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.

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.

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

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**

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***

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'

Data Size :

> 27 MB

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.

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.

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
```

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, header=No

# add subject column to the dataframe
X_train['subject'] = pd.read_csv('UCI_HAR_Dataset/train/subject_train.txt', header=None, sc

y_train = pd.read_csv('UCI_HAR_Dataset/train/y_train.txt', names=['Activity'], squeeze=True
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	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyA mad
6212	0.380322	-0.009925	-0.172745	0.125378	-0.160388	-0.04863	0.076071	-0.115

1 rows × 564 columns

In [13]:

```
train.shape
```

Out[13]:

```
(7352, 564)
```

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=None,

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

# get y labels from the txt file
y_test = pd.read_csv('UCI_HAR_Dataset/test/y_test.txt', names=['Activity'], squeeze=True)
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	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyA mad
2376	0.142909	-0.022732	-0.077417	-0.300135	-0.087465	-0.268216	-0.379653	-0.077

1 rows × 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),gravityMea
n)',
       'angle(tBodyGyroMean,gravityMean)',
       'angle(tBodyGyroJerkMean,gravityMean)', 'angle(X,gravityMean)',
       'angle(Y,gravityMean)', 'angle(Z,gravityMean)', 'subject', 'Activit
y',
       'ActivityName'],
      dtype='object', length=564)
```

Data Cleaning

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
```

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
```

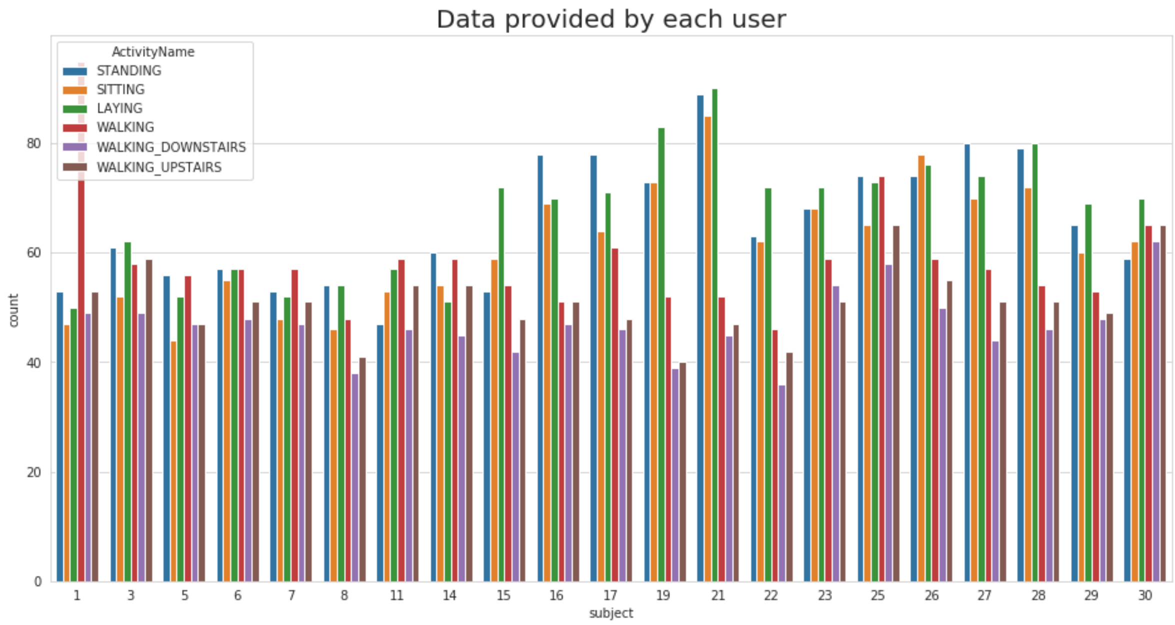
3. Check for data imbalance

In [20]:

```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('whitegrid')
```

In [21]:

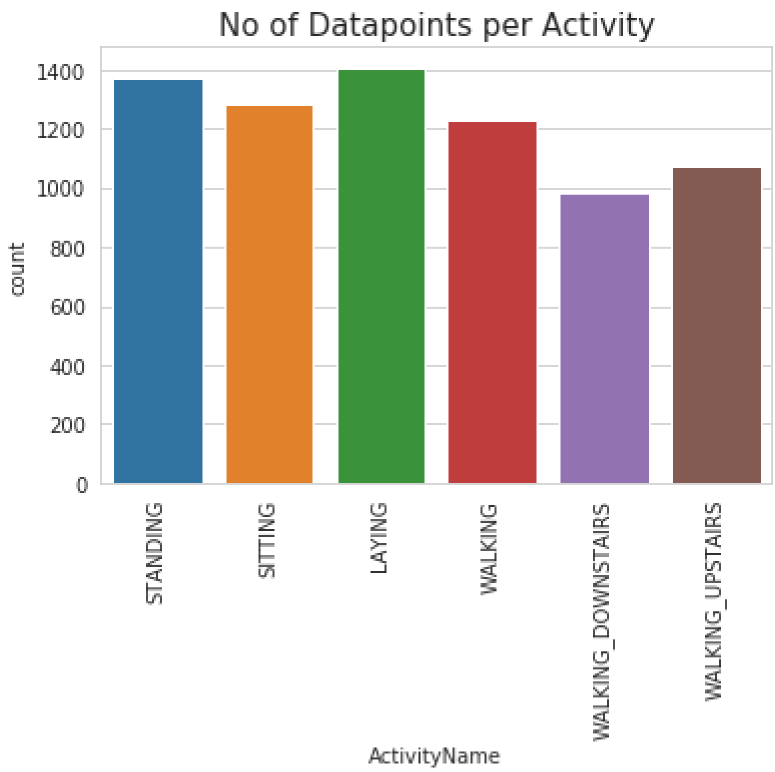
```
plt.figure(figsize=(16,8))
plt.title('Data provided by each user', fontsize=20)
sns.countplot(x='subject',hue='ActivityName', data = train)
plt.show()
```



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()
```



Observation

> Our data is well balanced (almost)

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)
```

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)
```

Exploratory Data Analysis

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

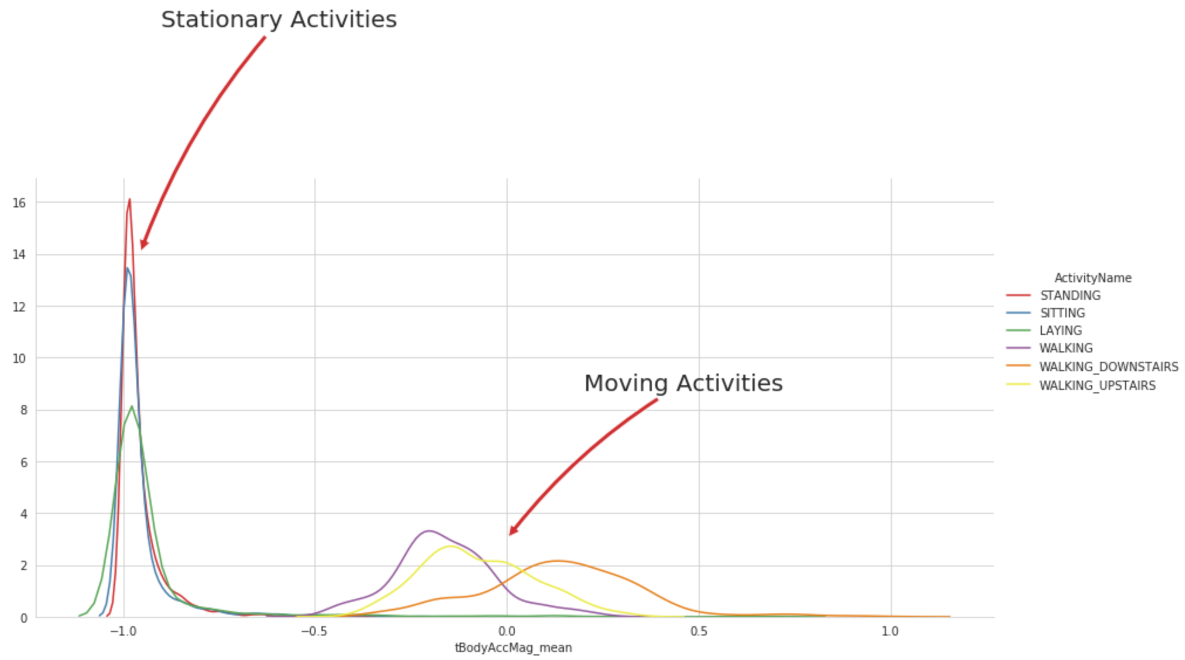
1. Featuring Engineering from Domain Knowledge

- **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.

2. Stationary and Moving activities are completely different

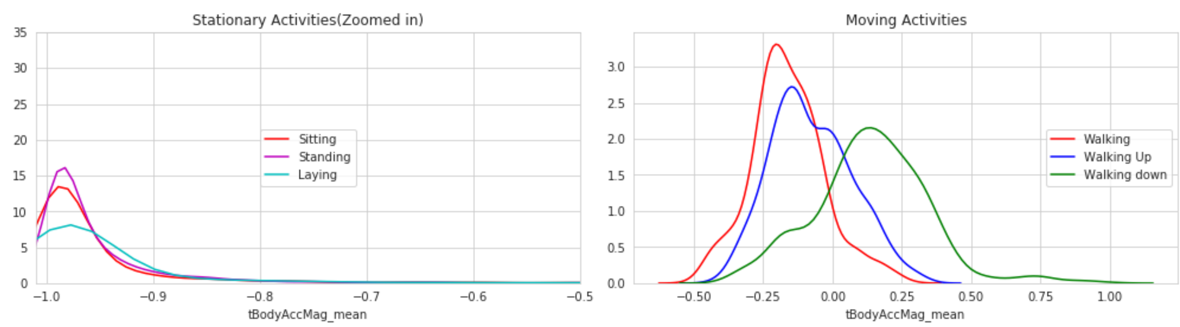
In [36]:

```
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 down')
plt.legend(loc='center right')


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

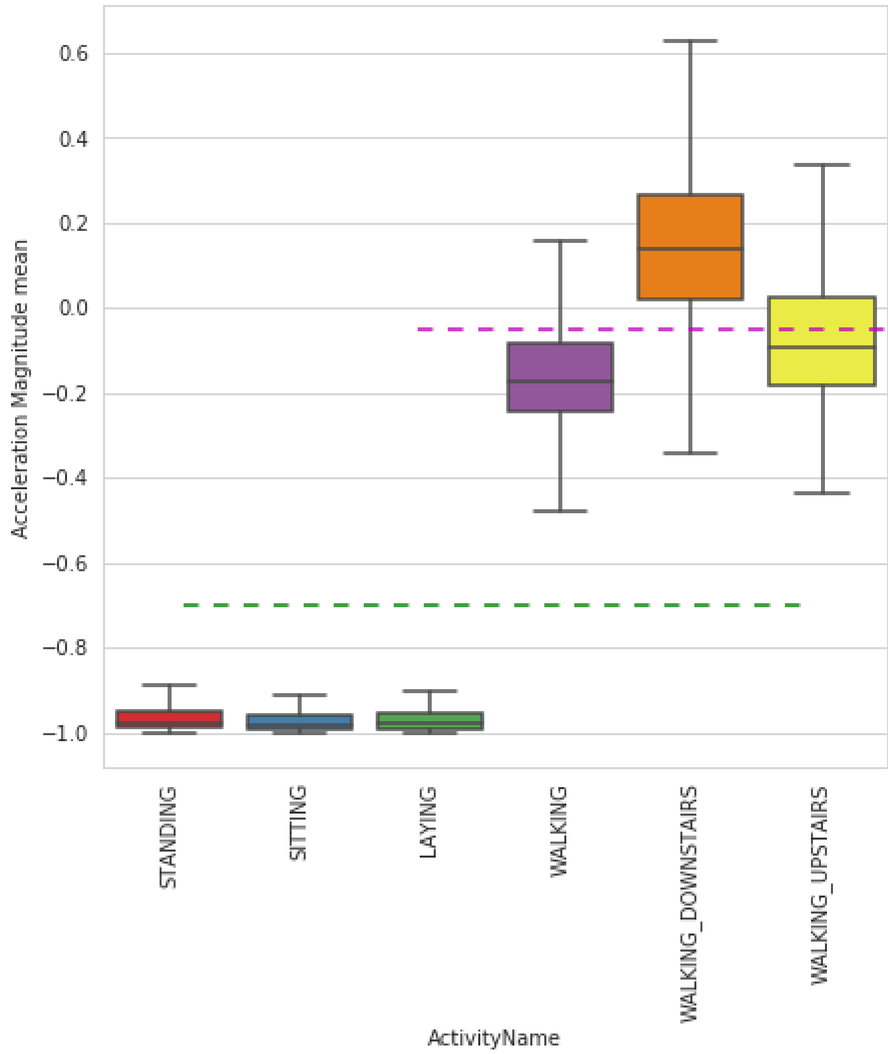


3. Magnitude of an acceleration can saperate it well

In [41]:

```
plt.figure(figsize=(7,7))
sns.boxplot(x='ActivityName', y='tBodyAccMag_mean',data=train, showfliers=False, saturatior
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>



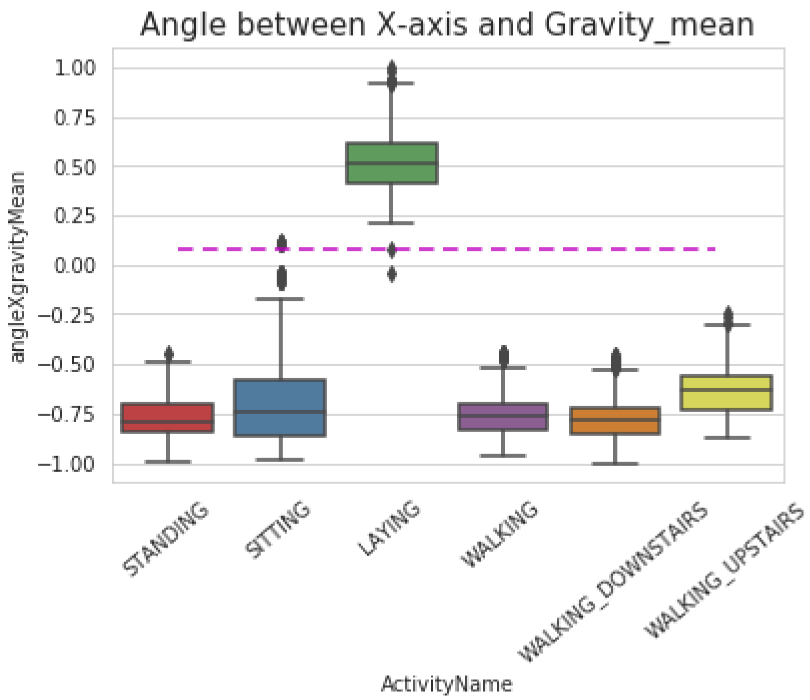
__ Observations__:

- 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. 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()
```

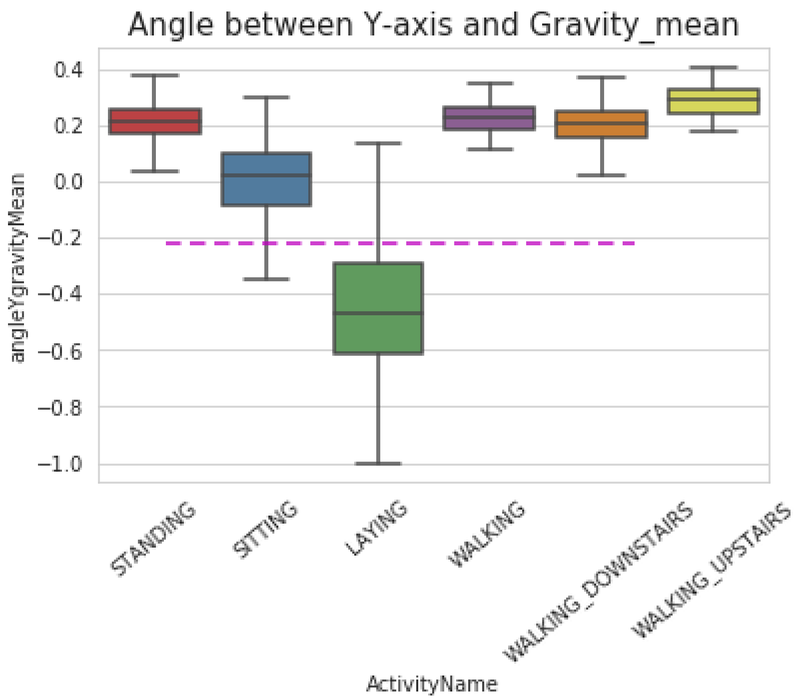


__ Observations__:

- 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()
```



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'.format(p
        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])
```

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=2000)
```

```
erations in 11.058s)
[t-SNE] Iteration 700: error = 1.1939315, gradient norm = 0.0000586 (50 it
erations in 11.072s)
[t-SNE] Iteration 750: error = 1.1858423, gradient norm = 0.0000530 (50 it
erations in 11.082s)
[t-SNE] Iteration 800: error = 1.1796997, gradient norm = 0.0000490 (50 it
erations in 11.086s)
[t-SNE] Iteration 850: error = 1.1750507, gradient norm = 0.0000472 (50 it
erations in 11.079s)
[t-SNE] Iteration 900: error = 1.1714048, gradient norm = 0.0000439 (50 it
erations in 11.071s)
[t-SNE] Iteration 950: error = 1.1685311, gradient norm = 0.0000415 (50 it
erations in 11.069s)
[t-SNE] Iteration 1000: error = 1.1659497, gradient norm = 0.0000405 (50 i
terations 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...
```

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	tBodyAcc_std_Y
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111

1 rows × 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,))
```

Let's model with our data

Labels that are useful in plotting confusion matrix

In [43]:

```
labels=['LAYING', 'SITTING','STANDING','WALKING','WALKING_DOWNSTAIRS','WALKING_UPSTAIRS']
```

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')
```

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=True,
                 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 confu
    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
```

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 GridSearch
    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(model.b
```

1. Logistic Regression with Grid Search

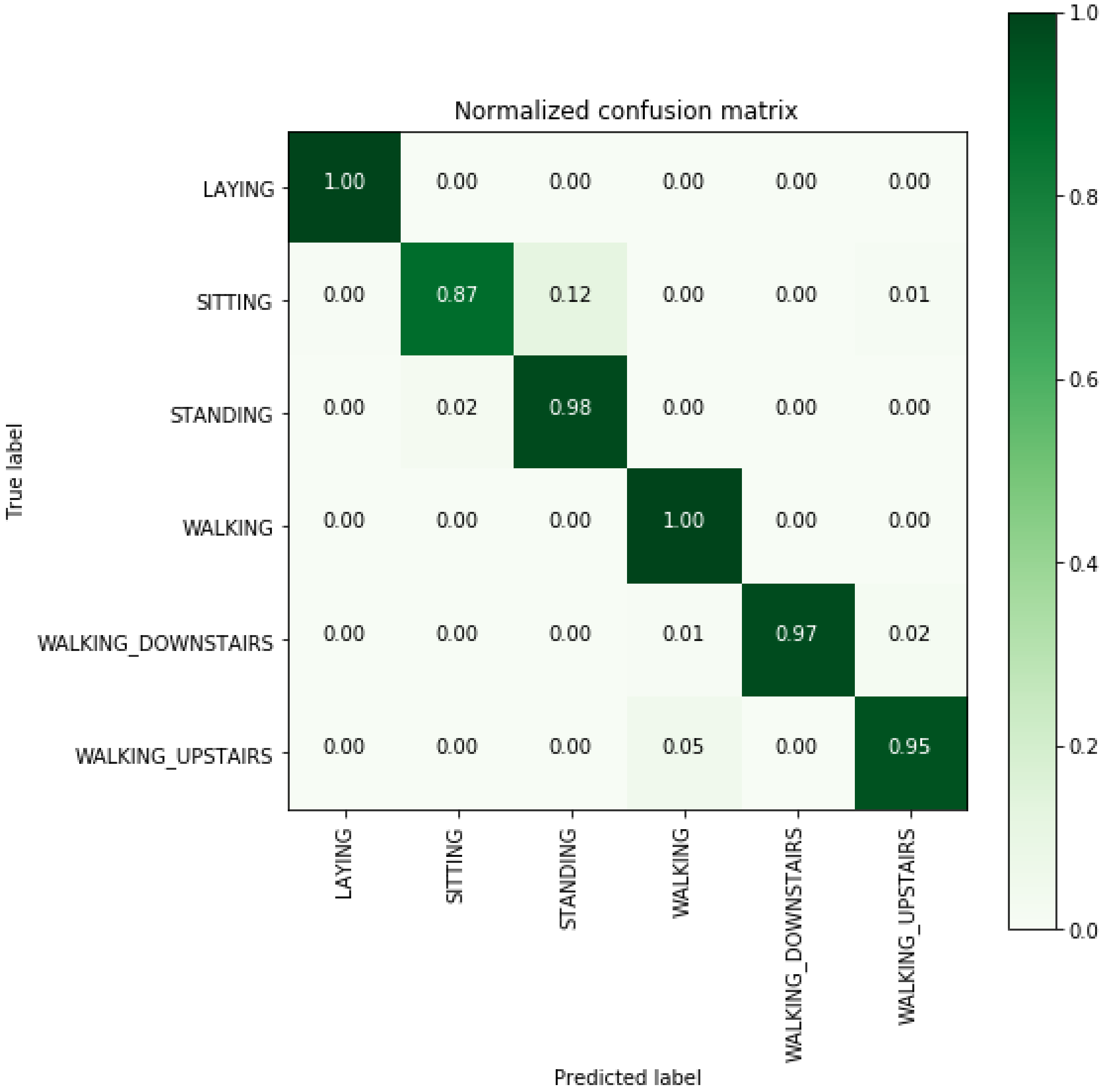
In [11]:

```
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, class
```

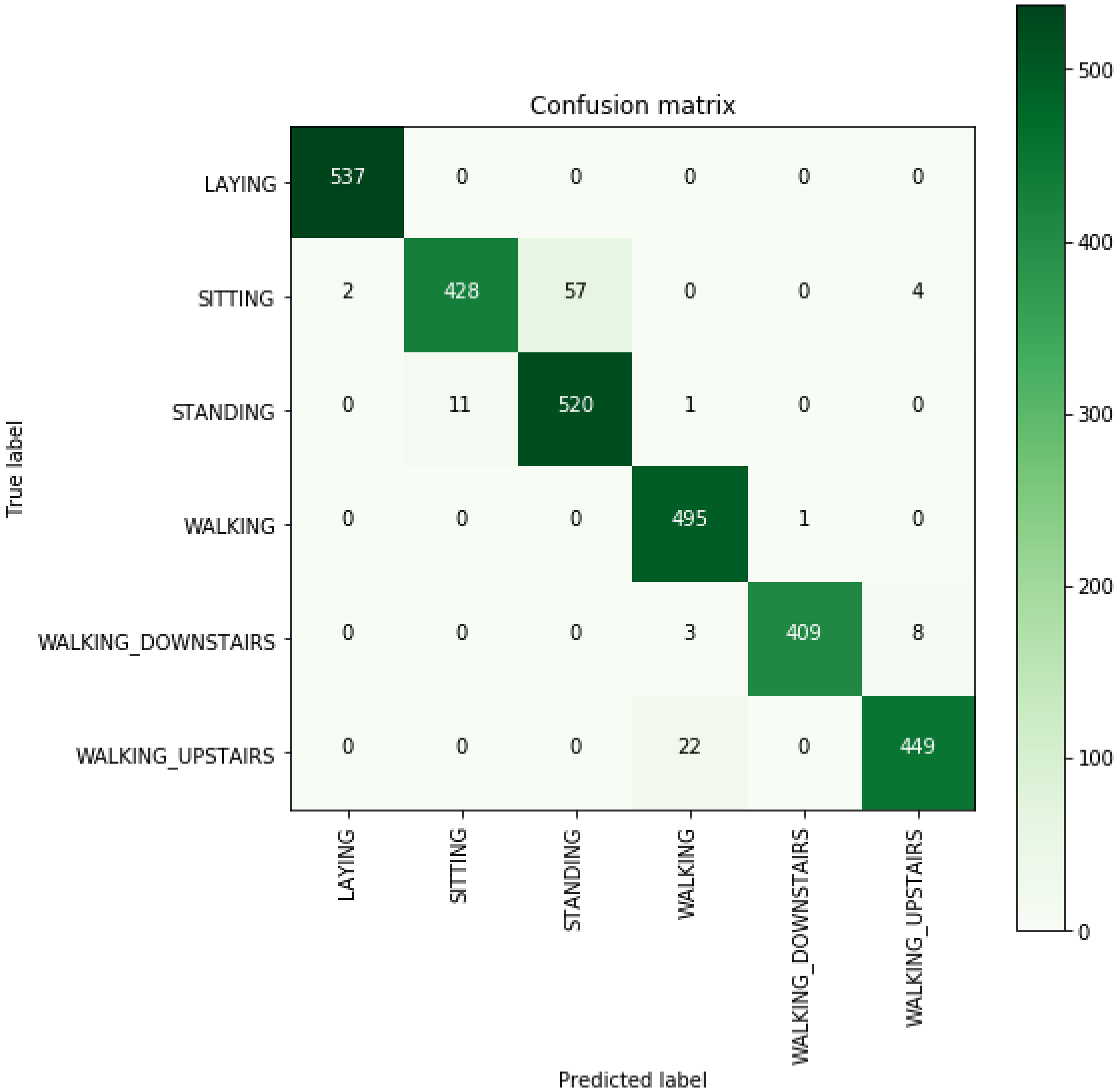
```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits

[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=plt.cm
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_intercep
t=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
```

2. Linear SVC with GridSearch

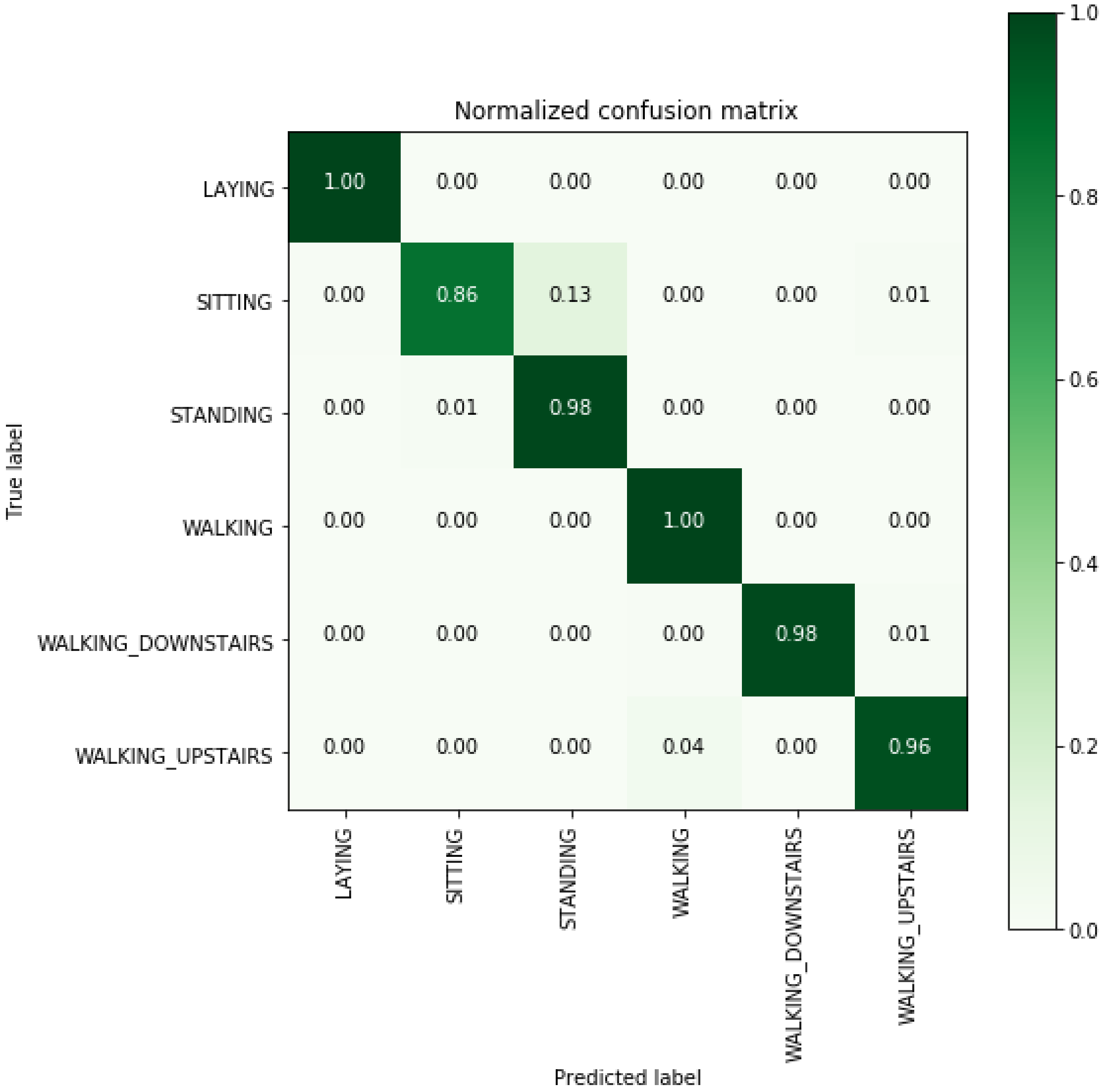
In [15]:

```
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, class_la
```

```
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
```

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, class_
```

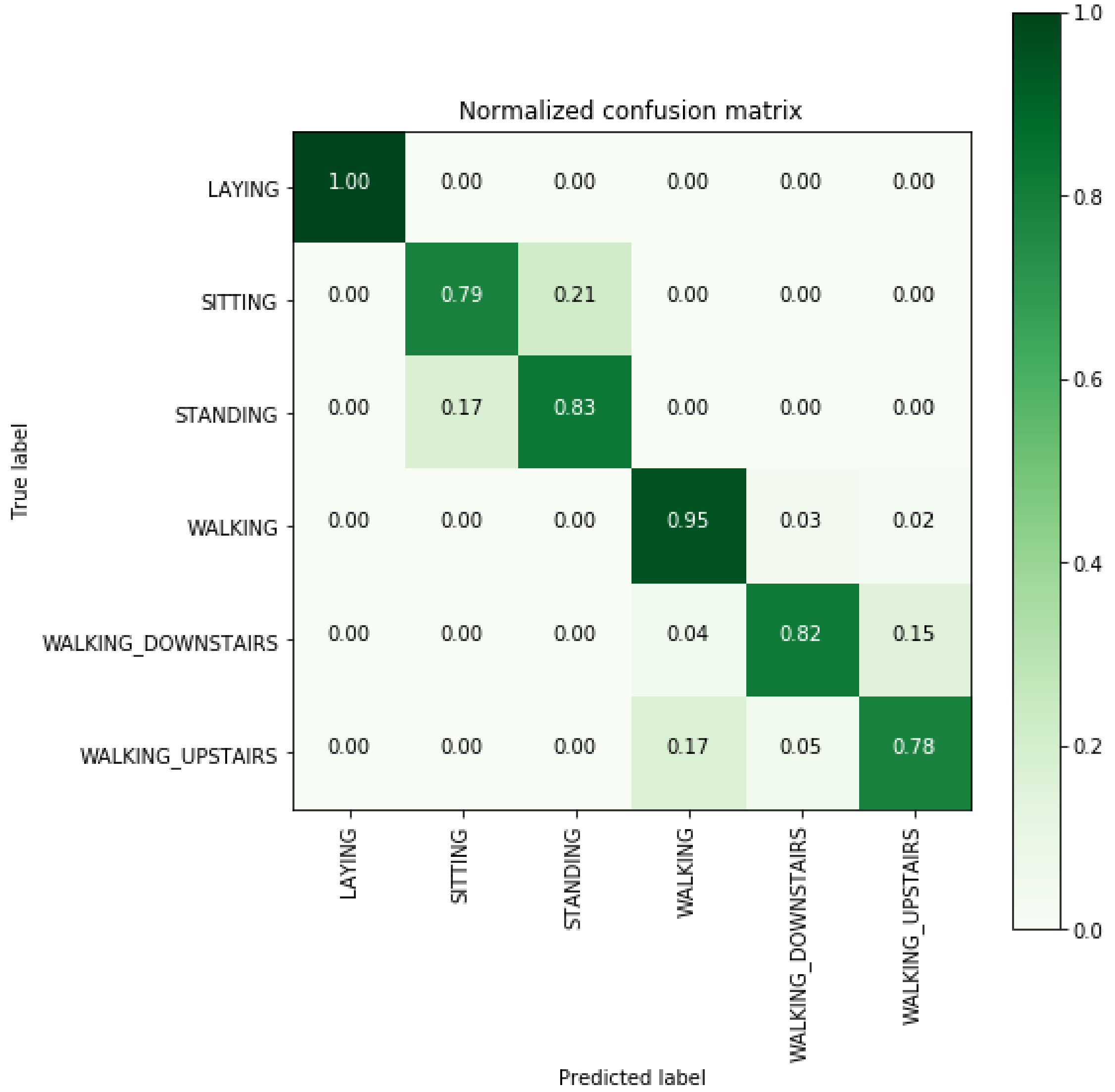
```
training the model..
Done


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
```

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_labels=lab
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_dept
h=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
```

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_labels=l
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
```

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_labels
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
```

7. Comparing all models

In [22]:

```
print('\n                      Accuracy     Error')
print('                     ----------   --------')
print('Logistic Regression : {:.04}%       {:.04}%'.format(log_reg_grid_results['accuracy']
                                                  100-(log_reg_grid_results['accuracy'] * 1

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

print('rbf SVM classifier  : {:.04}%      {:.04}% '.format(rbf_svm_grid_results['accuracy']
                                                          100-(rbf_svm_grid_results['accura

print('DecisionTree        : {:.04}%      {:.04}% '.format(dt_grid_results['accuracy'] * 10
                                                        100-(dt_grid_results['accuracy'] *

print('Random Forest       : {:.04}%      {:.04}% '.format(rfc_grid_results['accuracy'] * 1
                                                           100-(rfc_grid_results['accuracy'
print('GradientBoosting DT : {:.04}%      {:.04}% '.format(rfc_grid_results['accuracy'] * 1
                                                        100-(rfc_grid_results['accuracy'] *
```

```
                      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%
```

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.

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 - a
cc: 0.4376 - val_loss: 1.1805 - val_acc: 0.4496
Epoch 2/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.9842 - a
cc: 0.5749 - val_loss: 0.9447 - val_acc: 0.5857
Epoch 3/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.7991 - a
cc: 0.6470 - val_loss: 0.7865 - val_acc: 0.6132
Epoch 4/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.6984 - a
cc: 0.6661 - val_loss: 0.8261 - val_acc: 0.5901
Epoch 5/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.6306 - a
cc: 0.6876 - val_loss: 0.7671 - val_acc: 0.6434
Epoch 6/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.6168 - a
cc: 0.7084 - val_loss: 0.8407 - val_acc: 0.6590
Epoch 7/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.6056 - a
cc: 0.7361 - val_loss: 0.6495 - val_acc: 0.7248
Epoch 8/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.5260 - a
cc: 0.7719 - val_loss: 0.6340 - val_acc: 0.7265
Epoch 9/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.4605 - a
cc: 0.7900 - val_loss: 0.6768 - val_acc: 0.7296
Epoch 10/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.4405 - a
cc: 0.7999 - val_loss: 0.5573 - val_acc: 0.7530
Epoch 11/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.4180 - a
cc: 0.8013 - val_loss: 0.5859 - val_acc: 0.7201
Epoch 12/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.4083 - a
cc: 0.8198 - val_loss: 0.5773 - val_acc: 0.7625
Epoch 13/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.3706 - a
cc: 0.8560 - val_loss: 0.6319 - val_acc: 0.8504
Epoch 14/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.3456 - a
cc: 0.8832 - val_loss: 0.4920 - val_acc: 0.8717
Epoch 15/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2947 - a
cc: 0.9135 - val_loss: 0.6581 - val_acc: 0.8554
Epoch 16/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.3015 - a
cc: 0.9159 - val_loss: 0.4791 - val_acc: 0.8833
Epoch 17/30
7352/7352 [==============================] - 52s 7ms/step - loss: 0.2472 - a
```

```
cc: 0.9317 - val_loss: 0.5137 - val_acc: 0.8785
Epoch 18/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2784 - a
cc: 0.9271 - val_loss: 0.7416 - val_acc: 0.8364
Epoch 19/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2505 - a
cc: 0.9306 - val_loss: 0.4745 - val_acc: 0.8894
Epoch 20/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2093 - a
cc: 0.9344 - val_loss: 0.5829 - val_acc: 0.8775
Epoch 21/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2218 - a
cc: 0.9370 - val_loss: 0.4609 - val_acc: 0.8931
Epoch 22/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1966 - a
cc: 0.9414 - val_loss: 0.4116 - val_acc: 0.9046
Epoch 23/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1827 - a
cc: 0.9403 - val_loss: 0.4737 - val_acc: 0.8979
Epoch 24/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1801 - a
cc: 0.9393 - val_loss: 0.6009 - val_acc: 0.8860
Epoch 25/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1896 - a
cc: 0.9433 - val_loss: 0.4729 - val_acc: 0.9063
Epoch 26/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2555 - a
cc: 0.9334 - val_loss: 0.4608 - val_acc: 0.9070
Epoch 27/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1791 - a
cc: 0.9434 - val_loss: 0.4300 - val_acc: 0.9080
Epoch 28/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2444 - a
cc: 0.9339 - val_loss: 0.4088 - val_acc: 0.9101
Epoch 29/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1938 - a
cc: 0.9393 - val_loss: 0.4978 - val_acc: 0.9050
Epoch 30/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1598 - a
cc: 0.9450 - val_loss: 0.4559 - val_acc: 0.9013
```

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_loss: 0.9680 - val_acc: 0.5409
Epoch 2/30
7352/7352 [==============================] - 107s 15ms/step - loss: 0.8821 -
acc: 0.6051 - val_loss: 0.8140 - val_acc: 0.6284
Epoch 3/30
7352/7352 [==============================] - 106s 14ms/step - loss: 0.7624 -
acc: 0.6359 - val_loss: 0.8088 - val_acc: 0.6037
Epoch 4/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.7258 -
acc: 0.6302 - val_loss: 0.7932 - val_acc: 0.6189
Epoch 5/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.7122 -
acc: 0.6474 - val_loss: 0.7969 - val_acc: 0.6189
Epoch 6/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.6977 -
acc: 0.6515 - val_loss: 0.7787 - val_acc: 0.6152
Epoch 7/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.6750 -
acc: 0.6790 - val_loss: 0.7335 - val_acc: 0.6793
Epoch 8/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.6167 -
acc: 0.7329 - val_loss: 0.7110 - val_acc: 0.6990
Epoch 9/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.5178 -
acc: 0.7889 - val_loss: 0.6528 - val_acc: 0.7357
Epoch 10/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.4557 -
acc: 0.8215 - val_loss: 0.5696 - val_acc: 0.8521
Epoch 11/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.4006 -
acc: 0.8554 - val_loss: 0.7078 - val_acc: 0.8093
Epoch 12/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.3518 -
acc: 0.8936 - val_loss: 0.4328 - val_acc: 0.8884
Epoch 13/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2959 -
acc: 0.9102 - val_loss: 0.5183 - val_acc: 0.8595
Epoch 14/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.2716 -
acc: 0.9240 - val_loss: 0.5887 - val_acc: 0.8568
Epoch 15/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.2532 -
acc: 0.9223 - val_loss: 0.4996 - val_acc: 0.8887
Epoch 16/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2409 -
acc: 0.9295 - val_loss: 0.4287 - val_acc: 0.8992
Epoch 17/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2296 -
```

```
acc: 0.9342 - val_loss: 0.4177 - val_acc: 0.8931
Epoch 18/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2039 -
acc: 0.9377 - val_loss: 0.5764 - val_acc: 0.8962
Epoch 19/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2141 -
acc: 0.9331 - val_loss: 0.4349 - val_acc: 0.9080
Epoch 20/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.2001 -
acc: 0.9382 - val_loss: 0.5034 - val_acc: 0.8914
Epoch 21/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1917 -
acc: 0.9348 - val_loss: 0.4654 - val_acc: 0.9108
Epoch 22/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1970 -
acc: 0.9362 - val_loss: 0.4669 - val_acc: 0.8989
Epoch 23/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1801 -
acc: 0.9425 - val_loss: 0.5325 - val_acc: 0.8928
Epoch 24/30
7352/7352 [==============================] - 106s 14ms/step - loss: 0.1680 -
acc: 0.9446 - val_loss: 0.5077 - val_acc: 0.9030
Epoch 25/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1835 -
acc: 0.9418 - val_loss: 0.5613 - val_acc: 0.9067
Epoch 26/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1692 -
acc: 0.9449 - val_loss: 0.4361 - val_acc: 0.9148
Epoch 27/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1722 -
acc: 0.9421 - val_loss: 0.6196 - val_acc: 0.8985
Epoch 28/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.1739 -
acc: 0.9434 - val_loss: 0.4876 - val_acc: 0.9131
Epoch 29/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1833 -
acc: 0.9421 - val_loss: 0.6746 - val_acc: 0.8999
Epoch 30/30
7352/7352 [==============================] - 105s 14ms/step - loss: 0.1730 -
acc: 0.9431 - val_loss: 0.4763 - val_acc: 0.9084
```

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]:

```python
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=(timest
# 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_loss: 1.2625 - val_acc: 0.5175
Epoch 2/10
7352/7352 [==============================] - 105s 14ms/step - loss: 1.2066 -
acc: 0.5011 - val_loss: 1.5878 - val_acc: 0.3549
Epoch 3/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.9923 -
acc: 0.5695 - val_loss: 0.9060 - val_acc: 0.6162
Epoch 4/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.9109 -
acc: 0.5839 - val_loss: 0.8547 - val_acc: 0.5962
Epoch 5/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7995 -
acc: 0.6223 - val_loss: 0.7806 - val_acc: 0.6176
Epoch 6/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.8123 -
acc: 0.6062 - val_loss: 0.8927 - val_acc: 0.5887
Epoch 7/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7574 -
acc: 0.6319 - val_loss: 0.7507 - val_acc: 0.6050
Epoch 8/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7699 -
acc: 0.6411 - val_loss: 0.7285 - val_acc: 0.6159
Epoch 9/10
7352/7352 [==============================] - 106s 14ms/step - loss: 0.7106 -
acc: 0.6493 - val_loss: 0.8037 - val_acc: 0.5935
Epoch 10/10
7352/7352 [==============================] - 105s 14ms/step - loss: 0.7854 -
acc: 0.6389 - val_loss: 1.9405 - val_acc: 0.3936
```

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}.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))

    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()

    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):
    # 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(0,0.0002)}
        # 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(0,0.001)}}
        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(0,0.001)}}
        # 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 [43]:

```
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 Detecti
                                     return_space = True)
```

```
    pass

try:
    from hyperas.utils import eval_hyperopt_space
except:
    pass

>>> Hyperas search space:

def get_space():
    return {
        'conditional': hp.choice('conditional', ['one', 'two']),
        'LSTM': hp.choice('LSTM', [28,32,38]),
        'l2': hp.uniform('l2', 0,0.0002),
        'Dropout': hp.uniform('Dropout', 0.35,0.65),
        'LSTM_1': hp.choice('LSTM_1', [26,32,36]),
        'l2_1': hp.uniform('l2_1', 0,0.001),
        'Dropout_1': hp.uniform('Dropout_1', 0.5,0.7),
        'LSTM_2': hp.choice('LSTM_2', [28,32,36]),
```

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], 'Dro
pout_2': [0.5188826519950874], 'LSTM': [0], 'LSTM_1': [1], 'LSTM_2': [1],
'choiceval': [1], 'conditional': [0], 'l2': [0.00016900597529479822], 'l2_
1': [0.0006108763092812357], 'l2_2': [0.0007371698374615214], 'lr': [0.019
42874904782045], 'lr_1': [0.015993860150909475]}

{'Dropout': 0.36598023572757926, 'Dropout_1': 0.6047146037530785, 'Dropout
_2': 0.5188826519950874, 'LSTM': 28, 'LSTM_1': 32, 'LSTM_2': 32, 'choiceva
l': 'rmsprop', 'conditional': 'one', 'l2': 0.00016900597529479822, 'l2_1':
0.0006108763092812357, 'l2_2': 0.0007371698374615214, 'lr': 0.019428749047
82045, 'lr_1': 0.015993860150909475}
------------------------------------------------
Model 2 parameters
{'Dropout': [0.604072168386432], 'Dropout_1': [0.5642077861572957], 'Dropo
ut_2': [0.4689742513688654], 'LSTM': [0], 'LSTM_1': [1], 'LSTM_2': [0], 'c
hoiceval': [1], 'conditional': [1], 'l2': [2.221286943616341e-06], 'l2_1':
[0.0009770005173795487], 'l2_2': [0.0008366666847115819], 'lr': [0.0236052
71151689124], 'lr_1': [0.015140941766877332]}
```

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)))
```

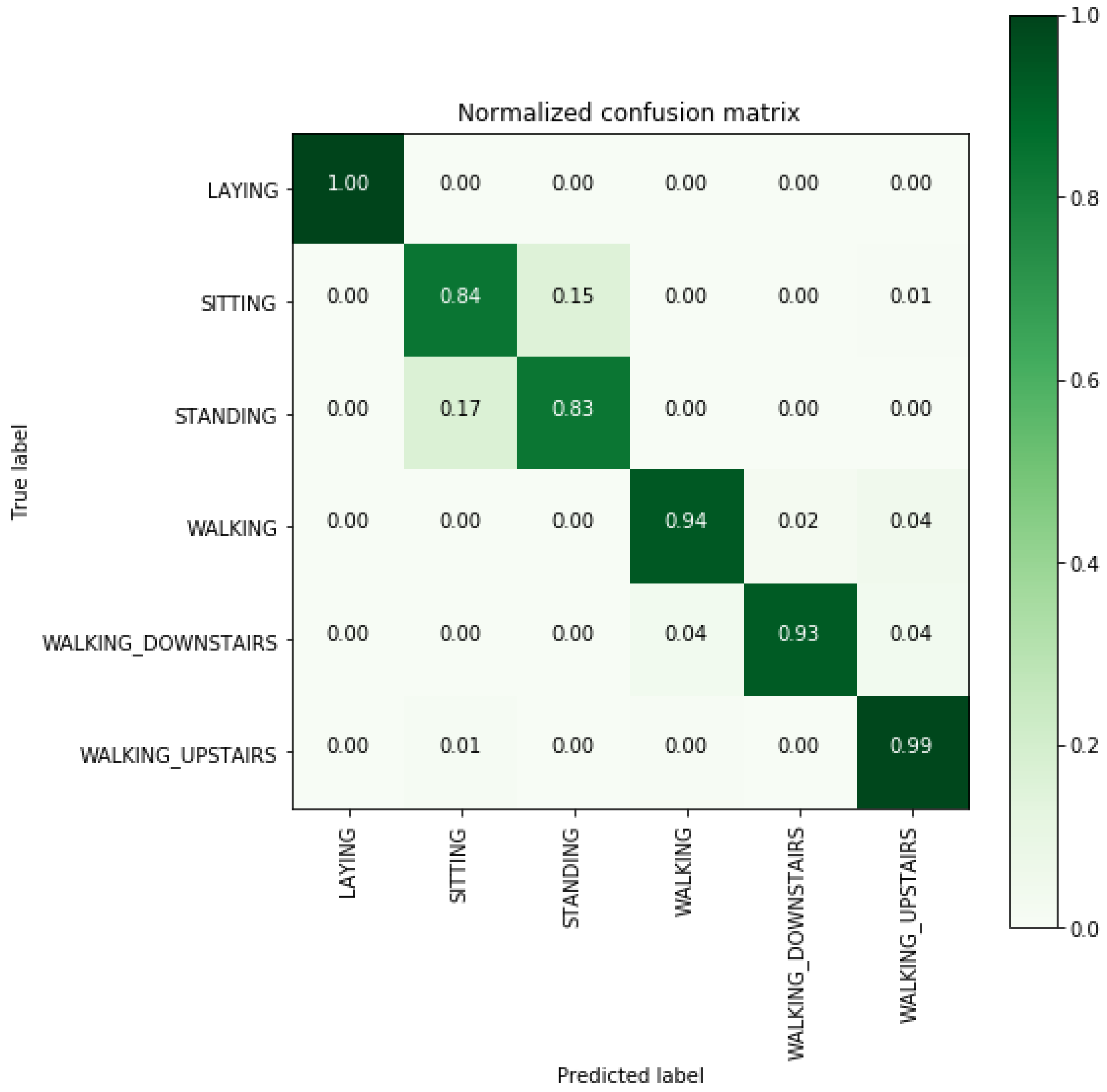
```
[[537   0   0   0   0   0]
 [  1 412  75   0   0   3]
 [  0  88 444   0   0   0]
 [  0   0   0 464  10  22]
 [  0   0   0  15 390  15]
 [  0   4   0   2   1 464]]
```

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 matri
plt.show()
```



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_unifor
model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_unifor
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_val), v
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 6s 764us/step - loss: 0.4207
- acc: 0.8403 - val_loss: 0.3384 - val_acc: 0.8748
Epoch 2/30
7352/7352 [==============================] - 5s 685us/step - loss: 0.1448
- acc: 0.9411 - val_loss: 0.3163 - val_acc: 0.8799
Epoch 3/30
7352/7352 [==============================] - 5s 672us/step - loss: 0.1177
- acc: 0.9486 - val_loss: 0.2963 - val_acc: 0.9226
Epoch 4/30
7352/7352 [==============================] - 5s 686us/step - loss: 0.0912
- acc: 0.9566 - val_loss: 0.2926 - val_acc: 0.9097
Epoch 5/30
7352/7352 [==============================] - 5s 691us/step - loss: 0.0987
- acc: 0.9567 - val_loss: 0.3676 - val_acc: 0.9036
Epoch 6/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.0841
- acc: 0.9619 - val_loss: 0.3184 - val_acc: 0.9036
```

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_unifor
                 kernel_regularizer=l2(0.1),input_shape=(128,9)))
model.add(Conv1D(filters=16, kernel_size=3, activation='relu',kernel_regularizer=l2(0.06),k
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_val), v
```

```
7352/7352 [==============================] - 5s 674us/step - loss: 0.1777
- acc: 0.9463 - val_loss: 0.3316 - val_acc: 0.8816
Epoch 25/30
7352/7352 [==============================] - 5s 683us/step - loss: 0.1785
- acc: 0.9448 - val_loss: 0.4006 - val_acc: 0.8622
Epoch 26/30
7352/7352 [==============================] - 5s 678us/step - loss: 0.1751
- acc: 0.9459 - val_loss: 0.5416 - val_acc: 0.8493
Epoch 27/30
7352/7352 [==============================] - 5s 697us/step - loss: 0.1773
- acc: 0.9476 - val_loss: 0.3382 - val_acc: 0.8989
Epoch 28/30
7352/7352 [==============================] - 5s 672us/step - loss: 0.1692
- acc: 0.9506 - val_loss: 0.3668 - val_acc: 0.8826
Epoch 29/30
7352/7352 [==============================] - 5s 677us/step - loss: 0.1742
- acc: 0.9478 - val_loss: 0.3855 - val_acc: 0.8904
Epoch 30/30
7352/7352 [==============================] - 5s 679us/step - loss: 0.1754
- acc: 0.9467 - val_loss: 0.3478 - val_acc: 0.8958
```

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}.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))

    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()

    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])}},activa
                 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_ini
    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 [25]:

```
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 Detecti
                                      return_space = True)
```

```
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/25
 - 7s - loss: 20.0633 - acc: 0.7391 - val_loss: 2.1763 - val_acc: 0.8130
Epoch 2/25
 - 3s - loss: 0.8582 - acc: 0.8762 - val_loss: 0.7603 - val_acc: 0.8293
Epoch 3/25
 - 3s - loss: 0.4883 - acc: 0.8893 - val_loss: 0.6756 - val_acc: 0.8171
Epoch 4/25
 - 3s - loss: 0.4394 - acc: 0.8945 - val_loss: 0.5831 - val_acc: 0.8656
Epoch 5/25
 - 3s - loss: 0.4184 - acc: 0.9032 - val_loss: 0.5638 - val_acc: 0.8741
Epoch 6/25
 - 3s - loss: 0.3750 - acc: 0.9139 - val_loss: 0.6264 - val_acc: 0.8575
Epoch 7/25
 - 3s - loss: 0.3726 - acc: 0.9121 - val_loss: 0.5143 - val_acc: 0.8765
Epoch 8/25
 - 3s - loss: 0.3521 - acc: 0.9165 - val_loss: 0.5094 - val_acc: 0.8724
Epoch 9/25
 - 3s - loss: 0.3458 - acc: 0.9158 - val_loss: 0.4961 - val_acc: 0.8734
```

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]:

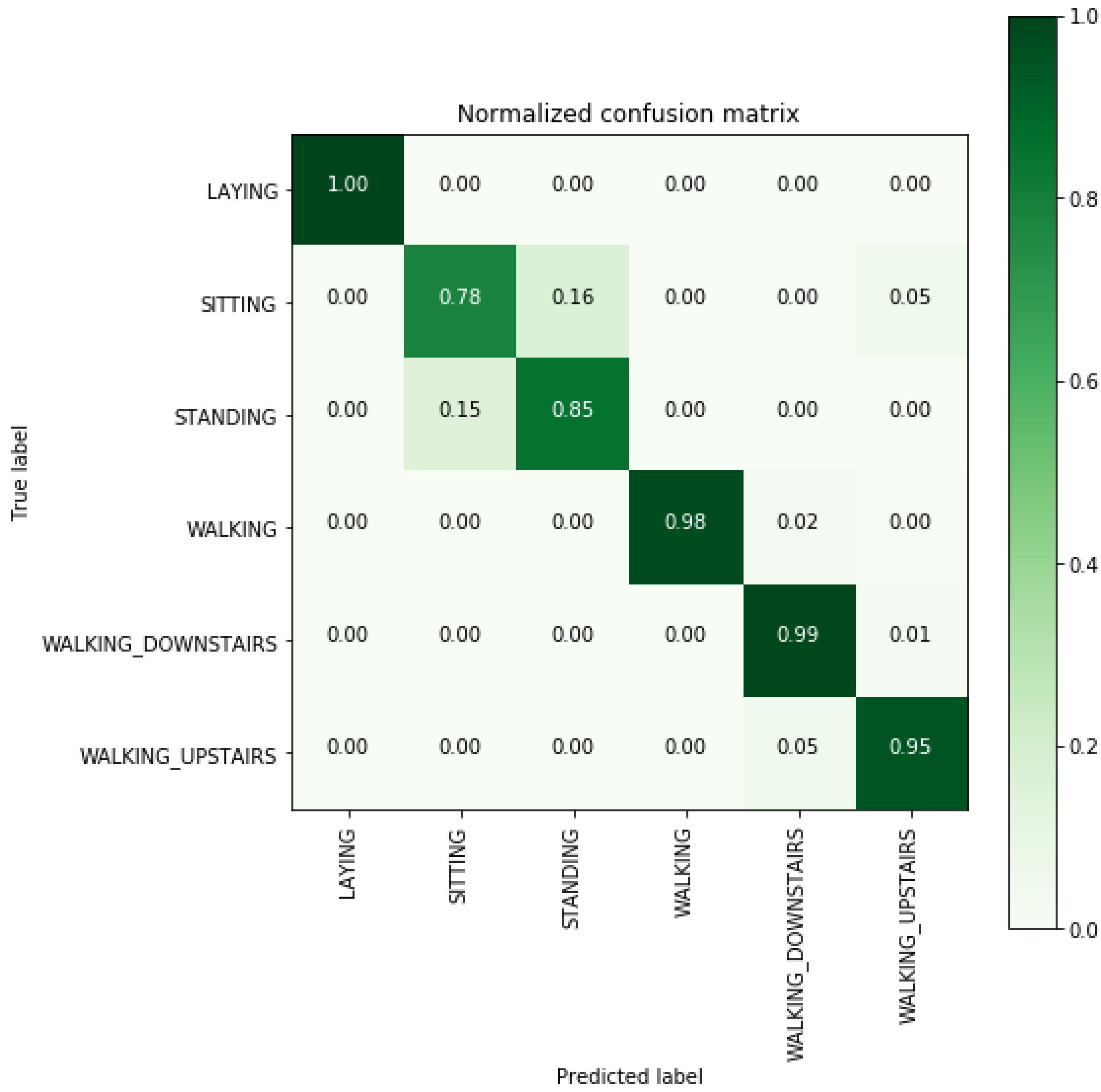
```
# Confusion Matrix
print(confusion_matrix_rnn(Y_val, best_model.predict(X_val)))
```

```
[[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 matri
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.

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 (https://www.mdpi.com/1424-8220/18/4/1055/pdf)](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[2]))
            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}.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))

    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]
        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_unifor
model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_unifor
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_val_
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 4s 580us/step - loss: 0.0549 -
acc: 0.9791 - val_loss: 0.0127 - val_acc: 0.9973
Epoch 2/20
7352/7352 [==============================] - 4s 482us/step - loss: 0.0021 -
acc: 0.9995 - val_loss: 0.0120 - val_acc: 0.9969
Epoch 3/20
7352/7352 [==============================] - 4s 484us/step - loss: 7.9422e-0
4 - acc: 0.9997 - val_loss: 0.0122 - val_acc: 0.9936
Epoch 4/20
7352/7352 [==============================] - 4s 483us/step - loss: 0.0029 -
acc: 0.9990 - val_loss: 0.0168 - val_acc: 0.9963
Epoch 5/20
7352/7352 [==============================] - 4s 481us/step - loss: 1.3106e-0
4 - acc: 1.0000 - val_loss: 0.0102 - val_acc: 0.9986
Epoch 6/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.7091e-0
5 - acc: 1.0000 - val_loss: 0.0124 - val_acc: 0.9983
Epoch 7/20
7352/7352 [==============================] - 4s 480us/step - loss: 0.0022 -
acc: 0.9997 - val_loss: 0.0162 - val_acc: 0.9932
Epoch 8/20
7352/7352 [==============================] - 4s 481us/step - loss: 0.0051 -
acc: 0.9989 - val_loss: 0.0063 - val_acc: 0.9993
Epoch 9/20
7352/7352 [==============================] - 4s 480us/step - loss: 3.4291e-0
5 - acc: 1.0000 - val_loss: 0.0101 - val_acc: 0.9966
Epoch 10/20
7352/7352 [==============================] - 4s 478us/step - loss: 2.1046e-0
4 - acc: 0.9999 - val_loss: 0.0056 - val_acc: 0.9993
Epoch 11/20
7352/7352 [==============================] - 4s 482us/step - loss: 3.0157e-0
5 - acc: 1.0000 - val_loss: 0.0079 - val_acc: 0.9986
Epoch 12/20
7352/7352 [==============================] - 4s 482us/step - loss: 5.7799e-0
6 - acc: 1.0000 - val_loss: 0.0070 - val_acc: 0.9990
Epoch 13/20
7352/7352 [==============================] - 4s 481us/step - loss: 1.4363e-0
6 - acc: 1.0000 - val_loss: 0.0071 - val_acc: 0.9990
Epoch 14/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.1018e-0
6 - acc: 1.0000 - val_loss: 0.0071 - val_acc: 0.9990
Epoch 15/20
7352/7352 [==============================] - 4s 483us/step - loss: 7.5717e-0
7 - acc: 1.0000 - val_loss: 0.0070 - val_acc: 0.9990
Epoch 16/20
7352/7352 [==============================] - 4s 480us/step - loss: 4.7786e-0
7 - acc: 1.0000 - val_loss: 0.0071 - val_acc: 0.9990
Epoch 17/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.0220e-0
6 - acc: 1.0000 - val_loss: 0.0071 - val_acc: 0.9990
Epoch 18/20
7352/7352 [==============================] - 4s 480us/step - loss: 1.7438e-0
6 - acc: 1.0000 - val_loss: 0.0066 - val_acc: 0.9990
```

```
Epoch 19/20
7352/7352 [==============================] - 4s 487us/step - loss: 6.3406e-0
7 - acc: 1.0000 - val_loss: 0.0069 - val_acc: 0.9990
Epoch 20/20
7352/7352 [==============================] - 4s 480us/step - loss: 5.5710e-0
7 - acc: 1.0000 - val_loss: 0.0072 - val_acc: 0.9990
```

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.

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
            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)
            #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}.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))

    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]
        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_unifor
model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_unifor
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_val_s),
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_loss: 0.2665 - val_acc: 0.8974
Epoch 2/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.2302 -
acc: 0.9240 - val_loss: 0.2560 - val_acc: 0.8942
Epoch 3/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.2163 -
acc: 0.9235 - val_loss: 0.2900 - val_acc: 0.8878
Epoch 4/20
4067/4067 [==============================] - 1s 351us/step - loss: 0.1732 -
acc: 0.9348 - val_loss: 0.3296 - val_acc: 0.8910
Epoch 5/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1471 -
acc: 0.9432 - val_loss: 0.2661 - val_acc: 0.9000
Epoch 6/20
4067/4067 [==============================] - 1s 354us/step - loss: 0.1296 -
acc: 0.9498 - val_loss: 0.2430 - val_acc: 0.9109
Epoch 7/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.1704 -
acc: 0.9422 - val_loss: 0.3748 - val_acc: 0.8795
Epoch 8/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.2979 -
acc: 0.9171 - val_loss: 0.2355 - val_acc: 0.8929
Epoch 9/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.2093 -
acc: 0.9375 - val_loss: 0.1853 - val_acc: 0.9083
Epoch 10/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.2048 -
acc: 0.9405 - val_loss: 0.3305 - val_acc: 0.9218
Epoch 11/20
4067/4067 [==============================] - 1s 355us/step - loss: 0.2393 -
acc: 0.9405 - val_loss: 0.2739 - val_acc: 0.9051
Epoch 12/20
4067/4067 [==============================] - 1s 351us/step - loss: 0.2640 -
acc: 0.9299 - val_loss: 0.1967 - val_acc: 0.9295
Epoch 13/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.2083 -
acc: 0.9388 - val_loss: 0.2722 - val_acc: 0.9051
Epoch 14/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.1886 -
acc: 0.9474 - val_loss: 0.2411 - val_acc: 0.9122
Epoch 15/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1870 -
acc: 0.9484 - val_loss: 0.1946 - val_acc: 0.9115
Epoch 16/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1710 -
acc: 0.9552 - val_loss: 0.2320 - val_acc: 0.9090
Epoch 17/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1718 -
acc: 0.9506 - val_loss: 0.2120 - val_acc: 0.9032
```

```
Epoch 18/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1699 -
acc: 0.9501 - val_loss: 0.1729 - val_acc: 0.9282
Epoch 19/20
4067/4067 [==============================] - 1s 353us/step - loss: 0.1520 -
acc: 0.9636 - val_loss: 0.1997 - val_acc: 0.9179
Epoch 20/20
4067/4067 [==============================] - 1s 352us/step - loss: 0.1927 -
acc: 0.9592 - val_loss: 0.2545 - val_acc: 0.9096
```

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])}},activa
                     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_initi
    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_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 [9]:

```
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 Detecti
                                      return_space = True)
```

```
>>> Imports:
#coding=utf-8

try:
    import os
except:
    pass

try:
    import numpy as np
except:
    pass

try:
    import tensorflow as tf
except:
    pass

try:
```

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'],activation=
                    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_initializer='
    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=optim)
    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.py:31: UserWarning: The `nb_epoch` argument in `fit` has
been renamed `epochs`.

Train on 4067 samples, validate on 1560 samples
Epoch 1/30
4067/4067 [==============================] - 1s 350us/step - loss: 10.6708 -
acc: 0.8375 - val_loss: 3.0312 - val_acc: 0.8923
Epoch 2/30
4067/4067 [==============================] - 1s 184us/step - loss: 1.2846 -
acc: 0.8960 - val_loss: 0.6160 - val_acc: 0.8788
Epoch 3/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.4912 -
acc: 0.8943 - val_loss: 0.4795 - val_acc: 0.8628
Epoch 4/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.3866 -
acc: 0.9053 - val_loss: 0.4627 - val_acc: 0.8506
Epoch 5/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.3421 -
acc: 0.9098 - val_loss: 0.4827 - val_acc: 0.8724
Epoch 6/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.3151 -
acc: 0.9166 - val_loss: 0.3515 - val_acc: 0.8968
Epoch 7/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.3091 -
acc: 0.9154 - val_loss: 0.3364 - val_acc: 0.8853
Epoch 8/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2749 -
acc: 0.9312 - val_loss: 0.4064 - val_acc: 0.8718
Epoch 9/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2743 -
acc: 0.9272 - val_loss: 0.3227 - val_acc: 0.9122
```

```
Epoch 10/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2576 -
acc: 0.9292 - val_loss: 0.2934 - val_acc: 0.9083
Epoch 11/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2791 -
acc: 0.9302 - val_loss: 0.3982 - val_acc: 0.8712
Epoch 12/30
4067/4067 [==============================] - 1s 185us/step - loss: 0.2315 -
acc: 0.9346 - val_loss: 0.3192 - val_acc: 0.9186
Epoch 13/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2301 -
acc: 0.9410 - val_loss: 0.3427 - val_acc: 0.8821
Epoch 14/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2294 -
acc: 0.9368 - val_loss: 0.2628 - val_acc: 0.9327
Epoch 15/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2371 -
acc: 0.9353 - val_loss: 0.2884 - val_acc: 0.9071
Epoch 16/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2146 -
acc: 0.9449 - val_loss: 0.3369 - val_acc: 0.8865
Epoch 17/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2065 -
acc: 0.9447 - val_loss: 0.2776 - val_acc: 0.9019
Epoch 18/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.2056 -
acc: 0.9420 - val_loss: 0.3021 - val_acc: 0.8891
Epoch 19/30
4067/4067 [==============================] - 1s 185us/step - loss: 0.2223 -
acc: 0.9398 - val_loss: 0.2380 - val_acc: 0.9205
Epoch 20/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1979 -
acc: 0.9442 - val_loss: 2.4294 - val_acc: 0.6051
Epoch 21/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.2421 -
acc: 0.9432 - val_loss: 0.2461 - val_acc: 0.9109
Epoch 22/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1836 -
acc: 0.9498 - val_loss: 0.2768 - val_acc: 0.9115
Epoch 23/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.1963 -
acc: 0.9457 - val_loss: 0.2667 - val_acc: 0.9077
Epoch 24/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1863 -
acc: 0.9462 - val_loss: 0.2308 - val_acc: 0.9128
Epoch 25/30
4067/4067 [==============================] - 1s 184us/step - loss: 0.1844 -
acc: 0.9462 - val_loss: 0.2726 - val_acc: 0.9038
Epoch 26/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1754 -
acc: 0.9525 - val_loss: 0.2099 - val_acc: 0.9417
Epoch 27/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1793 -
acc: 0.9511 - val_loss: 0.2814 - val_acc: 0.9077
Epoch 28/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1665 -
acc: 0.9555 - val_loss: 0.2140 - val_acc: 0.9378
Epoch 29/30
4067/4067 [==============================] - 1s 183us/step - loss: 0.1705 -
acc: 0.9575 - val_loss: 0.2413 - val_acc: 0.9359
Epoch 30/30
```

```
4067/4067 [==============================] - 1s 183us/step - loss: 0.1712 -
acc: 0.9577 - val_loss: 0.2297 - val_acc: 0.9391
```

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]:

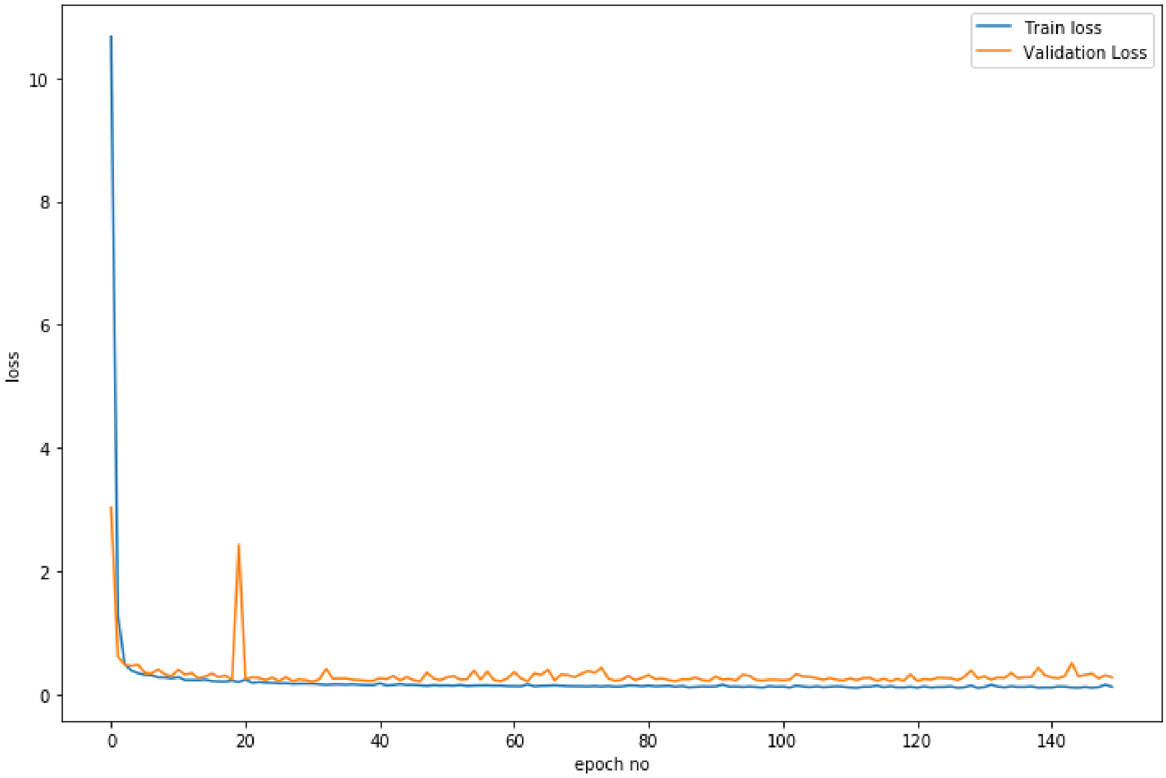
```
runtime_best_model,result = keras_fmin_fnct(runtime_param)
```

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
```

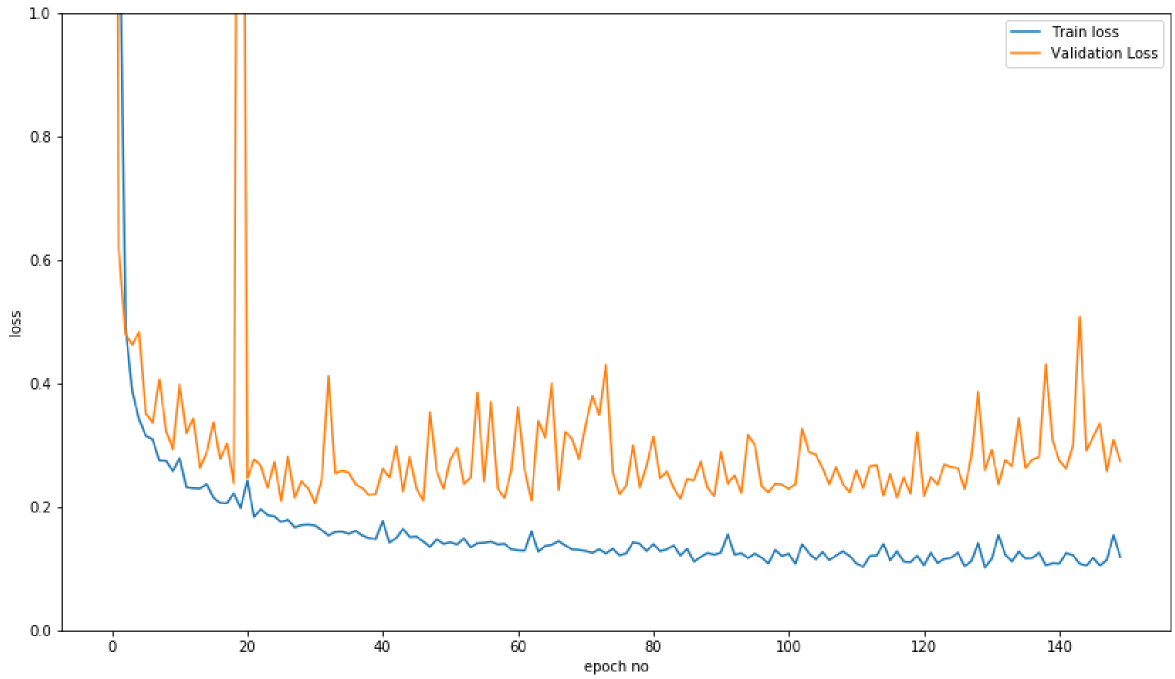
In [66]:

```
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()
```



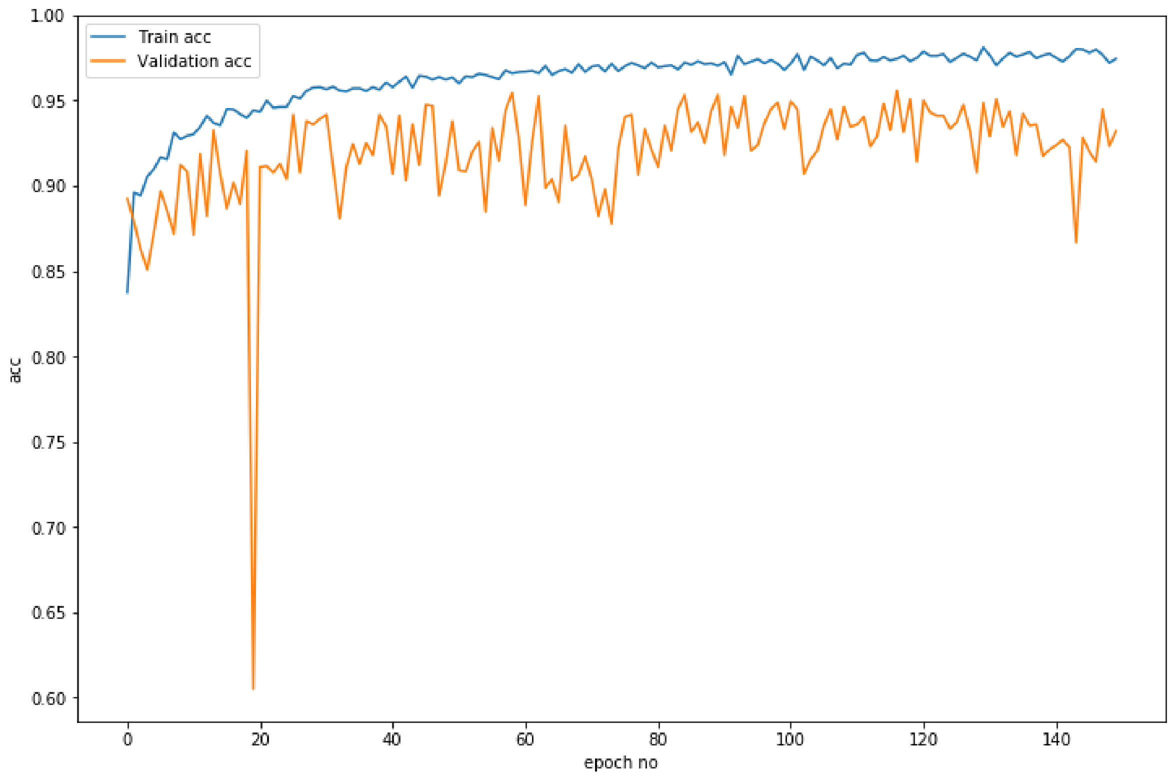
In [67]:

```
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()
```



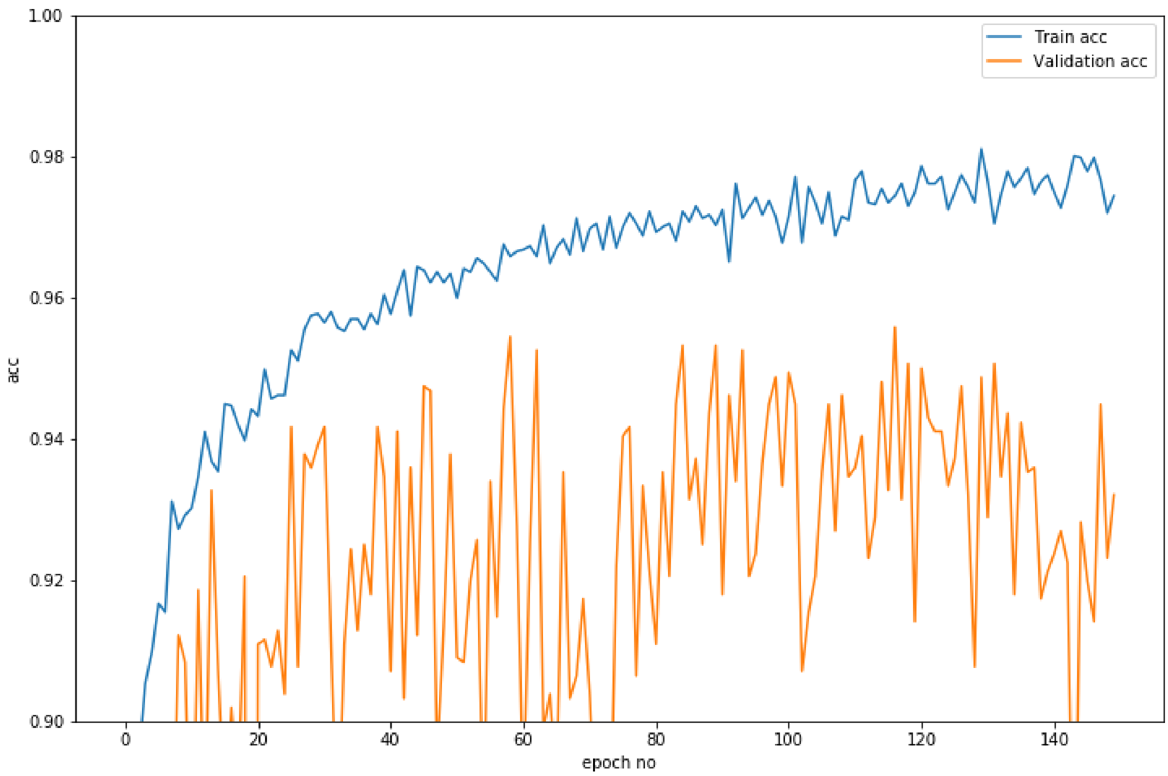
In [68]:

```
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 <tens
orflow.python.client.session.BaseSession._Callable object at 0x148471f420b
8>>
Traceback (most recent call last):
  File "/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site
-packages/tensorflow/python/client/session.py", line 1398, in __del__
    self._session._session, self._handle, status)
  File "/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site
-packages/tensorflow/python/framework/errors_impl.py", line 519, in __exit
__
    c_api.TF_GetCode(self.status.status))
tensorflow.python.framework.errors_impl.InvalidArgumentError: No such call
able handle: 149842480
/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-package
s/ipykernel_launcher.py:31: UserWarning: The `nb_epoch` argument in `fit`
has been renamed `epochs`.
```

In [78]:

```
_,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]:

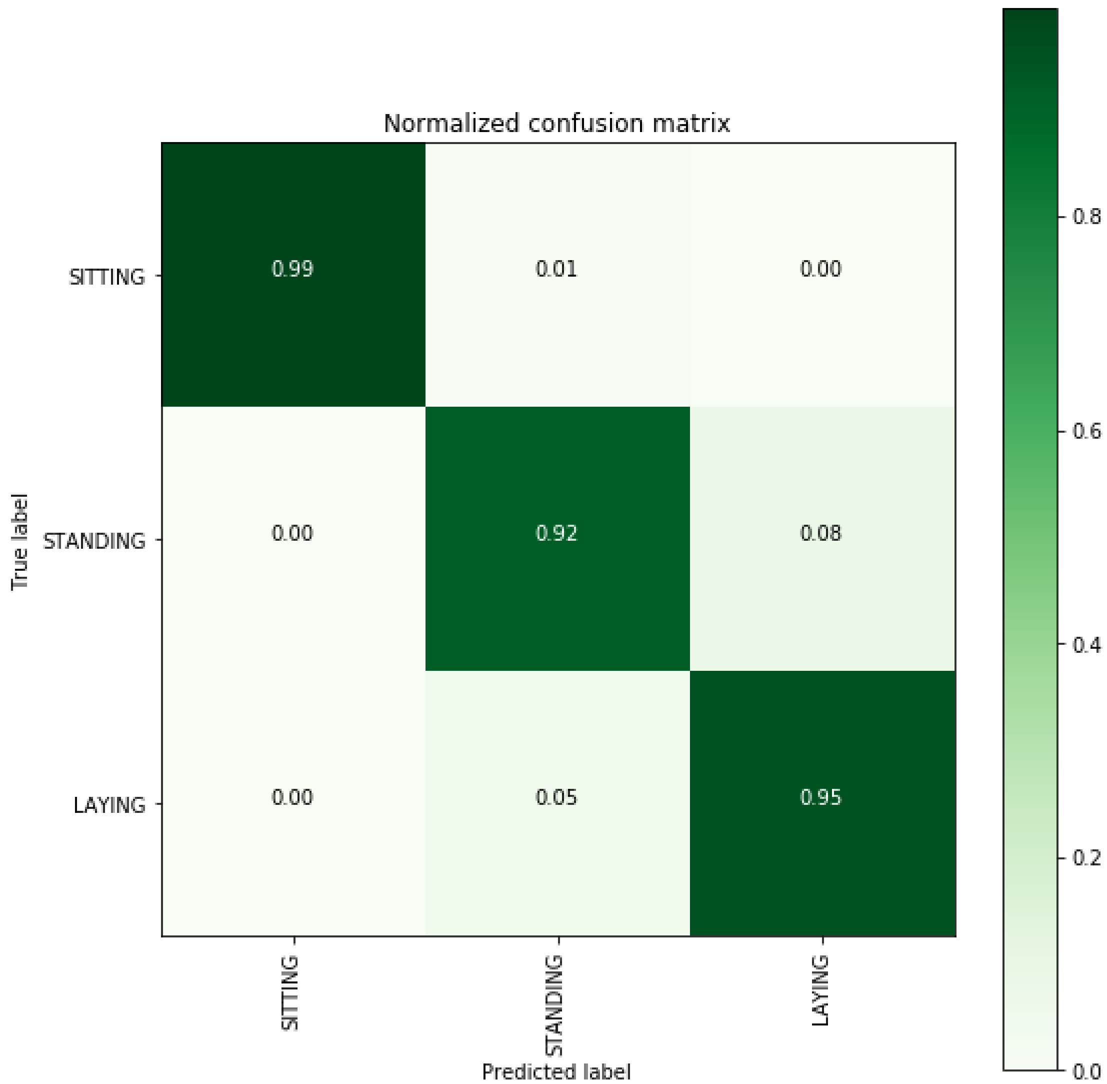
```
# Confusion Matrix
# Activities are the class labels
# It is a 3 class classification
from sklearn import metrics
ACTIVITIES = {
    0: 'SITTING',
    1: 'STANDING',
    2: 'LAYING',
}

# 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, title='N
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')
```

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[2]))
            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}.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))

    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]
        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_unifor
model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_unifor
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_val_s)
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_loss: 0.2909 - val_acc: 0.8885
Epoch 2/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2112
- acc: 0.9179 - val_loss: 0.3365 - val_acc: 0.8718
Epoch 3/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2055
- acc: 0.9179 - val_loss: 0.2613 - val_acc: 0.8981
Epoch 4/100
4067/4067 [==============================] - 2s 471us/step - loss: 0.1922
- acc: 0.9240 - val_loss: 0.2663 - val_acc: 0.8814
Epoch 5/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.2058
- acc: 0.9292 - val_loss: 0.1815 - val_acc: 0.9224
Epoch 6/100
4067/4067 [==============================] - 2s 469us/step - loss: 0.1774
- acc: 0.9336 - val_loss: 0.2734 - val_acc: 0.8814
```

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])}},activa
                 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_initi
    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 [10]:

```
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 Detectior
                                      return_space = True)
```

```
>>> Imports:
#coding=utf-8

try:
    import os
except:
    pass

try:
    import numpy as np
except:
    pass

try:
    import tensorflow as tf
except:
    pass

trv:
```

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'],activation=
                    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_initializer='
    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=optim)
    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_loss: 21.6438 - val_acc: 0.6936
Epoch 2/35
3285/3285 [==============================] - 1s 331us/step - loss: 13.4174 -
acc: 0.9428 - val_loss: 7.9785 - val_acc: 0.9250
Epoch 3/35
3285/3285 [==============================] - 1s 320us/step - loss: 4.8053 -
acc: 0.9772 - val_loss: 3.1436 - val_acc: 0.8457
Epoch 4/35
3285/3285 [==============================] - 1s 319us/step - loss: 1.7396 -
acc: 0.9851 - val_loss: 1.3414 - val_acc: 0.9423
Epoch 5/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.6754 -
acc: 0.9921 - val_loss: 0.7540 - val_acc: 0.9517
Epoch 6/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.3342 -
acc: 0.9906 - val_loss: 0.5434 - val_acc: 0.9654
Epoch 7/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.2152 -
acc: 0.9930 - val_loss: 0.5026 - val_acc: 0.9308
Epoch 8/35
3285/3285 [==============================] - 1s 322us/step - loss: 0.1851 -
acc: 0.9918 - val_loss: 0.4687 - val_acc: 0.9207
Epoch 9/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1573 -
acc: 0.9954 - val_loss: 0.3979 - val_acc: 0.9589
Epoch 10/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1468 -
acc: 0.9960 - val_loss: 0.4149 - val_acc: 0.9293
Epoch 11/35
3285/3285 [==============================] - 1s 330us/step - loss: 0.1295 -
acc: 0.9960 - val_loss: 0.3815 - val_acc: 0.9495
```

```
Epoch 12/35
3285/3285 [==============================] - 1s 325us/step - loss: 0.1278 -
acc: 0.9942 - val_loss: 0.3490 - val_acc: 0.9762
Epoch 13/35
3285/3285 [==============================] - 1s 326us/step - loss: 0.1144 -
acc: 0.9960 - val_loss: 0.3637 - val_acc: 0.9726
Epoch 14/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1066 -
acc: 0.9979 - val_loss: 0.3378 - val_acc: 0.9553
Epoch 15/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1332 -
acc: 0.9896 - val_loss: 0.3065 - val_acc: 0.9719
Epoch 16/35
3285/3285 [==============================] - 1s 322us/step - loss: 0.1043 -
acc: 0.9973 - val_loss: 0.3214 - val_acc: 0.9654
Epoch 17/35
3285/3285 [==============================] - 1s 320us/step - loss: 0.1074 -
acc: 0.9951 - val_loss: 0.2908 - val_acc: 0.9712
Epoch 18/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.0913 -
acc: 0.9982 - val_loss: 0.3016 - val_acc: 0.9625
Epoch 19/35
3285/3285 [==============================] - 1s 317us/step - loss: 0.1172 -
acc: 0.9884 - val_loss: 0.2784 - val_acc: 0.9805
Epoch 20/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.1035 -
acc: 0.9921 - val_loss: 0.2836 - val_acc: 0.9632
Epoch 21/35
3285/3285 [==============================] - 1s 317us/step - loss: 0.0959 -
acc: 0.9948 - val_loss: 0.2899 - val_acc: 0.9769
Epoch 22/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.0769 -
acc: 0.9994 - val_loss: 0.2944 - val_acc: 0.9690
Epoch 23/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.0766 -
acc: 0.9985 - val_loss: 0.2612 - val_acc: 0.9697
Epoch 24/35
3285/3285 [==============================] - 1s 319us/step - loss: 0.1604 -
acc: 0.9732 - val_loss: 0.4175 - val_acc: 0.8940
Epoch 25/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.1246 -
acc: 0.9951 - val_loss: 0.2583 - val_acc: 0.9676
Epoch 26/35
3285/3285 [==============================] - 1s 317us/step - loss: 0.0749 -
acc: 0.9997 - val_loss: 0.2711 - val_acc: 0.9553
Epoch 27/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0703 -
acc: 0.9997 - val_loss: 0.2728 - val_acc: 0.9712
Epoch 28/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0794 -
acc: 0.9957 - val_loss: 0.2454 - val_acc: 0.9813
Epoch 29/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.0679 -
acc: 0.9985 - val_loss: 0.2333 - val_acc: 0.9798
Epoch 30/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0769 -
acc: 0.9942 - val_loss: 0.2243 - val_acc: 0.9805
Epoch 31/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0952 -
acc: 0.9924 - val_loss: 0.2394 - val_acc: 0.9805
Epoch 32/35
```

```
3285/3285 [==============================] - 1s 323us/step - loss: 0.0615 -
acc: 0.9994 - val_loss: 0.2289 - val_acc: 0.9820
Epoch 33/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.0574 -
acc: 0.9988 - val_loss: 0.2460 - val_acc: 0.9726
Epoch 34/35
3285/3285 [==============================] - 1s 316us/step - loss: 0.1272 -
acc: 0.9784 - val_loss: 0.4408 - val_acc: 0.9250
Epoch 35/35
3285/3285 [==============================] - 1s 318us/step - loss: 0.1743 -
acc: 0.9860 - val_loss: 0.2274 - val_acc: 0.9704
```

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}
```

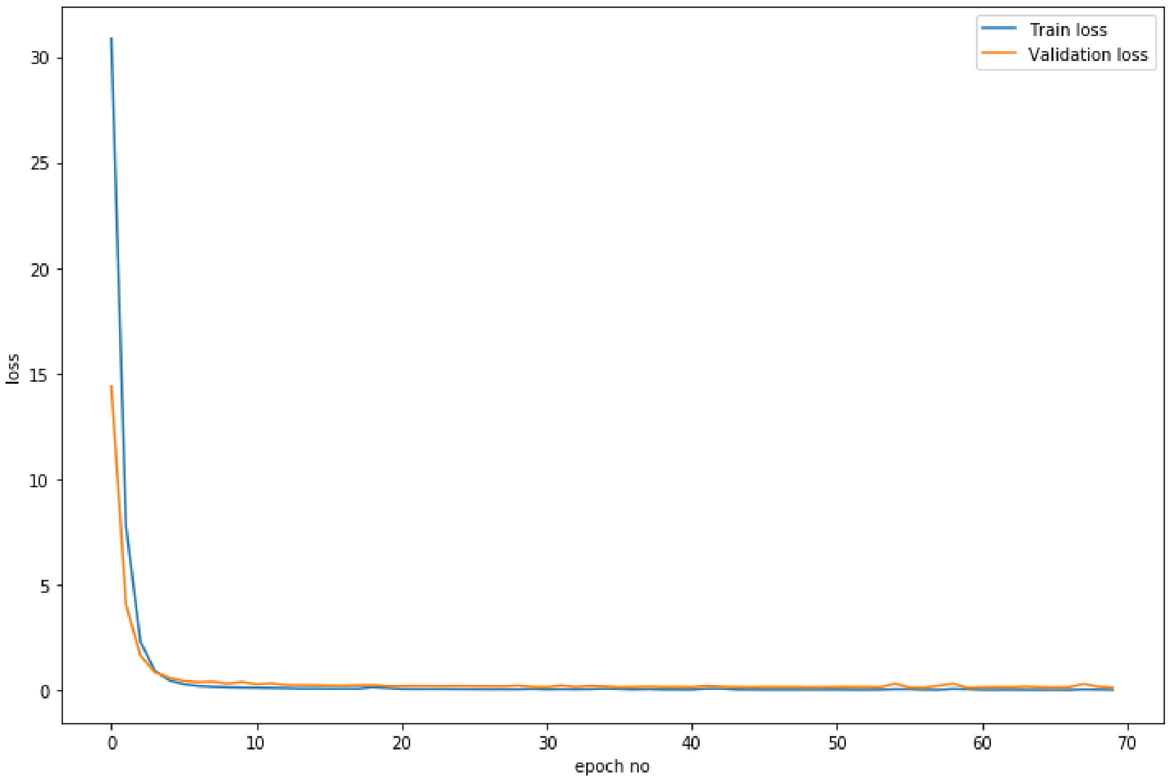
In [62]:

```
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
```

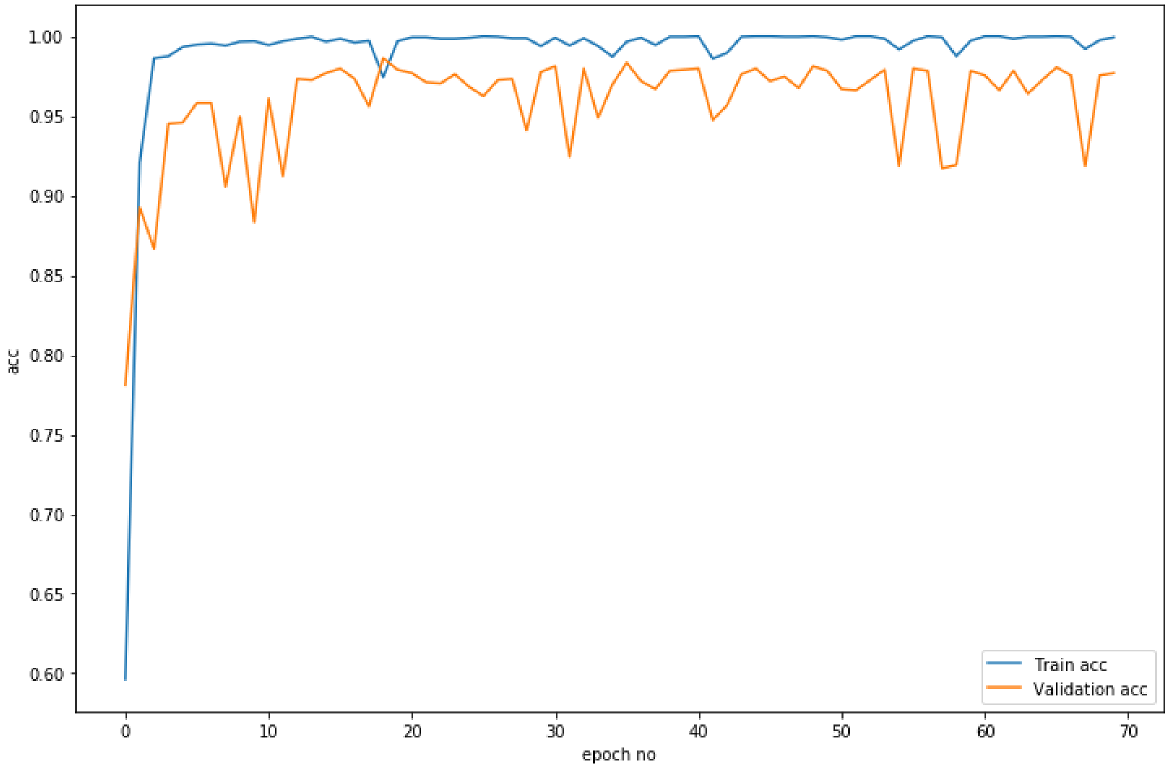
In [64]:

```
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_loss: 14.3953 - val_acc: 0.7808
Epoch 2/19
3285/3285 [==============================] - 1s 311us/step - loss: 7.8188 -
acc: 0.9209 - val_loss: 4.0805 - val_acc: 0.8926
Epoch 3/19
3285/3285 [==============================] - 1s 312us/step - loss: 2.3103 -
acc: 0.9863 - val_loss: 1.6611 - val_acc: 0.8666
Epoch 4/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.9391 -
acc: 0.9875 - val_loss: 0.8736 - val_acc: 0.9452
Epoch 5/19
3285/3285 [==============================] - 1s 311us/step - loss: 0.4885 -
acc: 0.9933 - val_loss: 0.6108 - val_acc: 0.9459
Epoch 6/19
3285/3285 [==============================] - 1s 311us/step - loss: 0.3024 -
acc: 0.9948 - val_loss: 0.4641 - val_acc: 0.9582
Epoch 7/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.2201 -
acc: 0.9954 - val_loss: 0.4053 - val_acc: 0.9582
Epoch 8/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1842 -
acc: 0.9942 - val_loss: 0.4262 - val_acc: 0.9056
Epoch 9/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.1602 -
acc: 0.9967 - val_loss: 0.3393 - val_acc: 0.9495
Epoch 10/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1459 -
acc: 0.9970 - val_loss: 0.4134 - val_acc: 0.8832
```

```
Epoch 11/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1402 -
acc: 0.9945 - val_loss: 0.3054 - val_acc: 0.9611
Epoch 12/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.1285 -
acc: 0.9970 - val_loss: 0.3474 - val_acc: 0.9120
Epoch 13/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.1155 -
acc: 0.9985 - val_loss: 0.2674 - val_acc: 0.9733
Epoch 14/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.1013 -
acc: 0.9997 - val_loss: 0.2624 - val_acc: 0.9726
Epoch 15/19
3285/3285 [==============================] - 1s 315us/step - loss: 0.1029 -
acc: 0.9967 - val_loss: 0.2534 - val_acc: 0.9769
Epoch 16/19
3285/3285 [==============================] - 1s 312us/step - loss: 0.0954 -
acc: 0.9985 - val_loss: 0.2426 - val_acc: 0.9798
Epoch 17/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.0997 -
acc: 0.9960 - val_loss: 0.2372 - val_acc: 0.9733
Epoch 18/19
3285/3285 [==============================] - 1s 310us/step - loss: 0.0949 -
acc: 0.9973 - val_loss: 0.2542 - val_acc: 0.9560
Epoch 19/19
3285/3285 [==============================] - 1s 313us/step - loss: 0.1709 -
acc: 0.9744 - val_loss: 0.2684 - val_acc: 0.9863
```

In [49]:

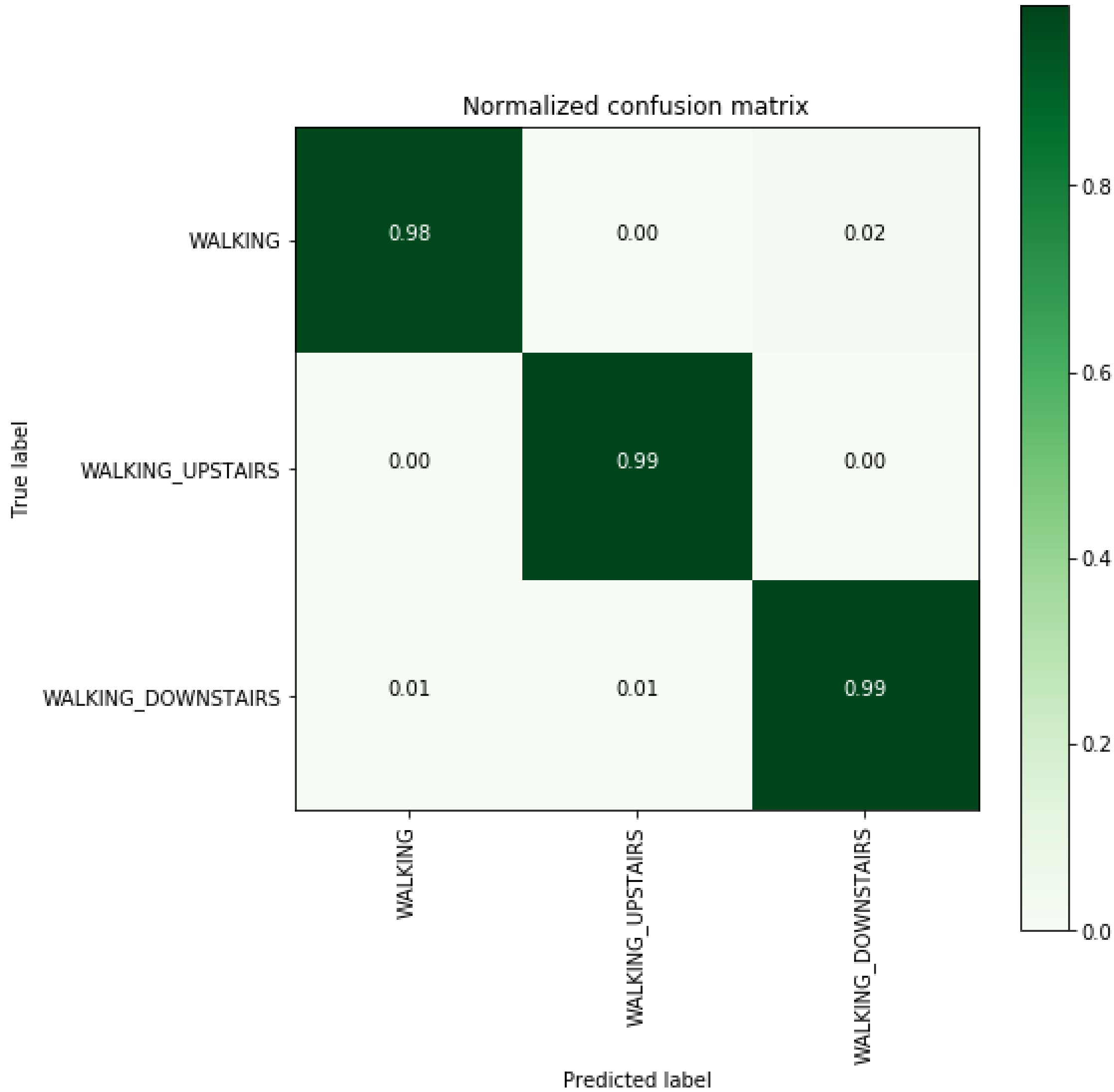
```
from sklearn import metrics
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
    2: 'WALKING_DOWNSTAIRS',
}

# 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]]
```

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.cm.Gr
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}.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))

    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 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,)
```

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]:

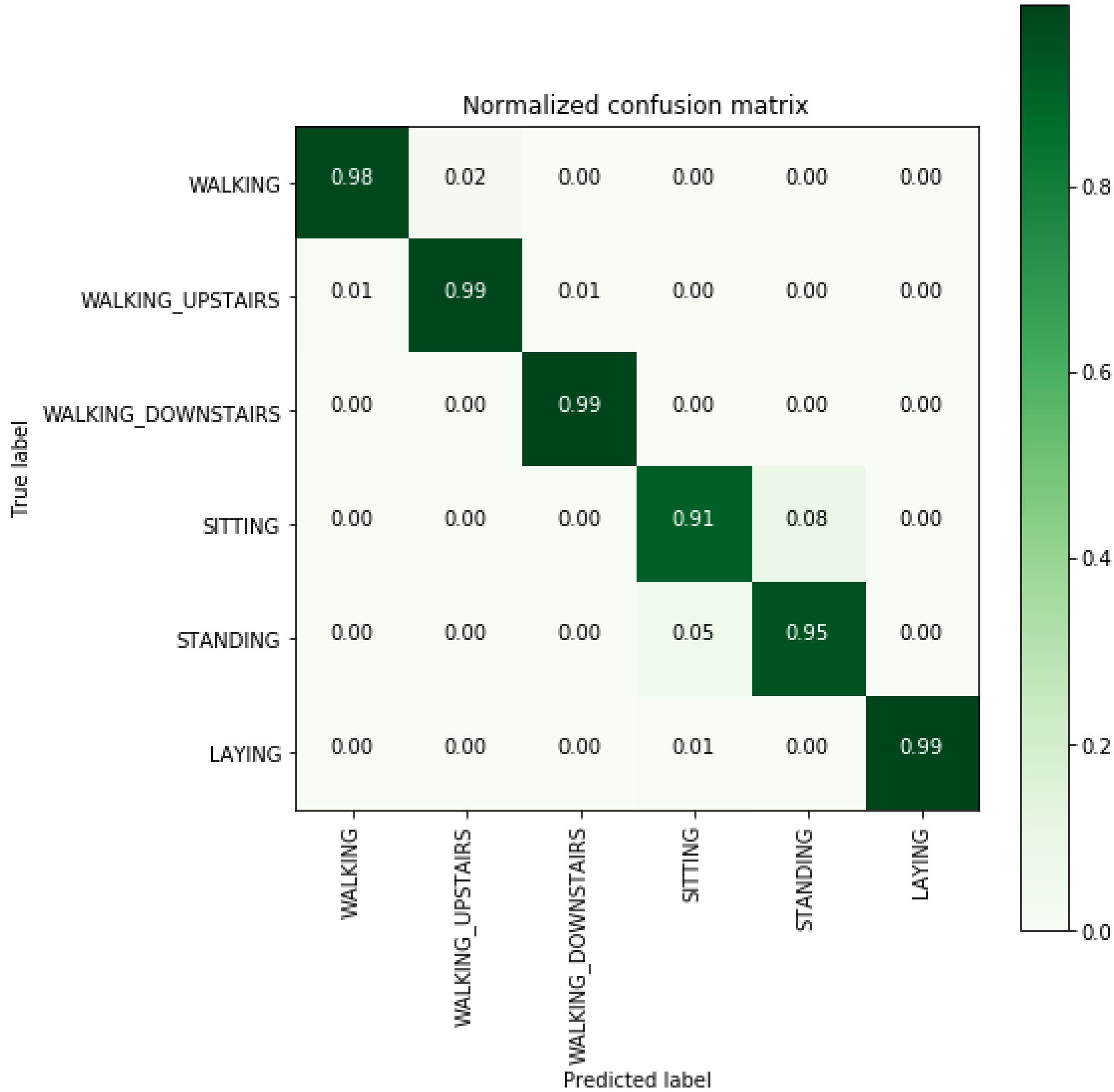
```
#confusion metric
cm = metrics.confusion_matrix(Y_val, final_pred_val,labels=range(1,7))
cm
```

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','LAYING']
plot_confusion_matrix(cm, classes=labels,
                      normalize=True, title='Normalized confusion matrix', cmap = plt.cm.Gr
plt.show()
```



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

In [ ]:

```

```