizers import L1L2
        2 reg = L1L2(0.01,0.01)
```



```
In [0]: 1 model = Sequential()
2 model.add(LSTM(100, input_shape=(timesteps, input_dim), kernel_initializer='g
3 model.add(BatchNormalization())
4 model.add(Dropout(0.70))
5 model.add(LSTM(50))
6 model.add(Dropout(0.70))
7 model.add(Dense(n_classes, activation='sigmoid'))
8 print("Model Summary: ")
9 model.summary()
```

Model Summary:

Layer (type)	Output Shape	Param #
=====		
lstm_1 (LSTM)	(None, 128, 100)	44000
batch_normalization_1 (Batch Normalization)	(None, 128, 100)	400
dropout_1 (Dropout)	(None, 128, 100)	0
lstm_2 (LSTM)	(None, 50)	30200
dropout_2 (Dropout)	(None, 50)	0
dense_1 (Dense)	(None, 6)	306
=====		
Total params: 74,906		
Trainable params: 74,706		
Non-trainable params: 200		

```
In [0]: 1 #Compiling the model
2 model.compile(loss='binary_crossentropy',
3               optimizer='rmsprop',
4               metrics=['accuracy'])
5 #checkpoint_3 = ModelCheckpoint("model_7.h5",monitor="val_acc",mode="max",sav
6 # Training the model
7 history = model.fit(X_train,
8                     Y_train,
9                     batch_size=batch_size,
10                    validation_data=(X_test, Y_test),
11                    epochs=30)
```

Train on 7352 samples, validate on 2947 samples

Epoch 1/30

7352/7352 [=====] - 142s 19ms/step - loss: 1.7124 - acc: 0.8491 - val\_loss: 1.1561 - val\_acc: 0.8787

Epoch 2/30

7352/7352 [=====] - 155s 21ms/step - loss: 0.6482 - acc: 0.9057 - val\_loss: 0.2787 - val\_acc: 0.9185

Epoch 3/30

7352/7352 [=====] - 149s 20ms/step - loss: 0.1732 - acc: 0.9380 - val\_loss: 0.1416 - val\_acc: 0.9497

Epoch 4/30

7352/7352 [=====] - 144s 20ms/step - loss: 0.1283 - acc: 0.9560 - val\_loss: 0.2491 - val\_acc: 0.9179

Epoch 5/30

7352/7352 [=====] - 139s 19ms/step - loss: 0.1061 - acc: 0.9635 - val\_loss: 0.1095 - val\_acc: 0.9603

Epoch 6/30

7352/7352 [=====] - 142s 19ms/step - loss: 0.0932 - acc: 0.9675 - val\_loss: 0.0858 - val\_acc: 0.9711

Epoch 7/30

7352/7352 [=====] - 147s 20ms/step - loss: 0.0934 - acc: 0.9688 - val\_loss: 0.1242 - val\_acc: 0.9653

Epoch 8/30

7352/7352 [=====] - 149s 20ms/step - loss: 0.0859 - acc: 0.9701 - val\_loss: 0.0848 - val\_acc: 0.9737

Epoch 9/30

7352/7352 [=====] - 136s 18ms/step - loss: 0.0819 - acc: 0.9717 - val\_loss: 0.1062 - val\_acc: 0.9677

Epoch 10/30

7352/7352 [=====] - 131s 18ms/step - loss: 0.0792 - acc: 0.9730 - val\_loss: 0.1340 - val\_acc: 0.9670

Epoch 11/30

7352/7352 [=====] - 132s 18ms/step - loss: 0.0764 - acc: 0.9738 - val\_loss: 0.1133 - val\_acc: 0.9653

Epoch 12/30

7352/7352 [=====] - 134s 18ms/step - loss: 0.0774 - acc: 0.9730 - val\_loss: 0.1358 - val\_acc: 0.9663

Epoch 13/30

7352/7352 [=====] - 132s 18ms/step - loss: 0.0765 - acc: 0.9749 - val\_loss: 0.1131 - val\_acc: 0.9694

Epoch 14/30

7352/7352 [=====] - 132s 18ms/step - loss: 0.0756 - acc: 0.9743 - val\_loss: 0.1204 - val\_acc: 0.9635

Epoch 15/30

```

7352/7352 [=====] - 132s 18ms/step - loss: 0.0728 - ac
c: 0.9741 - val_loss: 0.1308 - val_acc: 0.9645
Epoch 16/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0733 - ac
c: 0.9745 - val_loss: 0.1361 - val_acc: 0.9671
Epoch 17/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0723 - ac
c: 0.9728 - val_loss: 0.1258 - val_acc: 0.9702
Epoch 18/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0709 - ac
c: 0.9758 - val_loss: 0.1152 - val_acc: 0.9683
Epoch 19/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0714 - ac
c: 0.9759 - val_loss: 0.1075 - val_acc: 0.9705
Epoch 20/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0740 - ac
c: 0.9752 - val_loss: 0.1498 - val_acc: 0.9664
Epoch 21/30
7352/7352 [=====] - 137s 19ms/step - loss: 0.0663 - ac
c: 0.9757 - val_loss: 0.1044 - val_acc: 0.9693
Epoch 22/30
7352/7352 [=====] - 135s 18ms/step - loss: 0.0712 - ac
c: 0.9762 - val_loss: 0.0955 - val_acc: 0.9718
Epoch 23/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0718 - ac
c: 0.9758 - val_loss: 0.1498 - val_acc: 0.9660
Epoch 24/30
7352/7352 [=====] - 135s 18ms/step - loss: 0.0676 - ac
c: 0.9755 - val_loss: 0.1322 - val_acc: 0.9703
Epoch 25/30
7352/7352 [=====] - 136s 19ms/step - loss: 0.0683 - ac
c: 0.9767 - val_loss: 0.1402 - val_acc: 0.9680
Epoch 26/30
7352/7352 [=====] - 135s 18ms/step - loss: 0.0682 - ac
c: 0.9765 - val_loss: 0.1425 - val_acc: 0.9695
Epoch 27/30
7352/7352 [=====] - 135s 18ms/step - loss: 0.0683 - ac
c: 0.9766 - val_loss: 0.1134 - val_acc: 0.9727
Epoch 28/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0671 - ac
c: 0.9760 - val_loss: 0.1154 - val_acc: 0.9719
Epoch 29/30
7352/7352 [=====] - 134s 18ms/step - loss: 0.0652 - ac
c: 0.9771 - val_loss: 0.1547 - val_acc: 0.9682
Epoch 30/30
7352/7352 [=====] - 136s 18ms/step - loss: 0.0698 - ac
c: 0.9764 - val_loss: 0.1435 - val_acc: 0.9731

```

```

In [0]: 1 model_4 = openfromfile('model_final')
        2 history_4 = openfromfile('history_final')

```

```

In [0]: 1 model_final = savetofile(model, 'model_final')
        2 history_final = savetofile(history, 'history_final')

```

## Section 4: Plotting the error and accuracy

```

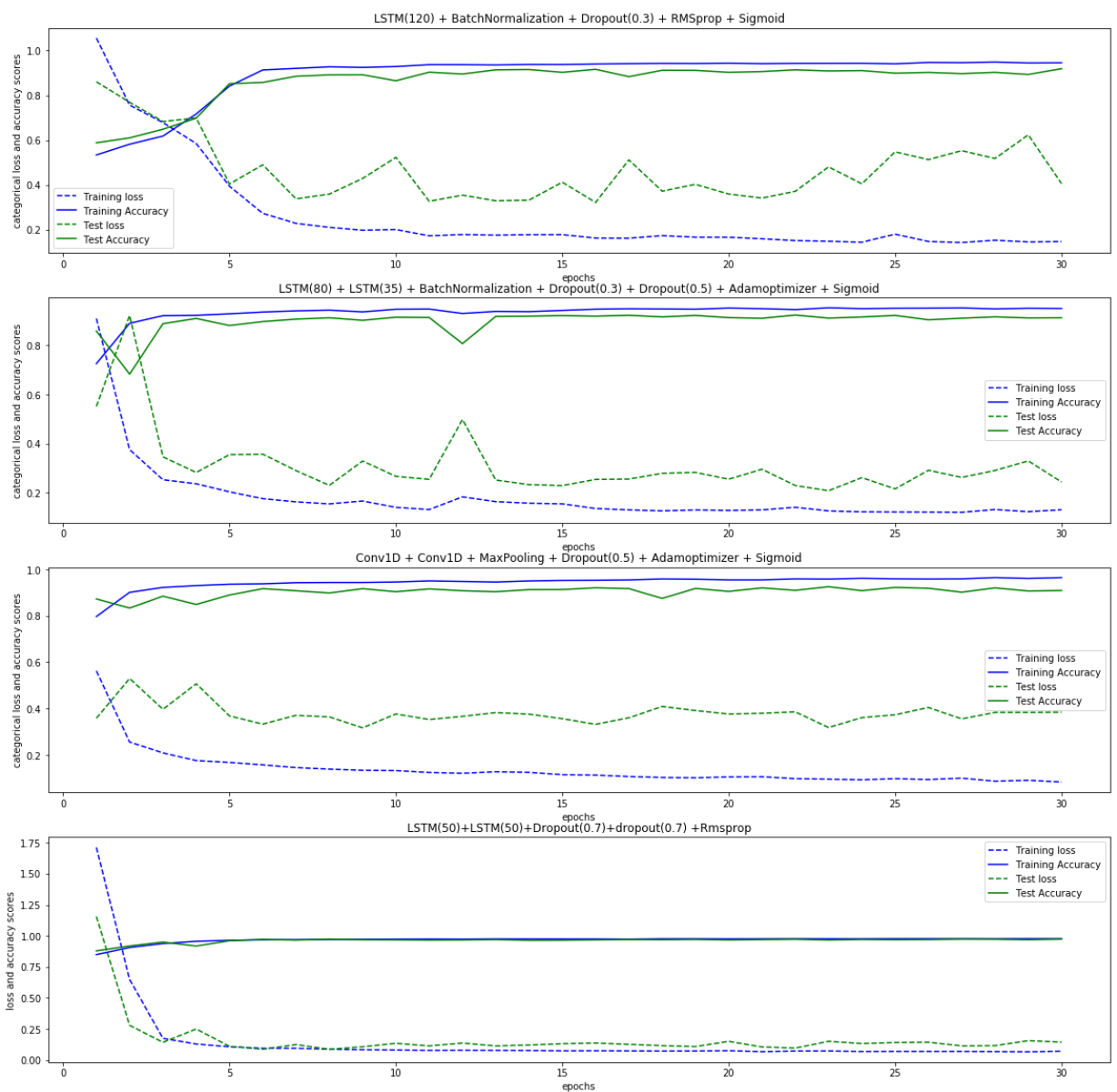
In [0]: 1 import pickle
2 import matplotlib.pyplot as plt
3 %matplotlib inline
4 #plotting for all the models
5
6 x = list(range(1,epochs+1))
7
8 plt.figure(figsize = (20,20))
9 plt.subplot(4,1,1)
10 plt.title('LSTM(120) + BatchNormalization + Dropout(0.3) + RMSprop + Sigmoid')
11 #plt.grid()
12 plt.plot(x,openfromfile("history_1").history['loss'],'b--',label = 'Training
13 plt.plot(x,openfromfile("history_1").history['acc'],'b',label = 'Training Acc
14 plt.plot(x,openfromfile("history_1").history['val_loss'],'g--',label = 'Test
15 plt.plot(x,openfromfile("history_1").history['val_acc'],'g',label = 'Test Acc
16 plt.xlabel('epochs')
17 plt.ylabel('categorical loss and accuracy scores')
18 plt.legend(loc = 'best')
19 print('\n\n')
20
21
22
23
24 plt.subplot(4,1,2)
25 plt.title('LSTM(80) + LSTM(35) + BatchNormalization + Dropout(0.3) + Dropout(
26 #plt.grid()
27 plt.plot(x,openfromfile("history_lstm2").history['loss'],'b--',label = 'Train
28 plt.plot(x,openfromfile("history_lstm2").history['acc'],'b',label = 'Training
29 plt.plot(x,openfromfile("history_lstm2").history['val_loss'],'g--',label = 'T
30 plt.plot(x,openfromfile("history_lstm2").history['val_acc'],'g',label = 'Test
31 plt.xlabel('epochs')
32 plt.ylabel('categorical loss and accuracy scores')
33 plt.legend(loc = 'best')
34 print('\n\n')
35
36
37
38 #cnn
39 plt.subplot(4,1,3)
40 plt.title('Conv1D + Conv1D + MaxPooling + Dropout(0.5) + Adamoptimizer + Sigm
41 #plt.grid()
42 plt.plot(x,openfromfile("history_cnn").history['loss'],'b--',label = 'Trainin
43 plt.plot(x,openfromfile("history_cnn").history['acc'],'b',label = 'Training A
44 plt.plot(x,openfromfile("history_cnn").history['val_loss'],'g--',label = 'Tes
45 plt.plot(x,openfromfile("history_cnn").history['val_acc'],'g',label = 'Test A
46 plt.xlabel('epochs')
47 plt.ylabel('categorical loss and accuracy scores')
48 plt.legend(loc = 'best')
49 print('\n\n')
50 #plt.show()
51
52 #
53 plt.subplot(4,1,4)
54 plt.title('LSTM(50)+LSTM(50)+Dropout(0.7)+dropout(0.7) +Rmsprop',size = 12)
55 plt.plot(x,openfromfile("history_final").history['loss'],'b--',label = 'Train
56 plt.plot(x,openfromfile("history_final").history['acc'],'b',label = 'Training

```

```

57 plt.plot(x,openfromfile("history_final").history['val_loss'],'g--',label = 'T
58 plt.plot(x,openfromfile("history_final").history['val_acc'],'g',label = 'Test
59 plt.xlabel('epochs')
60 plt.ylabel('loss and accuracy scores')
61 plt.legend(loc = 'best')
62 plt.show()
63

```



## Conclusion

```
In [0]: 1 # Conclusio
2 from prettytable import PrettyTable
3 table = PrettyTable()
4
5 table.field_names = ['Architecture', 'optimizer', 'loss', 'test accuracy']
6 table.add_row(['LSTM(32) + Dropout(0.3) + BatchNormaliztion', 'RMSprop', 'categorical c', '0.905'])
7 table.add_row(['LSTM(80) + Dropout(0.2) + LSTM(50) + Dropout(0.4)', 'Adam', 'categorical c', '0.9121'])
8 table.add_row(['Conv1D + Conv1D + MaxPooling + Dropout(0.5)', 'Adam', 'categorical c', '0.9091'])
9 table.add_row(['LSTM(100)+LSTM(50)+Dropout(0.7)+Dropout(0.7)', 'Rmsprop', 'bianry cro', '0.9682'])
10 print(table)
```

```
+-----+-----+-----+
+-----+-----+
|               Architecture               | optimizer |          lo
ss          | test accuracy |
+-----+-----+-----+
+-----+-----+-----+
| LSTM(32) + Dropout(0.3) + BatchNormaliztion | RMSprop | categorical c
ross entropy |    0.905    |
| LSTM(80) + Dropout(0.2) + LSTM(50) + Dropout(0.4) | Adam | categorical c
ross entropy |    0.9121    |
| Conv1D + Conv1D + MaxPooling + Dropout(0.5) | Adam | categorical c
ross entropy |    0.9091    |
| LSTM(100)+LSTM(50)+Dropout(0.7)+Dropout(0.7) | Rmsprop | bianry cro
ss entropy |    0.9682    |
+-----+-----+-----+
+-----+-----+-----+
```

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.

The startegy we employed for classification with help of deep learning models is we implemented 4 different models,3 with LSTM units and 1 with Conv1d.We tried hyper parameter tuing with hyperas also .

Finally we were able to get best accuracy of 0.96

```
In [0]: 1 #3 Classification of static and dynamic activities
```

## Classifiation of static and dynamic activities

so we will be classifying the activities in two parts,first is Dynamic activities and second are static activities using the divide and conqeor based approach

```
In [0]: 1 ## Classification dynamic activities
```



```
In [0]: 1 ! pip install hyperas
```

Collecting hyperas

Downloading <https://files.pythonhosted.org/packages/04/34/87ad6ffb42df9c1fa9c4c906f65813d42ad70d68c66af4ffff048c228cd4/hyperas-0.4.1-py3-none-any.whl> (h<https://files.pythonhosted.org/packages/04/34/87ad6ffb42df9c1fa9c4c906f65813d42ad70d68c66af4ffff048c228cd4/hyperas-0.4.1-py3-none-any.whl>)

Requirement already satisfied: jupyter in /usr/local/lib/python3.6/dist-packages (from hyperas) (1.0.0)

Requirement already satisfied: keras in /usr/local/lib/python3.6/dist-packages (from hyperas) (2.2.5)

Requirement already satisfied: nbconvert in /usr/local/lib/python3.6/dist-packages (from hyperas) (5.6.1)

Requirement already satisfied: entrypoints in /usr/local/lib/python3.6/dist-packages (from hyperas) (0.3)

Requirement already satisfied: nbformat in /usr/local/lib/python3.6/dist-packages (from hyperas) (5.0.3)

Requirement already satisfied: hyperopt in /usr/local/lib/python3.6/dist-packages (from hyperas) (0.1.2)

Requirement already satisfied: jupyter-console in /usr/local/lib/python3.6/dist-packages (from jupyter->hyperas) (5.2.0)

Requirement already satisfied: ipykernel in /usr/local/lib/python3.6/dist-packages (from jupyter->hyperas) (4.6.1)

Requirement already satisfied: notebook in /usr/local/lib/python3.6/dist-packages (from jupyter->hyperas) (5.2.2)

Requirement already satisfied: qtconsole in /usr/local/lib/python3.6/dist-packages (from jupyter->hyperas) (4.6.0)

Requirement already satisfied: ipywidgets in /usr/local/lib/python3.6/dist-packages (from jupyter->hyperas) (7.5.1)

Requirement already satisfied: keras-preprocessing>=1.1.0 in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (1.1.0)

Requirement already satisfied: pyyaml in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (3.13)

Requirement already satisfied: h5py in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (2.8.0)

Requirement already satisfied: keras-applications>=1.0.8 in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (1.0.8)

Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (1.12.0)

Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (1.4.1)

Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.6/dist-packages (from keras->hyperas) (1.17.5)

Requirement already satisfied: defusedxml in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (0.6.0)

Requirement already satisfied: jinja2>=2.4 in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (2.10.3)

Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (4.3.3)

Requirement already satisfied: mistune<2,>=0.8.1 in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (0.8.4)

Requirement already satisfied: testpath in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (0.4.4)

Requirement already satisfied: jupyter-core in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (4.6.1)

Requirement already satisfied: pandocfilters>=1.4.1 in /usr/local/lib/python

3.6/dist-packages (from nbconvert->hyperas) (1.4.2)  
Requirement already satisfied: pygments in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (2.1.3)  
Requirement already satisfied: bleach in /usr/local/lib/python3.6/dist-packages (from nbconvert->hyperas) (3.1.0)  
Requirement already satisfied: ipython-genutils in /usr/local/lib/python3.6/dist-packages (from nbformat->hyperas) (0.2.0)  
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in /usr/local/lib/python3.6/dist-packages (from nbformat->hyperas) (2.6.0)  
Requirement already satisfied: tqdm in /usr/local/lib/python3.6/dist-packages (from hyperopt->hyperas) (4.28.1)  
Requirement already satisfied: future in /usr/local/lib/python3.6/dist-packages (from hyperopt->hyperas) (0.16.0)  
Requirement already satisfied: pymongo in /usr/local/lib/python3.6/dist-packages (from hyperopt->hyperas) (3.10.0)  
Requirement already satisfied: networkx in /usr/local/lib/python3.6/dist-packages (from hyperopt->hyperas) (2.4)  
Requirement already satisfied: jupyter-client in /usr/local/lib/python3.6/dist-packages (from jupyter-console->jupyter->hyperas) (5.3.4)  
Requirement already satisfied: ipython in /usr/local/lib/python3.6/dist-packages (from jupyter-console->jupyter->hyperas) (5.5.0)  
Requirement already satisfied: prompt-toolkit<2.0.0,>=1.0.0 in /usr/local/lib/python3.6/dist-packages (from jupyter-console->jupyter->hyperas) (1.0.18)  
Requirement already satisfied: tornado>=4.0 in /usr/local/lib/python3.6/dist-packages (from ipykernel->jupyter->hyperas) (4.5.3)  
Requirement already satisfied: terminado>=0.3.3; sys\_platform != "win32" in /usr/local/lib/python3.6/dist-packages (from notebook->jupyter->hyperas) (0.8.3)  
Requirement already satisfied: widgetsnbextension~=3.5.0 in /usr/local/lib/python3.6/dist-packages (from ipywidgets->jupyter->hyperas) (3.5.1)  
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.6/dist-packages (from jinja2>=2.4->nbconvert->hyperas) (1.1.1)  
Requirement already satisfied: decorator in /usr/local/lib/python3.6/dist-packages (from traitlets>=4.2->nbconvert->hyperas) (4.4.1)  
Requirement already satisfied: webencodings in /usr/local/lib/python3.6/dist-packages (from bleach->nbconvert->hyperas) (0.5.1)  
Requirement already satisfied: pyzmq>=13 in /usr/local/lib/python3.6/dist-packages (from jupyter-client->jupyter-console->jupyter->hyperas) (17.0.0)  
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from jupyter-client->jupyter-console->jupyter->hyperas) (2.6.1)  
Requirement already satisfied: pickleshare in /usr/local/lib/python3.6/dist-packages (from ipython->jupyter-console->jupyter->hyperas) (0.7.5)  
Requirement already satisfied: simplegeneric>0.8 in /usr/local/lib/python3.6/dist-packages (from ipython->jupyter-console->jupyter->hyperas) (0.8.1)  
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.6/dist-packages (from ipython->jupyter-console->jupyter->hyperas) (42.0.2)  
Requirement already satisfied: pexpect; sys\_platform != "win32" in /usr/local/lib/python3.6/dist-packages (from ipython->jupyter-console->jupyter->hyperas) (4.7.0)  
Requirement already satisfied: wcwidth in /usr/local/lib/python3.6/dist-packages (from prompt-toolkit<2.0.0,>=1.0.0->jupyter-console->jupyter->hyperas) (0.1.8)  
Requirement already satisfied: ptyprocess; os\_name != "nt" in /usr/local/lib/python3.6/dist-packages (from terminado>=0.3.3; sys\_platform != "win32"->notebook->jupyter->hyperas) (0.6.0)

Installing collected packages: hyperas  
Successfully installed hyperas-0.4.1



```
In [0]: 1 from keras.models import Sequential
2 from keras.layers import LSTM
3 from keras.layers.core import Dense, Dropout
4 from hyperopt import Trials, STATUS_OK, tpe
5 from hyperas import optim
6 from hyperas.distributions import choice, uniform
7 warnings.simplefilter("ignore")
```

```
In [0]: 1 #saving data for loading it later in hyperas for hyper-parameter tuning
2 savetofile(X_train, 'train')
3 savetofile(X_test, 'test')
4 savetofile(Y_train, 'train_y')
5 savetofile(Y_test, 'test_y')
```

```
In [0]: 1 def data():
2     x_train = pickle.load(open('train'+".p", 'rb'))
3     y_train = pickle.load(open('train_y'+".p", 'rb'))
4     x_test = pickle.load(open("test"+".p", 'rb'))
5     y_test = pickle.load(open("test_y"+".p", 'rb'))
6     return x_train, y_train, x_test, y_test
```

```
In [0]: 1 #we tried the hyperparameter tuning but it is not working in this case as som
2 #this is the code I tried to implement gathering from multiple sources
3 #following source helped me to tune the parameters - https://towardsdatascien
4 """
5 def create_model(x_train, y_train, x_test, y_test):
6
7     epochs = 8
8     batch_size = 32
9     timesteps = x_train.shape[1]
10    input_dim = len(x_train[0][0])
11    n_classes = 6
12
13    model = Sequential()
14
15    model.add(LSTM(64, return_sequences = True, input_shape = (timesteps, inp
16    model.add(Dropout({{uniform(0, 1)}}))
17
18    model.add(LSTM({{choice([32, 16])}}))
19    model.add(Dropout({{uniform(0, 1)}}))
20
21    model.add(Dense(n_classes, activation='sigmoid'))
22
23    print(model.summary())
24
25    model.compile(loss='categorical_crossentropy', metrics=['accuracy'], opti
26
27    result = model.fit(x_train, y_train, batch_size = batch_size, epochs=epoc
28
29    validation_acc = np.amax(result.history['val_acc'])
30
31    print('Best validation acc of epoch:', validation_acc)
32
33    return {'loss': -validation_acc, 'status': STATUS_OK, 'model': model}
34    """
```

```

In [0]: 1 """
2 import warnings
3 warnings.filterwarnings('ignore')
4 best_run, best_model = optim.minimize(model=create_model, data=data, algo='tpe
5 x_train, y_train, x_test, y_test = data()
6
7 score = best_model.evaluate(x_test, y_test)
8
9 print('-----')
10 print('|          Accuracy          |')
11 print('-----')
12 acc = np.round((score[1]*100), 2)
13 print(str(acc)+"%\n")
14
15 print('-----')
16 print('|          Best Hyper-Parameters          |')
17 print('-----')
18 print(best_run)
19 print("\n\n")
20
21 true_labels = [np.argmax(i)+1 for i in y_test]
22 predicted_probs = best_model.predict(x_test)
23 predicted_labels = [np.argmax(i)+1 for i in predicted_probs]
24 print_confusionMatrix(true_labels, predicted_labels)
25 """
260 def exhaust(self):
261     n_done = len(self.trials)
--> 262     self.run(self.max_evals - n_done, block_until_done=self.async
hronous)
263     self.trials.refresh()
264     return self

/usr/local/lib/python3.6/dist-packages/hyperopt/fmin.py in run(self, N, block
_until_done)
225         else:
226             # -- loop over trials and do the jobs directl
y
--> 227             self.serial_evaluate()
228
229             try:

/usr/local/lib/python3.6/dist-packages/hyperopt/fmin.py in serial_evaluate(se
lf, N)
139         ctrl = base.Ctrl(self.trials, current_trial=trial)
140         try:

```

**Classifying the activities in Static and Dynamic and then combinig both the models using divide and conquer based approach**

```
In [0]: 1 #initializing the session
2 tf.set_random_seed(0)
3 session_conf = tf.ConfigProto(intra_op_parallelism_threads=1,
4                               inter_op_parallelism_threads=1)
5
6
```

## 2 class classification

```
In [0]: 1 ## Classifying data as 2 class dynamic vs static
2 ##data preparation
3
4 def load_y(subset):
5     """
6     The objective that we are trying to predict is a integer, from 1 to 6
7     that represents a human activity. We return a binary representation of
8     every sample objective as a 6 bits vector using One Hot Encoding
9     """
10    filename = f'drive/My Drive/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
11    y = _read_csv(filename)[0]
12    y[y<=3] = 0 #for all dynamic activities
13    y[y>3] = 1 #for all static activities
14    return pd.get_dummies(y).as_matrix()#getting the matrix
15
16 x_train,x_test = load_signals('train'), load_signals('test')
17 y_train,y_test = load_y('train'), load_y('test')
18 print(x_train.shape)
19 print(x_test.shape)
```

```
(7352, 2)
```

```
(2947, 2)
```

## Architecture 1 with adam optimizer for classifying 2 classes

```
In [0]: 1
2 sess = tf.Session(graph=tf.get_default_graph())
3 K.set_session(sess)
4 model_2c = Sequential()
5 model_2c.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initi
6 model_2c.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initi
7 model_2c.add(Dropout(0.6))
8 model_2c.add(MaxPooling1D(pool_size=2))
9 model_2c.add(Flatten())
10 model_2c.add(Dense(50, activation='relu'))
11 model_2c.add(Dense(2, activation='softmax'))
12 model_2c.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
=====		
conv1d_1 (Conv1D)	(None, 126, 32)	896
conv1d_2 (Conv1D)	(None, 124, 32)	3104
dropout_1 (Dropout)	(None, 124, 32)	0
max_pooling1d_1 (MaxPooling1D)	(None, 62, 32)	0
flatten_1 (Flatten)	(None, 1984)	0
dense_1 (Dense)	(None, 50)	99250
dense_2 (Dense)	(None, 2)	102
=====		
Total params: 103,352		
Trainable params: 103,352		
Non-trainable params: 0		

```
In [0]: 1 model_2c.compile(loss='categorical_crossentropy', optimizer='adam', metrics=[
        2 model_2c.fit(x_train,y_train, epochs=20, batch_size=16,validation_data=(x_test,
```

Train on 7352 samples, validate on 2947 samples

Epoch 1/20

7352/7352 [=====] - 3s 382us/step - loss: 0.0571 - acc: 0.9778 - val\_loss: 0.0136 - val\_acc: 0.9976

Epoch 2/20

7352/7352 [=====] - 2s 337us/step - loss: 0.0033 - acc: 0.9992 - val\_loss: 0.0169 - val\_acc: 0.9932

Epoch 3/20

7352/7352 [=====] - 3s 355us/step - loss: 9.8120e-04 - acc: 0.9995 - val\_loss: 0.0345 - val\_acc: 0.9888

Epoch 4/20

7352/7352 [=====] - 3s 358us/step - loss: 0.0012 - acc: 0.9997 - val\_loss: 0.0192 - val\_acc: 0.9936

Epoch 5/20

7352/7352 [=====] - 2s 338us/step - loss: 5.9842e-05 - acc: 1.0000 - val\_loss: 0.0260 - val\_acc: 0.9898

Epoch 6/20

7352/7352 [=====] - 2s 331us/step - loss: 4.4741e-05 - acc: 1.0000 - val\_loss: 0.0307 - val\_acc: 0.9895

Epoch 7/20

7352/7352 [=====] - 2s 325us/step - loss: 5.2726e-05 - acc: 1.0000 - val\_loss: 0.0284 - val\_acc: 0.9898

Epoch 8/20

7352/7352 [=====] - 2s 340us/step - loss: 4.7698e-05 - acc: 1.0000 - val\_loss: 0.0292 - val\_acc: 0.9895

Epoch 9/20

7352/7352 [=====] - 3s 373us/step - loss: 4.1584e-05 - acc: 1.0000 - val\_loss: 0.0374 - val\_acc: 0.9895

Epoch 10/20

7352/7352 [=====] - 2s 315us/step - loss: 3.8117e-05 - acc: 1.0000 - val\_loss: 0.0455 - val\_acc: 0.9891

Epoch 11/20

7352/7352 [=====] - 3s 363us/step - loss: 3.5981e-05 - acc: 1.0000 - val\_loss: 0.0427 - val\_acc: 0.9891

Epoch 12/20

7352/7352 [=====] - 3s 359us/step - loss: 3.3263e-05 - acc: 1.0000 - val\_loss: 0.0432 - val\_acc: 0.9891

Epoch 13/20

7352/7352 [=====] - 3s 356us/step - loss: 3.8532e-05 - acc: 1.0000 - val\_loss: 0.0491 - val\_acc: 0.9895

Epoch 14/20

7352/7352 [=====] - 3s 345us/step - loss: 3.4566e-05 - acc: 1.0000 - val\_loss: 0.0456 - val\_acc: 0.9895

Epoch 15/20

7352/7352 [=====] - 3s 354us/step - loss: 3.3491e-05 - acc: 1.0000 - val\_loss: 0.0475 - val\_acc: 0.9895

Epoch 16/20

7352/7352 [=====] - 2s 340us/step - loss: 3.3821e-05 - acc: 1.0000 - val\_loss: 0.0412 - val\_acc: 0.9898

Epoch 17/20

7352/7352 [=====] - 3s 345us/step - loss: 3.5012e-05 - acc: 1.0000 - val\_loss: 0.0437 - val\_acc: 0.9895

Epoch 18/20



```

7352/7352 [=====] - 2s 321us/step - loss: 3.6307e-05 -
acc: 1.0000 - val_loss: 0.0492 - val_acc: 0.9895
Epoch 19/20
7352/7352 [=====] - 3s 360us/step - loss: 0.0576 - ac
c: 0.9952 - val_loss: 0.1907 - val_acc: 0.9868
Epoch 20/20
7352/7352 [=====] - 3s 364us/step - loss: 0.0952 - ac
c: 0.9937 - val_loss: 0.0144 - val_acc: 0.9990

```

Out[90]: <keras.callbacks.History at 0x7feae7c11400>

```

In [0]: 1 #saving model
        2 model_2c.save('final_model_2c.h5')

```

## Classifying the static activities

```

In [0]: 1
        2 def load_y(subset):
        3     """
        4     The objective that we are trying to predict is a integer, from 1 to 6,
        5     that represents a human activity. We return a binary representation of
        6     every sample objective as a 6 bits vector using One Hot Encoding
        7     (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get\_dummies)
        8     """
        9     filename = f'drive/My Drive/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
       10     y = _read_csv(filename)[0]
       11     y_subset = y>3 #for static activities
       12     y = y[y_subset]
       13     return pd.get_dummies(y).as_matrix(),y_subset
       14
       15 Y_train_s,y_train_sub = load_y('train')
       16 Y_val_s,y_test_sub = load_y('test')
       17 X_train_s, X_val_s = load_signals('train'), load_signals('test')
       18 X_train_s = X_train_s[y_train_sub]
       19 X_val_s = X_val_s[y_test_sub]
       20
       21

```

## Architecture 2 with adam optimizer

```
In [0]: 1 np.random.seed(0)
2 #tf.set_random_seed(0)
3 #sess = tf.Session(graph=tf.get_default_graph())
4 #K.set_session(sess)
5 model = Sequential()
6 model.add(Conv1D(filters=128, kernel_size=7, activation='relu', kernel_initial
7 model.add(Conv1D(filters=96, kernel_size=3, activation='relu', kernel_initiali
8 model.add(Dropout(0.7))
9 model.add(MaxPooling1D(pool_size=3))
10 model.add(Flatten())
11 model.add(Dense(30, activation='relu'))
12 model.add(Dense(3, activation='softmax'))
13 model.summary()
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
=====		
conv1d_3 (Conv1D)	(None, 122, 128)	8192
conv1d_4 (Conv1D)	(None, 120, 96)	36960
dropout_2 (Dropout)	(None, 120, 96)	0
max_pooling1d_2 (MaxPooling1D)	(None, 40, 96)	0
flatten_2 (Flatten)	(None, 3840)	0
dense_3 (Dense)	(None, 30)	115230
dense_4 (Dense)	(None, 3)	93
=====		
Total params: 160,475		
Trainable params: 160,475		
Non-trainable params: 0		
=====		

```
In [0]: 1 import math
2 #adam = optimizers.Adam(lr=0.004)
3 model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['ac
4 model.fit(X_train_s,Y_train_s, epochs=100, batch_size=32,validation_data=(X_v
5 #K.clear_session()
6
```

Train on 4067 samples, validate on 1560 samples

Epoch 1/100

4067/4067 [=====] - 1s 292us/step - loss: 0.3541 - acc: 0.8785 - val\_loss: 0.3553 - val\_acc: 0.8814

Epoch 2/100

4067/4067 [=====] - 1s 198us/step - loss: 0.2323 - acc: 0.9142 - val\_loss: 0.2968 - val\_acc: 0.9006

Epoch 3/100

4067/4067 [=====] - 1s 182us/step - loss: 0.1686 - acc: 0.9343 - val\_loss: 0.2738 - val\_acc: 0.9058

Epoch 4/100

4067/4067 [=====] - 1s 173us/step - loss: 0.2100 - acc: 0.9343 - val\_loss: 0.2724 - val\_acc: 0.9083

Epoch 5/100

4067/4067 [=====] - 1s 185us/step - loss: 0.1412 - acc: 0.9452 - val\_loss: 0.2368 - val\_acc: 0.9192

Epoch 6/100

4067/4067 [=====] - 1s 170us/step - loss: 0.1148 - acc: 0.9577 - val\_loss: 0.2803 - val\_acc: 0.9115

```
In [0]: 1 #saving model
2 model.save('final_model_static.h5')
```

## Classifyinf dynamic activities

```
In [0]: 1 ##data preparation
2 def load_y(subset):
3
4     """
5     The objective that we are trying to predict is a integer, from 1 to 6,
6     that represents a human activity. We return a binary representation of
7     every sample objective as a 6 bits vector using One Hot Encoding
8     """
9     filename = f'drive/My Drive/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
10    y = _read_csv(filename)[0]
11    y_subset = y<=3 #classifying for dynamic activities
12    y = y[y_subset]
13    return pd.get_dummies(y).as_matrix(),y_subset
14
15    Y_train_d,y_train_sub = load_y('train')
16    Y_val_d,y_test_sub = load_y('test')
17    X_train_d, X_val_d = load_signals('train'), load_signals('test')
18    X_train_d = X_train_d[y_train_sub]
19    X_val_d = X_val_d[y_test_sub]
20
```

# Architecture 3 with adam optimizer

```
In [0]: 1 np.random.seed(0)
2 #tf.set_random_seed(0)
3 #sess = tf.Session(graph=tf.get_default_graph())
4 #K.set_session(sess)
5 model = Sequential()
6 model.add(Conv1D(filters=64, kernel_size=7, activation='relu',kernel_initiali
7 model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initiali
8 model.add(Dropout(0.6))
9 model.add(MaxPooling1D(pool_size=3))
10 model.add(Flatten())
11 model.add(Dense(30, activation='relu'))
12 model.add(Dense(3, activation='softmax'))
13 model.summary()
```

Model: "sequential\_3"

Layer (type)	Output Shape	Param #
=====		
conv1d_5 (Conv1D)	(None, 122, 64)	4096
conv1d_6 (Conv1D)	(None, 120, 32)	6176
dropout_3 (Dropout)	(None, 120, 32)	0
max_pooling1d_3 (MaxPooling1	(None, 40, 32)	0
flatten_3 (Flatten)	(None, 1280)	0
dense_5 (Dense)	(None, 30)	38430
dense_6 (Dense)	(None, 3)	93
=====		
Total params: 48,795		
Trainable params: 48,795		
Non-trainable params: 0		

```
In [0]: 1 import math
2 import keras
3 #adam = keras.optimizers.Adam(lr=0.004)
4 model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['ac
5 model.fit(X_train_s,Y_train_s, epochs=100, batch_size=32,validation_data=(X_v
6 #K.clear_session())
```

Train on 4067 samples, validate on 1560 samples

Epoch 1/100

4067/4067 [=====] - 1s 255us/step - loss: 0.3476 - acc: 0.8670 - val\_loss: 0.2779 - val\_acc: 0.8994

Epoch 2/100

4067/4067 [=====] - 1s 158us/step - loss: 0.2045 - acc: 0.9137 - val\_loss: 0.2820 - val\_acc: 0.9071

Epoch 3/100

4067/4067 [=====] - 1s 170us/step - loss: 0.1711 - acc: 0.9265 - val\_loss: 0.2314 - val\_acc: 0.9147

Epoch 4/100

4067/4067 [=====] - 1s 199us/step - loss: 0.1420 - acc: 0.9383 - val\_loss: 0.2294 - val\_acc: 0.9083

Epoch 5/100

4067/4067 [=====] - 1s 160us/step - loss: 0.1276 - acc: 0.9493 - val\_loss: 0.2400 - val\_acc: 0.9090

Epoch 6/100

4067/4067 [=====] - 1s 172us/step - loss: 0.1130 - acc: 0.9560 - val\_loss: 0.2280 - val\_acc: 0.9288

```
In [0]: 1 #saving model
2 model.save('final_model_dynamic.h5')
```

## Final model and results

```
In [0]: 1 #getting all the models
2 from keras.models import load_model
3 #getting the models
4 model_2class = load_model('final_model_2c.h5')
5 model_dynamic = load_model('final_model_dynamic.h5')
6 model_static = load_model('final_model_static.h5')
7 #for all the classes
8 class_2 = pickle.load(open('2class.p', 'rb'))
9 static = pickle.load(open('static.p', 'rb'))
10 dynamic = pickle.load(open('dynamic.p', 'rb'))
```

```

In [0]: 1 #predicting output activity
        2 def predict_activity(X):
        3     ##predicting whether dynamic or static
        4     predict_2class = model_2class.predict(transform_data(X,scale_2class))
        5     Y_pred_2class = np.argmax(predict_2class, axis=1)
        6     #static data filter
        7     X_static = X[Y_pred_2class==1]
        8     #dynamic data filter
        9     X_dynamic = X[Y_pred_2class==0]
       10     #predicting static activities
       11     predict_static = model_static.predict(transform_data(X_static,scale_stati
       12     predict_static = np.argmax(predict_static,axis=1)
       13     #adding 4 because need to get inal prediction lable as output
       14     predict_static = predict_static + 4
       15     #predicting dynamic activites
       16     predict_dynamic = model_dynamic.predict(transform_data(X_dynamic,scale_dy
       17     predict_dynamic = np.argmax(predict_dynamic,axis=1)
       18     #adding 1 because need to get inal prediction lable as output
       19     predict_dynamic = predict_dynamic + 1
       20     ##appending final output to one list in the same sequence of input data
       21     i,j = 0,0
       22     final_pred = []
       23     for mask in Y_pred_2class:
       24         if mask == 1:
       25             final_pred.append(predict_static[i])
       26             i = i + 1
       27         else:
       28             final_pred.append(predict_dynamic[j])
       29             j = j + 1
       30     return final_pred

```

```

In [0]: 1 ##predicting
        2 final_pred_val = predict_activity(X_test)
        3 final_pred_train = predict_activity(X_train)

```

```

In [1]: 1 ##accuracy of train and test
        2 from sklearn.metrics import accuracy_score
        3 print('Accuracy of train data:',accuracy_score(Y_train,final_pred_train))
        4 print('Accuracy of validation data:',accuracy_score(Y_val,final_pred_val))

```

Accuracy of train data: 0.963949945593036

Accuracy of validation data: 0.9518384798099763

**so here we finally get the best performing model with test accuracy of 0.95 and trainaccuracy of 0.96 using divide and conquer methods**