In [1]:

```
import zipfile
zip_ref = zipfile.ZipFile("HAR.zip", 'r')
zip_ref.extractall("Human")
zip_ref.close()
```

TASK
1)Do hyperparameter Tunning on lstm units

2)Try multiple Dropout rates

Instead of 1-layer lstm create 2-LSTM layers +large dropouts(here i am using large dropout beacause my chance of overfitting reduces) ¶

HumanActivityRecognition

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

This dataset is collected from 30 persons(referred as subjects in this dataset), performing different activities with a smartphone to their waists. The data is recorded with the help of sensors (accelerometer and Gyroscope) in that smartphone. This experiment was video recorded to label the data manually.

How data was recorded

By using the sensors(Gyroscope and accelerometer) in a smartphone, they have captured '3-axial linear acceleration'(*tAcc-XYZ*) from accelerometer and '3-axial angular velocity' (*tGyro-XYZ*) from Gyroscope with several variations.

> prefix 't' in those metrics denotes time.
>
> suffix 'XYZ' represents 3-axial signals in X , Y, and Z directions.

Feature names

1. These sensor signals are preprocessed by applying noise filters and then sampled in fixed-width windows(sliding windows) of 2.56 seconds each with 50% overlap. ie., each window has 128 readings.
2. From Each window, a feature vector was obtianed by calculating variables from the time and frequency domain.

> In our dataset, each datapoint represents a window with different readings

3. The accelertion signal was saperated into Body and Gravity acceleration signals(***tBodyAcc-XYZ*** and ***tGravityAcc-XYZ***) using some low pass filter with corner frequecy of 0.3Hz.
4. After that, the body linear acceleration and angular velocity were derived in time to obtian *jerk signals* (***tBodyAccJerk-XYZ*** and ***tBodyGyroJerk-XYZ***).
5. The magnitude of these 3-dimensional signals were calculated using the Euclidian norm. This magnitudes are represented as features with names like *tBodyAccMag*, *tGravityAccMag*, *tBodyAccJerkMag*, *tBodyGyroMag* and *tBodyGyroJerkMag*.
6. Finally, We've got frequency domain signals from some of the available signals by applying a FFT (Fast Fourier Transform). These signals obtained were labeled with ***prefix 'f'*** just like original signals with ***prefix 't'***. These signals are labeled as ***fBodyAcc-XYZ***, ***fBodyGyroMag*** etc.,.
7. These are the signals that we got so far.
    - tBodyAcc-XYZ
    - tGravityAcc-XYZ
    - tBodyAccJerk-XYZ
    - tBodyGyro-XYZ
    - tBodyGyroJerk-XYZ
    - tBodyAccMag
    - tGravityAccMag
    - tBodyAccJerkMag
    - tBodyGyroMag
    - tBodyGyroJerkMag
    - fBodyAcc-XYZ
    - fBodyAccJerk-XYZ
    - fBodyGyro-XYZ
    - fBodyAccMag
    - fBodyAccJerkMag
    - fBodyGyroMag
    - fBodyGyroJerkMag
8. We can esitmate some set of variables from the above signals. ie., We will estimate the following properties on each and every signal that we recoreded so far.
    - ***mean()***: Mean value
    - ***std()***: Standard deviation
    - ***mad()***: Median absolute deviation
    - ***max()***: Largest value in array
    - ***min()***: Smallest value in array
    - ***sma()***: Signal magnitude area
    - ***energy()***: Energy measure. Sum of the squares divided by the number of values.
    - ***iqr()***: Interquartile range
    - ***entropy()***: Signal entropy
    - ***arCoeff()***: Autorregresion coefficients with Burg order equal to 4
    - ***correlation()***: correlation coefficient between two signals
    - ***maxInds()***: index of the frequency component with largest magnitude
    - ***meanFreq()***: Weighted average of the frequency components to obtain a mean frequency
    - ***skewness()***: skewness of the frequency domain signal
    - ***kurtosis()***: kurtosis of the frequency domain signal
    - ***bandsEnergy()***: Energy of a frequency interval within the 64 bins of the FFT of each window.
    - ***angle()***: Angle between to vectors.

9. We can obtain some other vectors by taking the average of signals in a single window sample. These are used on the angle() variable' `

    - gravityMean
    - tBodyAccMean
    - tBodyAccJerkMean
    - tBodyGyroMean
    - tBodyGyroJerkMean

Y_Labels(Encoded)

- In the dataset, Y_labels are represented as numbers from 1 to 6 as their identifiers.
    - WALKING as **1**
    - WALKING_UPSTAIRS as **2**
    - WALKING_DOWNSTAIRS as **3**
    - SITTING as **4**
    - STANDING as **5**
    - LAYING as **6**

Train and test data were saperated

- The readings from ***70%*** of the volunteers were taken as ***trianing data*** and remaining ***30%*** subjects recordings were taken for ***test data***

Data

- All the data is present in 'UCI_HAR_dataset/' folder in present working directory.
    - Feature names are present in 'UCI_HAR_dataset/features.txt'
    - ***Train Data***
        - 'UCI_HAR_dataset/train/X_train.txt'
        - 'UCI_HAR_dataset/train/subject_train.txt'
        - 'UCI_HAR_dataset/train/y_train.txt'
    - ***Test Data***
        - 'UCI_HAR_dataset/test/X_test.txt'
        - 'UCI_HAR_dataset/test/subject_test.txt'
        - 'UCI_HAR_dataset/test/y_test.txt'

Data Size :

> 27 MB

Quick overview of the dataset :

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

    1. Walking
    2. WalkingUpstairs
    3. WalkingDownstairs

4. Standing
5. Sitting
6. Lying.

- Readings are divided into a window of 2.56 seconds with 50% overlapping.
- Accelerometer readings are divided into gravity acceleration and body acceleration readings, which has x,y and z components each.
- Gyroscope readings are the measure of angular velocities which has x,y and z components.
- Jerk signals are calculated for BodyAcceleration readings.
- Fourier Transforms are made on the above time readings to obtain frequency readings.
- Now, on all the base signal readings., mean, max, mad, sma, arcoefficient, engerybands,entropy etc., are calculated for each window.
- We get a feature vector of 561 features and these features are given in the dataset.
- Each window of readings is a datapoint of 561 features.

Problem Framework

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

Problem Statement

- Given a new datapoint we have to predict the Activity

In [2]:

```
import warnings
warnings.filterwarnings("ignore")

#Importing required libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE
from prettytable import PrettyTable
from sklearn.metrics import confusion_matrix
from keras.optimizers import Adam,RMSprop,SGD
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

```
Using TensorFlow backend.
```

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'])
```

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'Human/HAR/UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.
        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]:

```
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'Human/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]

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

In [7]:

```
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 [8]:

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

In [9]:

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

In [10]:

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

In [11]:

```
# Initializing parameters
epochs = 30
batch_size = 100
n_hidden = 32
```

In [12]:

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

In [13]:

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

In [14]:

```
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 [15]:

```
#utility function for getting the best parameters
def best_hyperparameters(n_units,dropout_rate):
    #Initiliazing the sequential model
    model = Sequential()
    #Configuring the parameters
    model.add(LSTM(n_units, input_shape=(timesteps, input_dim)))

    #Adding a dropout layer
    model.add(Dropout(dropout_rate))
    # Adding a dense output layer with softmax activation
    model.add(Dense(n_classes, activation='softmax'))
    print(model.summary())

    model.compile(loss='categorical_crossentropy', metrics=['accuracy'], optimizer= "rmsprc
    return model
```

In [16]:

```
#https://chrisalbon.com/deep_learning/keras/tuning_neural_network_hyperparameters/
#batch size means you can’t pass the entire dataset into the neural net at once. So, you di
n_units = [32,64,128]
dropout_rate = [0.3,0.4,0.5]

# Create hyperparameter options
hyperparameters = dict(n_units=n_units,dropout_rate=dropout_rate)

#Wrap Function In KerasClassifier
model1 = KerasClassifier(build_fn=best_hyperparameters,epochs = 30,batch_size = 64, verbose

# Create grid search
grid = GridSearchCV(estimator=model1, param_grid=hyperparameters)

# Fit grid search
grid_result = grid.fit(X_train, Y_train,validation_data=(X_test, Y_test))
print("Best accuracy : %f using %s" % (grid_result.best_score_, grid_result.best_params_))
```

```
WARNING:tensorflow:From /home/saikrishna6680/.local/lib/python3.7/site-pac
kages/tensorflow/python/framework/op_def_library.py:263: colocate_with (fr
om tensorflow.python.framework.ops) is deprecated and will be removed in a
future version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /home/saikrishna6680/.local/lib/python3.7/site-pac
kages/keras/backend/tensorflow_backend.py:3445: calling dropout (from tens
orflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed
in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1
- keep_prob`.
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 32)                5376
_________________________________________________________________
dropout_1 (Dropout)          (None, 32)                0
```

In [17]:

```
# summarize results
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.929679 using {'dropout_rate': 0.3, 'n_units': 128}
0.904244 (0.007861) with: {'dropout_rate': 0.3, 'n_units': 32}
0.910637 (0.016470) with: {'dropout_rate': 0.3, 'n_units': 64}
0.929679 (0.017983) with: {'dropout_rate': 0.3, 'n_units': 128}
0.876088 (0.017744) with: {'dropout_rate': 0.4, 'n_units': 32}
0.922334 (0.012251) with: {'dropout_rate': 0.4, 'n_units': 64}
0.919342 (0.009873) with: {'dropout_rate': 0.4, 'n_units': 128}
0.903292 (0.021721) with: {'dropout_rate': 0.5, 'n_units': 32}
0.921518 (0.011848) with: {'dropout_rate': 0.5, 'n_units': 64}
0.908052 (0.016542) with: {'dropout_rate': 0.5, 'n_units': 128}
```

LSTM with Best Hyperparameters

In [18]:

```
# Initializing paramtrers
epochs = 30
batch_size = 64
```

In [19]:

```
from keras.layers.normalization import BatchNormalization

# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(128, input_shape=(timesteps, input_dim), kernel_initializer='uniform'))
#Adding Batch Normalization
model.add(BatchNormalization())
# Adding a dropout layer
model.add(Dropout(0.3))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, kernel_initializer='uniform', activation='sigmoid'))

model.summary()

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

#Fitting the data to the model
history = model.fit(X_train, Y_train, nb_epoch=epochs, batch_size=batch_size, validation_da
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_29 (LSTM)               (None, 128)               70656     
_________________________________________________________________
batch_normalization_1 (Batch (None, 128)               512       
_________________________________________________________________
dropout_29 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_29 (Dense)             (None, 6)                 774       
=================================================================
Total params: 71,942
Trainable params: 71,686
Non-trainable params: 256
_________________________________________________________________

/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:20: UserWar
ning: The `nb_epoch` argument in `fit` has been renamed `epochs`.

Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 42s 6ms/step - loss: 1.2016 - a
cc: 0.4874 - val_loss: 1.2702 - val_acc: 0.4625
Epoch 2/30
7352/7352 [==============================] - 35s 5ms/step - loss: 1.0685 - a
cc: 0.5241 - val_loss: 1.0719 - val_acc: 0.6135
Epoch 3/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.8503 - a
cc: 0.6068 - val_loss: 0.7873 - val_acc: 0.5830
Epoch 4/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.8163 - a
cc: 0.5839 - val_loss: 1.3117 - val_acc: 0.4228
Epoch 5/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.8927 - a
cc: 0.5691 - val_loss: 0.8887 - val_acc: 0.5494
Epoch 6/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.7200 - a
cc: 0.6443 - val_loss: 0.7481 - val_acc: 0.6094
```

```
Epoch 7/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.6538 - a
cc: 0.6542 - val_loss: 0.6921 - val_acc: 0.6166
Epoch 8/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.6415 - a
cc: 0.6492 - val_loss: 0.7425 - val_acc: 0.5914
Epoch 9/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.5545 - a
cc: 0.6579 - val_loss: 1.0900 - val_acc: 0.5317
Epoch 10/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.5278 - a
cc: 0.6575 - val_loss: 0.5643 - val_acc: 0.6203
Epoch 11/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.5306 - a
cc: 0.6547 - val_loss: 0.6829 - val_acc: 0.6267
Epoch 12/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.4674 - a
cc: 0.6579 - val_loss: 0.7849 - val_acc: 0.6267
Epoch 13/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.4460 - a
cc: 0.6608 - val_loss: 0.6051 - val_acc: 0.6230
Epoch 14/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.4229 - a
cc: 0.6654 - val_loss: 0.5551 - val_acc: 0.6335
Epoch 15/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.4198 - a
cc: 0.6693 - val_loss: 0.6254 - val_acc: 0.6149
Epoch 16/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.4007 - a
cc: 0.6756 - val_loss: 0.5361 - val_acc: 0.6461
Epoch 17/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.3974 - a
cc: 0.7021 - val_loss: 0.4568 - val_acc: 0.7041
Epoch 18/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.3582 - a
cc: 0.7703 - val_loss: 0.5199 - val_acc: 0.7292
Epoch 19/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.3254 - a
cc: 0.7968 - val_loss: 0.3935 - val_acc: 0.7730
Epoch 20/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.3028 - a
cc: 0.8064 - val_loss: 0.4288 - val_acc: 0.7771
Epoch 21/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2750 - a
cc: 0.8073 - val_loss: 0.3722 - val_acc: 0.7737
Epoch 22/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2322 - a
cc: 0.8135 - val_loss: 0.3566 - val_acc: 0.7713
Epoch 23/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2254 - a
cc: 0.8301 - val_loss: 0.3466 - val_acc: 0.7774
Epoch 24/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2246 - a
cc: 0.8335 - val_loss: 0.3595 - val_acc: 0.8297
Epoch 25/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2270 - a
cc: 0.8575 - val_loss: 0.3377 - val_acc: 0.8205
Epoch 26/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2212 - a
cc: 0.8720 - val_loss: 0.3686 - val_acc: 0.8582
Epoch 27/30
```

```
7352/7352 [==============================] - 35s 5ms/step - loss: 0.2281 - a
cc: 0.8974 - val_loss: 0.3942 - val_acc: 0.8364
Epoch 28/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.1879 - a
cc: 0.9161 - val_loss: 0.3491 - val_acc: 0.9080
Epoch 29/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.1269 - a
cc: 0.9418 - val_loss: 0.2293 - val_acc: 0.9189
Epoch 30/30
7352/7352 [==============================] - 35s 5ms/step - loss: 0.1279 - a
cc: 0.9419 - val_loss: 0.2743 - val_acc: 0.9091
```

In [ ]:

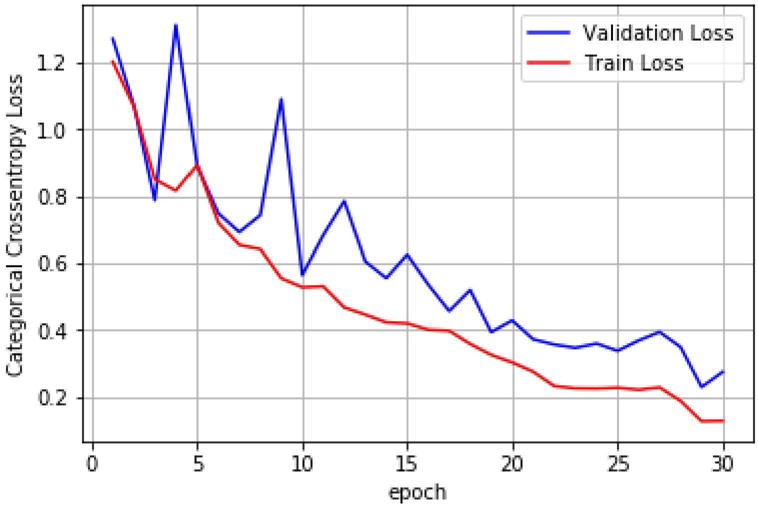
```
<h3> observation:- </h3>

my train loss is 0.127 and my validation loss 0.2743 it means my validation loss is slightl
```

In [20]:

```
import matplotlib.pyplot as plt
import numpy as np
import time
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid(True)
    fig.canvas.draw()
```

In [21]:

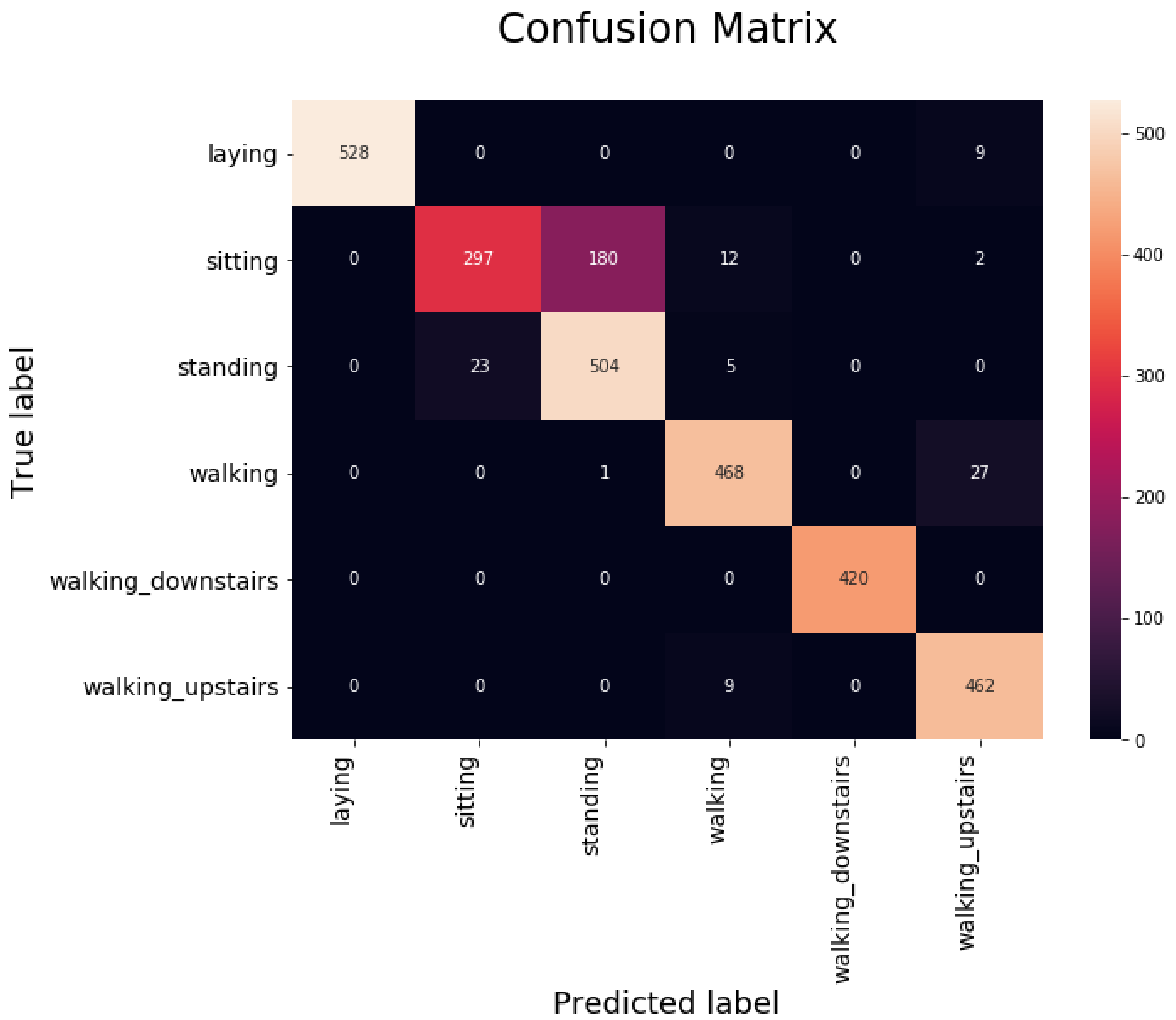
```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,epochs+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



In [22]:

```
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))

# 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(model.predict(X_test), axis=1)]

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_upstai
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, colum
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', fontsi
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', fonts
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.274255
Test Accuracy: 90.906006%
```



observation :-

my model is saying that 180 members standing are predicting as sitting these 180 members are misclassified

[2] LSTM with 2 layers with batch Normalization

In [28]:

```
# Initializing parameters
epochs = 30
batch_size = 64


# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(128,return_sequences=True, input_shape=(timesteps, input_dim)))
#Adding Batch Normalization
model.add(BatchNormalization())
# Adding a dropout layer
model.add(Dropout(0.9))

# Configuring the parameters
model.add(LSTM(128))
#Adding Batch Normalization
model.add(BatchNormalization())
# Adding a dropout layer
model.add(Dropout(0.9))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_32 (LSTM)               (None, 128, 128)          70656     
_________________________________________________________________
batch_normalization_3 (Batch (None, 128, 128)          512       
_________________________________________________________________
dropout_32 (Dropout)         (None, 128, 128)          0         
_________________________________________________________________
lstm_33 (LSTM)               (None, 128)               131584    
_________________________________________________________________
batch_normalization_4 (Batch (None, 128)               512       
_________________________________________________________________
dropout_33 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_31 (Dense)             (None, 6)                 774       
=================================================================
Total params: 204,038
Trainable params: 203,526
Non-trainable params: 512
_________________________________________________________________
None
```

In [29]:

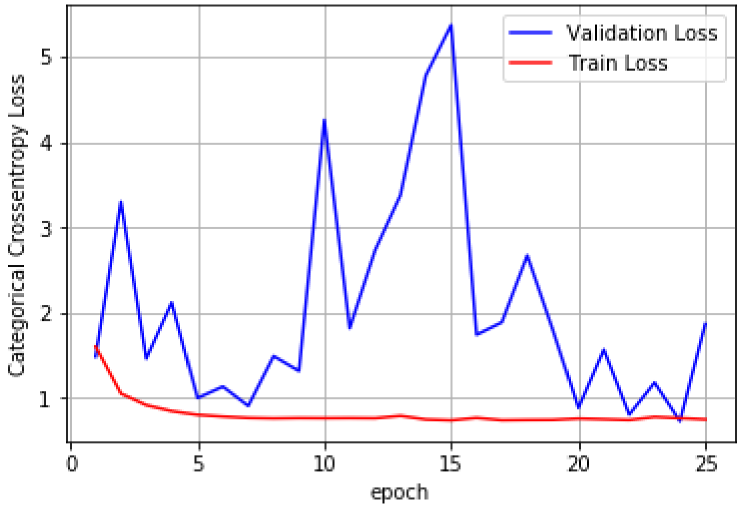
```
# Compiling the model
model.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'])

# Training the model
history = model.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_test),
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 99s 13ms/step - loss: 1.6037 -
acc: 0.4294 - val_loss: 1.4856 - val_acc: 0.4927
Epoch 2/30
7352/7352 [==============================] - 91s 12ms/step - loss: 1.0546 -
acc: 0.5603 - val_loss: 3.2995 - val_acc: 0.4961
Epoch 3/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.9186 -
acc: 0.5749 - val_loss: 1.4623 - val_acc: 0.5056
Epoch 4/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.8486 -
acc: 0.5834 - val_loss: 2.1186 - val_acc: 0.5049
Epoch 5/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.8047 -
acc: 0.5781 - val_loss: 1.0014 - val_acc: 0.5908
Epoch 6/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7839 -
acc: 0.5547 - val_loss: 1.1357 - val_acc: 0.5100
Epoch 7/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7683 -
acc: 0.5413 - val_loss: 0.9090 - val_acc: 0.5012
Epoch 8/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7632 -
acc: 0.5362 - val_loss: 1.4925 - val_acc: 0.4913
Epoch 9/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7667 -
acc: 0.5328 - val_loss: 1.3170 - val_acc: 0.4835
Epoch 10/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7653 -
acc: 0.5326 - val_loss: 4.2584 - val_acc: 0.3838
Epoch 11/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7665 -
acc: 0.5337 - val_loss: 1.8178 - val_acc: 0.4734
Epoch 12/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7649 -
acc: 0.5381 - val_loss: 2.7309 - val_acc: 0.4079
Epoch 13/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7929 -
acc: 0.5352 - val_loss: 3.3772 - val_acc: 0.4041
Epoch 14/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7500 -
acc: 0.5442 - val_loss: 4.7784 - val_acc: 0.3556
Epoch 15/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7404 -
acc: 0.5373 - val_loss: 5.3690 - val_acc: 0.3563
Epoch 16/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7691 -
acc: 0.5336 - val_loss: 1.7414 - val_acc: 0.4476
Epoch 17/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7414 -
acc: 0.5388 - val_loss: 1.8884 - val_acc: 0.4734
Epoch 18/30
```

```
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7444 -
acc: 0.5341 - val_loss: 2.6718 - val_acc: 0.4404
Epoch 19/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7456 -
acc: 0.5370 - val_loss: 1.8042 - val_acc: 0.4690
Epoch 20/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.7606 -
acc: 0.5307 - val_loss: 0.8873 - val_acc: 0.5025
Epoch 21/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.7527 -
acc: 0.5309 - val_loss: 1.5668 - val_acc: 0.4964
Epoch 22/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7440 -
acc: 0.5288 - val_loss: 0.8069 - val_acc: 0.5063
Epoch 23/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.7799 -
acc: 0.5407 - val_loss: 1.1817 - val_acc: 0.5063
Epoch 24/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.7657 -
acc: 0.5369 - val_loss: 0.7303 - val_acc: 0.5222
Epoch 25/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.7508 -
acc: 0.5373 - val_loss: 1.8674 - val_acc: 0.5005
Epoch 26/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.5044 - val_loss: nan - val_acc: 0.1683
Epoch 27/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 28/30
7352/7352 [==============================] - 92s 13ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 29/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 30/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
```

In [30]:

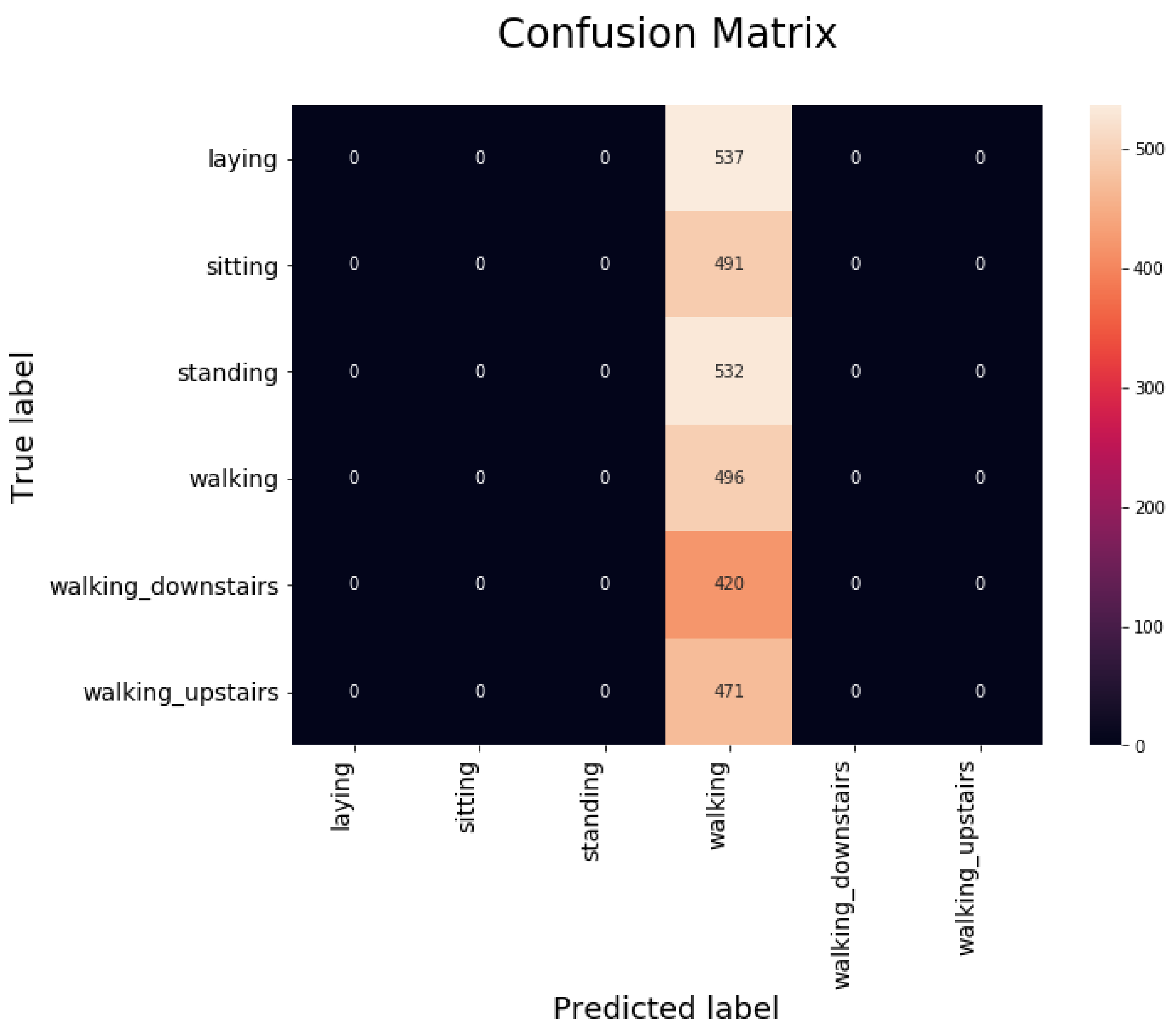
```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,epochs+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



In [31]:

```
# 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))

# 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(model.predict(X_test), axis=1)]

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_upstai
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, colum
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', fontsi
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', fonts
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: nan
Test Accuracy: 16.830675%
```



observation :-

My all points are missclassified here.

496 points which belongs to walking are correctly classified remaining all points are missclassified

With Batch Normalization only one layer

In [23]:

```
# Initializing parameters
epochs = 30
batch_size = 64


# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(128,return_sequences=True, input_shape=(timesteps, input_dim)))
#Adding Batch Normalization
model.add(BatchNormalization())
# Adding a dropout layer
model.add(Dropout(0.9))

# Configuring the parameters
model.add(LSTM(128))
# Adding a dropout layer
model.add(Dropout(0.9))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_30 (LSTM)               (None, 128, 128)          70656     
_________________________________________________________________
batch_normalization_2 (Batch (None, 128, 128)          512       
_________________________________________________________________
dropout_30 (Dropout)         (None, 128, 128)          0         
_________________________________________________________________
lstm_31 (LSTM)               (None, 128)               131584    
_________________________________________________________________
dropout_31 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_30 (Dense)             (None, 6)                 774       
=================================================================
Total params: 203,526
Trainable params: 203,270
Non-trainable params: 256
_________________________________________________________________
None
```

In [24]:

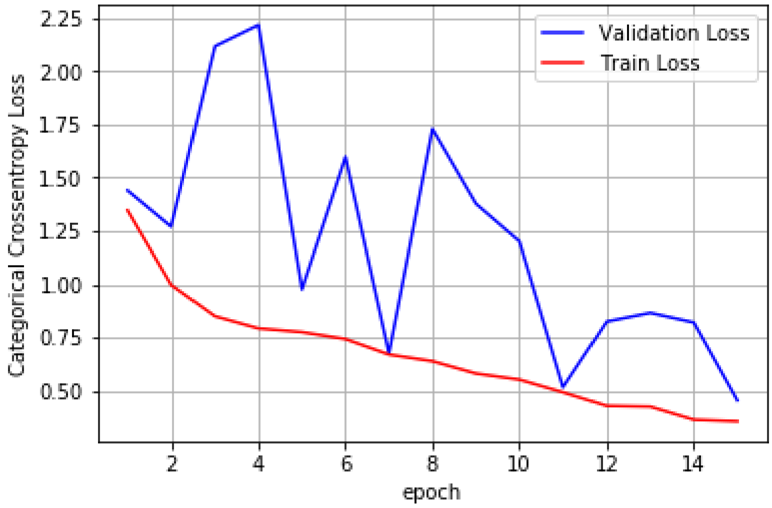
```
# Compiling the model
model.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'])

# Training the model
history = model.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_test),
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 99s 13ms/step - loss: 1.3459 -
acc: 0.4752 - val_loss: 1.4392 - val_acc: 0.4330
Epoch 2/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.9969 -
acc: 0.6011 - val_loss: 1.2699 - val_acc: 0.5789
Epoch 3/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.8500 -
acc: 0.6284 - val_loss: 2.1175 - val_acc: 0.4795
Epoch 4/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.7927 -
acc: 0.6396 - val_loss: 2.2173 - val_acc: 0.5243
Epoch 5/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.7752 -
acc: 0.6472 - val_loss: 0.9760 - val_acc: 0.6030
Epoch 6/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.7427 -
acc: 0.6725 - val_loss: 1.5975 - val_acc: 0.4886
Epoch 7/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.6700 -
acc: 0.6991 - val_loss: 0.6742 - val_acc: 0.7160
Epoch 8/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.6388 -
acc: 0.7327 - val_loss: 1.7286 - val_acc: 0.6125
Epoch 9/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.5809 -
acc: 0.7705 - val_loss: 1.3772 - val_acc: 0.6926
Epoch 10/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.5522 -
acc: 0.7942 - val_loss: 1.2010 - val_acc: 0.7095
Epoch 11/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.4925 -
acc: 0.8281 - val_loss: 0.5163 - val_acc: 0.8653
Epoch 12/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.4289 -
acc: 0.8662 - val_loss: 0.8249 - val_acc: 0.8134
Epoch 13/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.4252 -
acc: 0.8692 - val_loss: 0.8657 - val_acc: 0.8151
Epoch 14/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.3639 -
acc: 0.8883 - val_loss: 0.8204 - val_acc: 0.8178
Epoch 15/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.3563 -
acc: 0.8896 - val_loss: 0.4548 - val_acc: 0.8819
Epoch 16/30
7352/7352 [==============================] - 93s 13ms/step - loss: nan - ac
c: 0.6084 - val_loss: nan - val_acc: 0.1683
Epoch 17/30
7352/7352 [==============================] - 93s 13ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 18/30
```

```
7352/7352 [==============================] - 91s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 19/30
7352/7352 [==============================] - 92s 13ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 20/30
7352/7352 [==============================] - 91s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 21/30
7352/7352 [==============================] - 91s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 22/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 23/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 24/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 25/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 26/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 27/30
7352/7352 [==============================] - 91s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 28/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 29/30
7352/7352 [==============================] - 92s 12ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
Epoch 30/30
7352/7352 [==============================] - 92s 13ms/step - loss: nan - ac
c: 0.1668 - val_loss: nan - val_acc: 0.1683
```

In [25]:

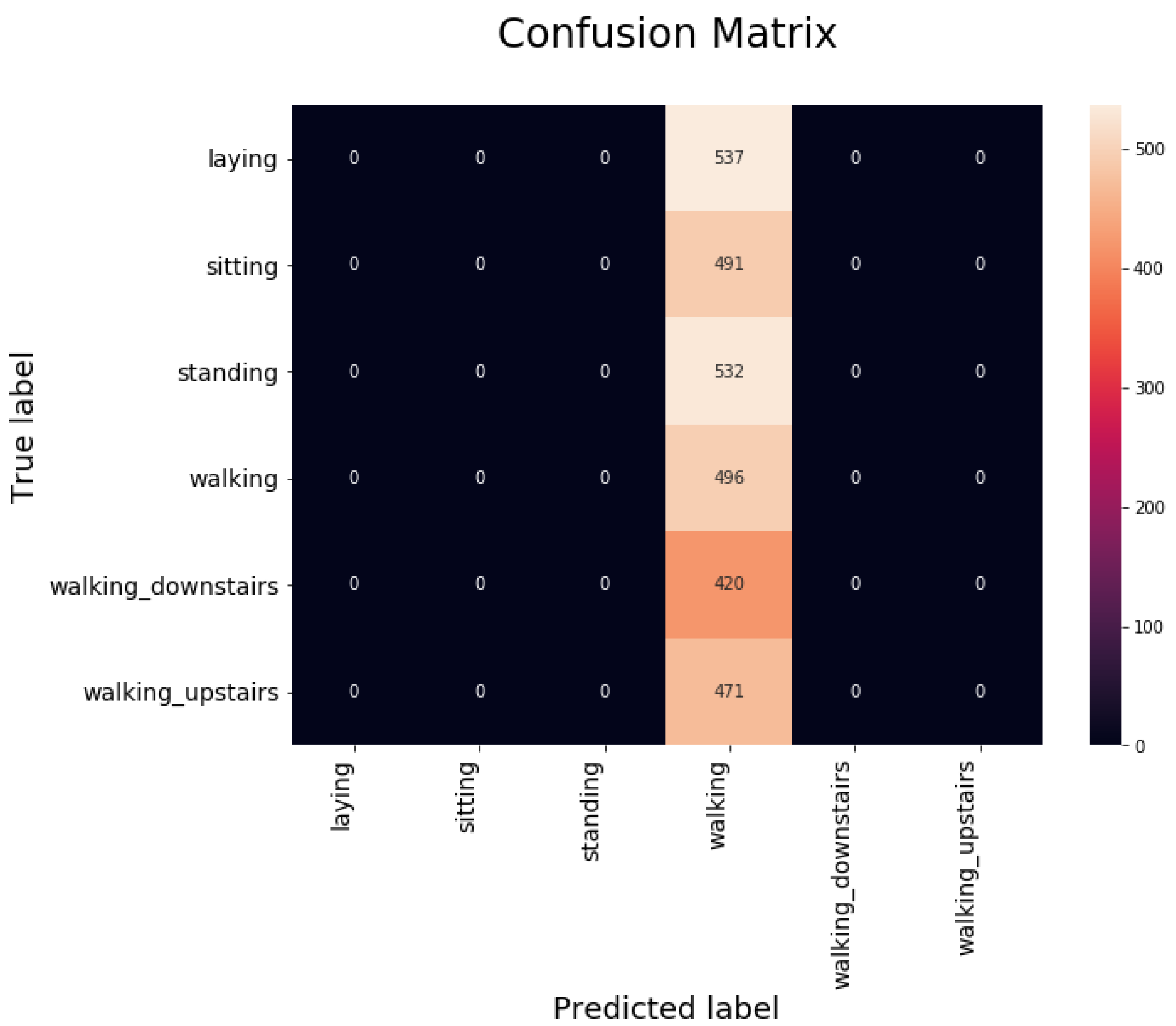
```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,epochs+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



In [26]:

```
# 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))

# 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(model.predict(X_test), axis=1)]

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_upstai
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, colum
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', fontsi
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', fonts
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: nan
Test Accuracy: 16.830675%
```



observation :-

My all points are missclassified here.

496 points which belongs to walking are correctly classified remaining all points are missclassified

Without Batch Normalization

In [32]:

```
# Initializing parameters
epochs = 30
batch_size = 64


# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(128,return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.9))

# Configuring the parameters
model.add(LSTM(128))
# Adding a dropout layer
model.add(Dropout(0.9))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_34 (LSTM)               (None, 128, 128)          70656     
_________________________________________________________________
dropout_34 (Dropout)         (None, 128, 128)          0         
_________________________________________________________________
lstm_35 (LSTM)               (None, 128)               131584    
_________________________________________________________________
dropout_35 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_32 (Dense)             (None, 6)                 774       
=================================================================
Total params: 203,014
Trainable params: 203,014
Non-trainable params: 0
_________________________________________________________________
None
```

In [33]:

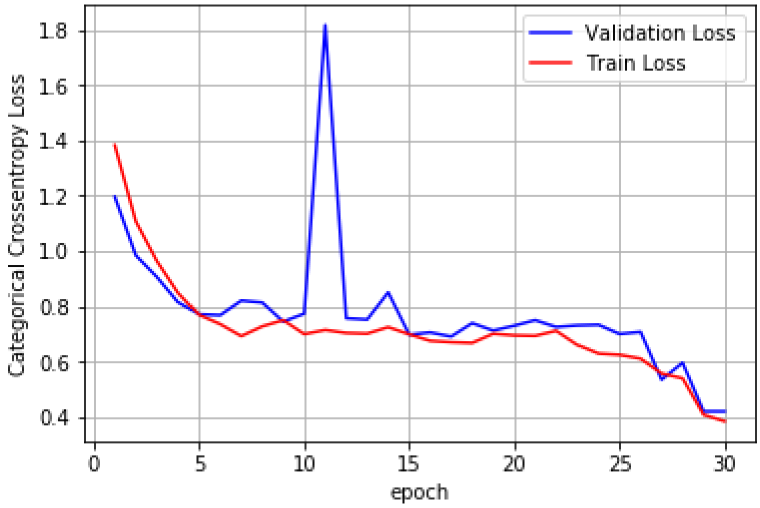
```
# Compiling the model
model.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['accuracy'])

# Training the model
history = model.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test, Y_test),
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 97s 13ms/step - loss: 1.3822 -
acc: 0.4085 - val_loss: 1.1957 - val_acc: 0.5283
Epoch 2/30
7352/7352 [==============================] - 89s 12ms/step - loss: 1.1073 -
acc: 0.5337 - val_loss: 0.9843 - val_acc: 0.6071
Epoch 3/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.9640 -
acc: 0.5702 - val_loss: 0.9063 - val_acc: 0.5100
Epoch 4/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.8492 -
acc: 0.5885 - val_loss: 0.8155 - val_acc: 0.5857
Epoch 5/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.7691 -
acc: 0.6236 - val_loss: 0.7711 - val_acc: 0.6132
Epoch 6/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7355 -
acc: 0.6306 - val_loss: 0.7680 - val_acc: 0.5952
Epoch 7/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6923 -
acc: 0.6402 - val_loss: 0.8207 - val_acc: 0.6047
Epoch 8/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7275 -
acc: 0.6473 - val_loss: 0.8138 - val_acc: 0.5996
Epoch 9/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7502 -
acc: 0.6317 - val_loss: 0.7447 - val_acc: 0.6369
Epoch 10/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6995 -
acc: 0.6461 - val_loss: 0.7735 - val_acc: 0.6308
Epoch 11/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7145 -
acc: 0.6406 - val_loss: 1.8173 - val_acc: 0.4635
Epoch 12/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7036 -
acc: 0.6462 - val_loss: 0.7568 - val_acc: 0.6169
Epoch 13/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7013 -
acc: 0.6542 - val_loss: 0.7522 - val_acc: 0.6254
Epoch 14/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7248 -
acc: 0.6500 - val_loss: 0.8507 - val_acc: 0.5836
Epoch 15/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6989 -
acc: 0.6325 - val_loss: 0.6976 - val_acc: 0.6257
Epoch 16/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6751 -
acc: 0.6576 - val_loss: 0.7056 - val_acc: 0.6267
Epoch 17/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6703 -
acc: 0.6559 - val_loss: 0.6907 - val_acc: 0.6308
Epoch 18/30
```

```
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6676 -
acc: 0.6563 - val_loss: 0.7393 - val_acc: 0.5884
Epoch 19/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7010 -
acc: 0.6473 - val_loss: 0.7125 - val_acc: 0.6278
Epoch 20/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6949 -
acc: 0.6591 - val_loss: 0.7299 - val_acc: 0.6162
Epoch 21/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6933 -
acc: 0.6553 - val_loss: 0.7499 - val_acc: 0.6515
Epoch 22/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.7116 -
acc: 0.6492 - val_loss: 0.7253 - val_acc: 0.6837
Epoch 23/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6605 -
acc: 0.6665 - val_loss: 0.7312 - val_acc: 0.6345
Epoch 24/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6293 -
acc: 0.6778 - val_loss: 0.7331 - val_acc: 0.6637
Epoch 25/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6247 -
acc: 0.7002 - val_loss: 0.7000 - val_acc: 0.6474
Epoch 26/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.6111 -
acc: 0.7429 - val_loss: 0.7074 - val_acc: 0.7099
Epoch 27/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.5573 -
acc: 0.7715 - val_loss: 0.5349 - val_acc: 0.8212
Epoch 28/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.5399 -
acc: 0.8051 - val_loss: 0.5961 - val_acc: 0.8507
Epoch 29/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.4081 -
acc: 0.8633 - val_loss: 0.4202 - val_acc: 0.8734
Epoch 30/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.3845 -
acc: 0.8772 - val_loss: 0.4200 - val_acc: 0.8836
```

In [34]:

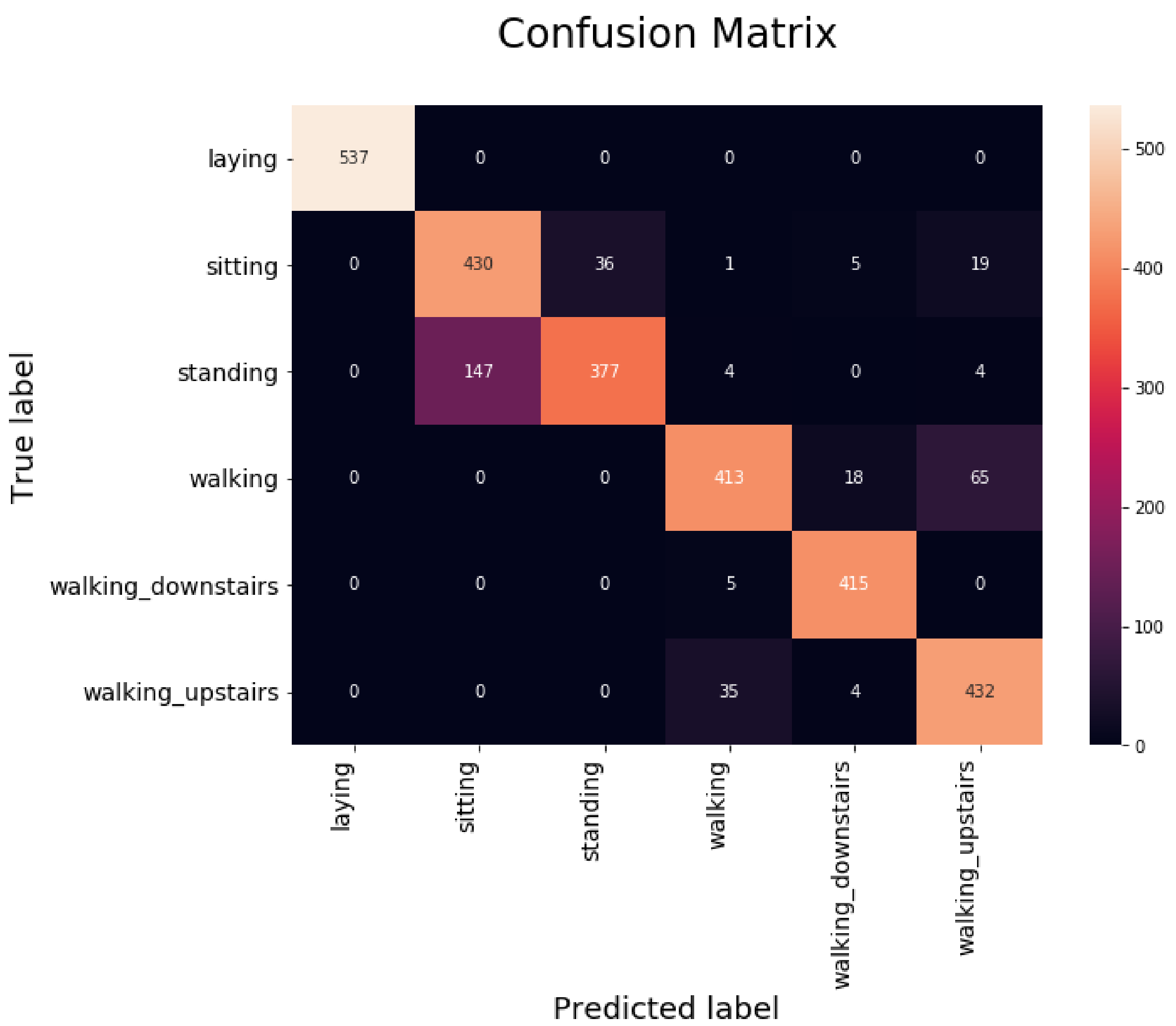
```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,epochs+1))

vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



In [35]:

```
# 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))

# 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(model.predict(X_test), axis=1)]

# Code for drawing seaborn heatmaps
class_names = ['laying','sitting','standing','walking','walking_downstairs','walking_upstai
df_heatmap = pd.DataFrame(confusion_matrix(Y_true, Y_predictions), index=class_names, colum
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', fontsi
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=90, ha='right', fonts
plt.ylabel('True label',size=18)
plt.xlabel('Predicted label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

```
Test Score: 0.420003
Test Accuracy: 88.361045%
```



observation :-

some points are missclassified here.

147 points which belongs to sitting are predicted as standing

36 points which actually belongs to standing predicted as sitting

65 points which actually belongs to walking upstairs predicted as walking

18 points which actually belongs to walkingdownstairs are predicted as walking

Model Performane Table

In [8]:

```
from prettytable import PrettyTable
print("\n Model performance table of LSTM")
x = PrettyTable()
x.field_names=["MODEL","Optimizer", "TRAIN_ACCURACY", "TEST_ACCURACY"]
x.add_row(["\n LSTM layer with 128 LSTM Units with single layer ", "rmsprop",94.19,90.91])
x.add_row(["\n LSTM layer with 128 LSTM Units with batch Normalization", "rmsprop",16.68,16
x.add_row(["\n LSTM layer with 128 LSTM Units only one layer batch Normalization","rmsprop"
x.add_row(["\n LSTM layer with 128 LSTM Units only two without batch Normalization","rmsprc
print(x)
```

```
 Model performance table of LSTM
+-----------------------------------------------------------------------+----
-------+----------------+---------------+
|                                 MODEL                                 | Opt
imizer | TRAIN_ACCURACY | TEST_ACCURACY |
+-----------------------------------------------------------------------+----
-------+----------------+---------------+
|                                                                       |  rm
sprop  |     94.19      |     90.91     |
|            LSTM layer with 128 LSTM Units with single layer           |
|                |               |
|                                                                       |  rm
sprop  |     16.68      |     16.83     |
|         LSTM layer with 128 LSTM Units with batch Normalization       |
|                |               |
|                                                                       |  rm
sprop  |     16.68      |     16.83     |
|    LSTM layer with 128 LSTM Units only one layer batch Normalization  |
|                |               |
|                                                                       |  rm
sprop  |     87.72      |     88.36     |
|   LSTM layer with 128 LSTM Units only two without batch Normalization |
|                |               |
+-----------------------------------------------------------------------+----
-------+----------------+---------------+
```

Conclusion

- This case study describes activity of a human and classify them into one of six classes whether he is WALKING, or WALKING_UPSTAIRS, or WALKING_DOWNSTAIRS,or SITTING, or STANDING, or LAYING.
- 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.
- There are 561 hand engineered features, which are built by domain experts.
- We do data cleaning stage - we checking for duplicate entries,null values,data imbalances.
- We did exploratory data analysis we can conclude moving and stationery activities can be very well seperated from each other.
- We had apply TSNE in order to reduce the dimensionality of the data and visualize them in 2D. where we can seperate maximum no of points.
- we build models by ML Algorithms This gave as an unbelievable accuracy of more than 96% on unseen data. This is pretty good. By looking at all the confusion matrices, we can tell that the model performed fairly well in determining the activities, except that it confuses between sitting and standing for example.
- In the real world, domain-knowledge, EDA and feature-engineering matters most. In this experiment, without a doubt Logistic Regression and Support Vector Machines are clear winners! They have been pretty good in classifying all the 6 classes of data. That too with very high precision and recall values. The individual F1 scores for each of the predicted classes also has very high values.
- In general, the Decision Trees did not perform well. Random Forests and GBDTs did better than Decision Trees. But, both RFs and GBDTs performed poorly as compared to the Logistic Regression and SVM models.
- Decision Tree,Random Forest, GBDT are performing badd hence we ignore Them.
- Now, since we are done with ML tenchinques, let's find out if we can use the raw data to build some deep learning models with better accuracy.

Steps Involved:-

1. Defining Task
2. Importing Libraries
3. Reading Csv file(loading Data)
4. Splitting Data into Train and Test
5. Defining Model (we will define sequential model, adding lstm units,we will add dropout to avoid overfitting model so far we defined model here we implement hyperparameter tunning by these we can achieve good results
6. we do hyperparameter tunning on different parameters like (no of epochs,dropouts,initializer,activation function,etc)

By this we come to know so and so parameters are giving good results without overfitting we choose those parameters and we define our models calculate results like accuracy,precision recall etc

I did hyperparameter tunning on lstm layers and on dropout we can do on all parameters due to less computational power i had limited this

In [ ]:

```

```