Human Activity Detection-Without Verbose

October 15, 2018

1 Human Activity Recognition

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.

2.2 Problem Statement

- Given a new datapoint we have to predict the Activity

In [1]:
```
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore")

# get the features from the file features.txt
features = list()
with open('UCI_HAR_Dataset/features.txt') as f:
    features = [line.split()[1] for line in f.readlines()]
print('No of Features: {}'.format(len(features)))
```

```
No of Features: 561
```

2.3 Obtain the train data

In [12]:
```
# get the data from txt files to pandas dataffame
X_train = pd.read_csv('UCI_HAR_Dataset/train/X_train.txt', delim_whitespace=True, head

# add subject column to the dataframe
X_train['subject'] = pd.read_csv('UCI_HAR_Dataset/train/subject_train.txt', header=Nor

y_train = pd.read_csv('UCI_HAR_Dataset/train/y_train.txt', names=['Activity'], squeeze
y_train_labels = y_train.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DOWNSTAIRS
                        4:'SITTING', 5:'STANDING',6:'LAYING'})

# put all columns in a single dataframe
train = X_train
train['Activity'] = y_train
train['ActivityName'] = y_train_labels
train.sample()
```

Out[12]:
```
      tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  \
6212           0.380322          -0.009925          -0.172745

      tBodyAcc-std()-X  tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  \
6212          0.125378         -0.160388          -0.04863          0.076071

      tBodyAcc-mad()-Y  tBodyAcc-mad()-Z  tBodyAcc-max()-X  \
6212         -0.115744         -0.016339           0.49712

             ...           angle(tBodyAccMean,gravity)  \
6212         ...                             -0.644849

      angle(tBodyAccJerkMean),gravityMean)  angle(tBodyGyroMean,gravityMean)  \
6212                              0.184224                          0.870293

      angle(tBodyGyroJerkMean,gravityMean)  angle(X,gravityMean)  \
6212                             -0.173777             -0.657367

      angle(Y,gravityMean)  angle(Z,gravityMean)  subject  Activity  \
6212              0.203386              0.237609       27         3

            ActivityName
6212  WALKING_DOWNSTAIRS

[1 rows x 564 columns]
```

In [13]:
```
train.shape
```

Out[13]:
```
(7352, 564)
```

2.4 Obtain the test data

In [14]:
```
# get the data from txt files to pandas dataffame
X_test = pd.read_csv('UCI_HAR_Dataset/test/X_test.txt', delim_whitespace=True, header=

# add subject column to the dataframe
X_test['subject'] = pd.read_csv('UCI_HAR_Dataset/test/subject_test.txt', header=None,

# get y labels from the txt file
y_test = pd.read_csv('UCI_HAR_Dataset/test/y_test.txt', names=['Activity'], squeeze=T
y_test_labels = y_test.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DOWNSTAIRS'
                       4:'SITTING', 5:'STANDING',6:'LAYING'})


# put all columns in a single dataframe
test = X_test
test['Activity'] = y_test
test['ActivityName'] = y_test_labels
test.sample()
```

Out[14]:
```
      tBodyAcc-mean()-X  tBodyAcc-mean()-Y  tBodyAcc-mean()-Z  \
2376           0.142909          -0.022732          -0.077417

      tBodyAcc-std()-X  tBodyAcc-std()-Y  tBodyAcc-std()-Z  tBodyAcc-mad()-X  \
2376         -0.300135         -0.087465         -0.268216         -0.379653

      tBodyAcc-mad()-Y  tBodyAcc-mad()-Z  tBodyAcc-max()-X        ...         \
2376         -0.077845         -0.291151         -0.016602        ...

      angle(tBodyAccMean,gravity)  angle(tBodyAccJerkMean),gravityMean)  \
2376                     0.653273                             -0.293463

      angle(tBodyGyroMean,gravityMean)  angle(tBodyGyroJerkMean,gravityMean)  \
2376                         -0.210501                             -0.449654

      angle(X,gravityMean)  angle(Y,gravityMean)  angle(Z,gravityMean)  \
2376             -0.426216              0.421082              0.239323

      subject  Activity      ActivityName
2376       20         2  WALKING_UPSTAIRS

[1 rows x 564 columns]
```

In [15]:
```
test.shape
```

Out[15]:
```
(2947, 564)
```

In [16]:
```
train.columns
```

```
Out[16]: Index(['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y', 'tBodyAcc-mean()-Z',
               'tBodyAcc-std()-X', 'tBodyAcc-std()-Y', 'tBodyAcc-std()-Z',
               'tBodyAcc-mad()-X', 'tBodyAcc-mad()-Y', 'tBodyAcc-mad()-Z',
               'tBodyAcc-max()-X',
               ...
               'angle(tBodyAccMean,gravity)', 'angle(tBodyAccJerkMean),gravityMean)',
               'angle(tBodyGyroMean,gravityMean)',
               'angle(tBodyGyroJerkMean,gravityMean)', 'angle(X,gravityMean)',
               'angle(Y,gravityMean)', 'angle(Z,gravityMean)', 'subject', 'Activity',
               'ActivityName'],
              dtype='object', length=564)
```

3 Data Cleaning

3.1 1. Check for Duplicates

```
In [17]: print('No of duplicates in train: {}'.format(sum(train.duplicated())))
         print('No of duplicates in test : {}'.format(sum(test.duplicated())))
```

```
No of duplicates in train: 0
No of duplicates in test : 0
```

3.2 2. Checking for NaN/null values

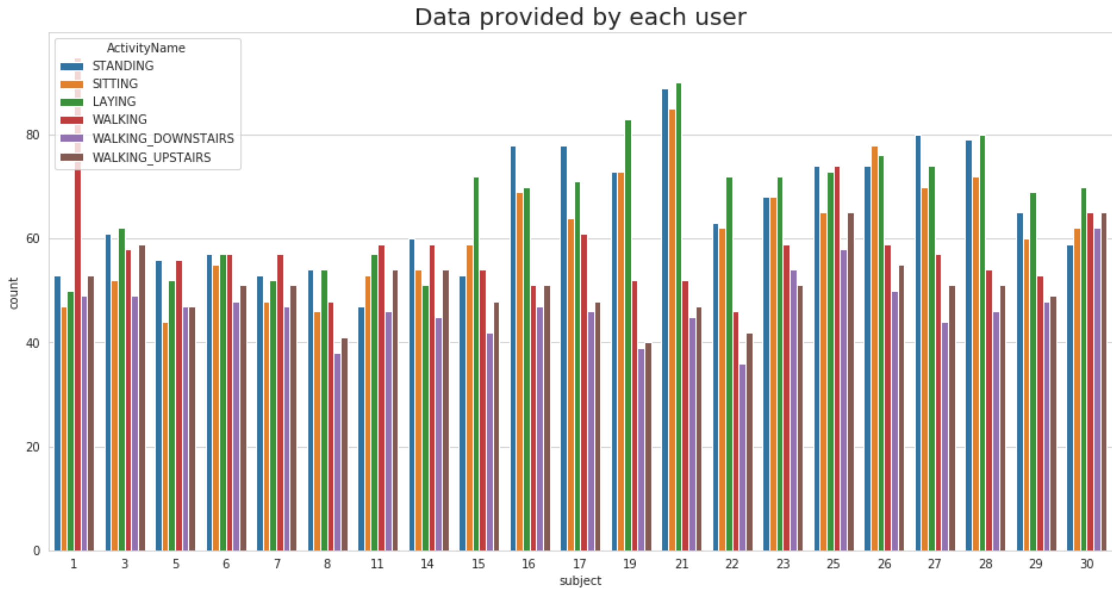
```
In [18]: print('We have {} NaN/Null values in train'.format(train.isnull().values.sum()))
         print('We have {} NaN/Null values in test'.format(test.isnull().values.sum()))
```

```
We have 0 NaN/Null values in train
We have 0 NaN/Null values in test
```

3.3 3. Check for data imbalance

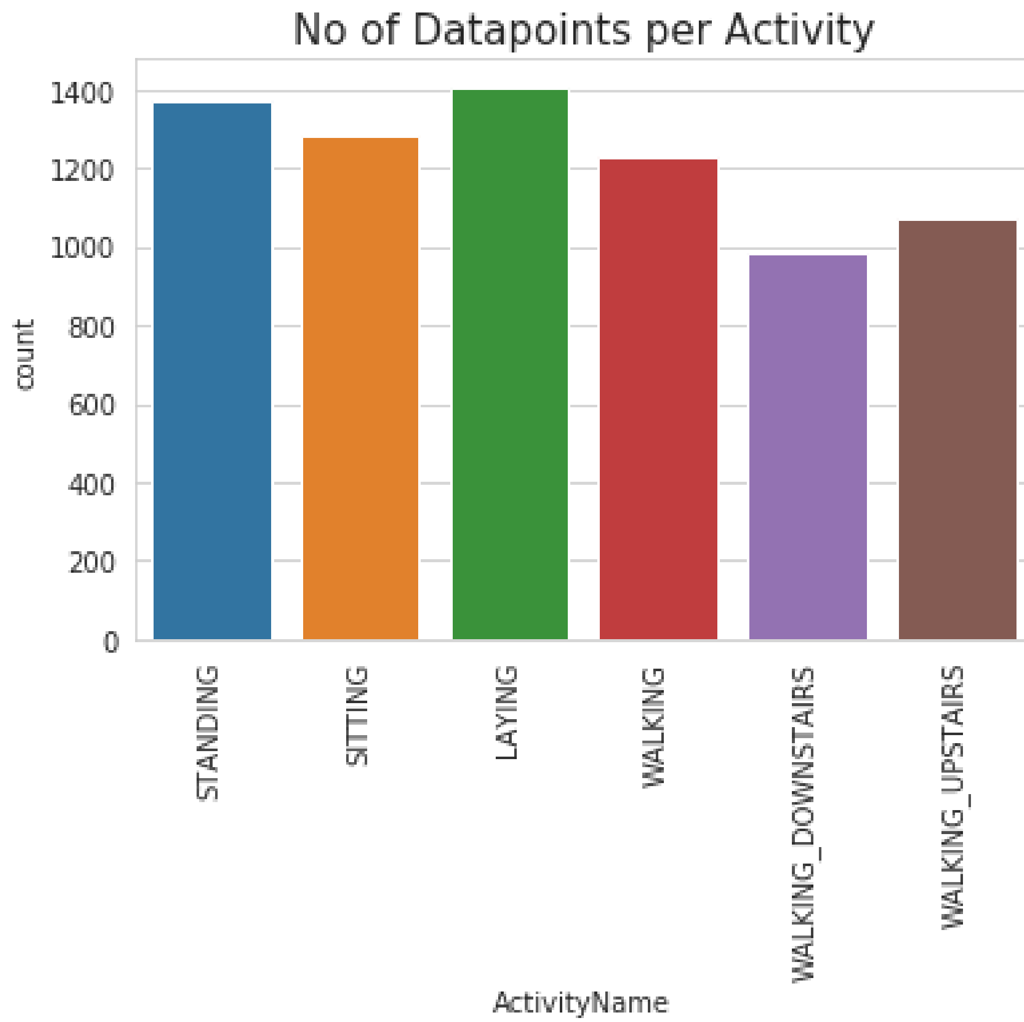
```
In [20]: import matplotlib.pyplot as plt
         import seaborn as sns

         sns.set_style('whitegrid')
```

```
In [21]: plt.figure(figsize=(16,8))
         plt.title('Data provided by each user', fontsize=20)
         sns.countplot(x='subject',hue='ActivityName', data = train)
         plt.show()
```



We have got almost same number of reading from all the subjects

In [22]:
```
plt.title('No of Datapoints per Activity', fontsize=15)
sns.countplot(train.ActivityName)
plt.xticks(rotation=90)
plt.show()
```



3.3.1 Observation

Our data is well balanced (almost)

3.4 4. Changing feature names

In [23]:
```
columns = train.columns

# Removing '()' from column names
columns = columns.str.replace('[()]','')
columns = columns.str.replace('[-]', '_')
columns = columns.str.replace('[,]','')

train.columns = columns
test.columns = columns
```

```
test.columns
```

```
Out[23]: Index(['tBodyAcc_mean_X', 'tBodyAcc_mean_Y', 'tBodyAcc_mean_Z',
                'tBodyAcc_std_X', 'tBodyAcc_std_Y', 'tBodyAcc_std_Z', 'tBodyAcc_mad_X',
                'tBodyAcc_mad_Y', 'tBodyAcc_mad_Z', 'tBodyAcc_max_X',
                ...
                'angletBodyAccMeangravity', 'angletBodyAccJerkMeangravityMean',
                'angletBodyGyroMeangravityMean', 'angletBodyGyroJerkMeangravityMean',
                'angleXgravityMean', 'angleYgravityMean', 'angleZgravityMean',
                'subject', 'Activity', 'ActivityName'],
               dtype='object', length=564)
```

3.5 5. Save this dataframe in a csv files

```
In [27]: train.to_csv('UCI_HAR_Dataset/csv_files/train.csv', index=False)
         test.to_csv('UCI_HAR_Dataset/csv_files/test.csv', index=False)
```

4 Exploratory Data Analysis

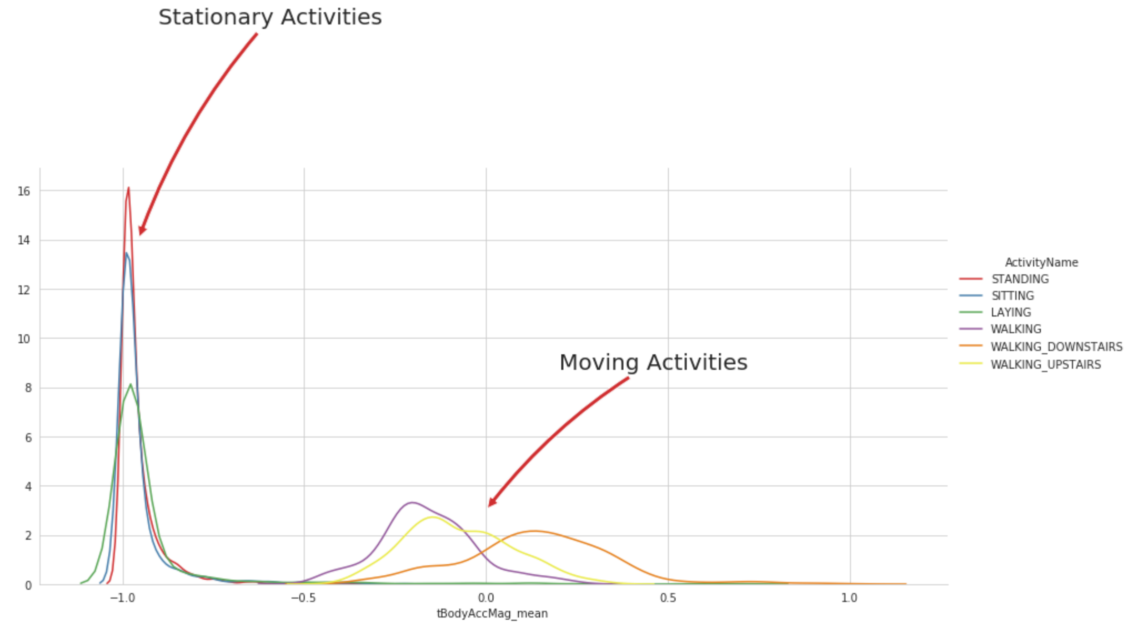
"***Without domain knowledge EDA has no meaning, without EDA a problem has no soul.***"

4.0.1 1. Featuring Engineering from Domain Knowledge

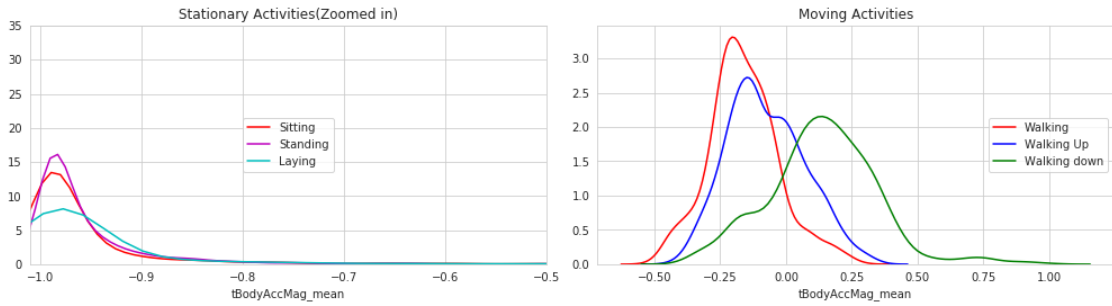
- **Static and Dynamic Activities**
  - In static activities (sit, stand, lie down) motion information will not be very useful.
  - In the dynamic activities (Walking, WalkingUpstairs,WalkingDownstairs) motion info will be significant.

4.0.2 2. Stationary and Moving activities are completely different

```
In [36]: sns.set_palette("Set1", desat=0.80)
         facetgrid = sns.FacetGrid(train, hue='ActivityName', size=6,aspect=2)
         facetgrid.map(sns.distplot,'tBodyAccMag_mean', hist=False)\
             .add_legend()
         plt.annotate("Stationary Activities", xy=(-0.956,14), xytext=(-0.9, 23), size=20,\
                      va='center', ha='left',\
                      arrowprops=dict(arrowstyle="simple",connectionstyle="arc3,rad=0.1"))

         plt.annotate("Moving Activities", xy=(0,3), xytext=(0.2, 9), size=20,\
                      va='center', ha='left',\
                      arrowprops=dict(arrowstyle="simple",connectionstyle="arc3,rad=0.1"))
         plt.show()
```



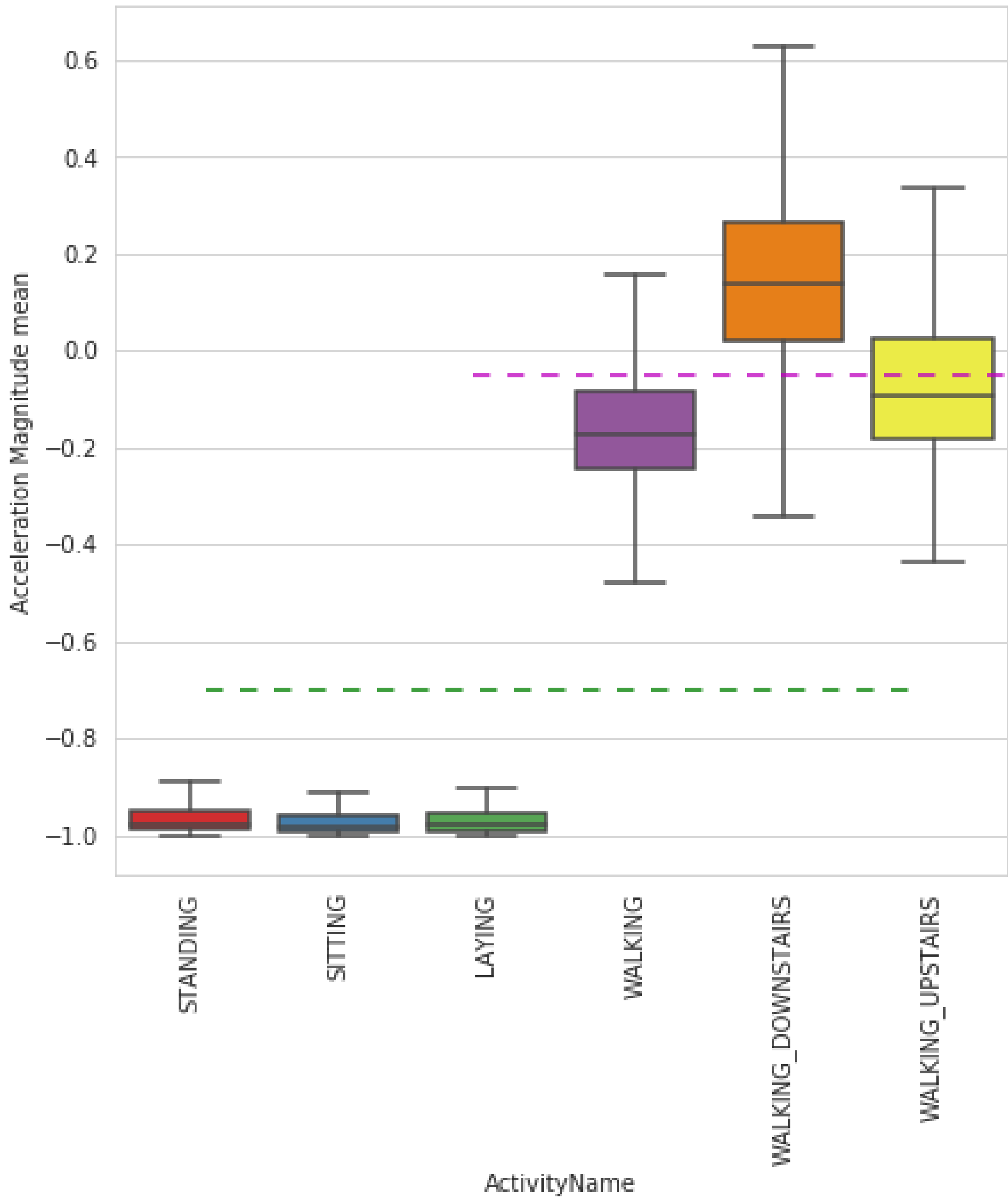
In [39]:
```
# for plotting purposes taking datapoints of each activity to a different dataframe
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

plt.figure(figsize=(14,7))
plt.subplot(2,2,1)
plt.title('Stationary Activities(Zoomed in)')
sns.distplot(df4['tBodyAccMag_mean'],color = 'r',hist = False, label = 'Sitting')
sns.distplot(df5['tBodyAccMag_mean'],color = 'm',hist = False,label = 'Standing')
sns.distplot(df6['tBodyAccMag_mean'],color = 'c',hist = False, label = 'Laying')
plt.axis([-1.01, -0.5, 0, 35])
plt.legend(loc='center')

plt.subplot(2,2,2)
plt.title('Moving Activities')
sns.distplot(df1['tBodyAccMag_mean'],color = 'red',hist = False, label = 'Walking')
sns.distplot(df2['tBodyAccMag_mean'],color = 'blue',hist = False,label = 'Walking Up')
sns.distplot(df3['tBodyAccMag_mean'],color = 'green',hist = False, label = 'Walking do
plt.legend(loc='center right')


plt.tight_layout()
plt.show()
```



4.0.3 3. Magnitude of an acceleration can saperate it well

In [41]:
```
plt.figure(figsize=(7,7))
sns.boxplot(x='ActivityName', y='tBodyAccMag_mean',data=train, showfliers=False, satu
plt.ylabel('Acceleration Magnitude mean')
plt.axhline(y=-0.7, xmin=0.1, xmax=0.9,dashes=(5,5), c='g')
plt.axhline(y=-0.05, xmin=0.4, dashes=(5,5), c='m')
plt.xticks(rotation=90)
plt.show()
```

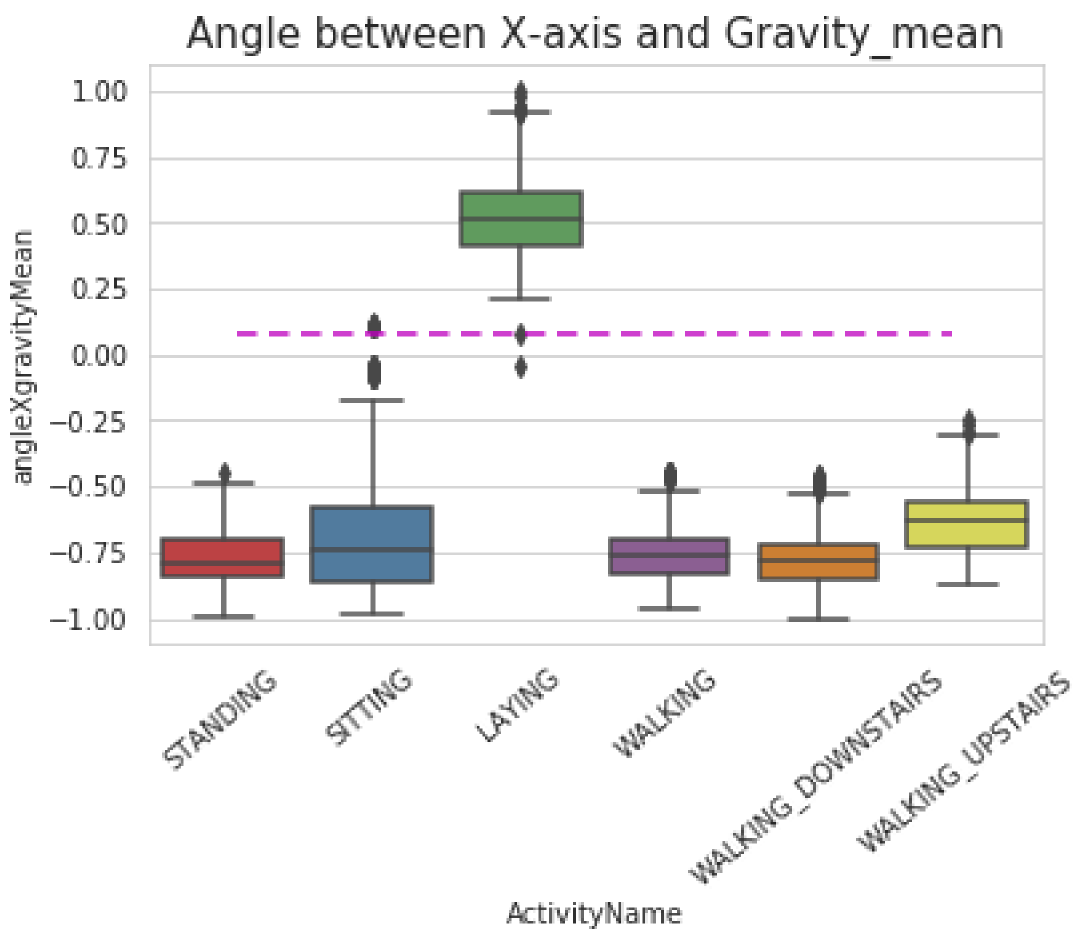
```
<matplotlib.figure.Figure at 0x1471d613b5f8>
```



__ Observations__: - If tAccMean is < -0.8 then the Activities are either Standing or Sitting or Laying. - If tAccMean is > -0.6 then the Activities are either Walking or WalkingDownstairs or WalkingUpstairs. - If tAccMean > 0.0 then the Activity is WalkingDownstairs. - We can classify 75% the Acitivity labels with some errors.

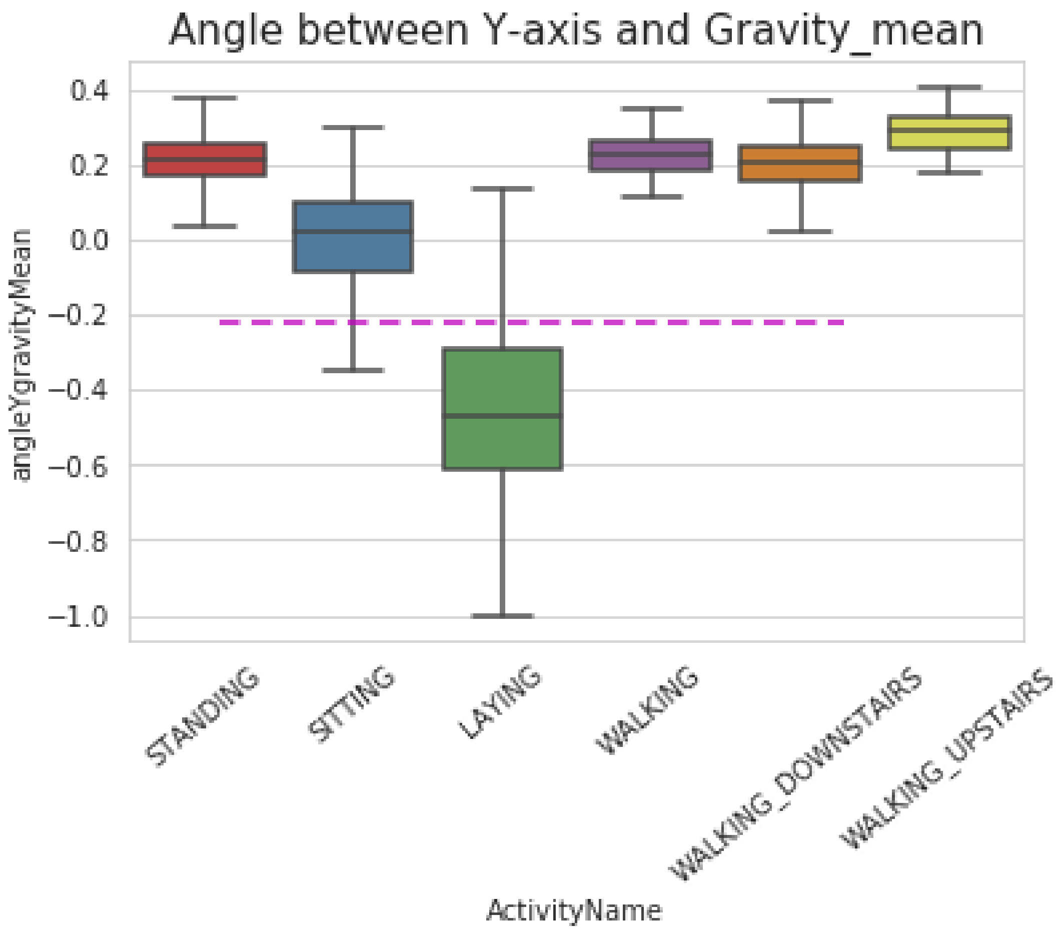
4.0.4 4. Position of GravityAccelerationComponants also matters

In [43]:
```
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title('Angle between X-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.show()
```



__ Observations__: * If angleX,gravityMean > 0 then Activity is Laying. * We can classify all datapoints belonging to Laying activity with just a single if else statement.

In [44]:
```
sns.boxplot(x='ActivityName', y='angleYgravityMean', data = train, showfliers=False)
plt.title('Angle between Y-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.axhline(y=-0.22, xmin=0.1, xmax=0.8, dashes=(5,3), c='m')
plt.show()
```



5 Apply t-sne on the data

In [45]:
```
import numpy as np
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns
```

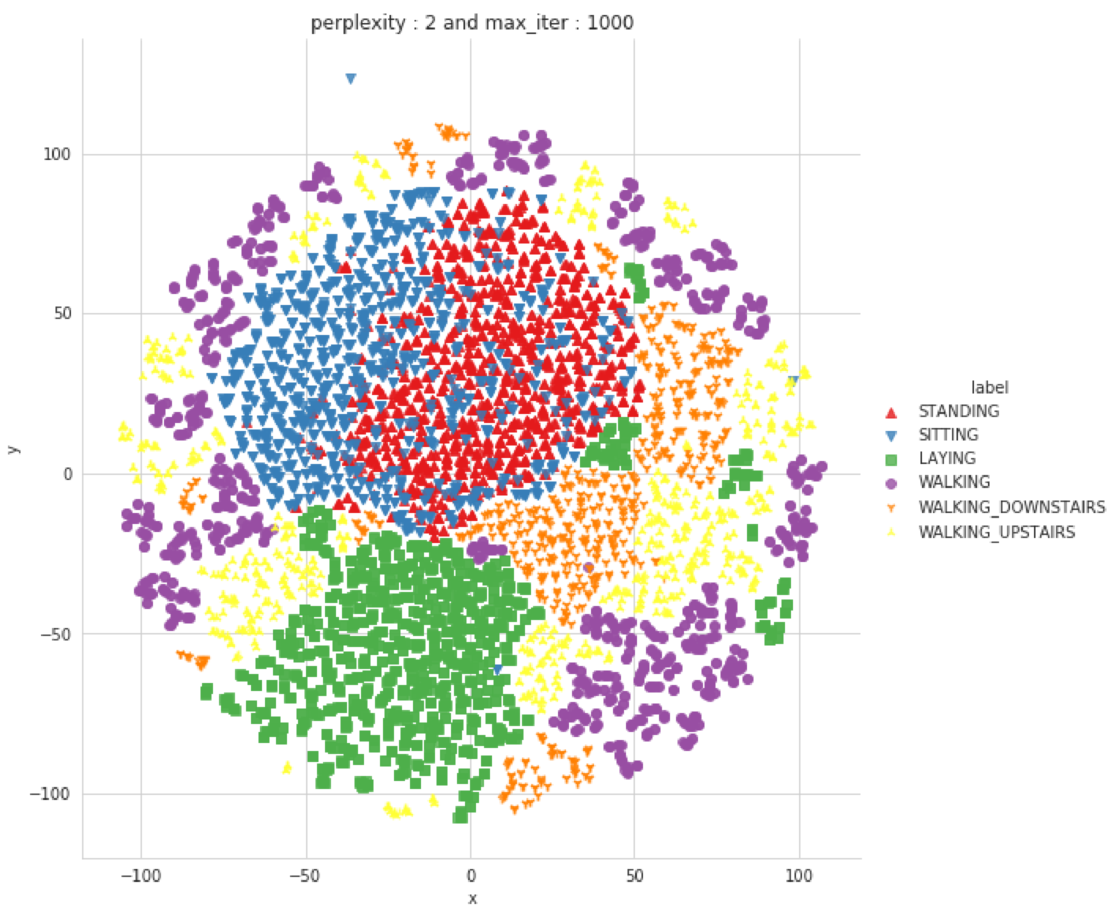
In [46]:
```
# performs t-sne with different perplexity values and their repective plots..

def perform_tsne(X_data, y_data, perplexities, n_iter=1000, img_name_prefix='t-sne'):

    for index,perplexity in enumerate(perplexities):
        # perform t-sne
        print('\nperforming tsne with perplexity {} and with {} iterations at max'.fo
        X_reduced = TSNE(verbose=2, perplexity=perplexity).fit_transform(X_data)
        print('Done..')
```

```
                # prepare the data for seaborn
                print('Creating plot for this t-sne visualization..')
                df = pd.DataFrame({'x':X_reduced[:,0], 'y':X_reduced[:,1] ,'label':y_data})

                # draw the plot in appropriate place in the grid
                sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False, size=8,\
                           palette="Set1",markers=['^','v','s','o', '1','2'])
                plt.title("perplexity : {} and max_iter : {}".format(perplexity, n_iter))
                img_name = img_name_prefix + '_perp_{}_iter_{}.png'.format(perplexity, n_iter)
                print('saving this plot as image in present working directory...')
                plt.savefig(img_name)
                plt.show()
                print('Done')
```

In [47]:
```
X_pre_tsne = train.drop(['subject', 'Activity','ActivityName'], axis=1)
y_pre_tsne = train['ActivityName']
perform_tsne(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[2,5,10,20,50])
```

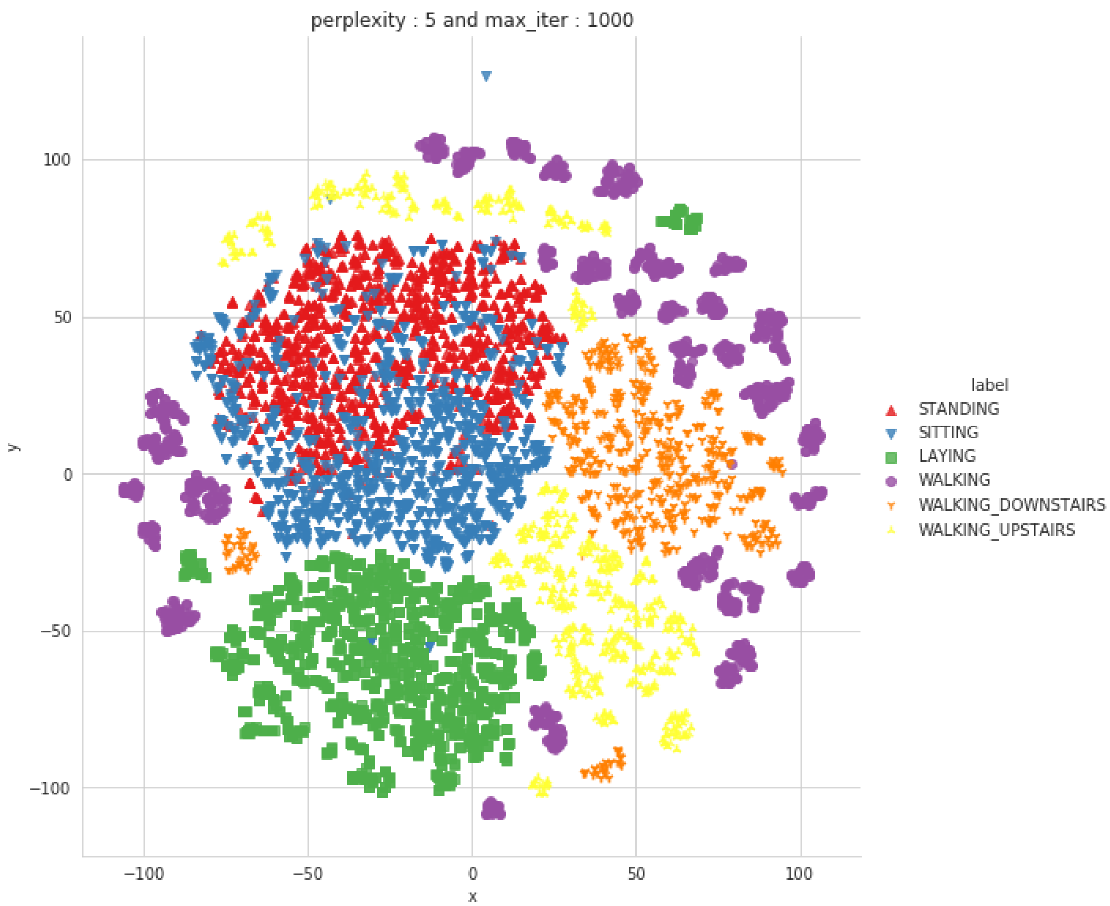
```
performing tsne with perplexity 2 and with 1000 iterations at max
[t-SNE] Computing 7 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.096s...
[t-SNE] Computed neighbors for 7352 samples in 27.701s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.635855
[t-SNE] Computed conditional probabilities in 0.052s
[t-SNE] Iteration 50: error = 124.7532959, gradient norm = 0.0285542 (50 iterations in 6.885s)
[t-SNE] Iteration 100: error = 106.8683777, gradient norm = 0.0273265 (50 iterations in 3.556s
[t-SNE] Iteration 150: error = 100.6163483, gradient norm = 0.0195194 (50 iterations in 2.591s
[t-SNE] Iteration 200: error = 97.3039246, gradient norm = 0.0156689 (50 iterations in 2.512s)
[t-SNE] Iteration 250: error = 95.0665588, gradient norm = 0.0124335 (50 iterations in 2.484s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 95.066559
[t-SNE] Iteration 300: error = 4.1143718, gradient norm = 0.0015598 (50 iterations in 2.224s)
[t-SNE] Iteration 350: error = 3.2087288, gradient norm = 0.0010000 (50 iterations in 1.990s)
[t-SNE] Iteration 400: error = 2.7785664, gradient norm = 0.0007231 (50 iterations in 2.024s)
[t-SNE] Iteration 450: error = 2.5142882, gradient norm = 0.0005710 (50 iterations in 2.042s)
[t-SNE] Iteration 500: error = 2.3313522, gradient norm = 0.0004800 (50 iterations in 2.062s)
[t-SNE] Iteration 550: error = 2.1932867, gradient norm = 0.0004106 (50 iterations in 2.078s)
[t-SNE] Iteration 600: error = 2.0840328, gradient norm = 0.0003637 (50 iterations in 2.089s)
[t-SNE] Iteration 650: error = 1.9942801, gradient norm = 0.0003322 (50 iterations in 2.104s)
[t-SNE] Iteration 700: error = 1.9186578, gradient norm = 0.0003031 (50 iterations in 2.119s)
```

```
[t-SNE] Iteration 750: error = 1.8537792, gradient norm = 0.0002782 (50 iterations in 2.127s)
[t-SNE] Iteration 800: error = 1.7970450, gradient norm = 0.0002557 (50 iterations in 2.133s)
[t-SNE] Iteration 850: error = 1.7470232, gradient norm = 0.0002375 (50 iterations in 2.144s)
[t-SNE] Iteration 900: error = 1.7022941, gradient norm = 0.0002236 (50 iterations in 2.137s)
[t-SNE] Iteration 950: error = 1.6622392, gradient norm = 0.0002098 (50 iterations in 2.146s)
[t-SNE] Iteration 1000: error = 1.6259054, gradient norm = 0.0002008 (50 iterations in 2.150s)
[t-SNE] Error after 1000 iterations: 1.625905
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```



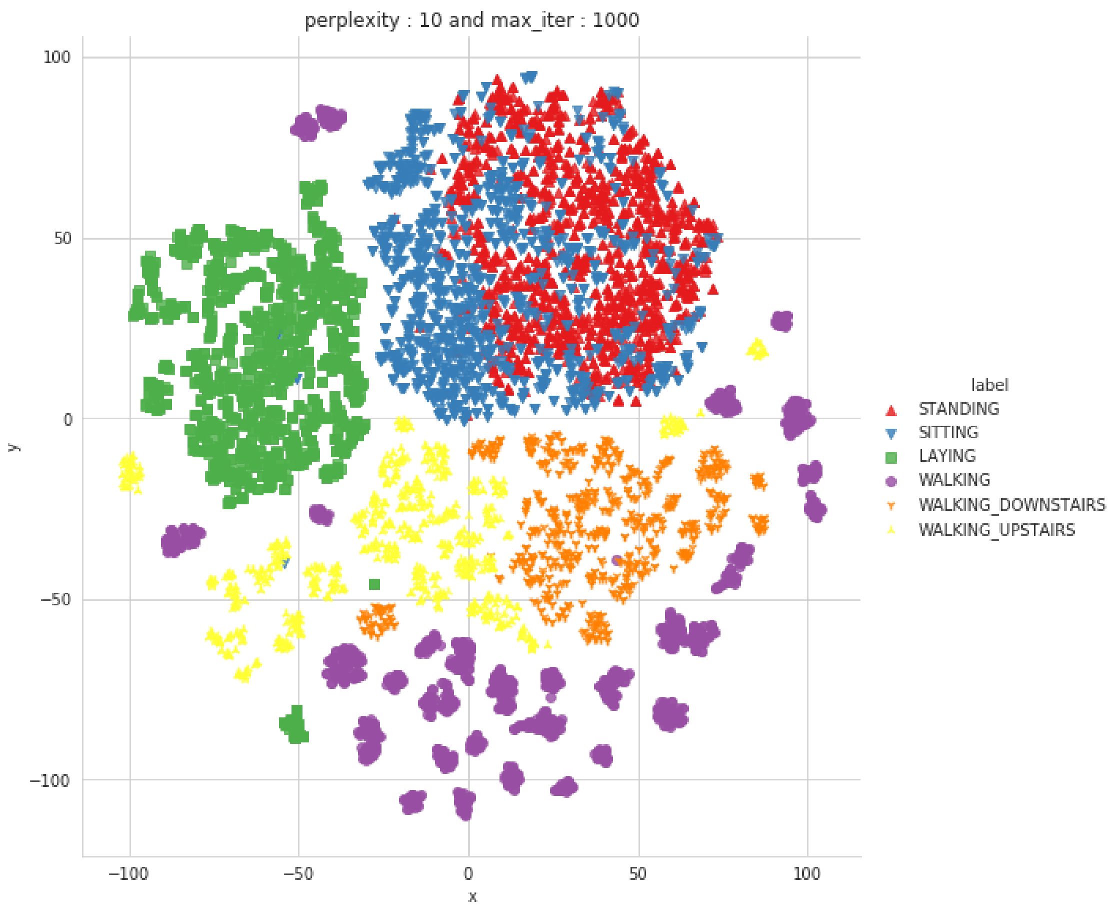

```
Done

performing tsne with perplexity 5 and with 1000 iterations at max
[t-SNE] Computing 16 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.085s...
[t-SNE] Computed neighbors for 7352 samples in 27.997s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
```

```
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.961265
[t-SNE] Computed conditional probabilities in 0.058s
[t-SNE] Iteration 50: error = 114.0592880, gradient norm = 0.0203027 (50 iterations in 5.592s)
[t-SNE] Iteration 100: error = 97.2689438, gradient norm = 0.0156565 (50 iterations in 2.620s)
[t-SNE] Iteration 150: error = 92.9875412, gradient norm = 0.0087415 (50 iterations in 2.308s)
[t-SNE] Iteration 200: error = 91.0414810, gradient norm = 0.0071048 (50 iterations in 2.266s)
[t-SNE] Iteration 250: error = 89.8754654, gradient norm = 0.0057384 (50 iterations in 2.205s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 89.875465
[t-SNE] Iteration 300: error = 3.5759211, gradient norm = 0.0014691 (50 iterations in 2.256s)
[t-SNE] Iteration 350: error = 2.8154438, gradient norm = 0.0007505 (50 iterations in 2.240s)
[t-SNE] Iteration 400: error = 2.4350181, gradient norm = 0.0005242 (50 iterations in 2.264s)
[t-SNE] Iteration 450: error = 2.2171905, gradient norm = 0.0004073 (50 iterations in 2.302s)
[t-SNE] Iteration 500: error = 2.0723400, gradient norm = 0.0003336 (50 iterations in 2.340s)
[t-SNE] Iteration 550: error = 1.9670427, gradient norm = 0.0002847 (50 iterations in 2.343s)
[t-SNE] Iteration 600: error = 1.8857234, gradient norm = 0.0002473 (50 iterations in 2.354s)
[t-SNE] Iteration 650: error = 1.8205318, gradient norm = 0.0002198 (50 iterations in 2.367s)
[t-SNE] Iteration 700: error = 1.7666595, gradient norm = 0.0001984 (50 iterations in 2.379s)
[t-SNE] Iteration 750: error = 1.7211496, gradient norm = 0.0001790 (50 iterations in 2.379s)
[t-SNE] Iteration 800: error = 1.6821029, gradient norm = 0.0001657 (50 iterations in 2.390s)
[t-SNE] Iteration 850: error = 1.6482807, gradient norm = 0.0001518 (50 iterations in 2.398s)
[t-SNE] Iteration 900: error = 1.6185459, gradient norm = 0.0001421 (50 iterations in 2.402s)
[t-SNE] Iteration 950: error = 1.5919563, gradient norm = 0.0001332 (50 iterations in 2.406s)
[t-SNE] Iteration 1000: error = 1.5682360, gradient norm = 0.0001277 (50 iterations in 2.403s)
[t-SNE] Error after 1000 iterations: 1.568236
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```




```
Done

performing tsne with perplexity 10 and with 1000 iterations at max
[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.085s...
[t-SNE] Computed neighbors for 7352 samples in 28.368s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.133828
[t-SNE] Computed conditional probabilities in 0.155s
[t-SNE] Iteration 50: error = 105.6137085, gradient norm = 0.0229994 (50 iterations in 4.228s)
[t-SNE] Iteration 100: error = 89.9958496, gradient norm = 0.0122725 (50 iterations in 3.063s)
[t-SNE] Iteration 150: error = 87.1489944, gradient norm = 0.0071774 (50 iterations in 2.760s)
```

```
[t-SNE] Iteration 200: error = 85.9672318, gradient norm = 0.0061608 (50 iterations in 2.772s)
[t-SNE] Iteration 250: error = 85.2867050, gradient norm = 0.0036593 (50 iterations in 2.769s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 85.286705
[t-SNE] Iteration 300: error = 3.1305749, gradient norm = 0.0013861 (50 iterations in 2.801s)
[t-SNE] Iteration 350: error = 2.4887924, gradient norm = 0.0006460 (50 iterations in 2.720s)
[t-SNE] Iteration 400: error = 2.1697743, gradient norm = 0.0004211 (50 iterations in 2.716s)
[t-SNE] Iteration 450: error = 1.9855604, gradient norm = 0.0003128 (50 iterations in 2.724s)
[t-SNE] Iteration 500: error = 1.8673357, gradient norm = 0.0002509 (50 iterations in 2.730s)
[t-SNE] Iteration 550: error = 1.7841893, gradient norm = 0.0002111 (50 iterations in 2.735s)
[t-SNE] Iteration 600: error = 1.7217950, gradient norm = 0.0001803 (50 iterations in 2.736s)
[t-SNE] Iteration 650: error = 1.6726514, gradient norm = 0.0001601 (50 iterations in 2.735s)
[t-SNE] Iteration 700: error = 1.6333241, gradient norm = 0.0001421 (50 iterations in 2.731s)
[t-SNE] Iteration 750: error = 1.6008626, gradient norm = 0.0001299 (50 iterations in 2.744s)
[t-SNE] Iteration 800: error = 1.5734997, gradient norm = 0.0001197 (50 iterations in 2.738s)
[t-SNE] Iteration 850: error = 1.5501360, gradient norm = 0.0001125 (50 iterations in 2.739s)
[t-SNE] Iteration 900: error = 1.5305120, gradient norm = 0.0001046 (50 iterations in 2.737s)
[t-SNE] Iteration 950: error = 1.5137104, gradient norm = 0.0000972 (50 iterations in 2.745s)
[t-SNE] Iteration 1000: error = 1.4986035, gradient norm = 0.0000922 (50 iterations in 2.751s)
[t-SNE] Error after 1000 iterations: 1.498603
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```




```
Done

performing tsne with perplexity 20 and with 1000 iterations at max
[t-SNE] Computing 61 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.085s...
[t-SNE] Computed neighbors for 7352 samples in 29.036s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.274335
[t-SNE] Computed conditional probabilities in 0.271s
[t-SNE] Iteration 50: error = 97.7926636, gradient norm = 0.0125853 (50 iterations in 10.212s)
[t-SNE] Iteration 100: error = 84.0754013, gradient norm = 0.0064392 (50 iterations in 5.176s)
[t-SNE] Iteration 150: error = 81.9258728, gradient norm = 0.0035655 (50 iterations in 4.332s)
```

```
[t-SNE] Iteration 200: error = 81.1771851, gradient norm = 0.0022705 (50 iterations in 4.284s)
[t-SNE] Iteration 250: error = 80.7830048, gradient norm = 0.0021464 (50 iterations in 4.261s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 80.783005
[t-SNE] Iteration 300: error = 2.7013526, gradient norm = 0.0013006 (50 iterations in 4.028s)
[t-SNE] Iteration 350: error = 2.1675630, gradient norm = 0.0005758 (50 iterations in 3.776s)
[t-SNE] Iteration 400: error = 1.9185538, gradient norm = 0.0003485 (50 iterations in 3.796s)
[t-SNE] Iteration 450: error = 1.7722032, gradient norm = 0.0002463 (50 iterations in 3.821s)
[t-SNE] Iteration 500: error = 1.6783440, gradient norm = 0.0001935 (50 iterations in 3.838s)
[t-SNE] Iteration 550: error = 1.6141162, gradient norm = 0.0001585 (50 iterations in 3.852s)
[t-SNE] Iteration 600: error = 1.5673211, gradient norm = 0.0001348 (50 iterations in 3.869s)
[t-SNE] Iteration 650: error = 1.5318861, gradient norm = 0.0001161 (50 iterations in 3.879s)
[t-SNE] Iteration 700: error = 1.5039140, gradient norm = 0.0001032 (50 iterations in 3.889s)
[t-SNE] Iteration 750: error = 1.4814334, gradient norm = 0.0000954 (50 iterations in 3.893s)
[t-SNE] Iteration 800: error = 1.4631746, gradient norm = 0.0000885 (50 iterations in 3.909s)
[t-SNE] Iteration 850: error = 1.4486455, gradient norm = 0.0000838 (50 iterations in 3.923s)
[t-SNE] Iteration 900: error = 1.4372107, gradient norm = 0.0000781 (50 iterations in 3.938s)
[t-SNE] Iteration 950: error = 1.4272782, gradient norm = 0.0000750 (50 iterations in 3.935s)
[t-SNE] Iteration 1000: error = 1.4186589, gradient norm = 0.0000716 (50 iterations in 3.933s)
[t-SNE] Error after 1000 iterations: 1.418659
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```


```
Done

performing tsne with perplexity 50 and with 1000 iterations at max
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.086s...
[t-SNE] Computed neighbors for 7352 samples in 29.958s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.437672
[t-SNE] Computed conditional probabilities in 0.563s
[t-SNE] Iteration 50: error = 87.2486420, gradient norm = 0.0071327 (50 iterations in 7.677s)
[t-SNE] Iteration 100: error = 75.6975098, gradient norm = 0.0044917 (50 iterations in 7.338s)
[t-SNE] Iteration 150: error = 74.6203918, gradient norm = 0.0024377 (50 iterations in 6.859s)
```

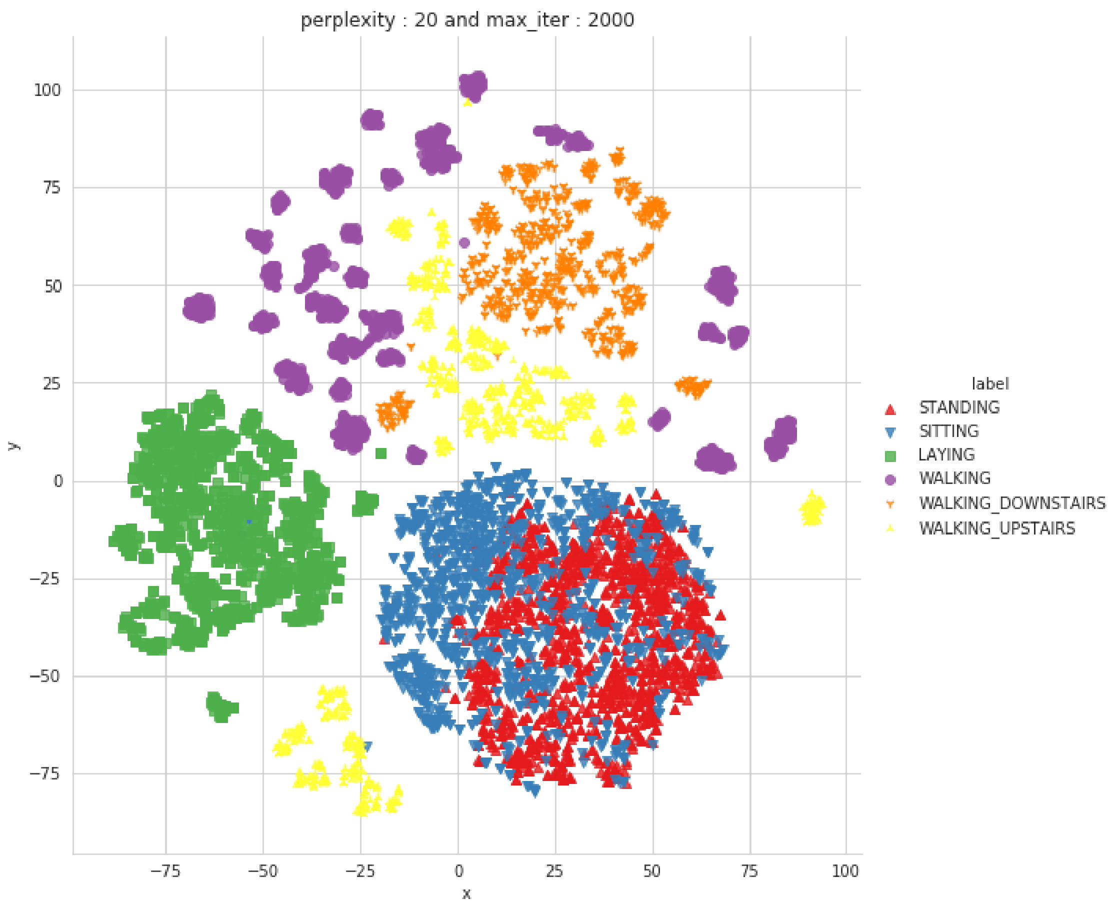
```
[t-SNE] Iteration 200: error = 74.2492752, gradient norm = 0.0015409 (50 iterations in 6.908s)
[t-SNE] Iteration 250: error = 74.0674744, gradient norm = 0.0012064 (50 iterations in 6.929s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 74.067474
[t-SNE] Iteration 300: error = 2.1519017, gradient norm = 0.0011851 (50 iterations in 6.938s)
[t-SNE] Iteration 350: error = 1.7552953, gradient norm = 0.0004863 (50 iterations in 6.881s)
[t-SNE] Iteration 400: error = 1.5867779, gradient norm = 0.0002808 (50 iterations in 6.877s)
[t-SNE] Iteration 450: error = 1.4929526, gradient norm = 0.0001902 (50 iterations in 6.869s)
[t-SNE] Iteration 500: error = 1.4330895, gradient norm = 0.0001395 (50 iterations in 6.872s)
[t-SNE] Iteration 550: error = 1.3918693, gradient norm = 0.0001124 (50 iterations in 6.866s)
[t-SNE] Iteration 600: error = 1.3627089, gradient norm = 0.0000937 (50 iterations in 6.858s)
[t-SNE] Iteration 650: error = 1.3417925, gradient norm = 0.0000828 (50 iterations in 6.860s)
[t-SNE] Iteration 700: error = 1.3263514, gradient norm = 0.0000745 (50 iterations in 6.865s)
[t-SNE] Iteration 750: error = 1.3148748, gradient norm = 0.0000693 (50 iterations in 6.873s)
[t-SNE] Iteration 800: error = 1.3062829, gradient norm = 0.0000676 (50 iterations in 6.880s)
[t-SNE] Iteration 850: error = 1.2999574, gradient norm = 0.0000594 (50 iterations in 6.882s)
[t-SNE] Iteration 900: error = 1.2946123, gradient norm = 0.0000580 (50 iterations in 6.883s)
[t-SNE] Iteration 950: error = 1.2901206, gradient norm = 0.0000535 (50 iterations in 6.876s)
[t-SNE] Iteration 1000: error = 1.2863228, gradient norm = 0.0000517 (50 iterations in 6.881s)
[t-SNE] Error after 1000 iterations: 1.286323
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```


```
Done
```

```
In [48]: X_pre_tsne = train.drop(['subject', 'Activity','ActivityName'], axis=1)
         y_pre_tsne = train['ActivityName']
         perform_tsne(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[20,50,90],n_iter=2
```

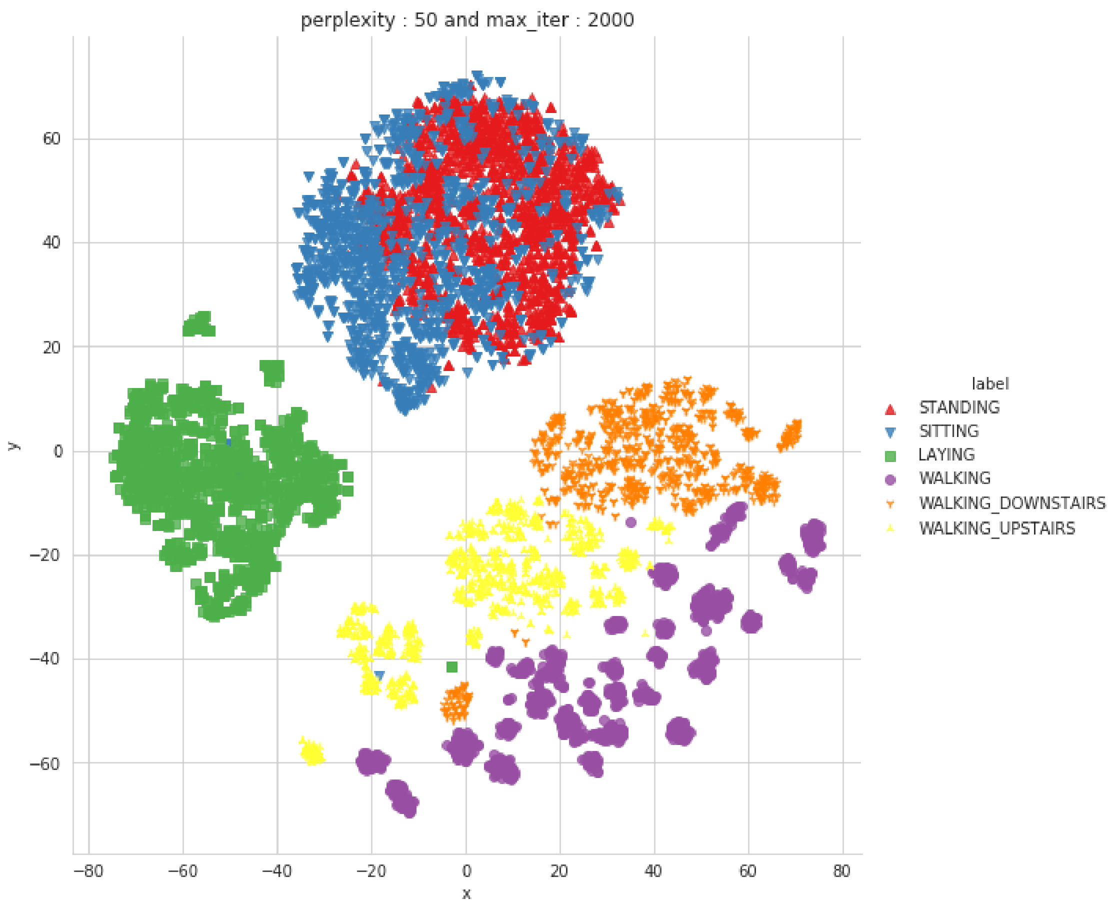
```
performing tsne with perplexity 20 and with 2000 iterations at max
[t-SNE] Computing 61 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.096s...
[t-SNE] Computed neighbors for 7352 samples in 29.076s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
```

```
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.274335
[t-SNE] Computed conditional probabilities in 0.268s
[t-SNE] Iteration 50: error = 97.7995453, gradient norm = 0.0148661 (50 iterations in 4.925s)
[t-SNE] Iteration 100: error = 84.0072556, gradient norm = 0.0072344 (50 iterations in 4.098s)
[t-SNE] Iteration 150: error = 81.9547729, gradient norm = 0.0038887 (50 iterations in 3.829s)
[t-SNE] Iteration 200: error = 81.1930771, gradient norm = 0.0023243 (50 iterations in 3.886s)
[t-SNE] Iteration 250: error = 80.7936783, gradient norm = 0.0017376 (50 iterations in 3.906s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 80.793678
[t-SNE] Iteration 300: error = 2.6971016, gradient norm = 0.0013003 (50 iterations in 3.848s)
[t-SNE] Iteration 350: error = 2.1623621, gradient norm = 0.0005753 (50 iterations in 3.746s)
[t-SNE] Iteration 400: error = 1.9135176, gradient norm = 0.0003476 (50 iterations in 3.750s)
[t-SNE] Iteration 450: error = 1.7679424, gradient norm = 0.0002466 (50 iterations in 3.763s)
[t-SNE] Iteration 500: error = 1.6742762, gradient norm = 0.0001907 (50 iterations in 3.771s)
[t-SNE] Iteration 550: error = 1.6101197, gradient norm = 0.0001570 (50 iterations in 3.776s)
[t-SNE] Iteration 600: error = 1.5637125, gradient norm = 0.0001333 (50 iterations in 3.787s)
[t-SNE] Iteration 650: error = 1.5287232, gradient norm = 0.0001169 (50 iterations in 3.789s)
[t-SNE] Iteration 700: error = 1.5011986, gradient norm = 0.0001056 (50 iterations in 3.797s)
[t-SNE] Iteration 750: error = 1.4793161, gradient norm = 0.0000964 (50 iterations in 3.805s)
[t-SNE] Iteration 800: error = 1.4618779, gradient norm = 0.0000929 (50 iterations in 3.807s)
[t-SNE] Iteration 850: error = 1.4484754, gradient norm = 0.0000847 (50 iterations in 3.801s)
[t-SNE] Iteration 900: error = 1.4374721, gradient norm = 0.0000808 (50 iterations in 3.802s)
[t-SNE] Iteration 950: error = 1.4281392, gradient norm = 0.0000762 (50 iterations in 3.805s)
[t-SNE] Iteration 1000: error = 1.4201696, gradient norm = 0.0000742 (50 iterations in 3.811s)
[t-SNE] Error after 1000 iterations: 1.420170
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```



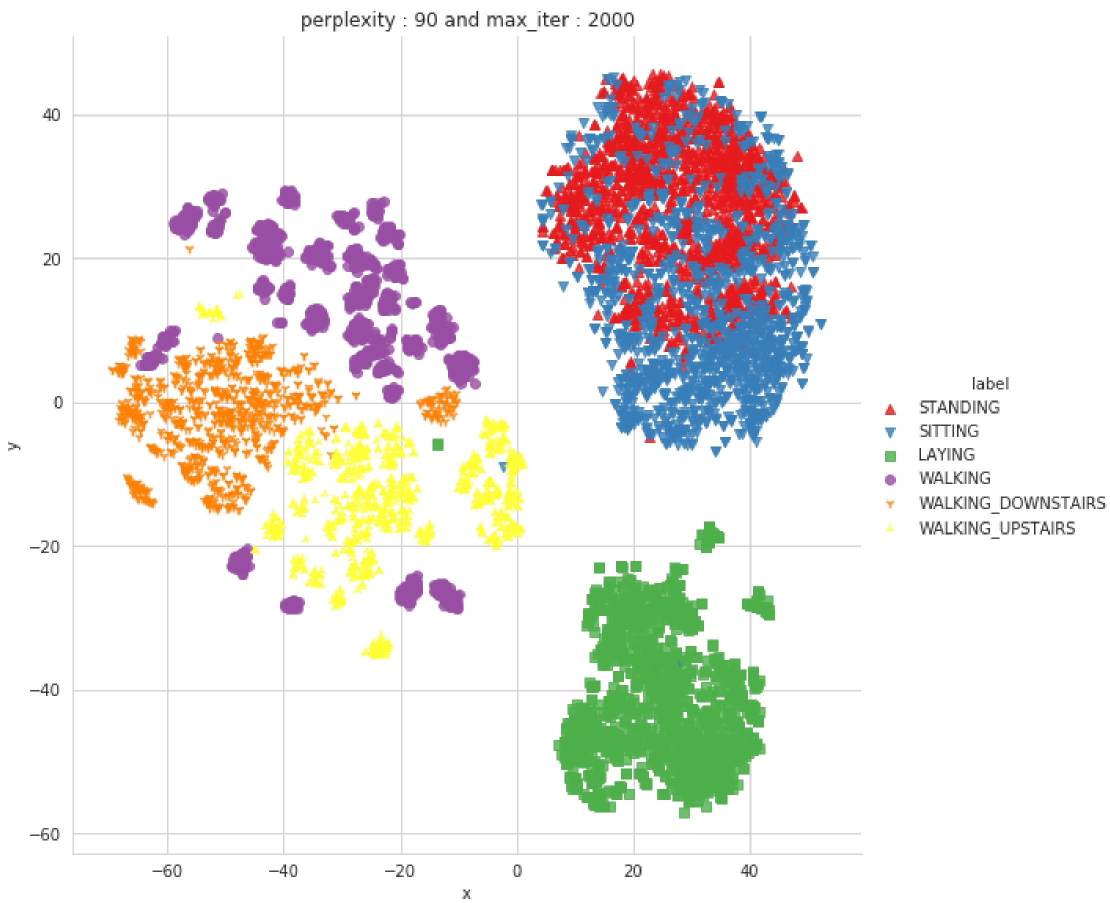

```
Done

performing tsne with perplexity 50 and with 2000 iterations at max
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.084s...
[t-SNE] Computed neighbors for 7352 samples in 29.811s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.437672
[t-SNE] Computed conditional probabilities in 0.563s
[t-SNE] Iteration 50: error = 86.5717087, gradient norm = 0.0175077 (50 iterations in 9.532s)
[t-SNE] Iteration 100: error = 75.5988235, gradient norm = 0.0040401 (50 iterations in 7.759s)
[t-SNE] Iteration 150: error = 74.7132950, gradient norm = 0.0022374 (50 iterations in 6.777s)
```

```
[t-SNE] Iteration 200: error = 74.3355331, gradient norm = 0.0015600 (50 iterations in 6.712s)
[t-SNE] Iteration 250: error = 74.1238327, gradient norm = 0.0013079 (50 iterations in 6.724s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 74.123833
[t-SNE] Iteration 300: error = 2.1673098, gradient norm = 0.0012021 (50 iterations in 6.918s)
[t-SNE] Iteration 350: error = 1.7651653, gradient norm = 0.0004890 (50 iterations in 6.872s)
[t-SNE] Iteration 400: error = 1.5937643, gradient norm = 0.0002820 (50 iterations in 6.877s)
[t-SNE] Iteration 450: error = 1.4993401, gradient norm = 0.0001900 (50 iterations in 6.881s)
[t-SNE] Iteration 500: error = 1.4392725, gradient norm = 0.0001415 (50 iterations in 6.878s)
[t-SNE] Iteration 550: error = 1.3982749, gradient norm = 0.0001117 (50 iterations in 6.861s)
[t-SNE] Iteration 600: error = 1.3687805, gradient norm = 0.0000930 (50 iterations in 6.867s)
[t-SNE] Iteration 650: error = 1.3471440, gradient norm = 0.0000831 (50 iterations in 6.870s)
[t-SNE] Iteration 700: error = 1.3317789, gradient norm = 0.0000741 (50 iterations in 6.895s)
[t-SNE] Iteration 750: error = 1.3202772, gradient norm = 0.0000682 (50 iterations in 6.894s)
[t-SNE] Iteration 800: error = 1.3111961, gradient norm = 0.0000654 (50 iterations in 6.898s)
[t-SNE] Iteration 850: error = 1.3041462, gradient norm = 0.0000611 (50 iterations in 6.877s)
[t-SNE] Iteration 900: error = 1.2984530, gradient norm = 0.0000579 (50 iterations in 6.878s)
[t-SNE] Iteration 950: error = 1.2937618, gradient norm = 0.0000519 (50 iterations in 6.887s)
[t-SNE] Iteration 1000: error = 1.2894143, gradient norm = 0.0000500 (50 iterations in 6.895s)
[t-SNE] Error after 1000 iterations: 1.289414
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```




```
Done

performing tsne with perplexity 90 and with 2000 iterations at max
[t-SNE] Computing 271 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.085s...
[t-SNE] Computed neighbors for 7352 samples in 30.783s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.540175
[t-SNE] Computed conditional probabilities in 0.960s
[t-SNE] Iteration 50: error = 77.8780289, gradient norm = 0.0304282 (50 iterations in 11.843s)
[t-SNE] Iteration 100: error = 69.3429031, gradient norm = 0.0028602 (50 iterations in 11.184s
[t-SNE] Iteration 150: error = 68.8140335, gradient norm = 0.0018916 (50 iterations in 10.861s
```

```
[t-SNE] Iteration 200: error = 68.6173096, gradient norm = 0.0011898 (50 iterations in 10.953s
[t-SNE] Iteration 250: error = 68.5081253, gradient norm = 0.0010420 (50 iterations in 11.034s
[t-SNE] KL divergence after 250 iterations with early exaggeration: 68.508125
[t-SNE] Iteration 300: error = 1.8464389, gradient norm = 0.0012062 (50 iterations in 11.311s)
[t-SNE] Iteration 350: error = 1.5126369, gradient norm = 0.0004407 (50 iterations in 11.089s)
[t-SNE] Iteration 400: error = 1.3816696, gradient norm = 0.0002530 (50 iterations in 11.059s)
[t-SNE] Iteration 450: error = 1.3117870, gradient norm = 0.0001741 (50 iterations in 11.065s)
[t-SNE] Iteration 500: error = 1.2696241, gradient norm = 0.0001230 (50 iterations in 11.059s)
[t-SNE] Iteration 550: error = 1.2407528, gradient norm = 0.0000947 (50 iterations in 11.048s)
[t-SNE] Iteration 600: error = 1.2200854, gradient norm = 0.0000762 (50 iterations in 11.047s)
[t-SNE] Iteration 650: error = 1.2050776, gradient norm = 0.0000659 (50 iterations in 11.058s)
[t-SNE] Iteration 700: error = 1.1939315, gradient norm = 0.0000586 (50 iterations in 11.072s)
[t-SNE] Iteration 750: error = 1.1858423, gradient norm = 0.0000530 (50 iterations in 11.082s)
[t-SNE] Iteration 800: error = 1.1796997, gradient norm = 0.0000490 (50 iterations in 11.086s)
[t-SNE] Iteration 850: error = 1.1750507, gradient norm = 0.0000472 (50 iterations in 11.079s)
[t-SNE] Iteration 900: error = 1.1714048, gradient norm = 0.0000439 (50 iterations in 11.071s)
[t-SNE] Iteration 950: error = 1.1685311, gradient norm = 0.0000415 (50 iterations in 11.069s)
[t-SNE] Iteration 1000: error = 1.1659497, gradient norm = 0.0000405 (50 iterations in 11.073s
[t-SNE] Error after 1000 iterations: 1.165950
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```




```
Done
```

5.1 Obtain the train and test data

```
In [2]: train = pd.read_csv('UCI_HAR_Dataset/csv_files/train.csv')
        test = pd.read_csv('UCI_HAR_Dataset/csv_files/test.csv')
        print(train.shape, test.shape)
```

```
(7352, 564) (2947, 564)
```

```
In [3]: train.head(1)
```

```
Out[3]:    tBodyAcc_mean_X  tBodyAcc_mean_Y  tBodyAcc_mean_Z  tBodyAcc_std_X  \
        0         0.288585        -0.020294        -0.132905       -0.995279

           tBodyAcc_std_Y  tBodyAcc_std_Z  tBodyAcc_mad_X  tBodyAcc_mad_Y  \
        0       -0.983111       -0.913526       -0.995112       -0.983185
```

```
   tBodyAcc_mad_Z  tBodyAcc_max_X      ...       angletBodyAccMeangravity  \
0       -0.923527       -0.934724      ...                      -0.112754

   angletBodyAccJerkMeangravityMean  angletBodyGyroMeangravityMean  \
0                            0.0304                      -0.464761

   angletBodyGyroJerkMeangravityMean  angleXgravityMean  angleYgravityMean  \
0                          -0.018446          -0.841247           0.179941

   angleZgravityMean  subject  Activity  ActivityName
0          -0.058627        1         5      STANDING

[1 rows x 564 columns]
```

In [4]:
```
# get X_train and y_train from csv files
X_train = train.drop(['subject', 'Activity', 'ActivityName'], axis=1)
y_train = train.ActivityName
```

In [5]:
```
# get X_test and y_test from test csv file
X_test = test.drop(['subject', 'Activity', 'ActivityName'], axis=1)
y_test = test.ActivityName
```

In [6]:
```
print('X_train and y_train : ({},{})'.format(X_train.shape, y_train.shape))
print('X_test  and y_test  : ({},{})'.format(X_test.shape, y_test.shape))
```

```
X_train and y_train : ((7352, 561),(7352,))
X_test  and y_test  : ((2947, 561),(2947,))
```

6 Let's model with our data

6.0.1 Labels that are useful in plotting confusion matrix

In [43]:
```
labels=['LAYING', 'SITTING','STANDING','WALKING','WALKING_DOWNSTAIRS','WALKING_UPSTAI
```

6.0.2 Function to plot the confusion matrix

In [176]:
```
import itertools
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
```

```
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

6.0.3 Generic function to run any model specified

```
In [177]: from datetime import datetime
          def perform_model(model, X_train, y_train, X_test, y_test, class_labels, cm_normalize
                           print_cm=True, cm_cmap=plt.cm.Greens):

              # to store results at various phases
              results = dict()

              # time at which model starts training
              train_start_time = datetime.now()
              print('training the model..')
              model.fit(X_train, y_train)
              print('Done \n \n')
              train_end_time = datetime.now()
              results['training_time'] =  train_end_time - train_start_time
              print('training_time(HH:MM:SS.ms) - {}\n\n'.format(results['training_time']))


              # predict test data
              print('Predicting test data')
              test_start_time = datetime.now()
              y_pred = model.predict(X_test)
              test_end_time = datetime.now()
              print('Done \n \n')
              results['testing_time'] = test_end_time - test_start_time
              print('testing time(HH:MM:SS:ms) - {}\n\n'.format(results['testing_time']))
              results['predicted'] = y_pred
```

```
    # calculate overall accuracty of the model
    accuracy = metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
    # store accuracy in results
    results['accuracy'] = accuracy
    print('---------------------')
    print('|      Accuracy      |')
    print('---------------------')
    print('\n    {}\n\n'.format(accuracy))


    # confusion matrix
    cm = metrics.confusion_matrix(y_test, y_pred)
    results['confusion_matrix'] = cm
    if print_cm:
        print('--------------------')
        print('| Confusion Matrix |')
        print('--------------------')
        print('\n {}'.format(cm))

    # plot confusin matrix
    plt.figure(figsize=(8,8))
    plt.grid(b=False)
    plot_confusion_matrix(cm, classes=class_labels, normalize=True, title='Normalized
    plt.show()

    # get classification report
    print('-------------------------')
    print('| Classifiction Report |')
    print('-------------------------')
    classification_report = metrics.classification_report(y_test, y_pred)
    # store report in results
    results['classification_report'] = classification_report
    print(classification_report)

    # add the trained  model to the results
    results['model'] = model

    return results
```

6.0.4 Method to print the gridsearch Attributes

```
In [178]: def print_grid_search_attributes(model):
    # Estimator that gave highest score among all the estimators formed in GridSearc
    print('--------------------------')
    print('|      Best Estimator     |')
    print('--------------------------')
    print('\n\t{}\n'.format(model.best_estimator_))
```

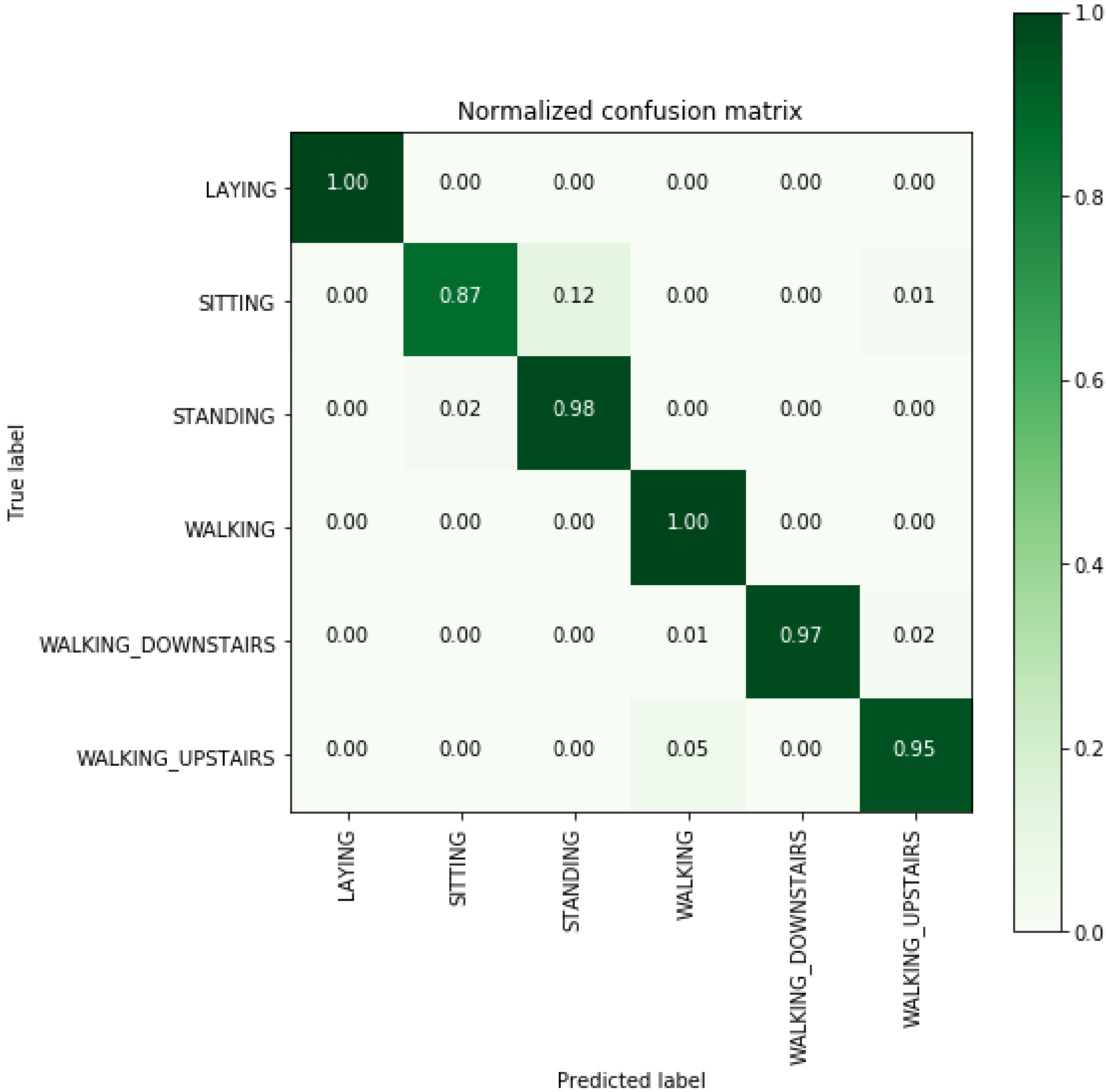
```
# parameters that gave best results while performing grid search
print('--------------------------')
print('|     Best parameters     |')
print('--------------------------')
print('\tParameters of best estimator : \n\n\t{}\n'.format(model.best_params_))


#  number of cross validation splits
print('---------------------------------')
print('|   No of CrossValidation sets   |')
print('--------------------------------')
print('\n\tTotal numbre of cross validation sets: {}\n'.format(model.n_splits_))


# Average cross validated score of the best estimator, from the Grid Search
print('--------------------------')
print('|        Best Score       |')
print('--------------------------')
print('\n\tAverage Cross Validate scores of best estimator : \n\n\t{}\n'.format(m
```

7 1. Logistic Regression with Grid Search

```
In [11]: from sklearn import linear_model
         from sklearn import metrics

         from sklearn.model_selection import GridSearchCV

In [12]: # start Grid search
         parameters = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1']}
         log_reg = linear_model.LogisticRegression()
         log_reg_grid = GridSearchCV(log_reg, param_grid=parameters, cv=3, verbose=1, n_jobs=8)
         log_reg_grid_results =  perform_model(log_reg_grid, X_train, y_train, X_test, y_test,
```

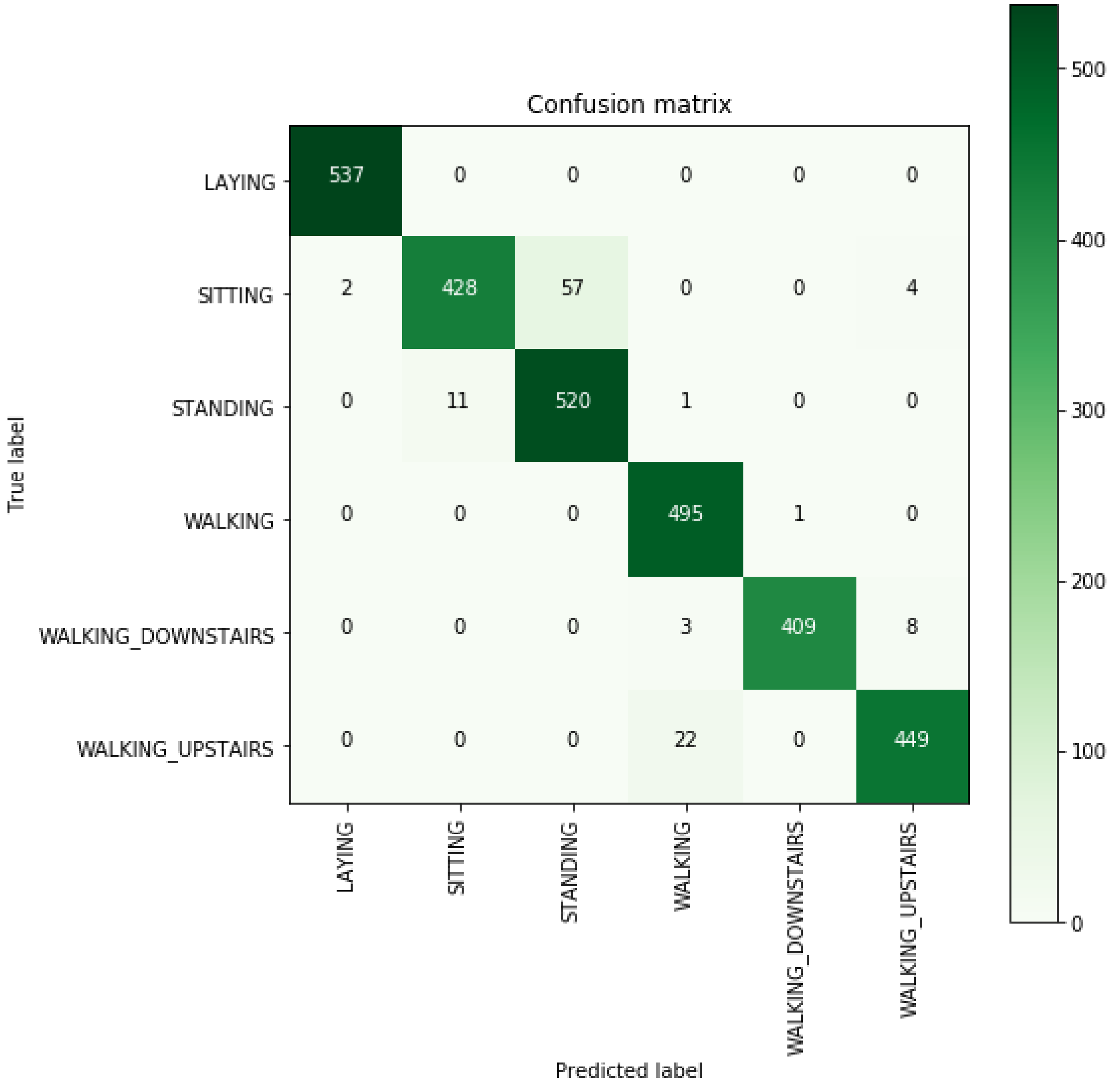
```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits


[Parallel(n_jobs=8)]: Done  36 out of  36 | elapsed:   31.3s finished


Done


training_time(HH:MM:SS.ms) - 0:00:41.152479
```

```
Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.021982


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

    0.9630132337970818


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

 [[537   0   0   0   0   0]
 [  2 428  57   0   0   4]
 [  0  11 520   1   0   0]
 [  0   0   0 495   1   0]
 [  0   0   0   3 409   8]
 [  0   0   0  22   0 449]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.87      0.92       491
          STANDING       0.90      0.98      0.94       532
           WALKING       0.95      1.00      0.97       496
WALKING_DOWNSTAIRS       1.00      0.97      0.99       420
  WALKING_UPSTAIRS       0.97      0.95      0.96       471

       avg / total       0.96      0.96      0.96      2947
```

```
In [13]: plt.figure(figsize=(8,8))
         plt.grid(b=False)
         plot_confusion_matrix(log_reg_grid_results['confusion_matrix'], classes=labels, cmap=p
         plt.show()
```




```
In [14]: # observe the attributes of the model
         print_grid_search_attributes(log_reg_grid_results['model'])

--------------------------
|      Best Estimator     |
--------------------------
```

```
        LogisticRegression(C=30, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'C': 30, 'penalty': 'l2'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|       Best Score        |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9460010881392819
```

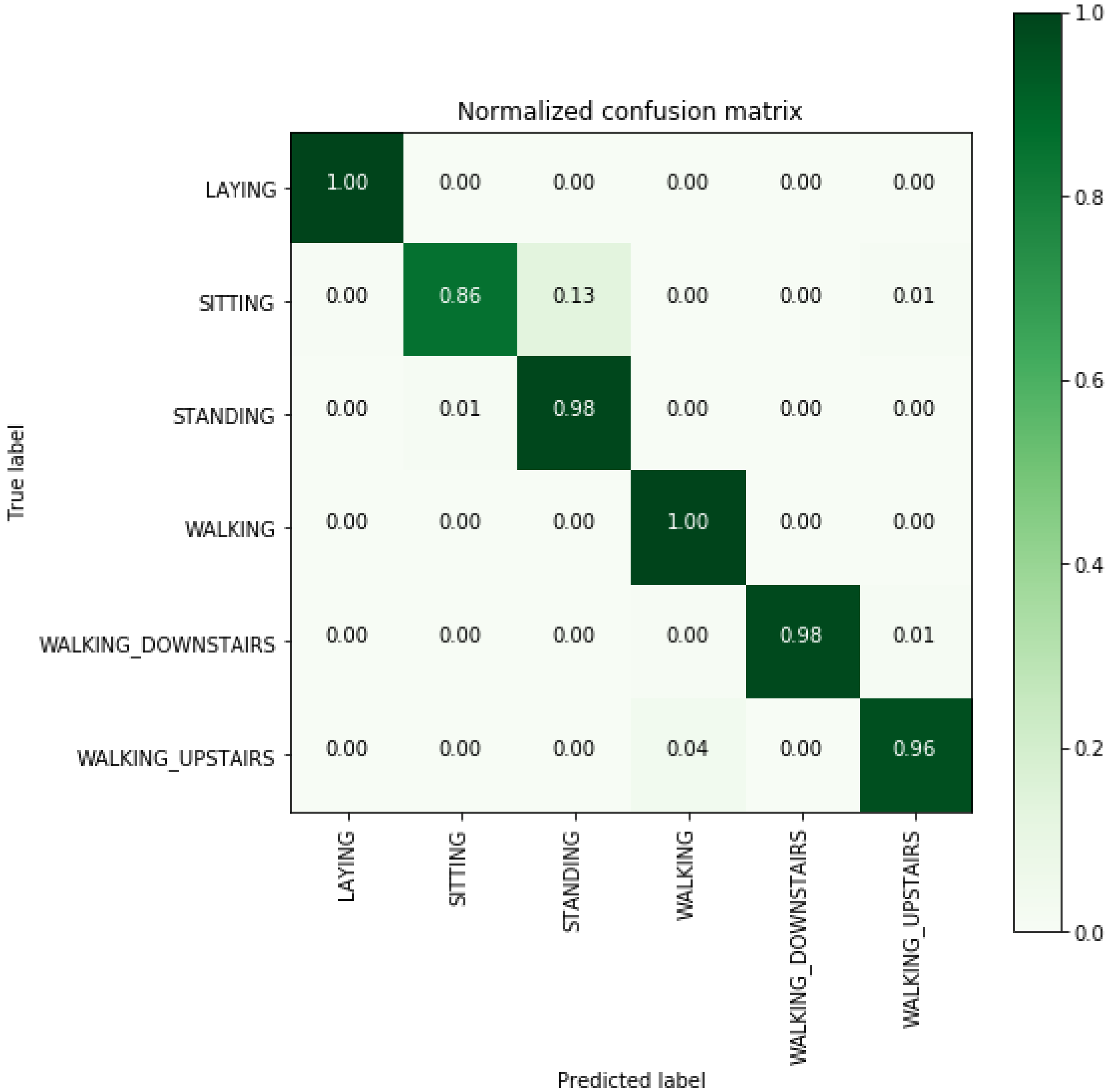
8 2. Linear SVC with GridSearch

```
In [15]: from sklearn.svm import LinearSVC
```

```
In [16]: parameters = {'C':[0.125, 0.5, 1, 2, 8, 16]}
         lr_svc = LinearSVC(tol=0.00005)
         lr_svc_grid = GridSearchCV(lr_svc, param_grid=parameters, n_jobs=8, verbose=1)
         lr_svc_grid_results = perform_model(lr_svc_grid, X_train, y_train, X_test, y_test, cla
```

```
training the model..
Fitting 3 folds for each of 6 candidates, totalling 18 fits


[Parallel(n_jobs=8)]: Done  18 out of  18 | elapsed:    9.5s finished


Done
```

```
training_time(HH:MM:SS.ms) - 0:00:13.065672


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.003324


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

    0.9650492025788938


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

 [[537   0   0   0   0   0]
 [  2 420  65   0   0   4]
 [  0   7 524   1   0   0]
 [  0   0   0 496   0   0]
 [  0   0   0   2 413   5]
 [  0   0   0  17   0 454]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.98      0.86      0.92       491
          STANDING       0.89      0.98      0.93       532
           WALKING       0.96      1.00      0.98       496
WALKING_DOWNSTAIRS       1.00      0.98      0.99       420
  WALKING_UPSTAIRS       0.98      0.96      0.97       471

       avg / total       0.97      0.97      0.96      2947
```

```
In [17]: print_grid_search_attributes(lr_svc_grid_results['model'])
```

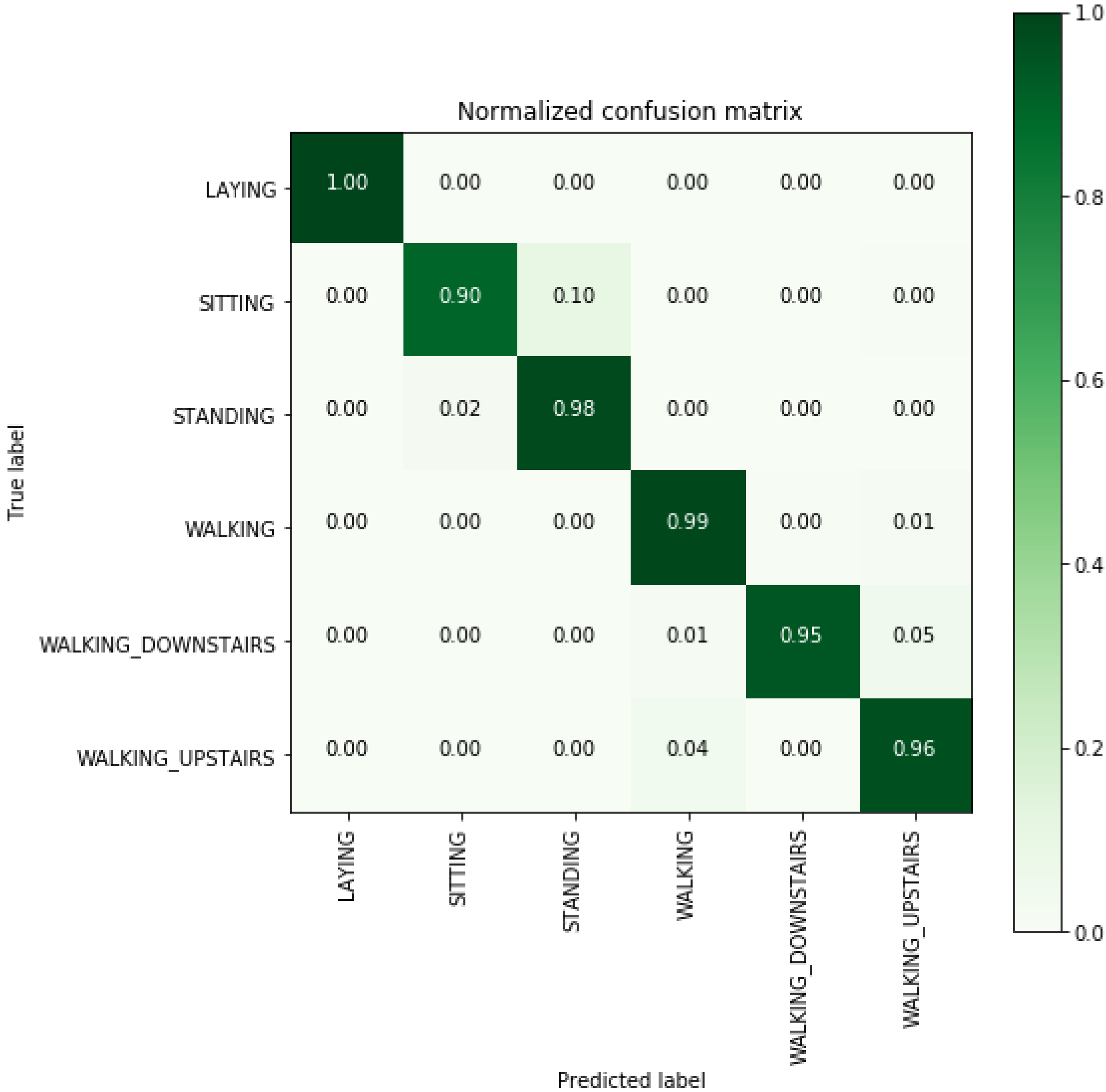
```
--------------------------
|      Best Estimator     |
--------------------------

        LinearSVC(C=1, class_weight=None, dual=True, fit_intercept=True,
     intercept_scaling=1, loss='squared_hinge', max_iter=1000,
     multi_class='ovr', penalty='l2', random_state=None, tol=5e-05,
     verbose=0)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'C': 1}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9455930359085963
```

9 3. Kernel SVM with GridSearch

```
In [18]: from sklearn.svm import SVC
         parameters = {'C':[2,8,16],\
                       'gamma': [ 0.0078125, 0.125, 2]}
         rbf_svm = SVC(kernel='rbf')
         rbf_svm_grid = GridSearchCV(rbf_svm,param_grid=parameters,n_jobs=8)
         rbf_svm_grid_results = perform_model(rbf_svm_grid, X_train, y_train, X_test, y_test, c
```

```
training the model..
Done
```

```
training_time(HH:MM:SS.ms) - 0:02:21.703537


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:02.286671


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

    0.9626739056667798


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

 [[537   0   0   0   0   0]
 [  0 441  48   0   0   2]
 [  0  12 520   0   0   0]
 [  0   0   0 489   2   5]
 [  0   0   0   4 397  19]
 [  0   0   0  17   1 453]]
```

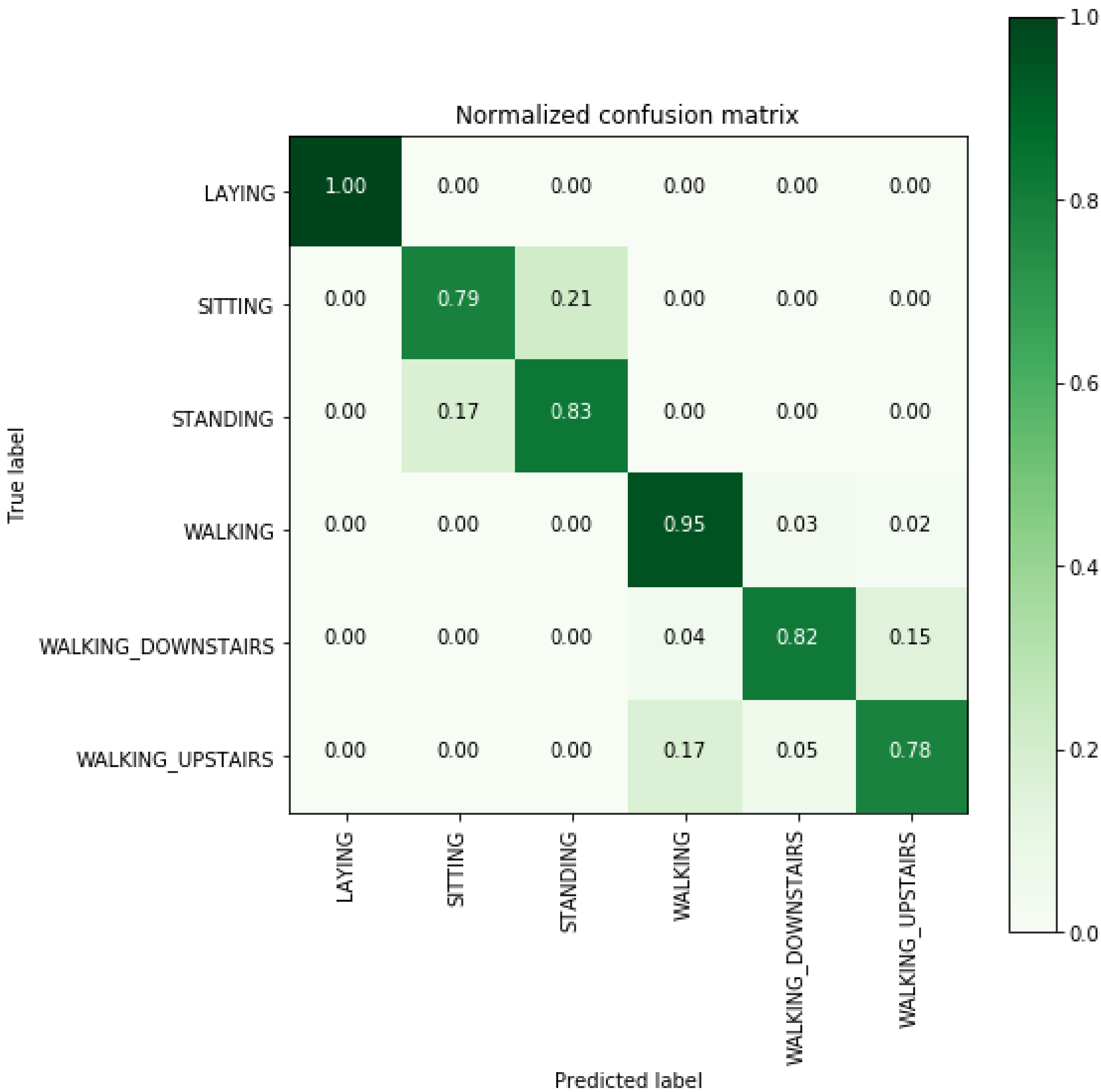



```
--------------------------
| Classifiction Report |
--------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.90      0.93       491
          STANDING       0.92      0.98      0.95       532
           WALKING       0.96      0.99      0.97       496
WALKING_DOWNSTAIRS       0.99      0.95      0.97       420
  WALKING_UPSTAIRS       0.95      0.96      0.95       471

       avg / total       0.96      0.96      0.96      2947
```

10 4. Decision Trees with GridSearchCV

```
In [19]: from sklearn.tree import DecisionTreeClassifier
         parameters = {'max_depth':np.arange(3,10,2)}
         dt = DecisionTreeClassifier()
         dt_grid = GridSearchCV(dt,param_grid=parameters, n_jobs=8)
         dt_grid_results = perform_model(dt_grid, X_train, y_train, X_test, y_test, class_label
         print_grid_search_attributes(dt_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:05.120427


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.002483


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

    0.8639294197488971


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

 [[537   0   0   0   0   0]
 [  0 386 105   0   0   0]
 [  0  93 439   0   0   0]
 [  0   0   0 472  16   8]
 [  0   0   0  16 343  61]
 [  0   0   0  78  24 369]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.81      0.79      0.80       491
          STANDING       0.81      0.83      0.82       532
           WALKING       0.83      0.95      0.89       496
WALKING_DOWNSTAIRS       0.90      0.82      0.85       420
  WALKING_UPSTAIRS       0.84      0.78      0.81       471

       avg / total       0.86      0.86      0.86      2947
```

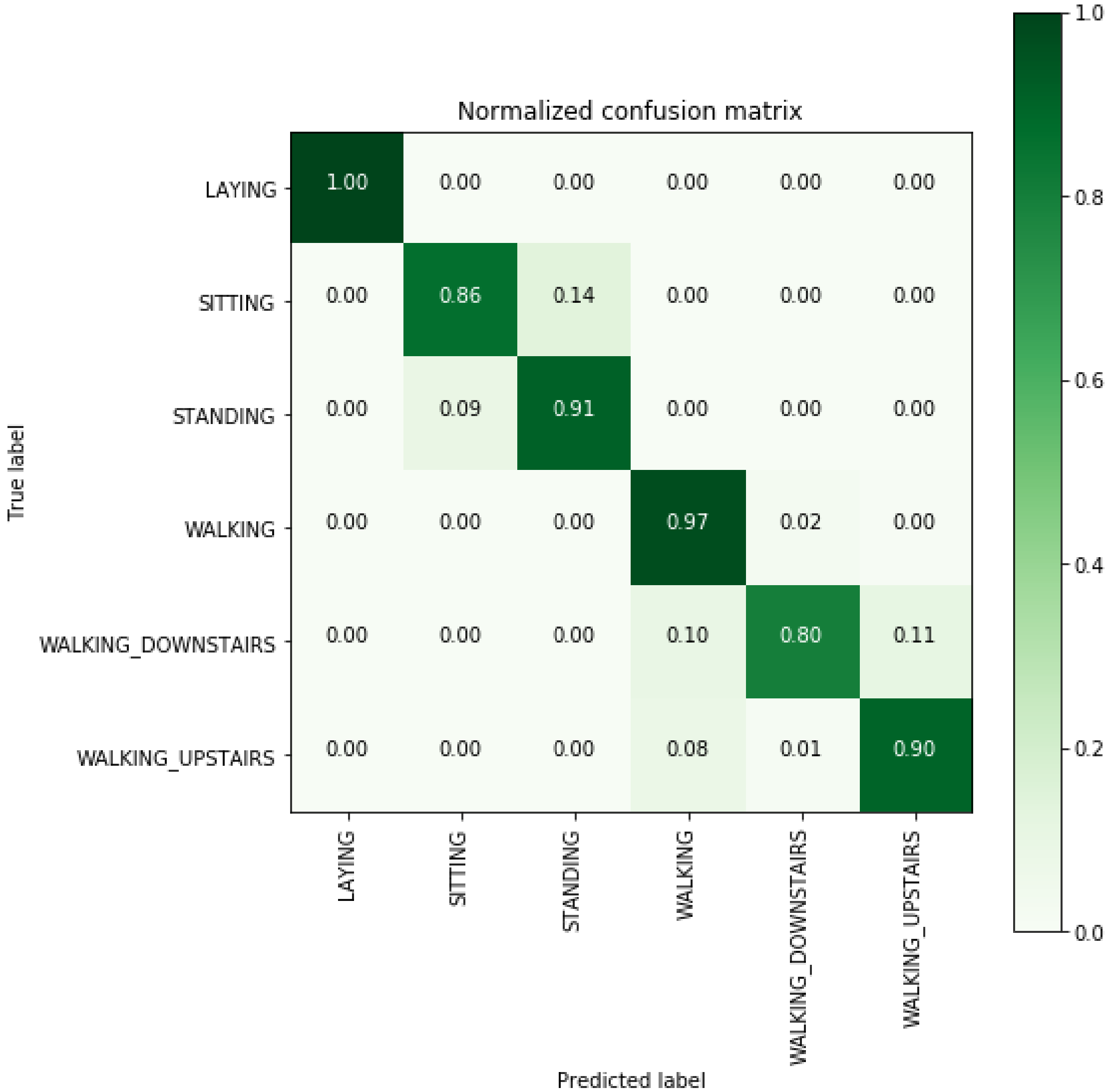
```
--------------------------
|      Best Estimator     |
--------------------------

        DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=7,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'max_depth': 7}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.8382752992383025
```

11 5. Random Forest Classifier with GridSearch

In [20]:
```
from sklearn.ensemble import RandomForestClassifier
params = {'n_estimators': np.arange(10,201,20), 'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=params, n_jobs=8)
rfc_grid_results = perform_model(rfc_grid, X_train, y_train, X_test, y_test, class_lal
print_grid_search_attributes(rfc_grid_results['model'])
```

```
training the model..
Done
```

```
training_time(HH:MM:SS.ms) - 0:01:59.069438


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.033301


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

    0.9107567017305734


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

 [[537   0   0   0   0   0]
 [  0 422  69   0   0   0]
 [  0  49 483   0   0   0]
 [  0   0   0 482  12   2]
 [  0   0   0  40 335  45]
 [  0   0   0  40   6 425]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.90      0.86      0.88       491
          STANDING       0.88      0.91      0.89       532
           WALKING       0.86      0.97      0.91       496
WALKING_DOWNSTAIRS       0.95      0.80      0.87       420
  WALKING_UPSTAIRS       0.90      0.90      0.90       471

       avg / total       0.91      0.91      0.91      2947
```

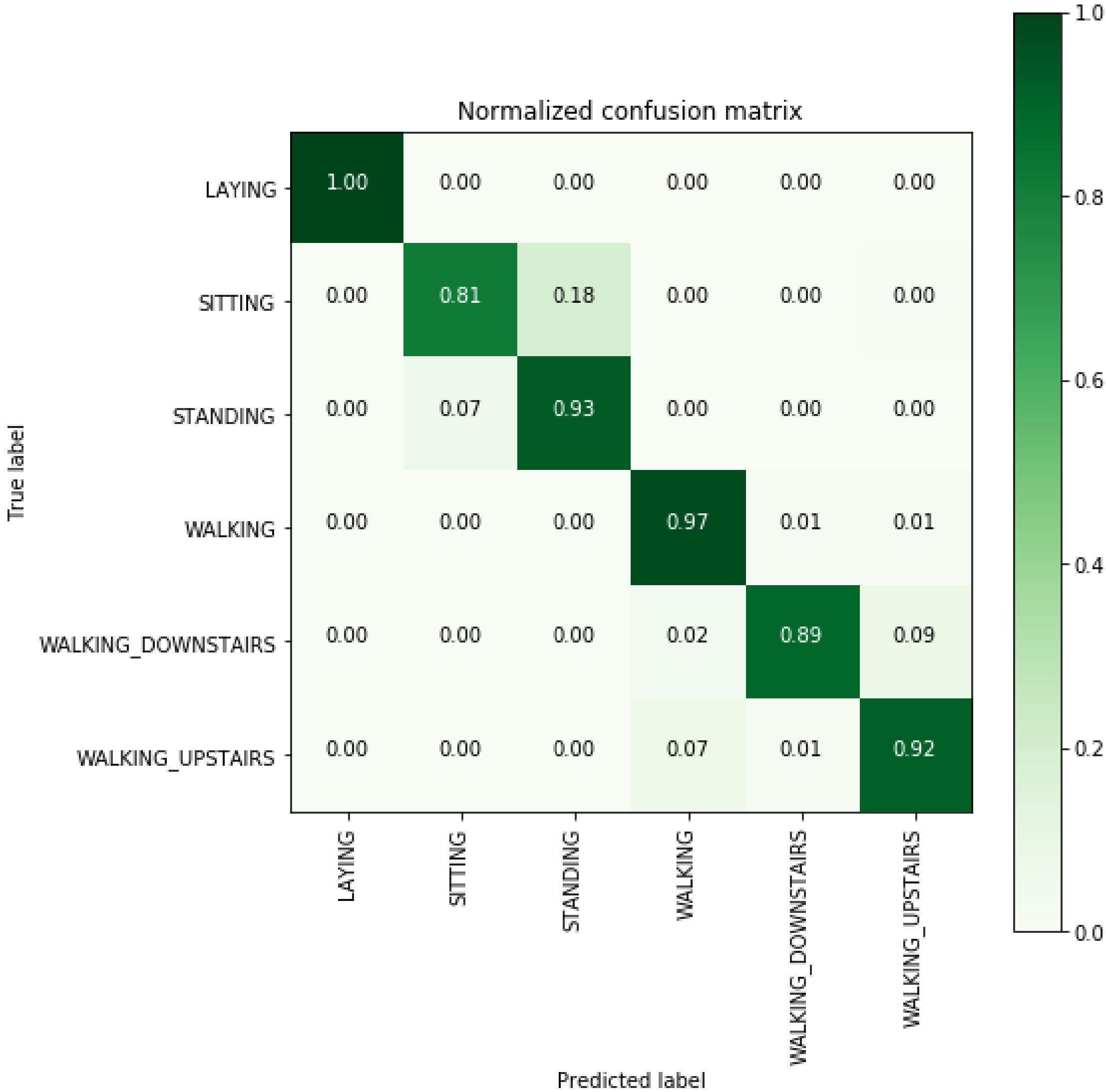
```
--------------------------
|      Best Estimator     |
--------------------------

        RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=7, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=130, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'max_depth': 7, 'n_estimators': 130}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9124047878128401
```

12 6. Gradient Boosted Decision Trees With GridSearch

```
In [21]: from sklearn.ensemble import GradientBoostingClassifier
         param_grid = {'max_depth': np.arange(5,8,1), \
                      'n_estimators':np.arange(130,170,10)}
         gbdt = GradientBoostingClassifier()
         gbdt_grid = GridSearchCV(gbdt, param_grid=param_grid, n_jobs=8)
         gbdt_grid_results = perform_model(gbdt_grid, X_train, y_train, X_test, y_test, class_l
         print_grid_search_attributes(gbdt_grid_results['model'])
```

```
training the model..
Done
```

```
training_time(HH:MM:SS.ms) - 0:17:12.707284


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.039210


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

    0.9226331862911435


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

 [[537   0   0   0   0   0]
 [  0 399  90   0   0   2]
 [  0  38 494   0   0   0]
 [  0   0   0 483   7   6]
 [  0   0   0  10 374  36]
 [  0   1   0  32   6 432]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.91      0.81      0.86       491
          STANDING       0.85      0.93      0.89       532
           WALKING       0.92      0.97      0.95       496
WALKING_DOWNSTAIRS       0.97      0.89      0.93       420
  WALKING_UPSTAIRS       0.91      0.92      0.91       471

       avg / total       0.92      0.92      0.92      2947
```

```
--------------------------
|      Best Estimator     |
--------------------------

        GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=5,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=150,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'max_depth': 5, 'n_estimators': 150}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9036996735582155
```

13 7. Comparing all models

In [22]:
```
print('\n                    Accuracy     Error')
print('                    ----------   --------')
print('Logistic Regression : {:.04}%      {:.04}%'.format(log_reg_grid_results['accu
                                                100-(log_reg_grid_results['accuracy

print('Linear SVC          : {:.04}%      {:.04}% '.format(lr_svc_grid_results['accu
                                                      100-(lr_svc_grid_results['accu
```

```
print('rbf SVM classifier  : {:.04}%     {:.04}% '.format(rbf_svm_grid_results['accu
                                                  100-(rbf_svm_grid_results['a

print('DecisionTree        : {:.04}%     {:.04}% '.format(dt_grid_results['accuracy']
                                                100-(dt_grid_results['accuracy

print('Random Forest       : {:.04}%     {:.04}% '.format(rfc_grid_results['accuracy
                                                   100-(rfc_grid_results['accu
print('GradientBoosting DT : {:.04}%     {:.04}% '.format(rfc_grid_results['accuracy
                                                100-(rfc_grid_results['accura
```

```
                     Accuracy     Error
                     ----------   --------
Logistic Regression : 96.3%       3.699%
Linear SVC          : 96.5%       3.495%
rbf SVM classifier  : 96.27%      3.733%
DecisionTree        : 86.39%      13.61%
Random Forest       : 91.08%      8.924%
GradientBoosting DT : 91.08%      8.924%
```

13.1 Using raw time series data and deep learning methods:

Approch 1 - Using LSTM
Approch 2 - Using CNN - CNN are useful to get best features and realtions between sequnce data using convolution.
Approch 3 - Using some cascading techniques.

13.2 LSTM

```
In [6]: # Importing libraries
        import numpy as np
        import pandas as pd
        from numpy import mean
        from numpy import std
        from numpy import dstack
        from pandas import read_csv
        from matplotlib import pyplot
        from sklearn.preprocessing import StandardScaler
        from keras.models import Sequential
        from keras.layers import Dense
        from keras.layers import Flatten
        from keras.layers import Dropout
        from keras.layers.convolutional import Conv1D
        from keras.layers.convolutional import MaxPooling1D
        from keras.utils import to_categorical
        from keras.models import Sequential
```

```
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

```
Using TensorFlow backend.
```

In [9]:
```
# Activities are the class labels
# It is a 6 class classification
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
    2: 'WALKING_DOWNSTAIRS',
    3: 'SITTING',
    4: 'STANDING',
    5: 'LAYING',
}

# Utility function to print the confusion matrix
def confusion_matrix(Y_true, Y_pred):
    Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1)])
    Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])

    return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])
```

In [10]:
```
# Data directory
DATADIR = 'UCI_HAR_Dataset'
# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
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"
]
```

In [11]:
```
# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
```

```
    def load_signals(subset):
        signals_data = []

        for signal in SIGNALS:
            filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.txt'
            signals_data.append(
                _read_csv(filename).as_matrix()
            )

        # 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)
        return np.transpose(signals_data, (1, 2, 0))
```

In [12]:
```
def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
    """
    filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]

    return pd.get_dummies(y).as_matrix()
```

In [13]:
```
def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_test = load_y('train'), load_y('test')

    return X_train, y_train, X_test,  y_test
```

In [12]:
```
# Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set_random_seed(42)
```

In [13]:
```
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

In [14]:
```
# Initializing parameters
epochs = 30
batch_size = 16
n_hidden = 32
```

In [14]:
```
# Utility function to count the number of classes
def _count_classes(y):
    return len(set([tuple(category) for category in y]))
```

In [16]:
```
# Loading the train and test data
X_train, Y_train, X_test,  Y_test = load_data()
```

In [17]:
```
timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = _count_classes(Y_train)
#n_classes  = 6
print(timesteps)
print(input_dim)
print(len(X_train))
```

```
128
9
7352
```

Base Model

In [14]:
```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
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
_________________________________________________________________
```

In [22]:
```
# Compiling the model
model.compile(loss='categorical_crossentropy',
```

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

In [23]:
```
# Training the model
model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 54s 7ms/step - loss: 1.3194 - acc: 0.4376 - val_lo
Epoch 2/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.9842 - acc: 0.5749 - val_lo
Epoch 3/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.7991 - acc: 0.6470 - val_lo
Epoch 4/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.6984 - acc: 0.6661 - val_lo
Epoch 5/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.6306 - acc: 0.6876 - val_lo
Epoch 6/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.6168 - acc: 0.7084 - val_lo
Epoch 7/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.6056 - acc: 0.7361 - val_lo
Epoch 8/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.5260 - acc: 0.7719 - val_lo
Epoch 9/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.4605 - acc: 0.7900 - val_lo
Epoch 10/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.4405 - acc: 0.7999 - val_lo
Epoch 11/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.4180 - acc: 0.8013 - val_lo
Epoch 12/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.4083 - acc: 0.8198 - val_lo
Epoch 13/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.3706 - acc: 0.8560 - val_lo
Epoch 14/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.3456 - acc: 0.8832 - val_lo
Epoch 15/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2947 - acc: 0.9135 - val_lo
Epoch 16/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.3015 - acc: 0.9159 - val_lo
Epoch 17/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.2472 - acc: 0.9317 - val_lo
Epoch 18/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2784 - acc: 0.9271 - val_lo
Epoch 19/30
```

```
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2505 - acc: 0.9306 - val_lo
Epoch 20/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2093 - acc: 0.9344 - val_lo
Epoch 21/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2218 - acc: 0.9370 - val_lo
Epoch 22/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1966 - acc: 0.9414 - val_lo
Epoch 23/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1827 - acc: 0.9403 - val_lo
Epoch 24/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1801 - acc: 0.9393 - val_lo
Epoch 25/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1896 - acc: 0.9433 - val_lo
Epoch 26/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2555 - acc: 0.9334 - val_lo
Epoch 27/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1791 - acc: 0.9434 - val_lo
Epoch 28/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2444 - acc: 0.9339 - val_lo
Epoch 29/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1938 - acc: 0.9393 - val_lo
Epoch 30/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1598 - acc: 0.9450 - val_lo
```

Out[23]: <keras.callbacks.History at 0x14f1ed870710>

Multi layer LSTM

In [16]:
```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(32,return_sequences=True,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))

model.add(LSTM(28,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.6))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_5 (LSTM)                (None, 128, 32)           5376
_________________________________________________________________
```

```
dropout_5 (Dropout)          (None, 128, 32)          0
_________________________________________________________________
lstm_6 (LSTM)                (None, 28)               6832
_________________________________________________________________
dropout_6 (Dropout)          (None, 28)               0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                174
=================================================================
Total params: 12,382
Trainable params: 12,382
Non-trainable params: 0
_________________________________________________________________
```

```
In [17]: # Compiling the model
         model.compile(loss='categorical_crossentropy',
                       optimizer='rmsprop',
                       metrics=['accuracy'])

In [18]: # Training the model
         model.fit(X_train,
                   Y_train,
                   batch_size=batch_size,
                   validation_data=(X_test, Y_test),
                   epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 109s 15ms/step - loss: 1.3081 - acc: 0.4561 - val_
Epoch 2/30
7352/7352 [==============================] - 107s 15ms/step - loss: 0.8821 - acc: 0.6051 - val_
Epoch 3/30
7352/7352 [==============================] - 106s 14ms/step - loss: 0.7624 - acc: 0.6359 - val_
Epoch 4/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.7258 - acc: 0.6302 - val_
Epoch 5/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.7122 - acc: 0.6474 - val_
Epoch 6/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.6977 - acc: 0.6515 - val_
Epoch 7/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.6750 - acc: 0.6790 - val_
Epoch 8/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.6167 - acc: 0.7329 - val_
Epoch 9/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.5178 - acc: 0.7889 - val_
Epoch 10/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.4557 - acc: 0.8215 - val_
Epoch 11/30
```

```
7352/7352 [==============================] - 104s 14ms/step - loss: 0.4006 - acc: 0.8554 - val_
Epoch 12/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.3518 - acc: 0.8936 - val_
Epoch 13/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2959 - acc: 0.9102 - val_
Epoch 14/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.2716 - acc: 0.9240 - val_
Epoch 15/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.2532 - acc: 0.9223 - val_
Epoch 16/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2409 - acc: 0.9295 - val_
Epoch 17/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2296 - acc: 0.9342 - val_
Epoch 18/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2039 - acc: 0.9377 - val_
Epoch 19/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2141 - acc: 0.9331 - val_
Epoch 20/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2001 - acc: 0.9382 - val_
Epoch 21/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1917 - acc: 0.9348 - val_
Epoch 22/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1970 - acc: 0.9362 - val_
Epoch 23/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1801 - acc: 0.9425 - val_
Epoch 24/30
7352/7352 [==============================] - 106s 14ms/step - loss: 0.1680 - acc: 0.9446 - val_
Epoch 25/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1835 - acc: 0.9418 - val_
Epoch 26/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1692 - acc: 0.9449 - val_
Epoch 27/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1722 - acc: 0.9421 - val_
Epoch 28/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.1739 - acc: 0.9434 - val_
Epoch 29/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1833 - acc: 0.9421 - val_
Epoch 30/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1730 - acc: 0.9431 - val_
```

```
Out[18]: <keras.callbacks.History at 0x14f13724bc88>
```

Above 2 layer LSTM is giving similar score as 1 layer LSTM which we trained above.

```
In [14]: from keras.regularizers import l2
```

```
In [20]: # Initiliazing the sequential model
         model = Sequential()
```

```
# Configuring the parameters
model.add(LSTM(32,recurrent_regularizer=l2(0.003),return_sequences=True,input_shape=(t
# Adding a dropout layer
model.add(Dropout(0.5))

model.add(LSTM(28,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.6))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_7 (LSTM)                (None, 128, 32)           5376
_________________________________________________________________
dropout_7 (Dropout)          (None, 128, 32)           0
_________________________________________________________________
lstm_8 (LSTM)                (None, 28)                6832
_________________________________________________________________
dropout_8 (Dropout)          (None, 28)                0
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 174
=================================================================
Total params: 12,382
Trainable params: 12,382
Non-trainable params: 0
_________________________________________________________________
```

In [21]:
```
# Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

In [22]:
```
# Training the model
History = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=10)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/10
7352/7352 [==============================] - 107s 15ms/step - loss: 1.4263 - acc: 0.4241 - val_
Epoch 2/10
7352/7352 [==============================] - 105s 14ms/step - loss: 1.2066 - acc: 0.5011 - val_
Epoch 3/10
```

```
7352/7352 [==============================] - 105s 14ms/step - loss: 0.9923 - acc: 0.5695 - val_
Epoch 4/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.9109 - acc: 0.5839 - val_
Epoch 5/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7995 - acc: 0.6223 - val_
Epoch 6/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.8123 - acc: 0.6062 - val_
Epoch 7/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7574 - acc: 0.6319 - val_
Epoch 8/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7699 - acc: 0.6411 - val_
Epoch 9/10
7352/7352 [==============================] - 106s 14ms/step - loss: 0.7106 - acc: 0.6493 - val_
Epoch 10/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7854 - acc: 0.6389 - val_
```

13.2.1 Hyperparameter Tuning Using Hyperas:

In [18]:
```
# Importing tensorflow
np.random.seed(36)
import tensorflow as tf
tf.set_random_seed(36)
```

In [5]:
```
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
from hyperopt import Trials, STATUS_OK, tpe
from hyperas import optim
from hyperas.distributions import choice, uniform
from hyperas.utils import eval_hyperopt_space
```

In [6]:
```
##gives train and validation data
def data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    # Data directory
    DATADIR = 'UCI_HAR_Dataset'
    # Raw data signals
    # Signals are from Accelerometer and Gyroscope
    # The signals are in x,y,z directions
    # Sensor signals are filtered to have only body acceleration
    # excluding the acceleration due to gravity
    # Triaxial acceleration from the accelerometer is total acceleration
    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"
                ]
            # Utility function to read the data from csv file
            def _read_csv(filename):
                return pd.read_csv(filename, delim_whitespace=True, header=None)

            # Utility function to load the load
            def load_signals(subset):
                signals_data = []

                for signal in SIGNALS:
                    filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.t
                    signals_data.append( _read_csv(filename).as_matrix())

                # 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)
                return np.transpose(signals_data, (1, 2, 0))

            def load_y(subset):
                """
                The objective that we are trying to predict is a integer, from 1 to 6,
                that represents a human activity. We return a binary representation of
                every sample objective as a 6 bits vector using One Hot Encoding
                (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.htm
                """
                filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
                y = _read_csv(filename)[0]
                return pd.get_dummies(y).as_matrix()

            X_train, X_val = load_signals('train'), load_signals('test')
            Y_train, Y_val = load_y('train'), load_y('test')

            return X_train, Y_train, X_val,  Y_val
```

In [7]:
```
from keras.regularizers import l2
import keras
```

In [8]:
```
##model
def model(X_train, Y_train, X_val, Y_val):
```

```python
# Importing tensorflow
np.random.seed(36)
import tensorflow as tf
tf.set_random_seed(36)
# Initiliazing the sequential model
model = Sequential()
if conditional({{choice(['one', 'two'])}}) == 'two':
    # Configuring the parameters
    model.add(LSTM({{choice([28,32,38])}},recurrent_regularizer=l2({{uniform(0,0.00
    # Adding a dropout layer
    model.add(Dropout({{uniform(0.35,0.65)}},name='Dropout2_1'))
    model.add(LSTM({{choice([26,32,36])}},recurrent_regularizer=l2({{uniform(0,0.00
    model.add(Dropout({{uniform(0.5,0.7)}},name='Dropout2_2'))
    # Adding a dense output layer with sigmoid activation
    model.add(Dense(6, activation='sigmoid'))
else:
    # Configuring the parameters
    model.add(LSTM({{choice([28,32,36])}},recurrent_regularizer=l2({{uniform(0,0.00
    # Adding a dropout layer
    model.add(Dropout({{uniform(0.35,0.55)}},name='Dropout1_1'))
    # Adding a dense output layer with sigmoid activation
    model.add(Dense(6, activation='sigmoid'))

adam = keras.optimizers.Adam(lr={{uniform(0.009,0.025)}})
rmsprop = keras.optimizers.RMSprop(lr={{uniform(0.009,0.025)}})

choiceval = {{choice(['adam', 'rmsprop'])}}

if choiceval == 'adam':
    optim = adam
else:
    optim = rmsprop

print(model.summary())

model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=optim

result = model.fit(X_train, Y_train,
          batch_size=16,
          nb_epoch=30,
          verbose=2,
          validation_data=(X_val, Y_val))

score, acc = model.evaluate(X_val, Y_val, verbose=0)
print('Test accuracy:', acc)
print('-------------------------------------------------------------------------
return {'loss': -acc, 'status': STATUS_OK, 'model': model}
```

```
In [ ]: X_train, Y_train, X_val, Y_val = data()
        trials = Trials()
        best_run, best_model, space = optim.minimize(model=model,
                                              data=data,
                                              algo=tpe.suggest,
                                              max_evals=15,
                                              trials=trials,notebook_name = 'Human Activity De
                                             return_space = True)
```

```
In [48]: total_trials = dict()
         for t, trial in enumerate(trials):
                 vals = trial.get('misc').get('vals')
                 print('Model',t+1,'parameters')
                 print(vals)
                 print()
                 z = eval_hyperopt_space(space, vals)
                 total_trials['M'+str(t+1)] = z
                 print(z)
                 print('--------------------------------------------------')
```

```
Model 1 parameters
{'Dropout': [0.36598023572757926], 'Dropout_1': [0.6047146037530785], 'Dropout_2': [0.51888265

{'Dropout': 0.36598023572757926, 'Dropout_1': 0.6047146037530785, 'Dropout_2': 0.5188826519950
--------------------------------------------------
Model 2 parameters
{'Dropout': [0.604072168386432], 'Dropout_1': [0.5642077861572957], 'Dropout_2': [0.46897425136

{'Dropout': 0.604072168386432, 'Dropout_1': 0.5642077861572957, 'Dropout_2': 0.46897425136886 5
--------------------------------------------------
Model 3 parameters
{'Dropout': [0.649118836907314], 'Dropout_1': [0.6408661828169875], 'Dropout_2': [0.50251163189

{'Dropout': 0.649118836907314, 'Dropout_1': 0.6408661828169875, 'Dropout_2': 0.502511631899755
--------------------------------------------------
Model 4 parameters
{'Dropout': [0.5709919477993022], 'Dropout_1': [0.6574295784428639], 'Dropout_2': [0.3937749866

{'Dropout': 0.5709919477993022, 'Dropout_1': 0.6574295784428639, 'Dropout_2': 0.393774986648198
--------------------------------------------------
Model 5 parameters
{'Dropout': [0.48051787644406624], 'Dropout_1': [0.5744163772727372], 'Dropout_2': [0.50866298

{'Dropout': 0.48051787644406624, 'Dropout_1': 0.5744163772727372, 'Dropout_2': 0.5086629864785
--------------------------------------------------
Model 6 parameters
{'Dropout': [0.5813560517914963], 'Dropout_1': [0.6046109124722276], 'Dropout_2': [0.535583263
```

```
{'Dropout': 0.5813560517914963, 'Dropout_1': 0.6046109124722276, 'Dropout_2': 0.53558326352904
-------------------------------------------------
Model 7 parameters
{'Dropout': [0.5293597400197904], 'Dropout_1': [0.5958807193410454], 'Dropout_2': [0.426175206

{'Dropout': 0.5293597400197904, 'Dropout_1': 0.5958807193410454, 'Dropout_2': 0.42617520692074
-------------------------------------------------
Model 8 parameters
{'Dropout': [0.5950749367948185], 'Dropout_1': [0.5997621117444732], 'Dropout_2': [0.499962157

{'Dropout': 0.5950749367948185, 'Dropout_1': 0.5997621117444732, 'Dropout_2': 0.49996215722658
-------------------------------------------------
Model 9 parameters
{'Dropout': [0.45037579382108217], 'Dropout_1': [0.6781762554752515], 'Dropout_2': [0.47948317

{'Dropout': 0.45037579382108217, 'Dropout_1': 0.6781762554752515, 'Dropout_2': 0.4794831735512
-------------------------------------------------
Model 10 parameters
{'Dropout': [0.45714950357785966], 'Dropout_1': [0.6894085538291769], 'Dropout_2': [0.45216713

{'Dropout': 0.45714950357785966, 'Dropout_1': 0.6894085538291769, 'Dropout_2': 0.4521671387578
-------------------------------------------------
Model 11 parameters
{'Dropout': [0.5808002757682877], 'Dropout_1': [0.660514929179723], 'Dropout_2': [0.4733734305

{'Dropout': 0.5808002757682877, 'Dropout_1': 0.660514929179723, 'Dropout_2': 0.473373430574583
-------------------------------------------------
Model 12 parameters
{'Dropout': [0.5666044972741778], 'Dropout_1': [0.5837804766498599], 'Dropout_2': [0.387089760

{'Dropout': 0.5666044972741778, 'Dropout_1': 0.5837804766498599, 'Dropout_2': 0.38708976069745
-------------------------------------------------
Model 13 parameters
{'Dropout': [0.47945603666694214], 'Dropout_1': [0.6410658485741121], 'Dropout_2': [0.43142896

{'Dropout': 0.47945603666694214, 'Dropout_1': 0.6410658485741121, 'Dropout_2': 0.4314289625256
-------------------------------------------------
Model 14 parameters
{'Dropout': [0.3802031741395868], 'Dropout_1': [0.6903389204823146], 'Dropout_2': [0.365434142

{'Dropout': 0.3802031741395868, 'Dropout_1': 0.6903389204823146, 'Dropout_2': 0.36543414253279
-------------------------------------------------
Model 15 parameters
{'Dropout': [0.578227610775208], 'Dropout_1': [0.6959943282933752], 'Dropout_2': [0.4519332465

{'Dropout': 0.578227610775208, 'Dropout_1': 0.6959943282933752, 'Dropout_2': 0.451933246549509
-------------------------------------------------
```

In [54]:
```
best_run
```

Out[54]:
```
{'Dropout': 0.3802031741395868,
 'Dropout_1': 0.6903389204823146,
 'Dropout_2': 0.3654341425327902,
 'LSTM': 2,
 'LSTM_1': 2,
 'LSTM_2': 1,
 'choiceval': 0,
 'conditional': 0,
 'l2': 0.00015208023802140732,
 'l2_1': 0.000643128044948208,
 'l2_2': 0.0007102309264917989,
 'lr': 0.016347608866364167,
 'lr_1': 0.024543333891182614}
```

In [55]:
```
#BEST MODEL PARAMS
total_trials['M14']
```

Out[55]:
```
{'Dropout': 0.3802031741395868,
 'Dropout_1': 0.6903389204823146,
 'Dropout_2': 0.3654341425327902,
 'LSTM': 38,
 'LSTM_1': 36,
 'LSTM_2': 32,
 'choiceval': 'adam',
 'conditional': 'one',
 'l2': 0.00015208023802140732,
 'l2_1': 0.000643128044948208,
 'l2_2': 0.0007102309264917989,
 'lr': 0.016347608866364167,
 'lr_1': 0.024543333891182614}
```

In [50]:
```
#layes of best model
best_model.layers
```

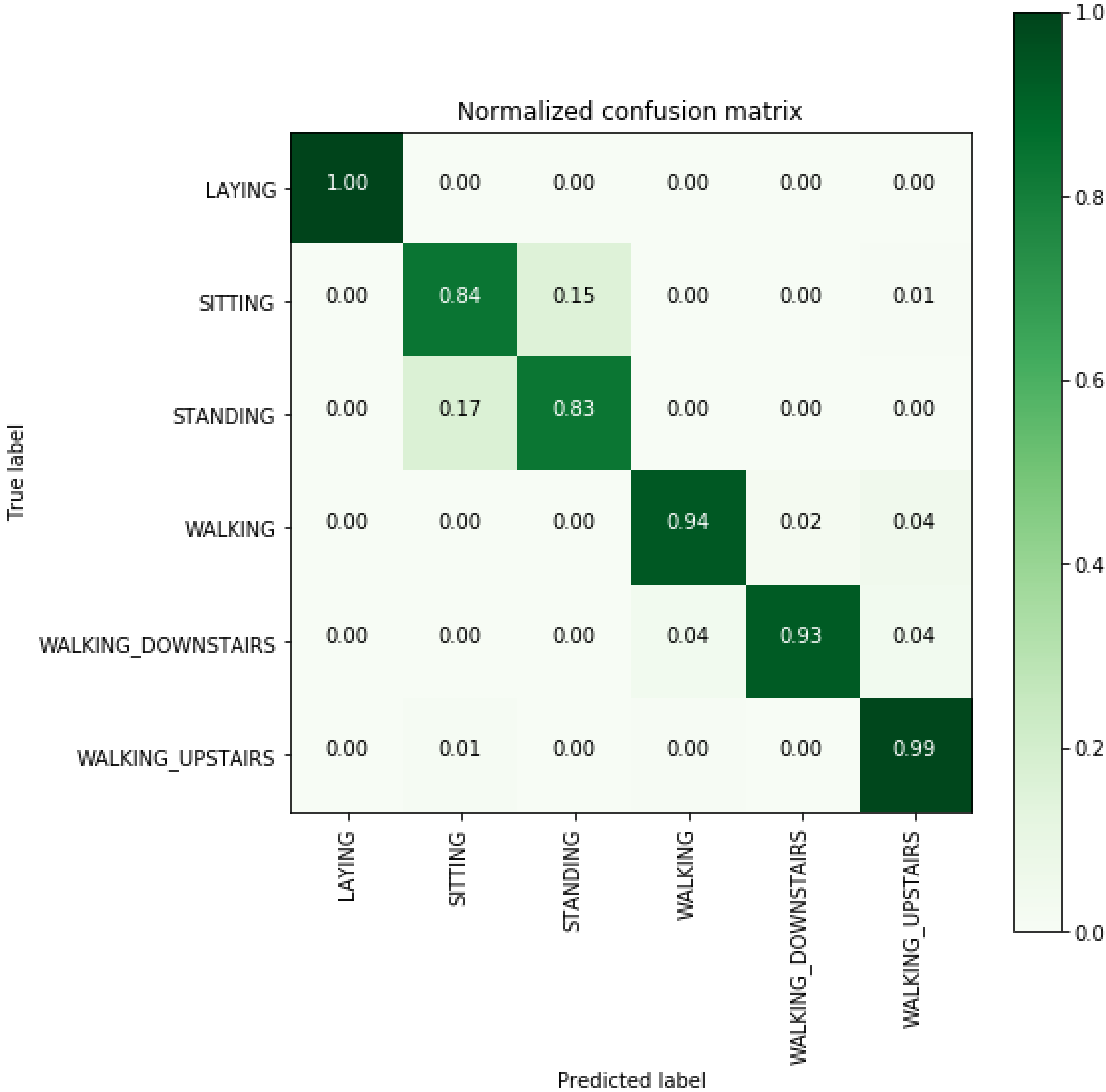
Out[50]:
```
[<keras.layers.recurrent.LSTM at 0x146c379d2ac8>,
 <keras.layers.core.Dropout at 0x146c379d2cc0>,
 <keras.layers.core.Dense at 0x146c379d2a90>]
```

In [51]:
```
X_train, Y_train, X_val, Y_val = data()
```

In [56]:
```
_,val_acc = best_model.evaluate(X_val, Y_val, verbose=0)
_,train_acc = best_model.evaluate(X_train, Y_train, verbose=0)
print('Train_accuracy',val_acc)
print('validation accuracy',val_acc)
```

```
Train_accuracy 0.94560663764961915
validation accuracy 0.9199185612487275
```

```
In [15]: # Activities are the class labels
         # It is a 6 class classification
         ACTIVITIES = {
             0: 'WALKING',
             1: 'WALKING_UPSTAIRS',
             2: 'WALKING_DOWNSTAIRS',
             3: 'SITTING',
             4: 'STANDING',
             5: 'LAYING',
         }

         # Utility function to print the confusion matrix
         def confusion_matrix_rnn(Y_true, Y_pred):
             Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1)])
             Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])

             #return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])
             return metrics.confusion_matrix(Y_true, Y_pred)

In [74]: # Confusion Matrix
         print(confusion_matrix_rnn(Y_val, best_model.predict(X_val)))

[[537   0   0   0   0   0]
 [  1 412  75   0   0   3]
 [  0  88 444   0   0   0]
 [  0   0   0 464  10  22]
 [  0   0   0  15 390  15]
 [  0   4   0   2   1 464]]

In [16]: from sklearn import metrics

In [80]: plt.figure(figsize=(8,8))
         cm = confusion_matrix_rnn(Y_val, best_model.predict(X_val))
         plot_confusion_matrix(cm, classes=labels, normalize=True, title='Normalized confusion
         plt.show()
```



13.3 Using CNN

In [2]:
```
import os
os.environ['PYTHONHASHSEED'] = '0'
import numpy as np
import tensorflow as tf
import random as rn
np.random.seed(36)
rn.seed(36)
tf.set_random_seed(36)
# Force TensorFlow to use single thread.
# Multiple threads are a potential source of non-reproducible results.
# For further details, see: https://stackoverflow.com/questions/42022950/
```

```
session_conf = tf.ConfigProto(intra_op_parallelism_threads=1,
                              inter_op_parallelism_threads=1)

from keras import backend as K

# The below tf.set_random_seed() will make random number generation
# in the TensorFlow backend have a well-defined initial state.
# For further details, see:
# https://www.tensorflow.org/api_docs/python/tf/set_random_seed

tf.set_random_seed(36)

sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)
```

```
Using TensorFlow backend.
```

In [3]:
```
# Importing libraries
import pandas as pd
from matplotlib import pyplot
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import Dropout
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

In [18]:
```
X_train, Y_train, X_val, Y_val = data()
```

In [19]:
```
###Scling data
from sklearn.base import BaseEstimator, TransformerMixin
class scaling_tseries_data(BaseEstimator, TransformerMixin):
    from sklearn.preprocessing import StandardScaler
    def __init__(self):
        self.scale = None

    def transform(self, X):
        temp_X1 = X.reshape((X.shape[0] * X.shape[1], X.shape[2]))
        temp_X1 = self.scale.transform(temp_X1)
        return temp_X1.reshape(X.shape)

    def fit(self, X):
        # remove overlaping
```

```
            remove = int(X.shape[1] / 2)
            temp_X = X[:, -remove:, :]
            # flatten data
            temp_X = temp_X.reshape((temp_X.shape[0] * temp_X.shape[1], temp_X.shape[2]))
            scale = StandardScaler()
            scale.fit(temp_X)
            self.scale = scale
            return self
```

```
In [20]: Scale = scaling_tseries_data()
         Scale.fit(X_train)
         X_train_sc = Scale.transform(X_train)
         X_val_sc = Scale.transform(X_val)
```

```
In [21]: print('Shape of scaled X train',X_train_sc.shape)
         print('Shape of scaled X test',X_val_sc.shape)
```

```
Shape of scaled X train (7352, 128, 9)
Shape of scaled X test (2947, 128, 9)
```

Base Model

```
In [26]: model = Sequential()
         model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_u
         model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_u
         model.add(Dropout(0.6))
         model.add(MaxPooling1D(pool_size=2))
         model.add(Flatten())
         model.add(Dense(50, activation='relu'))
         model.add(Dense(6, activation='softmax'))
         model.summary()
```

```
_________________________________________________________________
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 (MaxPooling1 (None, 62, 32)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1984)              0
_________________________________________________________________
dense_1 (Dense)              (None, 50)                99250
_________________________________________________________________
dense_2 (Dense)              (None, 6)                 306
```

```
=================================================================
Total params: 103,556
Trainable params: 103,556
Non-trainable params: 0
_________________________________________________________________
```

In [27]:
```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy']
```

In [28]:
```
model.fit(X_train_sc,Y_train, epochs=30, batch_size=16,validation_data=(X_val_sc, Y_va
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 6s 764us/step - loss: 0.4207 - acc: 0.8403 - val_l
Epoch 2/30
7352/7352 [==============================] - 5s 685us/step - loss: 0.1448 - acc: 0.9411 - val_l
Epoch 3/30
7352/7352 [==============================] - 5s 672us/step - loss: 0.1177 - acc: 0.9486 - val_l
Epoch 4/30
7352/7352 [==============================] - 5s 686us/step - loss: 0.0912 - acc: 0.9566 - val_l
Epoch 5/30
7352/7352 [==============================] - 5s 691us/step - loss: 0.0987 - acc: 0.9567 - val_l
Epoch 6/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.0841 - acc: 0.9619 - val_l
Epoch 7/30
7352/7352 [==============================] - 5s 695us/step - loss: 0.0727 - acc: 0.9659 - val_l
Epoch 8/30
7352/7352 [==============================] - 5s 671us/step - loss: 0.0827 - acc: 0.9630 - val_l
Epoch 9/30
7352/7352 [==============================] - 5s 695us/step - loss: 0.0726 - acc: 0.9690 - val_l
Epoch 10/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.0724 - acc: 0.9694 - val_l
Epoch 11/30
7352/7352 [==============================] - 5s 667us/step - loss: 0.0585 - acc: 0.9746 - val_l
Epoch 12/30
7352/7352 [==============================] - 5s 669us/step - loss: 0.0529 - acc: 0.9767 - val_l
Epoch 13/30
7352/7352 [==============================] - 5s 685us/step - loss: 0.0578 - acc: 0.9742 - val_l
Epoch 14/30
7352/7352 [==============================] - 5s 689us/step - loss: 0.0559 - acc: 0.9751 - val_l
Epoch 15/30
7352/7352 [==============================] - 5s 676us/step - loss: 0.0529 - acc: 0.9771 - val_l
Epoch 16/30
7352/7352 [==============================] - 5s 663us/step - loss: 0.0498 - acc: 0.9785 - val_l
Epoch 17/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.0427 - acc: 0.9833 - val_l
Epoch 18/30
7352/7352 [==============================] - 5s 675us/step - loss: 0.0397 - acc: 0.9841 - val_l
```

```
Epoch 19/30
7352/7352 [==============================] - 5s 651us/step - loss: 0.0475 - acc: 0.9804 - val_l
Epoch 20/30
7352/7352 [==============================] - 5s 699us/step - loss: 0.0378 - acc: 0.9831 - val_l
Epoch 21/30
7352/7352 [==============================] - 5s 691us/step - loss: 0.0353 - acc: 0.9867 - val_l
Epoch 22/30
7352/7352 [==============================] - 5s 692us/step - loss: 0.0427 - acc: 0.9827 - val_l
Epoch 23/30
7352/7352 [==============================] - 5s 669us/step - loss: 0.0379 - acc: 0.9837 - val_l
Epoch 24/30
7352/7352 [==============================] - 5s 674us/step - loss: 0.0331 - acc: 0.9871 - val_l
Epoch 25/30
7352/7352 [==============================] - 5s 687us/step - loss: 0.0259 - acc: 0.9883 - val_l
Epoch 26/30
7352/7352 [==============================] - 5s 695us/step - loss: 0.0530 - acc: 0.9834 - val_l
Epoch 27/30
7352/7352 [==============================] - 5s 674us/step - loss: 0.0692 - acc: 0.9822 - val_l
Epoch 28/30
7352/7352 [==============================] - 5s 676us/step - loss: 0.0664 - acc: 0.9849 - val_l
Epoch 29/30
7352/7352 [==============================] - 5s 673us/step - loss: 0.0675 - acc: 0.9845 - val_l
Epoch 30/30
7352/7352 [==============================] - 5s 671us/step - loss: 0.0531 - acc: 0.9897 - val_l
```

```
Out[28]: <keras.callbacks.History at 0x14761b299ac8>
```

it is giving some good score in train as well as test but it is overfitting so much. i will try some regularization in below models.

```
In [3]: from keras.regularizers import l2,l1
        import keras
        from keras.layers import BatchNormalization
```

```
In [117]: model = Sequential()
          model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_
                           kernel_regularizer=l2(0.1),input_shape=(128,9)))
          model.add(Conv1D(filters=16, kernel_size=3, activation='relu',kernel_regularizer=l2(0
          model.add(Dropout(0.65))
          model.add(MaxPooling1D(pool_size=2))
          model.add(Flatten())
          model.add(Dense(32, activation='relu'))
          model.add(Dense(6, activation='softmax'))
          model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
```

```
conv1d_67 (Conv1D)           (None, 126, 32)          896
_________________________________________________________________
conv1d_68 (Conv1D)           (None, 124, 16)          1552
_________________________________________________________________
dropout_39 (Dropout)         (None, 124, 16)          0
_________________________________________________________________
max_pooling1d_34 (MaxPooling (None, 62, 16)           0
_________________________________________________________________
flatten_34 (Flatten)         (None, 992)              0
_________________________________________________________________
dense_67 (Dense)             (None, 32)               31776
_________________________________________________________________
dense_68 (Dense)             (None, 6)                198
=================================================================
Total params: 34,422
Trainable params: 34,422
Non-trainable params: 0
_________________________________________________________________
```

In [118]:
```
import math
adam = keras.optimizers.Adam(lr=0.001)
rmsprop = keras.optimizers.RMSprop(lr=0.001)
def step_decay(epoch):
    return float(0.001 * math.pow(0.6, math.floor((1+epoch)/10)))
from keras.callbacks import LearningRateScheduler
lrate = LearningRateScheduler(step_decay)
callbacks_list = [lrate]

model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])
```

In [119]:
```
model.fit(X_train_sc,Y_train, epochs=30, batch_size=16,validation_data=(X_val_sc, Y_
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 6s 879us/step - loss: 4.3454 - acc: 0.7266 - val_
Epoch 2/30
7352/7352 [==============================] - 5s 676us/step - loss: 0.7579 - acc: 0.9121 - val_
Epoch 3/30
7352/7352 [==============================] - 5s 668us/step - loss: 0.3876 - acc: 0.9286 - val_
Epoch 4/30
7352/7352 [==============================] - 5s 673us/step - loss: 0.3123 - acc: 0.9283 - val_
Epoch 5/30
7352/7352 [==============================] - 5s 680us/step - loss: 0.2729 - acc: 0.9336 - val_
Epoch 6/30
7352/7352 [==============================] - 5s 676us/step - loss: 0.2629 - acc: 0.9327 - val_
Epoch 7/30
7352/7352 [==============================] - 5s 664us/step - loss: 0.2423 - acc: 0.9393 - val_
```

```
Epoch 8/30
7352/7352 [==============================] - 5s 681us/step - loss: 0.2327 - acc: 0.9380 - val_
Epoch 9/30
7352/7352 [==============================] - 5s 670us/step - loss: 0.2237 - acc: 0.9372 - val_
Epoch 10/30
7352/7352 [==============================] - 5s 687us/step - loss: 0.2221 - acc: 0.9377 - val_
Epoch 11/30
7352/7352 [==============================] - 5s 676us/step - loss: 0.2216 - acc: 0.9377 - val_
Epoch 12/30
7352/7352 [==============================] - 5s 684us/step - loss: 0.2085 - acc: 0.9416 - val_
Epoch 13/30
7352/7352 [==============================] - 5s 646us/step - loss: 0.2005 - acc: 0.9448 - val_
Epoch 14/30
7352/7352 [==============================] - 5s 687us/step - loss: 0.2075 - acc: 0.9446 - val_
Epoch 15/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.1980 - acc: 0.9434 - val_
Epoch 16/30
7352/7352 [==============================] - 5s 696us/step - loss: 0.1891 - acc: 0.9449 - val_
Epoch 17/30
7352/7352 [==============================] - 5s 660us/step - loss: 0.1909 - acc: 0.9434 - val_
Epoch 18/30
7352/7352 [==============================] - 5s 689us/step - loss: 0.1893 - acc: 0.9429 - val_
Epoch 19/30
7352/7352 [==============================] - 5s 661us/step - loss: 0.2002 - acc: 0.9389 - val_
Epoch 20/30
7352/7352 [==============================] - 5s 664us/step - loss: 0.1817 - acc: 0.9486 - val_
Epoch 21/30
7352/7352 [==============================] - 5s 670us/step - loss: 0.1828 - acc: 0.9472 - val_
Epoch 22/30
7352/7352 [==============================] - 5s 661us/step - loss: 0.1851 - acc: 0.9449 - val_
Epoch 23/30
7352/7352 [==============================] - 5s 672us/step - loss: 0.1841 - acc: 0.9456 - val_
Epoch 24/30
7352/7352 [==============================] - 5s 674us/step - loss: 0.1777 - acc: 0.9463 - val_
Epoch 25/30
7352/7352 [==============================] - 5s 683us/step - loss: 0.1785 - acc: 0.9448 - val_
Epoch 26/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.1751 - acc: 0.9459 - val_
Epoch 27/30
7352/7352 [==============================] - 5s 697us/step - loss: 0.1773 - acc: 0.9476 - val_
Epoch 28/30
7352/7352 [==============================] - 5s 672us/step - loss: 0.1692 - acc: 0.9506 - val_
Epoch 29/30
7352/7352 [==============================] - 5s 677us/step - loss: 0.1742 - acc: 0.9478 - val_
Epoch 30/30
7352/7352 [==============================] - 5s 679us/step - loss: 0.1754 - acc: 0.9467 - val_
```

Out[119]: <keras.callbacks.History at 0x14757856a6d8>

Hyper Parameter Tuning Using Hyperas

In [4]:
```
def data_scaled():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    # Data directory
    DATADIR = 'UCI_HAR_Dataset'
    # Raw data signals
    # Signals are from Accelerometer and Gyroscope
    # The signals are in x,y,z directions
    # Sensor signals are filtered to have only body acceleration
    # excluding the acceleration due to gravity
    # Triaxial acceleration from the accelerometer is total acceleration
    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"
        ]
    from sklearn.base import BaseEstimator, TransformerMixin
    class scaling_tseries_data(BaseEstimator, TransformerMixin):
        from sklearn.preprocessing import StandardScaler
        def __init__(self):
            self.scale = None

        def transform(self, X):
            temp_X1 = X.reshape((X.shape[0] * X.shape[1], X.shape[2]))
            temp_X1 = self.scale.transform(temp_X1)
            return temp_X1.reshape(X.shape)

        def fit(self, X):
            # remove overlaping
            remove = int(X.shape[1] / 2)
            temp_X = X[:, -remove:, :]
            # flatten data
            temp_X = temp_X.reshape((temp_X.shape[0] * temp_X.shape[1], temp_X.shape[2
            scale = StandardScaler()
            scale.fit(temp_X)
            self.scale = scale
```

```
                return self

        # Utility function to read the data from csv file
        def _read_csv(filename):
            return pd.read_csv(filename, delim_whitespace=True, header=None)

        # Utility function to load the load
        def load_signals(subset):
            signals_data = []

            for signal in SIGNALS:
                filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.t
                signals_data.append( _read_csv(filename).as_matrix())

            # 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)
            return np.transpose(signals_data, (1, 2, 0))

        def load_y(subset):
            """
            The objective that we are trying to predict is a integer, from 1 to 6,
            that represents a human activity. We return a binary representation of
            every sample objective as a 6 bits vector using One Hot Encoding
            (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.htm
            """
            filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
            y = _read_csv(filename)[0]
            return pd.get_dummies(y).as_matrix()

        X_train, X_val = load_signals('train'), load_signals('test')
        Y_train, Y_val = load_y('train'), load_y('test')
        ###Scling data
        Scale = scaling_tseries_data()
        Scale.fit(X_train)
        X_train = Scale.transform(X_train)
        X_val = Scale.transform(X_val)

        return X_train, Y_train, X_val,  Y_val
```

```
In [5]: X_train, Y_train, X_val,  Y_val = data_scaled()
```

```
In [6]: def model_cnn(X_train, Y_train, X_val, Y_val):
        # Importing tensorflow
        np.random.seed(36)
        import tensorflow as tf
        tf.set_random_seed(36)
        # Initiliazing the sequential model
```

```
        model = Sequential()

        model.add(Conv1D(filters={{choice([28,32,42])}}, kernel_size={{choice([3,5,7])}},ac
                     kernel_regularizer=l2({{uniform(0,2.5)}}),input_shape=(128,9)))

        model.add(Conv1D(filters={{choice([16,24,32])}}, kernel_size={{choice([3,5,7])}},
                         activation='relu',kernel_regularizer=l2({{uniform(0,1.5)}}),kernel
        model.add(Dropout({{uniform(0.45,0.7)}}))
        model.add(MaxPooling1D(pool_size={{choice([2,3])}}))
        model.add(Flatten())
        model.add(Dense({{choice([32,64])}}, activation='relu'))
        model.add(Dense(6, activation='softmax'))

        adam = keras.optimizers.Adam(lr={{uniform(0.00065,0.004)}})
        rmsprop = keras.optimizers.RMSprop(lr={{uniform(0.00065,0.004)}})

        choiceval = {{choice(['adam', 'rmsprop'])}}

        if choiceval == 'adam':
            optim = adam
        else:
            optim = rmsprop

        print(model.summary())

        model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=optim

        result = model.fit(X_train, Y_train,
                  batch_size={{choice([16,32,64])}},
                  nb_epoch={{choice([25,30,35])}},
                  verbose=2,
                  validation_data=(X_val, Y_val))

        score, acc = model.evaluate(X_val, Y_val, verbose=0)
        score1, acc1 = model.evaluate(X_train, Y_train, verbose=0)
        print('Train accuracy',acc1,'Test accuracy:', acc)
        print('------------------------------------------------------------------------
        return {'loss': -acc, 'status': STATUS_OK, 'model': model,'train_acc':acc1}
```

```
In [ ]: X_train, Y_train, X_val, Y_val = data_scaled()
        trials = Trials()
        best_run, best_model, space = optim.minimize(model=model_cnn,
                                              data=data_scaled,
                                              algo=tpe.suggest,
                                              max_evals=100,
                                              trials=trials,notebook_name = 'Human Activity De
                                              return_space = True)
```

```
In [10]: from hyperas.utils import eval_hyperopt_space
```

```
total_trials = dict()
total_list = []
for t, trial in enumerate(trials):
        vals = trial.get('misc').get('vals')
        z = eval_hyperopt_space(space, vals)
        total_trials['M'+str(t+1)] = z
```

In [11]:
```
best_run
```

Out[11]:
```
{'Dense': 1,
 'Dropout': 0.6397045095598795,
 'batch_size': 2,
 'choiceval': 0,
 'filters': 1,
 'filters_1': 1,
 'kernel_size': 2,
 'kernel_size_1': 0,
 'l2': 0.07999281751224634,
 'l2_1': 0.0012673510937627475,
 'lr': 0.0011215010543928203,
 'lr_1': 0.0021517590741381726,
 'nb_epoch': 0,
 'pool_size': 1}
```

In [12]:
```
#best Hyper params from hyperas
eval_hyperopt_space(space, best_run)
```

Out[12]:
```
{'Dense': 64,
 'Dropout': 0.6397045095598795,
 'batch_size': 64,
 'choiceval': 'adam',
 'filters': 32,
 'filters_1': 24,
 'kernel_size': 7,
 'kernel_size_1': 3,
 'l2': 0.07999281751224634,
 'l2_1': 0.0012673510937627475,
 'lr': 0.0011215010543928203,
 'lr_1': 0.0021517590741381726,
 'nb_epoch': 25,
 'pool_size': 3}
```

In [13]:
```
best_model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_119 (Conv1D)          (None, 122, 32)           2048
_________________________________________________________________
```

```
conv1d_120 (Conv1D)          (None, 120, 24)          2328
_________________________________________________________________
dropout_60 (Dropout)         (None, 120, 24)          0
_________________________________________________________________
max_pooling1d_60 (MaxPooling (None, 40, 24)           0
_________________________________________________________________
flatten_60 (Flatten)         (None, 960)              0
_________________________________________________________________
dense_119 (Dense)            (None, 64)               61504
_________________________________________________________________
dense_120 (Dense)            (None, 6)                390
=================================================================
Total params: 66,270
Trainable params: 66,270
Non-trainable params: 0
_________________________________________________________________
```

In [14]:
```
_,acc_val = best_model.evaluate(X_val,Y_val,verbose=0)
_,acc_train = best_model.evaluate(X_train,Y_train,verbose=0)
print('Train_accuracy',acc_train,'test_accuracy',acc_val)
```

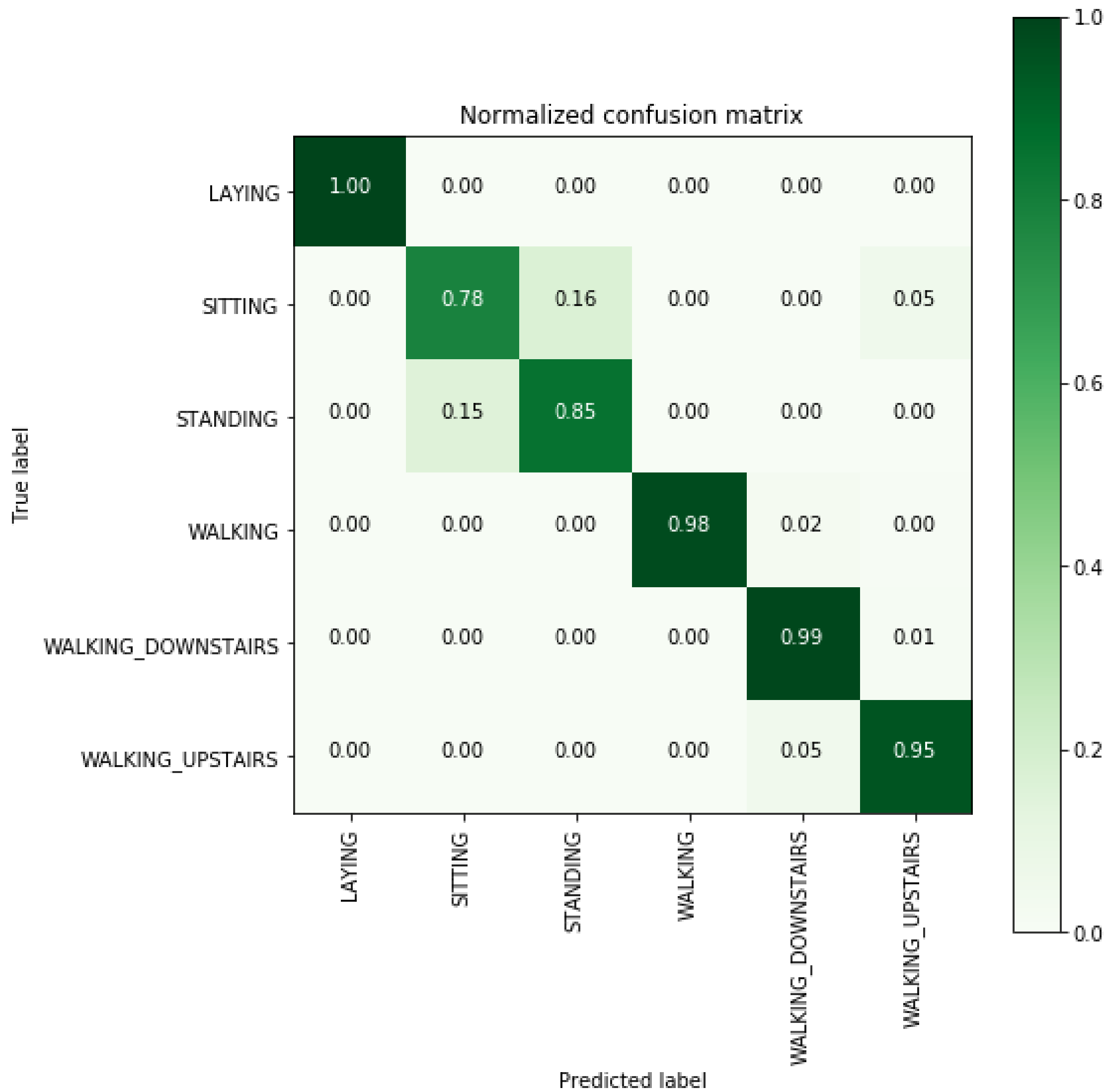
```
Train_accuracy 0.963139281828074 test_accuracy 0.9229725144214456
```

In [35]:
```
# Confusion Matrix
print(confusion_matrix_rnn(Y_val, best_model.predict(X_val)))
```

```
[[537   0   0   0   0   0]
 [  0 385  81   0   0  25]
 [  0  80 452   0   0   0]
 [  0   0   0 484  10   2]
 [  0   0   0   0 415   5]
 [  0   1   0   0  23 447]]
```

In [44]:
```
import matplotlib.pyplot as plt
plt.figure(figsize=(8,8))
cm = confusion_matrix_rnn(Y_val, best_model.predict(X_val))
plot_confusion_matrix(cm, classes=labels, normalize=True, title='Normalized confusion
plt.show()
```

```
<matplotlib.figure.Figure at 0x14f2465d4da0>


<matplotlib.figure.Figure at 0x14f24226c4a8>


<matplotlib.figure.Figure at 0x14f234cbe860>
```



We can observe some overfitting in the model. and it is also giving some good results and error is mainly due to static activities. so below model came up wit some different approch to overcome this problem.

13.3.1 Divide and Conquer-Based:

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
- in Data exploration section we observed that we can divide the data into dynamic and static

type so devided walking,waling_upstairs,walking_downstairs into category 0 i.e Dynamic, sitting, standing, laying into category 1 i.e. static. - Will use 2 more classifiers seperatly for classifying classes of dynamic and static activities. so that model can learn differnt features for static and dynamic activities

referred below paper
Divide and Conquer-Based 1D CNN Human Activity Recognition Using Test Data Sharpening (https://www.mdpi.com/1424-8220/18/4/1055/pdf)

In [2]:
```
import os
os.environ['PYTHONHASHSEED'] = '0'
import numpy as np
import tensorflow as tf
import random as rn
np.random.seed(0)
rn.seed(0)
tf.set_random_seed(0)
session_conf = tf.ConfigProto(intra_op_parallelism_threads=1,
                              inter_op_parallelism_threads=1)

from keras import backend as K

# The below tf.set_random_seed() will make random number generation
# in the TensorFlow backend have a well-defined initial state.
# For further details, see:
# https://www.tensorflow.org/api_docs/python/tf/set_random_seed

tf.set_random_seed(0)

sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)

# Importing libraries
import pandas as pd
from matplotlib import pyplot
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import Dropout
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

```
Using TensorFlow backend.
```

In [145]:
```
## Classifying data as 2 class dynamic vs static
##data preparation
def data_scaled_2class():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    # Data directory
    DATADIR = 'UCI_HAR_Dataset'
    # Raw data signals
    # Signals are from Accelerometer and Gyroscope
    # The signals are in x,y,z directions
    # Sensor signals are filtered to have only body acceleration
    # excluding the acceleration due to gravity
    # Triaxial acceleration from the accelerometer is total acceleration
    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"
        ]
    from sklearn.base import BaseEstimator, TransformerMixin
    class scaling_tseries_data(BaseEstimator, TransformerMixin):
        from sklearn.preprocessing import StandardScaler
        def __init__(self):
            self.scale = None

        def transform(self, X):
            temp_X1 = X.reshape((X.shape[0] * X.shape[1], X.shape[2]))
            temp_X1 = self.scale.transform(temp_X1)
            return temp_X1.reshape(X.shape)

        def fit(self, X):
            # remove overlaping
            remove = int(X.shape[1] / 2)
            temp_X = X[:, -remove:, :]
            # flatten data
            temp_X = temp_X.reshape((temp_X.shape[0] * temp_X.shape[1], temp_X.shape
            scale = StandardScaler()
            scale.fit(temp_X)
            ##saving for furter usage
            ## will use in predicton pipeline
            pickle.dump(scale,open('Scale_2class.p','wb'))
```

```
                self.scale = scale
                return self

        # Utility function to read the data from csv file
        def _read_csv(filename):
            return pd.read_csv(filename, delim_whitespace=True, header=None)

        # Utility function to load the load
        def load_signals(subset):
            signals_data = []

            for signal in SIGNALS:
                filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}
                signals_data.append( _read_csv(filename).as_matrix())

            # 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
            return np.transpose(signals_data, (1, 2, 0))

        def load_y(subset):
            """
            The objective that we are trying to predict is a integer, from 1 to 6,
            that represents a human activity. We return a binary representation of
            every sample objective as a 6 bits vector using One Hot Encoding
            (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.h
            """
            filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
            y = _read_csv(filename)[0]
            y[y<=3] = 0
            y[y>3] = 1
            return pd.get_dummies(y).as_matrix()

        X_train_2c, X_val_2c = load_signals('train'), load_signals('test')
        Y_train_2c, Y_val_2c = load_y('train'), load_y('test')
        ###Scling data
        Scale = scaling_tseries_data()
        Scale.fit(X_train_2c)
        X_train_2c = Scale.transform(X_train_2c)
        X_val_2c = Scale.transform(X_val_2c)
        return X_train_2c, Y_train_2c, X_val_2c,  Y_val_2c
```

```
In [144]: X_train_2c, Y_train_2c, X_val_2c,  Y_val_2c = data_scaled_2class()
```

```
In [68]: print(Y_train_2c.shape)
         print(Y_val_2c.shape)
```

```
(7352, 2)
```

```
(2947, 2)
```

Model for classifying data into Static and Dynamic activities

```
In [72]: K.clear_session()
         np.random.seed(0)
         tf.set_random_seed(0)
         sess = tf.Session(graph=tf.get_default_graph())
         K.set_session(sess)
         model = Sequential()
         model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_
         model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_
         model.add(Dropout(0.6))
         model.add(MaxPooling1D(pool_size=2))
         model.add(Flatten())
         model.add(Dense(50, activation='relu'))
         model.add(Dense(2, activation='softmax'))
         model.summary()
```

```
_________________________________________________________________
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 (MaxPooling1 (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 [73]: import math
         adam = keras.optimizers.Adam(lr=0.001)
```

```
In [74]: model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])
         model.fit(X_train_2c,Y_train_2c, epochs=20, batch_size=16,validation_data=(X_val_2c, Y
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 4s 580us/step - loss: 0.0549 - acc: 0.9791 - val_l
Epoch 2/20
7352/7352 [==============================] - 4s 482us/step - loss: 0.0021 - acc: 0.9995 - val_l
Epoch 3/20
7352/7352 [==============================] - 4s 484us/step - loss: 7.9422e-04 - acc: 0.9997 - v
Epoch 4/20
7352/7352 [==============================] - 4s 483us/step - loss: 0.0029 - acc: 0.9990 - val_l
Epoch 5/20
7352/7352 [==============================] - 4s 481us/step - loss: 1.3106e-04 - acc: 1.0000 - v
Epoch 6/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.7091e-05 - acc: 1.0000 - v
Epoch 7/20
7352/7352 [==============================] - 4s 480us/step - loss: 0.0022 - acc: 0.9997 - val_l
Epoch 8/20
7352/7352 [==============================] - 4s 481us/step - loss: 0.0051 - acc: 0.9989 - val_l
Epoch 9/20
7352/7352 [==============================] - 4s 480us/step - loss: 3.4291e-05 - acc: 1.0000 - v
Epoch 10/20
7352/7352 [==============================] - 4s 478us/step - loss: 2.1046e-04 - acc: 0.9999 - v
Epoch 11/20
7352/7352 [==============================] - 4s 482us/step - loss: 3.0157e-05 - acc: 1.0000 - v
Epoch 12/20
7352/7352 [==============================] - 4s 482us/step - loss: 5.7799e-06 - acc: 1.0000 - v
Epoch 13/20
7352/7352 [==============================] - 4s 481us/step - loss: 1.4363e-06 - acc: 1.0000 - v
Epoch 14/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.1018e-06 - acc: 1.0000 - v
Epoch 15/20
7352/7352 [==============================] - 4s 483us/step - loss: 7.5717e-07 - acc: 1.0000 - v
Epoch 16/20
7352/7352 [==============================] - 4s 480us/step - loss: 4.7786e-07 - acc: 1.0000 - v
Epoch 17/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.0220e-06 - acc: 1.0000 - v
Epoch 18/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.7438e-06 - acc: 1.0000 - v
Epoch 19/20
7352/7352 [==============================] - 4s 487us/step - loss: 6.3406e-07 - acc: 1.0000 - v
Epoch 20/20
7352/7352 [==============================] - 4s 480us/step - loss: 5.5710e-07 - acc: 1.0000 - v
```

Out[74]: <keras.callbacks.History at 0x1474816b9358>

In [75]:
```
_,acc_val = model.evaluate(X_val_2c,Y_val_2c,verbose=0)
_,acc_train = model.evaluate(X_train_2c,Y_train_2c,verbose=0)
print('Train_accuracy',acc_train,'test_accuracy',acc_val)
```

```
Train_accuracy 1.0 test_accuracy 0.9989820156090939
```

```
In [76]: ##saving model
         model.save('final_model_2class.h5')
```

This model is almost classifying data into dynammic or static correctly with very hig accuracy.

13.3.2 Classificaton of Static activities

```
In [149]: ##data preparation
          def data_scaled_static():
              """
              Obtain the dataset from multiple files.
              Returns: X_train, X_test, y_train, y_test
              """
              # Data directory
              DATADIR = 'UCI_HAR_Dataset'
              # Raw data signals
              # Signals are from Accelerometer and Gyroscope
              # The signals are in x,y,z directions
              # Sensor signals are filtered to have only body acceleration
              # excluding the acceleration due to gravity
              # Triaxial acceleration from the accelerometer is total acceleration
              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"
                  ]
              from sklearn.base import BaseEstimator, TransformerMixin
              class scaling_tseries_data(BaseEstimator, TransformerMixin):
                  from sklearn.preprocessing import StandardScaler
                  def __init__(self):
                      self.scale = None

                  def transform(self, X):
                      temp_X1 = X.reshape((X.shape[0] * X.shape[1], X.shape[2]))
                      temp_X1 = self.scale.transform(temp_X1)
                      return temp_X1.reshape(X.shape)

                  def fit(self, X):
                      # remove overlaping
```

```python
        remove = int(X.shape[1] / 2)
        temp_X = X[:, -remove:, :]
        # flatten data
        temp_X = temp_X.reshape((temp_X.shape[0] * temp_X.shape[1], temp_X.shape
        scale = StandardScaler()
        scale.fit(temp_X)
        #for furter use at prediction pipeline
        pickle.dump(scale,open('Scale_static.p','wb'))
        self.scale = scale
        return self

# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}
        signals_data.append( _read_csv(filename).as_matrix())

    # 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
    return np.transpose(signals_data, (1, 2, 0))

def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.h
    """
    filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    y_subset = y>3
    y = y[y_subset]
    return pd.get_dummies(y).as_matrix(),y_subset

Y_train_s,y_train_sub = load_y('train')
Y_val_s,y_test_sub = load_y('test')
X_train_s, X_val_s = load_signals('train'), load_signals('test')
X_train_s = X_train_s[y_train_sub]
X_val_s = X_val_s[y_test_sub]

###Scling data
```

```
            Scale = scaling_tseries_data()
            Scale.fit(X_train_s)
            X_train_s = Scale.transform(X_train_s)
            X_val_s = Scale.transform(X_val_s)

            return X_train_s, Y_train_s, X_val_s,  Y_val_s
```

```
In [150]: X_train_s, Y_train_s, X_val_s,  Y_val_s = data_scaled_static()
```

```
In [7]: print('X Shape of train data',X_train_s.shape, 'Y shape', Y_train_s.shape)
        print('X Shape of val data',X_val_s.shape,'Y shape',Y_val_s.shape)
```

```
X Shape of train data (4067, 128, 9) Y shape (4067, 3)
X Shape of val data (1560, 128, 9) Y shape (1560, 3)
```

```
In [8]: import keras
```

Baseline Model

```
In [24]: np.random.seed(0)
         tf.set_random_seed(0)
         sess = tf.Session(graph=tf.get_default_graph())
         K.set_session(sess)
         model = Sequential()
         model.add(Conv1D(filters=64, kernel_size=7, activation='relu',kernel_initializer='he_u
         model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_u
         model.add(Dropout(0.6))
         model.add(MaxPooling1D(pool_size=3))
         model.add(Flatten())
         model.add(Dense(30, activation='relu'))
         model.add(Dense(3, activation='softmax'))
         model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_3 (Conv1D)            (None, 122, 64)           4096
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 120, 32)           6176
_________________________________________________________________
dropout_2 (Dropout)          (None, 120, 32)           0
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 40, 32)            0
_________________________________________________________________
flatten_2 (Flatten)          (None, 1280)              0
_________________________________________________________________
dense_3 (Dense)              (None, 30)                38430
_________________________________________________________________
```

```
dense_4 (Dense)              (None, 3)                 93
=================================================================
Total params: 48,795
Trainable params: 48,795
Non-trainable params: 0

_________________________________________________________________
```

```
In [25]: import math
         adam = keras.optimizers.Adam(lr=0.004)
         model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])
         model.fit(X_train_s,Y_train_s, epochs=20, batch_size=32,validation_data=(X_val_s, Y_va
         K.clear_session()
```

```
Train on 4067 samples, validate on 1560 samples
Epoch 1/20
4067/4067 [==============================] - 2s 530us/step - loss: 0.4023 - acc: 0.8773 - val_l
Epoch 2/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.2302 - acc: 0.9240 - val_l
Epoch 3/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.2163 - acc: 0.9235 - val_l
Epoch 4/20
4067/4067 [==============================] - 1s 351us/step - loss: 0.1732 - acc: 0.9348 - val_l
Epoch 5/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1471 - acc: 0.9432 - val_l
Epoch 6/20
4067/4067 [==============================] - 1s 354us/step - loss: 0.1296 - acc: 0.9498 - val_l
Epoch 7/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.1704 - acc: 0.9422 - val_l
Epoch 8/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.2979 - acc: 0.9171 - val_l
Epoch 9/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.2093 - acc: 0.9375 - val_l
Epoch 10/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.2048 - acc: 0.9405 - val_l
Epoch 11/20
4067/4067 [==============================] - 1s 355us/step - loss: 0.2393 - acc: 0.9405 - val_l
Epoch 12/20
4067/4067 [==============================] - 1s 351us/step - loss: 0.2640 - acc: 0.9299 - val_l
Epoch 13/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.2083 - acc: 0.9388 - val_l
Epoch 14/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.1886 - acc: 0.9474 - val_l
Epoch 15/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1870 - acc: 0.9484 - val_l
Epoch 16/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1710 - acc: 0.9552 - val_l
Epoch 17/20
```

```
4067/4067 [==============================] - 1s 352us/step - loss: 0.1718 - acc: 0.9506 - val_
Epoch 18/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1699 - acc: 0.9501 - val_
Epoch 19/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.1520 - acc: 0.9636 - val_
Epoch 20/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1927 - acc: 0.9592 - val_
```

```
In [40]: def model_cnn(X_train_s, Y_train_s, X_val_s, Y_val_s):
             np.random.seed(0)
             tf.set_random_seed(0)
             sess = tf.Session(graph=tf.get_default_graph())
             K.set_session(sess)
             # Initiliazing the sequential model
             model = Sequential()

             model.add(Conv1D(filters={{choice([28,32,42])}}, kernel_size={{choice([3,5,7])}},a
                          kernel_regularizer=l2({{uniform(0,3)}}),input_shape=(128,9)))

             model.add(Conv1D(filters={{choice([16,24,32])}}, kernel_size={{choice([3,5,7])}},
                              activation='relu',kernel_regularizer=l2({{uniform(0,2)}}),kernel_
             model.add(Dropout({{uniform(0.45,0.7)}}))
             model.add(MaxPooling1D(pool_size={{choice([2,3,5])}}))
             model.add(Flatten())
             model.add(Dense({{choice([16,32,64])}}, activation='relu'))
             model.add(Dense(3, activation='softmax'))

             adam = keras.optimizers.Adam(lr={{uniform(0.00065,0.004)}})
             rmsprop = keras.optimizers.RMSprop(lr={{uniform(0.00065,0.004)}})

             choiceval = {{choice(['adam', 'rmsprop'])}}

             if choiceval == 'adam':
                 optim = adam
             else:
                 optim = rmsprop

             print(model.summary())

             model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=opti

             result = model.fit(X_train_s, Y_train_s,
                       batch_size={{choice([16,32,64])}},
                       nb_epoch={{choice([25,30,35])}},
                       verbose=2,
                       validation_data=(X_val_s, Y_val_s))
```

```
            score, acc = model.evaluate(X_val_s, Y_val_s, verbose=0)
            score1, acc1 = model.evaluate(X_train_s, Y_train_s, verbose=0)
            print('Train accuracy',acc1,'Test accuracy:', acc)
            print('------------------------------------------------------------------------
            K.clear_session()
            return {'loss': -acc, 'status': STATUS_OK,'train_acc':acc1}
```

```
In [ ]: X_train, Y_train, X_val, Y_val = data_scaled_static()
        trials = Trials()
        best_run, best_model, space = optim.minimize(model=model_cnn,
                                              data=data_scaled_static,
                                              algo=tpe.suggest,
                                              max_evals=120,rseed = 0,
                                              trials=trials,notebook_name = 'Human Activity De
                                              return_space = True)
```

```
In [12]: best_run
```

```
Out[12]: {'Dense': 2,
          'Dense_1': 2,
          'Dropout': 0.45377377480700615,
          'choiceval': 1,
          'filters': 1,
          'filters_1': 0,
          'kernel_size': 1,
          'kernel_size_1': 0,
          'l2': 0.0019801221163149862,
          'l2_1': 0.8236255110533577,
          'lr': 0.003918784585237195,
          'lr_1': 0.002237071747066137,
          'nb_epoch': 1,
          'pool_size': 0}
```

```
In [21]: from hyperas.utils import eval_hyperopt_space
         total_trials = dict()
         total_list = []
         for t, trial in enumerate(trials):
                 vals = trial.get('misc').get('vals')
                 z = eval_hyperopt_space(space, vals)
                 total_trials['M'+str(t+1)] = z


         #best Hyper params from hyperas
         best_params = eval_hyperopt_space(space, best_run)
         best_params
```

```
Out[21]: {'Dense': 64,
          'Dense_1': 64,
          'Dropout': 0.45377377480700615,
```

```
 'choiceval': 'rmsprop',
 'filters': 32,
 'filters_1': 16,
 'kernel_size': 5,
 'kernel_size_1': 3,
 'l2': 0.0019801221163149862,
 'l2_1': 0.8236255110533577,
 'lr': 0.003918784585237195,
 'lr_1': 0.002237071747066137,
 'nb_epoch': 30,
 'pool_size': 2}
```

```
In [3]: from keras.regularizers import l2
```

```
In [71]: ##model from hyperas
         def keras_fmin_fnct(space,verbose=1):
             np.random.seed(0)
             tf.set_random_seed(0)
             sess = tf.Session(graph=tf.get_default_graph())
             K.set_session(sess)
             # Initiliazing the sequential model
             model = Sequential()
             model.add(Conv1D(filters=space['filters'], kernel_size=space['kernel_size'],activa
                             kernel_initializer='he_uniform',
                             kernel_regularizer=l2(space['l2']),input_shape=(128,9)))
             model.add(Conv1D(filters=space['filters_1'], kernel_size=space['kernel_size_1'],
                         activation='relu',kernel_regularizer=l2(space['l2_1']),kernel_initial
             model.add(Dropout(space['Dropout']))
             model.add(MaxPooling1D(pool_size=space['pool_size']))
             model.add(Flatten())
             model.add(Dense(space['Dense'], activation='relu'))
             model.add(Dense(3, activation='softmax'))
             adam = keras.optimizers.Adam(lr=space['lr'])
             rmsprop = keras.optimizers.RMSprop(lr=space['lr_1'])
             choiceval = space['choiceval']
             if choiceval == 'adam':
                 optim = adam
             else:
                 optim = rmsprop
             print(model.summary())
             model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=opti
             result = model.fit(X_train_s, Y_train_s,
                             batch_size=space['Dense_1'],
                             nb_epoch=space['nb_epoch'],
                             verbose=verbose,
                             validation_data=(X_val_s, Y_val_s))
             #K.clear_session()
             return model,result
```

In [28]: best_model,result = keras_fmin_fnct(best_params)

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_3 (Conv1D)            (None, 124, 32)           1472
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 122, 16)           1552
_________________________________________________________________
dropout_2 (Dropout)          (None, 122, 16)           0
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 61, 16)            0
_________________________________________________________________
flatten_2 (Flatten)          (None, 976)               0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                62528
_________________________________________________________________
dense_4 (Dense)              (None, 3)                 195
=================================================================
Total params: 65,747
Trainable params: 65,747
Non-trainable params: 0
_________________________________________________________________
None

/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-packages/ipykernel_launcher

Train on 4067 samples, validate on 1560 samples
Epoch 1/30
4067/4067 [==============================] - 1s 350us/step - loss: 10.6708 - acc: 0.8375 - val_
Epoch 2/30
4067/4067 [==============================] - 1s 184us/step - loss: 1.2846 - acc: 0.8960 - val_l
Epoch 3/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.4912 - acc: 0.8943 - val_l
Epoch 4/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.3866 - acc: 0.9053 - val_l
Epoch 5/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.3421 - acc: 0.9098 - val_l
Epoch 6/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.3151 - acc: 0.9166 - val_l
Epoch 7/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.3091 - acc: 0.9154 - val_l
Epoch 8/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2749 - acc: 0.9312 - val_l
Epoch 9/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2743 - acc: 0.9272 - val_l
```

```
Epoch 10/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2576 - acc: 0.9292 - val_l
Epoch 11/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2791 - acc: 0.9302 - val_l
Epoch 12/30
4067/4067 [==============================] - 1s 185us/step - loss: 0.2315 - acc: 0.9346 - val_l
Epoch 13/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2301 - acc: 0.9410 - val_l
Epoch 14/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2294 - acc: 0.9368 - val_l
Epoch 15/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2371 - acc: 0.9353 - val_l
Epoch 16/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2146 - acc: 0.9449 - val_l
Epoch 17/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2065 - acc: 0.9447 - val_l
Epoch 18/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2056 - acc: 0.9420 - val_l
Epoch 19/30
4067/4067 [==============================] - 1s 185us/step - loss: 0.2223 - acc: 0.9398 - val_l
Epoch 20/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1979 - acc: 0.9442 - val_l
Epoch 21/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2421 - acc: 0.9432 - val_l
Epoch 22/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1836 - acc: 0.9498 - val_l
Epoch 23/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.1963 - acc: 0.9457 - val_l
Epoch 24/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1863 - acc: 0.9462 - val_l
Epoch 25/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.1844 - acc: 0.9462 - val_l
Epoch 26/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1754 - acc: 0.9525 - val_l
Epoch 27/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1793 - acc: 0.9511 - val_l
Epoch 28/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1665 - acc: 0.9555 - val_l
Epoch 29/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1705 - acc: 0.9575 - val_l
Epoch 30/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1712 - acc: 0.9577 - val_l
```

```
In [32]: _,acc_val = best_model.evaluate(X_val_s,Y_val_s,verbose=0)
         _,acc_train = best_model.evaluate(X_train_s,Y_train_s,verbose=0)
         print('Train_accuracy',acc_train,'test_accuracy',acc_val)
```

```
Train_accuracy 0.9628718957462503 test_accuracy 0.9391025641025641
```

i can observe that 23rd model is also giving good scores in runtime so will try once wit that params.

```
In [38]: runtime_param = total_trials['M23']
         runtime_param
```

```
Out[38]: {'Dense': 64,
          'Dense_1': 64,
          'Dropout': 0.45377377480700615,
          'choiceval': 'rmsprop',
          'filters': 32,
          'filters_1': 16,
          'kernel_size': 5,
          'kernel_size_1': 3,
          'l2': 0.0019801221163149862,
          'l2_1': 0.8236255110533577,
          'lr': 0.003918784585237195,
          'lr_1': 0.002237071747066137,
          'nb_epoch': 30,
          'pool_size': 2}
```

```
In [63]: runtime_param['nb_epoch'] = 150
```

```
In [64]: runtime_best_model,result = keras_fmin_fnct(runtime_param)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 124, 32)           1472
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 122, 16)           1552
_________________________________________________________________
dropout_1 (Dropout)          (None, 122, 16)           0
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 61, 16)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 976)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                62528
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 195
=================================================================
Total params: 65,747
Trainable params: 65,747
Non-trainable params: 0
_________________________________________________________________
None
```

```
/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-packages/ipykernel_launcher


Train on 4067 samples, validate on 1560 samples
Epoch 1/150
4067/4067 [==============================] - 1s 344us/step - loss: 10.6708 - acc: 0.8375 - val_
Epoch 2/150
4067/4067 [==============================] - 1s 186us/step - loss: 1.2846 - acc: 0.8960 - val_
Epoch 3/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.4912 - acc: 0.8943 - val_
Epoch 4/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.3866 - acc: 0.9053 - val_
Epoch 5/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.3421 - acc: 0.9098 - val_
Epoch 6/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.3151 - acc: 0.9166 - val_
Epoch 7/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.3091 - acc: 0.9154 - val_
Epoch 8/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2749 - acc: 0.9312 - val_
Epoch 9/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2743 - acc: 0.9272 - val_
Epoch 10/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.2576 - acc: 0.9292 - val_
Epoch 11/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2791 - acc: 0.9302 - val_
Epoch 12/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2315 - acc: 0.9346 - val_
Epoch 13/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2301 - acc: 0.9410 - val_
Epoch 14/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2294 - acc: 0.9368 - val_
Epoch 15/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2371 - acc: 0.9353 - val_
Epoch 16/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2146 - acc: 0.9449 - val_
Epoch 17/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2065 - acc: 0.9447 - val_
Epoch 18/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.2056 - acc: 0.9420 - val_
Epoch 19/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2223 - acc: 0.9398 - val_
Epoch 20/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1979 - acc: 0.9442 - val_
Epoch 21/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.2421 - acc: 0.9432 - val_
Epoch 22/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1836 - acc: 0.9498 - val_
```

```
Epoch 23/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1963 - acc: 0.9457 - val_
Epoch 24/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1863 - acc: 0.9462 - val_
Epoch 25/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1844 - acc: 0.9462 - val_
Epoch 26/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1754 - acc: 0.9525 - val_
Epoch 27/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1793 - acc: 0.9511 - val_
Epoch 28/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1665 - acc: 0.9555 - val_
Epoch 29/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1705 - acc: 0.9575 - val_
Epoch 30/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1712 - acc: 0.9577 - val_
Epoch 31/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1698 - acc: 0.9565 - val_
Epoch 32/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1621 - acc: 0.9580 - val_
Epoch 33/150
4067/4067 [==============================] - 1s 196us/step - loss: 0.1537 - acc: 0.9557 - val_
Epoch 34/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1592 - acc: 0.9552 - val_
Epoch 35/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1598 - acc: 0.9570 - val_
Epoch 36/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1561 - acc: 0.9570 - val_
Epoch 37/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1612 - acc: 0.9555 - val_
Epoch 38/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1535 - acc: 0.9577 - val_
Epoch 39/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1490 - acc: 0.9562 - val_
Epoch 40/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1476 - acc: 0.9604 - val_
Epoch 41/150
4067/4067 [==============================] - 1s 182us/step - loss: 0.1772 - acc: 0.9577 - val_
Epoch 42/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1421 - acc: 0.9609 - val_
Epoch 43/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1492 - acc: 0.9639 - val_
Epoch 44/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1643 - acc: 0.9575 - val_
Epoch 45/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1510 - acc: 0.9643 - val_
Epoch 46/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1519 - acc: 0.9639 - val_
```

```
Epoch 47/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1437 - acc: 0.9621 - val_
Epoch 48/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1351 - acc: 0.9636 - val_
Epoch 49/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1476 - acc: 0.9621 - val_
Epoch 50/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1399 - acc: 0.9634 - val_
Epoch 51/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1425 - acc: 0.9599 - val_
Epoch 52/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1390 - acc: 0.9641 - val_
Epoch 53/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1492 - acc: 0.9636 - val_
Epoch 54/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1344 - acc: 0.9656 - val_
Epoch 55/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1410 - acc: 0.9648 - val_
Epoch 56/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1417 - acc: 0.9636 - val_
Epoch 57/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1436 - acc: 0.9624 - val_
Epoch 58/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1390 - acc: 0.9675 - val_
Epoch 59/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1400 - acc: 0.9658 - val_
Epoch 60/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1312 - acc: 0.9666 - val_
Epoch 61/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1295 - acc: 0.9668 - val_
Epoch 62/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1288 - acc: 0.9673 - val_
Epoch 63/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1601 - acc: 0.9658 - val_
Epoch 64/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1275 - acc: 0.9702 - val_
Epoch 65/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1365 - acc: 0.9648 - val_
Epoch 66/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1385 - acc: 0.9671 - val_
Epoch 67/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1444 - acc: 0.9683 - val_
Epoch 68/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1374 - acc: 0.9661 - val_
Epoch 69/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1310 - acc: 0.9712 - val_
Epoch 70/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1302 - acc: 0.9666 - val_
```

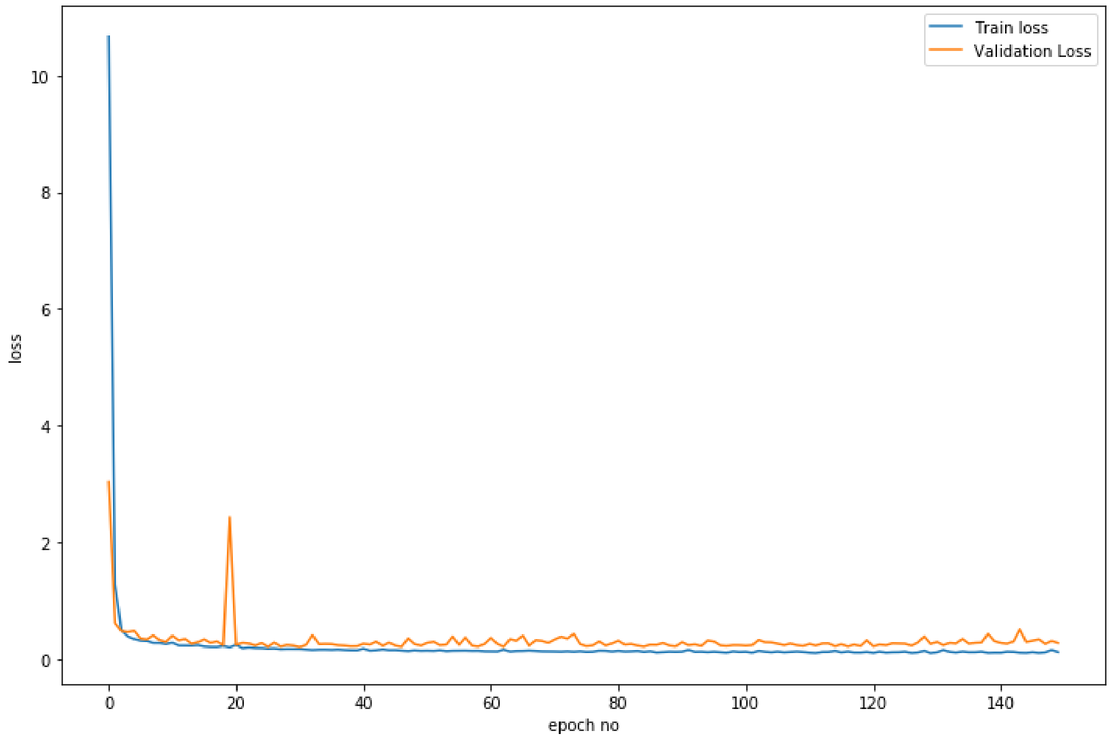
```
Epoch 71/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1283 - acc: 0.9698 - val_
Epoch 72/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1256 - acc: 0.9705 - val_
Epoch 73/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1311 - acc: 0.9668 - val_
Epoch 74/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1244 - acc: 0.9715 - val_
Epoch 75/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1321 - acc: 0.9671 - val_
Epoch 76/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1217 - acc: 0.9700 - val_
Epoch 77/150
4067/4067 [==============================] - 1s 182us/step - loss: 0.1246 - acc: 0.9720 - val_
Epoch 78/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1424 - acc: 0.9705 - val_
Epoch 79/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1402 - acc: 0.9688 - val_
Epoch 80/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1284 - acc: 0.9722 - val_
Epoch 81/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1396 - acc: 0.9693 - val_
Epoch 82/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1281 - acc: 0.9700 - val_
Epoch 83/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1311 - acc: 0.9705 - val_
Epoch 84/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1373 - acc: 0.9680 - val_
Epoch 85/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1213 - acc: 0.9722 - val_
Epoch 86/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1316 - acc: 0.9707 - val_
Epoch 87/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1110 - acc: 0.9730 - val_
Epoch 88/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1190 - acc: 0.9712 - val_
Epoch 89/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1252 - acc: 0.9717 - val_
Epoch 90/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1225 - acc: 0.9702 - val_
Epoch 91/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1260 - acc: 0.9725 - val_
Epoch 92/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1554 - acc: 0.9651 - val_
Epoch 93/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1225 - acc: 0.9761 - val_
Epoch 94/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1249 - acc: 0.9712 - val_
```

```
Epoch 95/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1170 - acc: 0.9727 - val_l
Epoch 96/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.1245 - acc: 0.9742 - val_l
Epoch 97/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1176 - acc: 0.9717 - val_l
Epoch 98/150
4067/4067 [==============================] - 1s 182us/step - loss: 0.1084 - acc: 0.9737 - val_l
Epoch 99/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1301 - acc: 0.9715 - val_l
Epoch 100/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1204 - acc: 0.9678 - val_l
Epoch 101/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1241 - acc: 0.9715 - val_l
Epoch 102/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1080 - acc: 0.9771 - val_l
Epoch 103/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1394 - acc: 0.9678 - val_l
Epoch 104/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1248 - acc: 0.9757 - val_l
Epoch 105/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.1148 - acc: 0.9734 - val_l
Epoch 106/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1267 - acc: 0.9705 - val_l
Epoch 107/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1139 - acc: 0.9749 - val_l
Epoch 108/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1211 - acc: 0.9688 - val_l
Epoch 109/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1279 - acc: 0.9715 - val_l
Epoch 110/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1206 - acc: 0.9710 - val_l
Epoch 111/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1085 - acc: 0.9766 - val_l
Epoch 112/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1028 - acc: 0.9779 - val_l
Epoch 113/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1205 - acc: 0.9734 - val_l
Epoch 114/150
4067/4067 [==============================] - 1s 192us/step - loss: 0.1214 - acc: 0.9732 - val_l
Epoch 115/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1396 - acc: 0.9754 - val_l
Epoch 116/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1134 - acc: 0.9734 - val_l
Epoch 117/150
4067/4067 [==============================] - 1s 182us/step - loss: 0.1283 - acc: 0.9744 - val_l
Epoch 118/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1112 - acc: 0.9761 - val_l
```

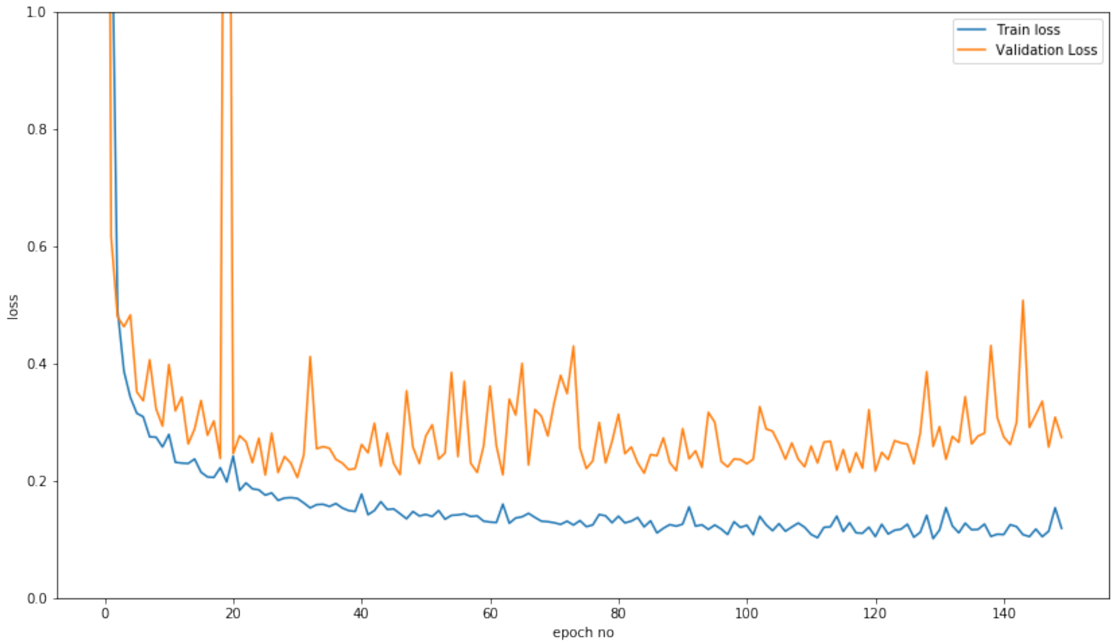
```
Epoch 119/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1104 - acc: 0.9730 - val_
Epoch 120/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1208 - acc: 0.9749 - val_
Epoch 121/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1047 - acc: 0.9786 - val_
Epoch 122/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.1258 - acc: 0.9761 - val_
Epoch 123/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1092 - acc: 0.9761 - val_
Epoch 124/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1156 - acc: 0.9771 - val_
Epoch 125/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.1174 - acc: 0.9725 - val_
Epoch 126/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1259 - acc: 0.9749 - val_
Epoch 127/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1037 - acc: 0.9774 - val_
Epoch 128/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1121 - acc: 0.9757 - val_
Epoch 129/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1411 - acc: 0.9734 - val_
Epoch 130/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1013 - acc: 0.9811 - val_
Epoch 131/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1160 - acc: 0.9764 - val_
Epoch 132/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1540 - acc: 0.9705 - val_
Epoch 133/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.1229 - acc: 0.9747 - val_
Epoch 134/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1112 - acc: 0.9779 - val_
Epoch 135/150
4067/4067 [==============================] - 1s 182us/step - loss: 0.1277 - acc: 0.9757 - val_
Epoch 136/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1165 - acc: 0.9769 - val_
Epoch 137/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1170 - acc: 0.9784 - val_
Epoch 138/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1261 - acc: 0.9747 - val_
Epoch 139/150
4067/4067 [==============================] - 1s 184us/step - loss: 0.1050 - acc: 0.9764 - val_
Epoch 140/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1088 - acc: 0.9774 - val_
Epoch 141/150
4067/4067 [==============================] - 1s 182us/step - loss: 0.1082 - acc: 0.9749 - val_
Epoch 142/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1251 - acc: 0.9727 - val_
```

```
Epoch 143/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1217 - acc: 0.9759 - val_l
Epoch 144/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1080 - acc: 0.9801 - val_l
Epoch 145/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1048 - acc: 0.9798 - val_l
Epoch 146/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1175 - acc: 0.9779 - val_l
Epoch 147/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1047 - acc: 0.9798 - val_l
Epoch 148/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1140 - acc: 0.9766 - val_l
Epoch 149/150
4067/4067 [==============================] - 1s 183us/step - loss: 0.1539 - acc: 0.9720 - val_l
Epoch 150/150
4067/4067 [==============================] - 1s 185us/step - loss: 0.1189 - acc: 0.9744 - val_l
```

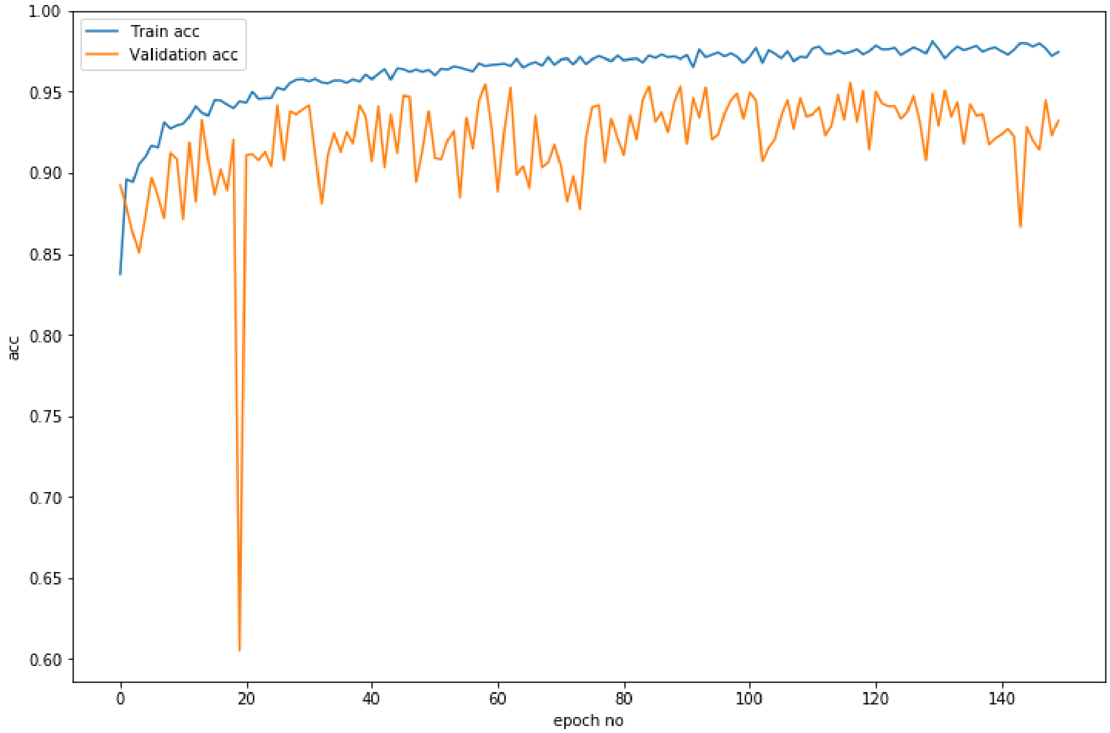
```
In [66]: plt.figure(figsize=(12,8))
         plt.plot(result.history['loss'],label='Train loss')
         plt.plot(result.history['val_loss'],label = 'Validation Loss')
         plt.xlabel('epoch no')
         plt.ylabel('loss')
         plt.legend()
         plt.show()
```



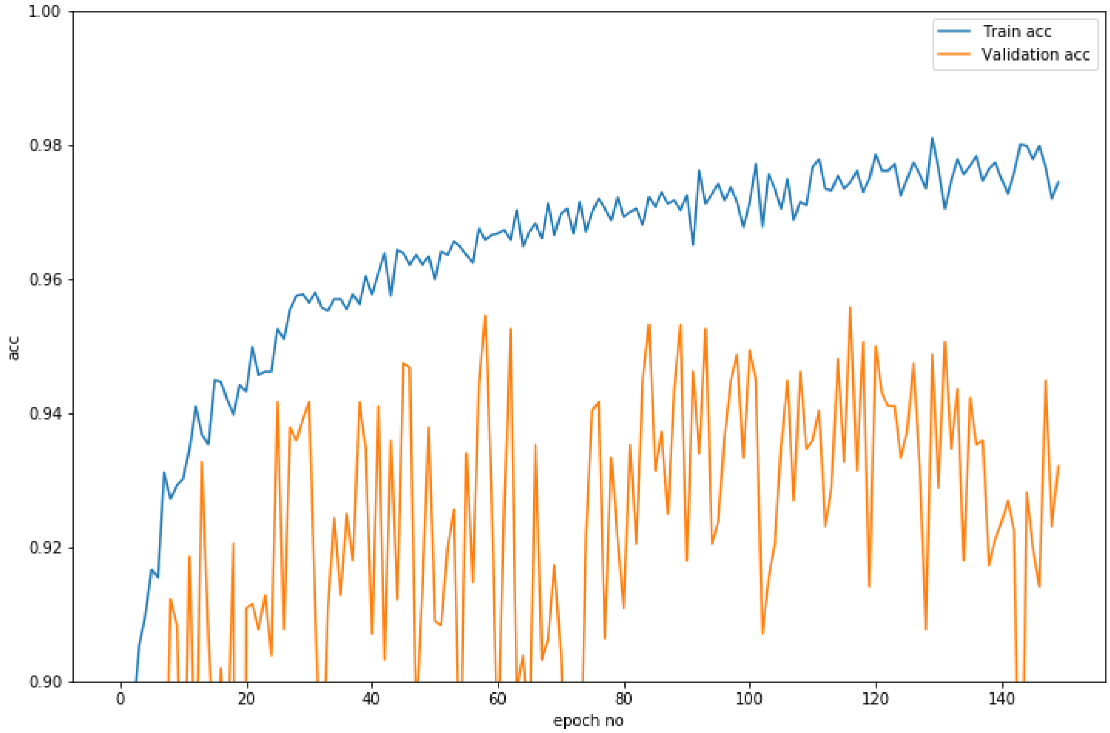
```
In [67]: plt.figure(figsize=(14,8))
         plt.plot(result.history['loss'],label='Train loss')
         plt.plot(result.history['val_loss'],label = 'Validation Loss')
         plt.ylim(0,1)
         plt.xlabel('epoch no')
         plt.ylabel('loss')
         plt.legend()
         plt.show()
```




```
In [68]: plt.figure(figsize=(12,8))
         plt.plot(result.history['acc'],label='Train acc')
         plt.plot(result.history['val_acc'],label = 'Validation acc')
         plt.xlabel('epoch no')
         plt.ylabel('acc')
         plt.legend()
         plt.show()
```




```
In [69]: plt.figure(figsize=(12,8))
         plt.plot(result.history['acc'],label='Train acc')
         plt.plot(result.history['val_acc'],label = 'Validation acc')
         plt.xlabel('epoch no')
         plt.ylabel('acc')
         plt.ylim(0.90,1)
         plt.legend()
         plt.show()
```



around 57-59 score is giving good accuracy wit less overfitting

```
In [77]: runtime_param['nb_epoch'] = 59
         best_model,result = keras_fmin_fnct(runtime_param)
```

```
Exception ignored in: <bound method BaseSession._Callable.__del__ of <tensorflow.python.client
Traceback (most recent call last):
  File "/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-packages/tensorflow/
    self._session._session, self._handle, status)
  File "/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-packages/tensorflow/
    c_api.TF_GetCode(self.status.status))
tensorflow.python.framework.errors_impl.InvalidArgumentError: No such callable handle: 14984248
/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-packages/ipykernel_launcher


_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 124, 32)           1472
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 122, 16)           1552
_________________________________________________________________
dropout_1 (Dropout)          (None, 122, 16)           0
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 61, 16)            0
```

```
_________________________________________________________________
flatten_1 (Flatten)          (None, 976)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                62528
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 195
=================================================================
Total params: 65,747
Trainable params: 65,747
Non-trainable params: 0
_________________________________________________________________
None
Train on 4067 samples, validate on 1560 samples
Epoch 1/59
4067/4067 [==============================] - 2s 383us/step - loss: 10.6708 - acc: 0.8375 - val_
Epoch 2/59
4067/4067 [==============================] - 1s 184us/step - loss: 1.2846 - acc: 0.8960 - val_l
Epoch 3/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.4912 - acc: 0.8943 - val_l
Epoch 4/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.3866 - acc: 0.9053 - val_l
Epoch 5/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.3421 - acc: 0.9098 - val_l
Epoch 6/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.3151 - acc: 0.9166 - val_l
Epoch 7/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.3091 - acc: 0.9154 - val_l
Epoch 8/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.2749 - acc: 0.9312 - val_l
Epoch 9/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.2743 - acc: 0.9272 - val_l
Epoch 10/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.2576 - acc: 0.9292 - val_l
Epoch 11/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.2791 - acc: 0.9302 - val_l
Epoch 12/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.2315 - acc: 0.9346 - val_l
Epoch 13/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.2301 - acc: 0.9410 - val_l
Epoch 14/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.2294 - acc: 0.9368 - val_l
Epoch 15/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.2371 - acc: 0.9353 - val_l
Epoch 16/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.2146 - acc: 0.9449 - val_l
Epoch 17/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.2065 - acc: 0.9447 - val_l
Epoch 18/59
```

```
4067/4067 [==============================] - 1s 184us/step - loss: 0.2056 - acc: 0.9420 - val_
Epoch 19/59
4067/4067 [==============================] - 1s 186us/step - loss: 0.2223 - acc: 0.9398 - val_
Epoch 20/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1979 - acc: 0.9442 - val_
Epoch 21/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.2421 - acc: 0.9432 - val_
Epoch 22/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1836 - acc: 0.9498 - val_
Epoch 23/59
4067/4067 [==============================] - 1s 187us/step - loss: 0.1963 - acc: 0.9457 - val_
Epoch 24/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1863 - acc: 0.9462 - val_
Epoch 25/59
4067/4067 [==============================] - 1s 186us/step - loss: 0.1844 - acc: 0.9462 - val_
Epoch 26/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1754 - acc: 0.9525 - val_
Epoch 27/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1793 - acc: 0.9511 - val_
Epoch 28/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1665 - acc: 0.9555 - val_
Epoch 29/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1705 - acc: 0.9575 - val_
Epoch 30/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1712 - acc: 0.9577 - val_
Epoch 31/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1698 - acc: 0.9565 - val_
Epoch 32/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1621 - acc: 0.9580 - val_
Epoch 33/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1537 - acc: 0.9557 - val_
Epoch 34/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1592 - acc: 0.9552 - val_
Epoch 35/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1598 - acc: 0.9570 - val_
Epoch 36/59
4067/4067 [==============================] - 1s 195us/step - loss: 0.1561 - acc: 0.9570 - val_
Epoch 37/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1612 - acc: 0.9555 - val_
Epoch 38/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1535 - acc: 0.9577 - val_
Epoch 39/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1490 - acc: 0.9562 - val_
Epoch 40/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1476 - acc: 0.9604 - val_
Epoch 41/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1772 - acc: 0.9577 - val_
Epoch 42/59
```

```
4067/4067 [==============================] - 1s 183us/step - loss: 0.1421 - acc: 0.9609 - val_l
Epoch 43/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1492 - acc: 0.9639 - val_l
Epoch 44/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1643 - acc: 0.9575 - val_l
Epoch 45/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1510 - acc: 0.9643 - val_l
Epoch 46/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1519 - acc: 0.9639 - val_l
Epoch 47/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1437 - acc: 0.9621 - val_l
Epoch 48/59
4067/4067 [==============================] - 1s 187us/step - loss: 0.1351 - acc: 0.9636 - val_l
Epoch 49/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1476 - acc: 0.9621 - val_l
Epoch 50/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1399 - acc: 0.9634 - val_l
Epoch 51/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1425 - acc: 0.9599 - val_l
Epoch 52/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1390 - acc: 0.9641 - val_l
Epoch 53/59
4067/4067 [==============================] - 1s 184us/step - loss: 0.1492 - acc: 0.9636 - val_l
Epoch 54/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1344 - acc: 0.9656 - val_l
Epoch 55/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1410 - acc: 0.9648 - val_l
Epoch 56/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1417 - acc: 0.9636 - val_l
Epoch 57/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1436 - acc: 0.9624 - val_l
Epoch 58/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1390 - acc: 0.9675 - val_l
Epoch 59/59
4067/4067 [==============================] - 1s 183us/step - loss: 0.1400 - acc: 0.9658 - val_l
```

In [78]:
```python
_,acc_val = best_model.evaluate(X_val_s,Y_val_s,verbose=0)
_,acc_train = best_model.evaluate(X_train_s,Y_train_s,verbose=0)
print('Train_accuracy',acc_train,'test_accuracy',acc_val)
```

```
Train_accuracy 0.9741824440619621 test_accuracy 0.9544871794871795
```

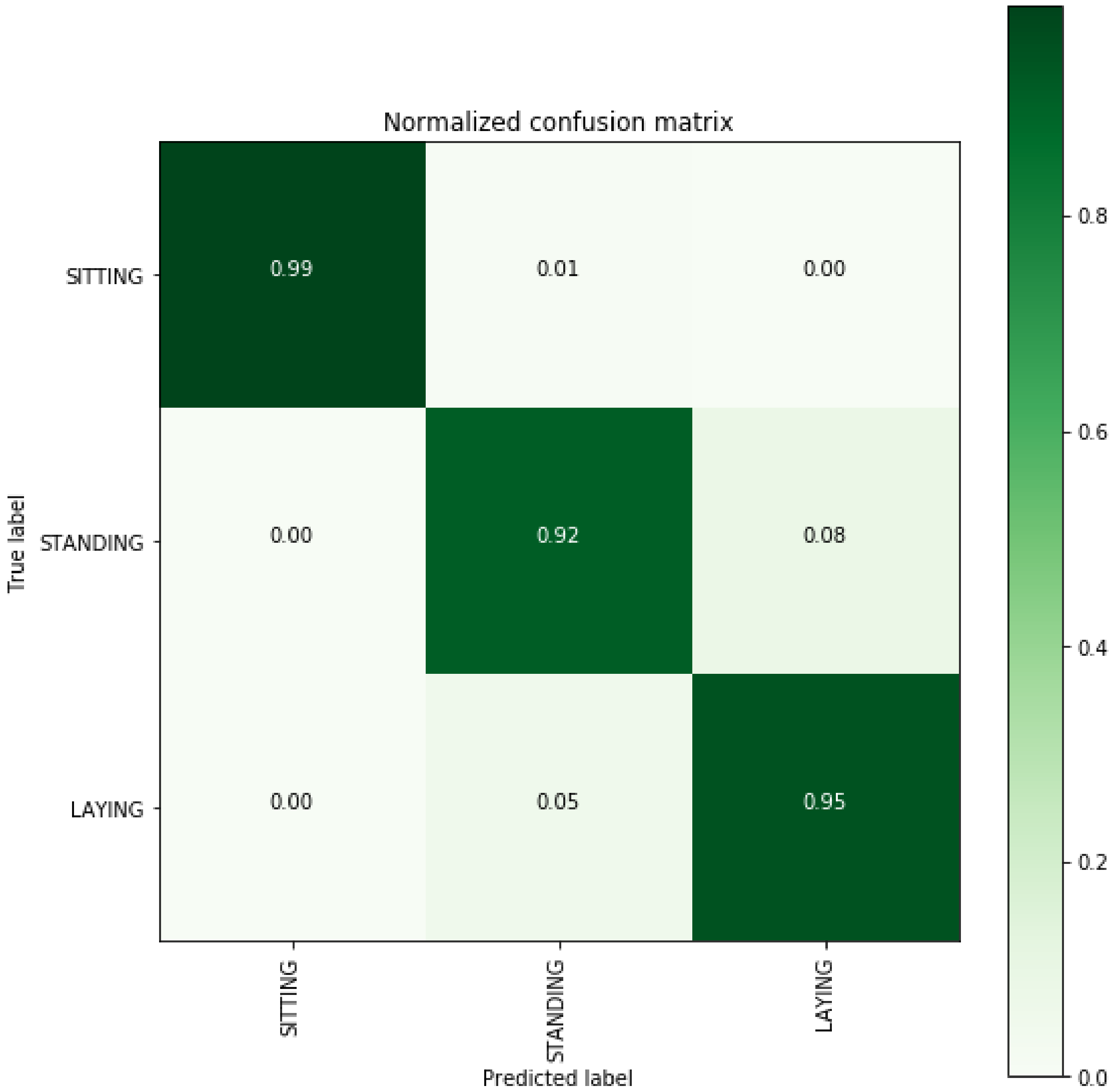
In [81]:
```python
# Confusion Matrix
# Activities are the class labels
# It is a 3 class classification
from sklearn import metrics
```

```
ACTIVITIES = {
    0: 'SITTING',
    1: 'STANDING',
    2: 'LAYING',
}

# Utility function to print the confusion matrix
def confusion_matrix_cnn(Y_true, Y_pred):
    Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1)])
    Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])

    #return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])
    return metrics.confusion_matrix(Y_true, Y_pred)

# Confusion Matrix
print(confusion_matrix_cnn(Y_val_s, best_model.predict(X_val_s)))
```

```
[[534   3   0]
 [  0 450  41]
 [  0  27 505]]
```

In [83]:
```
plt.figure(figsize=(8,8))
cm = confusion_matrix_cnn(Y_val_s, best_model.predict(X_val_s))
plot_confusion_matrix(cm, classes=['SITTING','STANDING','LAYING'], normalize=True, ti
plt.show()
```

```
<matplotlib.figure.Figure at 0x148471fbee10>
```



it was better than confusion metric with all data. We improved our model for classiying static activities alot than previous approc models.

```
In [84]: ##saving model
         best_model.save('final_model_static.h5')
```

13.3.3 Classification of Dynamic activities :

```
In [151]: ##data preparation
          def data_scaled_dynamic():
              """
              Obtain the dataset from multiple files.
              Returns: X_train, X_test, y_train, y_test
              """
```

```
# Data directory
DATADIR = 'UCI_HAR_Dataset'
# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
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"
    ]
from sklearn.base import BaseEstimator, TransformerMixin
class scaling_tseries_data(BaseEstimator, TransformerMixin):
    from sklearn.preprocessing import StandardScaler
    def __init__(self):
        self.scale = None

    def transform(self, X):
        temp_X1 = X.reshape((X.shape[0] * X.shape[1], X.shape[2]))
        temp_X1 = self.scale.transform(temp_X1)
        return temp_X1.reshape(X.shape)

    def fit(self, X):
        # remove overlaping
        remove = int(X.shape[1] / 2)
        temp_X = X[:, -remove:, :]
        # flatten data
        temp_X = temp_X.reshape((temp_X.shape[0] * temp_X.shape[1], temp_X.shape
        scale = StandardScaler()
        scale.fit(temp_X)
        pickle.dump(scale,open('Scale_dynamic.p','wb'))
        self.scale = scale
        return self

# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
```

```
        signals_data = []

        for signal in SIGNALS:
            filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}
            signals_data.append( _read_csv(filename).as_matrix())

        # 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
        return np.transpose(signals_data, (1, 2, 0))

    def load_y(subset):
        """
        The objective that we are trying to predict is a integer, from 1 to 6,
        that represents a human activity. We return a binary representation of
        every sample objective as a 6 bits vector using One Hot Encoding
        (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.h
        """
        filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
        y = _read_csv(filename)[0]
        y_subset = y<=3
        y = y[y_subset]
        return pd.get_dummies(y).as_matrix(),y_subset

    Y_train_d,y_train_sub = load_y('train')
    Y_val_d,y_test_sub = load_y('test')
    X_train_d, X_val_d = load_signals('train'), load_signals('test')
    X_train_d = X_train_d[y_train_sub]
    X_val_d = X_val_d[y_test_sub]

    ###Scling data
    Scale = scaling_tseries_data()
    Scale.fit(X_train_d)
    X_train_d = Scale.transform(X_train_d)
    X_val_d = Scale.transform(X_val_d)

    return X_train_d, Y_train_d, X_val_d,  Y_val_d
```

```
In [152]: X_train_d, Y_train_d, X_val_d,  Y_val_d = data_scaled_dynamic()
```

```
In [153]: print('Train X shape',X_train_d.shape,'Test X shape',X_val_d.shape)
          print('Train Y shape',Y_train_d.shape,'Test Y shape',Y_val_d.shape)
```

```
Train X shape (3285, 128, 9) Test X shape (1387, 128, 9)
Train Y shape (3285, 3) Test Y shape (1387, 3)
```

Baseline Model

```
In [96]: np.random.seed(0)
         tf.set_random_seed(0)
         sess = tf.Session(graph=tf.get_default_graph())
         K.set_session(sess)
         model = Sequential()
         model.add(Conv1D(filters=64, kernel_size=7, activation='relu',kernel_initializer='he_u
         model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_u
         model.add(Dropout(0.6))
         model.add(MaxPooling1D(pool_size=3))
         model.add(Flatten())
         model.add(Dense(30, activation='relu'))
         model.add(Dense(3, activation='softmax'))
         model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 122, 64)           4096
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 120, 32)           6176
_________________________________________________________________
dropout_1 (Dropout)          (None, 120, 32)           0
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 40, 32)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1280)              0
_________________________________________________________________
dense_1 (Dense)              (None, 30)                38430
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 93
=================================================================
Total params: 48,795
Trainable params: 48,795
Non-trainable params: 0
_________________________________________________________________
```

```
In [97]: import math
         adam = keras.optimizers.Adam(lr=0.004)
         model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])
         model.fit(X_train_s,Y_train_s, epochs=100, batch_size=16,validation_data=(X_val_s, Y_v
         K.clear_session()
```

```
Train on 4067 samples, validate on 1560 samples
Epoch 1/100
4067/4067 [==============================] - 3s 646us/step - loss: 0.3741 - acc: 0.8835 - val_l
Epoch 2/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2112 - acc: 0.9179 - val_l
```

```
Epoch 3/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2055 - acc: 0.9179 - val_
Epoch 4/100
4067/4067 [==============================] - 2s 471us/step - loss: 0.1922 - acc: 0.9240 - val_
Epoch 5/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2058 - acc: 0.9292 - val_
Epoch 6/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1774 - acc: 0.9336 - val_
Epoch 7/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1617 - acc: 0.9405 - val_
Epoch 8/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1881 - acc: 0.9363 - val_
Epoch 9/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2020 - acc: 0.9385 - val_
Epoch 10/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1497 - acc: 0.9476 - val_
Epoch 11/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2372 - acc: 0.9294 - val_
Epoch 12/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2053 - acc: 0.9348 - val_
Epoch 13/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2254 - acc: 0.9223 - val_
Epoch 14/100
4067/4067 [==============================] - 2s 482us/step - loss: 0.1488 - acc: 0.9410 - val_
Epoch 15/100
4067/4067 [==============================] - 2s 473us/step - loss: 0.1156 - acc: 0.9548 - val_
Epoch 16/100
4067/4067 [==============================] - 2s 474us/step - loss: 0.1348 - acc: 0.9523 - val_
Epoch 17/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2656 - acc: 0.9393 - val_
Epoch 18/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.4346 - acc: 0.9171 - val_
Epoch 19/100
4067/4067 [==============================] - 2s 467us/step - loss: 0.2026 - acc: 0.9385 - val_
Epoch 20/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.1679 - acc: 0.9511 - val_
Epoch 21/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.1626 - acc: 0.9525 - val_
Epoch 22/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1852 - acc: 0.9452 - val_
Epoch 23/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2965 - acc: 0.9233 - val_
Epoch 24/100
4067/4067 [==============================] - 2s 475us/step - loss: 0.2631 - acc: 0.9358 - val_
Epoch 25/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2342 - acc: 0.9432 - val_
Epoch 26/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.3714 - acc: 0.9257 - val_
```

```
Epoch 27/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.3692 - acc: 0.9312 - val_
Epoch 28/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.3338 - acc: 0.9380 - val_
Epoch 29/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.3166 - acc: 0.9462 - val_
Epoch 30/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.3306 - acc: 0.9437 - val_
Epoch 31/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.3000 - acc: 0.9466 - val_
Epoch 32/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2992 - acc: 0.9459 - val_
Epoch 33/100
4067/4067 [==============================] - 2s 476us/step - loss: 0.3235 - acc: 0.9430 - val_
Epoch 34/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2924 - acc: 0.9516 - val_
Epoch 35/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2561 - acc: 0.9439 - val_
Epoch 36/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1771 - acc: 0.9587 - val_
Epoch 37/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1556 - acc: 0.9653 - val_
Epoch 38/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1674 - acc: 0.9643 - val_
Epoch 39/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1850 - acc: 0.9619 - val_
Epoch 40/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2294 - acc: 0.9565 - val_
Epoch 41/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.8426 - acc: 0.8618 - val_
Epoch 42/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.3695 - acc: 0.9095 - val_
Epoch 43/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2976 - acc: 0.8957 - val_
Epoch 44/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.3169 - acc: 0.8842 - val_
Epoch 45/100
4067/4067 [==============================] - 2s 481us/step - loss: 0.2832 - acc: 0.9299 - val_
Epoch 46/100
4067/4067 [==============================] - 2s 473us/step - loss: 0.2590 - acc: 0.9253 - val_
Epoch 47/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.2411 - acc: 0.9058 - val_
Epoch 48/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2444 - acc: 0.9339 - val_
Epoch 49/100
4067/4067 [==============================] - 2s 471us/step - loss: 0.2571 - acc: 0.9398 - val_
Epoch 50/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.2081 - acc: 0.9329 - val_
```

```
Epoch 51/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.1975 - acc: 0.9459 - val_
Epoch 52/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.1934 - acc: 0.9506 - val_
Epoch 53/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1805 - acc: 0.9560 - val_
Epoch 54/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1955 - acc: 0.9422 - val_
Epoch 55/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.2695 - acc: 0.9420 - val_
Epoch 56/100
4067/4067 [==============================] - 2s 472us/step - loss: 0.2427 - acc: 0.9545 - val_
Epoch 57/100
4067/4067 [==============================] - 2s 472us/step - loss: 0.2529 - acc: 0.9486 - val_
Epoch 58/100
4067/4067 [==============================] - 2s 472us/step - loss: 0.2147 - acc: 0.9469 - val_
Epoch 59/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2057 - acc: 0.9599 - val_
Epoch 60/100
4067/4067 [==============================] - 2s 469us/step - loss: 1.0452 - acc: 0.8975 - val_
Epoch 61/100
4067/4067 [==============================] - 2s 470us/step - loss: 5.7147 - acc: 0.6027 - val_
Epoch 62/100
4067/4067 [==============================] - 2s 469us/step - loss: 5.6650 - acc: 0.6078 - val_
Epoch 63/100
4067/4067 [==============================] - 2s 469us/step - loss: 5.6250 - acc: 0.6164 - val_
Epoch 64/100
4067/4067 [==============================] - 2s 468us/step - loss: 5.5582 - acc: 0.6191 - val_
Epoch 65/100
4067/4067 [==============================] - 2s 469us/step - loss: 5.2745 - acc: 0.6410 - val_
Epoch 66/100
4067/4067 [==============================] - 2s 472us/step - loss: 0.2632 - acc: 0.9388 - val_
Epoch 67/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2281 - acc: 0.9550 - val_
Epoch 68/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.4060 - acc: 0.9353 - val_
Epoch 69/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.4286 - acc: 0.9071 - val_
Epoch 70/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.3854 - acc: 0.9142 - val_
Epoch 71/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.3436 - acc: 0.9415 - val_
Epoch 72/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2453 - acc: 0.9491 - val_
Epoch 73/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.1925 - acc: 0.9501 - val_
Epoch 74/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.1871 - acc: 0.9567 - val_
```

```
Epoch 75/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.2512 - acc: 0.9444 - val_
Epoch 76/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2315 - acc: 0.9481 - val_
Epoch 77/100
4067/4067 [==============================] - 2s 483us/step - loss: 0.2328 - acc: 0.9594 - val_
Epoch 78/100
4067/4067 [==============================] - 2s 471us/step - loss: 0.2192 - acc: 0.9619 - val_
Epoch 79/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.2219 - acc: 0.9584 - val_
Epoch 80/100
4067/4067 [==============================] - 2s 471us/step - loss: 0.2892 - acc: 0.9324 - val_
Epoch 81/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2685 - acc: 0.9223 - val_
Epoch 82/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.2445 - acc: 0.9385 - val_
Epoch 83/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2005 - acc: 0.9459 - val_
Epoch 84/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2433 - acc: 0.9417 - val_
Epoch 85/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.2071 - acc: 0.9275 - val_
Epoch 86/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1931 - acc: 0.9511 - val_
Epoch 87/100
4067/4067 [==============================] - 2s 471us/step - loss: 0.1786 - acc: 0.9629 - val_
Epoch 88/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1616 - acc: 0.9648 - val_
Epoch 89/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.1567 - acc: 0.9592 - val_
Epoch 90/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1951 - acc: 0.9636 - val_
Epoch 91/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.1813 - acc: 0.9646 - val_
Epoch 92/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.1771 - acc: 0.9629 - val_
Epoch 93/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.3397 - acc: 0.9570 - val_
Epoch 94/100
4067/4067 [==============================] - 2s 468us/step - loss: 3.7788 - acc: 0.7037 - val_
Epoch 95/100
4067/4067 [==============================] - 2s 468us/step - loss: 4.0658 - acc: 0.6922 - val_
Epoch 96/100
4067/4067 [==============================] - 2s 475us/step - loss: 3.0969 - acc: 0.7335 - val_
Epoch 97/100
4067/4067 [==============================] - 2s 467us/step - loss: 0.4589 - acc: 0.9171 - val_
Epoch 98/100
4067/4067 [==============================] - 2s 470us/step - loss: 0.3379 - acc: 0.9169 - val_
```

```
Epoch 99/100
4067/4067 [==============================] - 2s 468us/step - loss: 0.3399 - acc: 0.9184 - val_l
Epoch 100/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2668 - acc: 0.9341 - val_l
```

```
In [7]: def model_cnn(X_train_d, Y_train_d, X_val_d, Y_val_d):
            np.random.seed(0)
            tf.set_random_seed(0)
            sess = tf.Session(graph=tf.get_default_graph())
            K.set_session(sess)
            # Initiliazing the sequential model
            model = Sequential()

            model.add(Conv1D(filters={{choice([28,32,42])}}, kernel_size={{choice([3,5,7])}},ac
                             kernel_regularizer=l2({{uniform(0,3)}}),input_shape=(128,9)))

            model.add(Conv1D(filters={{choice([16,24,32])}}, kernel_size={{choice([3,5,7])}},
                                 activation='relu',kernel_regularizer=l2({{uniform(0,2)}}),kernel_i
            model.add(Dropout({{uniform(0.45,0.7)}}))
            model.add(MaxPooling1D(pool_size={{choice([2,3,5])}}))
            model.add(Flatten())
            model.add(Dense({{choice([16,32,64])}}, activation='relu'))
            model.add(Dense(3, activation='softmax'))

            adam = keras.optimizers.Adam(lr={{uniform(0.00065,0.004)}})
            rmsprop = keras.optimizers.RMSprop(lr={{uniform(0.00065,0.004)}})

            choiceval = {{choice(['adam', 'rmsprop'])}}

            if choiceval == 'adam':
                optim = adam
            else:
                optim = rmsprop

            print(model.summary())

            model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=optim

            result = model.fit(X_train_d, Y_train_d,
                      batch_size={{choice([16,32,64])}},
                      nb_epoch={{choice([35,40,55])}},
                      verbose=2,
                      validation_data=(X_val_d, Y_val_d))

            score, acc = model.evaluate(X_val_d, Y_val_d, verbose=0)
            score1, acc1 = model.evaluate(X_train_d, Y_train_d, verbose=0)
            print('Train accuracy',acc1,'Test accuracy:', acc)
```

```
    print('---------------------------------------------------------------------------
    K.clear_session()
    return {'loss': -acc, 'status': STATUS_OK,'train_acc':acc1}
```

```
In [8]: import pickle
        best_run, best_model, space = pickle.load(open('/home/u20112/final_result_cnn5.p','rb'
        trials = pickle.load(open('/home/u20112/trials_cnn5.p','rb'))
```

```
In [ ]: X_train_d, Y_train_d, X_val_d, Y_val_d = data_scaled_dynamic()
        trials = Trials()
        best_run, best_model, space = optim.minimize(model=model_cnn,
                                              data=data_scaled_dynamic,
                                              algo=tpe.suggest,
                                              max_evals=120,rseed = 0,
                                              trials=trials,notebook_name='Human Activity Dete
                                              return_space = True)
```

```
In [11]: from hyperas.utils import eval_hyperopt_space
         total_trials = dict()
         for t, trial in enumerate(trials):
                 vals = trial.get('misc').get('vals')
                 z = eval_hyperopt_space(space, vals)
                 total_trials['M'+str(t+1)] = z
         #best Hyper params from hyperas
         best_params = eval_hyperopt_space(space, best_run)
         best_params
```

```
Out[11]: {'Dense': 64,
          'Dense_1': 32,
          'Dropout': 0.6725241946290972,
          'choiceval': 'adam',
          'filters': 32,
          'filters_1': 32,
          'kernel_size': 7,
          'kernel_size_1': 7,
          'l2': 0.548595947917793,
          'l2_1': 0.28312064960787986,
          'lr': 0.00083263584783479,
          'lr_1': 0.0020986605171288,
          'nb_epoch': 35,
          'pool_size': 5}
```

```
In [18]: import keras
```

```
In [23]: #Hyperas model
         def model_hyperas(space,verbose=1):
             np.random.seed(0)
             tf.set_random_seed(0)
             sess = tf.Session(graph=tf.get_default_graph())
```

```
            K.set_session(sess)
            # Initiliazing the sequential model
            model = Sequential()
            model.add(Conv1D(filters=space['filters'], kernel_size=space['kernel_size'],activa
                            kernel_initializer='he_uniform',
                            kernel_regularizer=l2(space['l2']),input_shape=(128,9)))
            model.add(Conv1D(filters=space['filters_1'], kernel_size=space['kernel_size_1'],
                        activation='relu',kernel_regularizer=l2(space['l2_1']),kernel_initiali
            model.add(Dropout(space['Dropout']))
            model.add(MaxPooling1D(pool_size=space['pool_size']))
            model.add(Flatten())
            model.add(Dense(space['Dense'], activation='relu'))
            model.add(Dense(3, activation='softmax'))
            adam = keras.optimizers.Adam(lr=space['lr'])
            rmsprop = keras.optimizers.RMSprop(lr=space['lr_1'])
            choiceval = space['choiceval']
            if choiceval == 'adam':
                optim = adam
            else:
                optim = rmsprop
            print(model.summary())
            model.compile(loss='categorical_crossentropy', metrics=['accuracy'],optimizer=opti
            result = model.fit(X_train_d, Y_train_d,
                            batch_size=space['Dense_1'],
                            nb_epoch=space['nb_epoch'],
                            verbose=verbose,
                            validation_data=(X_val_d, Y_val_d))
            #K.clear_session()
            return model,result
```

```
In [24]: best_model,result = model_hyperas(best_params)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 122, 32)           2048
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 116, 32)           7200
_________________________________________________________________
dropout_1 (Dropout)          (None, 116, 32)           0
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 23, 32)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 736)               0
_________________________________________________________________
dense_1 (Dense)              (None, 64)                47168
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 195
```

```
=================================================================
Total params: 56,611
Trainable params: 56,611
Non-trainable params: 0
_________________________________________________________________
None
Train on 3285 samples, validate on 1387 samples
Epoch 1/35
3285/3285 [==============================] - 2s 553us/step - loss: 36.5170 - acc: 0.6493 - val_
Epoch 2/35
3285/3285 [==============================] - 1s 331us/step - loss: 13.4174 - acc: 0.9428 - val_
Epoch 3/35
3285/3285 [==============================] - 1s 320us/step - loss: 4.8053 - acc: 0.9772 - val_
Epoch 4/35
3285/3285 [==============================] - 1s 319us/step - loss: 1.7396 - acc: 0.9851 - val_
Epoch 5/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.6754 - acc: 0.9921 - val_
Epoch 6/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.3342 - acc: 0.9906 - val_
Epoch 7/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.2152 - acc: 0.9930 - val_
Epoch 8/35
3285/3285 [==============================] - 1s 322us/step - loss: 0.1851 - acc: 0.9918 - val_
Epoch 9/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1573 - acc: 0.9954 - val_
Epoch 10/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1468 - acc: 0.9960 - val_
Epoch 11/35
3285/3285 [==============================] - 1s 330us/step - loss: 0.1295 - acc: 0.9960 - val_
Epoch 12/35
3285/3285 [==============================] - 1s 325us/step - loss: 0.1278 - acc: 0.9942 - val_
Epoch 13/35
3285/3285 [==============================] - 1s 326us/step - loss: 0.1144 - acc: 0.9960 - val_
Epoch 14/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1066 - acc: 0.9979 - val_
Epoch 15/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1332 - acc: 0.9896 - val_
Epoch 16/35
3285/3285 [==============================] - 1s 322us/step - loss: 0.1043 - acc: 0.9973 - val_
Epoch 17/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1074 - acc: 0.9951 - val_
Epoch 18/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.0913 - acc: 0.9982 - val_
Epoch 19/35
3285/3285 [==============================] - 1s 317us/step - loss: 0.1172 - acc: 0.9884 - val_
Epoch 20/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.1035 - acc: 0.9921 - val_
Epoch 21/35
```

```
3285/3285 [==============================] - 1s 317us/step - loss: 0.0959 - acc: 0.9948 - val_l
Epoch 22/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.0769 - acc: 0.9994 - val_l
Epoch 23/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.0766 - acc: 0.9985 - val_l
Epoch 24/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.1604 - acc: 0.9732 - val_l
Epoch 25/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.1246 - acc: 0.9951 - val_l
Epoch 26/35
3285/3285 [==============================] - 1s 317us/step - loss: 0.0749 - acc: 0.9997 - val_l
Epoch 27/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0703 - acc: 0.9997 - val_l
Epoch 28/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0794 - acc: 0.9957 - val_l
Epoch 29/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.0679 - acc: 0.9985 - val_l
Epoch 30/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0769 - acc: 0.9942 - val_l
Epoch 31/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0952 - acc: 0.9924 - val_l
Epoch 32/35
3285/3285 [==============================] - 1s 323us/step - loss: 0.0615 - acc: 0.9994 - val_l
Epoch 33/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0574 - acc: 0.9988 - val_l
Epoch 34/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.1272 - acc: 0.9784 - val_l
Epoch 35/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.1743 - acc: 0.9860 - val_l
```

```
In [21]: _,acc_val = best_model.evaluate(X_val_d,Y_val_d,verbose=0)
         _,acc_train = best_model.evaluate(X_train_d,Y_train_d,verbose=0)
         print('Train_accuracy',acc_train,'test_accuracy',acc_val)
```

```
Train_accuracy 1.0 test_accuracy 0.9704397981254506
```

We can observe that some models are having around 0.99 accuracy for some epochs. will investgate some models(model 59, 99).

```
In [47]: M59 = total_trials['M59']
         M59
```

```
Out[47]: {'Dense': 32,
          'Dense_1': 32,
          'Dropout': 0.48642317342570957,
          'choiceval': 'adam',
          'filters': 32,
```

```
'filters_1': 32,
'kernel_size': 7,
'kernel_size_1': 7,
'l2': 0.10401484931072974,
'l2_1': 0.7228970346142163,
'lr': 0.000772514731035696,
'lr_1': 0.003074353392879209,
'nb_epoch': 35,
'pool_size': 5}
```

In [62]:
```
K.clear_session()
M59['nb_epoch'] = 70
best_model_all,result = model_hyperas(M59)
```

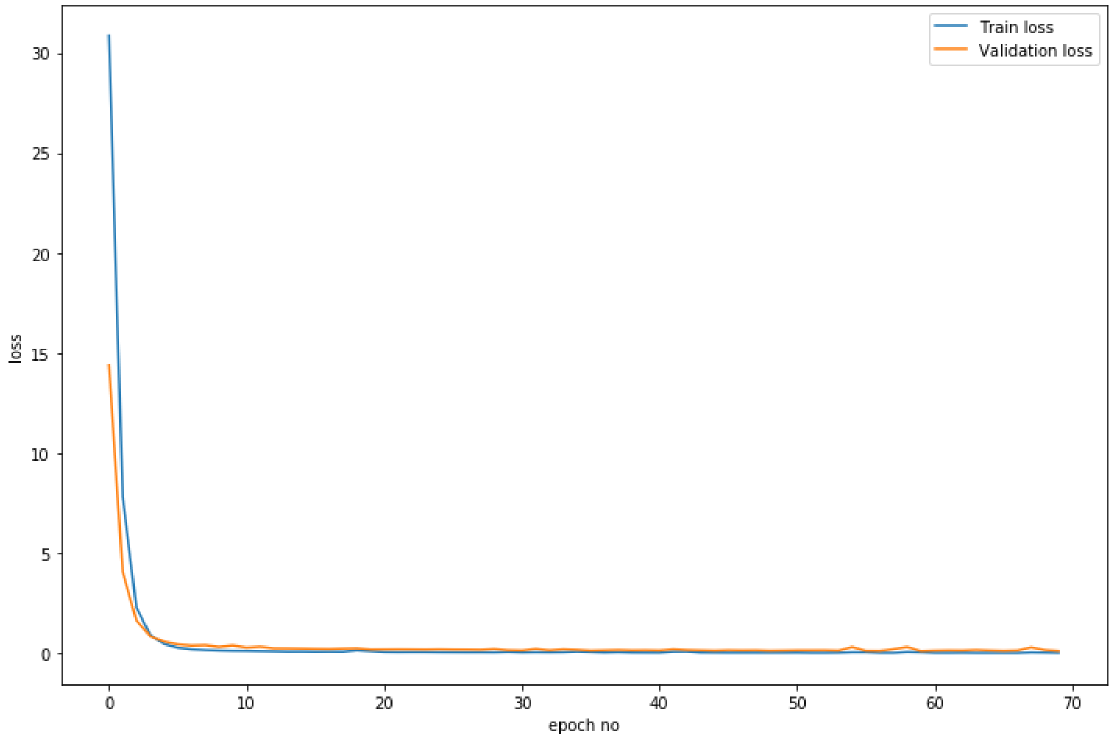
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 122, 32)           2048
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 116, 32)           7200
_________________________________________________________________
dropout_1 (Dropout)          (None, 116, 32)           0
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 23, 32)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 736)               0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                23584
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 99
=================================================================
Total params: 32,931
Trainable params: 32,931
Non-trainable params: 0
_________________________________________________________________
None
Train on 3285 samples, validate on 1387 samples
Epoch 1/70
3285/3285 [==============================] - 2s 597us/step - loss: 30.8432 - acc: 0.5963 - val_
Epoch 2/70
3285/3285 [==============================] - 1s 312us/step - loss: 7.8188 - acc: 0.9209 - val_l
Epoch 3/70
3285/3285 [==============================] - 1s 313us/step - loss: 2.3103 - acc: 0.9863 - val_l
Epoch 4/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.9391 - acc: 0.9875 - val_l
Epoch 5/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.4885 - acc: 0.9933 - val_l
Epoch 6/70
```

```
3285/3285 [==============================] - 1s 312us/step - loss: 0.3024 - acc: 0.9948 - val_
Epoch 7/70
3285/3285 [==============================] - 1s 313us/step - loss: 0.2201 - acc: 0.9954 - val_
Epoch 8/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.1842 - acc: 0.9942 - val_
Epoch 9/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.1602 - acc: 0.9967 - val_
Epoch 10/70
3285/3285 [==============================] - 1s 313us/step - loss: 0.1459 - acc: 0.9970 - val_
Epoch 11/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.1402 - acc: 0.9945 - val_
Epoch 12/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.1285 - acc: 0.9970 - val_
Epoch 13/70
3285/3285 [==============================] - 1s 317us/step - loss: 0.1155 - acc: 0.9985 - val_
Epoch 14/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.1013 - acc: 0.9997 - val_
Epoch 15/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.1029 - acc: 0.9967 - val_
Epoch 16/70
3285/3285 [==============================] - 1s 313us/step - loss: 0.0954 - acc: 0.9985 - val_
Epoch 17/70
3285/3285 [==============================] - 1s 313us/step - loss: 0.0997 - acc: 0.9960 - val_
Epoch 18/70
3285/3285 [==============================] - 1s 313us/step - loss: 0.0949 - acc: 0.9973 - val_
Epoch 19/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.1709 - acc: 0.9744 - val_
Epoch 20/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.1247 - acc: 0.9970 - val_
Epoch 21/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0822 - acc: 0.9994 - val_
Epoch 22/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.0757 - acc: 0.9994 - val_
Epoch 23/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0787 - acc: 0.9985 - val_
Epoch 24/70
3285/3285 [==============================] - 1s 315us/step - loss: 0.0778 - acc: 0.9985 - val_
Epoch 25/70
3285/3285 [==============================] - 1s 323us/step - loss: 0.0711 - acc: 0.9991 - val_
Epoch 26/70
3285/3285 [==============================] - 1s 314us/step - loss: 0.0691 - acc: 1.0000 - val_
Epoch 27/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.0662 - acc: 0.9997 - val_
Epoch 28/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0678 - acc: 0.9988 - val_
Epoch 29/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0651 - acc: 0.9988 - val_
Epoch 30/70
```

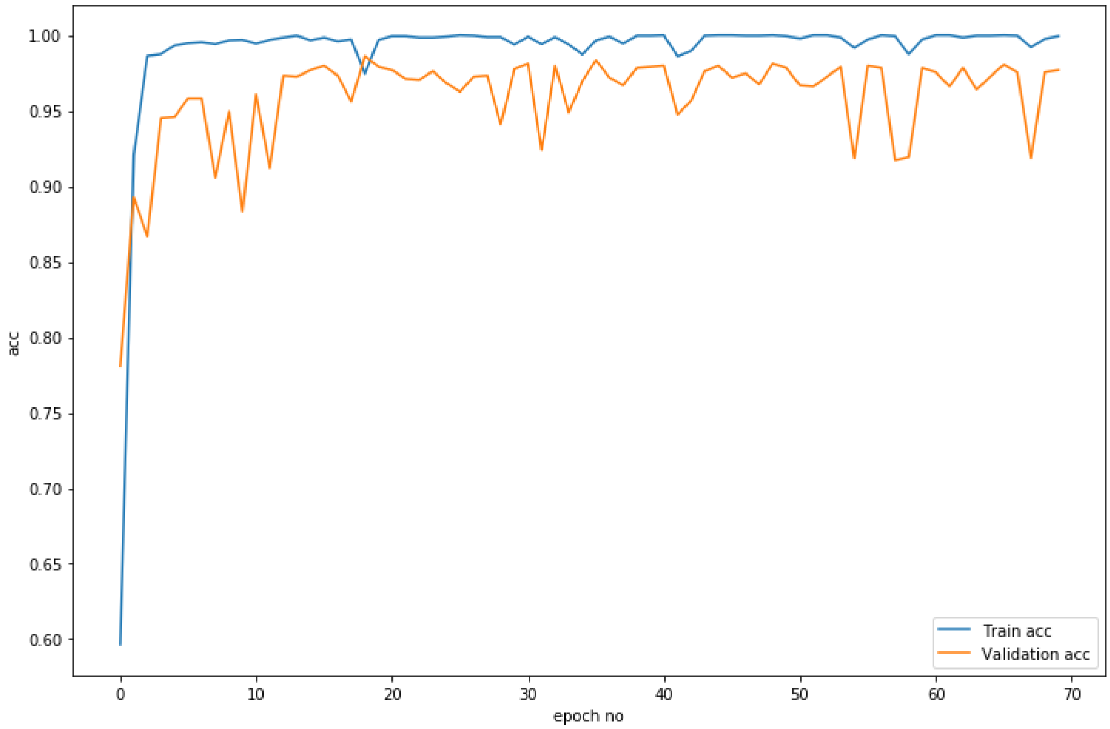
```
3285/3285 [==============================] - 1s 310us/step - loss: 0.0836 - acc: 0.9939 - val_
Epoch 31/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0618 - acc: 0.9991 - val_
Epoch 32/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0718 - acc: 0.9942 - val_
Epoch 33/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0659 - acc: 0.9988 - val_
Epoch 34/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0736 - acc: 0.9939 - val_
Epoch 35/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.1024 - acc: 0.9872 - val_
Epoch 36/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0790 - acc: 0.9967 - val_
Epoch 37/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0555 - acc: 0.9991 - val_
Epoch 38/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0731 - acc: 0.9945 - val_
Epoch 39/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0523 - acc: 0.9997 - val_
Epoch 40/70
3285/3285 [==============================] - 1s 313us/step - loss: 0.0496 - acc: 0.9997 - val_
Epoch 41/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.0468 - acc: 1.0000 - val_
Epoch 42/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.1016 - acc: 0.9860 - val_
Epoch 43/70
3285/3285 [==============================] - 1s 312us/step - loss: 0.1060 - acc: 0.9896 - val_
Epoch 44/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0531 - acc: 0.9997 - val_
Epoch 45/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0484 - acc: 1.0000 - val_
Epoch 46/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0448 - acc: 1.0000 - val_
Epoch 47/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0447 - acc: 0.9997 - val_
Epoch 48/70
3285/3285 [==============================] - 1s 309us/step - loss: 0.0443 - acc: 0.9997 - val_
Epoch 49/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0435 - acc: 1.0000 - val_
Epoch 50/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0445 - acc: 0.9994 - val_
Epoch 51/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0477 - acc: 0.9979 - val_
Epoch 52/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0388 - acc: 1.0000 - val_
Epoch 53/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0387 - acc: 1.0000 - val_
Epoch 54/70
```

```
3285/3285 [==============================] - 1s 311us/step - loss: 0.0454 - acc: 0.9985 - val_l
Epoch 55/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0723 - acc: 0.9918 - val_l
Epoch 56/70
3285/3285 [==============================] - 1s 309us/step - loss: 0.0712 - acc: 0.9973 - val_l
Epoch 57/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0404 - acc: 1.0000 - val_l
Epoch 58/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0399 - acc: 0.9994 - val_l
Epoch 59/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0866 - acc: 0.9875 - val_l
Epoch 60/70
3285/3285 [==============================] - 1s 308us/step - loss: 0.0687 - acc: 0.9973 - val_l
Epoch 61/70
3285/3285 [==============================] - 1s 309us/step - loss: 0.0385 - acc: 1.0000 - val_l
Epoch 62/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0370 - acc: 1.0000 - val_l
Epoch 63/70
3285/3285 [==============================] - 1s 309us/step - loss: 0.0416 - acc: 0.9985 - val_l
Epoch 64/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0354 - acc: 0.9997 - val_l
Epoch 65/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0348 - acc: 0.9997 - val_l
Epoch 66/70
3285/3285 [==============================] - 1s 309us/step - loss: 0.0340 - acc: 1.0000 - val_l
Epoch 67/70
3285/3285 [==============================] - 1s 309us/step - loss: 0.0327 - acc: 0.9997 - val_l
Epoch 68/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0624 - acc: 0.9921 - val_l
Epoch 69/70
3285/3285 [==============================] - 1s 310us/step - loss: 0.0514 - acc: 0.9976 - val_l
Epoch 70/70
3285/3285 [==============================] - 1s 311us/step - loss: 0.0376 - acc: 0.9994 - val_l
```

In [64]:
```
plt.figure(figsize=(12,8))
plt.plot(result.history['loss'],label='Train loss')
plt.plot(result.history['val_loss'],label = 'Validation loss')
plt.xlabel('epoch no')
plt.ylabel('loss')
plt.legend()
plt.show()
```




```
In [65]: plt.figure(figsize=(12,8))
         plt.plot(result.history['acc'],label='Train acc')
         plt.plot(result.history['val_acc'],label = 'Validation acc')
         plt.xlabel('epoch no')
         plt.ylabel('acc')
         plt.legend()
         plt.show()
```




```
In [45]: ##upto 19 epoces will give good score
         K.clear_session()
         M59['nb_epoch'] = 19
         best_model,result = model_hyperas(M59)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 122, 32)           2048
_________________________________________________________________
conv1d_2 (Conv1D)            (None, 116, 32)           7200
_________________________________________________________________
dropout_1 (Dropout)          (None, 116, 32)           0
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 23, 32)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 736)               0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                23584
_________________________________________________________________
dense_2 (Dense)              (None, 3)                 99
=================================================================
Total params: 32,931
Trainable params: 32,931
```

```
Non-trainable params: 0
_________________________________________________________________
None
Train on 3285 samples, validate on 1387 samples
Epoch 1/19
3285/3285 [==============================] - 2s 587us/step - loss: 30.8432 - acc: 0.5963 - val_
Epoch 2/19
3285/3285 [==============================] - 1s 311us/step - loss: 7.8188 - acc: 0.9209 - val_
Epoch 3/19
3285/3285 [==============================] - 1s 312us/step - loss: 2.3103 - acc: 0.9863 - val_
Epoch 4/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.9391 - acc: 0.9875 - val_
Epoch 5/19
3285/3285 [==============================] - 1s 311us/step - loss: 0.4885 - acc: 0.9933 - val_
Epoch 6/19
3285/3285 [==============================] - 1s 311us/step - loss: 0.3024 - acc: 0.9948 - val_
Epoch 7/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.2201 - acc: 0.9954 - val_
Epoch 8/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1842 - acc: 0.9942 - val_
Epoch 9/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.1602 - acc: 0.9967 - val_
Epoch 10/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1459 - acc: 0.9970 - val_
Epoch 11/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1402 - acc: 0.9945 - val_
Epoch 12/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.1285 - acc: 0.9970 - val_
Epoch 13/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1155 - acc: 0.9985 - val_
Epoch 14/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.1013 - acc: 0.9997 - val_
Epoch 15/19
3285/3285 [==============================] - 1s 315us/step - loss: 0.1029 - acc: 0.9967 - val_
Epoch 16/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.0954 - acc: 0.9985 - val_
Epoch 17/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.0997 - acc: 0.9960 - val_
Epoch 18/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.0949 - acc: 0.9973 - val_
Epoch 19/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.1709 - acc: 0.9744 - val_
```

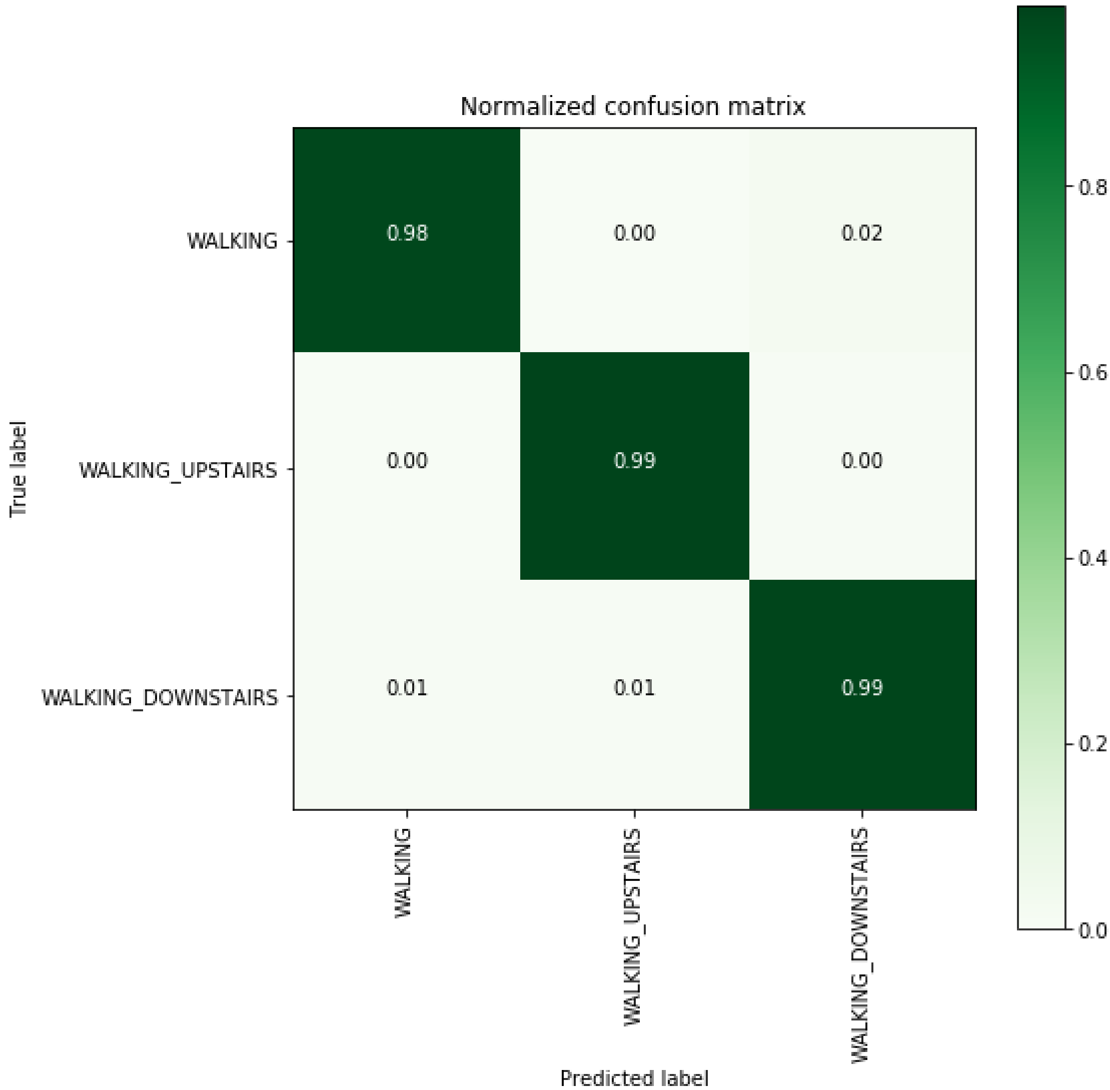
In [49]:
```
from sklearn import metrics
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
```

```python
        2: 'WALKING_DOWNSTAIRS',
    }

    # Utility function to print the confusion matrix
    def confusion_matrix_cnn(Y_true, Y_pred):
        Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1)])
        Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])

        #return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])
        return metrics.confusion_matrix(Y_true, Y_pred)

    # Confusion Matrix
    print(confusion_matrix_cnn(Y_val_d, best_model.predict(X_val_d)))
```

```
[[486   0  10]
 [  1 417   2]
 [  3   3 465]]
```

```python
In [57]: plt.figure(figsize=(8,8))
         cm = confusion_matrix_cnn(Y_val_d, best_model.predict(X_val_d))
         plot_confusion_matrix(cm, classes=['WALKING','WALKING_UPSTAIRS','WALKING_DOWNSTAIRS']
                               normalize=True, title='Normalized confusion matrix', cmap = plt
         plt.show()
```

```
<matplotlib.figure.Figure at 0x147481785470>
```



it is also giving good scores than previous

```
In [58]: #saving model
         best_model.save('final_model_dynamic.h5')
```

```
In [154]: def data():
              """
              Obtain the dataset from multiple files.
              Returns: X_train, X_test, y_train, y_test
              """
              # Data directory
              DATADIR = 'UCI_HAR_Dataset'
              # Raw data signals
              # Signals are from Accelerometer and Gyroscope
```

```
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
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"
    ]
# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}
        signals_data.append( _read_csv(filename).as_matrix())

    # 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
    return np.transpose(signals_data, (1, 2, 0))

def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.h
    """
    filename = f'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    return y

X_train, X_val = load_signals('train'), load_signals('test')
Y_train, Y_val = load_y('train'), load_y('test')

return X_train, Y_train, X_val,  Y_val
```

In [155]: `X_train, Y_train, X_val,  Y_val = data()`

In [167]: `print('shape of test Y',Y_val.shape)`

```
shape of test Y (2947,)
```

13.3.4 Final prediction pipeline

In [159]:
```
##loading keras models and picle files for scaling data
from keras.models import load_model
import pickle
model_2class = load_model('final_model_2class.h5')
model_dynamic = load_model('final_model_dynamic.h5')
model_static = load_model('final_model_static.h5')
scale_2class = pickle.load(open('Scale_2class.p','rb'))
scale_static = pickle.load(open('Scale_static.p','rb'))
scale_dynamic = pickle.load(open('Scale_dynamic.p','rb'))
```

In [162]:
```
##scaling the data
def transform_data(X,scale):
    X_temp = X.reshape((X.shape[0] * X.shape[1], X.shape[2]))
    X_temp = scale.transform(X_temp)
    return X_temp.reshape(X.shape)
```

In [169]:
```
#predicting output activity
def predict_activity(X):
    ##predicting whether dynamic or static
    predict_2class = model_2class.predict(transform_data(X,scale_2class))
    Y_pred_2class =  np.argmax(predict_2class, axis=1)
    #static data filter
    X_static = X[Y_pred_2class==1]
    #dynamic data filter
    X_dynamic = X[Y_pred_2class==0]
    #predicting static activities
    predict_static = model_static.predict(transform_data(X_static,scale_static))
    predict_static = np.argmax(predict_static,axis=1)
    #adding 4 because need to get inal prediction lable as output
    predict_static = predict_static + 4
    #predicting dynamic activites
    predict_dynamic = model_dynamic.predict(transform_data(X_dynamic,scale_dynamic))
    predict_dynamic = np.argmax(predict_dynamic,axis=1)
    #adding 1 because need to get inal prediction lable as output
    predict_dynamic = predict_dynamic + 1
    ##appending final output to one list in the same sequence of input data
    i,j = 0,0
    final_pred = []
    for mask in Y_pred_2class:
        if mask == 1:
```

```
                final_pred.append(predict_static[i])
                i = i + 1
            else:
                final_pred.append(predict_dynamic[j])
                j = j + 1
        return final_pred
```

In [170]:
```
##predicting
final_pred_val = predict_activity(X_val)
final_pred_train = predict_activity(X_train)
```

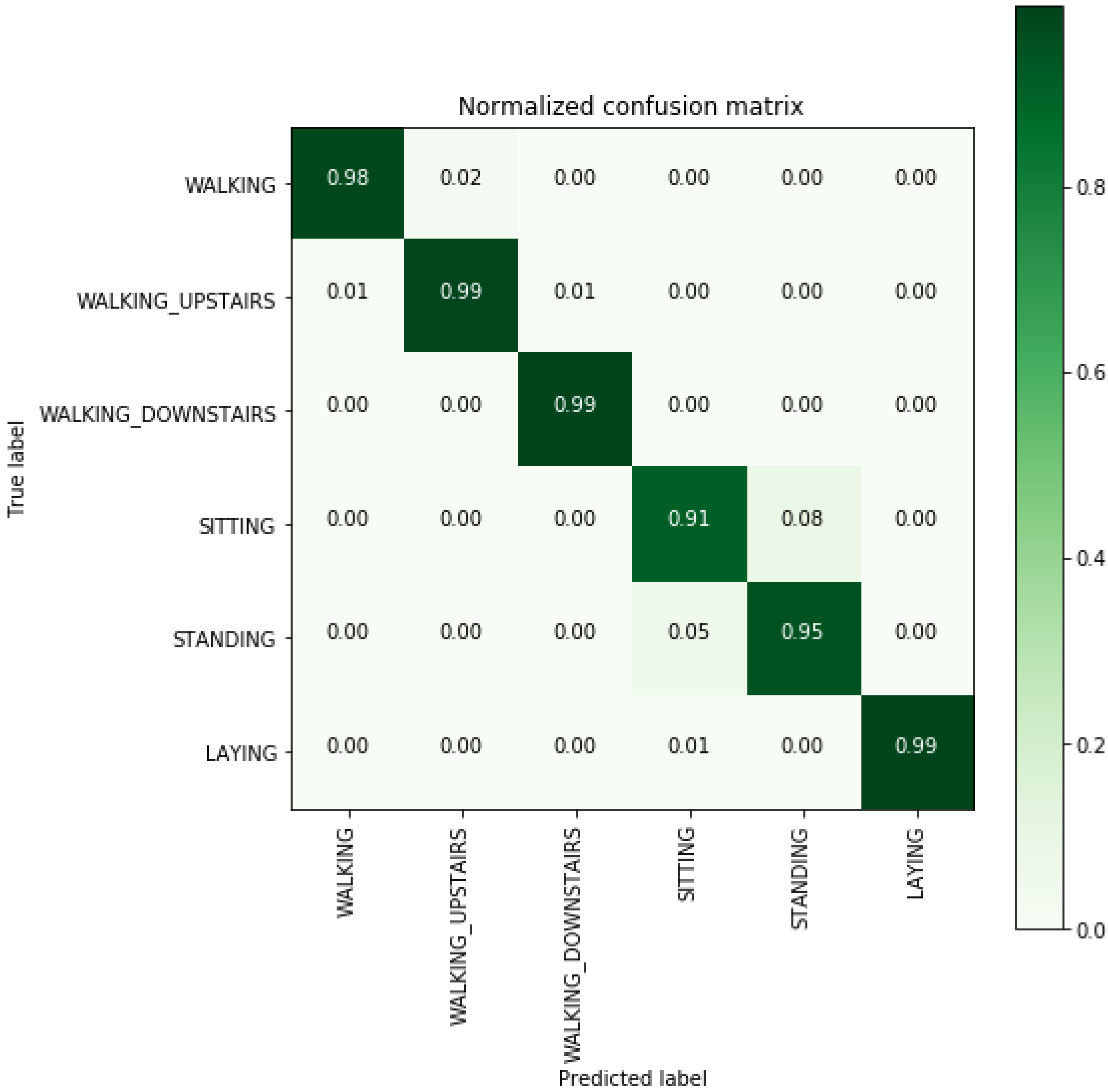
In [173]:
```
##accuracy of train and test
from sklearn.metrics import accuracy_score
print('Accuracy of train data',accuracy_score(Y_train,final_pred_train))
print('Accuracy of validation data',accuracy_score(Y_val,final_pred_val))
```

```
Accuracy of train data 0.9832698585418934
Accuracy of validation data 0.9684424838819138
```

In [182]:
```
#confusion metric
cm = metrics.confusion_matrix(Y_val, final_pred_val,labels=range(1,7))
cm
```

Out[182]:
```
array([[486,  10,   0,   0,   0,   0],
       [  3, 465,   3,   0,   0,   0],
       [  1,   2, 417,   0,   0,   0],
       [  1,   2,   0, 447,  41,   0],
       [  0,   0,   0,  27, 505,   0],
       [  0,   0,   0,   3,   0, 534]])
```

In [184]:
```
plt.figure(figsize=(8,8))
labels=['WALKING','WALKING_UPSTAIRS','WALKING_DOWNSTAIRS','SITTING','STANDING','LAYI
plot_confusion_matrix(cm, classes=labels,
                      normalize=True, title='Normalized confusion matrix', cmap = pl
plt.show()
```



Divide and Conquer approch with CNN is giving good result with final test accuracy of ~0.97. and train accuracy ~0.98.