Human Activity Recognition Problem

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 [125]:
```
import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=UserWarning)

import itertools
from datetime import datetime
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams["font.family"] = 'DejaVu Sans'
import seaborn as sns

# To be able to save images on server
import matplotlib
matplotlib.use('Agg')
from matplotlib import pyplot

from sklearn.manifold import TSNE
from sklearn.metrics import confusion_matrix
from sklearn import linear_model
from sklearn import metrics
from sklearn.model_selection import GridSearchCV
from sklearn.svm import LinearSVC
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier

# Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set_random_seed(42)

from keras import backend as K
from keras.models import Sequential
from keras.layers import LSTM , BatchNormalization
from keras.layers.core import Dense, Dropout
from keras.regularizers import L1L2
```

In [2]:
```
# 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 [6]:
```
# 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=None, names=f
eatures)

# add subject column to the dataframe
X_train['subject'] = pd.read_csv('UCI_HAR_dataset/train/subject_train.txt', header=None, squeeze=True)

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[6]:

	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	tBo r
2872	0.270531	-0.02003	-0.13885	-0.99541	-0.975719	-0.943967	-0.995795	-0.972381	-0.936507	-0.9

1 rows × 564 columns

In [7]:
```
train.shape
```

Out[7]: (7352, 564)

Obtain the test data

In [8]:
```
# 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, names=feat
ures)

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

# 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[8]:

	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	tBo r
1887	0.277531	-0.015711	-0.1131	-0.996947	-0.98728	-0.986408	-0.997356	-0.986709	-0.985017	-0.9

1 rows × 564 columns

In [9]:
```
test.shape
```

Out[9]: (2947, 564)

Data Cleaning

1. Check for Duplicates

In [10]:
```
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

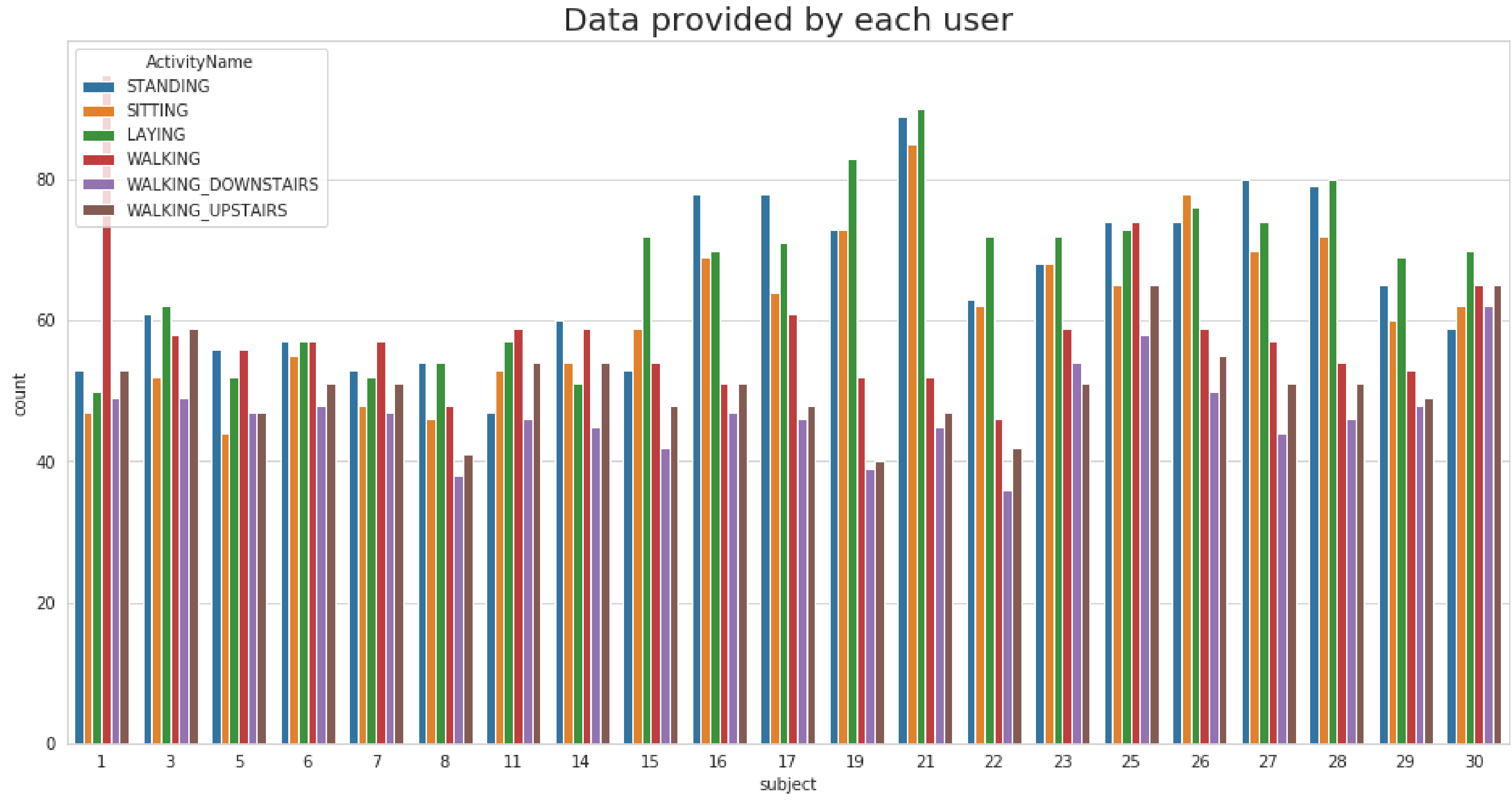
In [11]:
```
print('We have {} NaN/Null values in train'.format(train.isnull().values.sum()))
print('We have {} NaN/Null values in test'.format(test.isnull().values.sum()))
```

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

3. Check for data imbalance

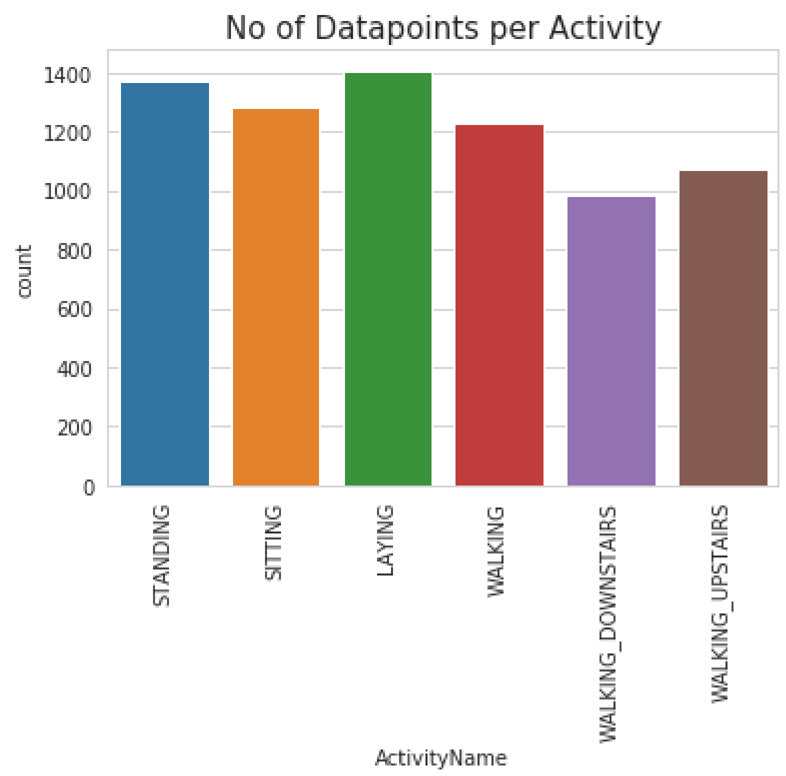
In [12]:
```
sns.set_style('whitegrid')
plt.rcParams['font.family'] = 'Dejavu Sans'
```

In [13]:
```
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 [14]:
```
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 [15]:
```
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[15]:
```
Index(['tBodyAccmeanX', 'tBodyAccmeanY', 'tBodyAccmeanZ', 'tBodyAccstdX',
       'tBodyAccstdY', 'tBodyAccstdZ', 'tBodyAccmadX', 'tBodyAccmadY',
       'tBodyAccmadZ', 'tBodyAccmaxX',
       ...
       'angletBodyAccMeangravity', 'angletBodyAccJerkMeangravityMean',
       'angletBodyGyroMeangravityMean', 'angletBodyGyroJerkMeangravityMean',
       'angleXgravityMean', 'angleYgravityMean', 'angleZgravityMean',
       'subject', 'Activity', 'ActivityName'],
      dtype='object', length=564)
```

5. Save this dataframe in a csv files

In [16]:
```
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

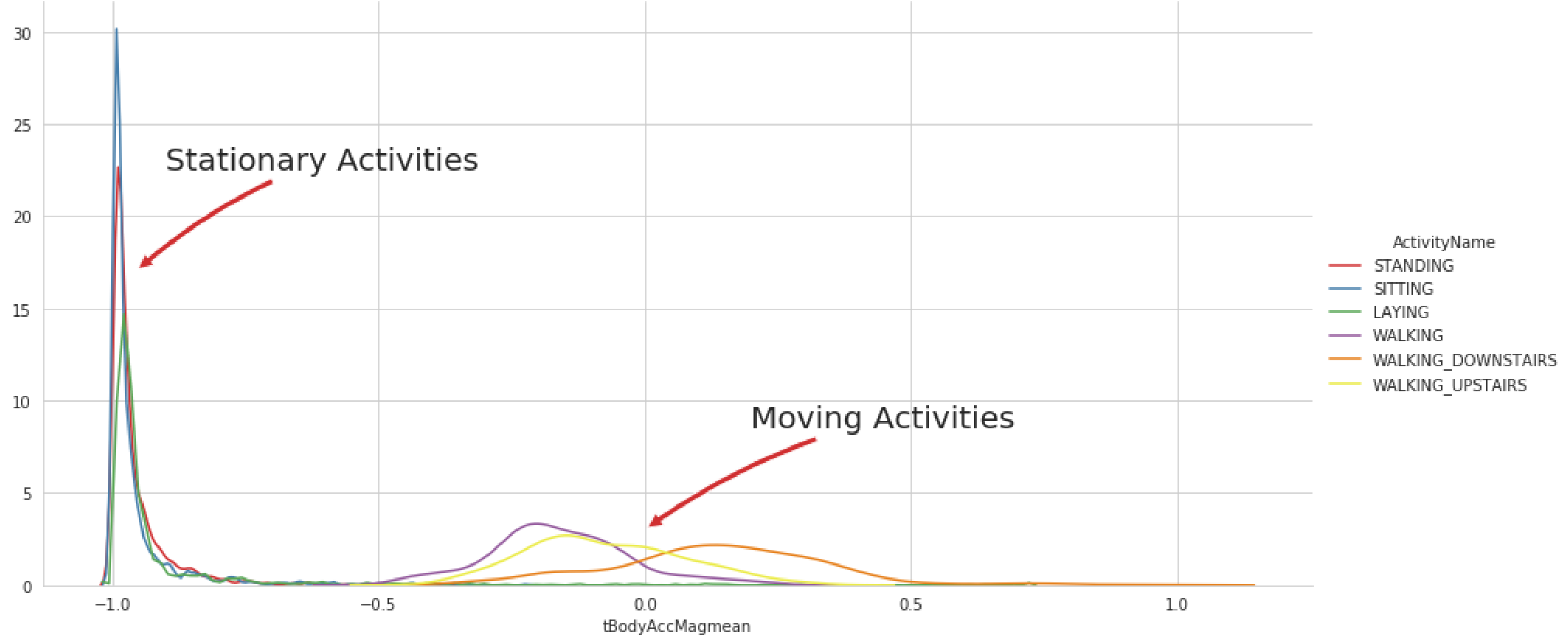
"***Without domain knowledge, EDA has no meaning, without EDA a problem has no soul.***"

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.

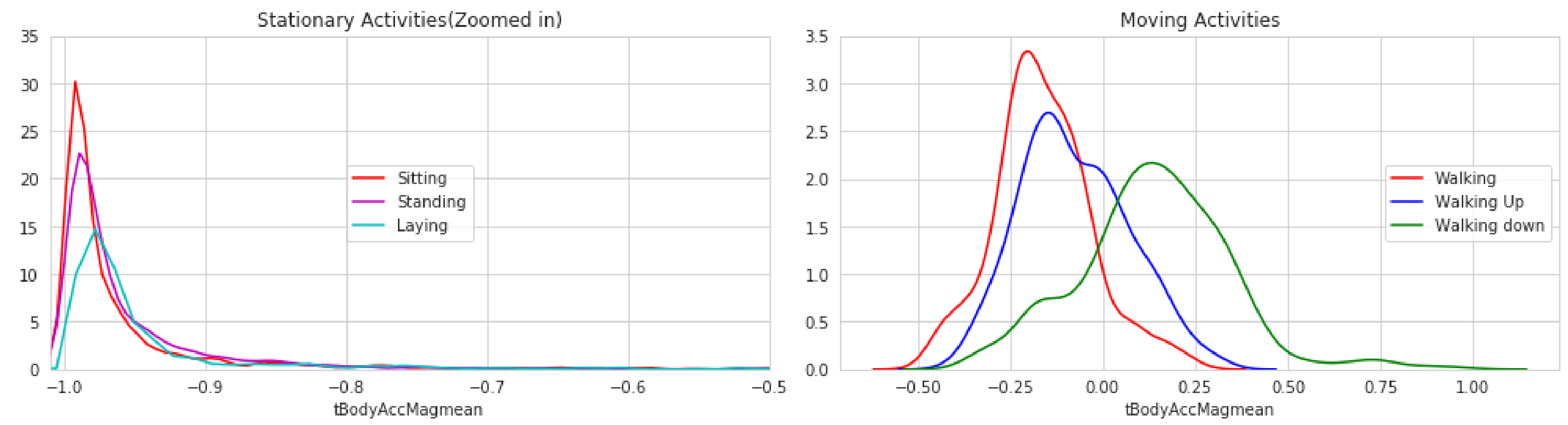
2. Stationary and Moving activities are completely different

In [17]:
```
sns.set_palette("Set1", desat=0.80)
facetgrid = sns.FacetGrid(train, hue='ActivityName', height=6,aspect=2)
facetgrid.map(sns.distplot,'tBodyAccMagmean', hist=False)\
    .add_legend()
plt.annotate("Stationary Activities", xy=(-0.956,17), 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 [18]:

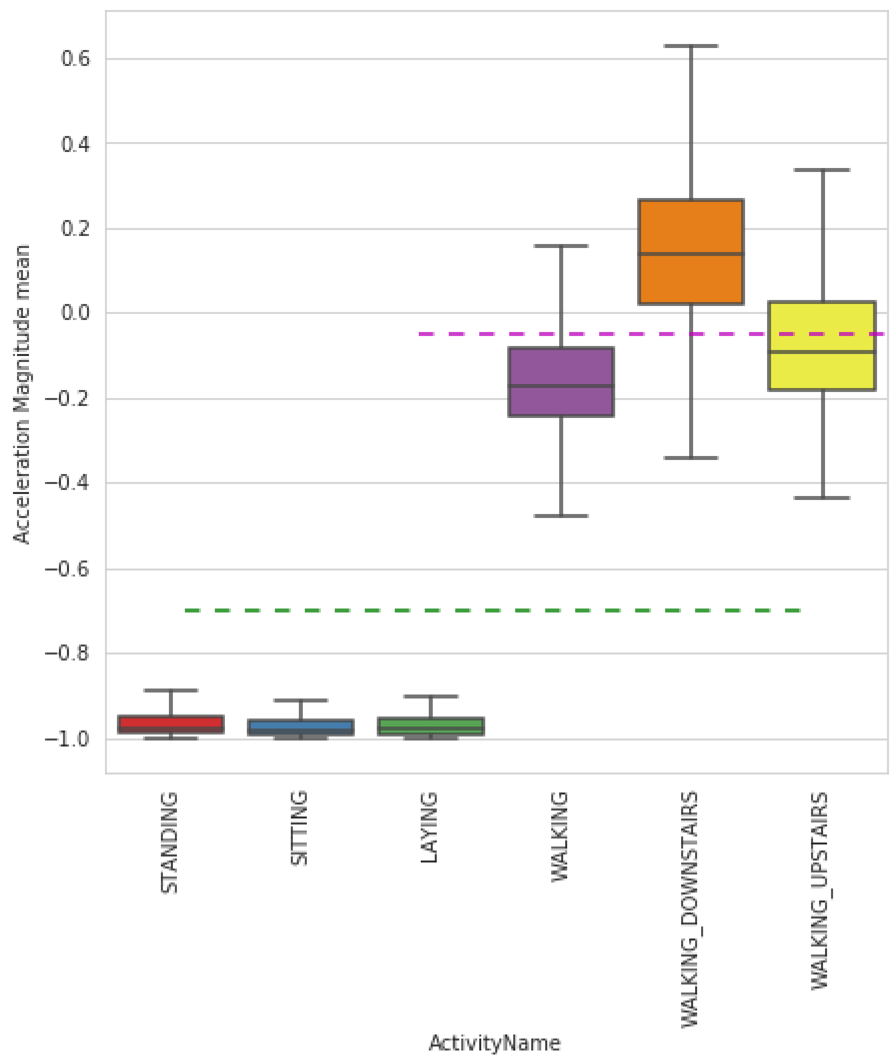
```
# for plotting purposes taking datapoints of each activity to a different dataframe
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

plt.figure(figsize=(14,7))
plt.subplot(2,2,1)
plt.title('Stationary Activities(Zoomed in)')
sns.distplot(df4['tBodyAccMagmean'],color = 'r',hist = False, label = 'Sitting')
sns.distplot(df5['tBodyAccMagmean'],color = 'm',hist = False,label = 'Standing')
sns.distplot(df6['tBodyAccMagmean'],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['tBodyAccMagmean'],color = 'red',hist = False, label = 'Walking')
sns.distplot(df2['tBodyAccMagmean'],color = 'blue',hist = False,label = 'Walking Up')
sns.distplot(df3['tBodyAccMagmean'],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 [19]:

```
plt.figure(figsize=(7,7))
sns.boxplot(x='ActivityName', y='tBodyAccMagmean',data=train, showfliers=False, saturation=1)
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()
```

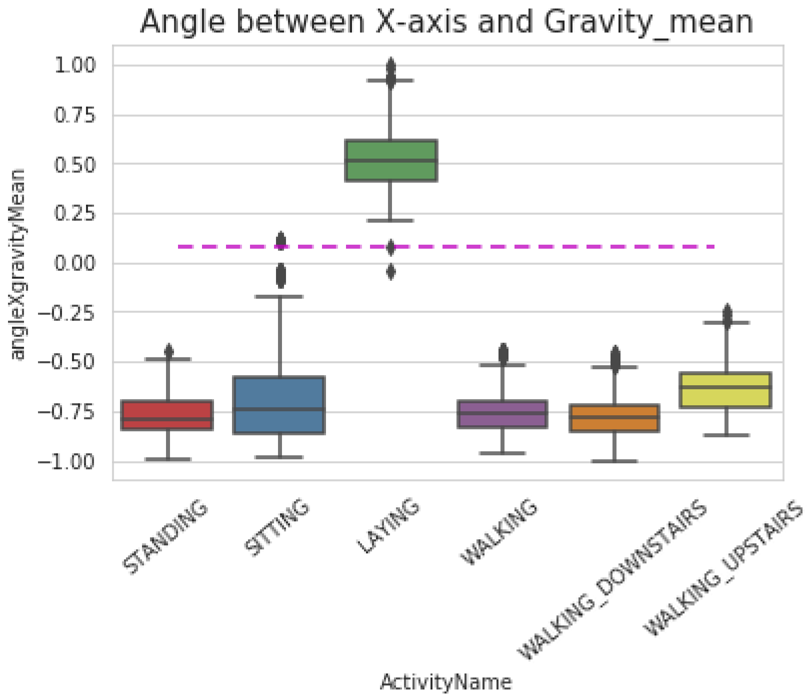


Observations:

- 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

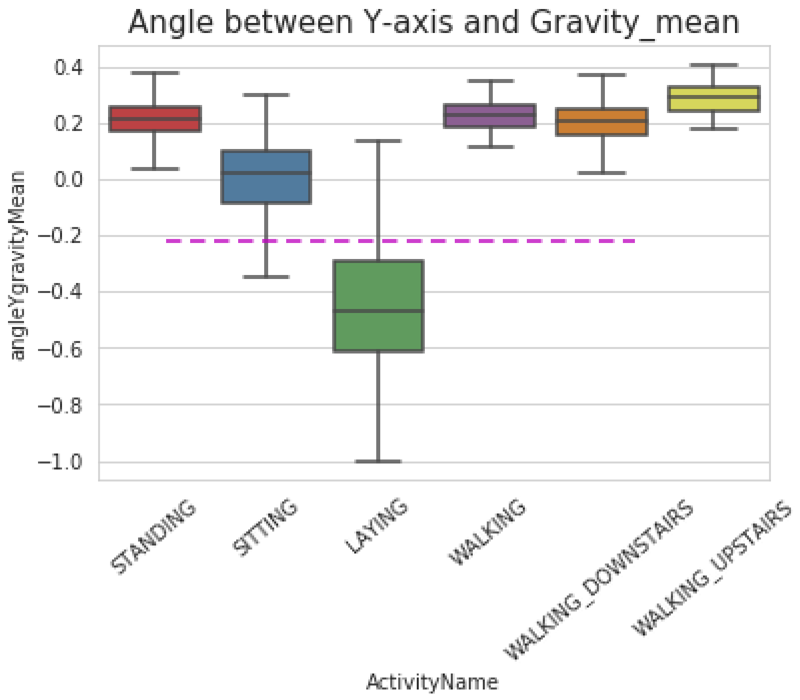
In [20]:
```
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title('Angle between X-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.show()
```



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 [21]:
```
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()
```

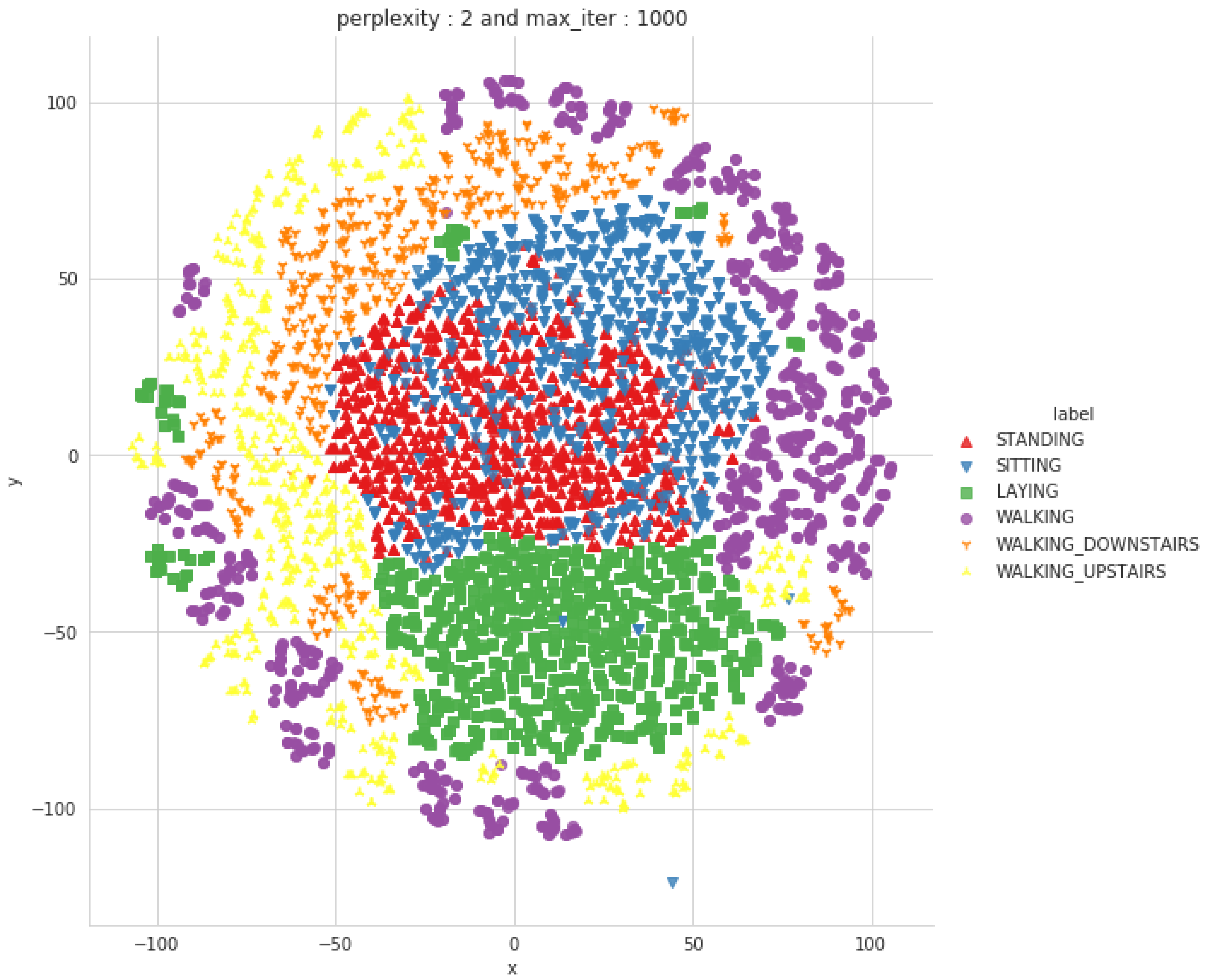


Apply t-sne on the data

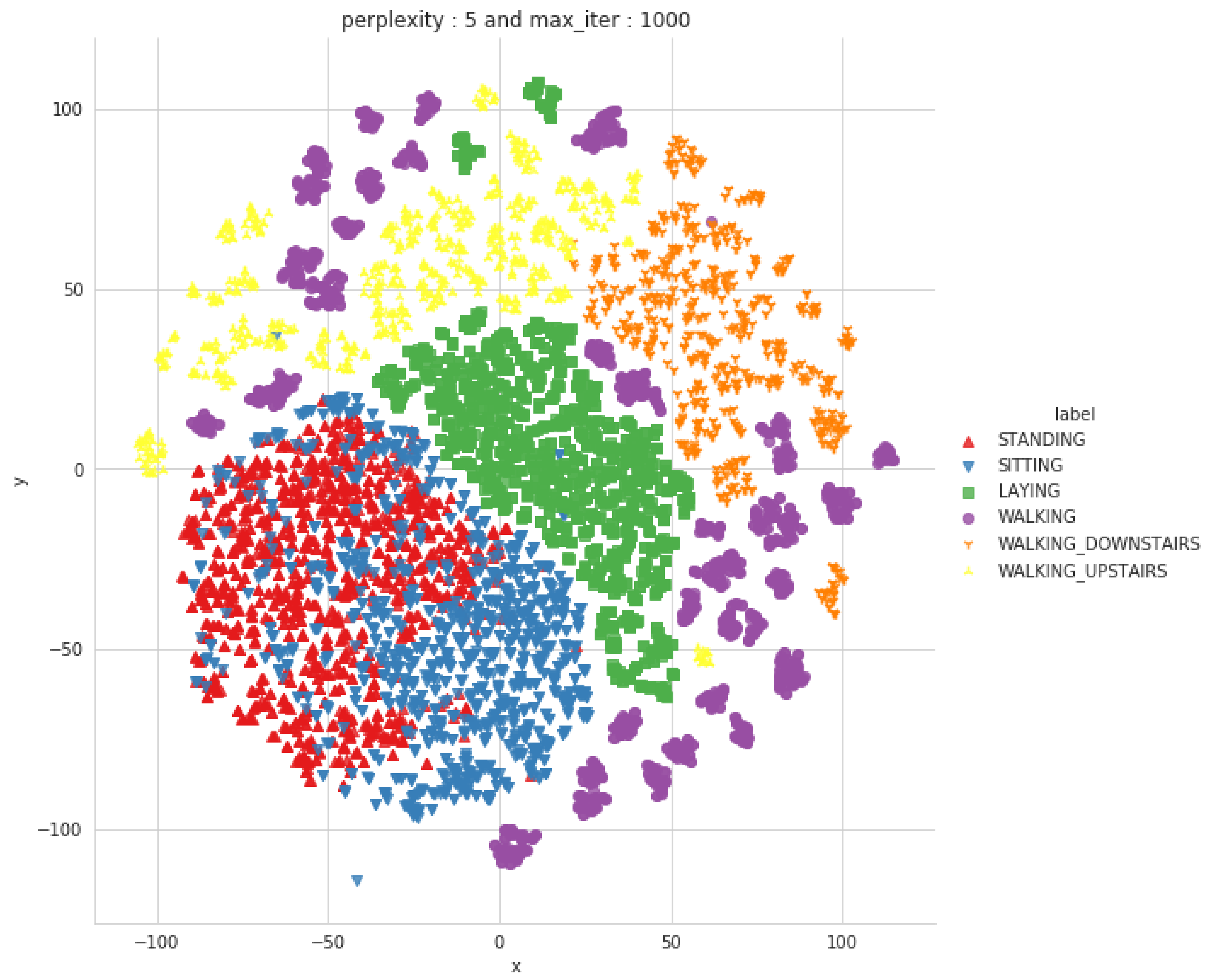
In [22]:
```
# performs t-sne with different perplexity values and their repective plots..
def perform_tsne(X_data, y_data, perplexities, n_iter=1000, img_name_prefix='t-sne'):

    for index,perplexity in enumerate(perplexities):
        # perform t-sne
        print('\nperforming tsne with perplexity {} and with {} iterations at max'.format(perplexity,
n_iter))
        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 [23]:
```
X_pre_tsne = train.drop(['subject', 'Activity','ActivityName'], axis=1)
y_pre_tsne = train['ActivityName']
perform_tsne(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[2,5,10,20,50])
```

```
performing tsne with perplexity 2 and with 1000 iterations at max
[t-SNE] Computing 7 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.170s...
[t-SNE] Computed neighbors for 7352 samples in 31.144s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.635855
[t-SNE] Computed conditional probabilities in 0.028s
[t-SNE] Iteration 50: error = 124.5738525, gradient norm = 0.0296602 (50 iterations in 5.255s)
[t-SNE] Iteration 100: error = 107.1510468, gradient norm = 0.0297832 (50 iterations in 3.191s)
[t-SNE] Iteration 150: error = 100.8849564, gradient norm = 0.0190584 (50 iterations in 2.336s)
[t-SNE] Iteration 200: error = 97.4607620, gradient norm = 0.0157084 (50 iterations in 2.260s)
[t-SNE] Iteration 250: error = 95.1622620, gradient norm = 0.0130789 (50 iterations in 2.232s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 95.162262
[t-SNE] Iteration 300: error = 4.1142921, gradient norm = 0.0015596 (50 iterations in 2.020s)
[t-SNE] Iteration 350: error = 3.2060137, gradient norm = 0.0009984 (50 iterations in 1.868s)
[t-SNE] Iteration 400: error = 2.7765975, gradient norm = 0.0007158 (50 iterations in 1.990s)
[t-SNE] Iteration 450: error = 2.5130556, gradient norm = 0.0005601 (50 iterations in 1.952s)
[t-SNE] Iteration 500: error = 2.3295407, gradient norm = 0.0004789 (50 iterations in 1.936s)
[t-SNE] Iteration 550: error = 2.1922219, gradient norm = 0.0004095 (50 iterations in 1.951s)
[t-SNE] Iteration 600: error = 2.0831914, gradient norm = 0.0003656 (50 iterations in 1.937s)
[t-SNE] Iteration 650: error = 1.9932876, gradient norm = 0.0003318 (50 iterations in 2.037s)
[t-SNE] Iteration 700: error = 1.9175169, gradient norm = 0.0003024 (50 iterations in 2.022s)
[t-SNE] Iteration 750: error = 1.8528048, gradient norm = 0.0002762 (50 iterations in 2.023s)
[t-SNE] Iteration 800: error = 1.7965311, gradient norm = 0.0002552 (50 iterations in 1.975s)
[t-SNE] Iteration 850: error = 1.7464951, gradient norm = 0.0002381 (50 iterations in 1.961s)
[t-SNE] Iteration 900: error = 1.7021343, gradient norm = 0.0002246 (50 iterations in 2.015s)
[t-SNE] Iteration 950: error = 1.6620091, gradient norm = 0.0002131 (50 iterations in 1.988s)
[t-SNE] Iteration 1000: error = 1.6257184, gradient norm = 0.0001977 (50 iterations in 1.982s)
[t-SNE] KL divergence after 1000 iterations: 1.625718
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```

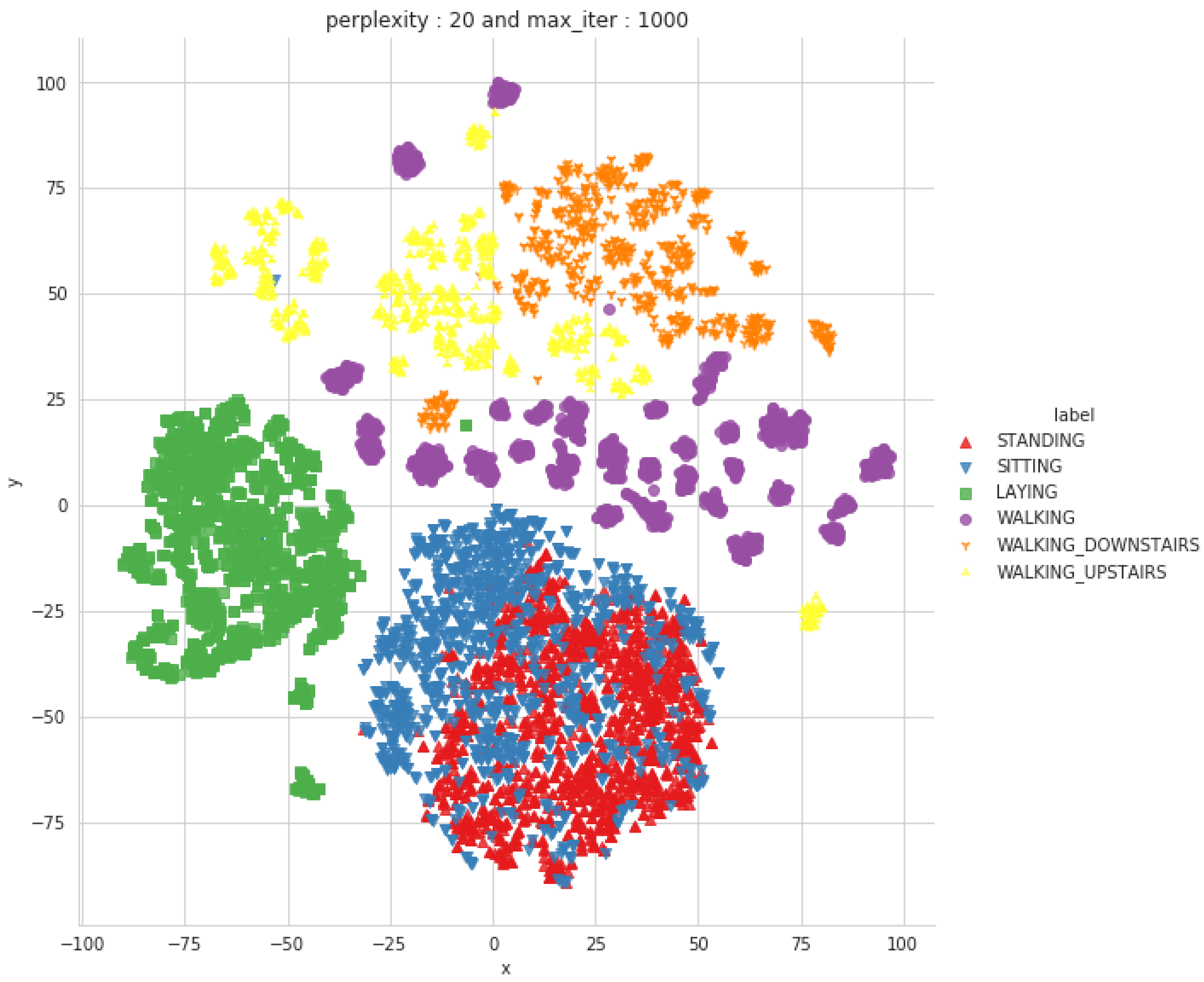



```
Done

performing tsne with perplexity 5 and with 1000 iterations at max
[t-SNE] Computing 16 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.191s...
[t-SNE] Computed neighbors for 7352 samples in 31.631s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.961265
[t-SNE] Computed conditional probabilities in 0.040s
[t-SNE] Iteration 50: error = 114.0045013, gradient norm = 0.0218148 (50 iterations in 3.931s)
[t-SNE] Iteration 100: error = 97.7540359, gradient norm = 0.0201030 (50 iterations in 2.377s)
[t-SNE] Iteration 150: error = 93.4471817, gradient norm = 0.0081666 (50 iterations in 2.035s)
[t-SNE] Iteration 200: error = 91.5198059, gradient norm = 0.0067892 (50 iterations in 1.946s)
[t-SNE] Iteration 250: error = 90.3294373, gradient norm = 0.0059565 (50 iterations in 1.949s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 90.329437
[t-SNE] Iteration 300: error = 3.5774119, gradient norm = 0.0014642 (50 iterations in 1.920s)
[t-SNE] Iteration 350: error = 2.8179550, gradient norm = 0.0007576 (50 iterations in 1.841s)
[t-SNE] Iteration 400: error = 2.4356155, gradient norm = 0.0005241 (50 iterations in 1.860s)
[t-SNE] Iteration 450: error = 2.2181222, gradient norm = 0.0004086 (50 iterations in 1.911s)
[t-SNE] Iteration 500: error = 2.0728469, gradient norm = 0.0003349 (50 iterations in 1.898s)
[t-SNE] Iteration 550: error = 1.9676163, gradient norm = 0.0002853 (50 iterations in 1.926s)
[t-SNE] Iteration 600: error = 1.8863214, gradient norm = 0.0002456 (50 iterations in 1.901s)
[t-SNE] Iteration 650: error = 1.8211229, gradient norm = 0.0002209 (50 iterations in 1.897s)
[t-SNE] Iteration 700: error = 1.7675735, gradient norm = 0.0001959 (50 iterations in 1.920s)
[t-SNE] Iteration 750: error = 1.7220205, gradient norm = 0.0001791 (50 iterations in 1.914s)
[t-SNE] Iteration 800: error = 1.6831133, gradient norm = 0.0001638 (50 iterations in 1.917s)
[t-SNE] Iteration 850: error = 1.6491792, gradient norm = 0.0001539 (50 iterations in 1.938s)
[t-SNE] Iteration 900: error = 1.6194623, gradient norm = 0.0001419 (50 iterations in 1.908s)
[t-SNE] Iteration 950: error = 1.5934302, gradient norm = 0.0001322 (50 iterations in 1.934s)
[t-SNE] Iteration 1000: error = 1.5701127, gradient norm = 0.0001244 (50 iterations in 1.931s)
[t-SNE] KL divergence after 1000 iterations: 1.570113
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```

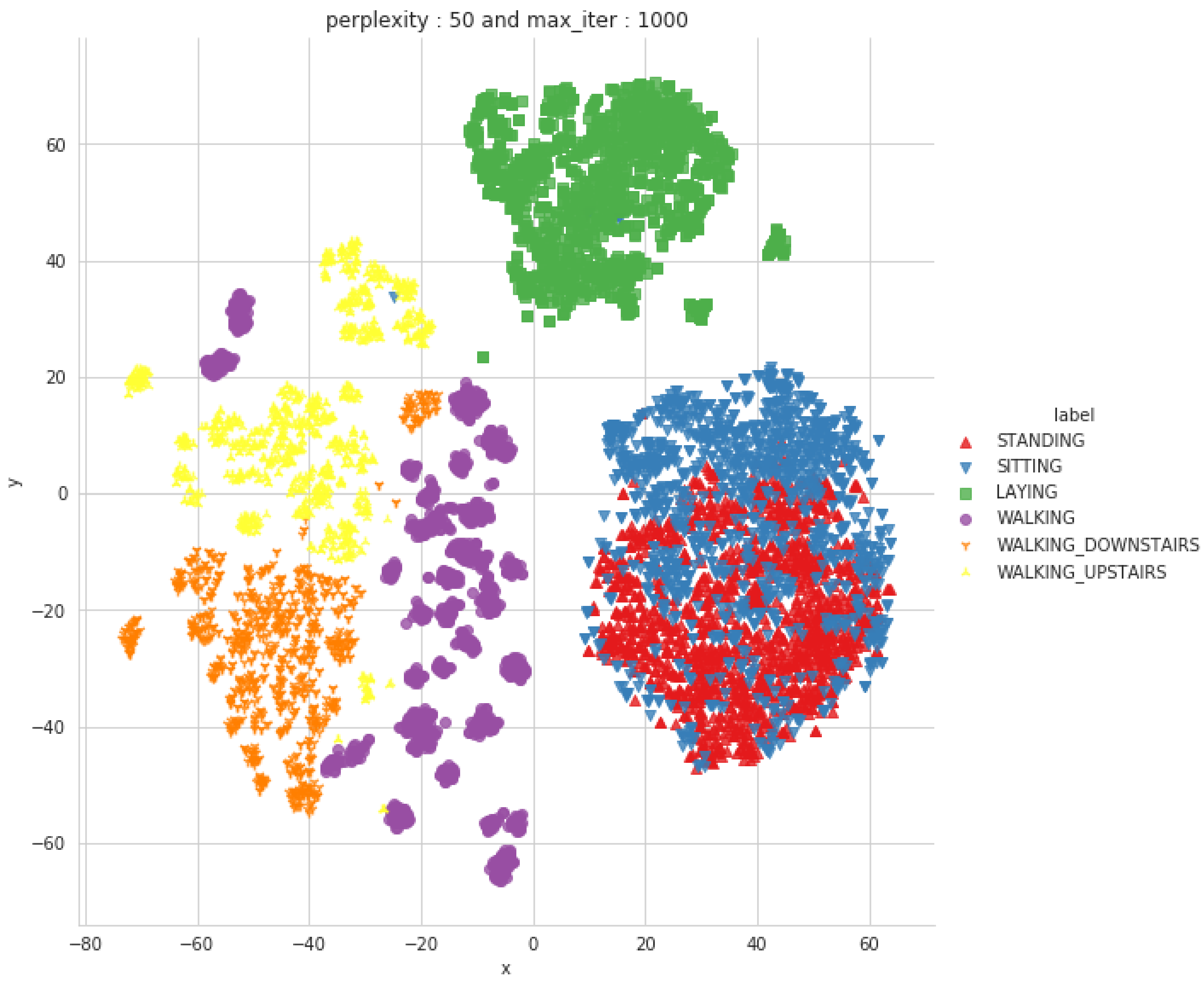



```
Done

performing tsne with perplexity 10 and with 1000 iterations at max
[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.184s...
[t-SNE] Computed neighbors for 7352 samples in 32.098s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.133828
[t-SNE] Computed conditional probabilities in 0.075s
[t-SNE] Iteration 50: error = 105.5975342, gradient norm = 0.0265865 (50 iterations in 3.493s)
[t-SNE] Iteration 100: error = 90.2277222, gradient norm = 0.0105441 (50 iterations in 2.326s)
[t-SNE] Iteration 150: error = 87.1800156, gradient norm = 0.0058049 (50 iterations in 2.068s)
[t-SNE] Iteration 200: error = 85.9355545, gradient norm = 0.0036519 (50 iterations in 2.065s)
[t-SNE] Iteration 250: error = 85.2444153, gradient norm = 0.0025938 (50 iterations in 1.966s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 85.244415
[t-SNE] Iteration 300: error = 3.1290836, gradient norm = 0.0013881 (50 iterations in 1.900s)
[t-SNE] Iteration 350: error = 2.4865267, gradient norm = 0.0006460 (50 iterations in 1.895s)
[t-SNE] Iteration 400: error = 2.1677175, gradient norm = 0.0004223 (50 iterations in 1.908s)
[t-SNE] Iteration 450: error = 1.9836645, gradient norm = 0.0003125 (50 iterations in 1.932s)
[t-SNE] Iteration 500: error = 1.8657217, gradient norm = 0.0002491 (50 iterations in 1.938s)
[t-SNE] Iteration 550: error = 1.7822043, gradient norm = 0.0002117 (50 iterations in 1.917s)
[t-SNE] Iteration 600: error = 1.7194588, gradient norm = 0.0001798 (50 iterations in 1.929s)
[t-SNE] Iteration 650: error = 1.6704119, gradient norm = 0.0001596 (50 iterations in 1.998s)
[t-SNE] Iteration 700: error = 1.6307381, gradient norm = 0.0001444 (50 iterations in 2.030s)
[t-SNE] Iteration 750: error = 1.5978731, gradient norm = 0.0001297 (50 iterations in 1.948s)
[t-SNE] Iteration 800: error = 1.5702615, gradient norm = 0.0001194 (50 iterations in 2.055s)
[t-SNE] Iteration 850: error = 1.5463381, gradient norm = 0.0001106 (50 iterations in 2.073s)
[t-SNE] Iteration 900: error = 1.5259278, gradient norm = 0.0001043 (50 iterations in 2.066s)
[t-SNE] Iteration 950: error = 1.5087668, gradient norm = 0.0000966 (50 iterations in 2.050s)
[t-SNE] Iteration 1000: error = 1.4936571, gradient norm = 0.0000922 (50 iterations in 1.996s)
[t-SNE] KL divergence after 1000 iterations: 1.493657
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```


```
Done

performing tsne with perplexity 20 and with 1000 iterations at max
[t-SNE] Computing 61 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.185s...
[t-SNE] Computed neighbors for 7352 samples in 32.602s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.274335
[t-SNE] Computed conditional probabilities in 0.142s
[t-SNE] Iteration 50: error = 97.8273087, gradient norm = 0.0185177 (50 iterations in 3.108s)
[t-SNE] Iteration 100: error = 83.8836975, gradient norm = 0.0064890 (50 iterations in 2.504s)
[t-SNE] Iteration 150: error = 81.8936844, gradient norm = 0.0048022 (50 iterations in 2.218s)
[t-SNE] Iteration 200: error = 81.1817780, gradient norm = 0.0075951 (50 iterations in 2.202s)
[t-SNE] Iteration 250: error = 80.7856369, gradient norm = 0.0018122 (50 iterations in 2.178s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 80.785637
[t-SNE] Iteration 300: error = 2.7073162, gradient norm = 0.0013089 (50 iterations in 2.261s)
[t-SNE] Iteration 350: error = 2.1718423, gradient norm = 0.0005850 (50 iterations in 2.165s)
[t-SNE] Iteration 400: error = 1.9216920, gradient norm = 0.0003498 (50 iterations in 2.168s)
[t-SNE] Iteration 450: error = 1.7746754, gradient norm = 0.0002482 (50 iterations in 2.195s)
[t-SNE] Iteration 500: error = 1.6804155, gradient norm = 0.0001926 (50 iterations in 2.186s)
[t-SNE] Iteration 550: error = 1.6163112, gradient norm = 0.0001575 (50 iterations in 2.188s)
[t-SNE] Iteration 600: error = 1.5695801, gradient norm = 0.0001348 (50 iterations in 2.222s)
[t-SNE] Iteration 650: error = 1.5341690, gradient norm = 0.0001198 (50 iterations in 2.183s)
[t-SNE] Iteration 700: error = 1.5066086, gradient norm = 0.0001067 (50 iterations in 2.184s)
[t-SNE] Iteration 750: error = 1.4844245, gradient norm = 0.0000992 (50 iterations in 2.172s)
[t-SNE] Iteration 800: error = 1.4670590, gradient norm = 0.0000913 (50 iterations in 2.188s)
[t-SNE] Iteration 850: error = 1.4528230, gradient norm = 0.0000852 (50 iterations in 2.176s)
[t-SNE] Iteration 900: error = 1.4407786, gradient norm = 0.0000817 (50 iterations in 2.191s)
[t-SNE] Iteration 950: error = 1.4306071, gradient norm = 0.0000762 (50 iterations in 2.187s)
[t-SNE] Iteration 1000: error = 1.4219763, gradient norm = 0.0000724 (50 iterations in 2.202s)
[t-SNE] KL divergence after 1000 iterations: 1.421976
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```




```
Done

performing tsne with perplexity 50 and with 1000 iterations at max
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.185s...
[t-SNE] Computed neighbors for 7352 samples in 33.970s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.437672
[t-SNE] Computed conditional probabilities in 0.344s
[t-SNE] Iteration 50: error = 86.8576126, gradient norm = 0.0147354 (50 iterations in 4.192s)
[t-SNE] Iteration 100: error = 75.6796341, gradient norm = 0.0045453 (50 iterations in 3.721s)
[t-SNE] Iteration 150: error = 74.6311874, gradient norm = 0.0023849 (50 iterations in 2.901s)
[t-SNE] Iteration 200: error = 74.2492905, gradient norm = 0.0016185 (50 iterations in 2.929s)
[t-SNE] Iteration 250: error = 74.0620575, gradient norm = 0.0012495 (50 iterations in 2.978s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 74.062057
[t-SNE] Iteration 300: error = 2.1505814, gradient norm = 0.0011883 (50 iterations in 2.804s)
[t-SNE] Iteration 350: error = 1.7544994, gradient norm = 0.0004870 (50 iterations in 2.664s)
[t-SNE] Iteration 400: error = 1.5867132, gradient norm = 0.0002781 (50 iterations in 2.675s)
[t-SNE] Iteration 450: error = 1.4930662, gradient norm = 0.0001878 (50 iterations in 2.692s)
[t-SNE] Iteration 500: error = 1.4334233, gradient norm = 0.0001401 (50 iterations in 2.695s)
[t-SNE] Iteration 550: error = 1.3925681, gradient norm = 0.0001117 (50 iterations in 2.671s)
[t-SNE] Iteration 600: error = 1.3633409, gradient norm = 0.0000950 (50 iterations in 2.677s)
[t-SNE] Iteration 650: error = 1.3421924, gradient norm = 0.0000820 (50 iterations in 2.652s)
[t-SNE] Iteration 700: error = 1.3267561, gradient norm = 0.0000754 (50 iterations in 2.688s)
[t-SNE] Iteration 750: error = 1.3154731, gradient norm = 0.0000698 (50 iterations in 2.656s)
[t-SNE] Iteration 800: error = 1.3065718, gradient norm = 0.0000648 (50 iterations in 2.695s)
[t-SNE] Iteration 850: error = 1.2996116, gradient norm = 0.0000618 (50 iterations in 2.642s)
[t-SNE] Iteration 900: error = 1.2942611, gradient norm = 0.0000596 (50 iterations in 2.698s)
[t-SNE] Iteration 950: error = 1.2900971, gradient norm = 0.0000615 (50 iterations in 2.704s)
[t-SNE] Iteration 1000: error = 1.2868505, gradient norm = 0.0000561 (50 iterations in 2.679s)
[t-SNE] KL divergence after 1000 iterations: 1.286850
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```



Done

Apply Machine Learning Models

In [24]:
```
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 [25]:
```
train.head(3)
```

Out[25]:

	tBodyAccmeanX	tBodyAccmeanY	tBodyAccmeanZ	tBodyAccstdX	tBodyAccstdY	tBodyAccstdZ	tBodyAccmad
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520

3 rows × 564 columns

In [28]:
```
# get x_train and y_train from csv files
x_train = train.drop(['subject', 'Activity', 'ActivityName'], axis=1)
y_train = train.ActivityName

# get x_test and y_test from test csv file
x_test = test.drop(['subject', 'Activity', 'ActivityName'], axis=1)
y_test = test.ActivityName

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,))
```

Labels that are useful in plotting confusion matrix

In [30]:
```
labels=['LAYING', 'SITTING','STANDING','WALKING','WALKING_DOWNSTAIRS','WALKING_UPSTAIRS']
```

Function to plot the confusion matrix

In [31]:
```
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 [33]:
```
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 confusion matri
x', cmap = cm_cmap)
    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
```

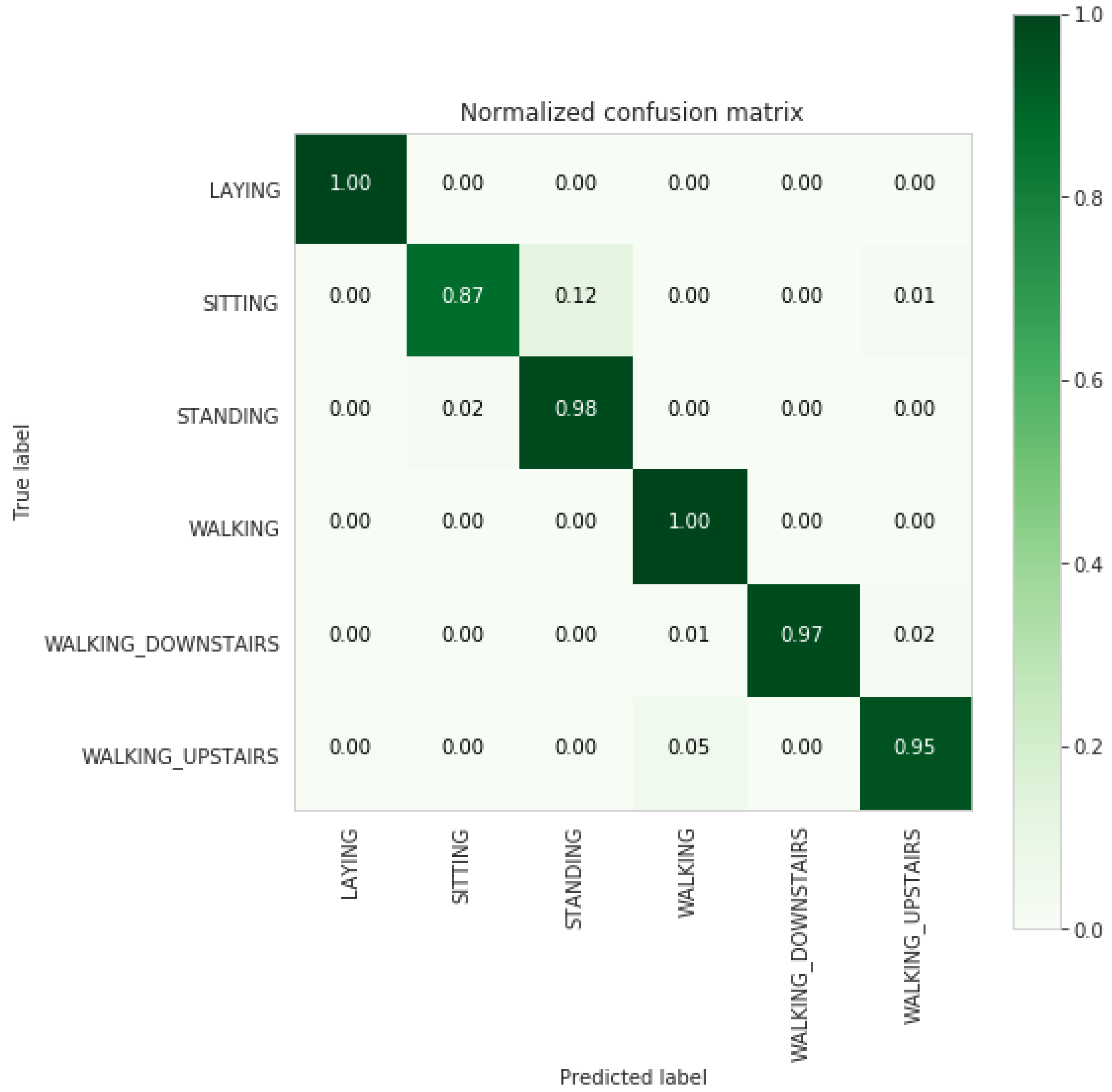
Method to print the gridsearch Attributes

In [35]:
```
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.best_score_
))
```

1. Logistic Regression with Grid Search

In [42]:
```
# 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=-1)
log_reg_grid_results =  perform_model(log_reg_grid, x_train, y_train, x_test, y_test, class_labels=lab
els)
```

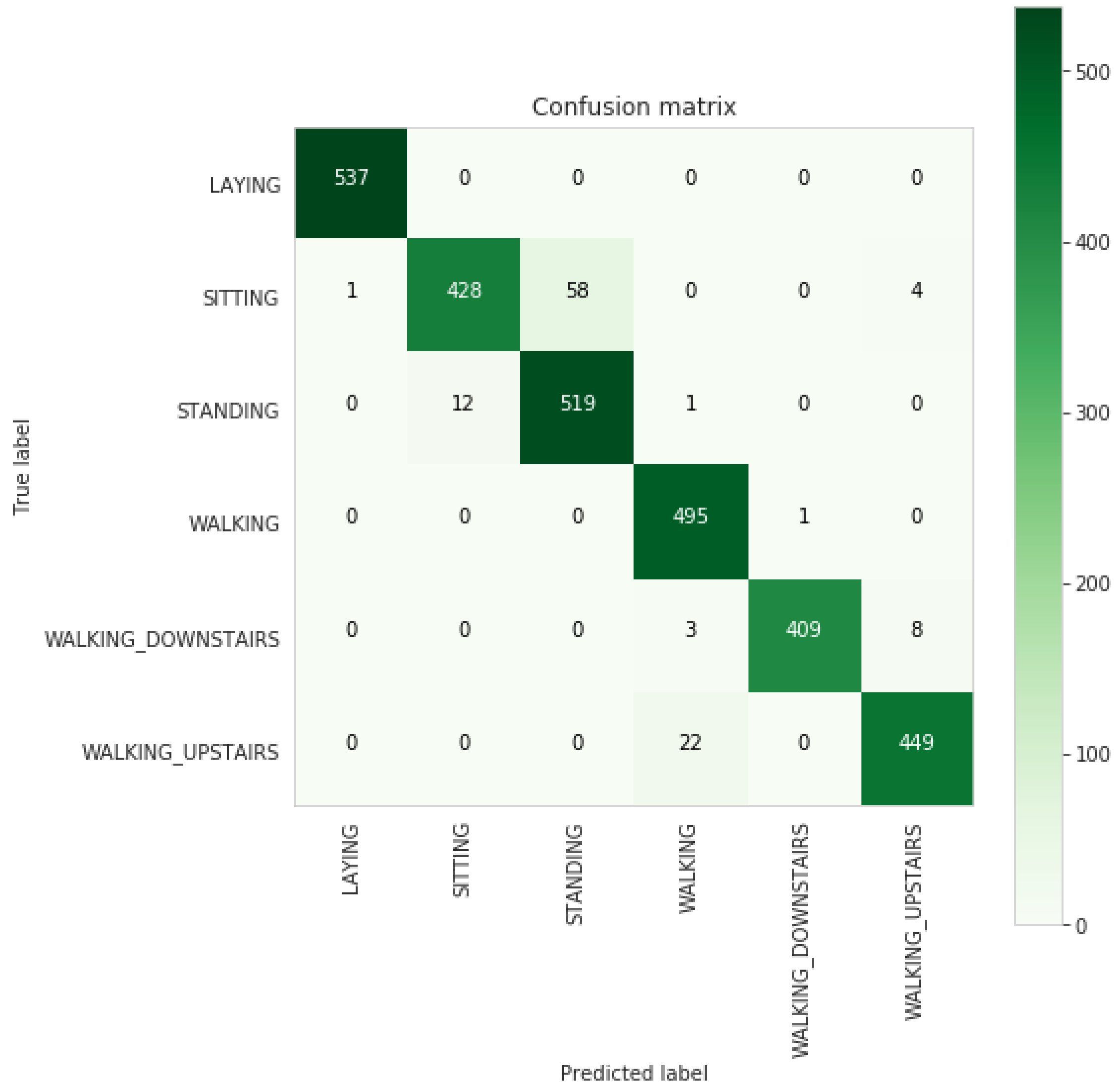
```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 6 concurrent workers.
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed:   46.4s finished

Done


training_time(HH:MM:SS.ms) - 0:00:52.450343


Predicting test data
Done


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


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

    0.9626739056667798


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

 [[537   0   0   0   0   0]
 [  1 428  58   0   0   4]
 [  0  12 519   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

         micro avg       0.96      0.96      0.96      2947
         macro avg       0.97      0.96      0.96      2947
      weighted avg       0.96      0.96      0.96      2947
```

In [44]:

```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(log_reg_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.Greens)
plt.show()
```



In [45]:

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

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

        LogisticRegression(C=30, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          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 :

        0.9461371055495104
```

2. Linear SVC with GridSearch

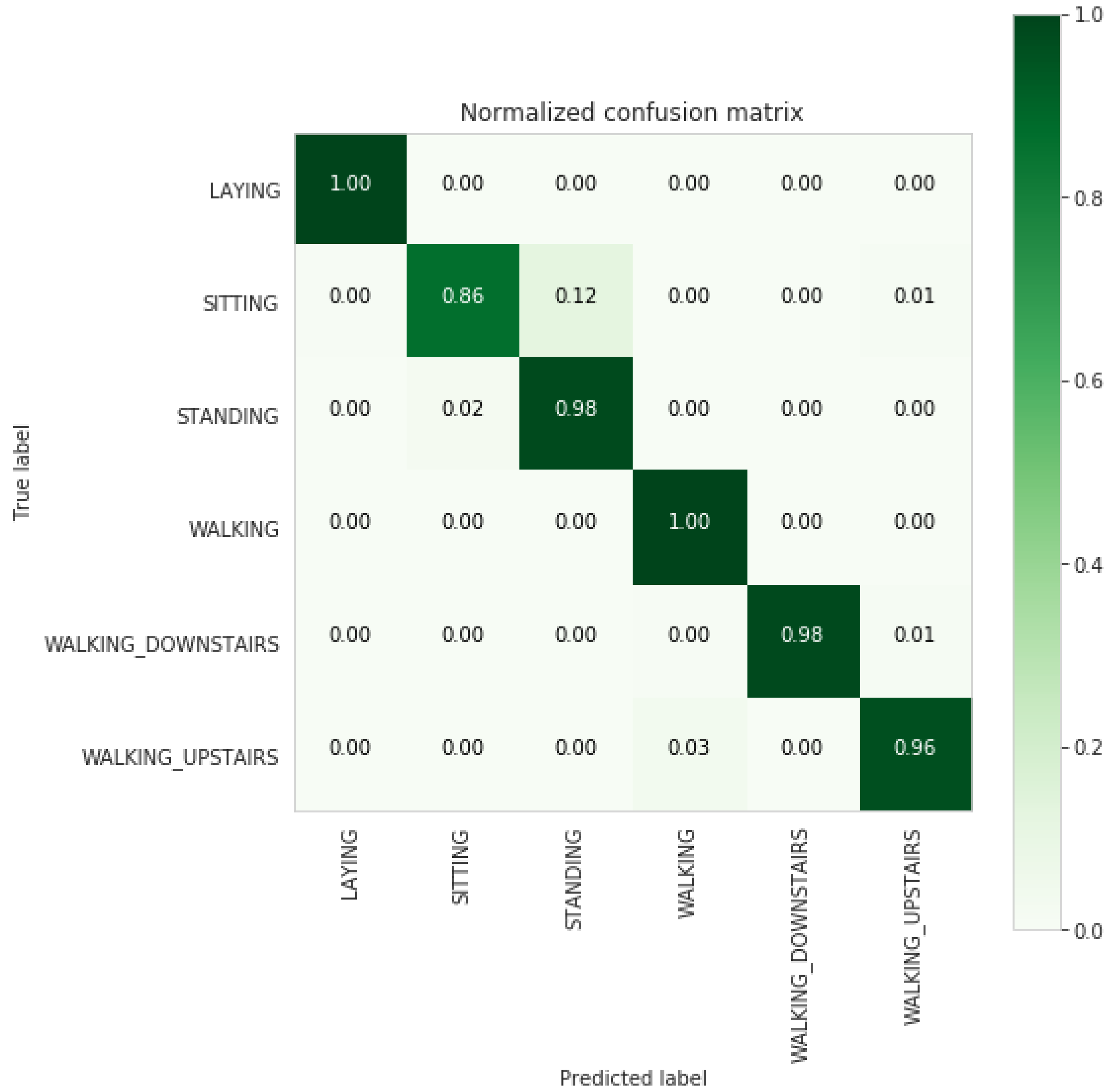
In [46]:

```
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=-1, verbose=1)
lr_svc_grid_results = perform_model(lr_svc_grid, x_train, y_train, x_test, y_test, class_labels=labels
)
```

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 6 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:   12.6s finished
```

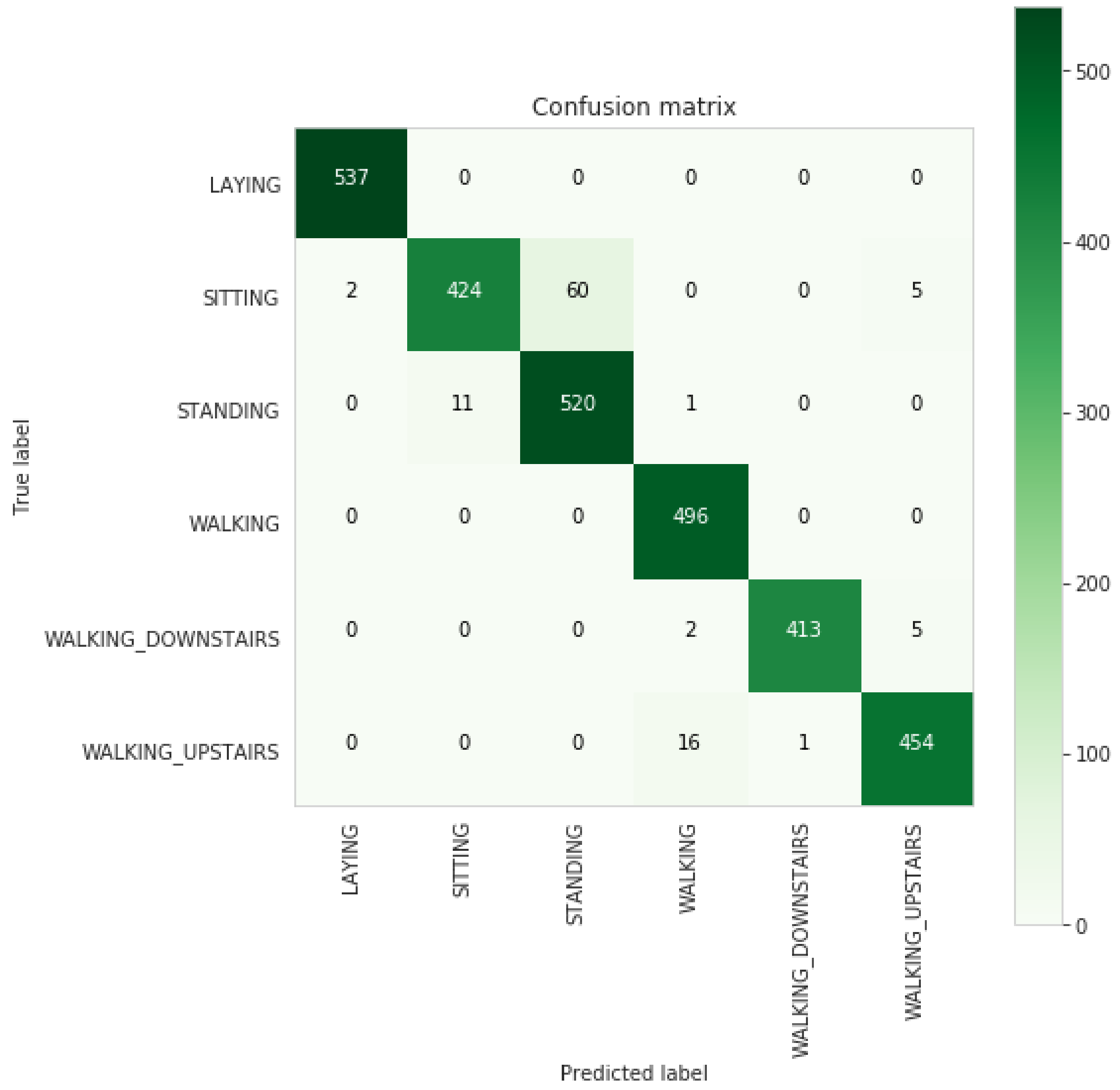
```
Done


training_time(HH:MM:SS.ms) - 0:00:16.079952


Predicting test data
Done


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


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

    0.9650492025788938


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

 [[537   0   0   0   0   0]
 [  2 424  60   0   0   5]
 [  0  11 520   1   0   0]
 [  0   0   0 496   0   0]
 [  0   0   0   2 413   5]
 [  0   0   0  16   1 454]]
```




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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.86      0.92       491
          STANDING       0.90      0.98      0.94       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

         micro avg       0.97      0.97      0.97      2947
         macro avg       0.97      0.96      0.97      2947
      weighted avg       0.97      0.97      0.96      2947
```

In [47]:

```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(lr_svc_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.Greens)
plt.show()
```



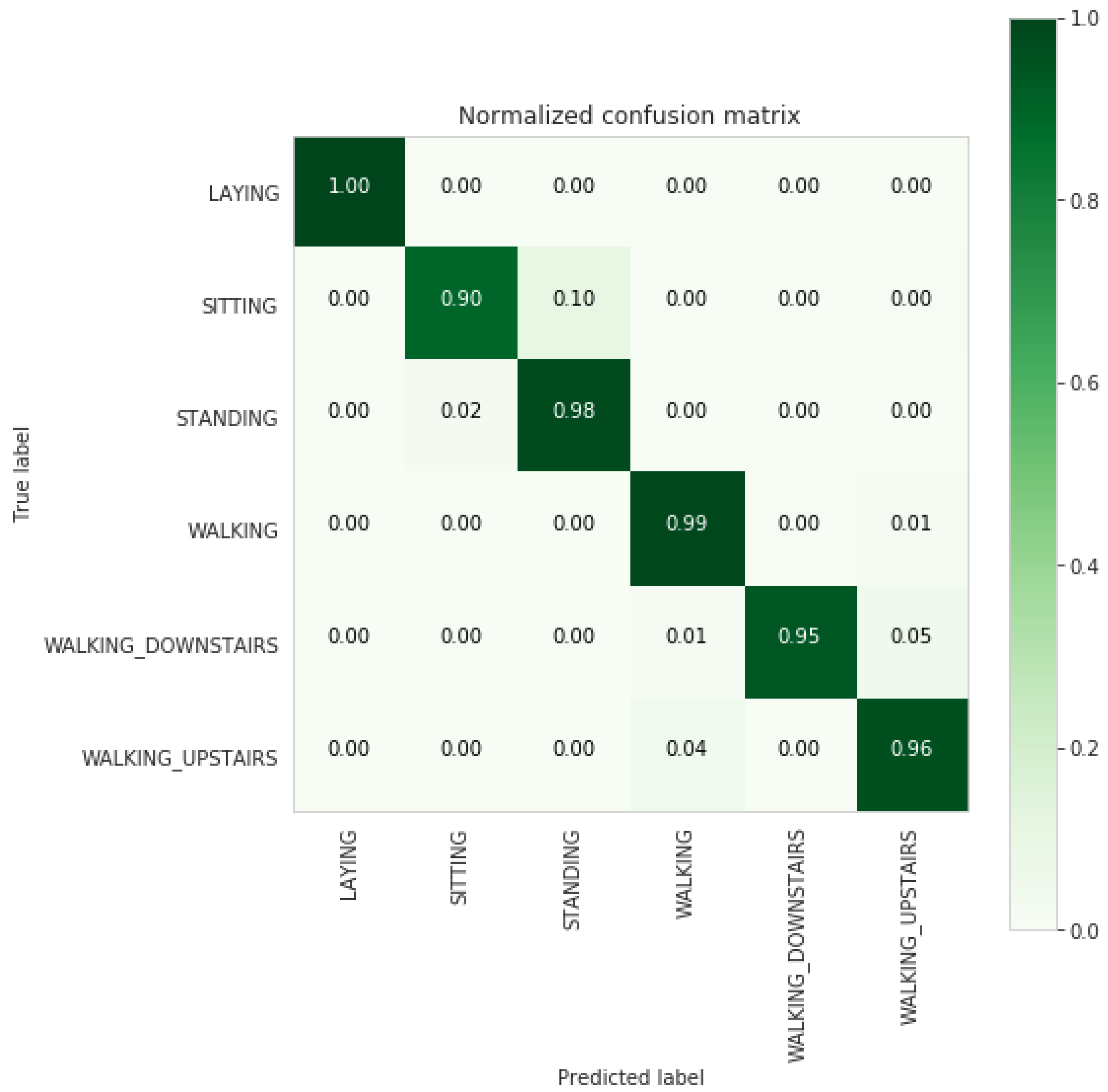
In [48]:
```
print_grid_search_attributes(lr_svc_grid_results['model'])
```

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

        LinearSVC(C=2, 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': 2}

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.9461371055495104
```

3. RBF Kernel SVM with GridSearch

In [49]:
```
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=-1)
rbf_svm_grid_results = perform_model(rbf_svm_grid, x_train, y_train, x_test, y_test, class_labels=labe
ls)
```

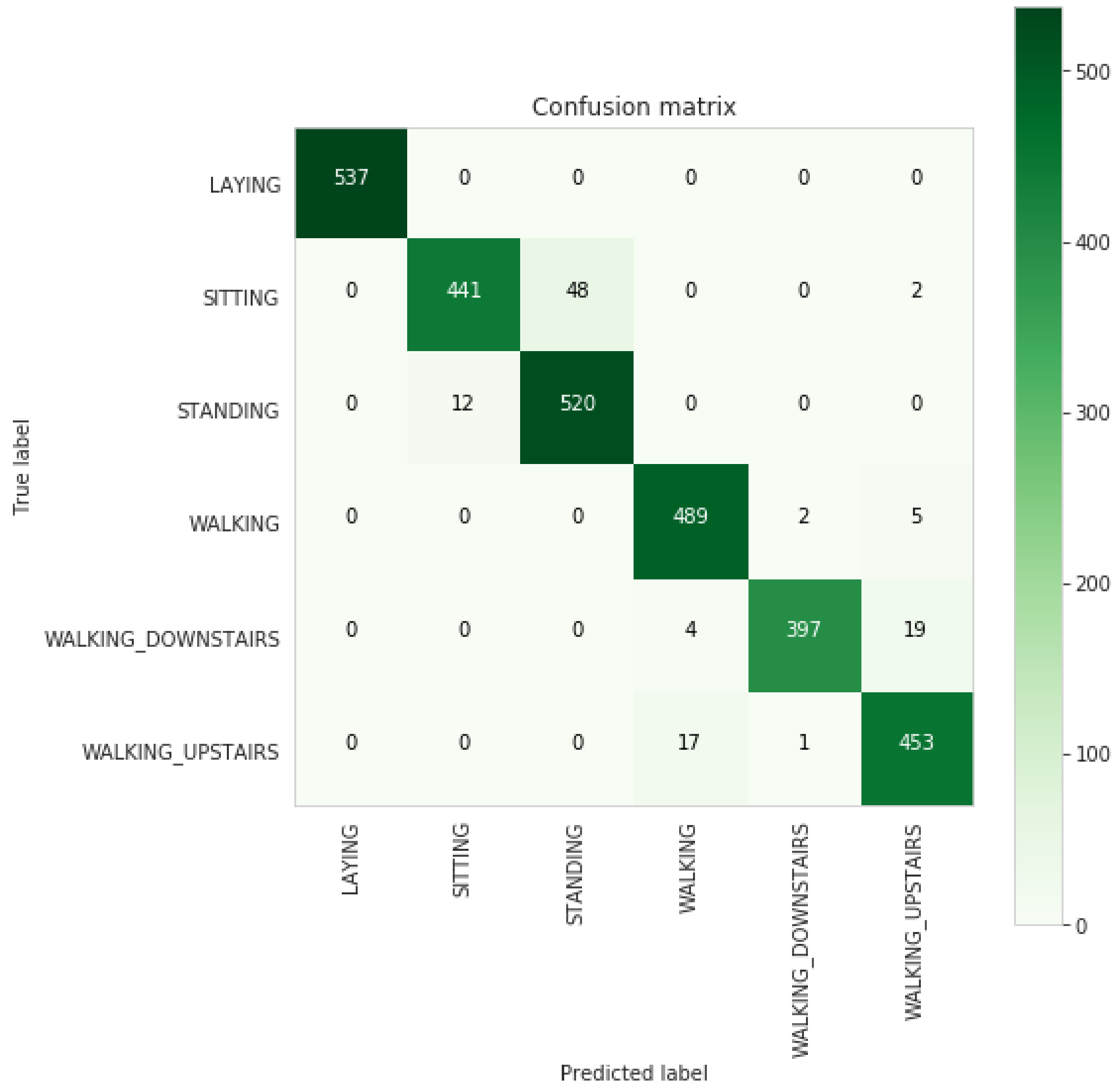
```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:03:27.976105


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:02.113316


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

    0.9626739056667798


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

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




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

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

         micro avg       0.96      0.96      0.96      2947
         macro avg       0.96      0.96      0.96      2947
      weighted avg       0.96      0.96      0.96      2947
```

In [50]:

```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(rbf_svm_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.Greens)
plt.show()
```



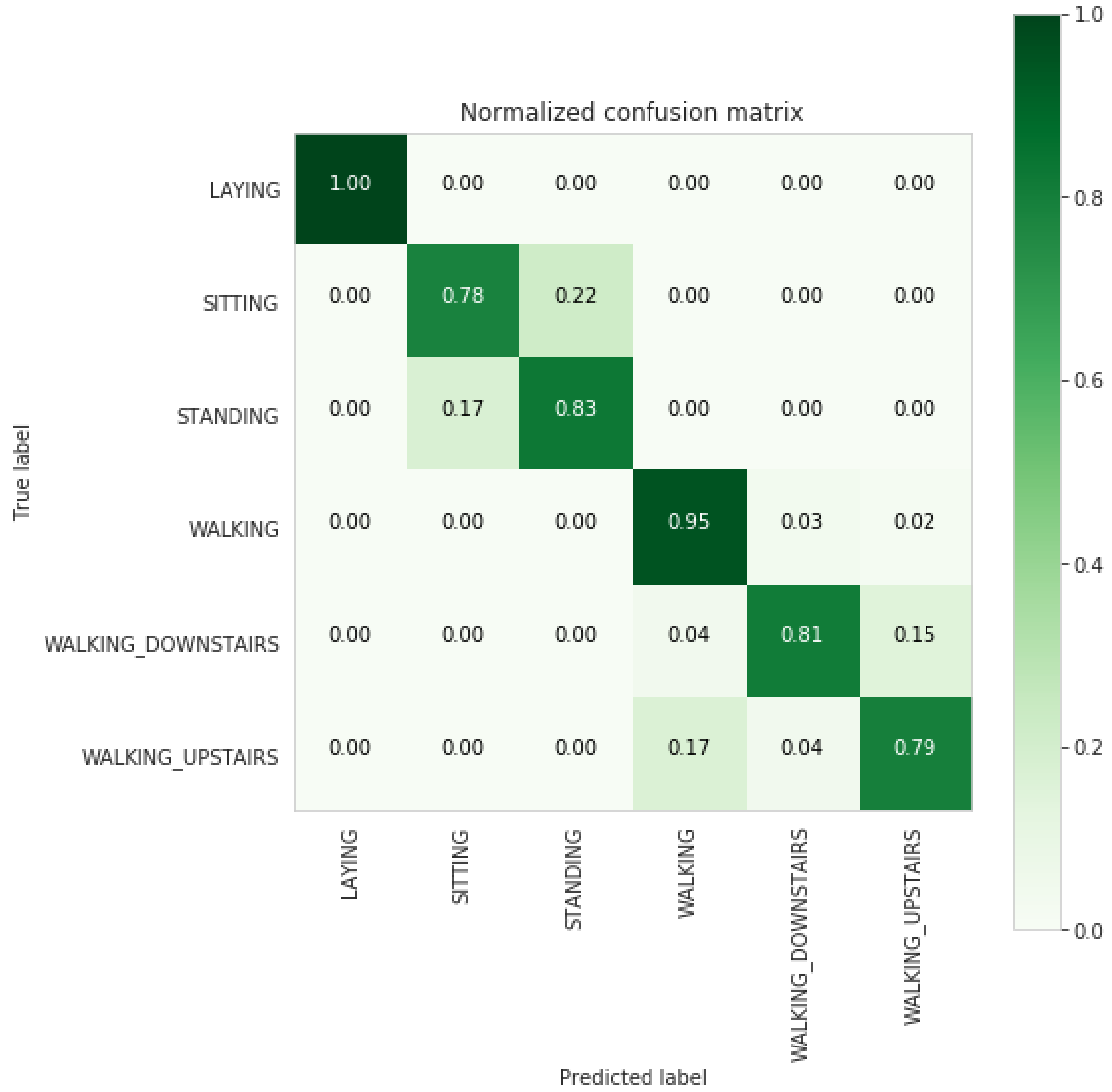
In [51]:
```
print_grid_search_attributes(rbf_svm_grid_results['model'])
```

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

        SVC(C=16, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.0078125, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)

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

        {'C': 16, 'gamma': 0.0078125}

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.9440968443960827
```

4. Decision Tree with GridSearch

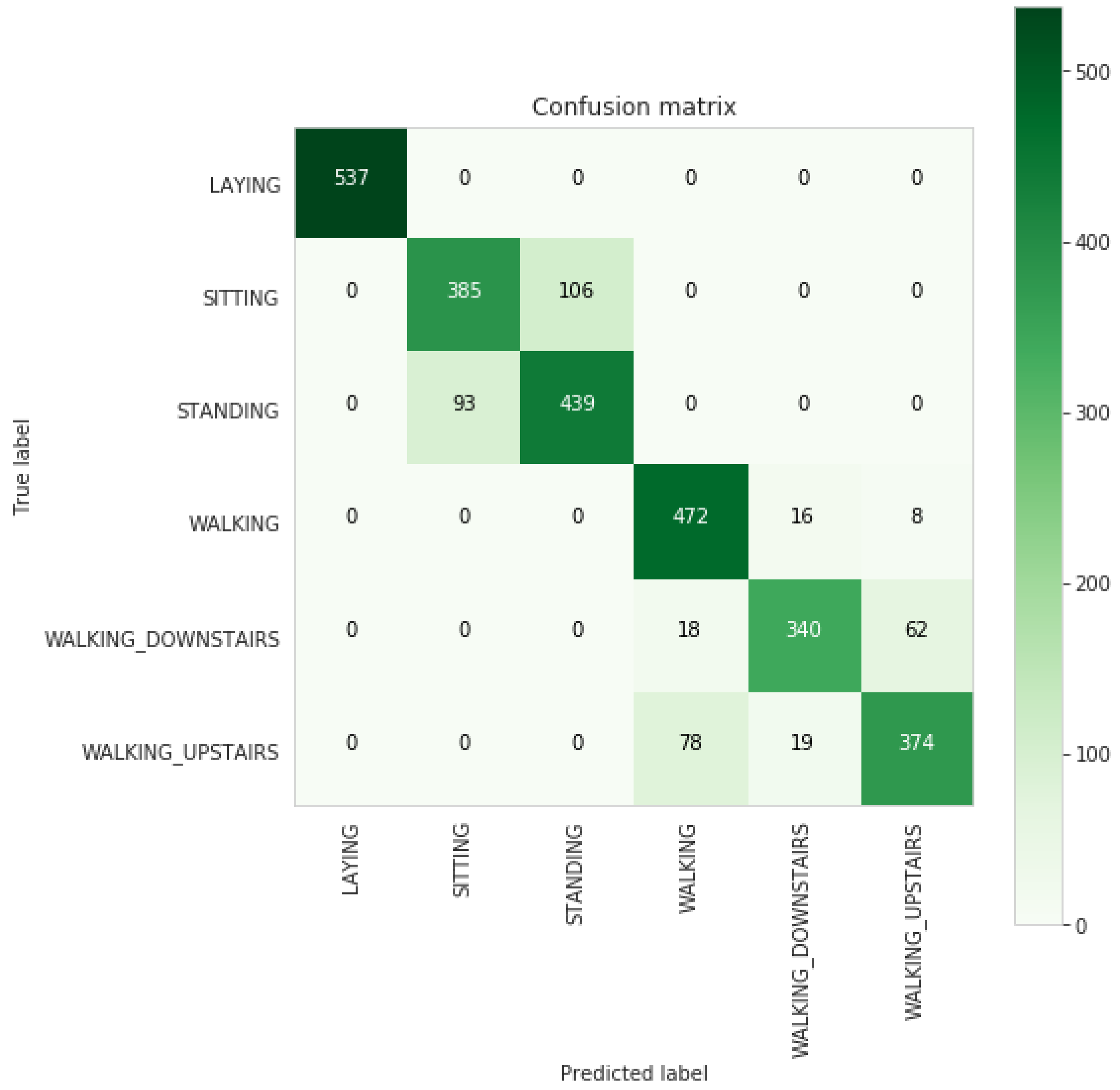
In [53]:
```
parameters = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=parameters, n_jobs=-1)
dt_grid_results = perform_model(dt_grid, x_train, y_train, x_test, y_test, class_labels=labels)
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:06.461770


Predicting test data
Done


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


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

    0.8642687478791992


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

 [[537   0   0   0   0   0]
 [  0 385 106   0   0   0]
 [  0  93 439   0   0   0]
 [  0   0   0 472  16   8]
 [  0   0   0  18 340  62]
 [  0   0   0  78  19 374]]
```




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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.81      0.78      0.79       491
          STANDING       0.81      0.83      0.82       532
           WALKING       0.83      0.95      0.89       496
WALKING_DOWNSTAIRS       0.91      0.81      0.86       420
  WALKING_UPSTAIRS       0.84      0.79      0.82       471

         micro avg       0.86      0.86      0.86      2947
         macro avg       0.87      0.86      0.86      2947
      weighted avg       0.87      0.86      0.86      2947
```

In [54]:
```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(dt_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.Greens)
plt.show()
```



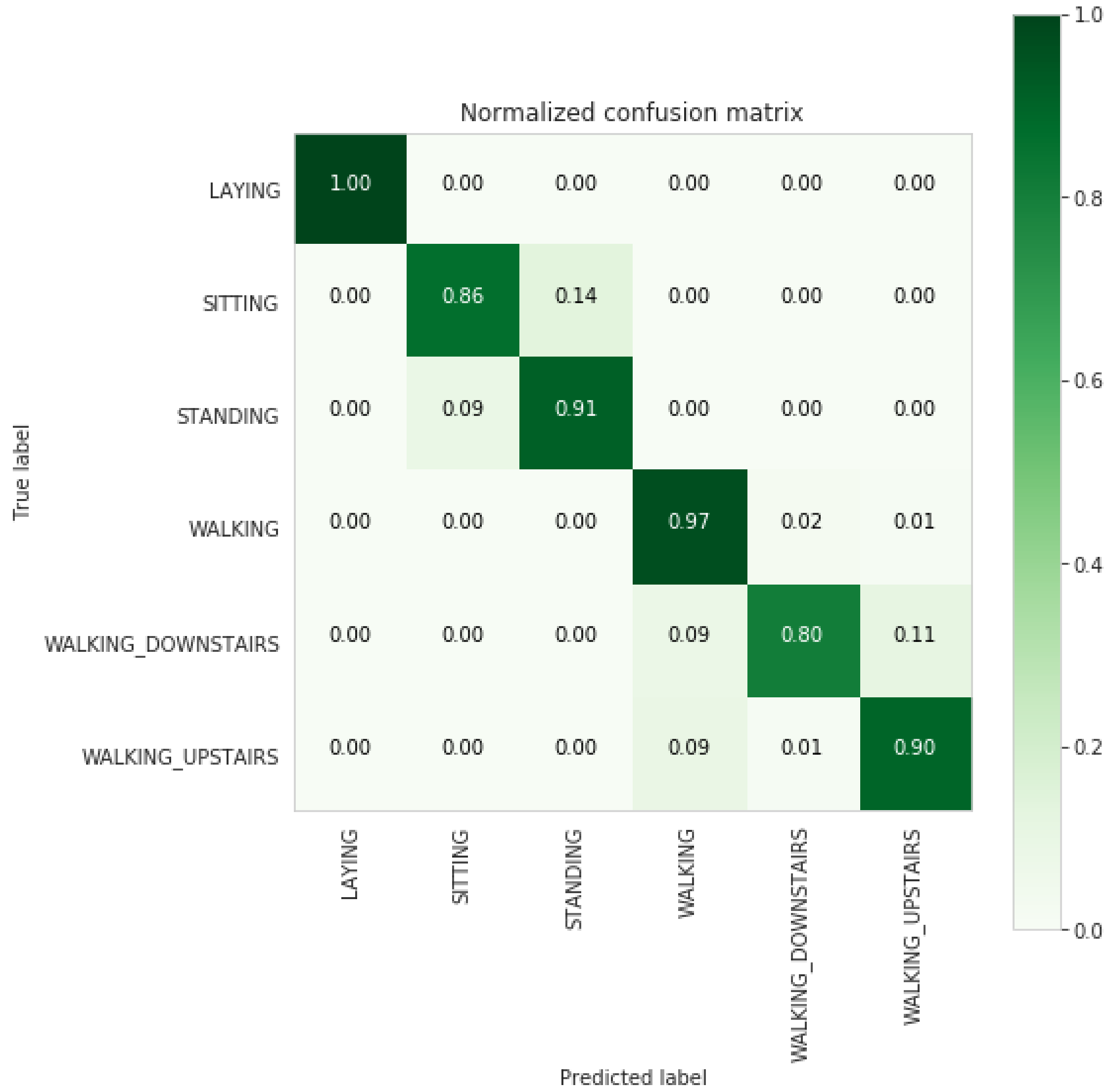
In [55]:
```
print_grid_search_attributes(dt_grid_results['model'])
```

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

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

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

        {'max_depth': 7}

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.8403155603917302
```

5. Random Forest Classifier with GridSearch

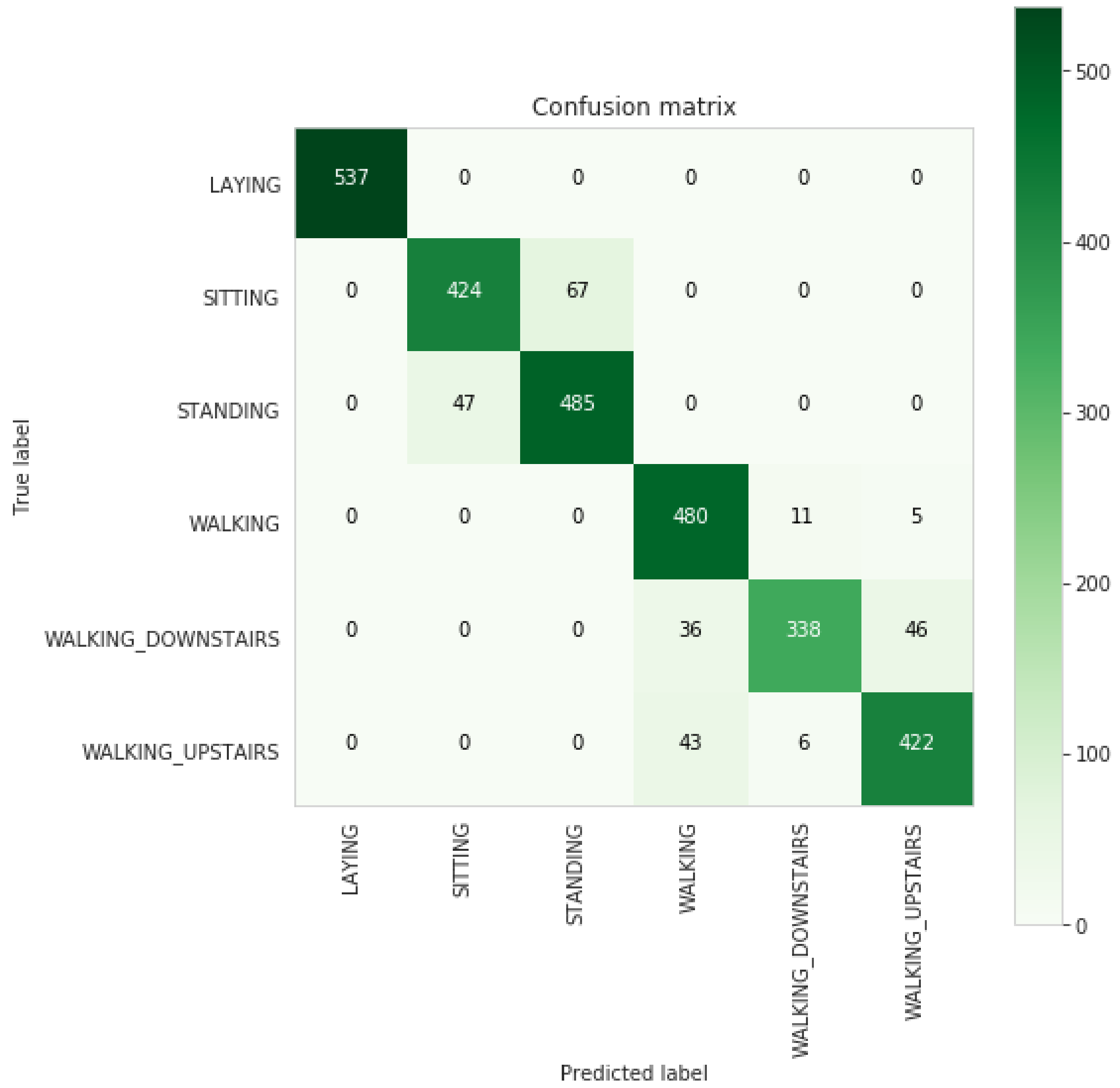
In [56]:
```
params = {'n_estimators': np.arange(10,201,20), 'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=params, n_jobs=-1)
rfc_grid_results = perform_model(rfc_grid, x_train, y_train, x_test, y_test, class_labels=labels)
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:02:11.295306


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.039897


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

    0.9114353579911775


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

 [[537   0   0   0   0   0]
 [  0 424  67   0   0   0]
 [  0  47 485   0   0   0]
 [  0   0   0 480  11   5]
 [  0   0   0  36 338  46]
 [  0   0   0  43   6 422]]
```




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

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

         micro avg       0.91      0.91      0.91      2947
         macro avg       0.91      0.91      0.91      2947
      weighted avg       0.91      0.91      0.91      2947
```

In [57]:
```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(rfc_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.Greens)
plt.show()
```



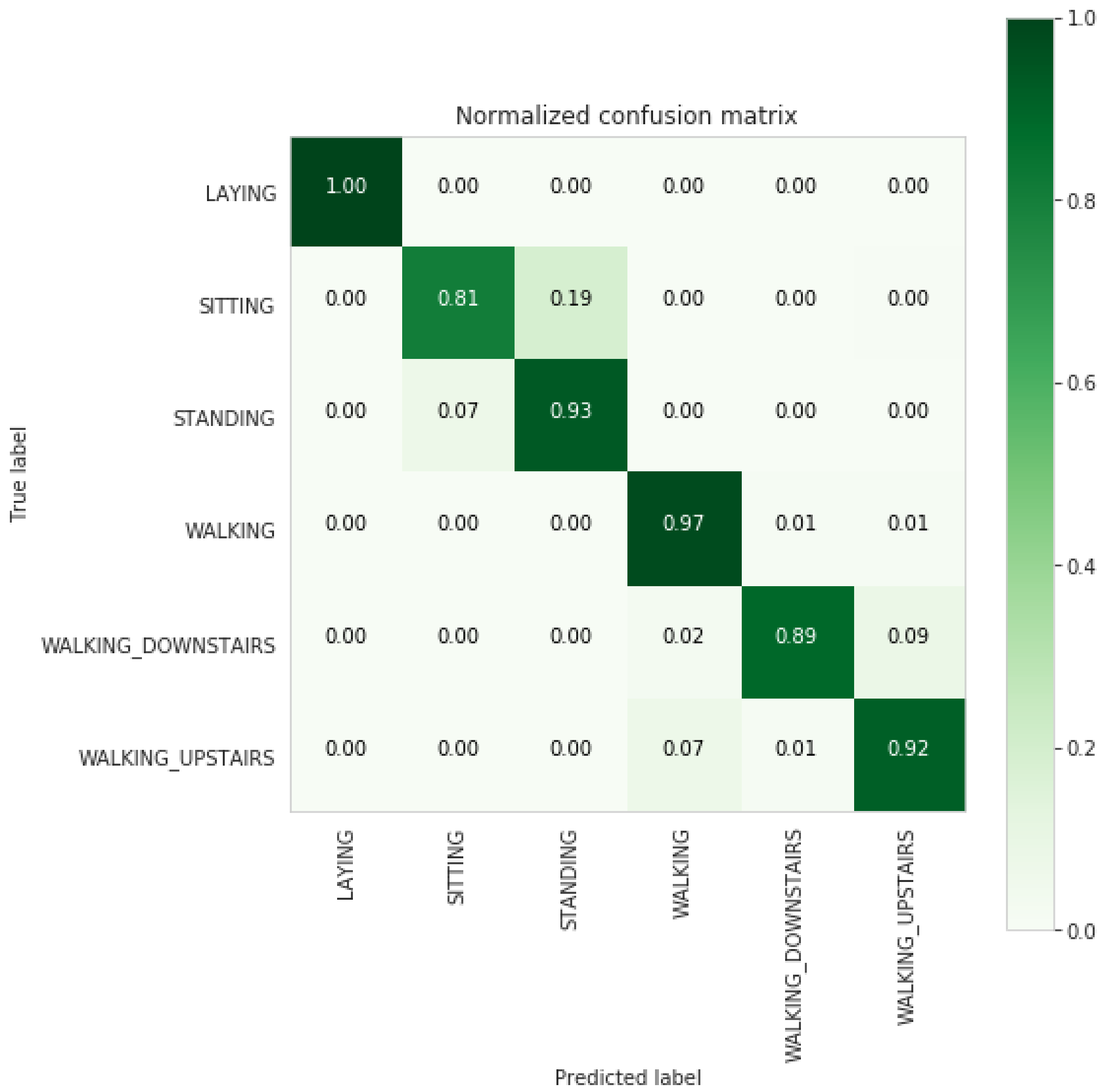
In [58]:
```
print_grid_search_attributes(rfc_grid_results['model'])
```

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

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

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

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

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.9163492927094669
```

6. Gradient Boosted Decision Trees With GridSearch

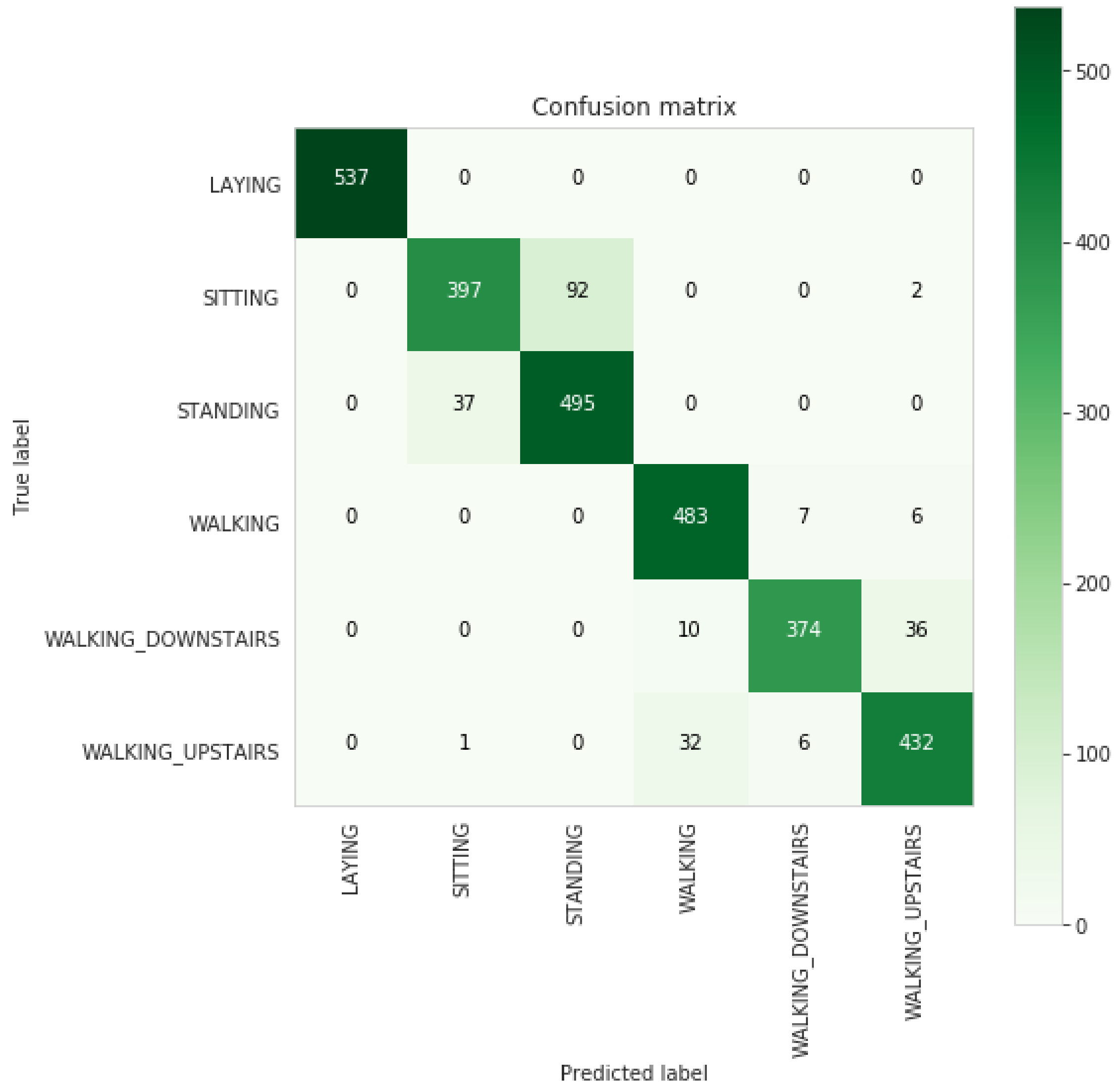
In [59]:
```
param_grid = {'max_depth': np.arange(5,8,1), \
             'n_estimators':np.arange(130,170,10)}
gbdt = GradientBoostingClassifier()
gbdt_grid = GridSearchCV(gbdt, param_grid=param_grid, n_jobs=-1)
gbdt_grid_results = perform_model(gbdt_grid, x_train, y_train, x_test, y_test, class_labels=labels)
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:16:17.551946


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.046864


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

    0.9222938581608415


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

 [[537   0   0   0   0   0]
 [  0 397  92   0   0   2]
 [  0  37 495   0   0   0]
 [  0   0   0 483   7   6]
 [  0   0   0  10 374  36]
 [  0   1   0  32   6 432]]
```




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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.91      0.81      0.86       491
          STANDING       0.84      0.93      0.88       532
           WALKING       0.92      0.97      0.95       496
WALKING_DOWNSTAIRS       0.97      0.89      0.93       420
  WALKING_UPSTAIRS       0.91      0.92      0.91       471

         micro avg       0.92      0.92      0.92      2947
         macro avg       0.92      0.92      0.92      2947
      weighted avg       0.92      0.92      0.92      2947
```

In [60]:
```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(gbdt_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.Greens)
plt.show()
```



In [61]:
```python
print_grid_search_attributes(gbdt_grid_results['model'])
```

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

        GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=5,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=140,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=1.0, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)

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

        {'max_depth': 5, 'n_estimators': 140}

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.9050598476605005
```

7. Comparing all models

In [62]:
```
print('\n                     Accuracy     Error')
print('                     ----------   --------')
print('Logistic Regression : {:.04}%       {:.04}%'.format(log_reg_grid_results['accuracy'] * 100,\
                                          100-(log_reg_grid_results['accuracy'] * 100)))

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

print('RBF SVM classifier  : {:.04}%      {:.04}% '.format(rbf_svm_grid_results['accuracy'] * 100,\
                                                  100-(rbf_svm_grid_results['accuracy'] * 100
)))

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

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

```
                      Accuracy     Error
                      ----------   --------
Logistic Regression : 96.27%        3.733%
Linear SVC          : 96.5%        3.495%
RBF SVM classifier  : 96.27%       3.733%
DecisionTree        : 86.43%       13.57%
Random Forest       : 91.14%       8.856%
GradientBoosting DT : 91.14%       8.856%
```

> We can choose ***Logistic regression*** or ***Linear SVC*** or ***RBF SVM***.

Apply Deep Learning Models

In [63]:
```
# 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',
}

# 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 [88]:
```python
# Utility function to print the confusion matrix
def confusion_matrix_dl(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'])

# 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()

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, X_test, y_train, y_test

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

In [67]:
```python
# Configuring a session
session_conf = tf.ConfigProto(
    intra_op_parallelism_threads=1,
    inter_op_parallelism_threads=1
)

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

In [68]:
```python
# Initializing parameters
epochs = 30
batch_size = 16
n_hidden = 32
```

In [69]:
```python
# Loading the train and test data
x_train, x_test, y_train, y_test = load_data()
```

In [70]:
```python
timesteps = len(x_train[0])
input_dim = len(x_train[0][0])
n_classes = _count_classes(y_train)

print(timesteps)
print(input_dim)
print(len(x_train))
```

```
128
9
7352
```

1-Layer of LSTM

In [71]:
```
# 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 [72]:
```
# Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

In [73]:
```
# 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 [==============================] - 32s 4ms/step - loss: 1.3325 - acc: 0.4347 - val_loss: 1.1
713 - val_acc: 0.4713606 - ETA: 3s - loss: 1.3514 - acc: 0.42 - ETA: 3s - loss:  - ETA: 1s - loss: 1.3
4 - ETA: 0s - loss: 1.3374 - acc:  - ETA: 0s - loss: 1.3341 - acc: 0.
Epoch 2/30
7352/7352 [==============================] - 31s 4ms/step - loss: 1.0133 - acc: 0.5559 - val_loss: 1.0
255 - val_acc: 0.4835
Epoch 3/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.8272 - acc: 0.6385 - val_loss: 0.8
061 - val_acc: 0.6047
Epoch 4/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.7009 - acc: 0.6533 - val_loss: 0.7
685 - val_acc: 0.6064c:
Epoch 5/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.6608 - acc: 0.6766 - val_loss: 0.6
847 - val_acc: 0.6420
Epoch 6/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.6041 - acc: 0.6970 - val_loss: 1.5
301 - val_acc: 0.51680.6003 - acc: 0.69 - ETA: 1s - loss: 0.60
Epoch 7/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.5672 - acc: 0.7393 - val_loss: 0.6
781 - val_acc: 0.7180
Epoch 8/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.5517 - acc: 0.7659 - val_loss: 0.6
712 - val_acc: 0.7408
Epoch 9/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.4684 - acc: 0.7888 - val_loss: 0.5
915 - val_acc: 0.7523
Epoch 10/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.4357 - acc: 0.7896 - val_loss: 0.6
229 - val_acc: 0.7343
Epoch 11/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.4037 - acc: 0.7977 - val_loss: 0.6
334 - val_acc: 0.7333
Epoch 12/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.3682 - acc: 0.8107 - val_loss: 0.5
140 - val_acc: 0.7523
Epoch 13/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.3203 - acc: 0.8271 - val_loss: 0.6
954 - val_acc: 0.7553
Epoch 14/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.3557 - acc: 0.8403 - val_loss: 0.7
033 - val_acc: 0.7343
Epoch 15/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.3180 - acc: 0.8521 - val_loss: 0.5
350 - val_acc: 0.7408
Epoch 16/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.3097 - acc: 0.8594 - val_loss: 0.7
219 - val_acc: 0.7533
Epoch 17/30
7352/7352 [==============================] - 32s 4ms/step - loss: 0.2982 - acc: 0.8704 - val_loss: 0.6
023 - val_acc: 0.7777 - loss: 0.30
Epoch 18/30
7352/7352 [==============================] - 32s 4ms/step - loss: 0.2814 - acc: 0.8724 - val_loss: 0.7
013 - val_acc: 0.8286
Epoch 19/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.2752 - acc: 0.8800 - val_loss: 0.4
954 - val_acc: 0.8744
Epoch 20/30
7352/7352 [==============================] - 32s 4ms/step - loss: 0.2618 - acc: 0.8945 - val_loss: 0.6
708 - val_acc: 0.8795
Epoch 21/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.2632 - acc: 0.8961 - val_loss: 0.4
103 - val_acc: 0.8945
Epoch 22/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.2749 - acc: 0.9076 - val_loss: 0.5
197 - val_acc: 0.8728
Epoch 23/30
7352/7352 [==============================] - 32s 4ms/step - loss: 0.2350 - acc: 0.9317 - val_loss: 0.4
270 - val_acc: 0.8945
Epoch 24/30
7352/7352 [==============================] - 32s 4ms/step - loss: 0.1878 - acc: 0.9411 - val_loss: 0.4
359 - val_acc: 0.8843
Epoch 25/30
7352/7352 [==============================] - 31s 4ms/step - loss: 0.1657 - acc: 0.9476 - val_loss: 0.4
397 - val_acc: 0.8867
Epoch 26/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2000 - acc: 0.9431 - val_loss: 0.4
584 - val_acc: 0.8860
Epoch 27/30
7352/7352 [==============================] - 34s 5ms/step - loss: 0.1695 - acc: 0.9455 - val_loss: 0.5
922 - val_acc: 0.8853ss: 0.1688 - ETA: 0s - loss: 0.1707 - ac
Epoch 28/30
7352/7352 [==============================] - 32s 4ms/step - loss: 0.1900 - acc: 0.9438 - val_loss: 0.4
488 - val_acc: 0.8945
Epoch 29/30
```

```
7352/7352 [==============================] - 32s 4ms/step - loss: 0.1692 - acc: 0.9434 - val_loss: 0.4
201 - val_acc: 0.8999
Epoch 30/30
7352/7352 [==============================] - 33s 4ms/step - loss: 0.1605 - acc: 0.9471 - val_loss: 0.3
736 - val_acc: 0.9053
```

Out[73]:

```
<keras.callbacks.History at 0x15847c8b4e0>
```

In [89]:

```python
# Confusion Matrix
print(confusion_matrix_dl(y_test, model.predict(x_test)))
```

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 510        0         0        0                   0
SITTING                  0      407        80        0                   1
STANDING                 0      103       429        0                   0
WALKING                  0        0         0      464                  25
WALKING_DOWNSTAIRS       0        0         0        0                 419
WALKING_UPSTAIRS         0        0         0        7                  25

Pred                WALKING_UPSTAIRS
True
LAYING                            27
SITTING                            3
STANDING                           0
WALKING                            7
WALKING_DOWNSTAIRS                 1
WALKING_UPSTAIRS                 439
```

In [78]:

```python
score = model.evaluate(x_test, y_test)
```

```
2947/2947 [==============================] - 1s 281us/step
```

In [79]:

```python
score
```

Out[79]:

```
[0.3735676897443261, 0.9053274516457415]
```

2-Layer of LSTM with more hyperparameter tunning

Tuning the Number of neurons with dropout of 0.50

Configuration:

In [126]:

```python
# Initializing parameters
n_epochs = 30
n_batch = 16
n_classes = _count_classes(y_train)

# Bias regularizer value - we will use elasticnet
reg = L1L2(0.01, 0.01)
```

In [158]:

```python
# Plot Confusion Matrix
def plot_confusion_matrix_lstm(y_test, y_predict):
    result = confusion_matrix(y_test, y_predict)

    plt.figure(figsize=(12, 10))
    sns.heatmap(result,
                xticklabels= list(ACTIVITIES.values()),
                yticklabels=list(ACTIVITIES.values()),
                annot=True, fmt="d");
    plt.title("Confusion matrix")
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()

# Plot train and cross validation loss
def plot_train_cv_loss(trained_model, epochs, colors=['b']):
    fig, ax = plt.subplots(1,1)
    ax.set_xlabel('epoch')
    ax.set_ylabel('Categorical Crossentropy Loss')
    x_axis_values = list(range(1,epochs+1))

    validation_loss = trained_model.history['val_loss']
    train_loss = trained_model.history['loss']

    ax.plot(x_axis_values, validation_loss, 'b', label="Validation Loss")
    ax.plot(x_axis_values, train_loss, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()
```

32 neurons in LSTM Layer with dropout of 0.50

In [137]:
```
# Model execution
model = Sequential()
model.add(LSTM(32, input_shape=(timesteps, input_dim), return_sequences=True,bias_regularizer=reg ))
model.add(BatchNormalization())
model.add(Dropout(0.50))
model.add(LSTM(32))
model.add(Dropout(0.50))
model.add(Dense(n_classes, activation='sigmoid'))
print("Model Summary: ")
model.summary()
```

```
Model Summary:
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_26 (LSTM)               (None, 128, 32)           5376      
_________________________________________________________________
batch_normalization_4 (Batch (None, 128, 32)           128       
_________________________________________________________________
dropout_26 (Dropout)         (None, 128, 32)           0         
_________________________________________________________________
lstm_27 (LSTM)               (None, 32)                8320      
_________________________________________________________________
dropout_27 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_14 (Dense)             (None, 6)                 198       
=================================================================
Total params: 14,022
Trainable params: 13,958
Non-trainable params: 64
_________________________________________________________________
```

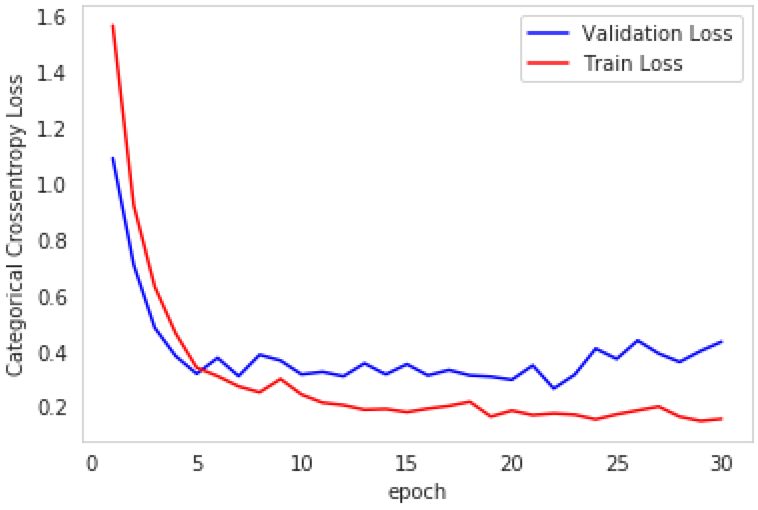
In [138]:
```
model.compile(loss='categorical_crossentropy',
          optimizer='adam',
          metrics=['accuracy'])
```

In [139]:
```
start = datetime.now()

# Training the model
trained_model  = model.fit(x_train,
                           y_train,
                           batch_size=n_batch,
                           validation_data=(x_test, y_test),
                           epochs=n_epochs)

print("\n Time Taken: ",datetime.now() - start)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 72s 10ms/step - loss: 1.5656 - acc: 0.5880 - val_loss: 1.
0906 - val_acc: 0.7092
Epoch 2/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.9216 - acc: 0.7437 - val_loss: 0.7
103 - val_acc: 0.8117
Epoch 3/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.6326 - acc: 0.8190 - val_loss: 0.4
852 - val_acc: 0.8595
Epoch 4/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.4648 - acc: 0.8685 - val_loss: 0.
3838 - val_acc: 0.8856
Epoch 5/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.3426 - acc: 0.8992 - val_loss: 0.
3206 - val_acc: 0.9023
Epoch 6/30
7352/7352 [==============================] - 73s 10ms/step - loss: 0.3120 - acc: 0.9074 - val_loss: 0.
3773 - val_acc: 0.8721
Epoch 7/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.2754 - acc: 0.9138 - val_loss: 0.
3121 - val_acc: 0.9050
Epoch 8/30
7352/7352 [==============================] - 73s 10ms/step - loss: 0.2541 - acc: 0.9178 - val_loss: 0.
3884 - val_acc: 0.8887
Epoch 9/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.3017 - acc: 0.8993 - val_loss: 0.
3678 - val_acc: 0.8884
Epoch 10/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.2461 - acc: 0.9180 - val_loss: 0.
3182 - val_acc: 0.9046
Epoch 11/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.2170 - acc: 0.9280 - val_loss: 0.
3272 - val_acc: 0.9050
Epoch 12/30
7352/7352 [==============================] - 70s 9ms/step - loss: 0.2082 - acc: 0.9293 - val_loss: 0.3
115 - val_acc: 0.9094
Epoch 13/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1917 - acc: 0.9331 - val_loss: 0.
3579 - val_acc: 0.9006
Epoch 14/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.1943 - acc: 0.9336 - val_loss: 0.3
184 - val_acc: 0.9189
Epoch 15/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.1831 - acc: 0.9381 - val_loss: 0.3
548 - val_acc: 0.9036
Epoch 16/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.1957 - acc: 0.9331 - val_loss: 0.3
145 - val_acc: 0.9131
Epoch 17/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.2053 - acc: 0.9293 - val_loss: 0.3
338 - val_acc: 0.8839
Epoch 18/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2202 - acc: 0.9278 - val_loss: 0.
3146 - val_acc: 0.9097
Epoch 19/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.1672 - acc: 0.9370 - val_loss: 0.3
101 - val_acc: 0.9063
Epoch 20/30
7352/7352 [==============================] - 70s 9ms/step - loss: 0.1886 - acc: 0.9343 - val_loss: 0.2
990 - val_acc: 0.9121
Epoch 21/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.1726 - acc: 0.9400 - val_loss: 0.
3504 - val_acc: 0.9094
Epoch 22/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.1784 - acc: 0.9376 - val_loss: 0.
2676 - val_acc: 0.9158
Epoch 23/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.1739 - acc: 0.9363 - val_loss: 0.
3174 - val_acc: 0.9152
Epoch 24/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1573 - acc: 0.9412 - val_loss: 0.
4106 - val_acc: 0.9046
Epoch 25/30
7352/7352 [==============================] - 70s 9ms/step - loss: 0.1752 - acc: 0.9372 - val_loss: 0.3
737 - val_acc: 0.9101
Epoch 26/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.1892 - acc: 0.9363 - val_loss: 0.
4395 - val_acc: 0.8724
Epoch 27/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.2031 - acc: 0.9316 - val_loss: 0.3
930 - val_acc: 0.8948
Epoch 28/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.1670 - acc: 0.9402 - val_loss: 0.3
628 - val_acc: 0.9094
Epoch 29/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.1516 - acc: 0.9426 - val_loss: 0.4
```

```
020 - val_acc: 0.9036
Epoch 30/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.1588 - acc: 0.9444 - val_loss: 0.4
351 - val_acc: 0.8853

 Time Taken:  0:35:06.953677
```

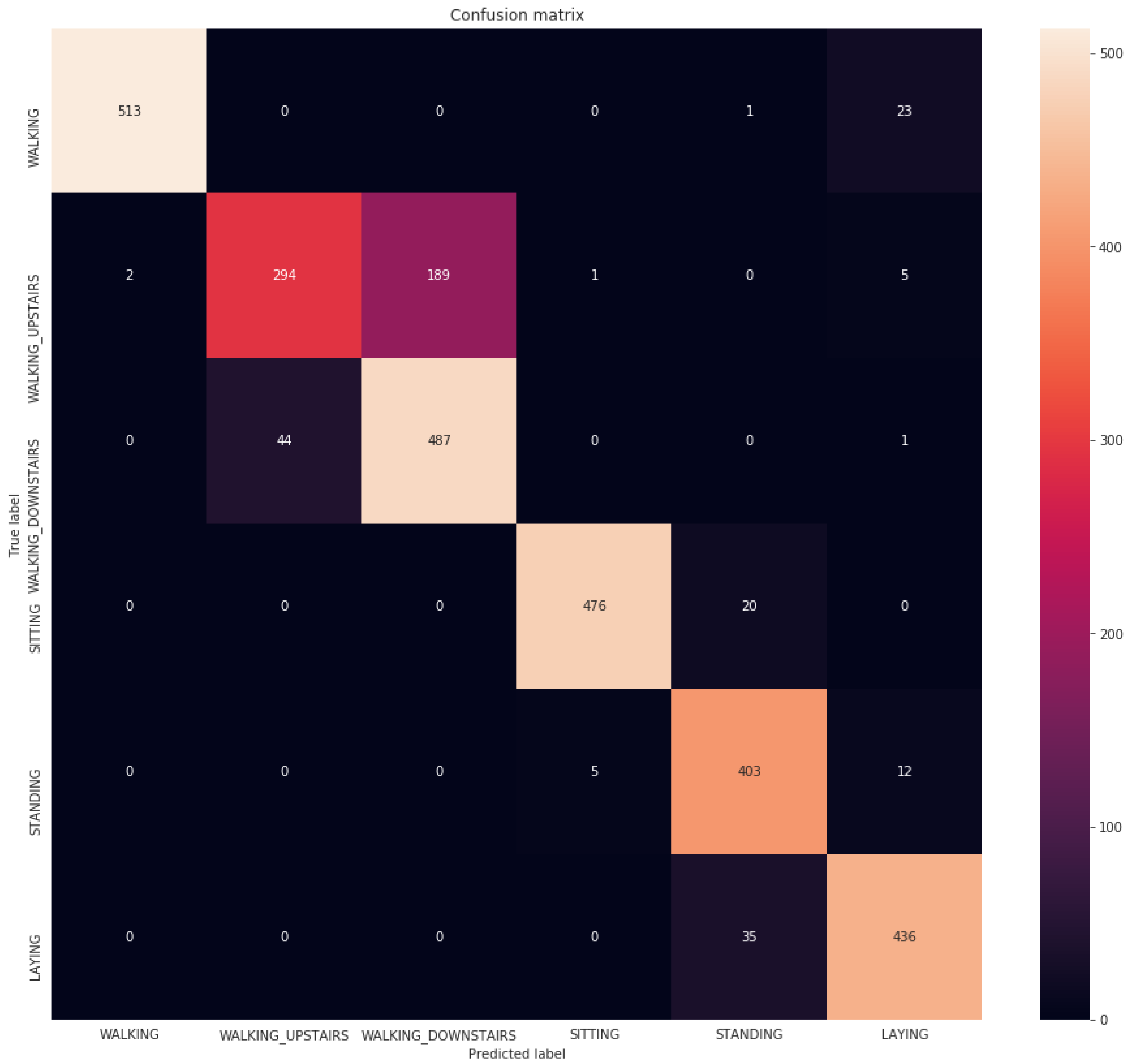
In [141]:
```python
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, n_epochs)
```



From epoch 10, we starts to overfit the model, so best value for epoch is 10

In [150]:
```python
print()
scores = model.evaluate(x_test, y_test, verbose=0)
print("Test Accuracy: %f%%" % (scores[1]*100))
print()

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
Y_predictions = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(x_test), axis=1)])

# Confusion Matrix
plot_confusion_matrix_lstm(Y_true, Y_predictions)
```

```
Test Accuracy: 88.530709%
```



48 neurons in LSTM Layer with dropout of 0.50

In [151]:

```
# Model execution
model = Sequential()
model.add(LSTM(48, input_shape=(timesteps, input_dim), return_sequences=True, bias_regularizer=reg))
model.add(BatchNormalization())
model.add(Dropout(0.50))
model.add(LSTM(32))
model.add(Dropout(0.50))
model.add(Dense(n_classes, activation='sigmoid'))
print("Model Summary: ")
model.summary()
```

```
Model Summary:
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_28 (LSTM)               (None, 128, 48)           11136     
_________________________________________________________________
batch_normalization_5 (Batch (None, 128, 48)           192       
_________________________________________________________________
dropout_28 (Dropout)         (None, 128, 48)           0         
_________________________________________________________________
lstm_29 (LSTM)               (None, 32)                10368     
_________________________________________________________________
dropout_29 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_15 (Dense)             (None, 6)                 198       
=================================================================
Total params: 21,894
Trainable params: 21,798
Non-trainable params: 96
_________________________________________________________________
```

In [152]:

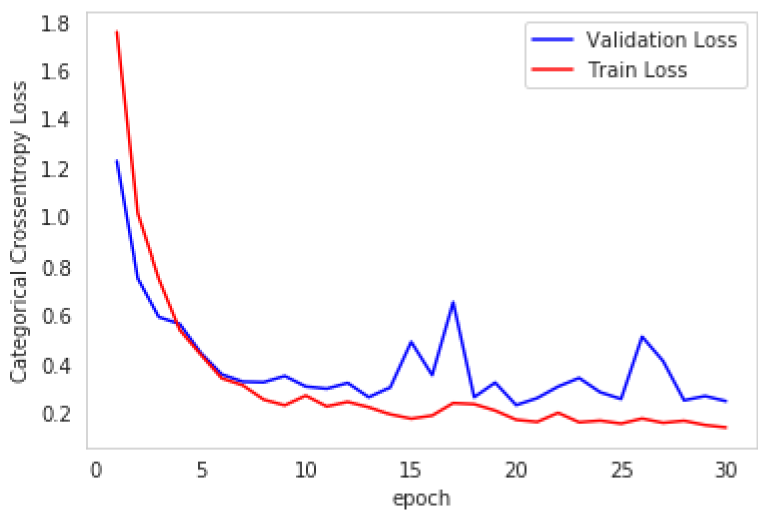
```
model.compile(loss='categorical_crossentropy',
          optimizer='adam',
          metrics=['accuracy'])
```

In [153]:
```
start = datetime.now()

# Training the model
trained_model  = model.fit(x_train,
                           y_train,
                           batch_size=n_batch,
                           validation_data=(x_test, y_test),
                           epochs=n_epochs)

print("\n Time Taken: ",datetime.now() - start)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 76s 10ms/step - loss: 1.7586 - acc: 0.5837 - val_loss: 1.
2299 - val_acc: 0.6675
Epoch 2/30
7352/7352 [==============================] - 72s 10ms/step - loss: 1.0160 - acc: 0.7074 - val_loss: 0.
7532 - val_acc: 0.7988
Epoch 3/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.7515 - acc: 0.7224 - val_loss: 0.
5955 - val_acc: 0.7876
Epoch 4/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.5420 - acc: 0.8143 - val_loss: 0.
5667 - val_acc: 0.7798
Epoch 5/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.4415 - acc: 0.8561 - val_loss: 0.
4487 - val_acc: 0.8361
Epoch 6/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.3445 - acc: 0.8966 - val_loss: 0.
3606 - val_acc: 0.8850
Epoch 7/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.3159 - acc: 0.9036 - val_loss: 0.
3307 - val_acc: 0.8816
Epoch 8/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.2572 - acc: 0.9195 - val_loss: 0.
3285 - val_acc: 0.8945
Epoch 9/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.2339 - acc: 0.9233 - val_loss: 0.
3539 - val_acc: 0.8992
Epoch 10/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.2736 - acc: 0.9123 - val_loss: 0.
3110 - val_acc: 0.8653
Epoch 11/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.2294 - acc: 0.9200 - val_loss: 0.
3019 - val_acc: 0.9046
Epoch 12/30
7352/7352 [==============================] - 73s 10ms/step - loss: 0.2481 - acc: 0.9166 - val_loss: 0.
3255 - val_acc: 0.8951
Epoch 13/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.2261 - acc: 0.9232 - val_loss: 0.
2671 - val_acc: 0.9135
Epoch 14/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.1972 - acc: 0.9343 - val_loss: 0.
3065 - val_acc: 0.9091
Epoch 15/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1792 - acc: 0.9373 - val_loss: 0.
4938 - val_acc: 0.8103
Epoch 16/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1920 - acc: 0.9317 - val_loss: 0.
3573 - val_acc: 0.9087
Epoch 17/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2430 - acc: 0.9223 - val_loss: 0.
6563 - val_acc: 0.7448
Epoch 18/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.2388 - acc: 0.9163 - val_loss: 0.
2671 - val_acc: 0.9097
Epoch 19/30
7352/7352 [==============================] - 70s 9ms/step - loss: 0.2124 - acc: 0.9219 - val_loss: 0.3
269 - val_acc: 0.8924
Epoch 20/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.1749 - acc: 0.9348 - val_loss: 0.
2347 - val_acc: 0.9206
Epoch 21/30
7352/7352 [==============================] - 72s 10ms/step - loss: 0.1659 - acc: 0.9393 - val_loss: 0.
2634 - val_acc: 0.9128
Epoch 22/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.2032 - acc: 0.9280 - val_loss: 0.
3107 - val_acc: 0.9087
Epoch 23/30
7352/7352 [==============================] - 71s 10ms/step - loss: 0.1645 - acc: 0.9377 - val_loss: 0.
3459 - val_acc: 0.8985
Epoch 24/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1714 - acc: 0.9339 - val_loss: 0.
2876 - val_acc: 0.8999
Epoch 25/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1590 - acc: 0.9423 - val_loss: 0.
2597 - val_acc: 0.9192
Epoch 26/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1798 - acc: 0.9378 - val_loss: 0.
5151 - val_acc: 0.8649
Epoch 27/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1622 - acc: 0.9402 - val_loss: 0.
4152 - val_acc: 0.9013
Epoch 28/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1707 - acc: 0.9378 - val_loss: 0.
2544 - val_acc: 0.9152
Epoch 29/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1530 - acc: 0.9448 - val_loss: 0.
```

```
2718 - val_acc: 0.9148
Epoch 30/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1431 - acc: 0.9465 - val_loss: 0.
2508 - val_acc: 0.9148

 Time Taken:  0:35:34.397904
```

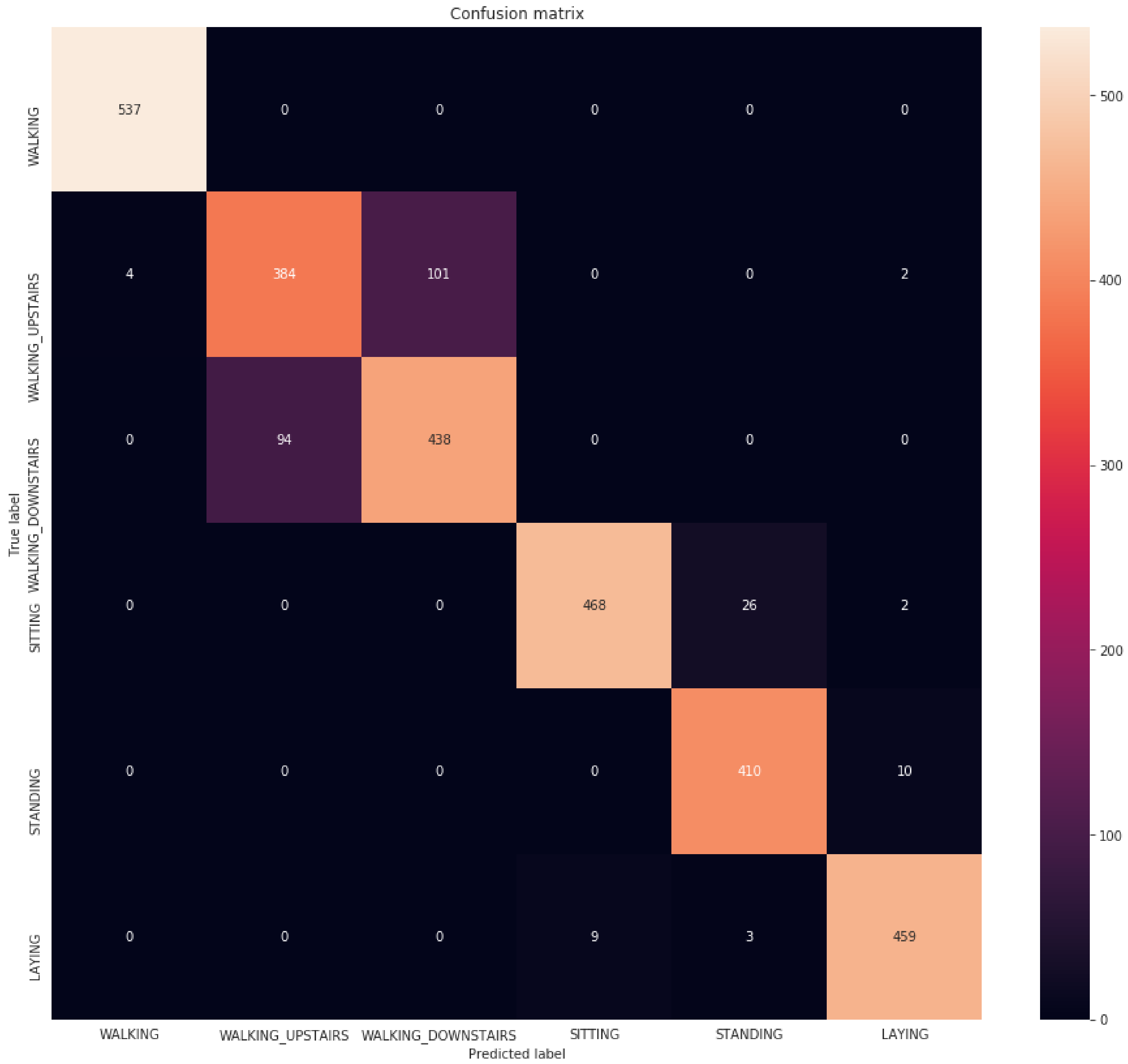
In [155]:
```
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, n_epochs)
```



From epoch 7, we starts to overfit the model, so best value for epoch is 7

In [156]:
```
print()
scores = model.evaluate(x_test, y_test, verbose=0)
print("Test Accuracy: %f%%" % (scores[1]*100))
print()

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
Y_predictions = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(x_test), axis=1)])

# Confusion Matrix
plot_confusion_matrix_lstm(Y_true, Y_predictions)
```

```
Test Accuracy: 91.482864%
```



64 neurons in LSTM Layer with dropout of 0.50

In [159]:
```
# Model execution
model = Sequential()
model.add(LSTM(64, input_shape=(timesteps, input_dim), return_sequences=True, bias_regularizer=reg))
model.add(BatchNormalization())
model.add(Dropout(0.50))
model.add(LSTM(48))
model.add(Dropout(0.50))
model.add(Dense(n_classes, activation='sigmoid'))
print("Model Summary: ")
model.summary()
```

```
Model Summary:
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_30 (LSTM)               (None, 128, 64)           18944     
_________________________________________________________________
batch_normalization_6 (Batch (None, 128, 64)           256       
_________________________________________________________________
dropout_30 (Dropout)         (None, 128, 64)           0         
_________________________________________________________________
lstm_31 (LSTM)               (None, 48)                21696     
_________________________________________________________________
dropout_31 (Dropout)         (None, 48)                0         
_________________________________________________________________
dense_16 (Dense)             (None, 6)                 294       
=================================================================
Total params: 41,190
Trainable params: 41,062
Non-trainable params: 128
_________________________________________________________________
```

In [160]:
```
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

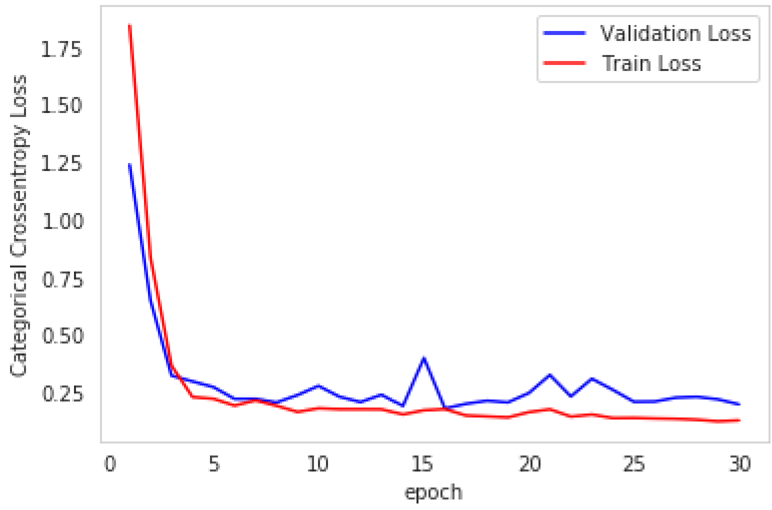
In [161]:
```
start = datetime.now()

# Training the model
trained_model  = model.fit(x_train,
                           y_train,
                           batch_size=n_batch,
                           validation_data=(x_test, y_test),
                           epochs=n_epochs)

print("\n Time Taken: ",datetime.now() - start)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 79s 11ms/step - loss: 1.8453 - acc: 0.6298 - val_loss: 1.
2404 - val_acc: 0.7421
Epoch 2/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.8378 - acc: 0.8448 - val_loss: 0.
6518 - val_acc: 0.8283
Epoch 3/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.3691 - acc: 0.9154 - val_loss: 0.
3260 - val_acc: 0.8914
Epoch 4/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.2331 - acc: 0.9255 - val_loss: 0.
3009 - val_acc: 0.8968
Epoch 5/30
7352/7352 [==============================] - 79s 11ms/step - loss: 0.2254 - acc: 0.9279 - val_loss: 0.
2761 - val_acc: 0.8999
Epoch 6/30
7352/7352 [==============================] - 79s 11ms/step - loss: 0.1959 - acc: 0.9309 - val_loss: 0.
2250 - val_acc: 0.9223
Epoch 7/30
7352/7352 [==============================] - 78s 11ms/step - loss: 0.2182 - acc: 0.9234 - val_loss: 0.
2251 - val_acc: 0.8968
Epoch 8/30
7352/7352 [==============================] - 78s 11ms/step - loss: 0.1953 - acc: 0.9294 - val_loss: 0.
2093 - val_acc: 0.9186
Epoch 9/30
7352/7352 [==============================] - 79s 11ms/step - loss: 0.1683 - acc: 0.9380 - val_loss: 0.
2415 - val_acc: 0.9087
Epoch 10/30
7352/7352 [==============================] - 78s 11ms/step - loss: 0.1841 - acc: 0.9291 - val_loss: 0.
2813 - val_acc: 0.9192
Epoch 11/30
7352/7352 [==============================] - 78s 11ms/step - loss: 0.1801 - acc: 0.9355 - val_loss: 0.
2343 - val_acc: 0.9141
Epoch 12/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1800 - acc: 0.9332 - val_loss: 0.
2111 - val_acc: 0.9243
Epoch 13/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1796 - acc: 0.9316 - val_loss: 0.
2430 - val_acc: 0.9040
Epoch 14/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1574 - acc: 0.9391 - val_loss: 0.
1944 - val_acc: 0.9253
Epoch 15/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1756 - acc: 0.9334 - val_loss: 0.
4028 - val_acc: 0.8802
Epoch 16/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1805 - acc: 0.9347 - val_loss: 0.
1834 - val_acc: 0.9216
Epoch 17/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1527 - acc: 0.9433 - val_loss: 0.
2034 - val_acc: 0.9216
Epoch 18/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1488 - acc: 0.9423 - val_loss: 0.
2169 - val_acc: 0.9152
Epoch 19/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.1444 - acc: 0.9433 - val_loss: 0.
2097 - val_acc: 0.9287
Epoch 20/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1674 - acc: 0.9395 - val_loss: 0.
2505 - val_acc: 0.9196
Epoch 21/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1797 - acc: 0.9377 - val_loss: 0.
3290 - val_acc: 0.9053
Epoch 22/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1479 - acc: 0.9427 - val_loss: 0.
2355 - val_acc: 0.9192
Epoch 23/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1570 - acc: 0.9440 - val_loss: 0.
3125 - val_acc: 0.8880
Epoch 24/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1415 - acc: 0.9445 - val_loss: 0.
2643 - val_acc: 0.9175
Epoch 25/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1423 - acc: 0.9470 - val_loss: 0.
2125 - val_acc: 0.9253
Epoch 26/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1399 - acc: 0.9468 - val_loss: 0.
2134 - val_acc: 0.9274
Epoch 27/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1382 - acc: 0.9504 - val_loss: 0.
2304 - val_acc: 0.9125
Epoch 28/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1345 - acc: 0.9486 - val_loss: 0.
2339 - val_acc: 0.9223
Epoch 29/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1274 - acc: 0.9494 - val_loss: 0.
```

```
2231 - val_acc: 0.9260
Epoch 30/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.1316 - acc: 0.9461 - val_loss: 0.
2014 - val_acc: 0.9311

 Time Taken:  0:37:39.334980
```

In [162]:

```
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, n_epochs)
```

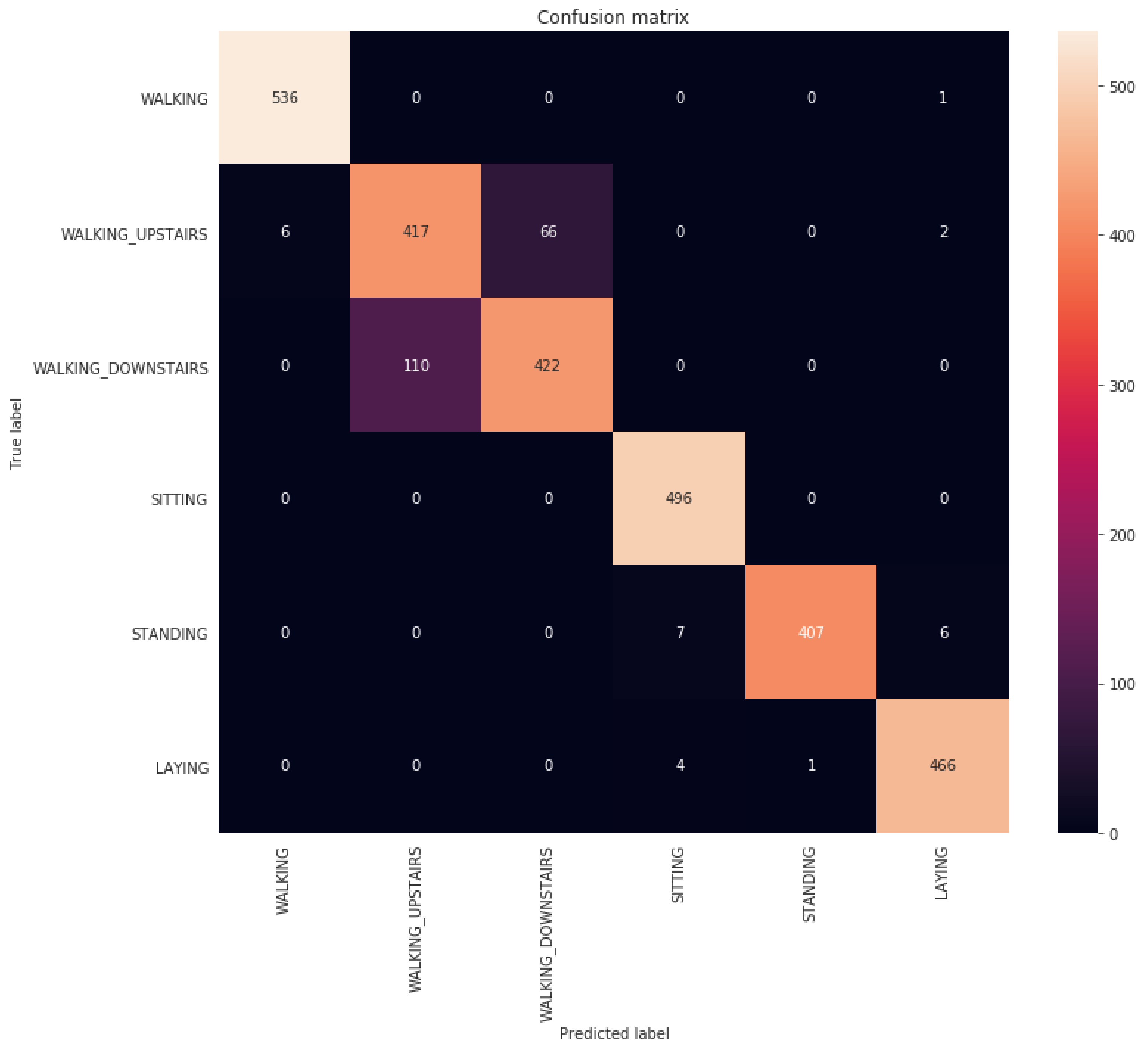


From epoch 8, we starts to overfit the model, so best value for epoch is 8

In [163]:

```
print()
scores = model.evaluate(x_test, y_test, verbose=0)
print("Test Accuracy: %f%%" % (scores[1]*100))
print()

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
Y_predictions = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(x_test), axis=1)])

# Confusion Matrix
plot_confusion_matrix_lstm(Y_true, Y_predictions)
```

```
Test Accuracy: 93.111639%
```



Tuning the number of neurons with dropout of 0.70

Configuration:

In [164]:
```
# Initializing parameters
n_epochs = 30
n_batch = 16
n_classes = _count_classes(y_train)

# Bias regularizer value - we will use elasticnet
reg = L1L2(0.01, 0.01)
```

32 neurons in LSTM Layer with dropout of 0.70

In [165]:
```
# Model execution
model = Sequential()
model.add(LSTM(32, input_shape=(timesteps, input_dim), return_sequences=True, bias_regularizer=reg))
model.add(BatchNormalization())
model.add(Dropout(0.70))
model.add(LSTM(32))
model.add(Dropout(0.70))
model.add(Dense(n_classes, activation='sigmoid'))
print("Model Summary: ")
model.summary()
```

```
Model Summary:
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_32 (LSTM)               (None, 128, 32)           5376      
_________________________________________________________________
batch_normalization_7 (Batch (None, 128, 32)           128       
_________________________________________________________________
dropout_32 (Dropout)         (None, 128, 32)           0         
_________________________________________________________________
lstm_33 (LSTM)               (None, 32)                8320      
_________________________________________________________________
dropout_33 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_17 (Dense)             (None, 6)                 198       
=================================================================
Total params: 14,022
Trainable params: 13,958
Non-trainable params: 64
_________________________________________________________________
```

In [166]:

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

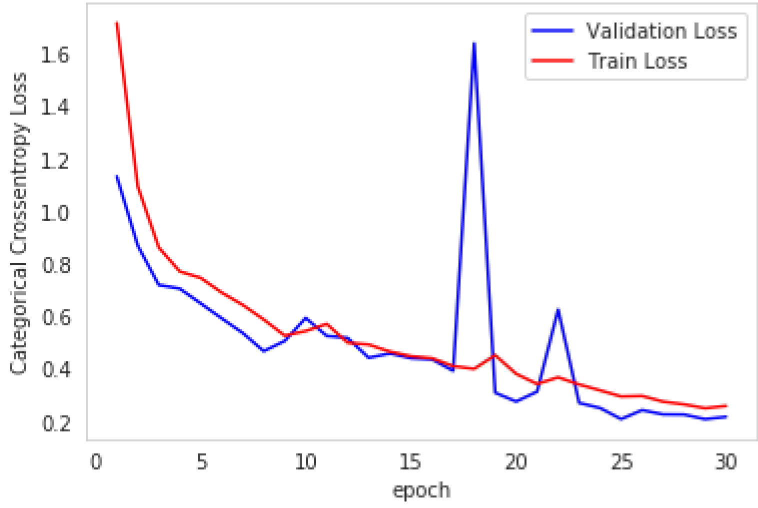
In [167]:

```
start = datetime.now()

# Training the model
trained_model  = model.fit(x_train,
                           y_train,
                           batch_size=n_batch,
                           validation_data=(x_test, y_test),
                           epochs=n_epochs)

print("\n Time Taken: ",datetime.now() - start)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 73s 10ms/step - loss: 1.7200 - acc: 0.5092 - val_loss: 1.
1351 - val_acc: 0.6637
Epoch 2/30
7352/7352 [==============================] - 69s 9ms/step - loss: 1.0967 - acc: 0.6045 - val_loss: 0.8
715 - val_acc: 0.6783
Epoch 3/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.8645 - acc: 0.6485 - val_loss: 0.7
218 - val_acc: 0.6709
Epoch 4/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.7733 - acc: 0.6591 - val_loss: 0.7
077 - val_acc: 0.6461
Epoch 5/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.7486 - acc: 0.6693 - val_loss: 0.6
514 - val_acc: 0.7346
Epoch 6/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.6926 - acc: 0.7013 - val_loss: 0.5
943 - val_acc: 0.7557
Epoch 7/30
7352/7352 [==============================] - 69s 9ms/step - loss: 0.6458 - acc: 0.7312 - val_loss: 0.5
387 - val_acc: 0.7577
Epoch 8/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.5900 - acc: 0.7558 - val_loss: 0.4
696 - val_acc: 0.7913
Epoch 9/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.5288 - acc: 0.7758 - val_loss: 0.5
086 - val_acc: 0.7530
Epoch 10/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.5462 - acc: 0.7850 - val_loss: 0.5
960 - val_acc: 0.7604
Epoch 11/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.5733 - acc: 0.7636 - val_loss: 0.5
277 - val_acc: 0.7557
Epoch 12/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.5016 - acc: 0.7899 - val_loss: 0.5
197 - val_acc: 0.7981
Epoch 13/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.4947 - acc: 0.8025 - val_loss: 0.4
442 - val_acc: 0.7845
Epoch 14/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.4675 - acc: 0.8105 - val_loss: 0.4
606 - val_acc: 0.7930
Epoch 15/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.4500 - acc: 0.8230 - val_loss: 0.4
424 - val_acc: 0.7794
Epoch 16/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.4422 - acc: 0.8241 - val_loss: 0.4
382 - val_acc: 0.7967
Epoch 17/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.4123 - acc: 0.8419 - val_loss: 0.3
946 - val_acc: 0.7937
Epoch 18/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.4020 - acc: 0.8519 - val_loss: 1.6
426 - val_acc: 0.6230
Epoch 19/30
7352/7352 [==============================] - 68s 9ms/step - loss: 0.4541 - acc: 0.8448 - val_loss: 0.3
112 - val_acc: 0.8819
Epoch 20/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.3831 - acc: 0.8708 - val_loss: 0.2
774 - val_acc: 0.8996
Epoch 21/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.3443 - acc: 0.8897 - val_loss: 0.3
153 - val_acc: 0.8836
Epoch 22/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.3697 - acc: 0.8798 - val_loss: 0.6
281 - val_acc: 0.7913
Epoch 23/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.3425 - acc: 0.8905 - val_loss: 0.2
721 - val_acc: 0.9111
Epoch 24/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.3199 - acc: 0.8983 - val_loss: 0.2
527 - val_acc: 0.9067
Epoch 25/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2967 - acc: 0.9075 - val_loss: 0.2
106 - val_acc: 0.9121
Epoch 26/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2987 - acc: 0.9064 - val_loss: 0.2
447 - val_acc: 0.9118
Epoch 27/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2770 - acc: 0.9095 - val_loss: 0.2
284 - val_acc: 0.9009
Epoch 28/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2665 - acc: 0.9125 - val_loss: 0.2
278 - val_acc: 0.9148
Epoch 29/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2519 - acc: 0.9195 - val_loss: 0.2
```

```
101 - val_acc: 0.9145
Epoch 30/30
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2606 - acc: 0.9157 - val_loss: 0.2
190 - val_acc: 0.9189

 Time Taken:  0:33:54.897715
```

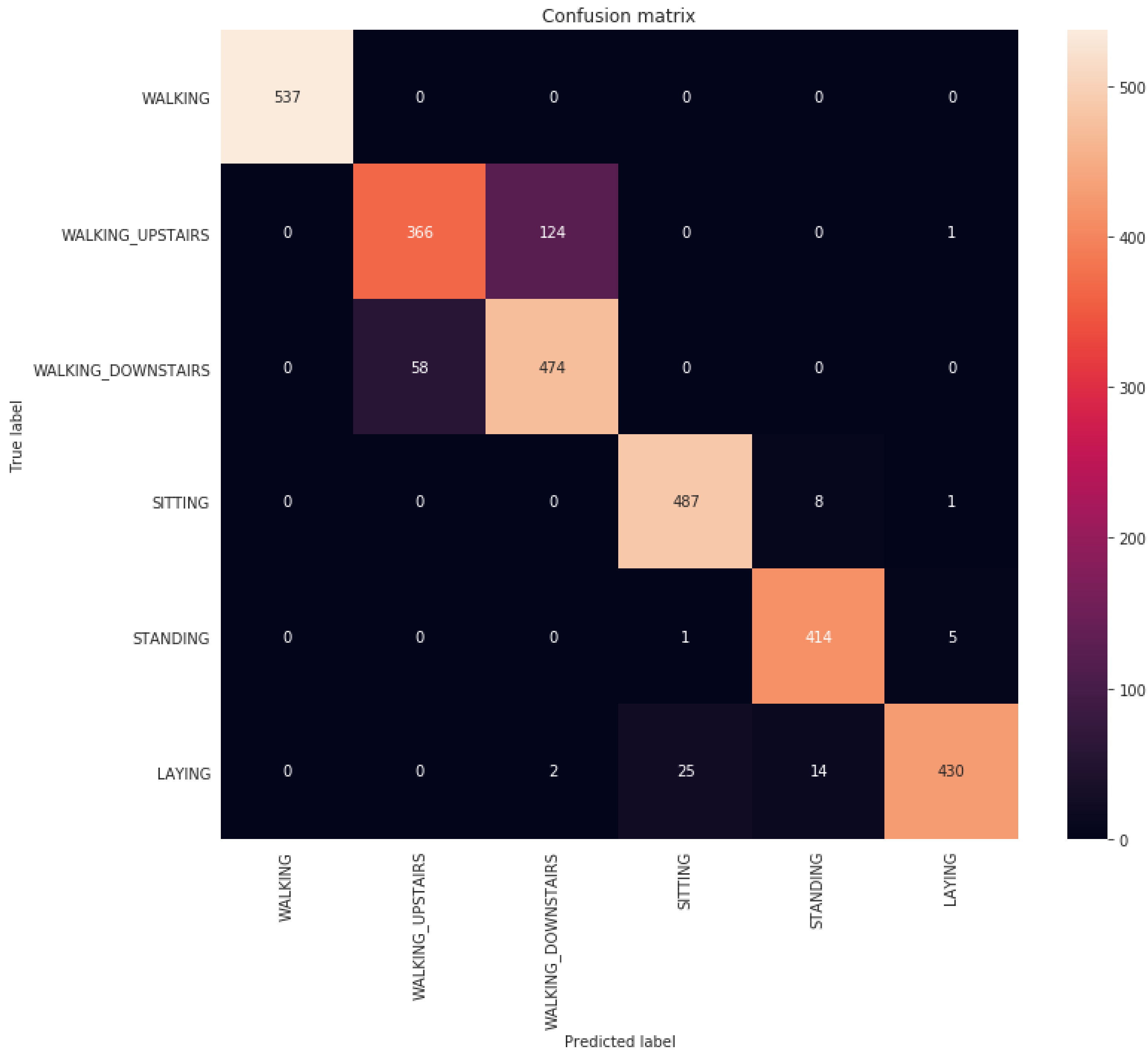
In [168]:
```
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, n_epochs)
```



From epoch 9, we starts to overfit the model, so best value for epoch is 9

In [169]:
```
print()
scores = model.evaluate(x_test, y_test, verbose=0)
print("Test Accuracy: %f%%" % (scores[1]*100))
print()

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
Y_predictions = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(x_test), axis=1)])

# Confusion Matrix
plot_confusion_matrix_lstm(Y_true, Y_predictions)
```

```
Test Accuracy: 91.890058%
```



48 neurons in LSTM Layer with dropout of 0.70

In [170]:

```
# Model execution
model = Sequential()
model.add(LSTM(48, input_shape=(timesteps, input_dim), return_sequences=True, bias_regularizer=reg))
model.add(BatchNormalization())
model.add(Dropout(0.70))
model.add(LSTM(32))
model.add(Dropout(0.70))
model.add(Dense(n_classes, activation='sigmoid'))
print("Model Summary: ")
model.summary()
```

```
Model Summary:
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_34 (LSTM)               (None, 128, 48)           11136     
_________________________________________________________________
batch_normalization_8 (Batch (None, 128, 48)           192       
_________________________________________________________________
dropout_34 (Dropout)         (None, 128, 48)           0         
_________________________________________________________________
lstm_35 (LSTM)               (None, 32)                10368     
_________________________________________________________________
dropout_35 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_18 (Dense)             (None, 6)                 198       
=================================================================
Total params: 21,894
Trainable params: 21,798
Non-trainable params: 96
_________________________________________________________________
```

In [171]:

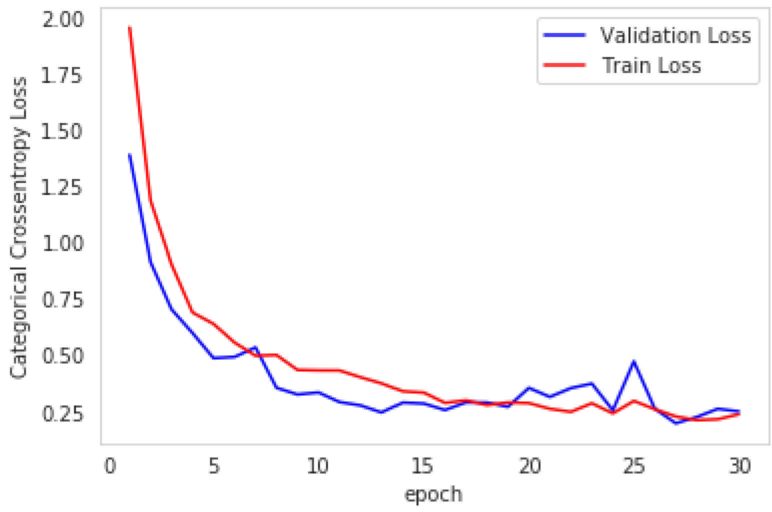
```
model.compile(loss='categorical_crossentropy',
          optimizer='adam',
          metrics=['accuracy'])
```

In [172]:
```
start = datetime.now()

# Training the model
trained_model  = model.fit(x_train,
                           y_train,
                           batch_size=n_batch,
                           validation_data=(x_test, y_test),
                           epochs=n_epochs)

print("\n Time Taken: ",datetime.now() - start)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 74s 10ms/step - loss: 1.9616 - acc: 0.5328 - val_loss: 1.
3936 - val_acc: 0.6882
Epoch 2/30
7352/7352 [==============================] - 70s 10ms/step - loss: 1.1900 - acc: 0.6726 - val_loss: 0.
9176 - val_acc: 0.7645
Epoch 3/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.9071 - acc: 0.6967 - val_loss: 0.
7071 - val_acc: 0.7448
Epoch 4/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.6931 - acc: 0.7511 - val_loss: 0.
6015 - val_acc: 0.7350
Epoch 5/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.6422 - acc: 0.7685 - val_loss: 0.
4896 - val_acc: 0.8392
Epoch 6/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.5594 - acc: 0.8014 - val_loss: 0.
4949 - val_acc: 0.7879
Epoch 7/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.5005 - acc: 0.8213 - val_loss: 0.
5374 - val_acc: 0.7211
Epoch 8/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.5035 - acc: 0.8215 - val_loss: 0.
3574 - val_acc: 0.8897
Epoch 9/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.4370 - acc: 0.8536 - val_loss: 0.
3277 - val_acc: 0.8921
Epoch 10/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.4351 - acc: 0.8512 - val_loss: 0.
3366 - val_acc: 0.8853
Epoch 11/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.4346 - acc: 0.8658 - val_loss: 0.
2939 - val_acc: 0.9046
Epoch 12/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.4044 - acc: 0.8666 - val_loss: 0.
2789 - val_acc: 0.8996
Epoch 13/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.3771 - acc: 0.8845 - val_loss: 0.
2476 - val_acc: 0.9091
Epoch 14/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.3418 - acc: 0.8923 - val_loss: 0.
2914 - val_acc: 0.8979
Epoch 15/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.3358 - acc: 0.8935 - val_loss: 0.
2870 - val_acc: 0.8965
Epoch 16/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2902 - acc: 0.9091 - val_loss: 0.
2583 - val_acc: 0.9023
Epoch 17/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.3015 - acc: 0.9051 - val_loss: 0.
2921 - val_acc: 0.9009
Epoch 18/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2804 - acc: 0.9135 - val_loss: 0.
2917 - val_acc: 0.8884
Epoch 19/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2919 - acc: 0.9116 - val_loss: 0.
2725 - val_acc: 0.9060
Epoch 20/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2891 - acc: 0.9109 - val_loss: 0.
3569 - val_acc: 0.8782
Epoch 21/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2637 - acc: 0.9157 - val_loss: 0.
3168 - val_acc: 0.9043
Epoch 22/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2502 - acc: 0.9240 - val_loss: 0.
3559 - val_acc: 0.9050
Epoch 23/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2884 - acc: 0.9076 - val_loss: 0.
3761 - val_acc: 0.8677
Epoch 24/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2434 - acc: 0.9275 - val_loss: 0.
2570 - val_acc: 0.9135
Epoch 25/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2988 - acc: 0.9081 - val_loss: 0.
4753 - val_acc: 0.8799
Epoch 26/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2619 - acc: 0.9229 - val_loss: 0.
2638 - val_acc: 0.9128
Epoch 27/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2294 - acc: 0.9278 - val_loss: 0.
1990 - val_acc: 0.9243
Epoch 28/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2133 - acc: 0.9327 - val_loss: 0.
2272 - val_acc: 0.9213
Epoch 29/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2171 - acc: 0.9321 - val_loss: 0.
```

```
2637 - val_acc: 0.9067
Epoch 30/30
7352/7352 [==============================] - 70s 10ms/step - loss: 0.2393 - acc: 0.9253 - val_loss: 0.
2521 - val_acc: 0.9118

 Time Taken:  0:35:04.995551
```

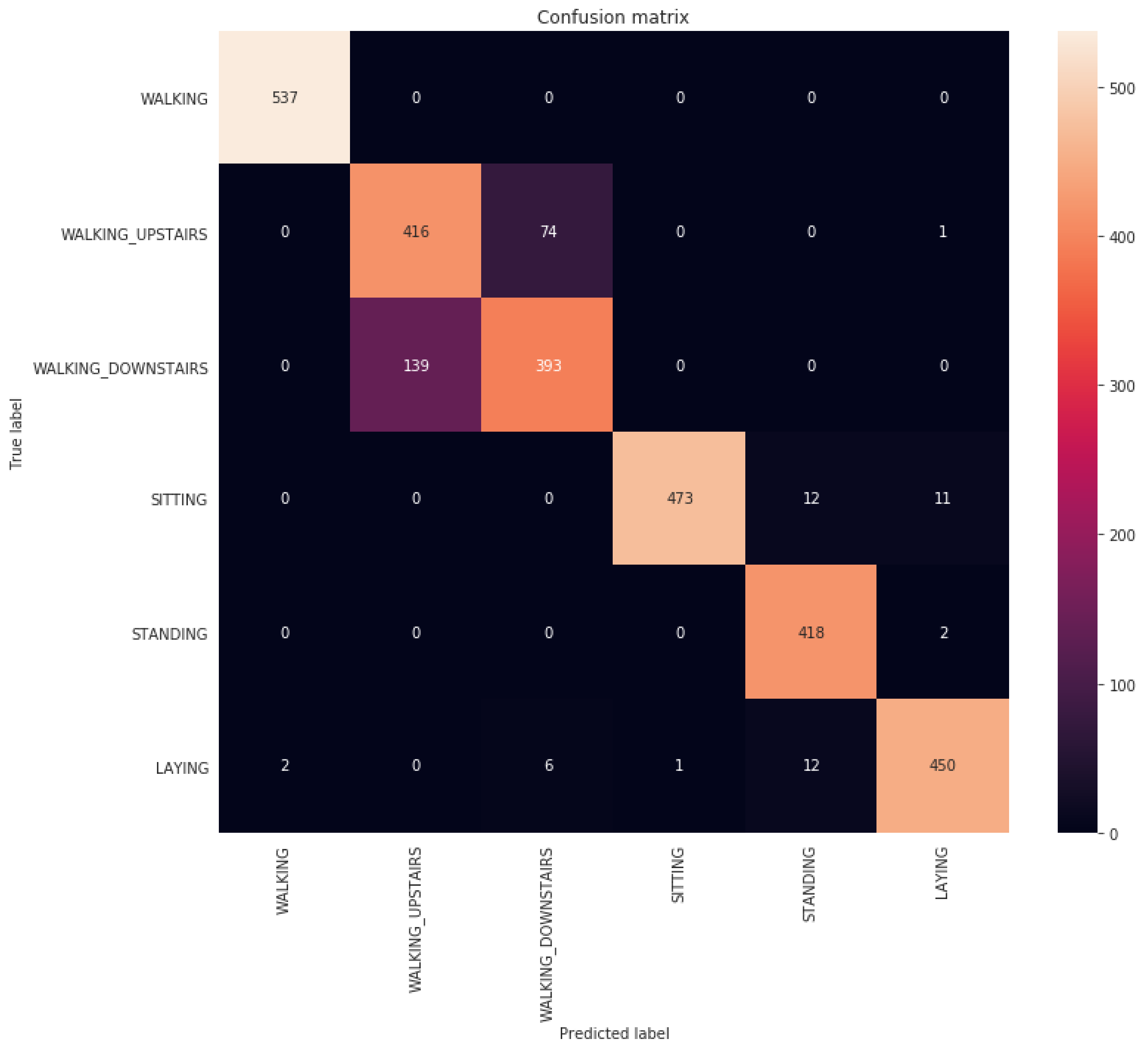
In [173]:
```
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, n_epochs)
```



From epoch 16, we starts to overfit the model, so best value for epoch is 16

In [174]:
```
print()
scores = model.evaluate(x_test, y_test, verbose=0)
print("Test Accuracy: %f%%" % (scores[1]*100))
print()

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
Y_predictions = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(x_test), axis=1)])

# Confusion Matrix
plot_confusion_matrix_lstm(Y_true, Y_predictions)
```

```
Test Accuracy: 91.177469%
```



64 neurons in LSTM Layer with dropout of 0.70

In [175]:

```
# Model execution
model = Sequential()
model.add(LSTM(64, input_shape=(timesteps, input_dim), return_sequences=True, bias_regularizer=reg))
model.add(BatchNormalization())
model.add(Dropout(0.70))
model.add(LSTM(48))
model.add(Dropout(0.70))
model.add(Dense(n_classes, activation='sigmoid'))
print("Model Summary: ")
model.summary()
```

```
Model Summary:
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_36 (LSTM)               (None, 128, 64)           18944     
_________________________________________________________________
batch_normalization_9 (Batch (None, 128, 64)           256       
_________________________________________________________________
dropout_36 (Dropout)         (None, 128, 64)           0         
_________________________________________________________________
lstm_37 (LSTM)               (None, 48)                21696     
_________________________________________________________________
dropout_37 (Dropout)         (None, 48)                0         
_________________________________________________________________
dense_19 (Dense)             (None, 6)                 294       
=================================================================
Total params: 41,190
Trainable params: 41,062
Non-trainable params: 128
_________________________________________________________________
```

In [176]:

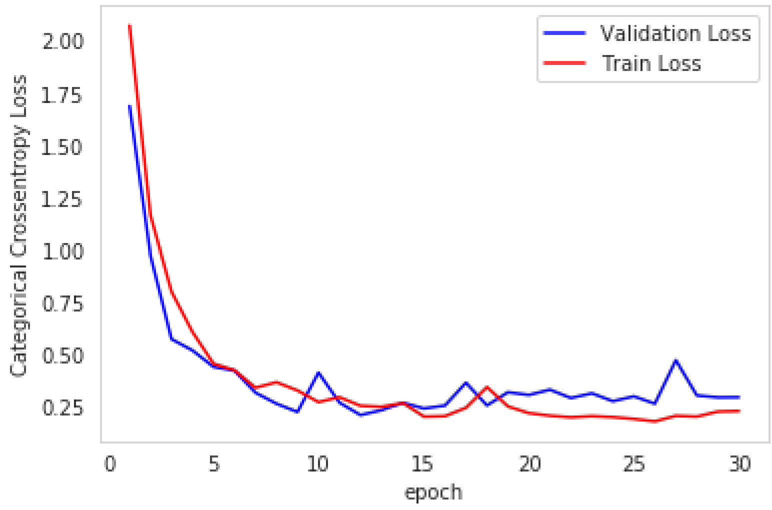
```
model.compile(loss='categorical_crossentropy',
          optimizer='adam',
          metrics=['accuracy'])
```

In [177]:
```
start = datetime.now()

# Training the model
trained_model  = model.fit(x_train,
                           y_train,
                           batch_size=n_batch,
                           validation_data=(x_test, y_test),
                           epochs=n_epochs)

print("\n Time Taken: ",datetime.now() - start)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 79s 11ms/step - loss: 2.0756 - acc: 0.5249 - val_loss: 1.
6901 - val_acc: 0.4968
Epoch 2/30
7352/7352 [==============================] - 76s 10ms/step - loss: 1.1660 - acc: 0.6571 - val_loss: 0.
9750 - val_acc: 0.7438
Epoch 3/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.8037 - acc: 0.7206 - val_loss: 0.
5763 - val_acc: 0.8164
Epoch 4/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.6107 - acc: 0.7952 - val_loss: 0.
5221 - val_acc: 0.7998
Epoch 5/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.4589 - acc: 0.8573 - val_loss: 0.
4435 - val_acc: 0.8677
Epoch 6/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.4276 - acc: 0.8713 - val_loss: 0.
4253 - val_acc: 0.8453
Epoch 7/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.3439 - acc: 0.8945 - val_loss: 0.
3199 - val_acc: 0.9030
Epoch 8/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.3700 - acc: 0.8894 - val_loss: 0.
2672 - val_acc: 0.8955
Epoch 9/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.3307 - acc: 0.8947 - val_loss: 0.
2276 - val_acc: 0.9189
Epoch 10/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.2750 - acc: 0.9165 - val_loss: 0.
4161 - val_acc: 0.8059
Epoch 11/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2983 - acc: 0.9003 - val_loss: 0.
2722 - val_acc: 0.9019
Epoch 12/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2574 - acc: 0.9162 - val_loss: 0.
2127 - val_acc: 0.9226
Epoch 13/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2524 - acc: 0.9161 - val_loss: 0.
2360 - val_acc: 0.9111
Epoch 14/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2702 - acc: 0.9172 - val_loss: 0.
2715 - val_acc: 0.9009
Epoch 15/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2054 - acc: 0.9297 - val_loss: 0.
2443 - val_acc: 0.9138
Epoch 16/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2077 - acc: 0.9320 - val_loss: 0.
2583 - val_acc: 0.9158
Epoch 17/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2479 - acc: 0.9233 - val_loss: 0.
3677 - val_acc: 0.9043
Epoch 18/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.3468 - acc: 0.9000 - val_loss: 0.
2588 - val_acc: 0.9172
Epoch 19/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2541 - acc: 0.9217 - val_loss: 0.
3220 - val_acc: 0.9023
Epoch 20/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2221 - acc: 0.9244 - val_loss: 0.
3090 - val_acc: 0.8948
Epoch 21/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2099 - acc: 0.9293 - val_loss: 0.
3343 - val_acc: 0.9033
Epoch 22/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.2021 - acc: 0.9302 - val_loss: 0.
2945 - val_acc: 0.9179
Epoch 23/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2078 - acc: 0.9329 - val_loss: 0.
3167 - val_acc: 0.9189
Epoch 24/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2029 - acc: 0.9298 - val_loss: 0.
2791 - val_acc: 0.9141
Epoch 25/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1944 - acc: 0.9353 - val_loss: 0.
3023 - val_acc: 0.9152
Epoch 26/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1826 - acc: 0.9407 - val_loss: 0.
2672 - val_acc: 0.9199
Epoch 27/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2092 - acc: 0.9319 - val_loss: 0.
4755 - val_acc: 0.8931
Epoch 28/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2056 - acc: 0.9316 - val_loss: 0.
3067 - val_acc: 0.9043
Epoch 29/30
7352/7352 [==============================] - 74s 10ms/step - loss: 0.2296 - acc: 0.9278 - val_loss: 0.
```

```
2973 - val_acc: 0.9026
Epoch 30/30
7352/7352 [==============================] - 75s 10ms/step - loss: 0.2322 - acc: 0.9214 - val_loss: 0.
2978 - val_acc: 0.8890

 Time Taken:  0:37:18.885674
```

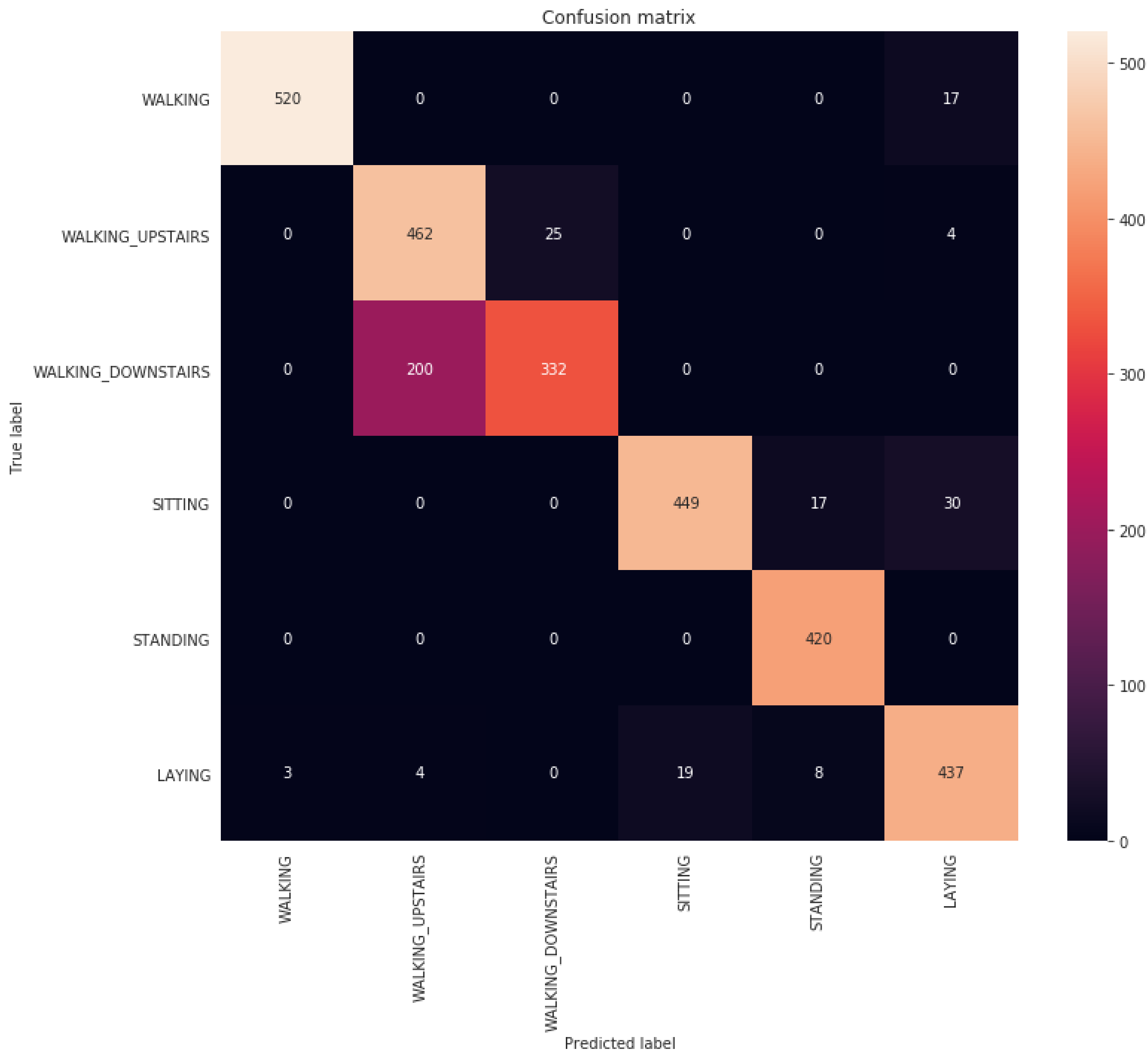
In [178]:
```
print()
print()

# Plot train and cross validation error
plot_train_cv_loss(trained_model, n_epochs)
```



From epoch 7, we starts to overfit the model, so best value for epoch is 7

In [179]:
```
print()
scores = model.evaluate(x_test, y_test, verbose=0)
print("Test Accuracy: %f%%" % (scores[1]*100))
print()

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(y_test, axis=1)])
Y_predictions = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(x_test), axis=1)])

# Confusion Matrix
plot_confusion_matrix_lstm(Y_true, Y_predictions)
```

```
Test Accuracy: 88.903970%
```



Conclusion

In [3]:
```
from prettytable import PrettyTable
ptable = PrettyTable()
ptable.title = " Model Comparision "
ptable.field_names = ["LSTM Layers",'No. of Neurons in LSTM Layer','Dropout', 'Best Epoch']
ptable.add_row(["2","32","0.50","10"])
ptable.add_row(["2","48","0.50","7"])
ptable.add_row(["2","64","0.50","8"])
ptable.add_row(["\n","\n","\n","\n"])
ptable.add_row(["2","32","0.70","9"])
ptable.add_row(["2","48","0.70","16"])
ptable.add_row(["2","64","0.70","7"])
print(ptable)
```

```
+-------------------------------------------------------------------+
|                         Model Comparision                         |
+-------------+------------------------------+---------+------------+
| LSTM Layers | No. of Neurons in LSTM Layer | Dropout | Best Epoch |
+-------------+------------------------------+---------+------------+
|      2      |              32              |   0.50  |     10     |
|      2      |              48              |   0.50  |     7      |
|      2      |              64              |   0.50  |     8      |
|             |                              |         |            |
|             |                              |         |            |
|      2      |              32              |   0.70  |     9      |
|      2      |              48              |   0.70  |     16     |
|      2      |              64              |   0.70  |     7      |
+-------------+------------------------------+---------+------------+
```

From all the plots, we have observed that 64 neurons with 0.50 dropout rate will be the good choice, among all the models.