Implemant HUMAN ACTIVITY RECOGNITION via LSTM with different Architecture

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.

Quick overview of the dataset :

Accelerometer and Gyroscope readings are taken from 30 volunteers(referred as subjects) while performing the following 6 Activities.

Walking WalkingUpstairs WalkingDownstairs Standing Sitting Lying.

Readings are divided into a window of 2.56 seconds with 50% overlapping.

Accelerometer readings are divided into gravity acceleration and body acceleration readings, which has x,y and z components each.

Gyroscope readings are the measure of angular velocities which has x,y and z components.

Jerk signals are calculated for BodyAcceleration readings.

Fourier Transforms are made on the above time readings to obtain frequency readings.

Now, on all the base signal readings., mean, max, mad, sma, arcoefficient, engerybands,entropy etc., are calculated for each window.

We get a feature vector of 561 features and these features are given in the dataset.

Each window of readings is a datapoint of 561 features.

Problem Framework

30 subjects(volunteers) data is randomly split to 70%(21) test and 30%(7) train data. Each datapoint corresponds one of the 6 Activities.

Problem Statement

Given a new datapoint we have to predict the Activity

In [1]:

```
import pandas as pd
import numpy as np
```

In [3]:

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

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

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

Data

In [4]:

```
# Data directory
DATADIR = 'UCI_HAR_Dataset'
```

In [5]:

```
# 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 [6]:

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

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

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

    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
    return np.transpose(signals_data, (1, 2, 0))
```

In [7]:

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

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

In [8]:

```
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
```

In [9]:

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

```
C:\Users\HIMANSHU NEGI\Anaconda3\lib\site-packages\h5py\__init__.py:36: Fu
tureWarning: Conversion of the second argument of issubdtype from `float`
to `np.floating` is deprecated. In future, it will be treated as `np.float
64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
```

In [12]:

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

In [13]:

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

In [14]:

```
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

In [49]:

```
# Initializing parameters
epochs = 20
batch_size = 16
n_hidden2 = 18
n_hidden1 = 36
```

In [50]:

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

In [51]:

```
# Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
```

```
C:\Users\HIMANSHU NEGI\Anaconda3\lib\site-packages\ipykernel_launcher.py:1
2: FutureWarning: Method .as_matrix will be removed in a future version. U
se .values instead.
  if sys.path[0] == '':
```

In [52]:

```
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
```

- Defining the Architecture of LSTM

(1) Model having 1 LSTM layer with 32 LSTM Units

In [29]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(32, 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_11 (LSTM)               (None, 32)                5376      
_________________________________________________________________
dropout_6 (Dropout)          (None, 32)                0         
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 198       
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
```

In [30]:

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

In [31]:

```
# 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 1/20
7352/7352 [==============================] - 74s 10ms/step - loss: 1.3657
- acc: 0.4223 - val_loss: 1.2432 - val_acc: 0.4476
Epoch 2/20
7352/7352 [==============================] - 72s 10ms/step - loss: 1.1265
- acc: 0.4933 - val_loss: 1.0647 - val_acc: 0.4472
Epoch 3/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.9105 -
acc: 0.5741 - val_loss: 0.9171 - val_acc: 0.5843
Epoch 4/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.7974 -
acc: 0.6465 - val_loss: 0.8289 - val_acc: 0.6016
Epoch 5/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.6969 -
acc: 0.6568 - val_loss: 0.7589 - val_acc: 0.6098
Epoch 6/20
7352/7352 [==============================] - 70s 10ms/step - loss: 0.6716
- acc: 0.6560 - val_loss: 0.8594 - val_acc: 0.6047
Epoch 7/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.7123 -
acc: 0.6536 - val_loss: 0.7254 - val_acc: 0.6166
Epoch 8/20
7352/7352 [==============================] - 75s 10ms/step - loss: 0.6294
- acc: 0.6831 - val_loss: 0.7531 - val_acc: 0.6094
Epoch 9/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.5643 -
acc: 0.7058 - val_loss: 0.7404 - val_acc: 0.6630
Epoch 10/20
7352/7352 [==============================] - 76s 10ms/step - loss: 0.5790
- acc: 0.7360 - val_loss: 0.5795 - val_acc: 0.7435
Epoch 11/20
7352/7352 [==============================] - 50s 7ms/step - loss: 0.5650 -
acc: 0.7646 - val_loss: 0.6684 - val_acc: 0.7703
Epoch 12/20
7352/7352 [==============================] - 50s 7ms/step - loss: 0.5135 -
acc: 0.7930 - val_loss: 0.5949 - val_acc: 0.7482
Epoch 13/20
7352/7352 [==============================] - 49s 7ms/step - loss: 0.4577 -
acc: 0.8089 - val_loss: 0.5362 - val_acc: 0.7889
Epoch 14/20
7352/7352 [==============================] - 51s 7ms/step - loss: 0.5020 -
acc: 0.8127 - val_loss: 0.4887 - val_acc: 0.7967
Epoch 15/20
7352/7352 [==============================] - 62s 8ms/step - loss: 0.4043 -
acc: 0.8430 - val_loss: 0.6778 - val_acc: 0.8066
Epoch 16/20
7352/7352 [==============================] - 48s 7ms/step - loss: 0.3501 -
acc: 0.8777 - val_loss: 0.4626 - val_acc: 0.8527
Epoch 17/20
7352/7352 [==============================] - 48s 7ms/step - loss: 0.3009 -
acc: 0.9061 - val_loss: 0.4234 - val_acc: 0.8724
Epoch 18/20
7352/7352 [==============================] - 50s 7ms/step - loss: 0.2400 -
acc: 0.9266 - val_loss: 0.4140 - val_acc: 0.8707
Epoch 19/20
7352/7352 [==============================] - 49s 7ms/step - loss: 0.2388 -
acc: 0.9246 - val_loss: 0.3638 - val_acc: 0.8860
Epoch 20/20
7352/7352 [==============================] - 46s 6ms/step - loss: 0.2132 -
acc: 0.9327 - val_loss: 0.4219 - val_acc: 0.8792
```

Out[31]:

```
<keras.callbacks.History at 0x1611c2a5fd0>
```

In [32]:

```
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAI
RS  \
True
LAYING                 512        0         0        0
0
SITTING                  1      385       102        2
0
STANDING                 0      101       429        2
0
WALKING                  0        1         3      485
4
WALKING_DOWNSTAIRS       0        0         0       27                  3
89
WALKING_UPSTAIRS         1        0         1       56
22

Pred                WALKING_UPSTAIRS
True
LAYING                            25
SITTING                            1
STANDING                           0
WALKING                            3
WALKING_DOWNSTAIRS                 4
WALKING_UPSTAIRS                 391
```

In [33]:

```
score = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 2s 621us/step
```

In [34]:

```
score
```

Out[34]:

```
[0.4219474009271998, 0.8791991856124872]
```

(2) Model having 1 LSTM layer with 64 LSTM Units and 'rmsprop' as an optimizer

In [35]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(64, 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_12 (LSTM)               (None, 64)                18944     
_________________________________________________________________
dropout_7 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_2 (Dense)              (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
```

In [36]:

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

In [37]:

```
# 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 1/20
7352/7352 [==============================] - 54s 7ms/step - loss: 1.2354 -
acc: 0.4479 - val_loss: 1.2075 - val_acc: 0.3868
Epoch 2/20
7352/7352 [==============================] - 53s 7ms/step - loss: 1.0049 -
acc: 0.5355 - val_loss: 0.9058 - val_acc: 0.5826
Epoch 3/20
7352/7352 [==============================] - 53s 7ms/step - loss: 0.7873 -
acc: 0.6240 - val_loss: 0.7922 - val_acc: 0.6047
Epoch 4/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.7871 -
acc: 0.6310 - val_loss: 0.7214 - val_acc: 0.6115
Epoch 5/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.6317 -
acc: 0.6597 - val_loss: 0.7588 - val_acc: 0.6206
Epoch 6/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.5755 -
acc: 0.6814 - val_loss: 0.7319 - val_acc: 0.6237
Epoch 7/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.5225 -
acc: 0.7531 - val_loss: 0.6146 - val_acc: 0.7988
Epoch 8/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.3943 -
acc: 0.8794 - val_loss: 0.4592 - val_acc: 0.8670
Epoch 9/20
7352/7352 [==============================] - 56s 8ms/step - loss: 0.2852 -
acc: 0.9138 - val_loss: 0.3710 - val_acc: 0.8721
Epoch 10/20
7352/7352 [==============================] - 56s 8ms/step - loss: 0.2336 -
acc: 0.9274 - val_loss: 0.8979 - val_acc: 0.7944
Epoch 11/20
7352/7352 [==============================] - 55s 8ms/step - loss: 0.2195 -
acc: 0.9286 - val_loss: 0.3862 - val_acc: 0.8870
Epoch 12/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1841 -
acc: 0.9361 - val_loss: 0.3423 - val_acc: 0.8887
Epoch 13/20
7352/7352 [==============================] - 55s 7ms/step - loss: 0.1989 -
acc: 0.9314 - val_loss: 0.4002 - val_acc: 0.8958
Epoch 14/20
7352/7352 [==============================] - 55s 7ms/step - loss: 0.1692 -
acc: 0.9403 - val_loss: 0.2981 - val_acc: 0.9118
Epoch 15/20
7352/7352 [==============================] - 55s 8ms/step - loss: 0.1765 -
acc: 0.9402 - val_loss: 0.3853 - val_acc: 0.8846
Epoch 16/20
7352/7352 [==============================] - 55s 8ms/step - loss: 0.1503 -
acc: 0.9455 - val_loss: 0.3878 - val_acc: 0.9111
Epoch 17/20
7352/7352 [==============================] - 55s 7ms/step - loss: 0.1496 -
acc: 0.9452 - val_loss: 0.2945 - val_acc: 0.9063
Epoch 18/20
7352/7352 [==============================] - 55s 7ms/step - loss: 0.1426 -
acc: 0.9441 - val_loss: 0.4237 - val_acc: 0.8887
Epoch 19/20
7352/7352 [==============================] - 55s 7ms/step - loss: 0.1393 -
acc: 0.9478 - val_loss: 0.3919 - val_acc: 0.8965
Epoch 20/20
7352/7352 [==============================] - 55s 7ms/step - loss: 0.1491 -
acc: 0.9463 - val_loss: 0.5296 - val_acc: 0.8887
```

```
Out[37]:

<keras.callbacks.History at 0x1611cebd160>
```

In [38]:

```
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAI
RS  \
True
LAYING                 510        0        27        0
0
SITTING                  0      383       105        0
1
STANDING                 0      108       424        0
0
WALKING                  0        0         0      440
54
WALKING_DOWNSTAIRS       0        0         0        3                 4
17
WALKING_UPSTAIRS         0        0         0        4
22

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            2
STANDING                           0
WALKING                            2
WALKING_DOWNSTAIRS                 0
WALKING_UPSTAIRS                 445
```

In [39]:

```
score = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 3s 903us/step
```

In [40]:

```
score
```

```
Out[40]:

[0.5296491873798939, 0.8887003732609433]
```

(3) Model having 2 LSTM layer with 32 LSTM Units and 'rmsprop' as an optimizer

In [59]:

```
# Initiliazing the sequential model
model4 = Sequential()
# Configuring the parameters
model4.add(LSTM(32,return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model4.add(Dropout(0.5))

# Configuring the parameters
model4.add(LSTM(32))
# Adding a dropout layer
model4.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model4.add(Dense(n_classes, activation='sigmoid'))
print(model4.summary())

# Compiling the model
model4.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'
])

# Training the model
history4 = model4.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_
test),epochs=epochs)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_21 (LSTM)               (None, 128, 32)           5376      
_________________________________________________________________
dropout_15 (Dropout)         (None, 128, 32)           0         
_________________________________________________________________
lstm_22 (LSTM)               (None, 32)                8320      
_________________________________________________________________
dropout_16 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_5 (Dense)              (None, 6)                 198       
=================================================================
Total params: 13,894
Trainable params: 13,894
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 116s 16ms/step - loss: 1.2293
- acc: 0.4739 - val_loss: 1.0718 - val_acc: 0.5511
Epoch 2/20
7352/7352 [==============================] - 94s 13ms/step - loss: 0.8660
- acc: 0.6144 - val_loss: 0.9926 - val_acc: 0.5443
Epoch 3/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.7223
- acc: 0.6919 - val_loss: 0.9335 - val_acc: 0.5775
Epoch 4/20
7352/7352 [==============================] - 94s 13ms/step - loss: 0.6039
- acc: 0.7514 - val_loss: 0.6213 - val_acc: 0.7377
Epoch 5/20
7352/7352 [==============================] - 95s 13ms/step - loss: 0.5112
- acc: 0.7767 - val_loss: 0.5726 - val_acc: 0.7526
Epoch 6/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.4599
- acc: 0.8084 - val_loss: 0.5772 - val_acc: 0.8259
Epoch 7/20
7352/7352 [==============================] - 95s 13ms/step - loss: 0.3722
- acc: 0.8681 - val_loss: 0.5780 - val_acc: 0.8449
Epoch 8/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.3117
- acc: 0.9064 - val_loss: 0.4944 - val_acc: 0.8751
Epoch 9/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.2528
- acc: 0.9237 - val_loss: 0.5478 - val_acc: 0.8571
Epoch 10/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.2194
- acc: 0.9378 - val_loss: 0.5815 - val_acc: 0.8636
Epoch 11/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1888
- acc: 0.9365 - val_loss: 0.5230 - val_acc: 0.8911
Epoch 12/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.2101
- acc: 0.9334 - val_loss: 0.5186 - val_acc: 0.8843
Epoch 13/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1820
- acc: 0.9374 - val_loss: 0.5300 - val_acc: 0.8795
Epoch 14/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1796
- acc: 0.9426 - val_loss: 0.4395 - val_acc: 0.8941
```

```
Epoch 15/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1554
- acc: 0.9449 - val_loss: 0.6407 - val_acc: 0.8890
Epoch 16/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1763
- acc: 0.9422 - val_loss: 0.6363 - val_acc: 0.8738
Epoch 17/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1534
- acc: 0.9486 - val_loss: 0.9969 - val_acc: 0.8575
Epoch 18/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1770
- acc: 0.9436 - val_loss: 0.4199 - val_acc: 0.9019
Epoch 19/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1640
- acc: 0.9452 - val_loss: 0.4450 - val_acc: 0.9016
Epoch 20/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1538
- acc: 0.9497 - val_loss: 0.4741 - val_acc: 0.9080
```

In [61]:

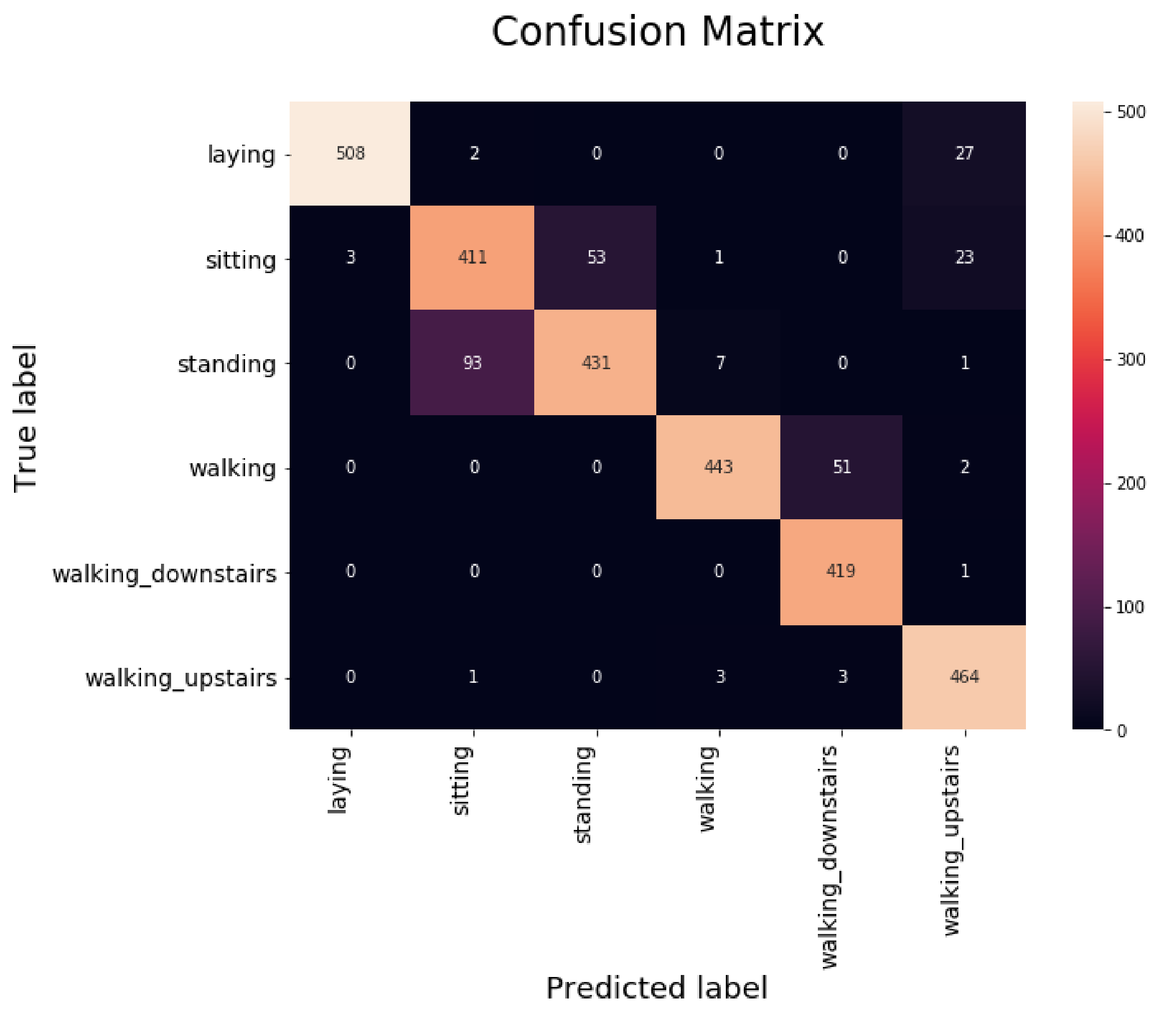
```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix
scores4 = model4.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores4[0]))
print("Test Accuracy: %f%%" % (scores4[1]*100))

# Confusion Matrix
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(model4.predict(X_test), axi
s=1)])

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_up
stairs']
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, c
olumns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', f
ontsize=14)
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.474115
Test Accuracy: 90.804208%
```



(4) Model having 2 LSTM layer with 32 LSTM Units and 'rmsprop' as an optimizer

In [72]:

```
# Initiliazing the sequential model
model7 = Sequential()
# Configuring the parameters
model7.add(LSTM(32,return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model7.add(Dropout(0.4))

# Configuring the parameters
model7.add(LSTM(32))
# Adding a dropout layer
model7.add(Dropout(0.4))
# Adding a dense output layer with sigmoid activation
model7.add(Dense(n_classes, activation='sigmoid'))
print(model7.summary())

# Compiling the model
model7.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'
])

# Training the model
history7 = model7.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_
test),epochs=30)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_26 (LSTM)               (None, 128, 32)           5376      
_________________________________________________________________
dropout_20 (Dropout)         (None, 128, 32)           0         
_________________________________________________________________
lstm_27 (LSTM)               (None, 32)                8320      
_________________________________________________________________
dropout_21 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_9 (Dense)              (None, 6)                 198       
=================================================================
Total params: 13,894
Trainable params: 13,894
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 112s 15ms/step - loss: 1.1430
- acc: 0.5148 - val_loss: 0.9322 - val_acc: 0.5490
Epoch 2/30
7352/7352 [==============================] - 116s 16ms/step - loss: 0.7485
- acc: 0.6473 - val_loss: 0.7438 - val_acc: 0.6105
Epoch 3/30
7352/7352 [==============================] - 151s 21ms/step - loss: 0.6597
- acc: 0.7055 - val_loss: 0.7685 - val_acc: 0.6800
Epoch 4/30
7352/7352 [==============================] - 114s 15ms/step - loss: 0.5819
- acc: 0.7447 - val_loss: 0.5570 - val_acc: 0.7693
Epoch 5/30
7352/7352 [==============================] - 103s 14ms/step - loss: 0.5028
- acc: 0.7806 - val_loss: 0.6238 - val_acc: 0.7513
Epoch 6/30
7352/7352 [==============================] - 104s 14ms/step - loss: 0.4340
- acc: 0.8084 - val_loss: 0.5107 - val_acc: 0.8314
Epoch 7/30
7352/7352 [==============================] - 121s 16ms/step - loss: 0.3709
- acc: 0.8663 - val_loss: 0.5936 - val_acc: 0.8202
Epoch 8/30
7352/7352 [==============================] - 168s 23ms/step - loss: 0.2850
- acc: 0.9106 - val_loss: 0.4576 - val_acc: 0.8802
Epoch 9/30
7352/7352 [==============================] - 166s 23ms/step - loss: 0.2369
- acc: 0.9236 - val_loss: 0.4088 - val_acc: 0.8839
Epoch 10/30
7352/7352 [==============================] - 168s 23ms/step - loss: 0.1951
- acc: 0.9346 - val_loss: 0.3617 - val_acc: 0.8979
Epoch 11/30
7352/7352 [==============================] - 164s 22ms/step - loss: 0.1827
- acc: 0.9369 - val_loss: 0.6861 - val_acc: 0.8381
Epoch 12/30
7352/7352 [==============================] - 170s 23ms/step - loss: 0.1798
- acc: 0.9392 - val_loss: 0.3199 - val_acc: 0.9063
Epoch 13/30
7352/7352 [==============================] - 175s 24ms/step - loss: 0.1682
- acc: 0.9436 - val_loss: 0.3391 - val_acc: 0.9050
Epoch 14/30
7352/7352 [==============================] - 159s 22ms/step - loss: 0.1495
- acc: 0.9495 - val_loss: 0.3261 - val_acc: 0.9030
```

```
Epoch 15/30
7352/7352 [==============================] - 151s 20ms/step - loss: 0.1568
- acc: 0.9440 - val_loss: 0.2831 - val_acc: 0.9257
Epoch 16/30
7352/7352 [==============================] - 151s 21ms/step - loss: 0.1412
- acc: 0.9490 - val_loss: 0.4067 - val_acc: 0.9108
Epoch 17/30
7352/7352 [==============================] - 153s 21ms/step - loss: 0.1427
- acc: 0.9493 - val_loss: 0.3324 - val_acc: 0.9084
Epoch 18/30
7352/7352 [==============================] - 165s 22ms/step - loss: 0.1548
- acc: 0.9468 - val_loss: 0.3240 - val_acc: 0.9165
Epoch 19/30
7352/7352 [==============================] - 160s 22ms/step - loss: 0.1355
- acc: 0.9484 - val_loss: 0.3541 - val_acc: 0.9131
Epoch 20/30
7352/7352 [==============================] - 149s 20ms/step - loss: 0.1464
- acc: 0.9489 - val_loss: 0.4399 - val_acc: 0.8975
Epoch 21/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.1597
- acc: 0.9448 - val_loss: 0.3024 - val_acc: 0.9192
Epoch 22/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.1336
- acc: 0.9508 - val_loss: 0.3142 - val_acc: 0.9226
Epoch 23/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.1433
- acc: 0.9484 - val_loss: 0.3331 - val_acc: 0.9257
Epoch 24/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.1431
- acc: 0.9470 - val_loss: 0.2522 - val_acc: 0.9277
Epoch 25/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.1340
- acc: 0.9498 - val_loss: 0.3704 - val_acc: 0.9162
Epoch 26/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.1334
- acc: 0.9524 - val_loss: 0.2666 - val_acc: 0.9192
Epoch 27/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.1325
- acc: 0.9486 - val_loss: 0.2636 - val_acc: 0.9125
Epoch 28/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.1261
- acc: 0.9518 - val_loss: 0.3061 - val_acc: 0.9091
Epoch 29/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.1382
- acc: 0.9501 - val_loss: 0.3471 - val_acc: 0.9175
Epoch 30/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.1260
- acc: 0.9543 - val_loss: 0.3902 - val_acc: 0.9053
```

In [74]:

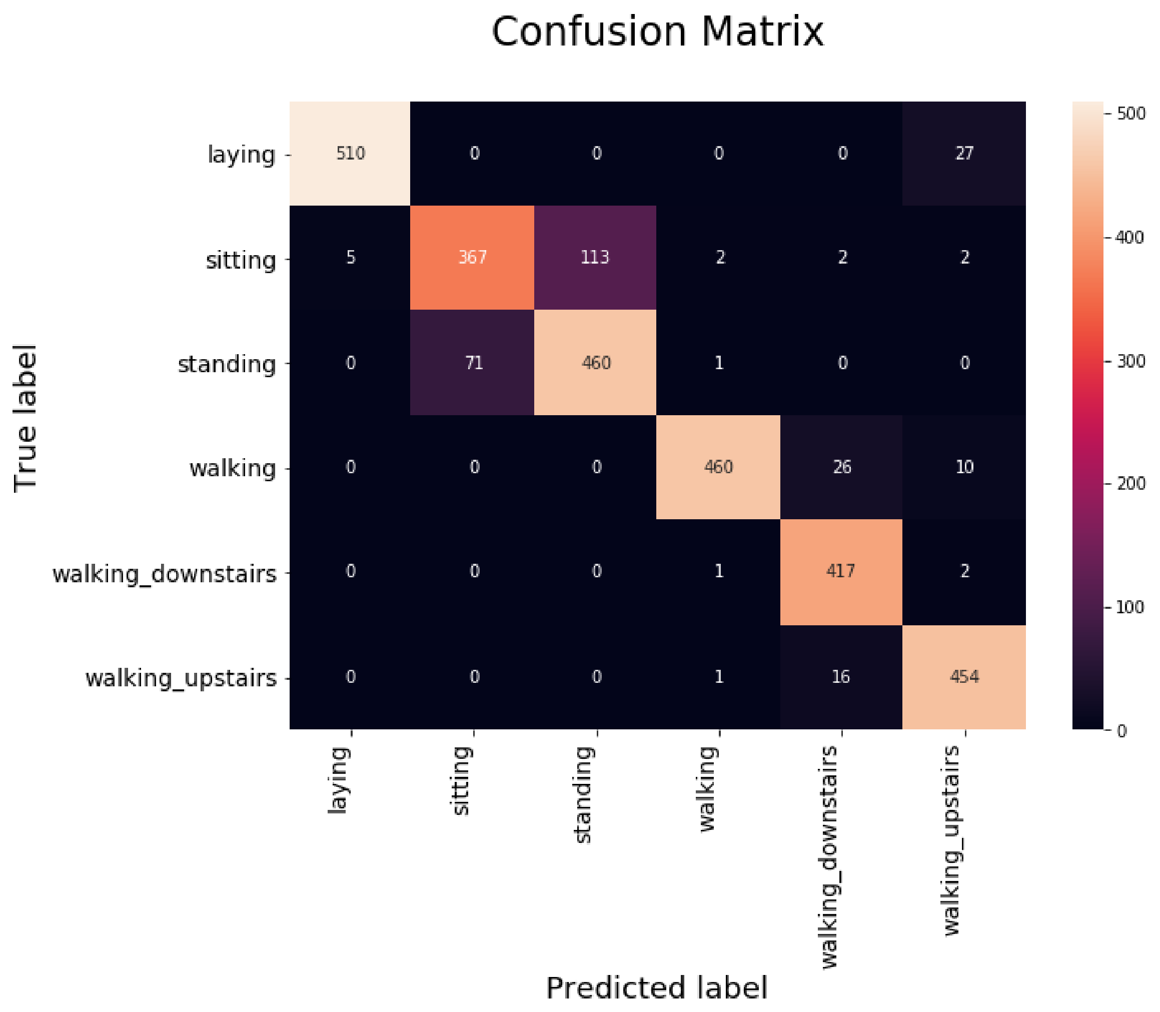
```
scores7 = model7.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores7[0]))
print("Test Accuracy: %f%%" % (scores7[1]*100))

# Confusion Matrix
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(model7.predict(X_test), axi
s=1)])

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_up
stairs']
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, c
olumns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', f
ontsize=14)
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.390201
Test Accuracy: 90.532745%
```



	laying	sitting	standing	walking	walking_downstairs	walking_upstairs
laying	510	0	0	0	0	27
sitting	5	367	113	2	2	2
standing	0	71	460	1	0	0
walking	0	0	0	460	26	10
walking_downstairs	0	0	0	1	417	2
walking_upstairs	0	0	0	1	16	454

(5) Model having 2 LSTM layer with 64 LSTM Units

In [75]:

```
# Initiliazing the sequential model
model8 = Sequential()
# Configuring the parameters
model8.add(LSTM(64,return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model8.add(Dropout(0.3))

# Configuring the parameters
model8.add(LSTM(64))
# Adding a dropout layer
model8.add(Dropout(0.3))
# Adding a dense output layer with sigmoid activation
model8.add(Dense(n_classes, activation='sigmoid'))
print(model8.summary())

# Compiling the model
model8.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'
])

# Training the model
history8 = model8.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_
test),epochs=30)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_30 (LSTM)               (None, 128, 64)           18944     
_________________________________________________________________
dropout_24 (Dropout)         (None, 128, 64)           0         
_________________________________________________________________
lstm_31 (LSTM)               (None, 64)                33024     
_________________________________________________________________
dropout_25 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_11 (Dense)             (None, 6)                 390       
=================================================================
Total params: 52,358
Trainable params: 52,358
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 126s 17ms/step - loss: 1.0656
- acc: 0.5140 - val_loss: 0.8124 - val_acc: 0.5928
Epoch 2/30
7352/7352 [==============================] - 122s 17ms/step - loss: 0.7328
- acc: 0.6503 - val_loss: 0.7082 - val_acc: 0.7292
Epoch 3/30
7352/7352 [==============================] - 122s 17ms/step - loss: 0.6599
- acc: 0.7157 - val_loss: 0.6380 - val_acc: 0.7126
Epoch 4/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.5255
- acc: 0.7816 - val_loss: 0.5473 - val_acc: 0.7947
Epoch 5/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.3961
- acc: 0.8505 - val_loss: 0.4307 - val_acc: 0.8351
Epoch 6/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.2608
- acc: 0.9104 - val_loss: 0.3643 - val_acc: 0.8785
Epoch 7/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.2043
- acc: 0.9276 - val_loss: 0.3512 - val_acc: 0.8890
Epoch 8/30
7352/7352 [==============================] - 122s 17ms/step - loss: 0.1735
- acc: 0.9374 - val_loss: 0.3139 - val_acc: 0.9040
Epoch 9/30
7352/7352 [==============================] - 135s 18ms/step - loss: 0.1540
- acc: 0.9406 - val_loss: 0.3518 - val_acc: 0.9080
Epoch 10/30
7352/7352 [==============================] - 120s 16ms/step - loss: 0.1568
- acc: 0.9392 - val_loss: 0.3272 - val_acc: 0.9091
Epoch 11/30
7352/7352 [==============================] - 120s 16ms/step - loss: 0.1413
- acc: 0.9457 - val_loss: 0.2985 - val_acc: 0.9091
Epoch 12/30
7352/7352 [==============================] - 120s 16ms/step - loss: 0.1362
- acc: 0.9465 - val_loss: 0.3764 - val_acc: 0.8921
Epoch 13/30
7352/7352 [==============================] - 120s 16ms/step - loss: 0.1336
- acc: 0.9497 - val_loss: 0.4482 - val_acc: 0.8843
Epoch 14/30
7352/7352 [==============================] - 122s 17ms/step - loss: 0.1318
- acc: 0.9527 - val_loss: 0.3553 - val_acc: 0.8921
```

```
Epoch 15/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1350
- acc: 0.9518 - val_loss: 0.4011 - val_acc: 0.9002
Epoch 16/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1283
- acc: 0.9483 - val_loss: 0.4361 - val_acc: 0.9036
Epoch 17/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1323
- acc: 0.9497 - val_loss: 0.3424 - val_acc: 0.9101
Epoch 18/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1254
- acc: 0.9527 - val_loss: 0.4371 - val_acc: 0.9040
Epoch 19/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1225
- acc: 0.9498 - val_loss: 0.3420 - val_acc: 0.9063
Epoch 20/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1308
- acc: 0.9493 - val_loss: 0.3504 - val_acc: 0.9040
Epoch 21/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1227
- acc: 0.9508 - val_loss: 0.3189 - val_acc: 0.9148
Epoch 22/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1258
- acc: 0.9518 - val_loss: 0.3695 - val_acc: 0.9125
Epoch 23/30
7352/7352 [==============================] - 126s 17ms/step - loss: 0.1190
- acc: 0.9548 - val_loss: 0.4747 - val_acc: 0.8962
Epoch 24/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1221
- acc: 0.9533 - val_loss: 0.3035 - val_acc: 0.9186
Epoch 25/30
7352/7352 [==============================] - 143s 20ms/step - loss: 0.1213
- acc: 0.9538 - val_loss: 0.3753 - val_acc: 0.9223
Epoch 26/30
7352/7352 [==============================] - 139s 19ms/step - loss: 0.1304
- acc: 0.9518 - val_loss: 0.3458 - val_acc: 0.8999
Epoch 27/30
7352/7352 [==============================] - 198s 27ms/step - loss: 0.1144
- acc: 0.9543 - val_loss: 0.3485 - val_acc: 0.9155
Epoch 28/30
7352/7352 [==============================] - 175s 24ms/step - loss: 0.1286
- acc: 0.9489 - val_loss: 0.4093 - val_acc: 0.9006
Epoch 29/30
7352/7352 [==============================] - 126s 17ms/step - loss: 0.1334
- acc: 0.9495 - val_loss: 0.3099 - val_acc: 0.9036
Epoch 30/30
7352/7352 [==============================] - 134s 18ms/step - loss: 0.1364
- acc: 0.9523 - val_loss: 0.4480 - val_acc: 0.9094
```

In [76]:

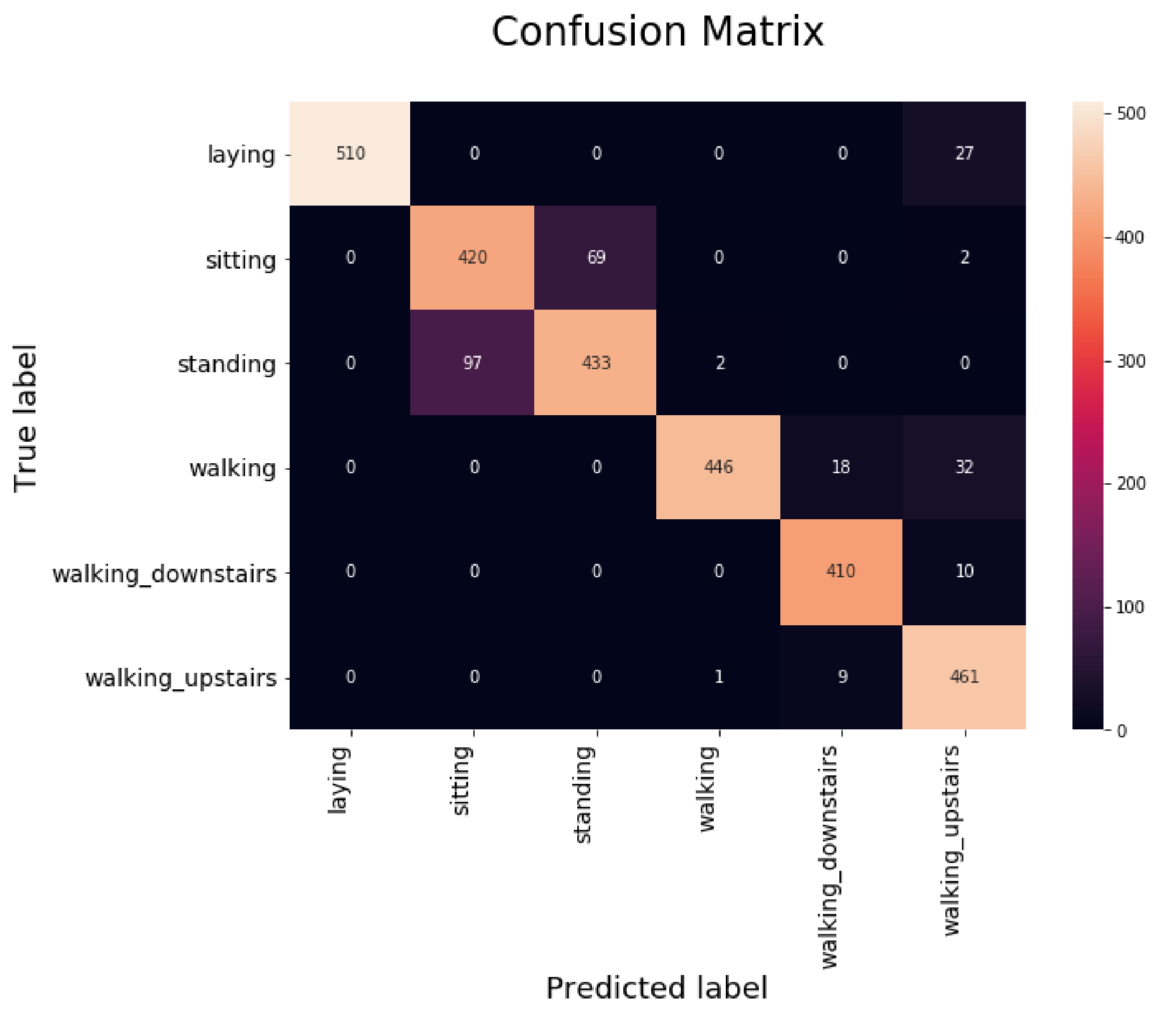
```
scores8 = model8.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores8[0]))
print("Test Accuracy: %f%%" % (scores8[1]*100))

# Confusion Matrix
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(model8.predict(X_test), axi
s=1)])

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_up
stairs']
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, c
olumns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', f
ontsize=14)
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.448009
Test Accuracy: 90.939939%
```



True label \ Predicted label	laying	sitting	standing	walking	walking_downstairs	walking_upstairs
laying	510	0	0	0	0	27
sitting	0	420	69	0	0	2
standing	0	97	433	2	0	0
walking	0	0	0	446	18	32
walking_downstairs	0	0	0	0	410	10
walking_upstairs	0	0	0	1	9	461

(6) Model having 2 LSTM layer with 64 LSTM Units

In [77]:

```
# Initiliazing the sequential model
model9 = Sequential()
# Configuring the parameters
model9.add(LSTM(64,return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model9.add(Dropout(0.5))

# Configuring the parameters
model9.add(LSTM(64))
# Adding a dropout layer
model9.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model9.add(Dense(n_classes, activation='sigmoid'))
print(model9.summary())

# Compiling the model
model9.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'
])

# Training the model
history9 = model9.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_
test),epochs=30)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_32 (LSTM)               (None, 128, 64)           18944     
_________________________________________________________________
dropout_26 (Dropout)         (None, 128, 64)           0         
_________________________________________________________________
lstm_33 (LSTM)               (None, 64)                33024     
_________________________________________________________________
dropout_27 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_12 (Dense)             (None, 6)                 390       
=================================================================
Total params: 52,358
Trainable params: 52,358
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 142s 19ms/step - loss: 1.0596
- acc: 0.5354 - val_loss: 0.8040 - val_acc: 0.6057
Epoch 2/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.7153
- acc: 0.6545 - val_loss: 0.7176 - val_acc: 0.6518
Epoch 3/30
7352/7352 [==============================] - 144s 20ms/step - loss: 0.7113
- acc: 0.6729 - val_loss: 0.6954 - val_acc: 0.7061
Epoch 4/30
7352/7352 [==============================] - 182s 25ms/step - loss: 0.5630
- acc: 0.7380 - val_loss: 0.6496 - val_acc: 0.7374
Epoch 5/30
7352/7352 [==============================] - 179s 24ms/step - loss: 0.4935
- acc: 0.7738 - val_loss: 0.7803 - val_acc: 0.7302
Epoch 6/30
7352/7352 [==============================] - 131s 18ms/step - loss: 0.4744
- acc: 0.7822 - val_loss: 0.6037 - val_acc: 0.7438
Epoch 7/30
7352/7352 [==============================] - 164s 22ms/step - loss: 0.4461
- acc: 0.7829 - val_loss: 0.7946 - val_acc: 0.7384
Epoch 8/30
7352/7352 [==============================] - 128s 17ms/step - loss: 0.4657
- acc: 0.7769 - val_loss: 0.5941 - val_acc: 0.7557
Epoch 9/30
7352/7352 [==============================] - 126s 17ms/step - loss: 0.4341
- acc: 0.7950 - val_loss: 0.6260 - val_acc: 0.7465
Epoch 10/30
7352/7352 [==============================] - 128s 17ms/step - loss: 0.3719
- acc: 0.8362 - val_loss: 0.5230 - val_acc: 0.8429
Epoch 11/30
7352/7352 [==============================] - 153s 21ms/step - loss: 0.3067
- acc: 0.8979 - val_loss: 0.4232 - val_acc: 0.8687
Epoch 12/30
7352/7352 [==============================] - 226s 31ms/step - loss: 0.2034
- acc: 0.9343 - val_loss: 0.3980 - val_acc: 0.8728
Epoch 13/30
7352/7352 [==============================] - 137s 19ms/step - loss: 0.1850
- acc: 0.9414 - val_loss: 0.4111 - val_acc: 0.8887
Epoch 14/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1811
- acc: 0.9370 - val_loss: 0.3506 - val_acc: 0.8941
```

```
Epoch 15/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1631
- acc: 0.9418 - val_loss: 0.3627 - val_acc: 0.9074
Epoch 16/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1604
- acc: 0.9438 - val_loss: 0.6482 - val_acc: 0.8588
Epoch 17/30
7352/7352 [==============================] - 126s 17ms/step - loss: 0.1462
- acc: 0.9404 - val_loss: 0.3852 - val_acc: 0.9013
Epoch 18/30
7352/7352 [==============================] - 129s 18ms/step - loss: 0.1399
- acc: 0.9461 - val_loss: 0.3426 - val_acc: 0.9087
Epoch 19/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1365
- acc: 0.9461 - val_loss: 0.3597 - val_acc: 0.9141
Epoch 20/30
7352/7352 [==============================] - 137s 19ms/step - loss: 0.1318
- acc: 0.9498 - val_loss: 0.4201 - val_acc: 0.9097
Epoch 21/30
7352/7352 [==============================] - 140s 19ms/step - loss: 0.1375
- acc: 0.9487 - val_loss: 0.4146 - val_acc: 0.9070
Epoch 22/30
7352/7352 [==============================] - 130s 18ms/step - loss: 0.1296
- acc: 0.9493 - val_loss: 0.3749 - val_acc: 0.9203
Epoch 23/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1329
- acc: 0.9525 - val_loss: 0.4103 - val_acc: 0.8941
Epoch 24/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1401
- acc: 0.9487 - val_loss: 0.4844 - val_acc: 0.8860
Epoch 25/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1471
- acc: 0.9482 - val_loss: 0.4122 - val_acc: 0.9053
Epoch 26/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1242
- acc: 0.9505 - val_loss: 0.4268 - val_acc: 0.9057
Epoch 27/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1408
- acc: 0.9479 - val_loss: 0.5572 - val_acc: 0.8945
Epoch 28/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.1318
- acc: 0.9523 - val_loss: 0.5135 - val_acc: 0.9077
Epoch 29/30
7352/7352 [==============================] - 129s 18ms/step - loss: 0.1437
- acc: 0.9474 - val_loss: 0.6846 - val_acc: 0.8907
Epoch 30/30
7352/7352 [==============================] - 130s 18ms/step - loss: 0.1325
- acc: 0.9516 - val_loss: 0.5240 - val_acc: 0.9050
```

In [78]:

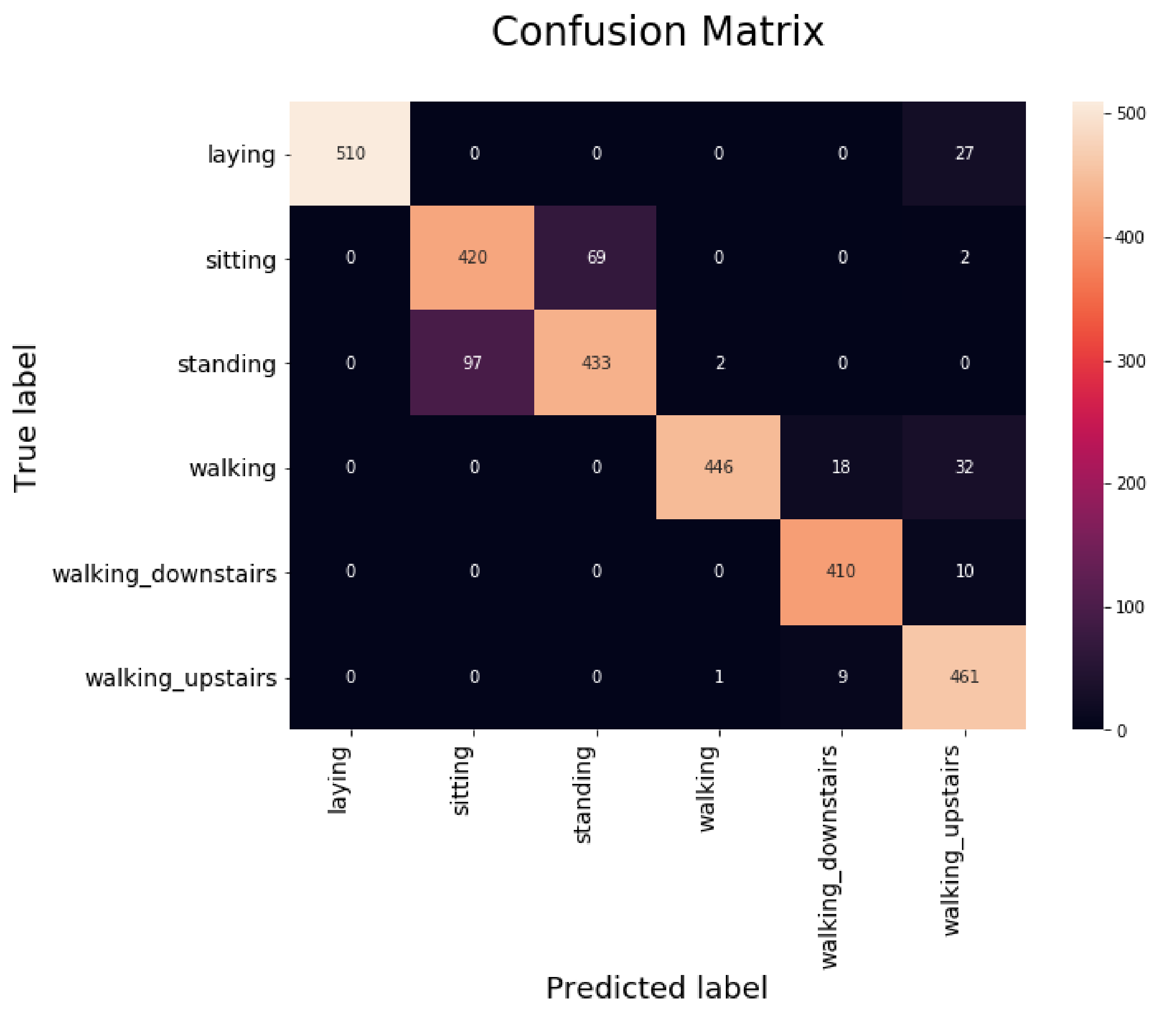
```
scores9 = model9.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores9[0]))
print("Test Accuracy: %f%%" % (scores9[1]*100))

# Confusion Matrix
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(model8.predict(X_test), axi
s=1)])

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_up
stairs']
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, c
olumns=class_names )
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', fo
ntsize=14)
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', f
ontsize=14)
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.523963
Test Accuracy: 90.498812%
```



CONCLUSION

(b). Table (Model performances) :

In [83]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model","Epocs","DROPOUT","Training_Accuracy% ", "Test_Accuracy% "]

x.add_row(["1 LSTM layer with 32 LSTM Units(Optimizer-->rmsprop)",20,.5,93.27,87.91])

x.add_row(["1 LSTM layer with 64 LSTM Units(Optimizer-->rmsprop)",20,.5,94.63,88.87])

x.add_row(["2 LSTM layer with 32 LSTM Units(Optimizer-->rmsprop)",20,.5,94.97,90.80])

x.add_row(["2 LSTM layer with 32 LSTM Units(Optimizer-->rmsprop)",30,.4,95.43,90.53])

x.add_row(["2 LSTM layer with 64 LSTM Units(Optimizer-->rmsprop)",30,.3,95.23,90.93])

x.add_row(["2 LSTM layer with 64 LSTM Units(Optimizer-->rmsprop)",30,.5,95.16,90.49])

print(x)
```

```
+------------------------------------------------------+-------+---------+
--------------------+-----------------+
|                        Model                         | Epocs | DROPOUT |
Training_Accuracy%  | Test_Accuracy%  |
+------------------------------------------------------+-------+---------+
--------------------+-----------------+
| 1 LSTM layer with 32 LSTM Units(Optimizer-->rmsprop) |   20  |   0.5   |
93.27        |      87.91      |
| 1 LSTM layer with 64 LSTM Units(Optimizer-->rmsprop) |   20  |   0.5   |
94.63        |      88.87      |
| 2 LSTM layer with 32 LSTM Units(Optimizer-->rmsprop) |   20  |   0.5   |
94.97        |       90.8      |
| 2 LSTM layer with 32 LSTM Units(Optimizer-->rmsprop) |   30  |   0.4   |
95.43        |      90.53      |
| 2 LSTM layer with 64 LSTM Units(Optimizer-->rmsprop) |   30  |   0.3   |
95.23        |      90.93      |
| 2 LSTM layer with 64 LSTM Units(Optimizer-->rmsprop) |   30  |   0.5   |
95.16        |      90.49      |
+------------------------------------------------------+-------+---------+
--------------------+-----------------+
```

(a). Procedure Followed :

STEP 1 :- Load the data and split into training_data and test_data

STEP 2:-Try out different LSTM architectures

STEP 3:- Find test score and accuracy for each model

STEP 4:- Draw confusion matrix using seaborn heatmap for each model

Steps taken explanation :

In above problem we are having multi-class problem which we have solved via. deep learning LSTM models.

Since we are having time series data with 9 signals which we use as the feature so we are using LSTM models.

We have taken model with different architecture and hyterparameter tuning like no. of layers ,epocs,dropout rate here we have taken RMS-PROP as the optimiser.

We find out test score and accuracy to see how good is our deep learning model.

We also plot the confusion matrix using seaborn heatmap between true class label and predected class label to see the how much labels are classified, we observed that in standing and sitting there is little confusion.

At the end we plot pretty table to compair different LSTM models.

Finel Observation:

We observe that our deep LSTM models are doing very good i.e around 90% accuracy with time series data i.e without feature engineering and with less data.

We can have better results with deep LSTM models as we have large data sets.