Human Activity Recognition

December 23, 2018

1 Human Activity Recognition

```
In [1]: # importing libraries

        import pandas as pd
        import numpy as np
        import warnings
        warnings.filterwarnings('ignore')
```

```
In [2]: # 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',
        }
```

2 Data

```
In [3]: # Data directory
        DATADIR = 'UCI_HAR_Dataset'
```

```
In [4]: # 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 [5]:
```
# 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 [6]:
```
# load_y function  to get the y_train dataset
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 [7]:
```
# load data function
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)

In [10]: # Configuring a session
         session_conf = tf.ConfigProto(
             intra_op_parallelism_threads=1,
             inter_op_parallelism_threads=1
         )

In [12]: # Import Keras
         from keras import backend as K
         sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
         K.set_session(sess)
```

```
Using TensorFlow backend.
```

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

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

In [15]: # Utility function to count the number of classes
         def _count_classes(y):
             return len(set([tuple(category) for category in y]))

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

In [17]: 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
```

3 Model having 1 LSTM layer with 32 LSTM Units

In [18]:
```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary() #summary of the model

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

# Training the model
model_history1 = model.fit(X_train, Y_train, batch_size=batch_size,validation_data=(X
```

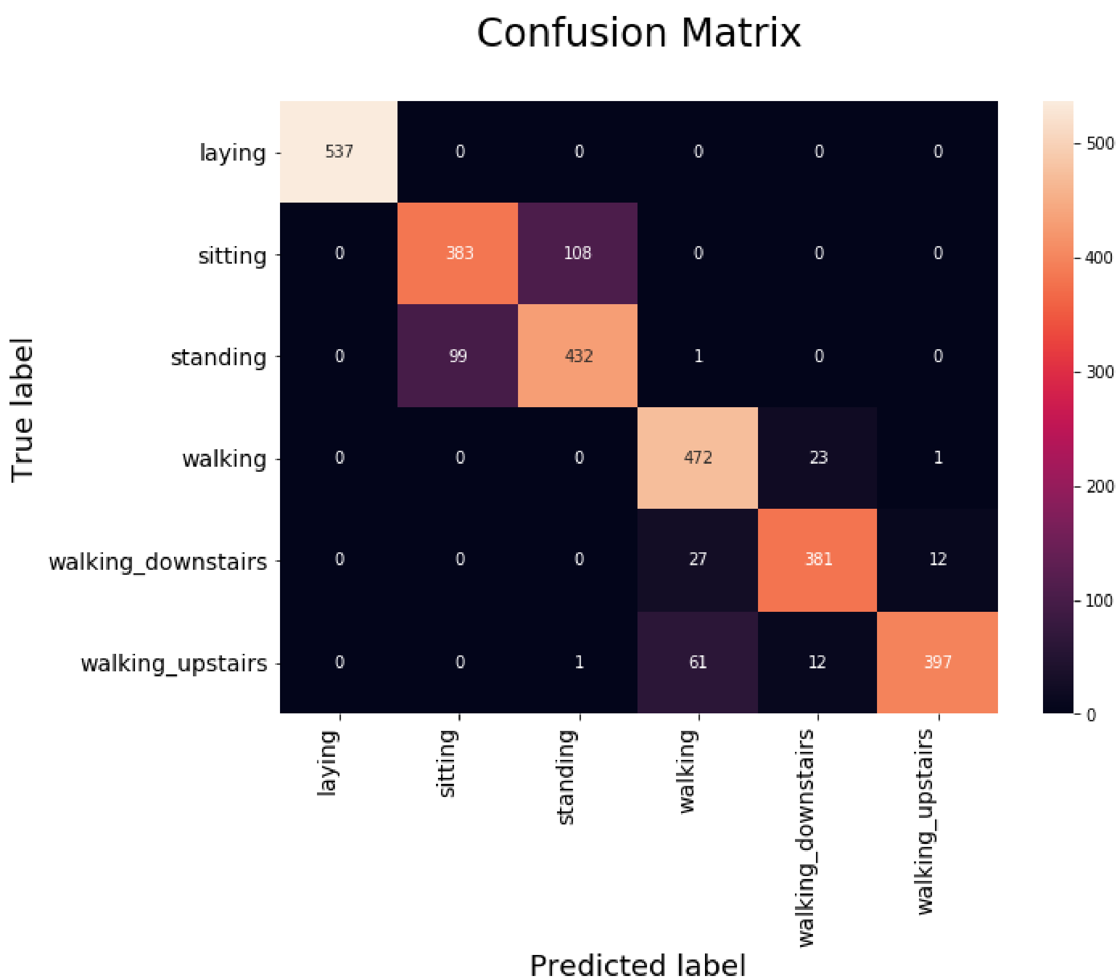
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 32)                5376
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 198
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 46s 6ms/step - loss: 1.3139 - acc: 0.4358 - val_lo
Epoch 2/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.9788 - acc: 0.5773 - val_lo
Epoch 3/30
7352/7352 [==============================] - 46s 6ms/step - loss: 0.7977 - acc: 0.6457 - val_lo
Epoch 4/30
7352/7352 [==============================] - 51s 7ms/step - loss: 0.6989 - acc: 0.6582 - val_lo
Epoch 5/30
7352/7352 [==============================] - 46s 6ms/step - loss: 0.6359 - acc: 0.6797 - val_lo
Epoch 6/30
7352/7352 [==============================] - 46s 6ms/step - loss: 0.5819 - acc: 0.6865 - val_lo
Epoch 7/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.5676 - acc: 0.7058 - val_lo
Epoch 8/30
7352/7352 [==============================] - 46s 6ms/step - loss: 0.5583 - acc: 0.7217 - val_lo
```

```
Epoch 9/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.5386 - acc: 0.7557 - val_lo
Epoch 10/30
7352/7352 [==============================] - 46s 6ms/step - loss: 0.4804 - acc: 0.7911 - val_lo
Epoch 11/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.4320 - acc: 0.8052 - val_lo
Epoch 12/30
7352/7352 [==============================] - 46s 6ms/step - loss: 0.4279 - acc: 0.8062 - val_lo
Epoch 13/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.3911 - acc: 0.8130 - val_lo
Epoch 14/30
7352/7352 [==============================] - 43s 6ms/step - loss: 0.3898 - acc: 0.8313 - val_lo
Epoch 15/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.3308 - acc: 0.8942 - val_lo
Epoch 16/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.2891 - acc: 0.9176 - val_lo
Epoch 17/30
7352/7352 [==============================] - 47s 6ms/step - loss: 0.2660 - acc: 0.9246 - val_lo
Epoch 18/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.2538 - acc: 0.9251 - val_lo
Epoch 19/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2502 - acc: 0.9312 - val_lo
Epoch 20/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.1980 - acc: 0.9382 - val_lo
Epoch 21/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2018 - acc: 0.9372 - val_lo
Epoch 22/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2455 - acc: 0.9310 - val_lo
Epoch 23/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2194 - acc: 0.9329 - val_lo
Epoch 24/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.2282 - acc: 0.9304 - val_lo
Epoch 25/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2166 - acc: 0.9359 - val_lo
Epoch 26/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2173 - acc: 0.9350 - val_lo
Epoch 27/30
7352/7352 [==============================] - 44s 6ms/step - loss: 0.2224 - acc: 0.9353 - val_lo
Epoch 28/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.1961 - acc: 0.9385 - val_lo
Epoch 29/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.1876 - acc: 0.9416 - val_lo
Epoch 30/30
7352/7352 [==============================] - 45s 6ms/step - loss: 0.1999 - acc: 0.9411 - val_lo
```

In [19]:
```python
#importing library
import matplotlib.pyplot as plt
```

```
%matplotlib inline
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Final evaluation of the model
scores = model.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores[0]))
print("Test Accuracy: %f%%" % (scores[1]*100))

# Plotting Confusion Matrix
Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_test, axis=1)])
Y_prediction = pd.Series([ACTIVITIES[y] for y in np.argmax(model.predict(X_test), axi

# Plotting seaborn heatmaps
labels = ['laying','sitting','standing','walking','walking_downstairs','walking_upsta
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_prediction), index=labels, colum
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

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

```
Test Score: 0.488270
Test Accuracy: 88.293180%
```



4 Model having 1 LSTM layer with 48 LSTM Units and 'adam' as an optimizer

```
In [20]: # Initiliazing the sequential model
         model1 = Sequential()
         # Configuring the parameters
         model1.add(LSTM(48, input_shape=(timesteps, input_dim)))
         # Adding a dropout layer
         model1.add(Dropout(0.5))
         # Adding a dense output layer with sigmoid activation
         model1.add(Dense(n_classes, activation='sigmoid'))
         print(model1.summary()) #summary of the model

         # Compiling the model
         model1.compile(loss='categorical_crossentropy',optimizer='adam',metrics=['accuracy'])
```

```
# Training the model
model_history2 = model1.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_t
```

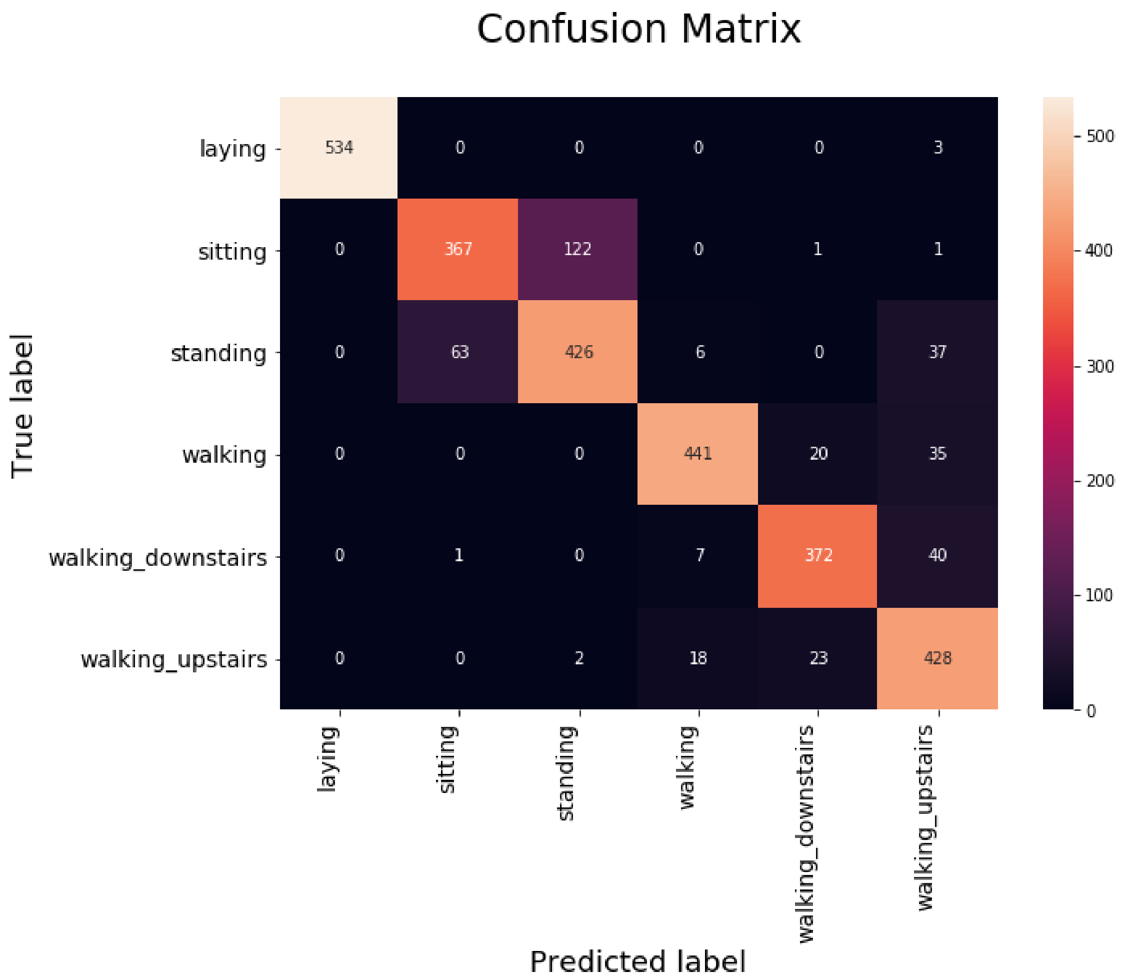
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_2 (LSTM)                (None, 48)                11136
_________________________________________________________________
dropout_2 (Dropout)          (None, 48)                0
_________________________________________________________________
dense_2 (Dense)              (None, 6)                 294
=================================================================
Total params: 11,430
Trainable params: 11,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 49s 7ms/step - loss: 1.4210 - acc: 0.3677 - val_lo
Epoch 2/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.3615 - acc: 0.3659 - val_lo
Epoch 3/30
7352/7352 [==============================] - 49s 7ms/step - loss: 1.2965 - acc: 0.4147 - val_lo
Epoch 4/30
7352/7352 [==============================] - 48s 6ms/step - loss: 1.2413 - acc: 0.4645 - val_lo
Epoch 5/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.1199 - acc: 0.5102 - val_lo
Epoch 6/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.0028 - acc: 0.5439 - val_lo
Epoch 7/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.0453 - acc: 0.5098 - val_lo
Epoch 8/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.1810 - acc: 0.4523 - val_lo
Epoch 9/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.2428 - acc: 0.4329 - val_lo
Epoch 10/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.9496 - acc: 0.5747 - val_lo
Epoch 11/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.0623 - acc: 0.5399 - val_lo
Epoch 12/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.8686 - acc: 0.6114 - val_lo
Epoch 13/30
7352/7352 [==============================] - 48s 7ms/step - loss: 1.0787 - acc: 0.4974 - val_lo
Epoch 14/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.9513 - acc: 0.5822 - val_lo
Epoch 15/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.8773 - acc: 0.5929 - val_lo
```

```
Epoch 16/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.7541 - acc: 0.6250 - val_lo
Epoch 17/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.7139 - acc: 0.6499 - val_lo
Epoch 18/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.7097 - acc: 0.6468 - val_lo
Epoch 19/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.6794 - acc: 0.6575 - val_lo
Epoch 20/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.6810 - acc: 0.6553 - val_lo
Epoch 21/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.6905 - acc: 0.6468 - val_lo
Epoch 22/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.6648 - acc: 0.6712 - val_lo
Epoch 23/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.6891 - acc: 0.6727 - val_lo
Epoch 24/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.6327 - acc: 0.7331 - val_lo
Epoch 25/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.5341 - acc: 0.8074 - val_lo
Epoch 26/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.3767 - acc: 0.8696 - val_lo
Epoch 27/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.3015 - acc: 0.9015 - val_lo
Epoch 28/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.3263 - acc: 0.8989 - val_lo
Epoch 29/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.3337 - acc: 0.8976 - val_lo
Epoch 30/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.2294 - acc: 0.9272 - val_lo
```

In [21]:
```python
# Final evaluation of the model
scores1 = model1.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores1[0]))
print("Test Accuracy: %f%%" % (scores1[1]*100))

# plotting 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(model1.predict(X_test), ax

# Plotting seaborn heatmaps
labels = ['laying','sitting','standing','walking','walking_downstairs','walking_upstai
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=labels, colum
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Initializing tick labels for heatmap
```

```
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right',
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.344224
Test Accuracy: 87.139464%
```



5 Model having 1 LSTM layer with 48 LSTM Units and 'rmsprop' as an optim.

```
In [22]: # Initiliazing the sequential model
         model2 = Sequential()
```

```python
# Configuring the parameters
model2.add(LSTM(48, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model2.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model2.add(Dense(n_classes, activation='sigmoid'))
print(model2.summary()) #summary of the model

# Compiling the model
model2.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy

# Training the model
model_history3 = model2.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_
```

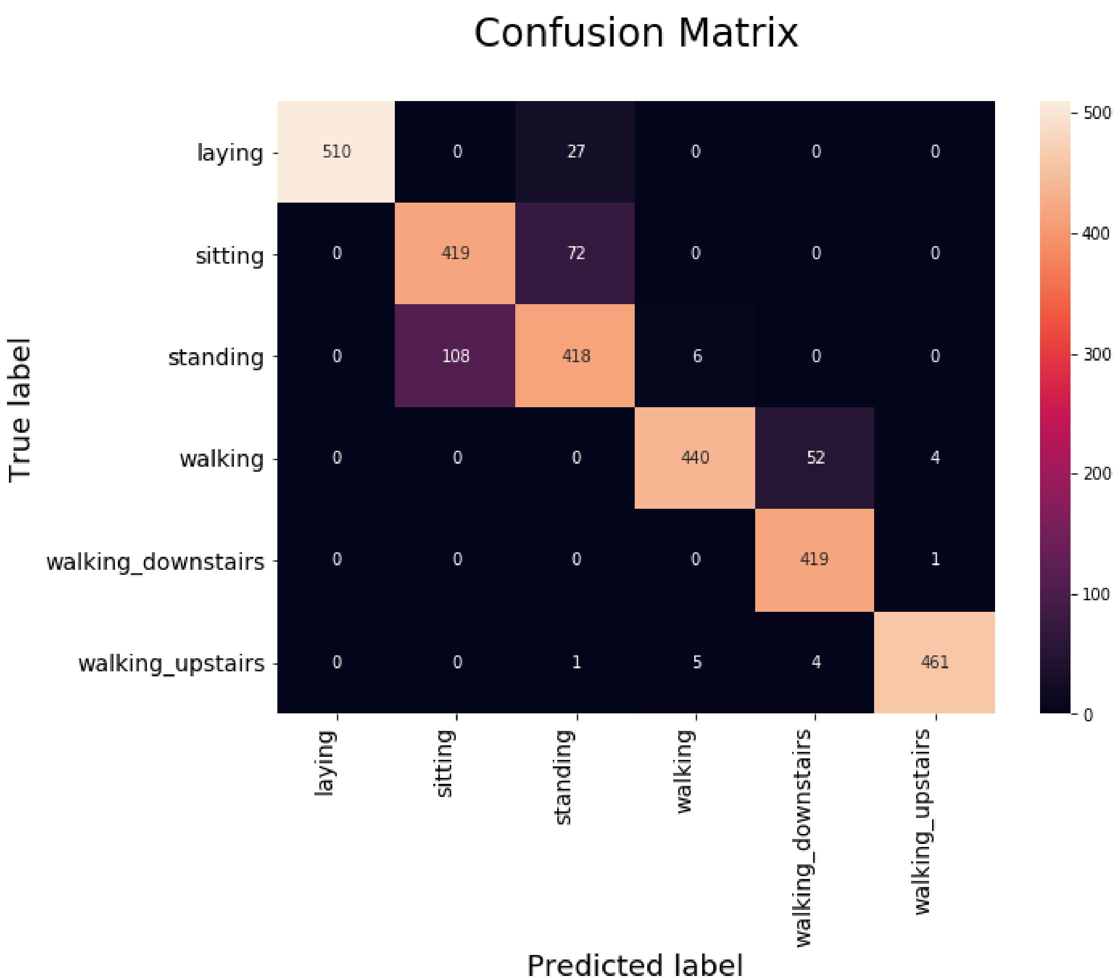
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 48)                11136
_________________________________________________________________
dropout_3 (Dropout)          (None, 48)                0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 294
=================================================================
Total params: 11,430
Trainable params: 11,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 53s 7ms/step - loss: 1.2313 - acc: 0.4780 - val_lo
Epoch 2/30
7352/7352 [==============================] - 47s 6ms/step - loss: 0.8782 - acc: 0.6073 - val_lo
Epoch 3/30
7352/7352 [==============================] - 48s 6ms/step - loss: 0.7840 - acc: 0.6542 - val_lo
Epoch 4/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.6928 - acc: 0.6900 - val_lo
Epoch 5/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.6225 - acc: 0.7348 - val_lo
Epoch 6/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.5056 - acc: 0.8290 - val_lo
Epoch 7/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.3532 - acc: 0.8900 - val_lo
Epoch 8/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.2994 - acc: 0.9113 - val_lo
Epoch 9/30
7352/7352 [==============================] - 48s 6ms/step - loss: 0.2638 - acc: 0.9212 - val_lo
Epoch 10/30
```

```
7352/7352 [==============================] - 48s 7ms/step - loss: 0.2297 - acc: 0.9276 - val_lo
Epoch 11/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.2190 - acc: 0.9336 - val_lo
Epoch 12/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.2153 - acc: 0.9329 - val_lo
Epoch 13/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.2055 - acc: 0.9376 - val_lo
Epoch 14/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.1898 - acc: 0.9366 - val_lo
Epoch 15/30
7352/7352 [==============================] - 50s 7ms/step - loss: 0.2032 - acc: 0.9319 - val_lo
Epoch 16/30
7352/7352 [==============================] - 50s 7ms/step - loss: 0.1801 - acc: 0.9416 - val_lo
Epoch 17/30
7352/7352 [==============================] - 48s 7ms/step - loss: 0.1810 - acc: 0.9423 - val_lo
Epoch 18/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1714 - acc: 0.9452 - val_lo
Epoch 19/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1654 - acc: 0.9411 - val_lo
Epoch 20/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1795 - acc: 0.9455 - val_lo
Epoch 21/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1676 - acc: 0.9404 - val_lo
Epoch 22/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1811 - acc: 0.9423 - val_lo
Epoch 23/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1563 - acc: 0.9449 - val_lo
Epoch 24/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1495 - acc: 0.9449 - val_lo
Epoch 25/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1740 - acc: 0.9436 - val_lo
Epoch 26/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1564 - acc: 0.9446 - val_lo
Epoch 27/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1648 - acc: 0.9475 - val_lo
Epoch 28/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1504 - acc: 0.9438 - val_lo
Epoch 29/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1501 - acc: 0.9468 - val_lo
Epoch 30/30
7352/7352 [==============================] - 49s 7ms/step - loss: 0.1647 - acc: 0.9471 - val_lo
```

In [23]:
```python
# Final evaluation of the model
scores2 = model2.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores2[0]))
print("Test Accuracy: %f%%" % (scores2[1]*100))
```

```python
#  plotting 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(model2.predict(X_test), a

# Plotting for drawing seaborn heatmaps
labels = ['laying','sitting','standing','walking','walking_downstairs','walking_upsta
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=labels, colu
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

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

```
Test Score: 0.410484
Test Accuracy: 90.498812%
```



6 Model having 1 LSTM layer with 64 LSTM Units and 'rmsprop' as an optimiz.

In [24]:
```
# Initiliazing the sequential model
model3 = Sequential()
# Configuring the parameters
model3.add(LSTM(64, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model3.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model3.add(Dense(n_classes, activation='sigmoid'))
print(model3.summary())

# Compiling the model
model3.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy
```

```
# Training the model
model_history4 = model3.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_t
```

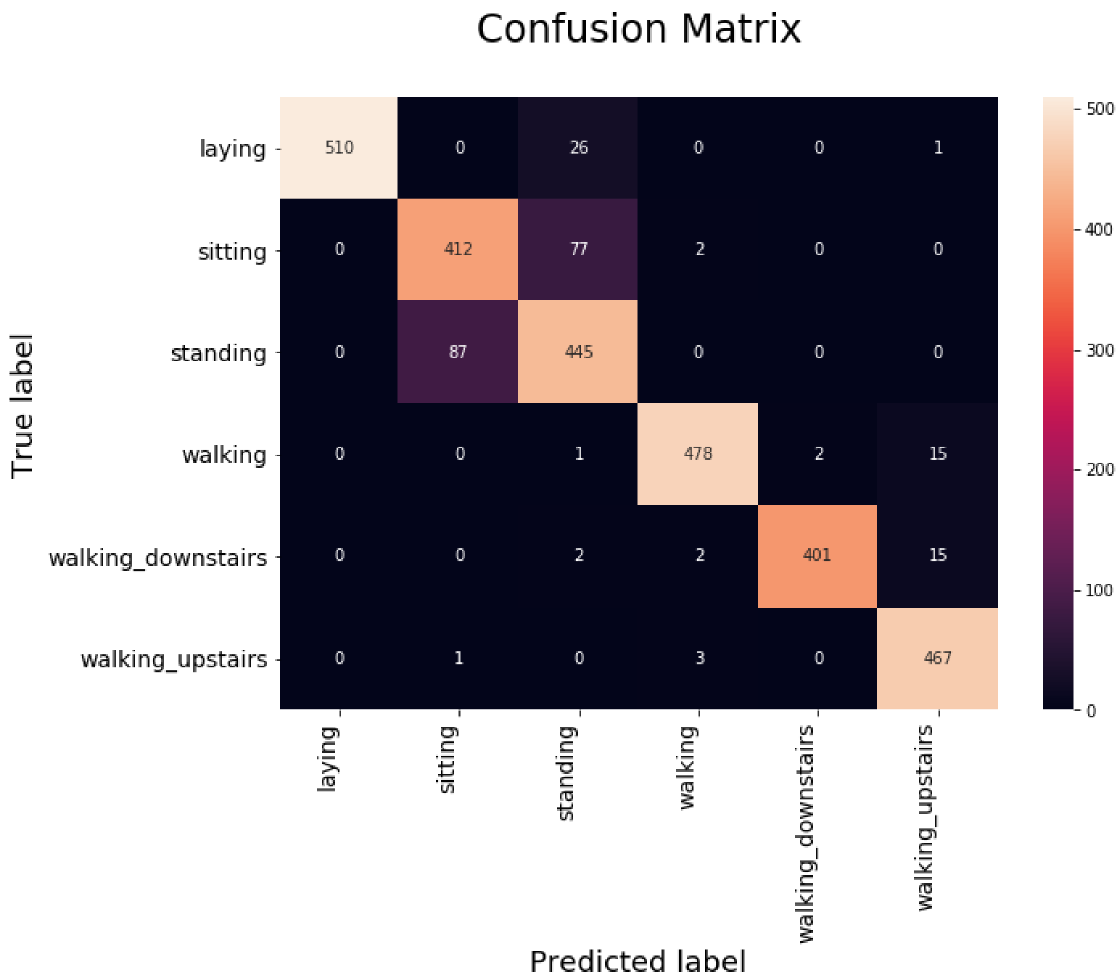
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, 64)                18944
_________________________________________________________________
dropout_4 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 390
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 55s 8ms/step - loss: 1.2746 - acc: 0.4457 - val_lo
Epoch 2/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.9587 - acc: 0.6020 - val_lo
Epoch 3/30
7352/7352 [==============================] - 54s 7ms/step - loss: 1.0225 - acc: 0.5890 - val_lo
Epoch 4/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.7561 - acc: 0.6812 - val_lo
Epoch 5/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.6203 - acc: 0.7402 - val_lo
Epoch 6/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.4874 - acc: 0.8249 - val_lo
Epoch 7/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.3588 - acc: 0.8905 - val_lo
Epoch 8/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2826 - acc: 0.9042 - val_lo
Epoch 9/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.2855 - acc: 0.9033 - val_lo
Epoch 10/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.2367 - acc: 0.9197 - val_lo
Epoch 11/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.2891 - acc: 0.9064 - val_lo
Epoch 12/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.2101 - acc: 0.9327 - val_lo
Epoch 13/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1883 - acc: 0.9309 - val_lo
Epoch 14/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1781 - acc: 0.9354 - val_lo
Epoch 15/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1812 - acc: 0.9344 - val_lo
```

```
Epoch 16/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1701 - acc: 0.9414 - val_lo
Epoch 17/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1603 - acc: 0.9446 - val_lo
Epoch 18/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1494 - acc: 0.9460 - val_lo
Epoch 19/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1555 - acc: 0.9445 - val_lo
Epoch 20/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1413 - acc: 0.9498 - val_lo
Epoch 21/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1674 - acc: 0.9444 - val_lo
Epoch 22/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1550 - acc: 0.9430 - val_lo
Epoch 23/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1551 - acc: 0.9450 - val_lo
Epoch 24/30
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1679 - acc: 0.9440 - val_lo
Epoch 25/30
7352/7352 [==============================] - 55s 8ms/step - loss: 0.1543 - acc: 0.9472 - val_lo
Epoch 26/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1457 - acc: 0.9459 - val_lo
Epoch 27/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1383 - acc: 0.9476 - val_lo
Epoch 28/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1412 - acc: 0.9508 - val_lo
Epoch 29/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1496 - acc: 0.9464 - val_lo
Epoch 30/30
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1439 - acc: 0.9490 - val_lo
```

In [25]:
```
# Final evaluation of the model
scores3 = model3.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores3[0]))
print("Test Accuracy: %f%%" % (scores3[1]*100))

# Plotting 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(model3.predict(X_test), ax

# Code for plotting seaborn heatmaps
labels = ['laying','sitting','standing','walking','walking_downstairs','walking_upsta
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=labels, colu
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Initializing tick labels for heatmap
```

```
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right',
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.299268
Test Accuracy: 92.059722%
```



7 Model having 2 LSTM layer with 32 LSTM Units and 'rmsprop' as an optimiz.

```
In [26]: # 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
model_history5 = model4.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_
```

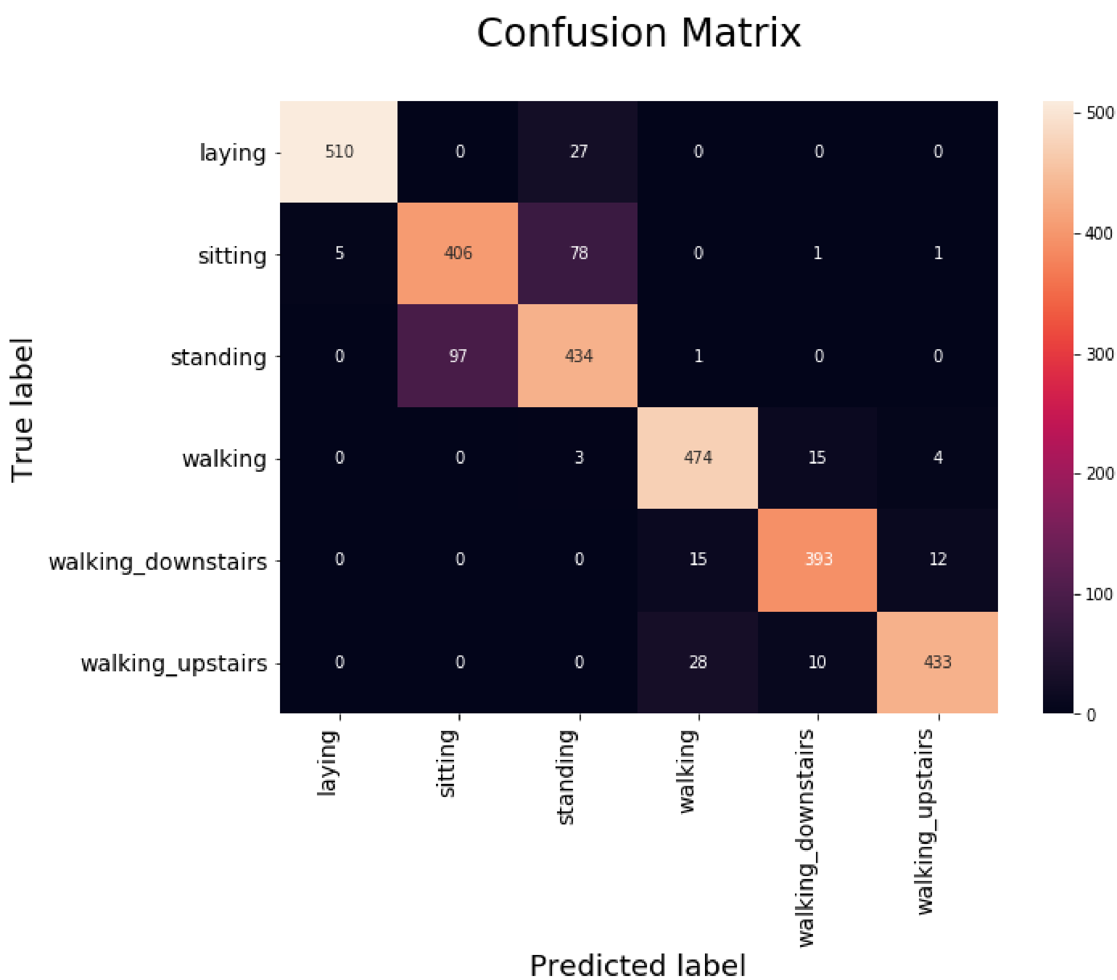
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_5 (LSTM)                (None, 128, 32)           5376
_________________________________________________________________
dropout_5 (Dropout)          (None, 128, 32)           0
_________________________________________________________________
lstm_6 (LSTM)                (None, 32)                8320
_________________________________________________________________
dropout_6 (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 1/30
7352/7352 [==============================] - 97s 13ms/step - loss: 1.2107 - acc: 0.5061 - val_
Epoch 2/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.7991 - acc: 0.6766 - val_
Epoch 3/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.6209 - acc: 0.7542 - val_
Epoch 4/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.4968 - acc: 0.7802 - val_
Epoch 5/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.4323 - acc: 0.8009 - val_
```

```
Epoch 6/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.4538 - acc: 0.8247 - val_
Epoch 7/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.3524 - acc: 0.8785 - val_
Epoch 8/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.3199 - acc: 0.9115 - val_
Epoch 9/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.2609 - acc: 0.9285 - val_
Epoch 10/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.2290 - acc: 0.9339 - val_
Epoch 11/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.2160 - acc: 0.9353 - val_
Epoch 12/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.2236 - acc: 0.9321 - val_
Epoch 13/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1718 - acc: 0.9455 - val_
Epoch 14/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1740 - acc: 0.9359 - val_
Epoch 15/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1693 - acc: 0.9423 - val_
Epoch 16/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1813 - acc: 0.9459 - val_
Epoch 17/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1687 - acc: 0.9472 - val_
Epoch 18/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1557 - acc: 0.9474 - val_
Epoch 19/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1479 - acc: 0.9471 - val_
Epoch 20/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1479 - acc: 0.9493 - val_
Epoch 21/30
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1465 - acc: 0.9509 - val_
Epoch 22/30
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1508 - acc: 0.9508 - val_
Epoch 23/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1512 - acc: 0.9489 - val_
Epoch 24/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1434 - acc: 0.9513 - val_
Epoch 25/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1805 - acc: 0.9414 - val_
Epoch 26/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1453 - acc: 0.9528 - val_
Epoch 27/30
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1385 - acc: 0.9520 - val_
Epoch 28/30
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1420 - acc: 0.9533 - val_
Epoch 29/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1288 - acc: 0.9547 - val_
```

```
Epoch 30/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1291 - acc: 0.9532 - val_l
```

```
In [27]: # Final evaluation of the model
         scores4 = model4.evaluate(X_test, Y_test, verbose=0)
         print("Test Score: %f" % (scores4[0]))
         print("Test Accuracy: %f%%" % (scores4[1]*100))

         # plotting 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), a

         # Plotting seaborn heatmaps
         labels = ['laying','sitting','standing','walking','walking_downstairs','walking_upsta
         df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=labels, colu
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

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

```
Test Score: 0.545492
Test Accuracy: 89.921955%
```



8 Model having 2 LSTM layer with 64 LSTM Units and 'rmsprop' as an optimiz.

In [28]:
```
# Initiliazing the sequential model
model5 = Sequential()

# Configuring the parameters
model5.add(LSTM(64,return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model5.add(Dropout(0.7))

# Configuring the parameters
model5.add(LSTM(64))
# Adding a dropout layer
model5.add(Dropout(0.7))
# Adding a dense output layer with sigmoid activation
```

```
model5.add(Dense(n_classes, activation='sigmoid'))
print(model5.summary()) # summary of the model

# Compiling the model
model5.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy

# Training the model
model_history6 = model5.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_
```

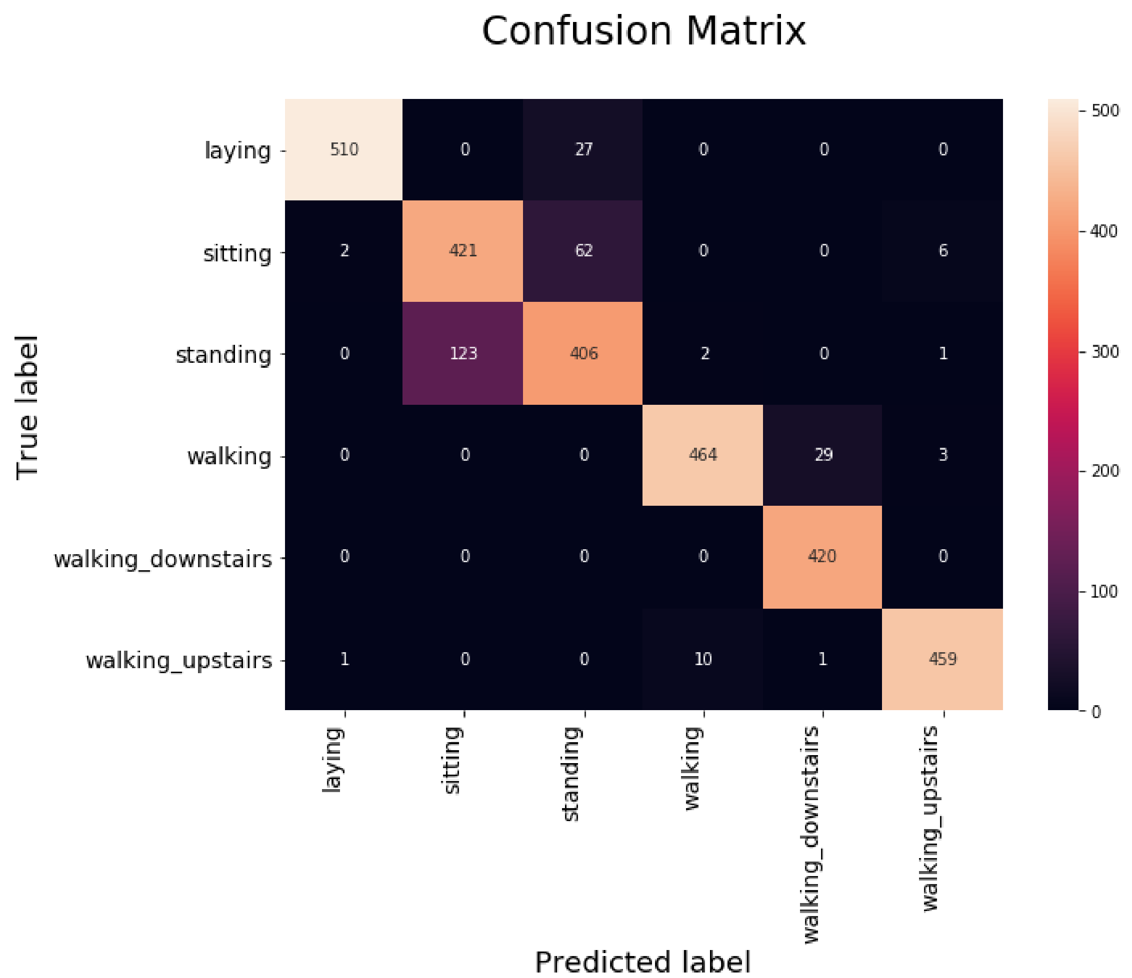
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_7 (LSTM)                (None, 128, 64)           18944
_________________________________________________________________
dropout_7 (Dropout)          (None, 128, 64)           0
_________________________________________________________________
lstm_8 (LSTM)                (None, 64)                33024
_________________________________________________________________
dropout_8 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_6 (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: 1.1611 - acc: 0.4890 - val_
Epoch 2/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.8021 - acc: 0.6549 - val_
Epoch 3/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.7392 - acc: 0.6670 - val_
Epoch 4/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.6489 - acc: 0.7338 - val_
Epoch 5/30
7352/7352 [==============================] - 123s 17ms/step - loss: 0.5545 - acc: 0.7625 - val_
Epoch 6/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.4380 - acc: 0.8164 - val_
Epoch 7/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.3323 - acc: 0.8966 - val_
Epoch 8/30
7352/7352 [==============================] - 128s 17ms/step - loss: 0.2380 - acc: 0.9301 - val_
Epoch 9/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.2048 - acc: 0.9370 - val_
Epoch 10/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1991 - acc: 0.9389 - val_
```

```
Epoch 11/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1775 - acc: 0.9429 - val_
Epoch 12/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1724 - acc: 0.9436 - val_
Epoch 13/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1628 - acc: 0.9453 - val_
Epoch 14/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1754 - acc: 0.9440 - val_
Epoch 15/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1556 - acc: 0.9465 - val_
Epoch 16/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1733 - acc: 0.9452 - val_
Epoch 17/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1737 - acc: 0.9448 - val_
Epoch 18/30
7352/7352 [==============================] - 126s 17ms/step - loss: 0.1698 - acc: 0.9442 - val_
Epoch 19/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1469 - acc: 0.9512 - val_
Epoch 20/30
7352/7352 [==============================] - 126s 17ms/step - loss: 0.1492 - acc: 0.9461 - val_
Epoch 21/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1532 - acc: 0.9490 - val_
Epoch 22/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1758 - acc: 0.9436 - val_
Epoch 23/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1528 - acc: 0.9489 - val_
Epoch 24/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1589 - acc: 0.9438 - val_
Epoch 25/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1522 - acc: 0.9437 - val_
Epoch 26/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1363 - acc: 0.9495 - val_
Epoch 27/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1480 - acc: 0.9459 - val_
Epoch 28/30
7352/7352 [==============================] - 124s 17ms/step - loss: 0.1347 - acc: 0.9495 - val_
Epoch 29/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1489 - acc: 0.9474 - val_
Epoch 30/30
7352/7352 [==============================] - 125s 17ms/step - loss: 0.1491 - acc: 0.9486 - val_
```

In [29]:
```
# Final evaluation of the model
scores5 = model5.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores5[0]))
print("Test Accuracy: %f%%" % (scores5[1]*100))

# Plotting 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(model5.predict(X_test), a

# Code for plotting seaborn heatmaps
labels = ['laying','sitting','standing','walking','walking_downstairs','walking_upsta
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=labels, colu
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

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

```
Test Score: 0.412691
Test Accuracy: 90.939939%
```



9 Table with their train accuracy and test accuracy

```
In [2]: #importing libraries
        from prettytable import PrettyTable

        x = PrettyTable()

        x.field_names = ["S.No.", "Model", "Training Accuracy", "Test Accuracy"]

        x.add_row([1.,"1 LSTM Layer With 32 LSTM Units(optimizer-rmsprop)", 0.9411,0.8829])
        x.add_row([2.,"1 LSTM Layer With 48 LSTM Units(optimizer-adam)", 0.9272,0.8714])

        x.add_row([3.,"1 LSTM Layer With 48 LSTM Units(optimizer-rmsprop)", 0.9471,0.9050])
        x.add_row([4.,"1 LSTM Layer With 64 LSTM Units(optimizer-rmsprop)", 0.9490,0.9206])

        x.add_row([5.,"2 LSTM Layer With 32 LSTM Units(optimizer-rmsprop)", 0.9532,0.8992])
        x.add_row([6.,"2 LSTM Layer With 64 LSTM Units(optimizer-rmsprop", 0.9486,0.9094])

        print(x)
```

```
+-------+----------------------------------------------------+-------------------+------------
| S.No. |                       Model                        | Training Accuracy | Test Accura
+-------+----------------------------------------------------+-------------------+------------
|  1.0  | 1 LSTM Layer With 32 LSTM Units(optimizer-rmsprop) |       0.9411      |     0.8829
|  2.0  |  1 LSTM Layer With 48 LSTM Units(optimizer-adam)   |       0.9272      |     0.8714
|  3.0  | 1 LSTM Layer With 48 LSTM Units(optimizer-rmsprop) |       0.9471      |     0.905
|  4.0  | 1 LSTM Layer With 64 LSTM Units(optimizer-rmsprop) |       0.949       |     0.9206
|  5.0  | 2 LSTM Layer With 32 LSTM Units(optimizer-rmsprop) |       0.9532      |     0.8992
|  6.0  | 2 LSTM Layer With 64 LSTM Units(optimizer-rmsprop  |       0.9486      |     0.9094
+-------+----------------------------------------------------+-------------------+------------
```

10 Conclusion :-

11 Procedure followed : -

STEP 1 :- Load the data
STEP 2 :- Split dataset into train and test dataset
STEP 3 :- Apply different LSTM architectures with different layers and optimizers
STEP 4 :- Calculate train and test accuracy of each architecture
STEP 5 :- PLot Confusion Matrix For each architecture with the help of seaborn
Step 6 :- Make a table where i mention each architecture with their train and test accurary