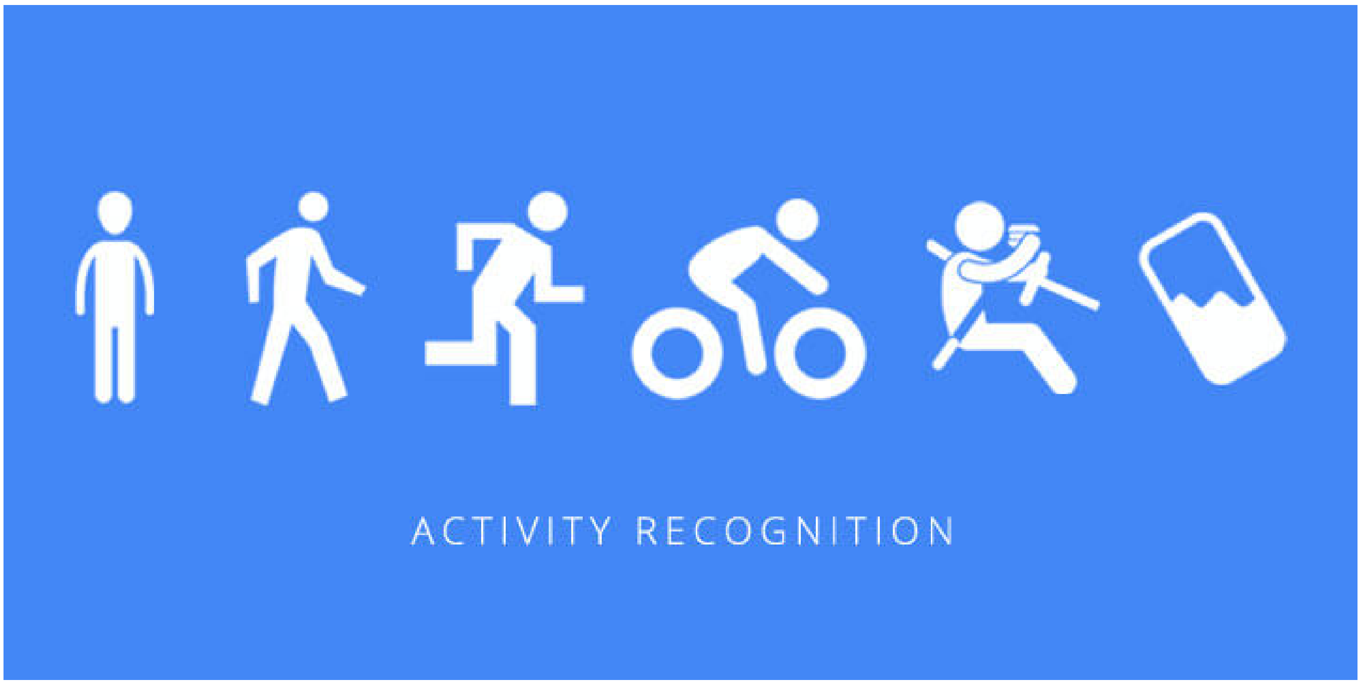

ACTIVITY RECOGNITION

1. BUSINESS PROBLEM

1.1 Description

Human activity recognition is the problem of classifying sequences of accelerometer data recorded by specialized harnesses or smart phones into known well-defined movements.

It is a challenging problem given the large number of observations produced each second, the temporal nature of the observations, and the lack of a clear way to relate accelerometer data to known movements.

Implementation : It can be used in Smartwatches, fitbit to record the daily activities of a person and help the person to maintain a balanced life.

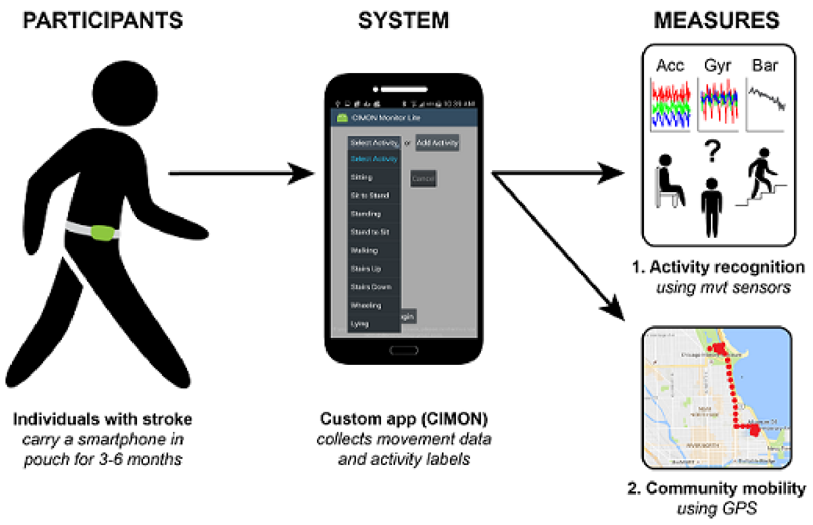
1.2 Problem Statement

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

- Classsical Machine Learning models using domain expert/engineered features
- Deep Learning models using raw time series features

1.3 Collection of Data

The experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years. Each person performed six activities (WALKING, WALKING_UPSTAIRS, WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments have been video-recorded to label the data manually. The obtained dataset has been randomly partitioned into two sets, where 70% of the volunteers was selected for generating the training data and 30% the test data.



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.

1) The sensor signals (accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window).

2) From Each window, a feature vector was obtianed by calculating variables from the time and frequency domain.

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.

- 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

2. MACHINE LEARNING PROBLEM

2.1 Data

2.1.1 Data Overview

Source : https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones (https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones)

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 4
- SITTING as 3
- 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***
- 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'

2.2 Mapping the real world problem to an ML problem

2.2.1 Type of Machine Leaning Problem

It is a **multiclass classification** problem, for given features we have to predict one of the 6 human activities.

2.2.2 Performance Metric

- multi log-loss
- Accuracy
- Precission,Recall and F1 score for each activity

3. EXTRACTION OF DATA AND FEATURES

In [3]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import itertools
from datetime import datetime

from sklearn.manifold import TSNE
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC, SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
from keras.wrappers.scikit_learn import KerasClassifier
from keras.models import load_model
from keras.utils.vis_utils import plot_model

from hyperopt import Trials, STATUS_OK, tpe
from hyperas import optim
from hyperas.distributions import choice, uniform
```

3.1 Loading of Data

3.1.1 Domain expert/engineered features

In [25]:

```
with open("UCI_HAR_Dataset/features.txt") as f:
    features = [line.split()[1] for line in f.readlines()]
print("Number of expert domain engineered features:  ",len(features))
```

```
Number of expert domain engineered features:   561
```

3.1.2 Loading the Train Data

In [26]:

```
X_train = pd.read_csv("UCI_HAR_Dataset/train/X_train.txt", delim_whitespace = True, hea
der = None, names = features)

X_train['subject'] = pd.read_csv("UCI_HAR_Dataset/train/subject_train.txt", header = No
ne, 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"})

train_data = X_train
train_data['Activity'] = y_train
train_data['ActivityName'] = y_train_labels
train_data.sample()
```

```
/opt/anaconda3/lib/python3.6/site-packages/pandas/io/parsers.py:678: UserW
arning: Duplicate names specified. This will raise an error in the future.
  return _read(filepath_or_buffer, kwds)
```

Out[26]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAc mad()
2775	0.265884	-0.020794	-0.128042	-0.995699	-0.993071	-0.978309	-0.99596

1 rows × 564 columns

In [27]:

```
print("Dimensions of Training Data: ",train_data.shape)
```

```
Dimensions of Training Data:  (7352, 564)
```

3.1.3 Loading the Test Data

In [28]:

```
X_test = pd.read_csv("UCI_HAR_Dataset/test/X_test.txt", delim_whitespace = True, header
 = None, names = features)

X_test['subject'] = pd.read_csv("UCI_HAR_Dataset/test/subject_test.txt", header = None,
 squeeze = True)

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"})

test_data = X_test
test_data['Activity'] = y_test
test_data['ActivityName'] = y_test_labels
test_data.sample()
```

```
/opt/anaconda3/lib/python3.6/site-packages/pandas/io/parsers.py:678: UserW
arning: Duplicate names specified. This will raise an error in the future.
  return _read(filepath_or_buffer, kwds)
```

Out[28]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAc mad()
1254	0.274152	-0.000265	-0.10381	-0.966143	-0.743047	-0.876623	-0.97268

1 rows × 564 columns

In [29]:

```
print("Dimensions of Test Data: ",test_data.shape)
```

```
Dimensions of Test Data:  (2947, 564)
```

3.2. Check for Duplicates

In [30]:

```
print("Number of duplicates in Training data: ",sum(train_data.duplicated()))
print("Number of duplicates in Test data: ",sum(test_data.duplicated()))
```

```
Number of duplicates in Training data:  0
Number of duplicates in Test data:  0
```

3.3 Checking for Missing values

In [31]:

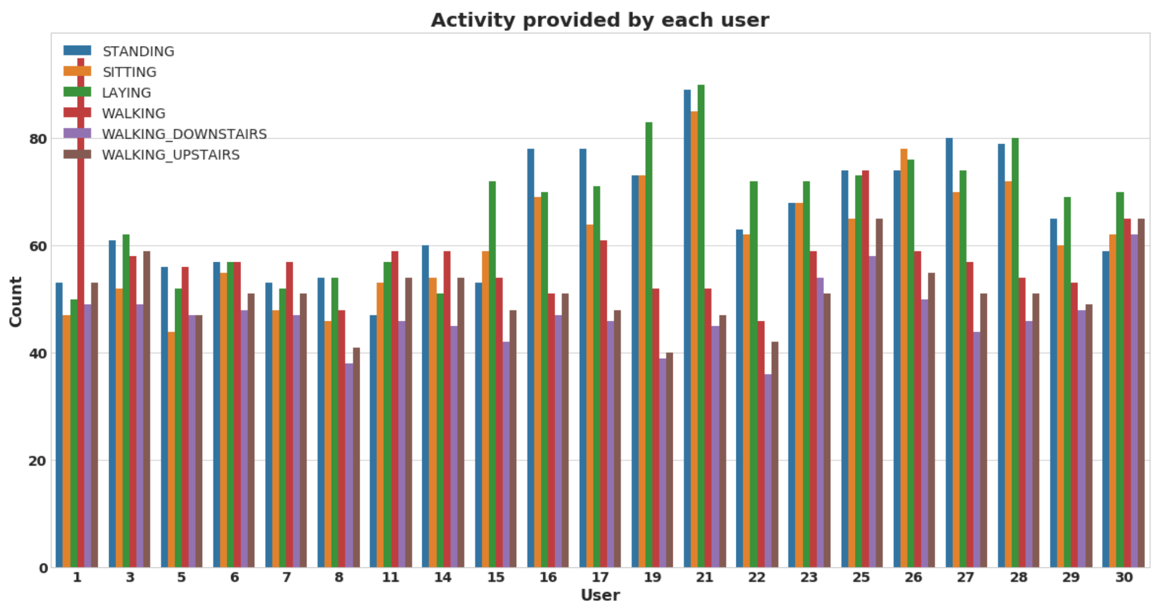
```
print("Number of NaN/null values in Training data: ",train_data.isnull().values.sum())
print("Number of NaN/null values in Test data: ",test_data.isnull().values.sum())
```

```
Number of NaN/null values in Training data:  0
Number of NaN/null values in Test data:  0
```

3.4 Check for data imbalance

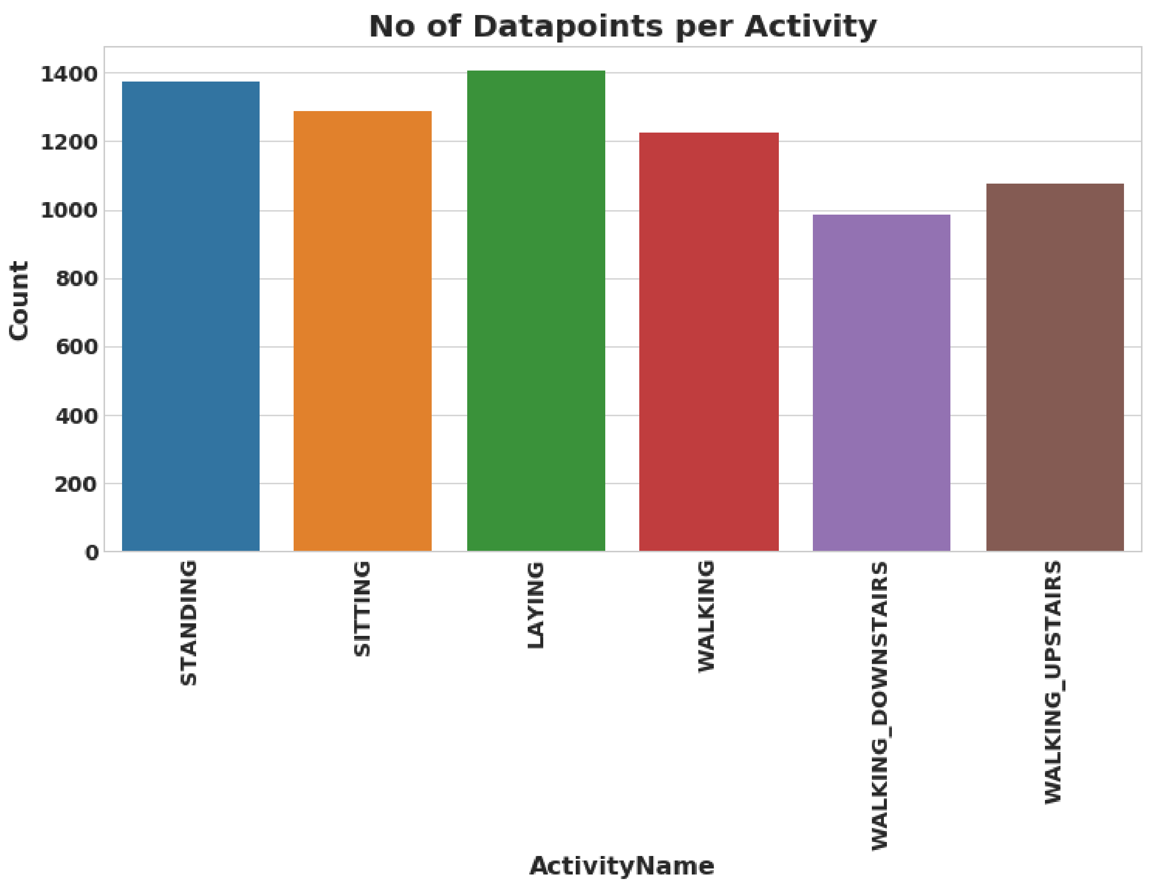
In [32]:

```
sns.set_style('whitegrid')
plt.rcParams['font.family'] = 'Dejavu Sans'
plt.figure(figsize = (20,10))

sns.countplot(x = "subject", hue = "ActivityName", data = train_data)
plt.title('Activity provided by each user', fontsize=20, fontweight = 'bold')
plt.xlabel("User", fontsize=16, fontweight = 'bold')
plt.xticks(fontsize=14, fontweight = 'bold')
plt.ylabel("Count", fontsize=16, fontweight = 'bold')
plt.yticks(fontsize=14, fontweight = 'bold')
plt.legend(fontsize=14)
plt.show()
```



In [33]:

```
plt.figure(figsize = (12,6))
sns.countplot(train_data.ActivityName)
plt.title('No of Datapoints per Activity', fontsize=20, fontweight = 'bold')
plt.xlabel("ActivityName", fontsize=16, fontweight = 'bold')
plt.xticks(rotation = 90,fontsize=14, fontweight = 'bold')
plt.ylabel("Count", fontsize=16, fontweight = 'bold')
plt.yticks(fontsize=14, fontweight = 'bold')
plt.show()
```



Obsevations:

- All the activities are almost well balanced.
- Hence, no need of balancing the dataset.

3.5. Changing engineered feature names

- Expert engineered feature names are preproprocesesd and cleaned to remove characters like ',','-','()' for simplicity.

In [34]:

```
columns = train_data.columns

columns = columns.str.replace('[()]','')
columns = columns.str.replace('[-]','')
columns = columns.str.replace('[,]','')

train_data.columns = columns
test_data.columns = columns

print(train_data.columns)
```

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

4. EXPLOARATORY DATA ANALYSIS

4.1 Featuring Engineering from Domain Knowledge

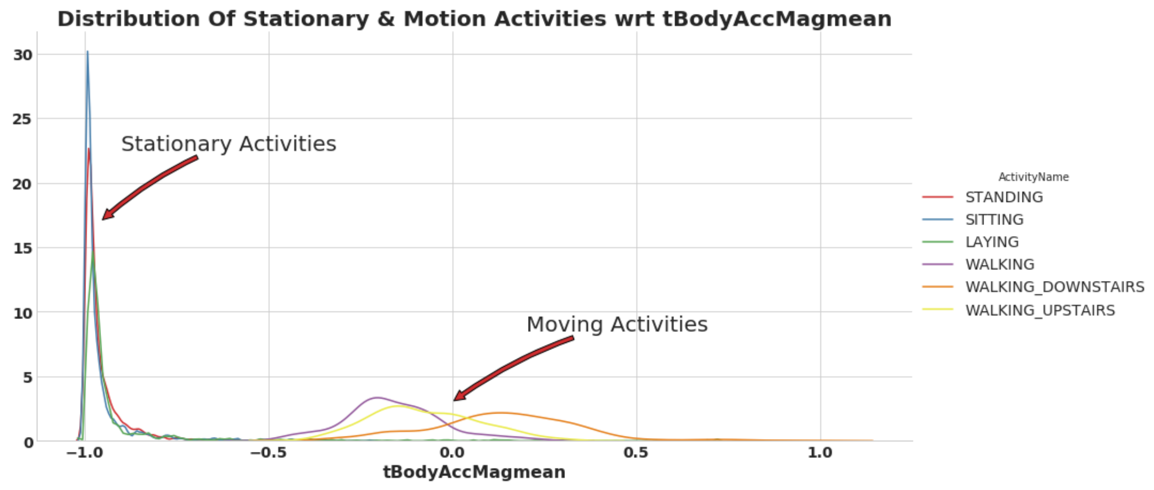
Static and Dynamic Activities

```
- In static activities (sit, stand, lie down).motion information will not be ver
y useful.
- In the dynamic activities (Walking, WalkingUpstairs,WalkingDownstairs) motion
 info will be significant.
```

4.1.1. Stationary and Motion activities are completely different

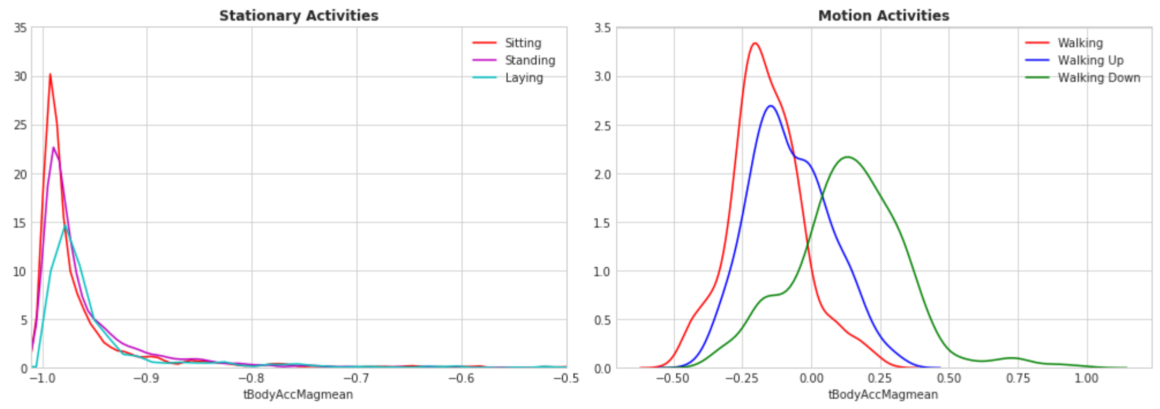
In [35]:

```
sns.set_palette("Set1", desat=0.80)
facetgrid = sns.FacetGrid(train_data, hue = 'ActivityName', size = 6, aspect = 2)
facetgrid.map(sns.distplot,'tBodyAccMagmean',hist = False).add_legend(fontsize=14)
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.title('Distribution Of Stationary & Motion Activities wrt tBodyAccMagmean', fontsiz
e=20, fontweight = 'bold')
plt.xlabel("tBodyAccMagmean", fontsize=16, fontweight = 'bold')
plt.xticks(fontsize=14, fontweight = 'bold')
plt.yticks(fontsize=14, fontweight = 'bold')
plt.show()
```



In [36]:

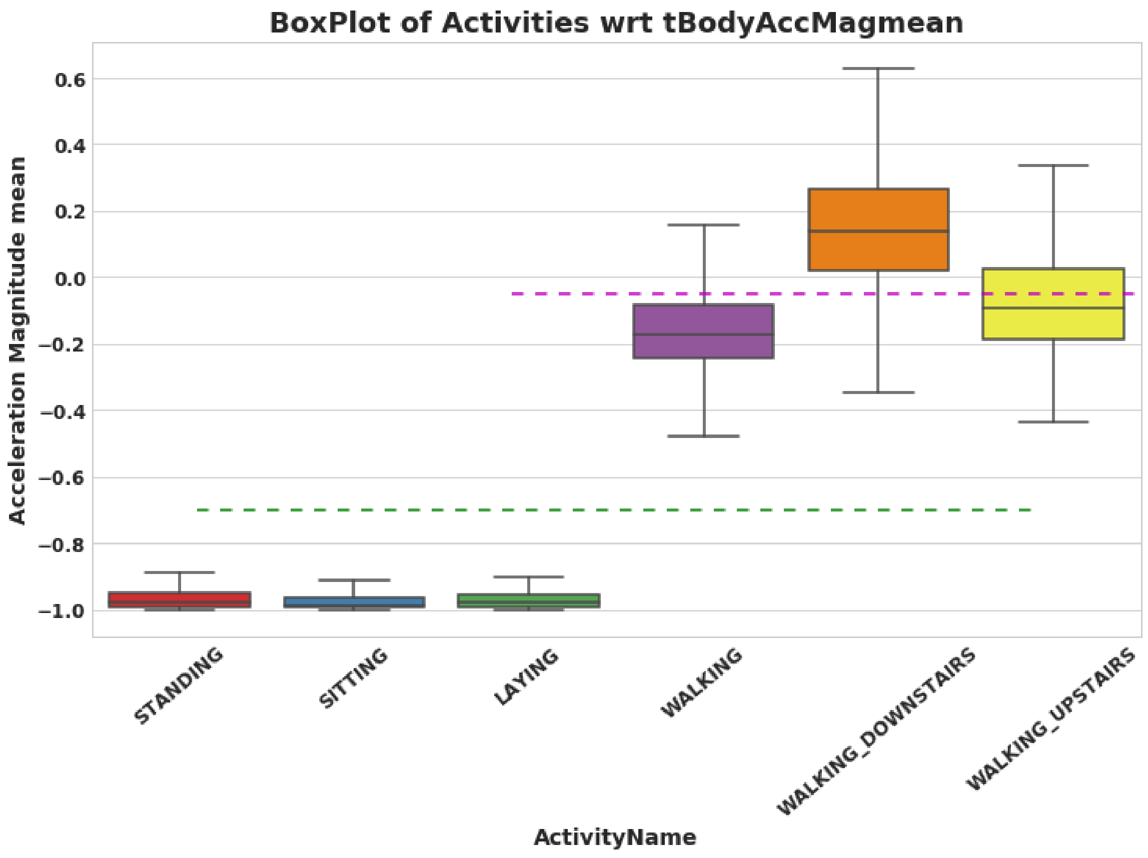
```
df1 = train_data[train_data['Activity'] == 1]
df2 = train_data[train_data['Activity'] == 2]
df3 = train_data[train_data['Activity'] == 3]
df4 = train_data[train_data['Activity'] == 4]
df5 = train_data[train_data['Activity'] == 5]
df6 = train_data[train_data['Activity'] == 6]

plt.figure(figsize = (14,5))
plt.subplot(1,2,1)
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.title("Stationary Activities",fontweight = 'bold')
plt.axis([-1.01, -0.5, 0, 35])
plt.legend()

plt.subplot(1,2,2)
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 Dow
n")
plt.title("Motion Activities",fontweight = 'bold')
plt.legend()

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



4.1.2 EDA: tBodyAccMagmean

In [37]:

```
plt.figure(figsize=(12,7))
sns.boxplot(x='ActivityName', y='tBodyAccMagmean',data=train_data, showfliers=False, sa
turation=1)
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.title("BoxPlot of Activities wrt tBodyAccMagmean", fontsize=18, fontweight = 'bold'
)
plt.xlabel("ActivityName", fontsize=14, fontweight = 'bold')
plt.xticks(rotation = 40,fontsize=12, fontweight = 'bold')
plt.ylabel("Acceleration Magnitude mean", fontsize=14, fontweight = 'bold')
plt.yticks(fontsize=12, fontweight = 'bold')
plt.show()
```



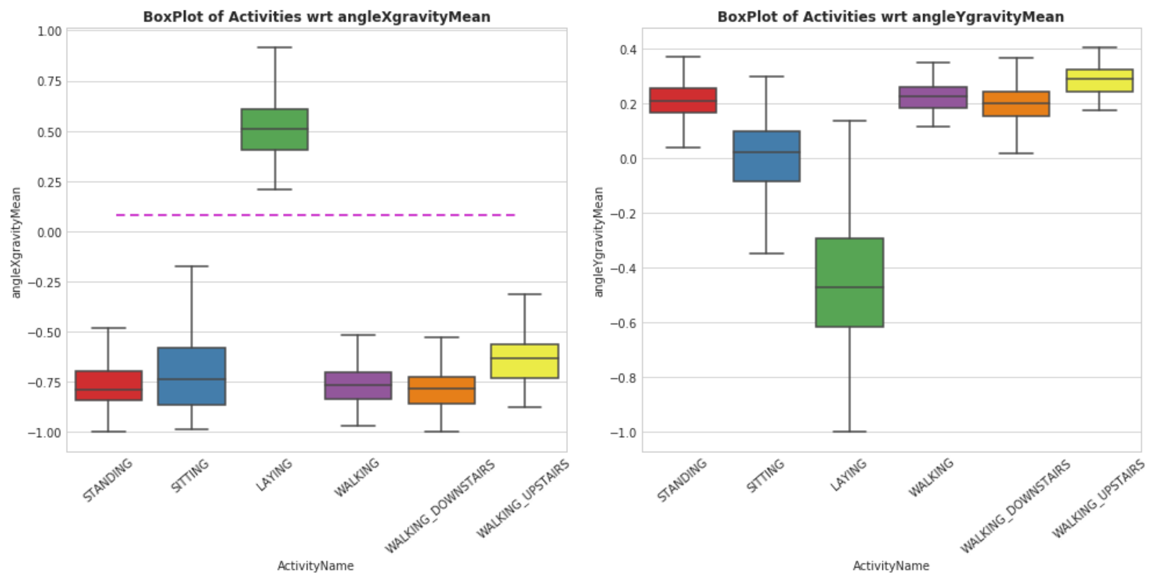
Observations:

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

4.1.3 EDA: angleXgravityMean & angleYgravityMean

In [38]:

```
plt.figure(figsize=(14,7))

plt.subplot(121)
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train_data,showfliers=False,
saturation=1)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title("BoxPlot of Activities wrt angleXgravityMean",fontweight = 'bold')
plt.xlabel("ActivityName")
plt.xticks(rotation = 40)
plt.ylabel("angleXgravityMean")

plt.subplot(122)
sns.boxplot(x='ActivityName', y='angleYgravityMean', data = train_data, showfliers=Fals
e, saturation=1)
plt.title("BoxPlot of Activities wrt angleYgravityMean", fontweight = 'bold')
plt.xlabel("ActivityName")
plt.xticks(rotation = 40)
plt.ylabel("angleYgravityMean")

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



Observations:

- If angleX,gravityMean > 0 then Activity is Laying.
- If angleY,gravityMean < -0.1 then Activity is Laying.
- We can classify all datapoints belonging to Laying activity with just a single if else statement.

4.2 Apply t-sne on the data

To visulaize all the expert domain features in 2D space, we perform tsne.

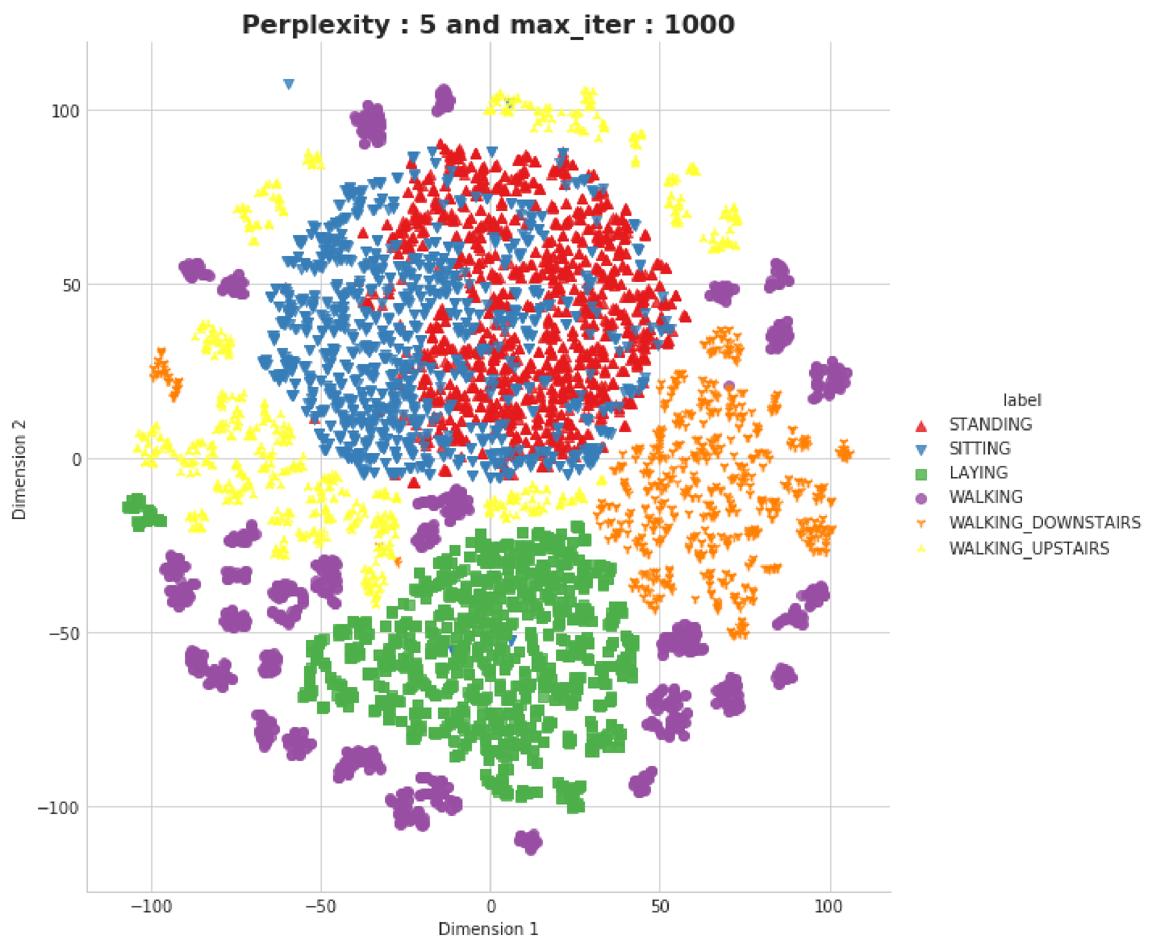
In [17]:

```
def tsne_visualization(X_data, y_data, perplexities, n_iter=1000, img_name_prefix='t-sn
e'):

    for index,perplexity in enumerate(perplexities):
        print('\nPerforming tsne with perplexity {} and with {} iterations at max'.form
at(perplexity, n_iter))
        X_reduced = TSNE(n_components = 2, verbose=0, perplexity=perplexity).fit_transf
orm(X_data)



        df = pd.DataFrame({'Dimension 1':X_reduced[:,0], 'Dimension 2':X_reduced[:,1] ,
'label':y_data})

        sns.lmplot(data=df, x='Dimension 1', y='Dimension 2', hue='label', fit_reg=Fals
e, size=8,\
                   palette="Set1",markers=['^','v','s','o', '1','2'])
        plt.title("Perplexity : {} and max_iter : {}".format(perplexity, n_iter), fonts
ize = 16, fontweight = 'bold')
        img_name = img_name_prefix + '_perp_{}_iter_{}.png'.format(perplexity, n_iter)
        plt.savefig(img_name)
        plt.show()
```

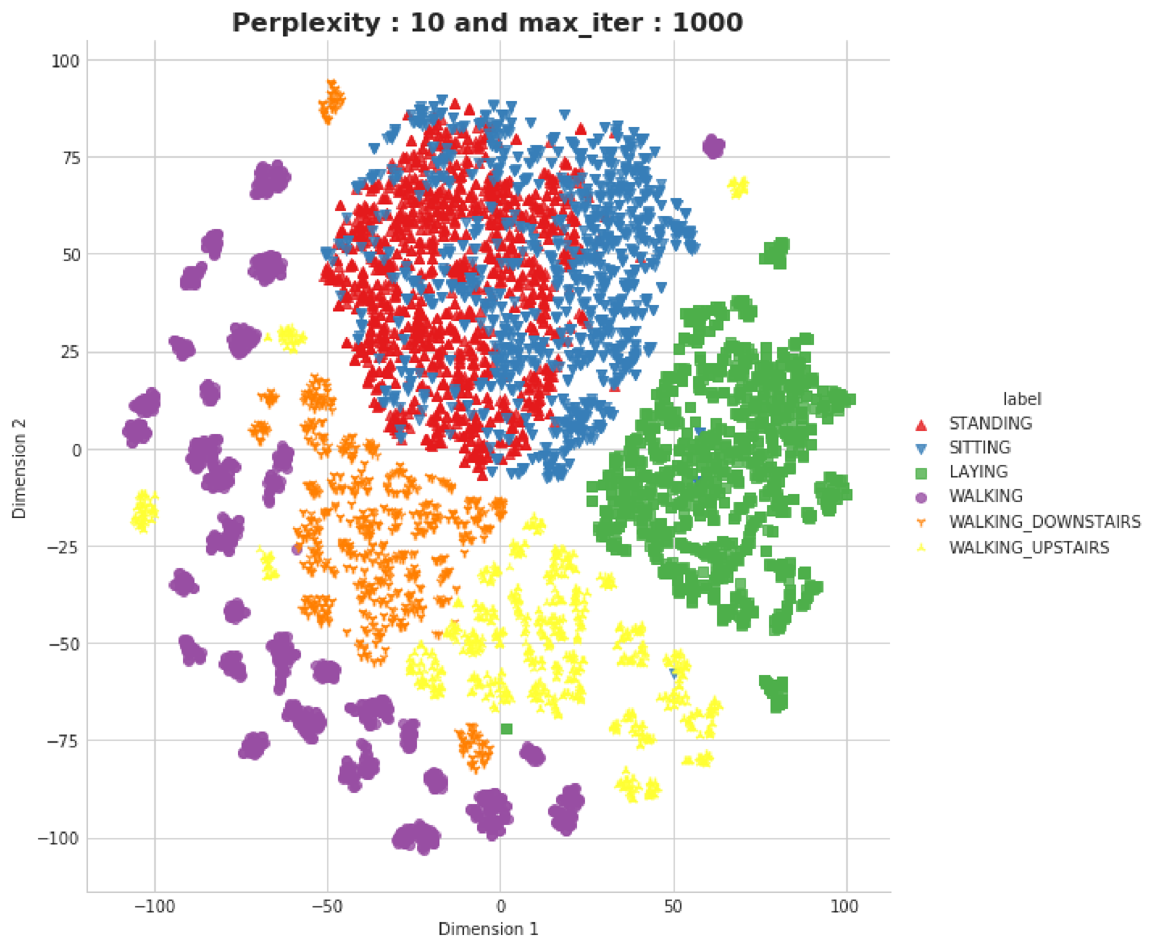
In [69]:

```
X_pre_tsne = train_data.drop(['subject', 'Activity','ActivityName'], axis=1)
y_pre_tsne = train_data['ActivityName']
tsne_visualization(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[5,10,20,50])
```

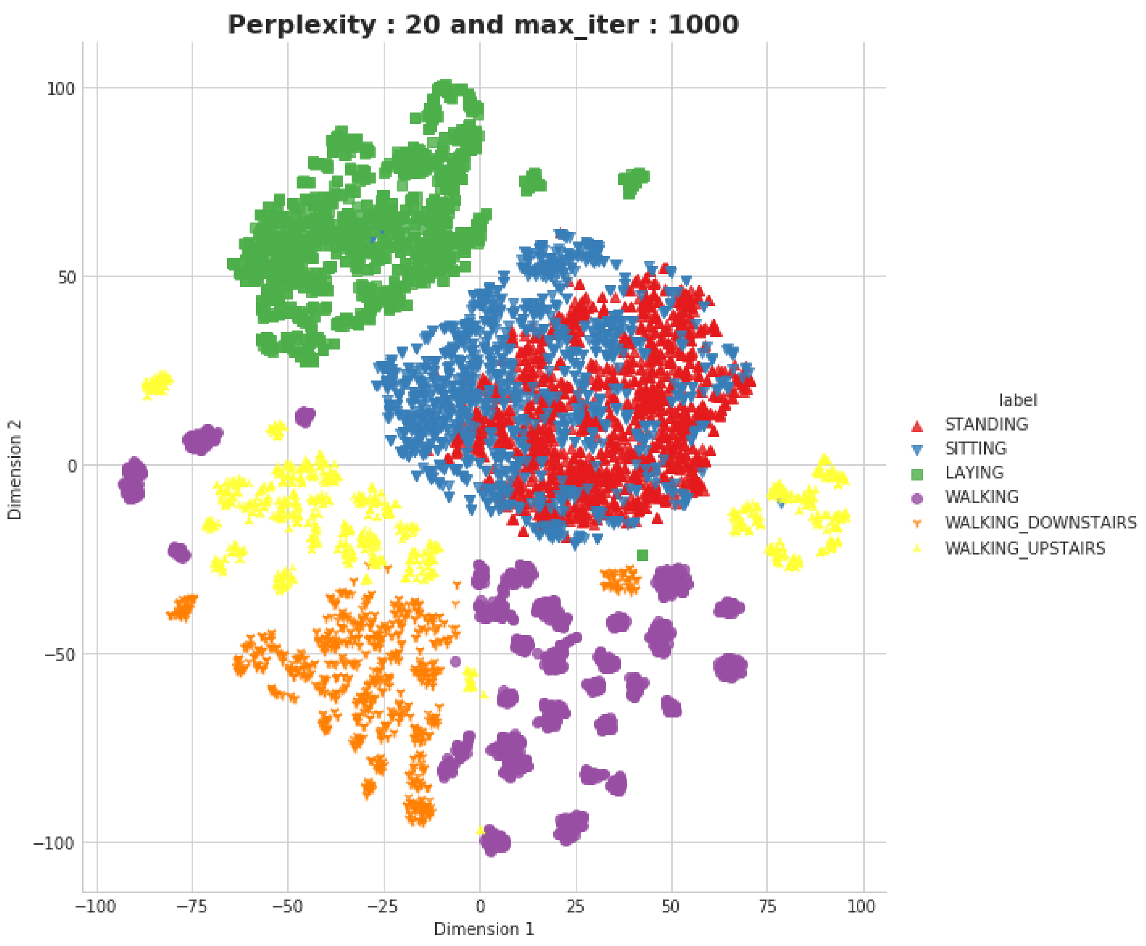
```
Performing tsne with perplexity 5 and with 1000 iterations at max
```



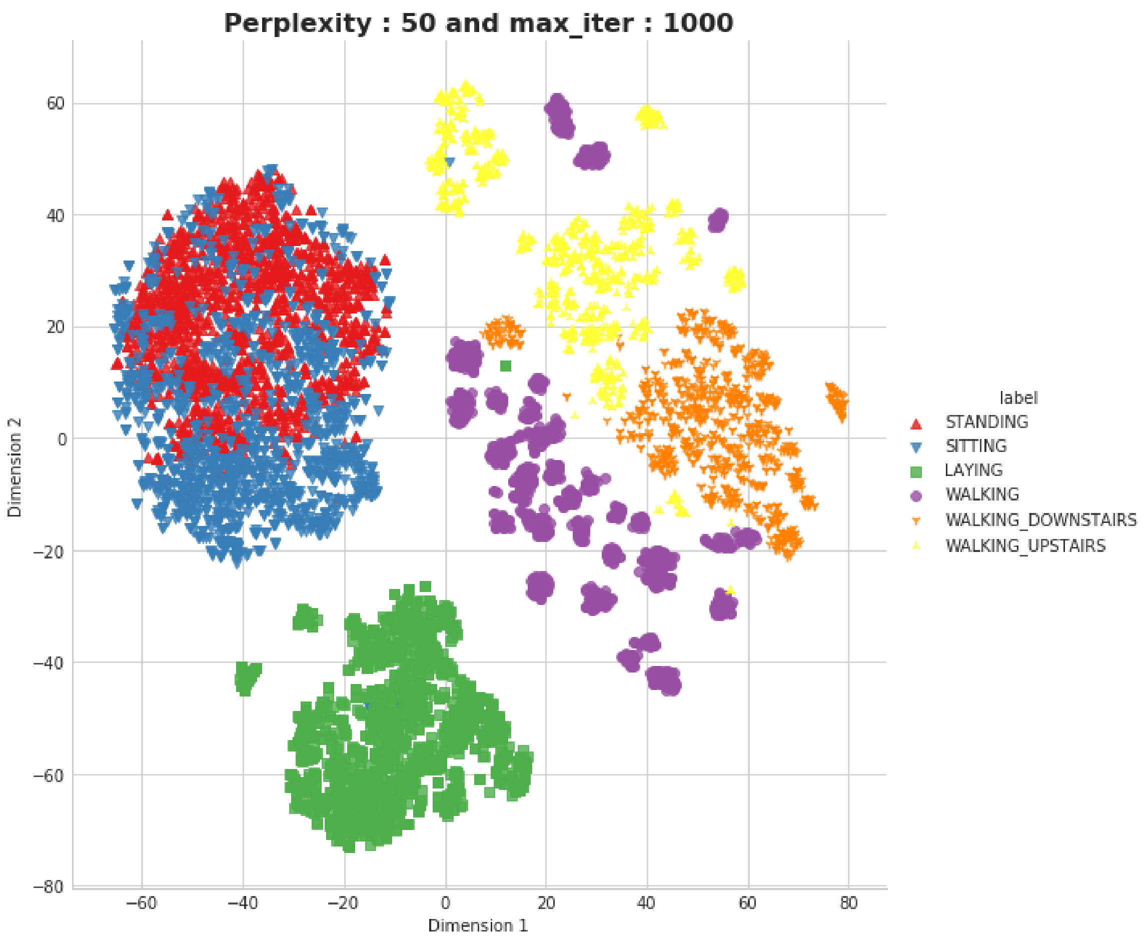
```
Performing tsne with perplexity 10 and with 1000 iterations at max
```



```
Performing tsne with perplexity 20 and with 1000 iterations at max
```



```
Performing tsne with perplexity 50 and with 1000 iterations at max
```



Observations:

- All the labels(human activities) are clearly well separated except STANDING and SITTING.
- STANDING and SITTING have some overlapping regions even after multiple perplexities.

5. CLASSICAL MACHINE LEARNING MODELS

Note: We use classical ML Models to predict the human activities on test data using the expert domain engineered features.

Obtain the train and test data

In [27]:

```
X_train = train_data.drop(['subject','Activity','ActivityName'], axis = 1)
y_train = train_data.ActivityName
```

In [19]:

```
X_test = test_data.drop(['subject','Activity','ActivityName'], axis = 1)
y_test = test_data.ActivityName
```

In [20]:

```
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,))
```

Function to plot the confusion matrix

In [ ]:

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

In [22]:

```
plt.rcParams["font.family"] = 'DejaVu Sans'

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,fontsize = 18, fontweight = 'bold')
    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',fontsize = 16, fontweight = 'bold')
    plt.xlabel('Predicted label',fontsize = 16, fontweight = 'bold')
```

Generic function to run any ML model specified

In [23]:

```
def perform_model(model, X_train, y_train, X_test, y_test, class_labels, cm_normalize=T
rue, \
                 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 = 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 = 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 c
onfusion matrix', cmap = cm_cmap)
    plt.show()

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

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

    return results
```

Method to print the gridsearch Attributes

In [24]:

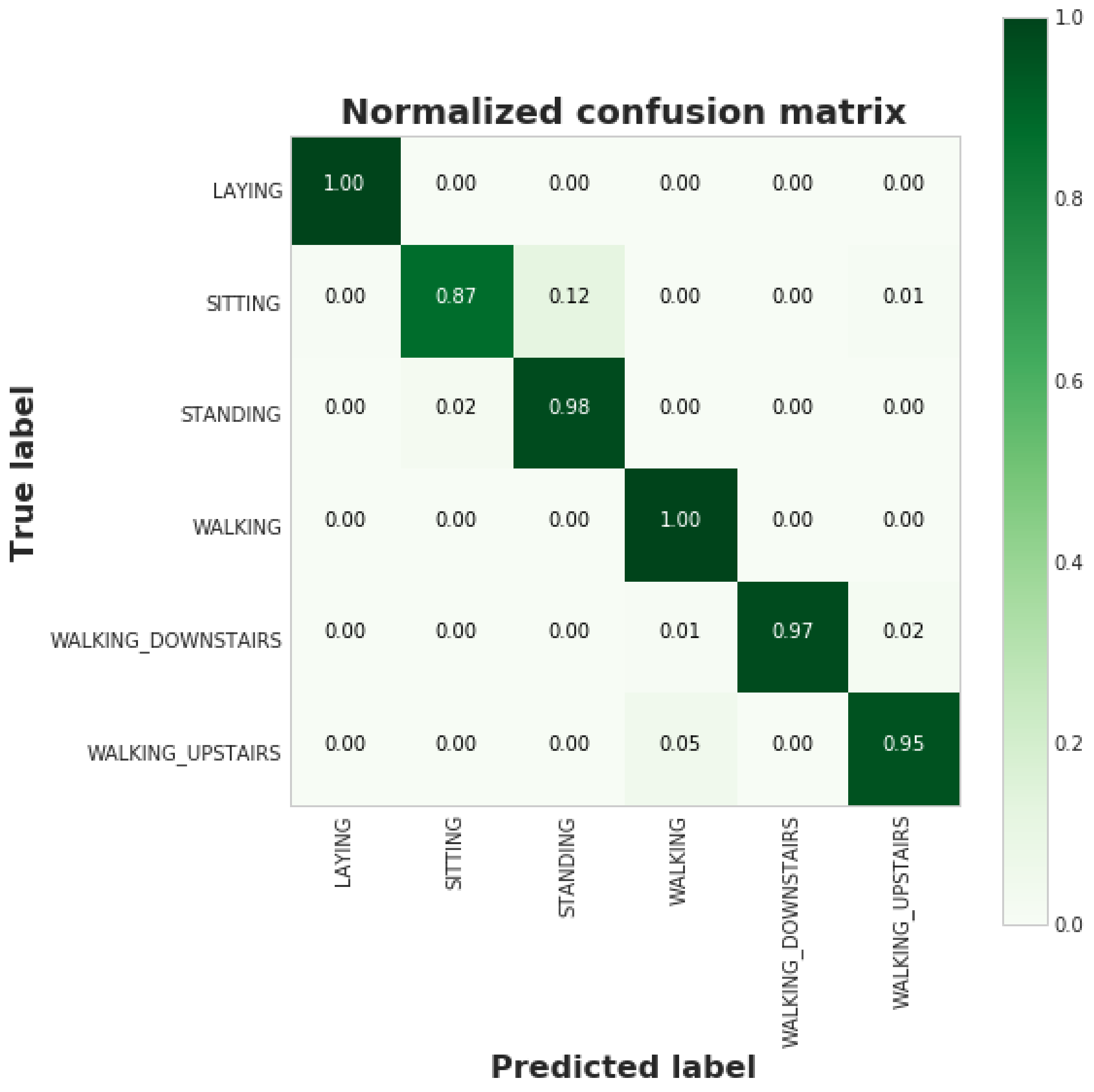
```
def print_grid_search_attributes(model):
    # Estimator that gave highest score among all the estimators formed in GridSearch
    print('--------------------------')
    print('|      Best Estimator     |')
    print('--------------------------')
    print('\n\t{}\n'.format(model.best_estimator_))


    # 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 number 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(mod
el.best_score_))
```

5.1 Logistic Regression with Grid Search

In [96]:

```
param_lr = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1']}
log_reg = LogisticRegression()
log_reg_grid = GridSearchCV(log_reg, param_grid = param_lr, cv = 3, verbose = 1, n_jobs
 = -1)
log_reg_grid_results = perform_model(log_reg_grid, X_train, y_train, X_test, y_test, cl
ass_labels = labels)
```

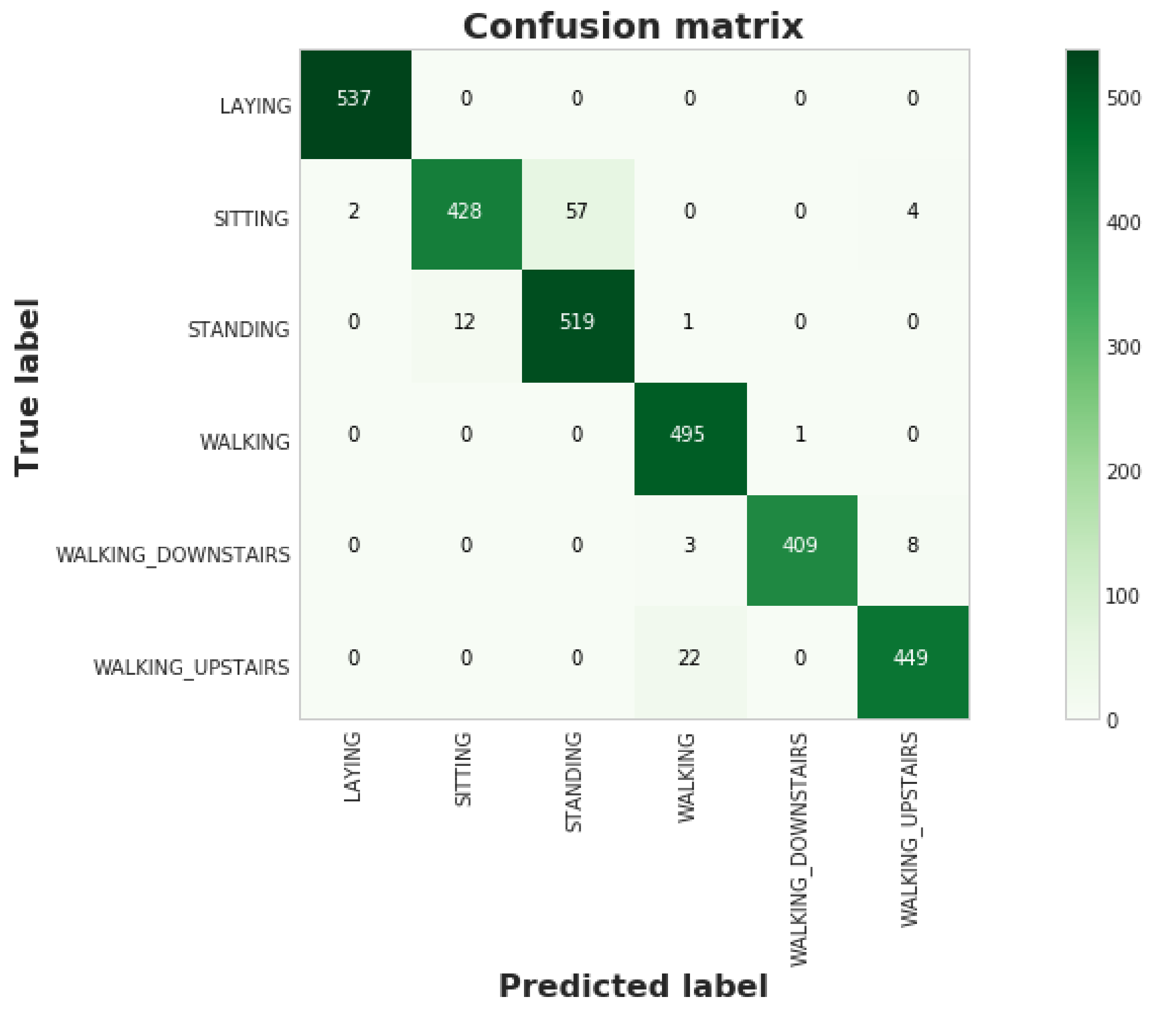
```
Training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits

[Parallel(n_jobs=-1)]: Done  34 out of  36 | elapsed:   17.9s remaining:
  1.1s
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed:   22.2s finished

Done


training_time(HH:MM:SS.ms) - 0:00:31.620763


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.006365


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

    0.9626739056667798


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

 [[537   0   0   0   0   0]
 [  2 428  57   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]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.87 0.12 0.00 0.00 0.01
0.00 0.02 0.98 0.00 0.00 0.00
0.00 0.00 0.00 1.00 0.00 0.00
0.00 0.00 0.00 0.01 0.97 0.02
0.00 0.00 0.00 0.05 0.00 0.95
1.0
0.8
0.6
0.4
0.2
0.0

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

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

        avg / total       0.96      0.96      0.96      2947
```

In [97]:

```
plt.figure(figsize=(14,7))
plt.grid(b=False)
plot_confusion_matrix(log_reg_grid_results['confusion_matrix'], classes=labels, cmap=pl
t.cm.Greens)
plt.show()
```



In [98]:

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

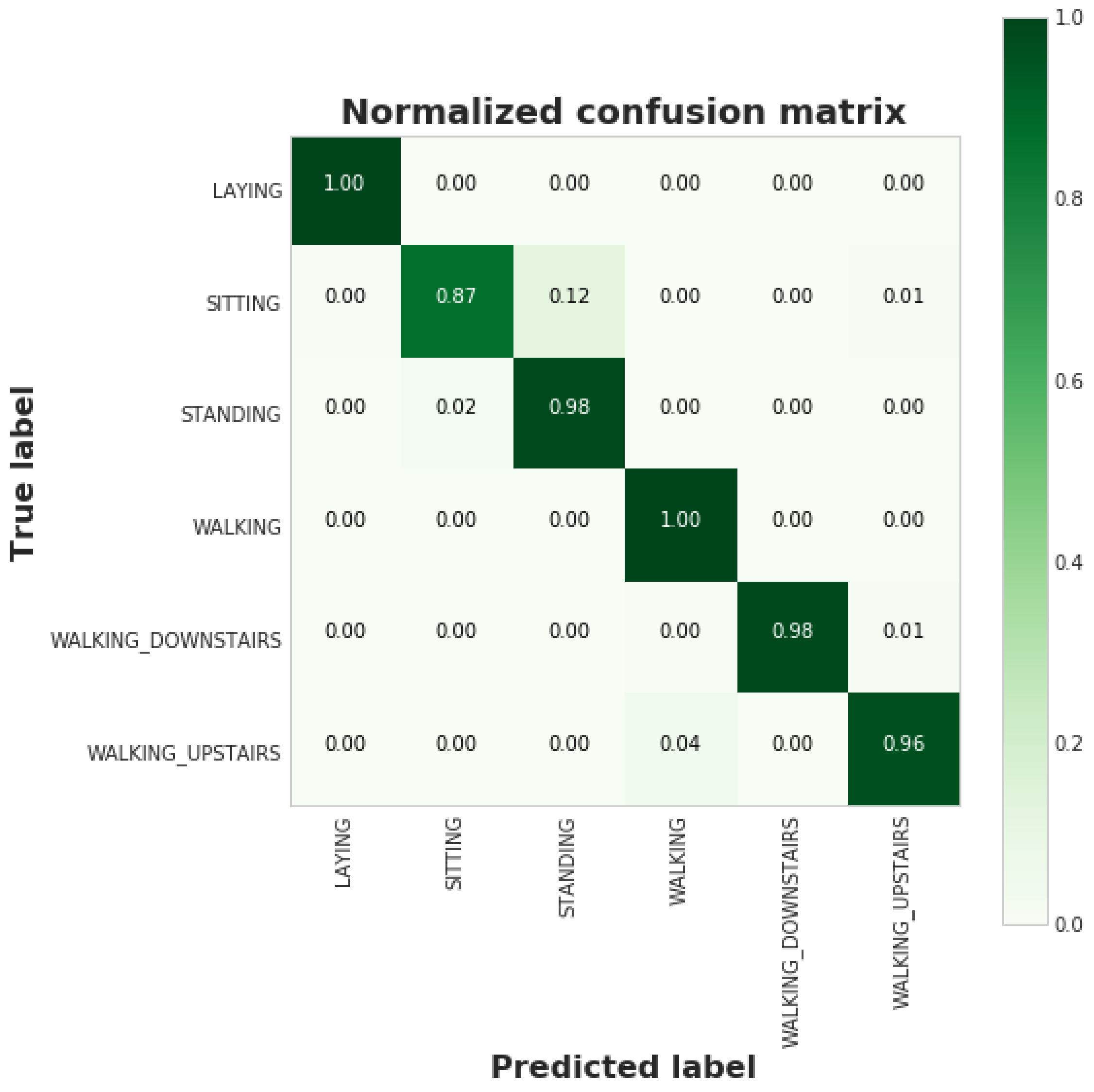
```
--------------------------
|      Best Estimator     |
--------------------------

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

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

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

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

        Total number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.9460010881392819
```

5.2 Linear SVC with GridSearch

In [99]:

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

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

[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:    6.2s finished

Done


training_time(HH:MM:SS.ms) - 0:00:12.523687


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.004569


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

    0.9657278588394977


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

 [[537   0   0   0   0   0]
 [  2 425  60   0   0   4]
 [  0  10 521   1   0   0]
 [  0   0   0 496   0   0]
 [  0   0   0   2 413   5]
 [  0   0   0  17   0 454]]
```

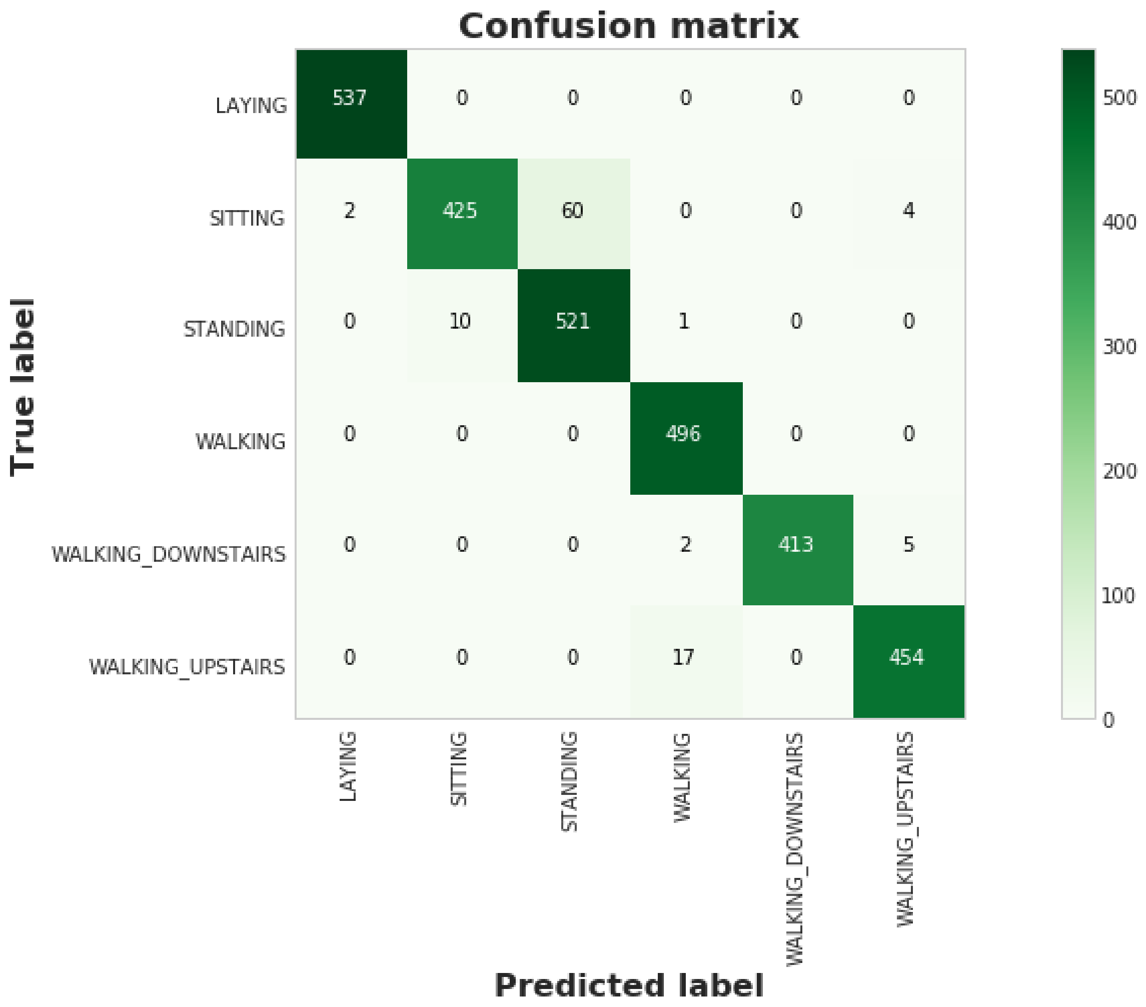


	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
LAYING	1.00	0.00	0.00	0.00	0.00	0.00
SITTING	0.00	0.87	0.12	0.00	0.00	0.01
STANDING	0.00	0.02	0.98	0.00	0.00	0.00
WALKING	0.00	0.00	0.00	1.00	0.00	0.00
WALKING_DOWNSTAIRS	0.00	0.00	0.00	0.00	0.98	0.01
WALKING_UPSTAIRS	0.00	0.00	0.00	0.04	0.00	0.96

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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.98      0.87      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

       avg / total       0.97      0.97      0.97      2947
```

In [100]:

```
plt.figure(figsize=(14,7))
plt.grid(b=False)
plot_confusion_matrix(lr_svc_grid_results['confusion_matrix'], classes=labels, cmap=plt
.cm.Greens)
plt.show()
```



In [101]:

```
print_grid_search_attributes(lr_svc_grid_results['model'])
```

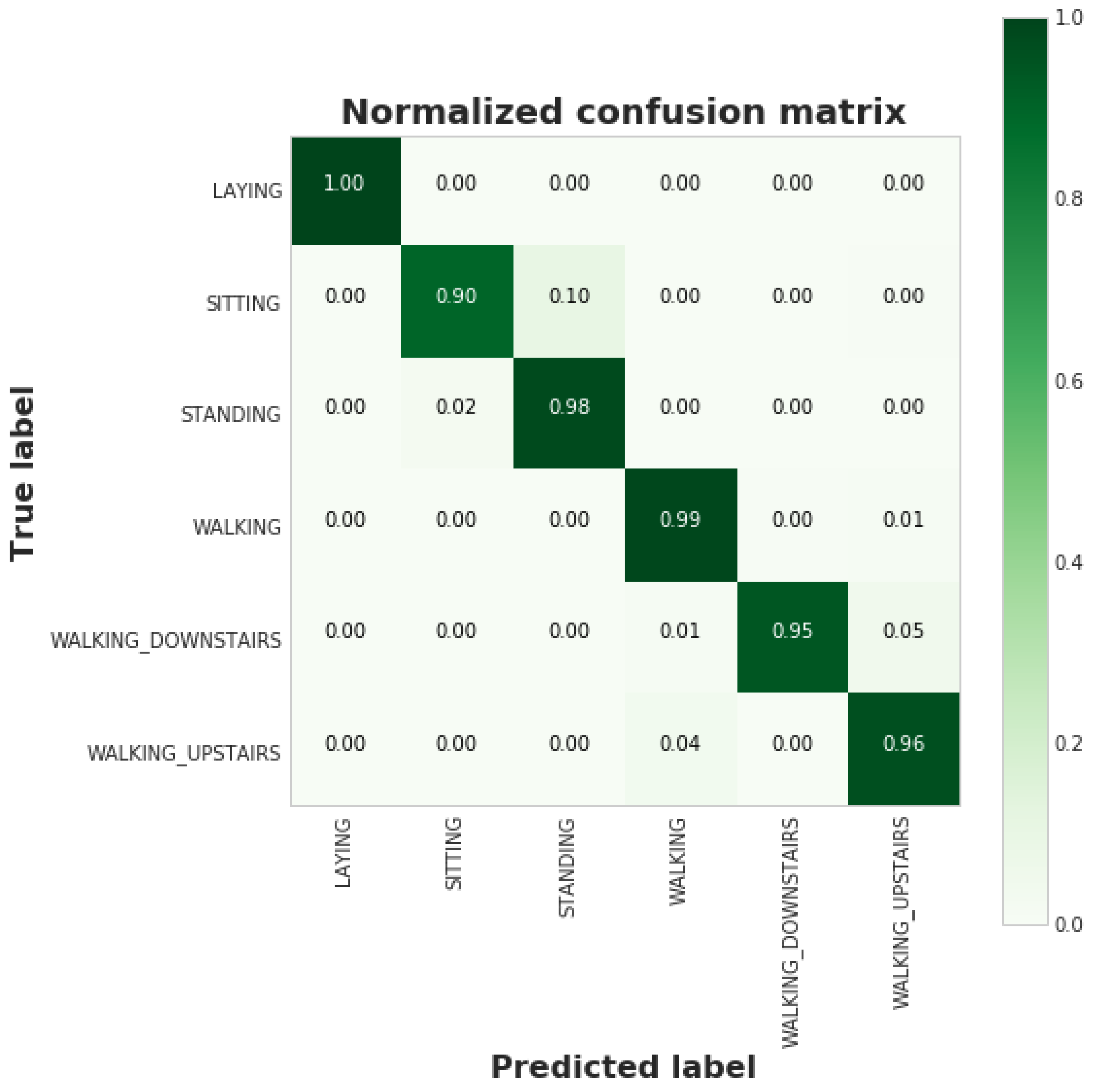
```
--------------------------
|      Best Estimator     |
--------------------------

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

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

        {'C': 1}

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

        Total number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.9458650707290533
```

5.3 Kernel SVM with GridSearch

In [37]:

```
param_rbfsvc = {'C':[2,8,16],
              'gamma': [ 0.0078125, 0.125, 2]}
rbf_svm = SVC(kernel='rbf')
rbf_svm_grid = GridSearchCV(rbf_svm,param_grid=param_rbfsvc, n_jobs=-1, verbose = 1)
rbf_svm_grid_results = perform_model(rbf_svm_grid, X_train, y_train, X_test, y_test, cl
ass_labels=labels)
```

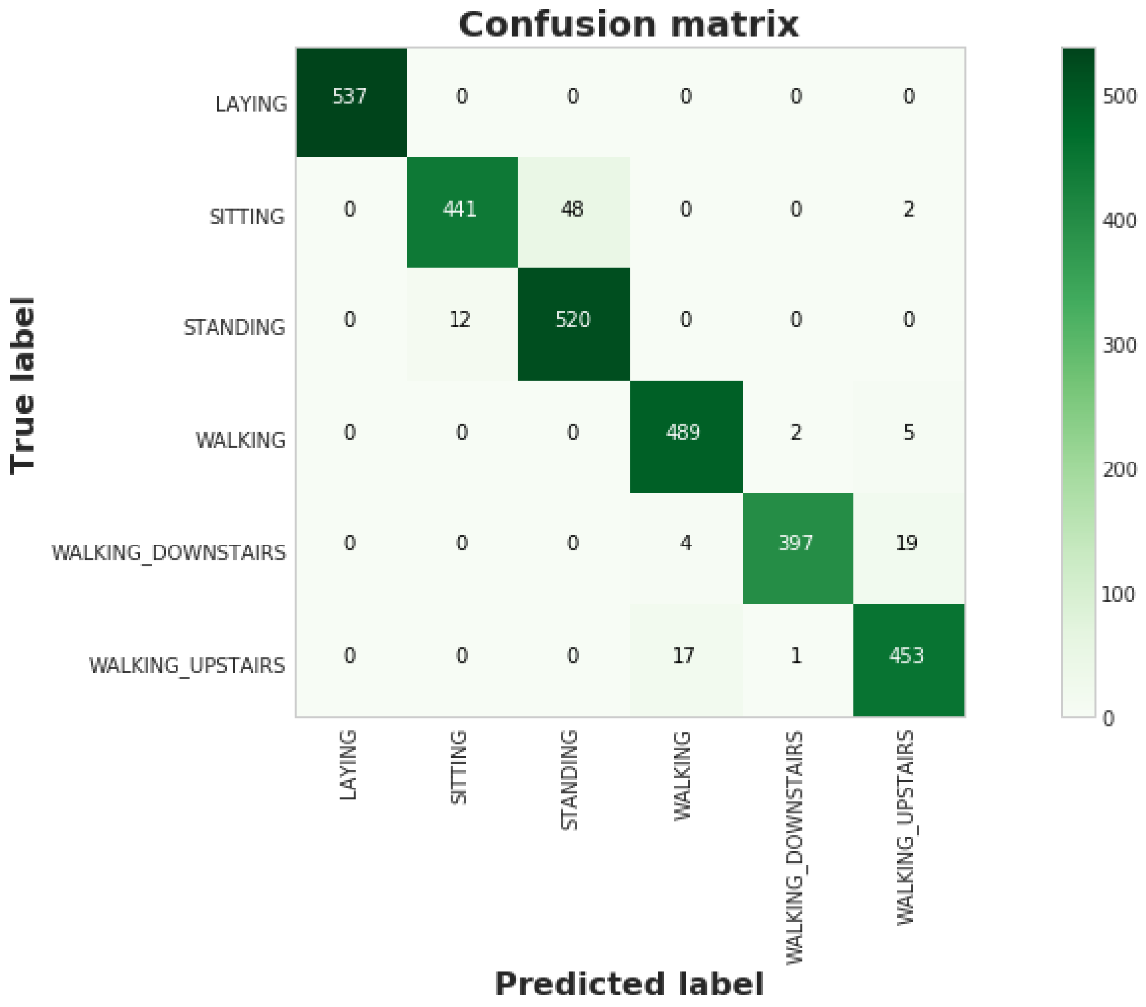
```
Training the model..
Fitting 3 folds for each of 9 candidates, totalling 27 fits

[Parallel(n_jobs=-1)]: Done  16 out of  27 | elapsed:   59.1s remaining:
40.6s
[Parallel(n_jobs=-1)]: Done  27 out of  27 | elapsed:  1.6min finished

Done


training_time(HH:MM:SS.ms) - 0:01:40.503690


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:03.493771


---------------------
|      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]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.90 0.10 0.00 0.00 0.00
0.00 0.02 0.98 0.00 0.00 0.00
0.00 0.00 0.00 0.99 0.00 0.01
0.00 0.00 0.00 0.01 0.95 0.05
0.00 0.00 0.00 0.04 0.00 0.96
1.0
0.8
0.6
0.4
0.2
0.0

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

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

       avg / total       0.96      0.96      0.96      2947
```

In [38]:

```
plt.figure(figsize=(14,7))
plt.grid(b=False)
plot_confusion_matrix(rbf_svm_grid_results['confusion_matrix'], classes=labels, cmap=pl
t.cm.Greens)
plt.show()
```



In [39]:

```
print_grid_search_attributes(rbf_svm_grid_results['model'])
```

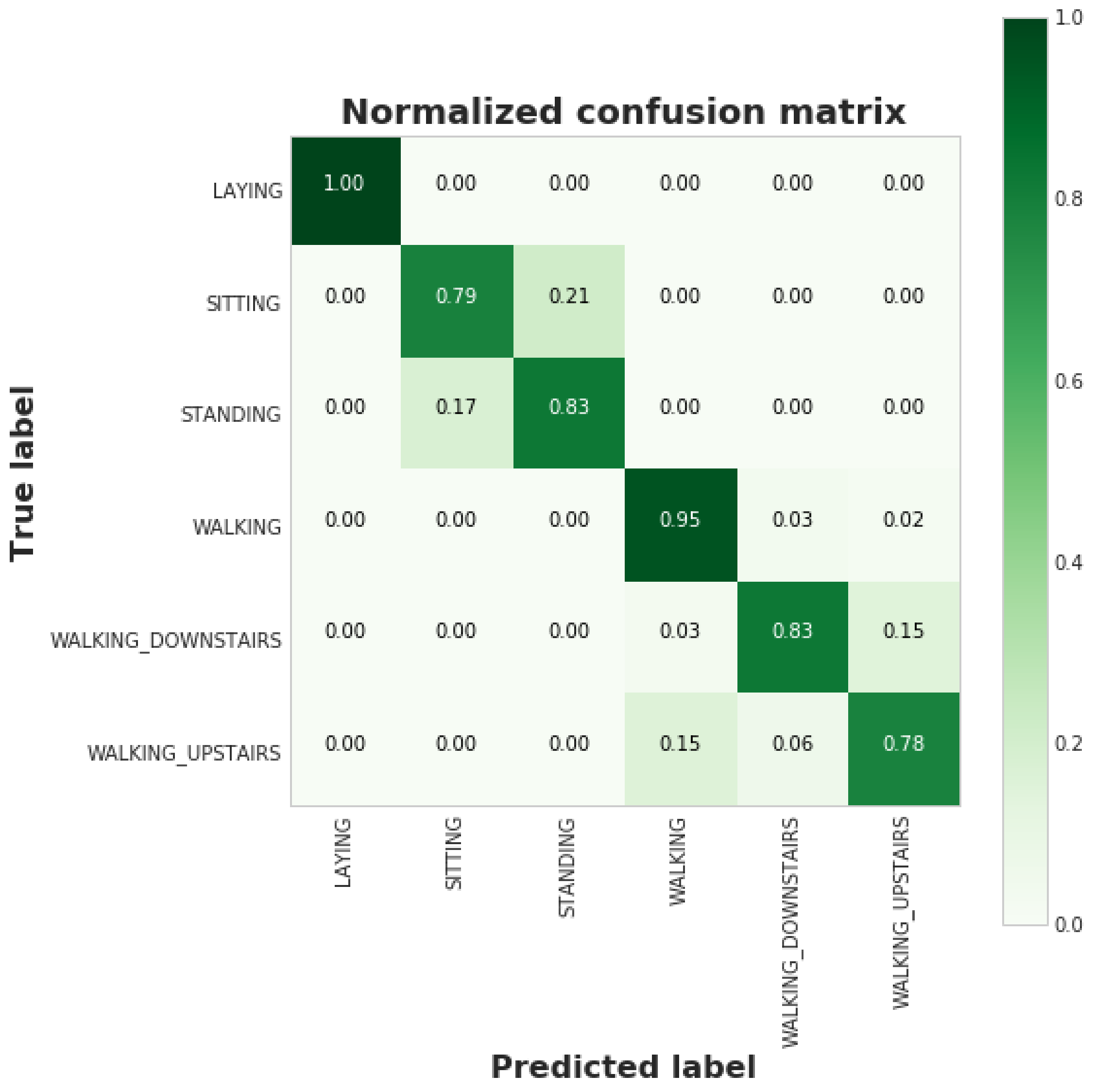
```
--------------------------
|      Best Estimator     |
--------------------------

        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 number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.9440968443960827
```

5.4 Decision Trees with GridSearchCV

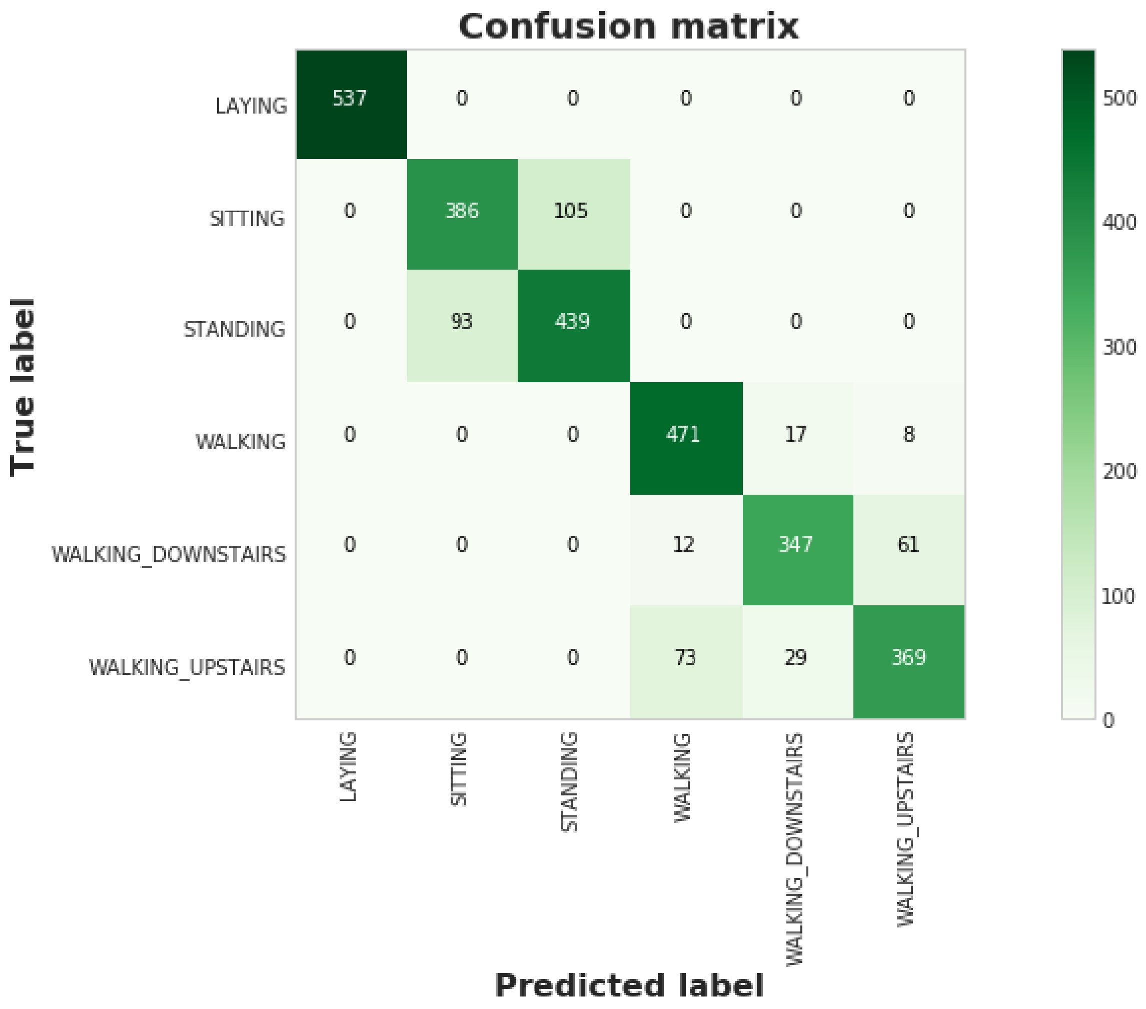
In [40]:

```
param_dt = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=param_dt, n_jobs=-1, verbose = 1)
dt_grid_results = perform_model(dt_grid, X_train, y_train, X_test, y_test, class_labels
=labels)

plt.figure(figsize=(14,7))
plt.grid(b=False)
plot_confusion_matrix(dt_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm.
Greens)
plt.show()
print_grid_search_attributes(dt_grid_results['model'])
```

```
Training the model..
Fitting 3 folds for each of 4 candidates, totalling 12 fits

[Parallel(n_jobs=-1)]: Done  12 out of  12 | elapsed:    4.0s remaining:
  0.0s
[Parallel(n_jobs=-1)]: Done  12 out of  12 | elapsed:    4.0s finished

Done


training_time(HH:MM:SS.ms) - 0:00:07.774189


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.003758


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

    0.8649474041398032


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

 [[537   0   0   0   0   0]
 [  0 386 105   0   0   0]
 [  0  93 439   0   0   0]
 [  0   0   0 471  17   8]
 [  0   0   0  12 347  61]
 [  0   0   0  73  29 369]]
```


Normalized confusion matrix
True label
Predicted label
LAYING 1.00 0.00 0.00 0.00 0.00 0.00
SITTING 0.00 0.79 0.21 0.00 0.00 0.00
STANDING 0.00 0.17 0.83 0.00 0.00 0.00
WALKING 0.00 0.00 0.00 0.95 0.03 0.02
WALKING_DOWNSTAIRS 0.00 0.00 0.00 0.03 0.83 0.15
WALKING_UPSTAIRS 0.00 0.00 0.00 0.15 0.06 0.78
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.0
0.8
0.6
0.4
0.2
0.0

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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.81      0.79      0.80       491
          STANDING       0.81      0.83      0.82       532
           WALKING       0.85      0.95      0.90       496
WALKING_DOWNSTAIRS       0.88      0.83      0.85       420
  WALKING_UPSTAIRS       0.84      0.78      0.81       471

       avg / total       0.87      0.86      0.86      2947
```



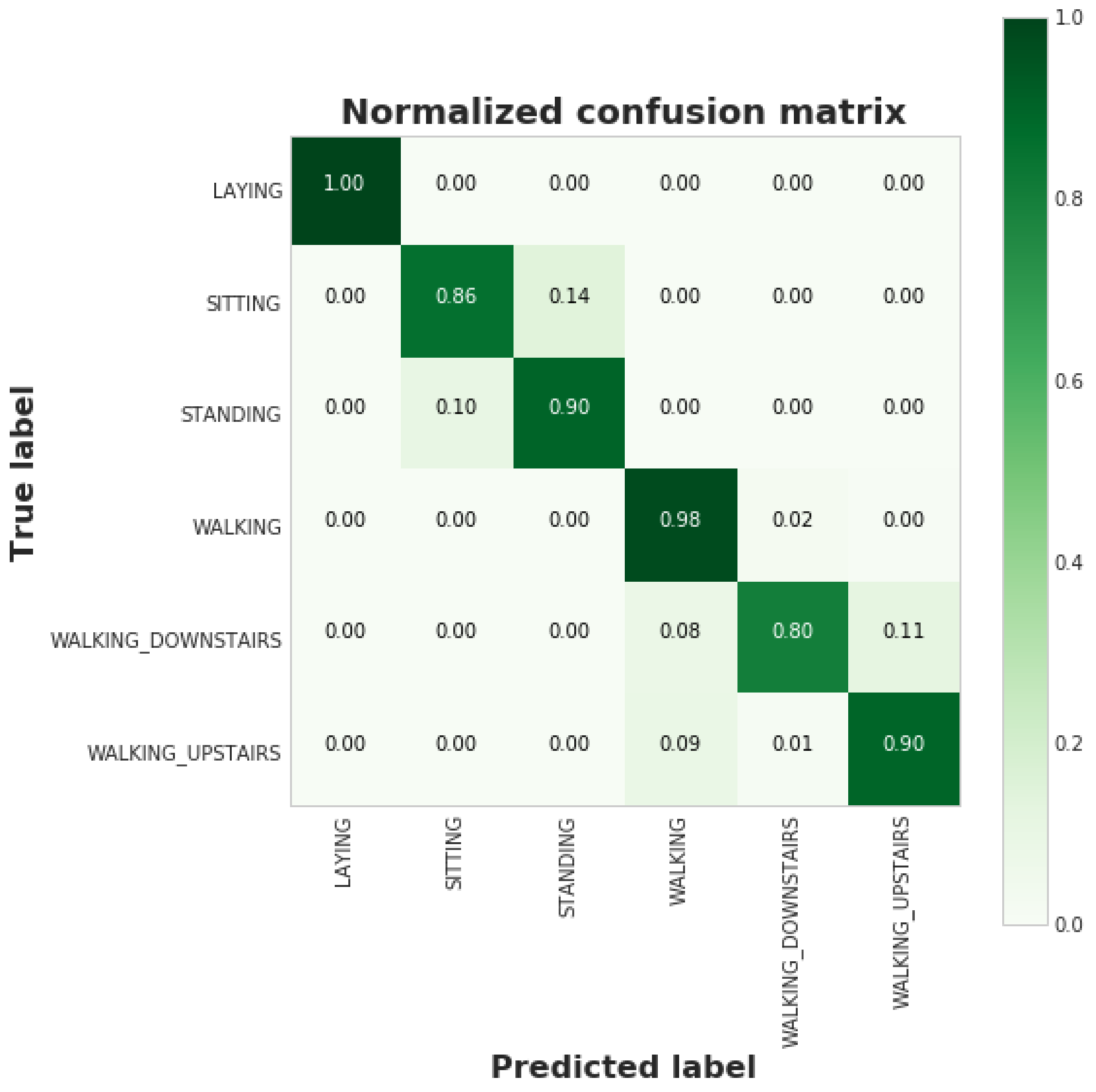
```
--------------------------
|      Best Estimator     |
--------------------------

        DecisionTreeClassifier(class_weight=None, criterion='gini', max_de
pth=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=Non
e,
            splitter='best')

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

        {'max_depth': 7}

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

        Total number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.8449401523394995
```

5.5 Random Forest Classifier with GridSearch

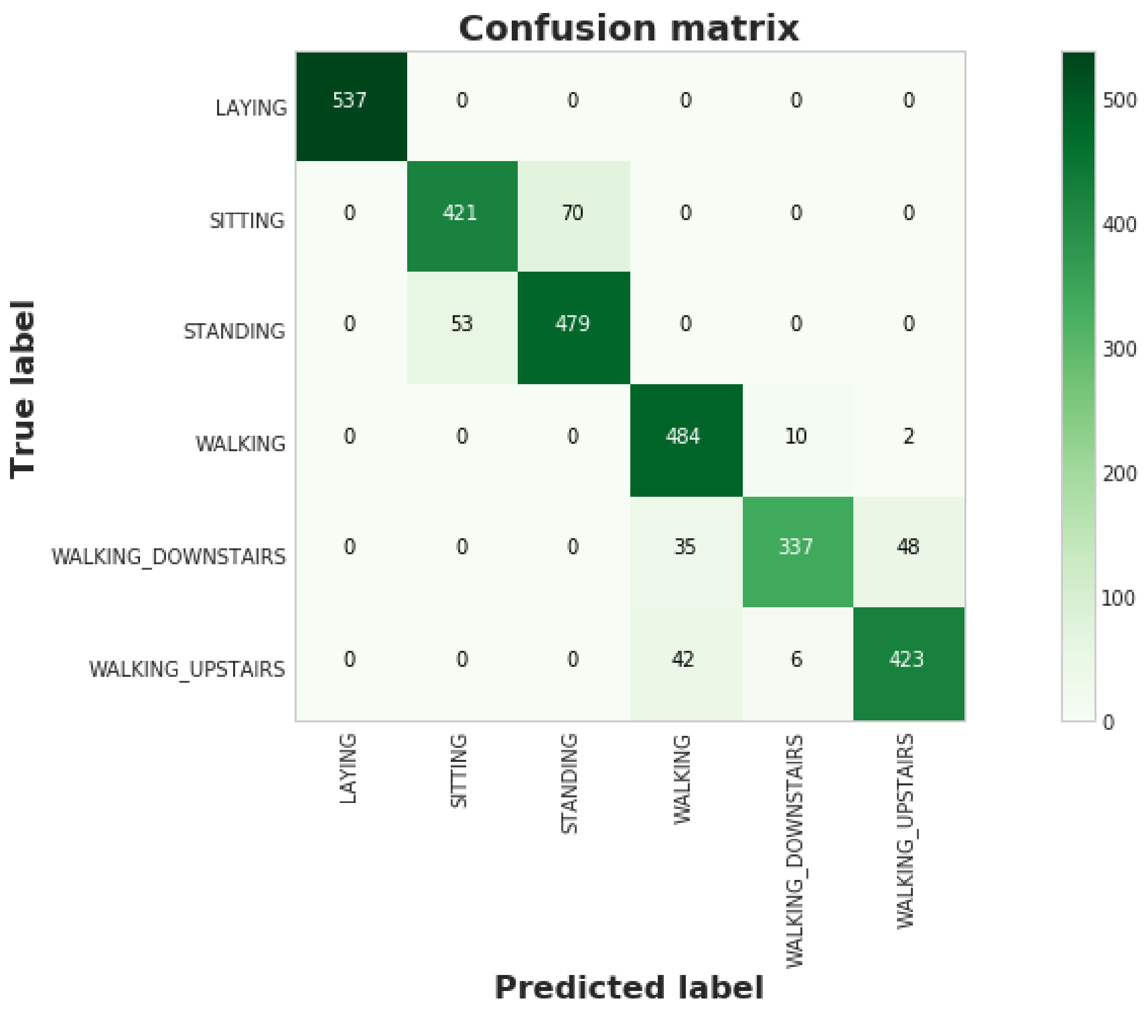
In [41]:

```
param_rf = {'n_estimators': np.arange(10,201,20),
          'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=param_rf, n_jobs=-1, verbose = 1)
rfc_grid_results = perform_model(rfc_grid, X_train, y_train, X_test, y_test, class_labe
ls=labels)

plt.figure(figsize=(14,7))
plt.grid(b=False)
plot_confusion_matrix(rfc_grid_results['confusion_matrix'], classes=labels, cmap=plt.cm
.Greens)
plt.show()
print_grid_search_attributes(rfc_grid_results['model'])
```

```
Training the model..
Fitting 3 folds for each of 60 candidates, totalling 180 fits

[Parallel(n_jobs=-1)]: Done  10 tasks      | elapsed:    3.6s
[Parallel(n_jobs=-1)]: Done 180 out of 180 | elapsed:  1.2min finished

Done


training_time(HH:MM:SS.ms) - 0:01:32.834696


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.085783


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

    0.9097387173396675


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

 [[537   0   0   0   0   0]
 [  0 421  70   0   0   0]
 [  0  53 479   0   0   0]
 [  0   0   0 484  10   2]
 [  0   0   0  35 337  48]
 [  0   0   0  42   6 423]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.86 0.14 0.00 0.00 0.00
0.00 0.10 0.90 0.00 0.00 0.00
0.00 0.00 0.00 0.98 0.02 0.00
0.00 0.00 0.00 0.08 0.80 0.11
0.00 0.00 0.00 0.09 0.01 0.90
1.0
0.8
0.6
0.4
0.2
0.0

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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.89      0.86      0.87       491
          STANDING       0.87      0.90      0.89       532
           WALKING       0.86      0.98      0.92       496
WALKING_DOWNSTAIRS       0.95      0.80      0.87       420
  WALKING_UPSTAIRS       0.89      0.90      0.90       471

       avg / total       0.91      0.91      0.91      2947
```



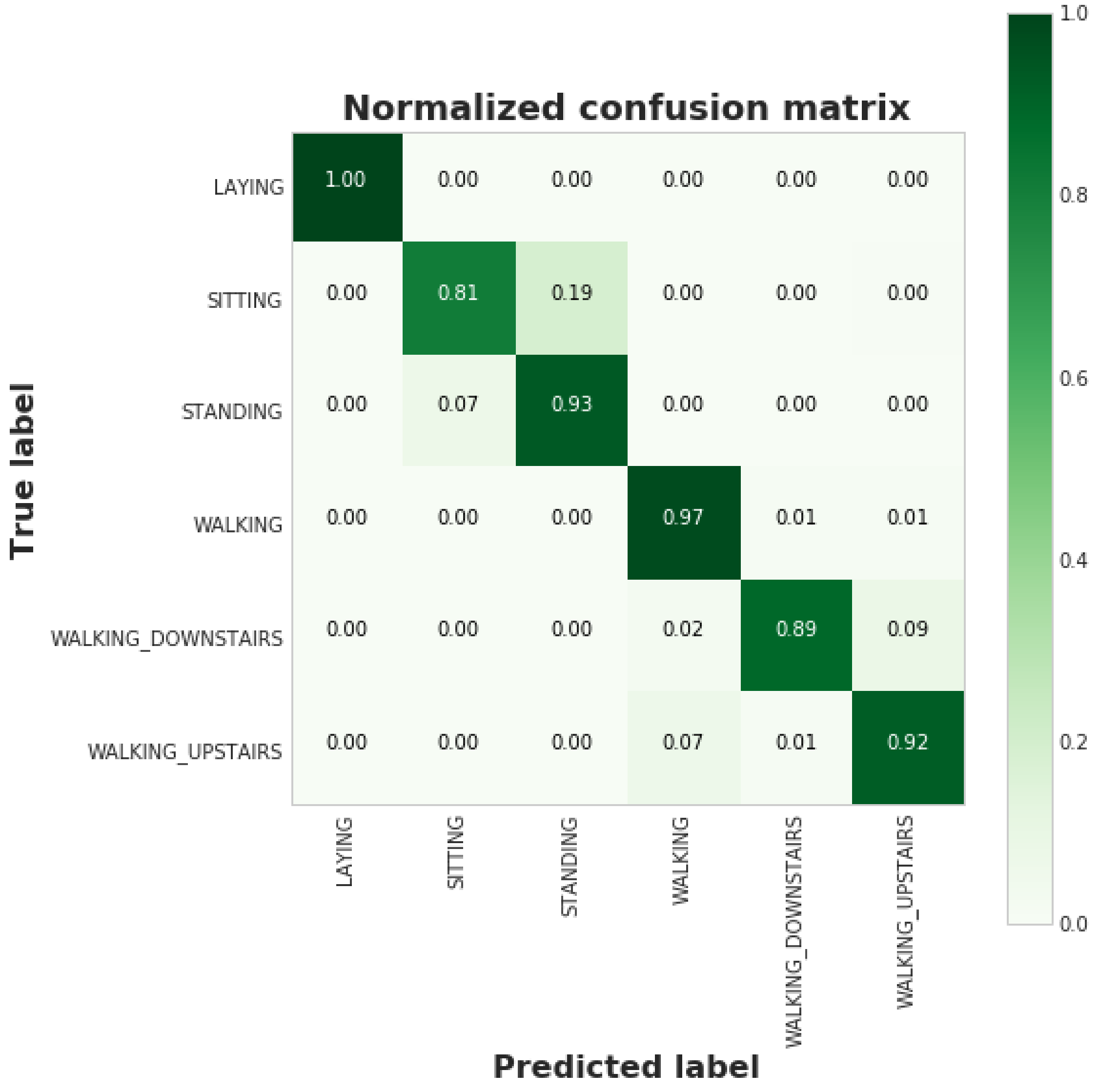
```
--------------------------
|      Best Estimator     |
--------------------------

        RandomForestClassifier(bootstrap=True, class_weight=None, criterio
n='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=190, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

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

        {'max_depth': 7, 'n_estimators': 190}

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

        Total number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.9134929270946681
```

5.6 Gradient Boosted Decision Trees With GridSearch

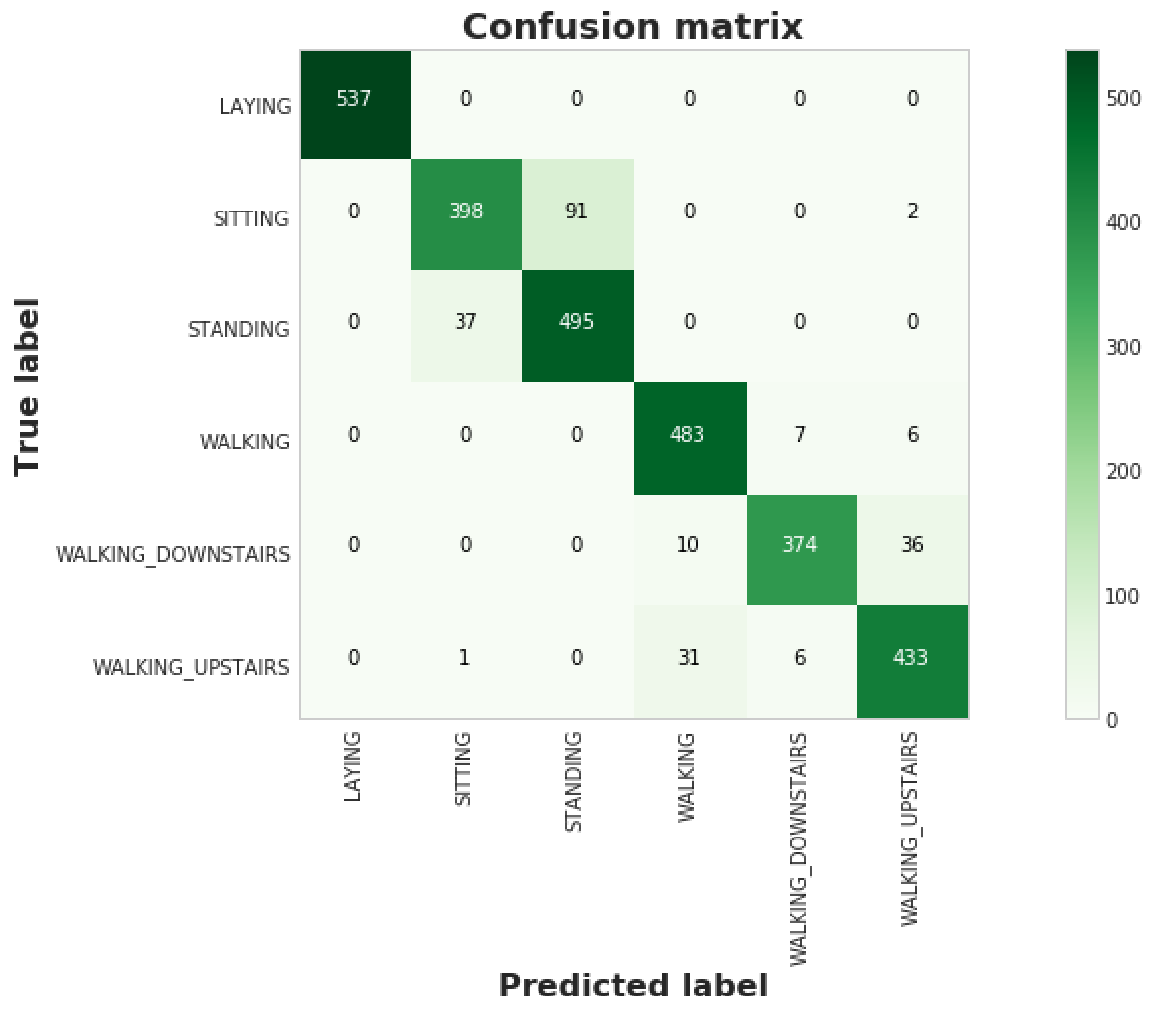
In [25]:

```
param_gradboost = {'max_depth': np.arange(5,8,1),
             'n_estimators':np.arange(130,170,10)}
gbdt = GradientBoostingClassifier()
gbdt_grid = GridSearchCV(gbdt, param_grid=param_gradboost, n_jobs= -1, verbose = 1)
gbdt_grid_results = perform_model(gbdt_grid, X_train, y_train, X_test, y_test, class_la
bels=labels)



plt.figure(figsize=(14,7))
plt.grid(b=False)
plot_confusion_matrix(gbdt_grid_results['confusion_matrix'], classes=labels, cmap=plt.c
m.Greens)
plt.show()
print_grid_search_attributes(gbdt_grid_results['model'])
```

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

[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed: 31.0min finished

Done


training_time(HH:MM:SS.ms) - 0:36:59.677486


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.124088


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

    0.9229725144214456


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

 [[537   0   0   0   0   0]
 [  0 398  91   0   0   2]
 [  0  37 495   0   0   0]
 [  0   0   0 483   7   6]
 [  0   0   0  10 374  36]
 [  0   1   0  31   6 433]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.81 0.19 0.00 0.00 0.00
0.00 0.07 0.93 0.00 0.00 0.00
0.00 0.00 0.00 0.97 0.01 0.01
0.00 0.00 0.00 0.02 0.89 0.09
0.00 0.00 0.00 0.07 0.01 0.92
1.0
0.8
0.6
0.4
0.2
0.0

```
-------------------------
| 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      0.89       532
           WALKING       0.92      0.97      0.95       496
WALKING_DOWNSTAIRS       0.97      0.89      0.93       420
  WALKING_UPSTAIRS       0.91      0.92      0.91       471

       avg / total       0.92      0.92      0.92      2947
```

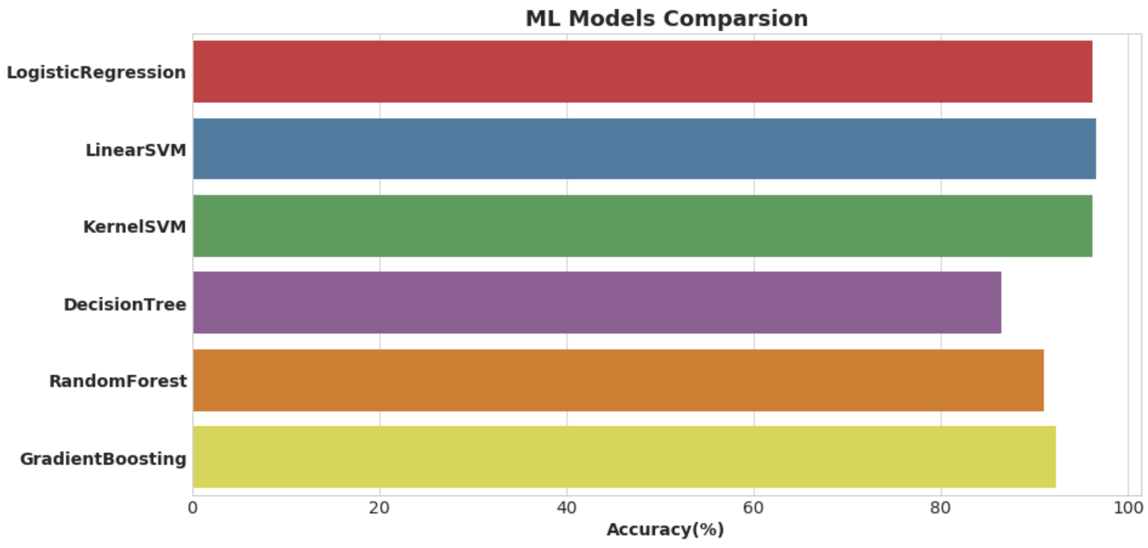


```
--------------------------
|      Best Estimator     |
--------------------------

        GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=5,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=160,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)

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

        {'max_depth': 5, 'n_estimators': 160}

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

        Total number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.903835690968444
```

Comparsion of various ML Models

In [28]:

```
model_names = ["LogisticRegression", "LinearSVM", "KernelSVM", "DecisionTree", "RandomF
orest", "GradientBoosting"]
model_accuracy = [96.26,96.57,96.26,86.49,90.97,92.29]
model_comparsion = pd.DataFrame(dict(x=model_names, y=model_accuracy))
model_comparsion.columns = ['Model', 'Accuracy']

plt.figure(figsize = (14,7))
sns.barplot("Accuracy","Model", data=model_comparsion)
plt.title("ML Models Comparsion", fontsize = 18, fontweight = 'bold')
plt.xlabel("Accuracy(%)", fontsize = 14, fontweight = 'bold')
plt.xticks(fontsize = 14)
plt.ylabel("")
plt.yticks(fontsize = 14, fontweight = 'bold')

plt.show()

print(model_comparsion)
```



```
                Model  Accuracy
0  LogisticRegression     96.26
1           LinearSVM     96.57
2           KernelSVM     96.26
3        DecisionTree     86.49
4        RandomForest     90.97
5    GradientBoosting     92.29
```

6. DEEP LEARNING(with raw timeseries features)

Note: We use Deep Learning models to predict the human activities using raw timeseries features instead of engineered features provided by domain experts.

Since here the raw features are temporal data(timeseries), we chose to use LSTM model to keep the sequential information.

In [33]:

```
# 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"
]
```

Loading the raw time series signals

In [34]:

```
# 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))
```

Loading the output labels

In [35]:

```
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()
```

Obtain the train and test data

In [36]:

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

    return X_train, y_train, X_test, y_test
```

In [37]:

```
# Importing tensorflow
np.random.seed(9)
import tensorflow as tf
tf.set_random_seed(9)
```

In [38]:

```
# Configuring a session
session_conf = tf.ConfigProto(
    intra_op_parallelism_threads=1,
    inter_op_parallelism_threads=1
)
```

In [39]:

```
from keras import backend as K
sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)
```

In [ ]:

```
X_train, Y_train, X_test, Y_test = load_data()

# joblib.load(X_train,"X_train.pkl")
# joblib.load(X_test,"X_test.pkl")
# joblib.load(Y_train,"Y_train.pkl")
# joblib.load(Y_test,"Y_test.pkl")
```

In [41]:

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

In [42]:

```
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
```

In [71]:

```
print("Dimensions of Train data: ",X_train.shape)
print("Dimensions of Test data: ",X_test.shape)
print("Number of classes/labels in Train data:",_count_classes(Y_train))
print("Number of classes/labels in Test data:",_count_classes(Y_test))
```

```
Dimensions of Train data:  (7352, 128, 9)
Dimensions of Test data:  (2947, 128, 9)
Number of classes/labels in Train data: 6
Number of classes/labels in Test data: 6
```

6.1 LSTM Model(2 Layered) using Hyperas

Reference 1 : https://towardsdatascience.com/a-guide-to-an-efficient-way-to-build-neural-network-architectures-part-i-hyper-parameter-8129009f131b (https://towardsdatascience.com/a-guide-to-an-efficient-way-to-build-neural-network-architectures-part-i-hyper-parameter-8129009f131b)

Reference 2 : https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-models-python-keras/ (https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-models-python-keras/)

6.1.1 Data Function

In [72]:

```
def data():

    X_train = joblib.load("X_train.pkl")
    Y_train = joblib.load("Y_train.pkl")
    X_test = joblib.load("X_test.pkl")
    Y_test = joblib.load("Y_test.pkl")

    return X_train, Y_train, X_test, Y_test
```

6.1.2 Model Function

In [73]:

```
def lstm_model(X_train,Y_train, X_test,Y_test):

    #Network parameters
    timesteps = len(X_train[0])
    input_dim = len(X_train[0][0])
    n_classes = 6
    epochs = 30
    batch_size = 32

    #======================Model Architecture===========================#
    model = Sequential()

    #1st LSTM Layer
    model.add(LSTM({{choice([64,32])}}, return_sequences = True, input_shape=(timesteps
, input_dim), name='lstm_1'))
    model.add(Dropout({{uniform(0, 1)}}, name='dropout_rate1'))

    #2nd LSTM Layer
    model.add(LSTM({{choice([32,16])}}, name='lstm_2'))
    model.add(Dropout({{uniform(0, 1)}}, name='dropout_rate2'))

    #Output Layer
    model.add(Dense(n_classes, activation='sigmoid', name='output_layer'))
    print(model.summary())

    #Training the model
    model.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accurac
y'])
    model.fit(X_train, Y_train,
              epochs = epochs,
              batch_size = batch_size,
              verbose = 1,
              validation_data = (X_test, Y_test))

    score, acc = model.evaluate(X_test, Y_test)
    print('Test accuracy: ', acc)

    return {'loss': -acc, 'status': STATUS_OK, 'model': model}
```

6.1.3 Execution and Finding the Best Model

In [ ]:

```
#Hyperparameter Tuning of the model
X_train, Y_train, X_test, Y_test = data()
best_run, best_model = optim.minimize(model=lstm_model,
                                      data=data,
                                      algo=tpe.suggest,
                                      max_evals = 12,
                                      trials=Trials(),
                                      verbose = True,
                                      notebook_name='HAR')
```

In [ ]:

```
#saving the best model
best_model.save('best_lstm_model.h5')
```

6.1.4 Best Model Evaluation

In [ ]:

```
print("\33[1m-------------------Evalutation of best performing model-------------------
----\33[0m\n")
score, acc = best_model.evaluate(X_test, Y_test, verbose = 0)
print("Test Loss: ", np.round(score,3))
print("Test Accuracy: ", np.round(acc * 100 ,3))

print("\n\33[1m-------------------Best performing model chosen hyper-parameters--------
-------\33[0m\n\n")
print(best_run)
```

```
-------------------Evalutation of best performing model-------------------
----

Test Loss:  0.389
Test Accuracy:  91.381

-------------------Best performing model chosen hyper-parameters----------
-----


{'Dropout': 0.7371698374615214, 'Dropout_1': 0.6517968154887782, 'LSTM':
 1, 'LSTM_1': 0}
```

Observations:

- Test Aaccuracy is 91.38%.
- TestLoss is 0.38.
- 'LSTM': 1 represents the best number of neurons in first LSTM layer is 32.
- 'LSTM_1': 0 represents the best number of neurons in second LSTM layer is 32.
- Best Dropout rate in the first hidden layer is 0.737.
- Best rate in the second hidden layer is 0.65.

6.1.5 Confusion Matrix,Precision,Recall

In [74]:

```
best_model = load_model('best_lstm_model.h5')
Y_pred = best_model.predict(X_test, verbose=1)
```

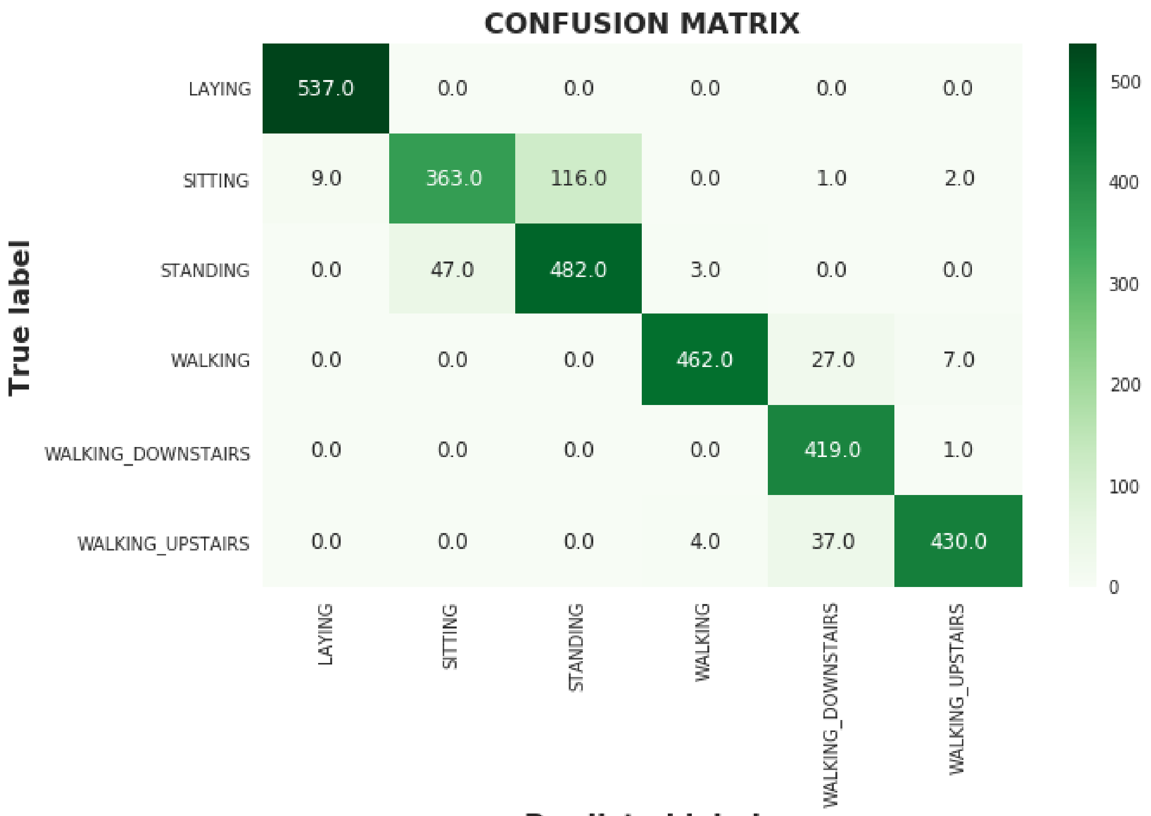
```
2947/2947 [==============================] - 17s 6ms/step
```

In [75]:

```
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
    2: 'WALKING_DOWNSTAIRS',
    3: 'SITTING',
    4: 'STANDING',
    5: 'LAYING',
}

labels=['LAYING', 'SITTING','STANDING','WALKING','WALKING_DOWNSTAIRS','WALKING_UPSTAIR
S']

Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_test, axis=1)])
Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])
```

In [114]:

```
conf_matrix = confusion_matrix(Y_true, Y_pred)
plt.figure(figsize = (10,7))
sns.heatmap(conf_matrix, cmap ='Greens', annot = True, fmt = ".1f", xticklabels = label
s, yticklabels = labels)
plt.title("CONFUSION MATRIX",fontsize = 16, fontweight = 'bold' )
plt.ylabel('True label',fontsize = 16, fontweight = 'bold')
plt.xlabel('Predicted label',fontsize = 16, fontweight = 'bold')

plt.tight_layout()
plt.show()



print('\n-------------------------')
print('| Classifiction Report |')
print('-------------------------')
print(classification_report(Y_true, Y_pred))
```


CONFUSION MATRIX
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
537.0 0.0 0.0 0.0 0.0 0.0
9.0 363.0 116.0 0.0 1.0 2.0
0.0 47.0 482.0 3.0 0.0 0.0
0.0 0.0 0.0 462.0 27.0 7.0
0.0 0.0 0.0 0.0 419.0 1.0
0.0 0.0 0.0 4.0 37.0 430.0
500
400
300
200
100
0

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

            LAYING       0.98      1.00      0.99       537
           SITTING       0.89      0.74      0.81       491
          STANDING       0.81      0.91      0.85       532
           WALKING       0.99      0.93      0.96       496
WALKING_DOWNSTAIRS       0.87      1.00      0.93       420
  WALKING_UPSTAIRS       0.98      0.91      0.94       471

       avg / total       0.92      0.91      0.91      2947
```

7. CONCLUSION

7.1 Classical ML Models Performance with expert features

ML Model	Test Accuracy
Logistic Regression	96.26 %
Linear SVM	96.57 %
Radial Kernel SVM	96.26 %
Decission Trees	86.49 %
Random Forest	90.97 %
Gradient Boost Decision Tree	92.29 %

7.2 Deep Learning LSTM Model with raw timeseries features

LSTM Model	Test Accuracy	Test Loss
Input Layer->32 LSTM->Dropout(0.73)-> 32 LSTM->Dropout(0.65)->Output Layer	91.381 %	0.38

- There is a slightly confusion between STANDING and SITTING in all models, rest of the activities are well predicted.
- It is observed that even a 2 layered LSTM model performs very well with an accuracy of 91.38 % and loss of 0.38 using the raw time series features.
- It can be concluded that Deep learning models can perform well even if we do not have engineered features/ domain knowledge.