HUMAN ACTIVITY RECOGNIZATION

In [569]:

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

In [570]:

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

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

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

Data

In [571]:

```
# 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 [572]:

```
from sklearn.preprocessing import StandardScaler
```

In [573]:

```
# 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():
    signals_data_train = []
    signals_data_test = []

    for signal in SIGNALS:
        filename_train = f'UCI_HAR_Dataset/train/Inertial Signals/{signal}_train.txt'
        df_train =  _read_csv(filename_train)
        # standardizing the data
```

```
        s = StandardScaler()
        df_train_std = s.fit_transform(df_train)
        df_train_std_df = pd.DataFrame(df_train_std)
        filename_test = f'UCI_HAR_Dataset/test/Inertial Signals/{signal}_test.txt'
        df_test =  _read_csv(filename_test)
        df_test_std = s.transform(df_test)
        df_test_std_df = pd.DataFrame(df_test_std)
        signals_data_train.append(df_train_std_df.values)
        signals_data_test.append(df_test_std_df.values)
        # 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)
    final_train = np.transpose(signals_data_train, (1, 2, 0))
    final_test = np.transpose(signals_data_test, (1, 2, 0))

      # 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 final_train, final_test
```

In [574]:

```
def load_y_2class(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]

    # Making Class labels for baseline classifier i.e. for all dynamic activities will be labled a
s 0 and static activities \
    # will be labeled as 1

    y[y==1] = 0
    y[y==2] = 0
    y[y==3] = 0
    y[y==4] = 1
    y[y==5] = 1
    y[y==6] = 1

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

In [575]:

```
def load_y_static(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]
    # intially static activities are labeled as 4,5,6 so we are filtering only static labels
    y_static_con = y>3 # preparing indices for the X_data
    y= y[y_static_con]
    return pd.get_dummies(y).values , y_static_con
```

In [576]:

```
def load_data_static():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """

    y_train,y_train_con  = load_y_static('train')
    y_test,y_test_con =load_y_static('test')
    X_train, X_test = load_signals()
    X_train_static = X_train[y_train_con] # taking only data with static value
    X_test_static = X_test[y_test_con]
```

```python
    return X_train_static, X_test_static, y_train, y_test
```

In [577]:

```python
def load_y_dynamic(subset):
    """
    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]
    y_dynamic_con = y<4
    y= y[y_dynamic_con]
    return pd.get_dummies(y).as_matrix() , y_dynamic_con
```

In [578]:

```python
def load_data_dynamic():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """

    y_train,y_train_con  = load_y_dynamic('train')
    y_test,y_test_con =load_y_dynamic('test')
    X_train, X_test = load_signals()
    X_train_dynamic = X_train[y_train_con] # taking only dynamic activity labeled data
    X_test_dynamic = X_test[y_test_con]


    return X_train_dynamic, X_test_dynamic, y_train, y_test
```

In [579]:

```python
def load_data_2class():
    """
    this is for dividing among static and dynamic
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals()
    y_train, y_test = load_y_2class('train'), load_y_2class('test')

    return X_train, X_test, y_train, y_test
```

In [580]:

```python
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 [581]:

```python
from sklearn.preprocessing import StandardScaler
```

In [582]:

```python
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 [583]:

```
# Loading static data
X_train_static, X_test_static, Y_train_static, Y_test_static = load_data_static()
```

In [584]:

```
print("shape of static x_train data",X_train_static.shape)
print("shape of static x_test data",X_test_static.shape)
print("shape of static y_train data",Y_train_static.shape)
print("shape of static y_test data",Y_test_static.shape)
```

```
shape of static x_train data (4067, 128, 9)
shape of static x_test data (1560, 128, 9)
shape of static y_train data (4067, 3)
shape of static y_test data (1560, 3)
```

In [585]:

```
# Loading dynamic data
X_train_dynamic, X_test_dynamic, Y_train_dynamic, Y_test_dynamic = load_data_dynamic()
```

In [586]:

```
print("shape of dynamic x_train data",X_train_dynamic.shape)
print("shape of dynamic x_test data",X_test_dynamic.shape)
print("shape of dynamic y_train data",Y_train_dynamic.shape)
print("shape of dynamic y_test data",Y_test_dynamic.shape)
```

```
shape of dynamic x_train data (3285, 128, 9)
shape of dynamic x_test data (1387, 128, 9)
shape of dynamic y_train data (3285, 3)
shape of dynamic y_test data (1387, 3)
```

In [587]:

```
# Loading the train and test whole data labeled as 0 and 1 for binary classification
X_train_2, X_test_2, Y_train_2, Y_test_2 = load_data_2class()
```

In [588]:

```
Y_test_2.shape
```

Out[588]:

```
(2947, 2)
```

In [589]:

```
# Loading the train and test whole data labeled as 1 to 6 for final classification
X_train, X_test, Y_train, Y_test = load_data()
```

In [590]:

```
# Importing tensorflow
import warnings
warnings.filterwarnings("ignore")
np.random.seed(42)
import tensorflow as tf
tf.compat.v1.set_random_seed(42)
```

In [591]:

```
# Configuring a session
session_conf = tf.compat.v1.ConfigProto()
```

In [592]:

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

In [593]:

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

In [594]:

```
# Initializing parameters
epochs = 20
batch_size = 32
```

In [595]:

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

In [596]:

```
X_train.shape
```

Out[596]:

```
(7352, 128, 9)
```

In [597]:

```
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))
print(n_classes)
```

```
128
9
7352
6
```

In [598]:

```
Y_train.shape
```

Out[598]:

```
(7352, 6)
```

- Defining the Architecture of LSTM

MODEL 1 WITH 256 LSTM UNITS AND DROPOUT = 0.5

In [599]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(256, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.7))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_3 (LSTM)                (None, 256)               272384    
_________________________________________________________________
dropout_33 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_64 (Dense)             (None, 6)                 1542      
=================================================================
Total params: 273,926
Trainable params: 273,926
Non-trainable params: 0
_________________________________________________________________
```

In [600]:

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

In [601]:

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

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 247s 34ms/step - loss: 1.0109 - acc: 0.5590 - val_los
s: 0.8028 - val_acc: 0.5589
Epoch 2/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.6508 - acc: 0.7111 - val_los
s: 0.6791 - val_acc: 0.7082
Epoch 3/20
7352/7352 [==============================] - 250s 34ms/step - loss: 0.3603 - acc: 0.8670 - val_los
s: 0.2927 - val_acc: 0.8921
Epoch 4/20
7352/7352 [==============================] - 248s 34ms/step - loss: 0.2136 - acc: 0.9248 - val_los
s: 0.3399 - val_acc: 0.9067
Epoch 5/20
7352/7352 [==============================] - 252s 34ms/step - loss: 0.1842 - acc: 0.9327 - val_los
s: 0.2983 - val_acc: 0.9158
Epoch 6/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1626 - acc: 0.9412 - val_los
s: 0.2658 - val_acc: 0.9152
Epoch 7/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.1526 - acc: 0.9426 - val_los
s: 0.2652 - val_acc: 0.9125
Epoch 8/20
7352/7352 [==============================] - 309s 42ms/step - loss: 0.1654 - acc: 0.9423 - val_los
s: 0.3396 - val_acc: 0.9186
Epoch 9/20
7352/7352 [==============================] - 343s 47ms/step - loss: 0.1361 - acc: 0.9482 - val_los
s: 0.3568 - val_acc: 0.9135
Epoch 10/20
7352/7352 [==============================] - 302s 41ms/step - loss: 0.1411 - acc: 0.9486 - val_los
s: 0.2813 - val_acc: 0.9186
Epoch 11/20
```

```
7352/7352 [==============================] - 250s 34ms/step - loss: 0.1313 - acc: 0.9493 - val_los
s: 0.3014 - val_acc: 0.9152
Epoch 12/20
7352/7352 [==============================] - 252s 34ms/step - loss: 0.1361 - acc: 0.9487 - val_los
s: 0.3272 - val_acc: 0.9023
Epoch 13/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.1233 - acc: 0.9512 - val_los
s: 0.3753 - val_acc: 0.9125
Epoch 14/20
7352/7352 [==============================] - 263s 36ms/step - loss: 0.1332 - acc: 0.9493 - val_los
s: 0.3809 - val_acc: 0.9023
Epoch 15/20
7352/7352 [==============================] - 272s 37ms/step - loss: 0.1225 - acc: 0.9491 - val_los
s: 0.3146 - val_acc: 0.8968
Epoch 16/20
7352/7352 [==============================] - 275s 37ms/step - loss: 0.1396 - acc: 0.9437 - val_los
s: 0.3089 - val_acc: 0.9057
Epoch 17/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.1364 - acc: 0.9471 - val_los
s: 0.2736 - val_acc: 0.9321
Epoch 18/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.1260 - acc: 0.9512 - val_los
s: 0.4522 - val_acc: 0.9226
Epoch 19/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.1355 - acc: 0.9527 - val_los
s: 0.5346 - val_acc: 0.9091
Epoch 20/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.1160 - acc: 0.9548 - val_los
s: 0.4181 - val_acc: 0.9172
```

Out[601]:

```
<keras.callbacks.History at 0x14f0107b8d0>
```

In [602]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 537        0         0        0                   0
SITTING                  0      365       123        0                   0
STANDING                 0       53       476        3                   0
WALKING                  0        0         1      469                  26
WALKING_DOWNSTAIRS       0        0         0        2                 408
WALKING_UPSTAIRS         0        1         1        2                  19

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            3
STANDING                           0
WALKING                            0
WALKING_DOWNSTAIRS                10
WALKING_UPSTAIRS                 448
```

In [603]:

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

```
2947/2947 [==============================] - 31s 11ms/step
```

In [604]:

```python
score
```

Out[604]:

```
[0.41806976127311524, 0.9172039362063115]
```

getting test accuraccy 0.925

MODEL 2 TRY CNN LAYERS

In [605]:

```
from keras.layers import Conv1D, Conv2D
from keras.layers import MaxPooling1D
from keras.layers import Dense, Activation, Flatten
from keras.layers import TimeDistributed
from hyperas.distributions import uniform , choice
from keras.layers.normalization import BatchNormalization
```

In [608]:

```
model = Sequential()
model.add(Conv1D(filters=128, kernel_size=7,activation='relu',
                kernel_regularizer=regularizers.l2(0.0007),input_shape=(128,9)))

model.add(Conv1D(filters=32, kernel_size=5, activation='relu'))
model.add(Dropout(0.6))
model.add(MaxPooling1D(pool_size=5))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(6, activation='softmax'))
```

In [609]:

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

In [610]:

```
# Training the model
history=model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=30)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 17s 2ms/step - loss: 0.3447 - acc: 0.8765 - val_loss:
0.3057 - val_acc: 0.9196
Epoch 2/30
7352/7352 [==============================] - 12s 2ms/step - loss: 0.1457 - acc: 0.9468 - val_loss:
0.2750 - val_acc: 0.9165
Epoch 3/30
7352/7352 [==============================] - 12s 2ms/step - loss: 0.1177 - acc: 0.9539 - val_loss:
0.2717 - val_acc: 0.9094
Epoch 4/30
7352/7352 [==============================] - 12s 2ms/step - loss: 0.1210 - acc: 0.9585 - val_loss:
0.2908 - val_acc: 0.9172
Epoch 5/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.1129 - acc: 0.9608 - val_loss:
0.3173 - val_acc: 0.9199
Epoch 6/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.1027 - acc: 0.9646 - val_loss:
0.2687 - val_acc: 0.9182
Epoch 7/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0895 - acc: 0.9693 - val_loss:
0.3473 - val_acc: 0.9152
Epoch 8/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0874 - acc: 0.9701 - val_loss:
0.3463 - val_acc: 0.9257
Epoch 9/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0870 - acc: 0.9729 - val_loss:
0.3411 - val_acc: 0.9318
Epoch 10/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0940 - acc: 0.9725 - val_loss:
```

```
0.3384 - val_acc: 0.9308
Epoch 11/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0950 - acc: 0.9729 - val_loss:
0.2994 - val_acc: 0.9315
Epoch 12/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0833 - acc: 0.9744 - val_loss:
0.3596 - val_acc: 0.9213
Epoch 13/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0774 - acc: 0.9774 - val_loss:
0.4036 - val_acc: 0.9182
Epoch 14/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0738 - acc: 0.9774 - val_loss:
0.3936 - val_acc: 0.9165
Epoch 15/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0801 - acc: 0.9781 - val_loss:
0.4387 - val_acc: 0.9203
Epoch 16/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0738 - acc: 0.9805 - val_loss:
0.5509 - val_acc: 0.9006
Epoch 17/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0662 - acc: 0.9778 - val_loss:
0.9739 - val_acc: 0.8741
Epoch 18/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0787 - acc: 0.9780 - val_loss:
0.3623 - val_acc: 0.9247
Epoch 19/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0623 - acc: 0.9800 - val_loss:
0.4833 - val_acc: 0.9196
Epoch 20/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0652 - acc: 0.9801 - val_loss:
0.4131 - val_acc: 0.9342
Epoch 21/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0577 - acc: 0.9834 - val_loss:
0.3845 - val_acc: 0.9281
Epoch 22/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0639 - acc: 0.9835 - val_loss:
0.4837 - val_acc: 0.9182
Epoch 23/30
7352/7352 [==============================] - 10s 1ms/step - loss: 0.0611 - acc: 0.9818 - val_loss:
0.5226 - val_acc: 0.9179
Epoch 24/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0570 - acc: 0.9825 - val_loss:
0.4792 - val_acc: 0.9192
Epoch 25/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0510 - acc: 0.9838 - val_loss:
0.4524 - val_acc: 0.9267
Epoch 26/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0718 - acc: 0.9830 - val_loss:
0.5625 - val_acc: 0.9141
Epoch 27/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0781 - acc: 0.9838 - val_loss:
0.5346 - val_acc: 0.9294
Epoch 28/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0525 - acc: 0.9853 - val_loss:
0.5426 - val_acc: 0.9203
Epoch 29/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0551 - acc: 0.9842 - val_loss:
0.5541 - val_acc: 0.9121
Epoch 30/30
7352/7352 [==============================] - 11s 1ms/step - loss: 0.0691 - acc: 0.9846 - val_loss:
0.5513 - val_acc: 0.9199
```

In [615]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 537        0         0        0                   0
SITTING                  6      401        83        0                   0
STANDING                 0       71       461        0                   0
WALKING                  0        8         0      472                  16
WALKING_DOWNSTAIRS       0        1         0        4                 411
WALKING_UPSTAIRS         0        8         0        3                  31
```

```
Pred                  WALKING_UPSTAIRS
True
LAYING                               0
SITTING                              1
STANDING                             0
WALKING                              0
WALKING_DOWNSTAIRS                   4
WALKING_UPSTAIRS                   429
```

In [616]:

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

```
2947/2947 [==============================] - 1s 465us/step
```

In [617]:

```
score
```

Out[617]:

```
[0.5513466087953368, 0.9199185612487275]
```

MODEL 3 TWO LSTM LAYER

In [ ]:

```
from keras import regularizers
```

In [618]:

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

model.add(LSTM(28,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.6))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_4 (LSTM)                (None, 128, 32)           5376      
_________________________________________________________________
dropout_35 (Dropout)         (None, 128, 32)           0         
_________________________________________________________________
lstm_5 (LSTM)                (None, 28)                6832      
_________________________________________________________________
dropout_36 (Dropout)         (None, 28)                0         
_________________________________________________________________
dense_67 (Dense)             (None, 6)                 174       
=================================================================
Total params: 12,382
Trainable params: 12,382
Non-trainable params: 0
_________________________________________________________________
```

In [619]:

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

In [620]:

```
# Training the model
history=model.fit(X_train,
          Y_train,
          batch_size=32,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 101s 14ms/step - loss: 1.1560 - acc: 0.5570 - val_los
s: 0.8574 - val_acc: 0.5901
Epoch 2/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.7567 - acc: 0.6506 - val_loss
: 0.7961 - val_acc: 0.6335
Epoch 3/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.6427 - acc: 0.7297 - val_loss
: 0.6118 - val_acc: 0.7316
Epoch 4/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.5169 - acc: 0.8100 - val_loss
: 0.5924 - val_acc: 0.8191
Epoch 5/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.3997 - acc: 0.8738 - val_loss
: 0.4450 - val_acc: 0.8690
Epoch 6/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.3227 - acc: 0.9045 - val_loss
: 0.3793 - val_acc: 0.8914
Epoch 7/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.2806 - acc: 0.9185 - val_loss
: 0.3573 - val_acc: 0.8887
Epoch 8/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.2470 - acc: 0.9226 - val_loss
: 0.3585 - val_acc: 0.9009
Epoch 9/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.2353 - acc: 0.9293 - val_loss
: 0.3891 - val_acc: 0.8975
Epoch 10/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.2096 - acc: 0.9373 - val_loss
: 0.4256 - val_acc: 0.8911
Epoch 11/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.2078 - acc: 0.9380 - val_loss
: 0.4747 - val_acc: 0.8924
Epoch 12/20
7352/7352 [==============================] - 98s 13ms/step - loss: 0.1977 - acc: 0.9391 - val_loss
: 0.6156 - val_acc: 0.8785
Epoch 13/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1874 - acc: 0.9453 - val_loss
: 0.4269 - val_acc: 0.9087
Epoch 14/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1777 - acc: 0.9427 - val_loss
: 0.2883 - val_acc: 0.9250
Epoch 15/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1761 - acc: 0.9427 - val_loss
: 0.3699 - val_acc: 0.9158
Epoch 16/20
7352/7352 [==============================] - 97s 13ms/step - loss: 0.1755 - acc: 0.9452 - val_loss
: 0.3131 - val_acc: 0.9233
Epoch 17/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1667 - acc: 0.9430 - val_loss
: 0.3686 - val_acc: 0.9189
Epoch 18/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1733 - acc: 0.9482 - val_loss
: 0.4375 - val_acc: 0.9108
Epoch 19/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1650 - acc: 0.9489 - val_loss
: 0.3902 - val_acc: 0.9046
Epoch 20/20
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1629 - acc: 0.9426 - val_loss
: 0.3569 - val_acc: 0.9148
```

In [621]:

```
# Confusion Matrix
```

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 537        0         0        0                   0
SITTING                  3      421        45        3                   0
STANDING                 0      129       400        3                   0
WALKING                  0        0         1      471                   6
WALKING_DOWNSTAIRS       0        0         0        1                 400
WALKING_UPSTAIRS         0        0         0        2                   2

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                           19
STANDING                           0
WALKING                           18
WALKING_DOWNSTAIRS                19
WALKING_UPSTAIRS                 467
```

In [622]:

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

```
2947/2947 [==============================] - 4s 1ms/step
```

In [623]:

```
score
```

Out[623]:

```
[0.35691609237638755, 0.9148286392941974]
```

In [624]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 537        0         0        0                   0
SITTING                  3      421        45        3                   0
STANDING                 0      129       400        3                   0
WALKING                  0        0         1      471                   6
WALKING_DOWNSTAIRS       0        0         0        1                 400
WALKING_UPSTAIRS         0        0         0        2                   2

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                           19
STANDING                           0
WALKING                           18
WALKING_DOWNSTAIRS                19
WALKING_UPSTAIRS                 467
```

WE get almost same accuracy but with CNN architecture it is better but loss is decreasing

from the above observation we can see that after trying all
model we are not getting accuraccy above 92% because of the overlapping of sitting and standing
so we use divide the model into three parts the idea is taken from this research paper: https://www.mdpi.com/1424-8220/18/4/1055/pdf

1. into classes between static and dynamic .
2. classify 3 categories among static
3. classify 3 categories among dynamic

In [535]:

```
# Initiliazing the sequential model
model_half = Sequential()
model_half.add(Conv1D(64, kernel_size=3, activation= 'relu',input_shape=(128,9)))
model_half.add(Dropout(0.6))
model_half.add(MaxPooling1D(pool_size=3))
model_half.add(Flatten())
model_half.add(Dense(50, activation='relu'))
model_half.add(Dense(2, activation='softmax'))
model_half.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_46 (Conv1D)           (None, 126, 64)           1792
_________________________________________________________________
dropout_29 (Dropout)         (None, 126, 64)           0
_________________________________________________________________
max_pooling1d_28 (MaxPooling (None, 42, 64)            0
_________________________________________________________________
flatten_28 (Flatten)         (None, 2688)              0
_________________________________________________________________
dense_57 (Dense)             (None, 50)                134450
_________________________________________________________________
dense_58 (Dense)             (None, 2)                 102
=================================================================
Total params: 136,344
Trainable params: 136,344
Non-trainable params: 0
_________________________________________________________________
```

In [536]:

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

In [537]:

```
# Training the model
history = model_half.fit(X_train_2,
          Y_train_2,
          batch_size=batch_size,
          validation_data=(X_test_2, Y_test_2),
          epochs=10)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/10
7352/7352 [==============================] - 8s 1ms/step - loss: 0.0524 - acc: 0.9830 - val_loss:
0.0213 - val_acc: 0.9942
Epoch 2/10
7352/7352 [==============================] - 6s 831us/step - loss: 0.0014 - acc: 0.9996 -
val_loss: 0.0110 - val_acc: 0.9969
Epoch 3/10
7352/7352 [==============================] - 6s 771us/step - loss: 0.0027 - acc: 0.9993 -
val_loss: 0.0158 - val_acc: 0.9966
Epoch 4/10
7352/7352 [==============================] - 6s 807us/step - loss: 9.8023e-04 - acc: 0.9997 - val_
loss: 0.0114 - val_acc: 0.9976
Epoch 5/10
7352/7352 [==============================] - 6s 787us/step - loss: 9.1758e-05 - acc: 1.0000 - val_
loss: 0.0143 - val_acc: 0.9976
Epoch 6/10
7352/7352 [==============================] - 6s 803us/step - loss: 1.5712e-05 - acc: 1.0000 - val_
loss: 0.0141 - val_acc: 0.9973
Epoch 7/10
7352/7352 [==============================] - 6s 785us/step - loss: 4.1130e-05 - acc: 1.0000 - val_
loss: 0.0114 - val_acc: 0.9980
Epoch 8/10
7352/7352 [==============================] - 8s 1ms/step - loss: 6.4638e-07 - acc: 1.0000 - val_lo
ss: 0.0359 - val_acc: 0.9874
Epoch 9/10
```

```
7352/7352 [==============================] - 6s 798us/step - loss: 8.4785e-07 - acc: 1.0000 - val_
loss: 0.0183 - val_acc: 0.9952
Epoch 10/10
7352/7352 [==============================] - 6s 765us/step - loss: 1.2340e-06 - acc: 1.0000 - val_
loss: 0.0139 - val_acc: 0.9976
```

from the above observation you can see that model predicts between two class static and dynamic with almost 100% accuraccy

CLASSIFY WITHIN STATIC

In [538]:

```
model_static= Sequential()
model_static.add(Conv1D(filters=32, kernel_size=5,activation='relu',input_shape=(128,9)))
model_static.add(Conv1D(filters=16, kernel_size=3,
                 activation='relu'))
model_static.add(Dropout(0.5))
model_static.add(MaxPooling1D(pool_size=2))
model_static.add(Flatten())
model_static.add(Dense(64, activation='relu'))
model_static.add(Dense(3, activation='softmax'))
print(model_static.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_47 (Conv1D)           (None, 124, 32)           1472
_________________________________________________________________
conv1d_48 (Conv1D)           (None, 122, 16)           1552
_________________________________________________________________
dropout_30 (Dropout)         (None, 122, 16)           0
_________________________________________________________________
max_pooling1d_29 (MaxPooling (None, 61, 16)            0
_________________________________________________________________
flatten_29 (Flatten)         (None, 976)               0
_________________________________________________________________
dense_59 (Dense)             (None, 64)                62528
_________________________________________________________________
dense_60 (Dense)             (None, 3)                 195
=================================================================
Total params: 65,747
Trainable params: 65,747
Non-trainable params: 0
_________________________________________________________________
None
```

In [539]:

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

In [540]:

```
# Training the model
history = model_static.fit(X_train_static,
          Y_train_static,
          batch_size=64,
          validation_data=(X_test_static, Y_test_static),
          epochs=50)
```

```
Train on 4067 samples, validate on 1560 samples
Epoch 1/50
4067/4067 [==============================] - 4s 1ms/step - loss: 0.2592 - acc: 0.8800 - val_loss:
0.3110 - val_acc: 0.8718
Epoch 2/50
4067/4067 [==============================] - 2s 473us/step - loss: 0.2015 - acc: 0.9088 -
val_loss: 0.3202 - val_acc: 0.9051
Epoch 3/50
```

```
Epoch 3/50
4067/4067 [==============================] - 2s 475us/step - loss: 0.1964 - acc: 0.9179 -
val_loss: 0.3530 - val_acc: 0.8724
Epoch 4/50
4067/4067 [==============================] - 2s 480us/step - loss: 0.1723 - acc: 0.9228 -
val_loss: 0.3453 - val_acc: 0.8840
Epoch 5/50
4067/4067 [==============================] - 2s 481us/step - loss: 0.1564 - acc: 0.9287 -
val_loss: 0.3922 - val_acc: 0.8737
Epoch 6/50
4067/4067 [==============================] - 2s 487us/step - loss: 0.1520 - acc: 0.9309 -
val_loss: 0.4174 - val_acc: 0.8192
Epoch 7/50
4067/4067 [==============================] - 2s 475us/step - loss: 0.1387 - acc: 0.9375 -
val_loss: 0.4016 - val_acc: 0.8750
Epoch 8/50
4067/4067 [==============================] - 2s 474us/step - loss: 0.1371 - acc: 0.9422 -
val_loss: 0.4699 - val_acc: 0.8878
Epoch 9/50
4067/4067 [==============================] - 2s 496us/step - loss: 0.1228 - acc: 0.9452 -
val_loss: 0.4714 - val_acc: 0.8859
Epoch 10/50
4067/4067 [==============================] - 2s 526us/step - loss: 0.1159 - acc: 0.9484 -
val_loss: 0.4532 - val_acc: 0.8750
Epoch 11/50
4067/4067 [==============================] - 2s 474us/step - loss: 0.1091 - acc: 0.9516 -
val_loss: 0.4790 - val_acc: 0.8712
Epoch 12/50
4067/4067 [==============================] - 2s 477us/step - loss: 0.1010 - acc: 0.9548 -
val_loss: 0.4722 - val_acc: 0.8853
Epoch 13/50
4067/4067 [==============================] - 2s 492us/step - loss: 0.0947 - acc: 0.9592 -
val_loss: 0.4617 - val_acc: 0.9058
Epoch 14/50
4067/4067 [==============================] - 2s 471us/step - loss: 0.0864 - acc: 0.9619 -
val_loss: 0.4746 - val_acc: 0.8987
Epoch 15/50
4067/4067 [==============================] - 2s 483us/step - loss: 0.0822 - acc: 0.9641 -
val_loss: 0.4142 - val_acc: 0.8910
Epoch 16/50
4067/4067 [==============================] - 2s 476us/step - loss: 0.0970 - acc: 0.9671 -
val_loss: 0.4616 - val_acc: 0.9128
Epoch 17/50
4067/4067 [==============================] - 2s 470us/step - loss: 0.0731 - acc: 0.9673 -
val_loss: 0.5333 - val_acc: 0.8910
Epoch 18/50
4067/4067 [==============================] - 2s 479us/step - loss: 0.0804 - acc: 0.9683 -
val_loss: 0.4974 - val_acc: 0.8981
Epoch 19/50
4067/4067 [==============================] - 2s 476us/step - loss: 0.0663 - acc: 0.9732 -
val_loss: 0.4813 - val_acc: 0.9045
Epoch 20/50
4067/4067 [==============================] - 2s 479us/step - loss: 0.0700 - acc: 0.9720 -
val_loss: 0.5006 - val_acc: 0.8859
Epoch 21/50
4067/4067 [==============================] - 2s 473us/step - loss: 0.0506 - acc: 0.9789 -
val_loss: 0.4638 - val_acc: 0.9077
Epoch 22/50
4067/4067 [==============================] - 2s 476us/step - loss: 0.0594 - acc: 0.9744 -
val_loss: 0.4750 - val_acc: 0.9103
Epoch 23/50
4067/4067 [==============================] - 2s 505us/step - loss: 0.0553 - acc: 0.9766 -
val_loss: 0.5165 - val_acc: 0.9160
Epoch 24/50
4067/4067 [==============================] - 2s 475us/step - loss: 0.0561 - acc: 0.9752 -
val_loss: 0.5257 - val_acc: 0.9167
Epoch 25/50
4067/4067 [==============================] - 2s 472us/step - loss: 0.0511 - acc: 0.9781 -
val_loss: 0.5241 - val_acc: 0.8917
Epoch 26/50
4067/4067 [==============================] - 2s 478us/step - loss: 0.0480 - acc: 0.9823 -
val_loss: 0.5052 - val_acc: 0.9071
Epoch 27/50
4067/4067 [==============================] - 2s 500us/step - loss: 0.0553 - acc: 0.9830 -
val_loss: 0.5476 - val_acc: 0.9090
Epoch 28/50
4067/4067 [==============================] - 2s 488us/step - loss: 0.0468 - acc: 0.9840 -
val_loss: 0.5467 - val_acc: 0.9045
```

```
val_loss: 0.5467 - val_acc: 0.9045
Epoch 29/50
4067/4067 [==============================] - 2s 470us/step - loss: 0.0377 - acc: 0.9867 -
val_loss: 0.4818 - val_acc: 0.9250
Epoch 30/50
4067/4067 [==============================] - 2s 478us/step - loss: 0.0360 - acc: 0.9865 -
val_loss: 0.5511 - val_acc: 0.9244
Epoch 31/50
4067/4067 [==============================] - 2s 491us/step - loss: 0.0371 - acc: 0.9867 -
val_loss: 0.5509 - val_acc: 0.9154
Epoch 32/50
4067/4067 [==============================] - 2s 476us/step - loss: 0.0380 - acc: 0.9889 -
val_loss: 0.5708 - val_acc: 0.8897
Epoch 33/50
4067/4067 [==============================] - 2s 487us/step - loss: 0.0329 - acc: 0.9887 -
val_loss: 0.6179 - val_acc: 0.9167
Epoch 34/50
4067/4067 [==============================] - 2s 487us/step - loss: 0.0305 - acc: 0.9877 -
val_loss: 0.5850 - val_acc: 0.9128
Epoch 35/50
4067/4067 [==============================] - 2s 474us/step - loss: 0.0330 - acc: 0.9892 -
val_loss: 0.5552 - val_acc: 0.9205
Epoch 36/50
4067/4067 [==============================] - 2s 492us/step - loss: 0.0308 - acc: 0.9914 -
val_loss: 0.5444 - val_acc: 0.9295
Epoch 37/50
4067/4067 [==============================] - 2s 490us/step - loss: 0.0271 - acc: 0.9909 -
val_loss: 0.5325 - val_acc: 0.9179
Epoch 38/50
4067/4067 [==============================] - 2s 524us/step - loss: 0.0333 - acc: 0.9902 -
val_loss: 0.5206 - val_acc: 0.9179
Epoch 39/50
4067/4067 [==============================] - 2s 553us/step - loss: 0.0403 - acc: 0.9907 -
val_loss: 0.5986 - val_acc: 0.9090
Epoch 40/50
4067/4067 [==============================] - 2s 577us/step - loss: 0.0321 - acc: 0.9899 -
val_loss: 0.5893 - val_acc: 0.9128
Epoch 41/50
4067/4067 [==============================] - 2s 537us/step - loss: 0.0263 - acc: 0.9904 -
val_loss: 0.5411 - val_acc: 0.9263
Epoch 42/50
4067/4067 [==============================] - 2s 554us/step - loss: 0.0275 - acc: 0.9904 -
val_loss: 0.5893 - val_acc: 0.9109
Epoch 43/50
4067/4067 [==============================] - 2s 518us/step - loss: 0.0307 - acc: 0.9904 -
val_loss: 0.5970 - val_acc: 0.9122
Epoch 44/50
4067/4067 [==============================] - 2s 473us/step - loss: 0.0200 - acc: 0.9929 -
val_loss: 0.5816 - val_acc: 0.9237
Epoch 45/50
4067/4067 [==============================] - 2s 496us/step - loss: 0.0221 - acc: 0.9939 -
val_loss: 0.6133 - val_acc: 0.9032
Epoch 46/50
4067/4067 [==============================] - 2s 524us/step - loss: 0.0207 - acc: 0.9951 -
val_loss: 0.5976 - val_acc: 0.9212
Epoch 47/50
4067/4067 [==============================] - 2s 554us/step - loss: 0.0216 - acc: 0.9919 -
val_loss: 0.6262 - val_acc: 0.9064
Epoch 48/50
4067/4067 [==============================] - 2s 562us/step - loss: 0.0235 - acc: 0.9914 -
val_loss: 0.5643 - val_acc: 0.9231
Epoch 49/50
4067/4067 [==============================] - 2s 530us/step - loss: 0.0160 - acc: 0.9936 -
val_loss: 0.5862 - val_acc: 0.9154
Epoch 50/50
4067/4067 [==============================] - 2s 528us/step - loss: 0.0242 - acc: 0.9943 -
val_loss: 0.5835 - val_acc: 0.9237
```

we are getting test accuracy above 92% for static

CLASSIFY WITHING DYNAMIC

In [541]:

```python
model_dynamic = Sequential()
model_dynamic.add(Conv1D(filters=100, kernel_size=7, activation='relu',kernel_regularizer = regular
izers.l2(0.007),input_shape=(128,9)))
model_dynamic.add(Dropout(0.7))
model_dynamic.add(MaxPooling1D(pool_size=3))
model_dynamic.add(Flatten())
model_dynamic.add(Dense(50, activation='relu'))
model_dynamic.add(Dense(3, activation='softmax'))
model_dynamic.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv1d_49 (Conv1D)           (None, 122, 100)          6400      
_________________________________________________________________
dropout_31 (Dropout)         (None, 122, 100)          0         
_________________________________________________________________
max_pooling1d_30 (MaxPooling (None, 40, 100)           0         
_________________________________________________________________
flatten_30 (Flatten)         (None, 4000)              0         
_________________________________________________________________
dense_61 (Dense)             (None, 50)                200050    
_________________________________________________________________
dense_62 (Dense)             (None, 3)                 153       
=================================================================
Total params: 206,603
Trainable params: 206,603
Non-trainable params: 0
_________________________________________________________________
```

In [542]:

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

In [543]:

```python
# Training the model
history = model_dynamic.fit(X_train_dynamic,
          Y_train_dynamic,
          batch_size=30,
          validation_data=(X_test_dynamic, Y_test_dynamic),
          epochs=30)
```

```
Train on 3285 samples, validate on 1387 samples
Epoch 1/30
3285/3285 [==============================] - 6s 2ms/step - loss: 0.6818 - acc: 0.7973 - val_loss:
0.3798 - val_acc: 0.9315
Epoch 2/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.1528 - acc: 0.9805 - val_loss:
0.2361 - val_acc: 0.9524
Epoch 3/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.1058 - acc: 0.9927 - val_loss:
0.2766 - val_acc: 0.9445
Epoch 4/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0923 - acc: 0.9924 - val_loss:
0.3321 - val_acc: 0.9503
Epoch 5/30
3285/3285 [==============================] - 3s 1ms/step - loss: 0.0736 - acc: 0.9960 - val_loss:
0.2181 - val_acc: 0.9603
Epoch 6/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0534 - acc: 0.9976 - val_loss:
0.1871 - val_acc: 0.9553
Epoch 7/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0427 - acc: 0.9951 - val_loss:
0.5911 - val_acc: 0.8789
Epoch 8/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0340 - acc: 0.9976 - val_loss:
0.2288 - val_acc: 0.9423
Epoch 9/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0362 - acc: 0.9945 - val_loss:
0.1284 - val_acc: 0.9560
```

```
Epoch 10/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0332 - acc: 0.9967 - val_loss:
0.1905 - val_acc: 0.9510
Epoch 11/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0373 - acc: 0.9936 - val_loss:
0.1914 - val_acc: 0.9531
Epoch 12/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0485 - acc: 0.9930 - val_loss:
0.1776 - val_acc: 0.9546
Epoch 13/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0327 - acc: 0.9945 - val_loss:
0.2355 - val_acc: 0.9531
Epoch 14/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0281 - acc: 0.9945 - val_loss:
0.1795 - val_acc: 0.9553
Epoch 15/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0202 - acc: 0.9979 - val_loss:
0.2152 - val_acc: 0.9495
Epoch 16/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0233 - acc: 0.9957 - val_loss:
0.1861 - val_acc: 0.9603
Epoch 17/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0318 - acc: 0.9945 - val_loss:
0.1658 - val_acc: 0.9560
Epoch 18/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0249 - acc: 0.9967 - val_loss:
0.1372 - val_acc: 0.9503
Epoch 19/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0231 - acc: 0.9970 - val_loss:
0.1857 - val_acc: 0.9582
Epoch 20/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0182 - acc: 0.9970 - val_loss:
0.2907 - val_acc: 0.9438
Epoch 21/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0249 - acc: 0.9951 - val_loss:
0.2793 - val_acc: 0.9423
Epoch 22/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0240 - acc: 0.9960 - val_loss:
0.2258 - val_acc: 0.9553
Epoch 23/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0255 - acc: 0.9948 - val_loss:
0.1771 - val_acc: 0.9575
Epoch 24/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0161 - acc: 0.9976 - val_loss:
0.1921 - val_acc: 0.9488
Epoch 25/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0233 - acc: 0.9957 - val_loss:
0.1853 - val_acc: 0.9402
Epoch 26/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0173 - acc: 0.9973 - val_loss:
0.1882 - val_acc: 0.9495
Epoch 27/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0191 - acc: 0.9951 - val_loss:
0.2008 - val_acc: 0.9452
Epoch 28/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0324 - acc: 0.9942 - val_loss:
0.2295 - val_acc: 0.9495
Epoch 29/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0192 - acc: 0.9976 - val_loss:
0.1740 - val_acc: 0.9531
Epoch 30/30
3285/3285 [==============================] - 4s 1ms/step - loss: 0.0135 - acc: 0.9973 - val_loss:
0.2115 - val_acc: 0.9517
```

we are getting test accuracy 95% for dynamic

In [544]:

```
from sklearn.metrics import accuracy_score
```

In [545]:

```
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 y
```

In [546]:

```
Y_train,Y_test= load_y('train'), load_y('test')
X_train, X_test = load_signals_train(), load_signals_test()
```

In [547]:

```
def final_predict(data):
    class_pred = model_half.predict(data) #classify of static and dynamic
    prob_compare =  np.argmax(class_pred, axis=1) #return  index value of max probale class
    # prob_compare will have values of 0 and 1. 0 = Dynamic , 1 =  Static
    # send dynamic predicted label to dynamic classifier
    # send static predicted label to static classifier
    dynamic_data = data[prob_compare==0] #Dynamic data
    dynamic_pred = model_dynamic.predict(dynamic_data) #predicting label with dynamic classifier
    dynamic_label_pred = np.argmax(dynamic_pred,axis=1) #taking index of max probale class
    # dynamic_label_pred contains index of max probable class i.e 0,1 or 2
    # But our actual classes are 1,2 and 3.
    # So adding 1 to the predicted class to get actual class labels
    dynamic_ACTUALlabel_pred = dynamic_label_pred + 1

    static_data = data[prob_compare==1] #static data
    static_pred = model_static.predict(static_data) #predicting label with static classifier
    static_label_pred = np.argmax(static_pred,axis=1) #taking index of max probale class
    # static_label_pred contains index of max probable class i.e 0,1 or 2
    # But our actual classes are 4,5 and 6.
    # So adding 4 to the predicted class to get actual class labels
    static_ACTUALlabel_pred = static_label_pred + 4

    # Now we got prediction for static and dynamic data
    # But we need in combine format

    static,dynamic = 0,0
    final_prediction = []
    for class_2 in prob_compare:
        if class_2 == 0:
            final_prediction.append(dynamic_ACTUALlabel_pred[dynamic])
            dynamic = dynamic + 1
        else:
            final_prediction.append(static_ACTUALlabel_pred[static])
            static = static + 1
    return final_prediction
```

In [548]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix as cm
import seaborn as sns
```

In [549]:

```
def plot_confusion_matrix(test_y, predict_y):
    C = cm(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i are predicted class j

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in that column

    # C = [[1, 2],
    #     [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
```

```
diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in that row
    # C = [[1, 2],
    #     [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to rows in two
diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                       [3/4, 4/6]]

    labels =[ 'WALKING',
    'WALKING_UPSTAIRS',
    'WALKING_DOWNSTAIRS',
    'SITTING',
    'STANDING',
    'LAYING']
    # representing A in heatmap format
    print("-"*20, "Confusion matrix", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    print("-"*20, "Precision matrix (Columm Sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(B, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()

    # representing B in heatmap format
    print("-"*20, "Recall matrix (Row sum=1)", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(A, annot=True, cmap="YlGnBu", fmt=".3f", xticklabels=labels, yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
```

In [632]:

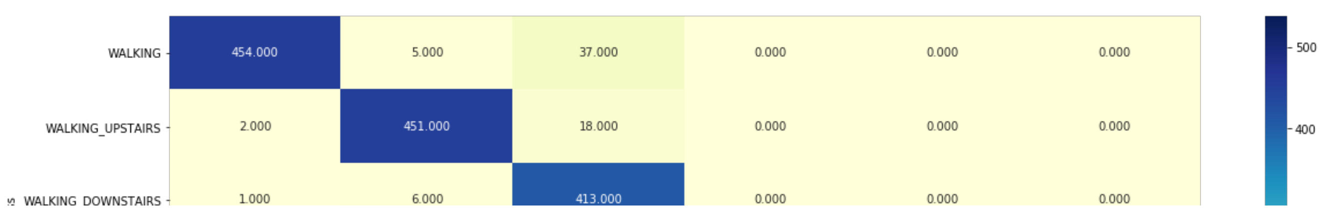
```
train_pred = final_predict(X_train)
print('Train data Accuracy',accuracy_score(Y_train,train_pred))
test_pred = final_predict(X_test)
print('Test data Accuracy',accuracy_score(Y_test,test_pred))
```

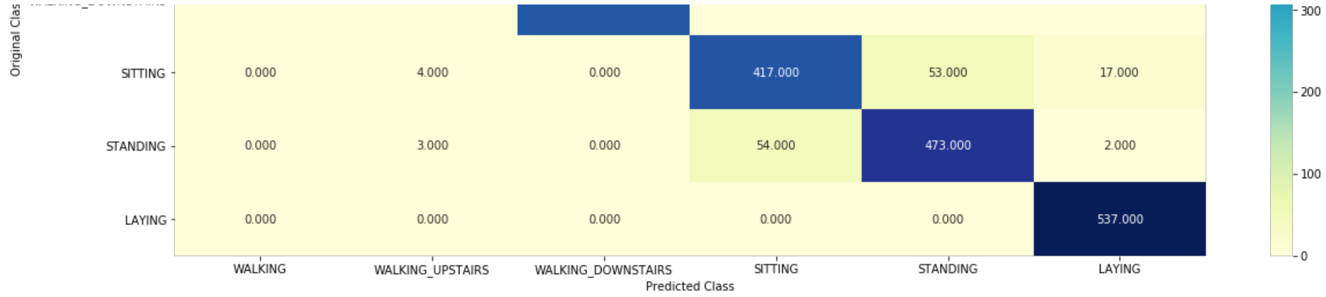
```
Train data Accuracy 0.9885919477693145
Test data Accuracy 0.9471007804546997
```

In [555]:

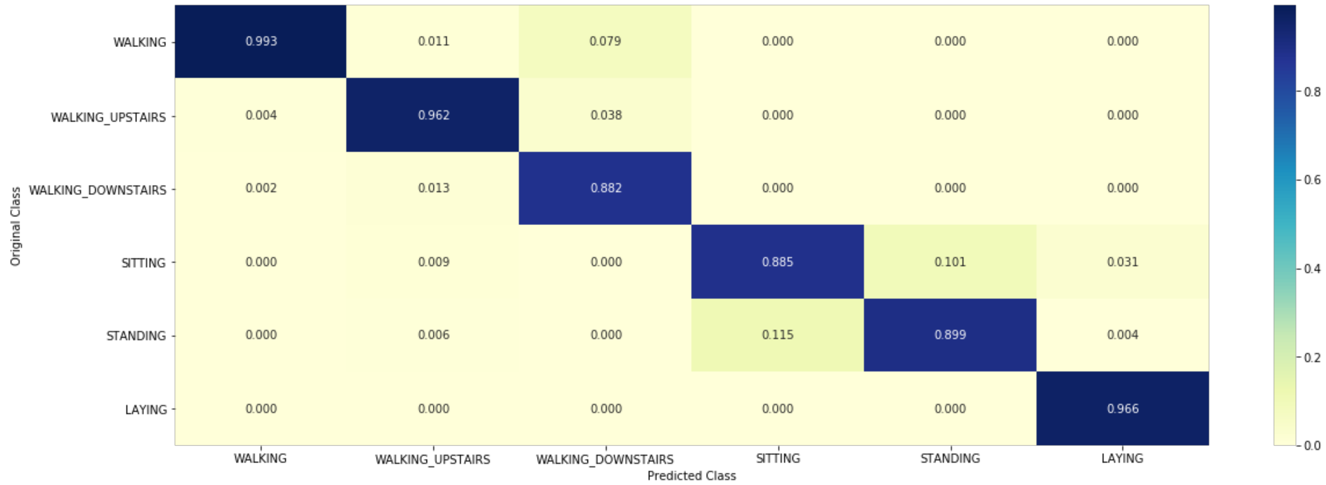
```
print("confusion matrix of train data")
plot_confusion_matrix(Y_test,test_pred)
```

```
confusion matrix of train data
-------------------- Confusion matrix --------------------
```

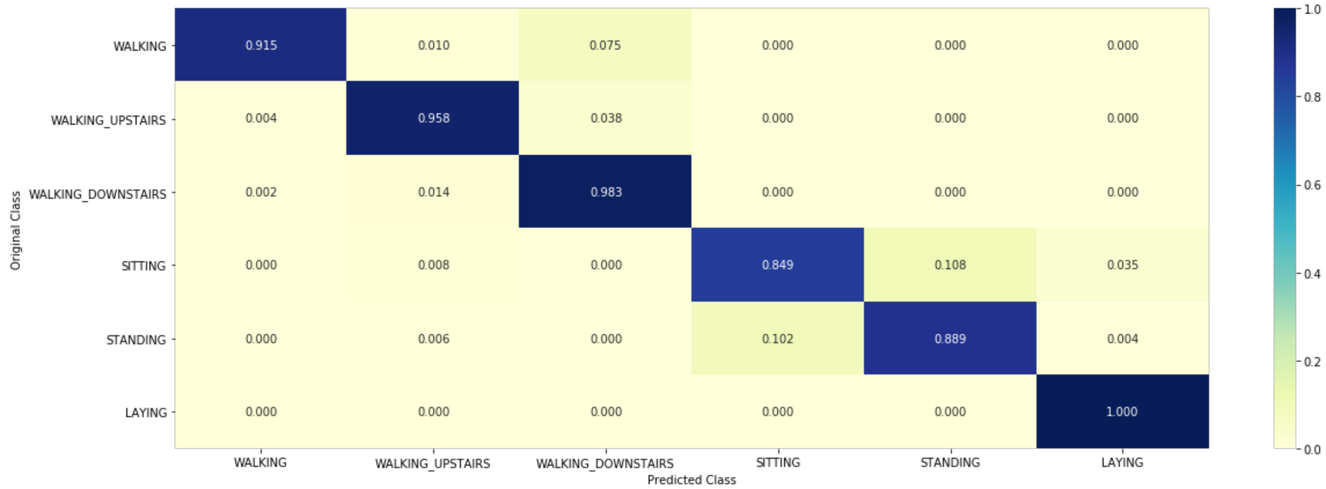





```
-------------------- Precision matrix (Columm Sum=1) --------------------
```




```
-------------------- Recall matrix (Row sum=1) --------------------
```



from the heat map observation You can see that Divide and Conquer technique works very well

In [629]:

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Models","Test auc",'test loss']
x.add_row(["with no of LSTM layers 256","0.917","0.418"])
x.add_row(["by trying CNN architecture","0.9199","0.55"])
x.add_row(["by adding two lstm layers","0.914","0.35"])
x.add_row(["by DIVIDE AND CONQUER METHOD","0.9471","--"])
```

In [630]:

```
print(x)
```

```
+-----------------------------+----------+-----------+
|            Models           | Test auc | test loss |
+-----------------------------+----------+-----------+
|  with no of LSTM layers 256 |  0.917   |   0.418   |
```

```
|  by trying CNN architecture  |  0.9199  |    0.55   |
|  by adding two lstm layers   |  0.914   |    0.35   |
| by DIVIDE AND CONQUER METHOD |  0.9471  |     --    |
+------------------------------+----------+-----------+
```

I follow the research paper architecture if you want to improve the accuracy more try hyperparameter tunning of deep learning which will improve accuracy maybe 1 or 2 percent

END