

HAR LSTM Assignment

```
In [26]: # Importing Libraries
import pandas as pd
import numpy as np
import scipy

from tensorflow.compat.v1 import ConfigProto
from tensorflow.compat.v1 import InteractiveSession

config = ConfigProto()
config.gpu_options.per_process_gpu_memory_fraction = 0.33
session = InteractiveSession(config=config)

import keras
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import BatchNormalization
from keras.layers import Dropout, Flatten, Conv1D
from keras.layers import Dense
from sklearn.metrics import accuracy_score

from keras.callbacks import EarlyStopping, CSVLogger, TensorBoard, ReduceLROnPlateau
```

```
C:\Users\family\Anaconda3\lib\site-packages\tensorflow\python\client\session.py:1735: UserWarning: An interactive session is already active. This can cause out-of-memory errors in some cases. You must explicitly call `InteractiveSession.close()` to release resources held by the other session(s).
  warnings.warn('An interactive session is already active. This can '
```

```
In [27]: # 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 [28]: # Data directory
DATADIR = 'UCI_HAR_Dataset'
```

```
In [29]: # 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 [30]: # Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

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

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

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

```
In [31]: 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 [32]: 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 [33]: # Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()

C:\Users\family\Anaconda3\lib\site-packages\ipykernel_launcher.py:12: Future
Warning: Method .as_matrix will be removed in a future version. Use .values
instead.
    if sys.path[0] == '':
C:\Users\family\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: Future
Warning: Method .as_matrix will be removed in a future version. Use .values
instead.
    # This is added back by InteractiveShellApp.init_path()
```

1. Simple 2 layer LSTM

```
In [79]: # Initiliazing the sequential model
model = Sequential()

# Configuring the parameters

# 1st Layer of LSTM
model.add(LSTM(128, input_shape=(128, 9), return_sequences=True, kernel_initializer='glorot_normal'))
# Adding a dropout layer
model.add(Dropout(0.2))

# 2nd Layer of LSTM
model.add(LSTM(64, kernel_initializer='glorot_normal'))
model.add(Dropout(0.5))

# Adding a dense output layer with sigmoid activation
model.add(Dense(6, activation='sigmoid'))
model.summary()

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

Model: "sequential_5"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 128, 128)	70656
dropout_5 (Dropout)	(None, 128, 128)	0
lstm_2 (LSTM)	(None, 64)	49408
dropout_6 (Dropout)	(None, 64)	0
dense_5 (Dense)	(None, 6)	390

Total params: 120,454

Trainable params: 120,454

Non-trainable params: 0

```
In [80]: # Training the model
model.fit(X_train,
          Y_train,
          batch_size=75,
          validation_data=(X_test, Y_test), epochs=100)
```

WARNING:tensorflow:From C:\Users\family\Anaconda3\lib\site-packages\tensorflow\python\ops\math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where

Train on 7352 samples, validate on 2947 samples

Epoch 1/100

7352/7352 [=====] - 22s 3ms/step - loss: 1.2818 - accuracy: 0.4702 - val_loss: 1.1241 - val_accuracy: 0.5073

Epoch 2/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.9431 - accuracy: 0.5861 - val_loss: 0.8120 - val_accuracy: 0.6817

Epoch 3/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.7796 - accuracy: 0.6733 - val_loss: 0.7196 - val_accuracy: 0.6899

Epoch 4/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.6075 - accuracy: 0.7582 - val_loss: 0.5810 - val_accuracy: 0.7496

Epoch 5/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.4916 - accuracy: 0.7904 - val_loss: 0.5486 - val_accuracy: 0.7706

Epoch 6/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.4150 - accuracy: 0.8271 - val_loss: 0.5966 - val_accuracy: 0.7862

Epoch 7/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.3631 - accuracy: 0.8912 - val_loss: 0.3594 - val_accuracy: 0.8731

Epoch 8/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.2398 - accuracy: 0.9263 - val_loss: 0.3678 - val_accuracy: 0.8799

Epoch 9/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.2137 - accuracy: 0.9344 - val_loss: 0.2750 - val_accuracy: 0.8965

Epoch 10/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.1792 - accuracy: 0.9389 - val_loss: 0.2374 - val_accuracy: 0.9138

Epoch 11/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.2094 - accuracy: 0.9229 - val_loss: 0.2595 - val_accuracy: 0.9046

Epoch 12/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.1605 - accuracy: 0.9422 - val_loss: 0.5527 - val_accuracy: 0.8609

Epoch 13/100

7352/7352 [=====] - 21s 3ms/step - loss: 0.1922 - accuracy: 0.9317 - val_loss: 0.3882 - val_accuracy: 0.8697

Epoch 14/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.1607 - accuracy: 0.9403 - val_loss: 0.3212 - val_accuracy: 0.8972

Epoch 15/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.1598 - accuracy: 0.9438 - val_loss: 0.7885 - val_accuracy: 0.8056

Epoch 16/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.2009 - a

ccuracy: 0.9310 - val_loss: 0.4235 - val_accuracy: 0.8714
Epoch 17/100
7352/7352 [=====] - 21s 3ms/step - loss: 0.1624 - a
ccuracy: 0.9436 - val_loss: 0.2887 - val_accuracy: 0.8996
Epoch 18/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1361 - a
ccuracy: 0.9475 - val_loss: 0.2749 - val_accuracy: 0.9128
Epoch 19/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1374 - a
ccuracy: 0.9497 - val_loss: 0.2438 - val_accuracy: 0.9203
Epoch 20/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1252 - a
ccuracy: 0.9501 - val_loss: 0.2404 - val_accuracy: 0.9253
Epoch 21/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1454 - a
ccuracy: 0.9452 - val_loss: 0.4725 - val_accuracy: 0.8741
Epoch 22/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1412 - a
ccuracy: 0.9501 - val_loss: 0.2898 - val_accuracy: 0.9091
Epoch 23/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1316 - a
ccuracy: 0.9516 - val_loss: 0.3423 - val_accuracy: 0.9063
Epoch 24/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1241 - a
ccuracy: 0.9501 - val_loss: 0.3153 - val_accuracy: 0.9067
Epoch 25/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1290 - a
ccuracy: 0.9513 - val_loss: 0.2757 - val_accuracy: 0.9070
Epoch 26/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1216 - a
ccuracy: 0.9531 - val_loss: 0.4003 - val_accuracy: 0.8789
Epoch 27/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1226 - a
ccuracy: 0.9535 - val_loss: 0.2877 - val_accuracy: 0.9108
Epoch 28/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1146 - a
ccuracy: 0.9574 - val_loss: 0.2977 - val_accuracy: 0.9097
Epoch 29/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1183 - a
ccuracy: 0.9559 - val_loss: 0.2960 - val_accuracy: 0.9125
Epoch 30/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1144 - a
ccuracy: 0.9561 - val_loss: 0.2954 - val_accuracy: 0.9111
Epoch 31/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1143 - a
ccuracy: 0.9553 - val_loss: 0.3298 - val_accuracy: 0.9148
Epoch 32/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1433 - a
ccuracy: 0.9523 - val_loss: 0.3059 - val_accuracy: 0.9118
Epoch 33/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1254 - a
ccuracy: 0.9524 - val_loss: 0.2731 - val_accuracy: 0.9203
Epoch 34/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1125 - a
ccuracy: 0.9548 - val_loss: 0.3178 - val_accuracy: 0.9233
Epoch 35/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1105 - a
ccuracy: 0.9548 - val_loss: 0.2981 - val_accuracy: 0.9203
Epoch 36/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1166 - a
ccuracy: 0.9517 - val_loss: 0.4157 - val_accuracy: 0.9013
Epoch 37/100

7352/7352 [=====] - 22s 3ms/step - loss: 0.1289 - a
ccuracy: 0.9509 - val_loss: 0.4628 - val_accuracy: 0.8884
Epoch 38/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.2523 - a
ccuracy: 0.9251 - val_loss: 0.3886 - val_accuracy: 0.8941
Epoch 39/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.2149 - a
ccuracy: 0.9329 - val_loss: 0.3416 - val_accuracy: 0.9084
Epoch 40/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1144 - a
ccuracy: 0.9553 - val_loss: 0.3218 - val_accuracy: 0.9125
Epoch 41/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1134 - a
ccuracy: 0.9523 - val_loss: 0.3552 - val_accuracy: 0.9026
Epoch 42/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1149 - a
ccuracy: 0.9539 - val_loss: 0.3364 - val_accuracy: 0.9121
Epoch 43/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1308 - a
ccuracy: 0.9505 - val_loss: 0.3073 - val_accuracy: 0.9179
Epoch 44/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1180 - a
ccuracy: 0.9527 - val_loss: 0.3540 - val_accuracy: 0.9067
Epoch 45/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1968 - a
ccuracy: 0.9321 - val_loss: 0.3570 - val_accuracy: 0.9030
Epoch 46/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1646 - a
ccuracy: 0.9433 - val_loss: 0.3478 - val_accuracy: 0.9087
Epoch 47/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1154 - a
ccuracy: 0.9543 - val_loss: 0.3401 - val_accuracy: 0.9111
Epoch 48/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1112 - a
ccuracy: 0.9550 - val_loss: 0.3364 - val_accuracy: 0.9080
Epoch 49/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1065 - a
ccuracy: 0.9570 - val_loss: 0.3581 - val_accuracy: 0.9070
Epoch 50/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1058 - a
ccuracy: 0.9542 - val_loss: 0.3661 - val_accuracy: 0.9111
Epoch 51/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1180 - a
ccuracy: 0.9521 - val_loss: 0.5082 - val_accuracy: 0.8935
Epoch 52/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1227 - a
ccuracy: 0.9484 - val_loss: 0.3639 - val_accuracy: 0.9203
Epoch 53/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1098 - a
ccuracy: 0.9506 - val_loss: 0.3505 - val_accuracy: 0.9213
Epoch 54/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1084 - a
ccuracy: 0.9551 - val_loss: 0.4031 - val_accuracy: 0.9189
Epoch 55/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1133 - a
ccuracy: 0.9544 - val_loss: 0.2353 - val_accuracy: 0.9287
Epoch 56/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1226 - a
ccuracy: 0.9523 - val_loss: 0.2549 - val_accuracy: 0.9213
Epoch 57/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1093 - a
ccuracy: 0.9542 - val_loss: 0.2458 - val_accuracy: 0.9243

Epoch 58/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1056 - accuracy: 0.9558 - val_loss: 0.3888 - val_accuracy: 0.9040
Epoch 59/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1160 - accuracy: 0.9553 - val_loss: 0.3312 - val_accuracy: 0.9057
Epoch 60/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1067 - accuracy: 0.9531 - val_loss: 0.3546 - val_accuracy: 0.9121
Epoch 61/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1187 - accuracy: 0.9483 - val_loss: 0.3328 - val_accuracy: 0.9216
Epoch 62/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1028 - accuracy: 0.9572 - val_loss: 0.3358 - val_accuracy: 0.9101
Epoch 63/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1031 - accuracy: 0.9563 - val_loss: 0.3775 - val_accuracy: 0.9108
Epoch 64/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1042 - accuracy: 0.9557 - val_loss: 0.3862 - val_accuracy: 0.9148
Epoch 65/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1159 - accuracy: 0.9501 - val_loss: 0.2362 - val_accuracy: 0.9298
Epoch 66/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1104 - accuracy: 0.9546 - val_loss: 0.2757 - val_accuracy: 0.9253
Epoch 67/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1005 - accuracy: 0.9551 - val_loss: 0.2939 - val_accuracy: 0.9203
Epoch 68/100
7352/7352 [=====] - 21s 3ms/step - loss: 0.1233 - accuracy: 0.9539 - val_loss: 0.3077 - val_accuracy: 0.9135
Epoch 69/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1055 - accuracy: 0.9547 - val_loss: 0.3305 - val_accuracy: 0.9101
Epoch 70/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1032 - accuracy: 0.9553 - val_loss: 0.3142 - val_accuracy: 0.9209
Epoch 71/100
7352/7352 [=====] - 21s 3ms/step - loss: 0.0956 - accuracy: 0.9577 - val_loss: 0.3167 - val_accuracy: 0.9206
Epoch 72/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1007 - accuracy: 0.9542 - val_loss: 0.5418 - val_accuracy: 0.9013
Epoch 73/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1021 - accuracy: 0.9566 - val_loss: 0.3876 - val_accuracy: 0.9138
Epoch 74/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1269 - accuracy: 0.9548 - val_loss: 0.5927 - val_accuracy: 0.8880
Epoch 75/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1984 - accuracy: 0.9342 - val_loss: 0.4757 - val_accuracy: 0.8619
Epoch 76/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1665 - accuracy: 0.9422 - val_loss: 0.3287 - val_accuracy: 0.8972
Epoch 77/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1106 - accuracy: 0.9558 - val_loss: 0.3224 - val_accuracy: 0.8999
Epoch 78/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1044 - a

ccuracy: 0.9593 - val_loss: 0.2954 - val_accuracy: 0.9158
Epoch 79/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0958 - a
ccuracy: 0.9603 - val_loss: 0.3340 - val_accuracy: 0.9080
Epoch 80/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0961 - a
ccuracy: 0.9611 - val_loss: 0.3241 - val_accuracy: 0.9135
Epoch 81/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1118 - a
ccuracy: 0.9539 - val_loss: 0.3146 - val_accuracy: 0.9036
Epoch 82/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1014 - a
ccuracy: 0.9569 - val_loss: 0.3208 - val_accuracy: 0.9111
Epoch 83/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0970 - a
ccuracy: 0.9589 - val_loss: 0.3255 - val_accuracy: 0.9152
Epoch 84/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1031 - a
ccuracy: 0.9559 - val_loss: 0.3702 - val_accuracy: 0.9070
Epoch 85/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0985 - a
ccuracy: 0.9572 - val_loss: 0.3227 - val_accuracy: 0.9169
Epoch 86/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0995 - a
ccuracy: 0.9569 - val_loss: 0.3351 - val_accuracy: 0.9121
Epoch 87/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0939 - a
ccuracy: 0.9606 - val_loss: 0.3435 - val_accuracy: 0.9111
Epoch 88/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0947 - a
ccuracy: 0.9599 - val_loss: 0.3477 - val_accuracy: 0.9138
Epoch 89/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1158 - a
ccuracy: 0.9518 - val_loss: 0.3108 - val_accuracy: 0.9186
Epoch 90/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0997 - a
ccuracy: 0.9570 - val_loss: 0.3305 - val_accuracy: 0.9172
Epoch 91/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1019 - a
ccuracy: 0.9561 - val_loss: 0.2361 - val_accuracy: 0.9155
Epoch 92/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.0964 - a
ccuracy: 0.9566 - val_loss: 0.2913 - val_accuracy: 0.9257
Epoch 93/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.2380 - a
ccuracy: 0.9120 - val_loss: 0.4270 - val_accuracy: 0.8697
Epoch 94/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1628 - a
ccuracy: 0.9314 - val_loss: 0.3257 - val_accuracy: 0.8867
Epoch 95/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1449 - a
ccuracy: 0.9430 - val_loss: 0.2255 - val_accuracy: 0.9094
Epoch 96/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1106 - a
ccuracy: 0.9548 - val_loss: 0.2556 - val_accuracy: 0.9118
Epoch 97/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1119 - a
ccuracy: 0.9562 - val_loss: 0.2538 - val_accuracy: 0.9145
Epoch 98/100
7352/7352 [=====] - 22s 3ms/step - loss: 0.1108 - a
ccuracy: 0.9518 - val_loss: 0.2391 - val_accuracy: 0.9104
Epoch 99/100


```

7352/7352 [=====] - 22s 3ms/step - loss: 0.1256 - a
ccuracy: 0.9489 - val_loss: 0.2442 - val_accuracy: 0.9253
Epoch 100/100
7352/7352 [=====] - 21s 3ms/step - loss: 0.1193 - a
ccuracy: 0.9528 - val_loss: 0.2453 - val_accuracy: 0.9240

```

Out[80]: <keras.callbacks.callbacks.History at 0x23dce5d21c8>

```

In [81]: # Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))

```

Pred \ True	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS
LAYING	537	0	0	0	0
SITTING	0	394	95	0	0
STANDING	0	83	449	0	0
WALKING	0	0	0	470	14
WALKING_DOWNSTAIRS	0	0	0	1	419
WALKING_UPSTAIRS	0	0	0	5	12

Pred \ True	WALKING_UPSTAIRS
LAYING	0
SITTING	2
STANDING	0
WALKING	12
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	454

```

In [82]: score = model.evaluate(X_test, Y_test)
score

```

```

2947/2947 [=====] - 9s 3ms/step

```

Out[82]: [0.24532297056183483, 0.9239904880523682]

2. 1-D CNN followed by 2 layer Bidirectional LSTM

```

In [9]: n_classes=6

# Initiliazing the sequential model
model = Sequential()

# Configuring the parameters
#CNN
model.add(keras.layers.Conv1D(filters=32,kernel_size=(1),strides=1,padding='valid',activation='relu'))
model.add(Dropout(0.5))

# 1st Layer of LSTM
model.add(keras.layers.Bidirectional(LSTM(32,return_sequences=True,kernel_initializer='glorot_normal'))))
# Adding a dropout layer
model.add(Dropout(0.5))

#LSTM
model.add(keras.layers.Bidirectional(LSTM(10 ,kernel_initializer='glorot_norma

```

```

1'))))
model.add(Dropout(0.5))

#DENSE
model.add(Dense(28,activation='relu'))

# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))

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

model.summary()

```

```

In [142]: # Training the model
model.fit(X_train,
          Y_train,
          batch_size=100,
          validation_data=(X_test, Y_test),
          epochs=100)

```

```

Train on 7352 samples, validate on 2947 samples
Epoch 1/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1460 - a
ccuracy: 0.9430 - val_loss: 0.3804 - val_accuracy: 0.8955
Epoch 2/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1587 - a
ccuracy: 0.9391 - val_loss: 0.4085 - val_accuracy: 0.8921
Epoch 3/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1525 - a
ccuracy: 0.9431 - val_loss: 0.3362 - val_accuracy: 0.8982
Epoch 4/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1392 - a
ccuracy: 0.9471 - val_loss: 0.3751 - val_accuracy: 0.8985
Epoch 5/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1381 - a
ccuracy: 0.9456 - val_loss: 0.3014 - val_accuracy: 0.9030
Epoch 6/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1395 - a
ccuracy: 0.9434 - val_loss: 0.3216 - val_accuracy: 0.9141
Epoch 7/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1481 - a
ccuracy: 0.9441 - val_loss: 0.3868 - val_accuracy: 0.8968
Epoch 8/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1582 - a
ccuracy: 0.9456 - val_loss: 0.3610 - val_accuracy: 0.9097
Epoch 9/100
7352/7352 [=====] - 25s 3ms/step - loss: 0.1478 - a
ccuracy: 0.9457 - val_loss: 0.3466 - val_accuracy: 0.9077
Epoch 10/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1367 - a
ccuracy: 0.9499 - val_loss: 0.3589 - val_accuracy: 0.9128
Epoch 11/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1342 - a
ccuracy: 0.9491 - val_loss: 0.3594 - val_accuracy: 0.9104
Epoch 12/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1291 - a
ccuracy: 0.9472 - val_loss: 0.3393 - val_accuracy: 0.9179
Epoch 13/100

```

7352/7352 [=====] - 26s 3ms/step - loss: 0.1297 - a
ccuracy: 0.9499 - val_loss: 0.3080 - val_accuracy: 0.9104
Epoch 14/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1293 - a
ccuracy: 0.9499 - val_loss: 0.4544 - val_accuracy: 0.9033
Epoch 15/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1291 - a
ccuracy: 0.9529 - val_loss: 0.4845 - val_accuracy: 0.8996
Epoch 16/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1383 - a
ccuracy: 0.9445 - val_loss: 0.3254 - val_accuracy: 0.9053
Epoch 17/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1319 - a
ccuracy: 0.9498 - val_loss: 0.4429 - val_accuracy: 0.8972
Epoch 18/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1257 - a
ccuracy: 0.9487 - val_loss: 0.3320 - val_accuracy: 0.9152
Epoch 19/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1153 - a
ccuracy: 0.9517 - val_loss: 0.3266 - val_accuracy: 0.9169
Epoch 20/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1213 - a
ccuracy: 0.9491 - val_loss: 0.3547 - val_accuracy: 0.9084
Epoch 21/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1306 - a
ccuracy: 0.9490 - val_loss: 0.3285 - val_accuracy: 0.9145
Epoch 22/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1257 - a
ccuracy: 0.9513 - val_loss: 0.3349 - val_accuracy: 0.9084
Epoch 23/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1516 - a
ccuracy: 0.9445 - val_loss: 0.4564 - val_accuracy: 0.9002
Epoch 24/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1307 - a
ccuracy: 0.9467 - val_loss: 0.3754 - val_accuracy: 0.9131
Epoch 25/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1206 - a
ccuracy: 0.9512 - val_loss: 0.4352 - val_accuracy: 0.9063
Epoch 26/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1247 - a
ccuracy: 0.9499 - val_loss: 0.3498 - val_accuracy: 0.9057
Epoch 27/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1226 - a
ccuracy: 0.9513 - val_loss: 0.4139 - val_accuracy: 0.9009
Epoch 28/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1126 - a
ccuracy: 0.9551 - val_loss: 0.4298 - val_accuracy: 0.9060
Epoch 29/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1179 - a
ccuracy: 0.9528 - val_loss: 0.3607 - val_accuracy: 0.9091
Epoch 30/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1177 - a
ccuracy: 0.9504 - val_loss: 0.3873 - val_accuracy: 0.9104
Epoch 31/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1250 - a
ccuracy: 0.9504 - val_loss: 0.3745 - val_accuracy: 0.9165
Epoch 32/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1180 - a
ccuracy: 0.9517 - val_loss: 0.3699 - val_accuracy: 0.9152
Epoch 33/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1178 - a
ccuracy: 0.9523 - val_loss: 0.2940 - val_accuracy: 0.9114

Epoch 34/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1235 - accuracy: 0.9502 - val_loss: 0.3252 - val_accuracy: 0.9158
Epoch 35/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1190 - accuracy: 0.9523 - val_loss: 0.3057 - val_accuracy: 0.9165
Epoch 36/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1141 - accuracy: 0.9538 - val_loss: 0.3922 - val_accuracy: 0.9131
Epoch 37/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1254 - accuracy: 0.9521 - val_loss: 0.3283 - val_accuracy: 0.9220
Epoch 38/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.2240 - accuracy: 0.9353 - val_loss: 0.4871 - val_accuracy: 0.9033
Epoch 39/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.2569 - accuracy: 0.9158 - val_loss: 0.4095 - val_accuracy: 0.9094
Epoch 40/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1870 - accuracy: 0.9353 - val_loss: 0.3674 - val_accuracy: 0.9111
Epoch 41/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1340 - accuracy: 0.9484 - val_loss: 0.3900 - val_accuracy: 0.9087
Epoch 42/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1293 - accuracy: 0.9489 - val_loss: 0.4196 - val_accuracy: 0.9050
Epoch 43/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1345 - accuracy: 0.9459 - val_loss: 0.3977 - val_accuracy: 0.9108
Epoch 44/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1238 - accuracy: 0.9512 - val_loss: 0.4015 - val_accuracy: 0.9087
Epoch 45/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1207 - accuracy: 0.9497 - val_loss: 0.3875 - val_accuracy: 0.9138
Epoch 46/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1217 - accuracy: 0.9494 - val_loss: 0.3926 - val_accuracy: 0.9084
Epoch 47/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1154 - accuracy: 0.9508 - val_loss: 0.3513 - val_accuracy: 0.9148
Epoch 48/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1163 - accuracy: 0.9524 - val_loss: 0.4061 - val_accuracy: 0.9114
Epoch 49/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1235 - accuracy: 0.9509 - val_loss: 0.3548 - val_accuracy: 0.9141
Epoch 50/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1170 - accuracy: 0.9536 - val_loss: 0.3650 - val_accuracy: 0.9189
Epoch 51/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1331 - accuracy: 0.9491 - val_loss: 0.3452 - val_accuracy: 0.9155
Epoch 52/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1184 - accuracy: 0.9509 - val_loss: 0.3585 - val_accuracy: 0.9172
Epoch 53/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1178 - accuracy: 0.9532 - val_loss: 0.3812 - val_accuracy: 0.9196
Epoch 54/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1222 - a

ccuracy: 0.9513 - val_loss: 0.3649 - val_accuracy: 0.9135
Epoch 55/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1149 - a
ccuracy: 0.9512 - val_loss: 0.3980 - val_accuracy: 0.9138
Epoch 56/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1417 - a
ccuracy: 0.9472 - val_loss: 0.3432 - val_accuracy: 0.9216
Epoch 57/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1148 - a
ccuracy: 0.9456 - val_loss: 0.3438 - val_accuracy: 0.9179
Epoch 58/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1137 - a
ccuracy: 0.9506 - val_loss: 0.4036 - val_accuracy: 0.9192
Epoch 59/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1424 - a
ccuracy: 0.9372 - val_loss: 0.4189 - val_accuracy: 0.9080
Epoch 60/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1265 - a
ccuracy: 0.9431 - val_loss: 0.3738 - val_accuracy: 0.9148
Epoch 61/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1366 - a
ccuracy: 0.9324 - val_loss: 0.3003 - val_accuracy: 0.8938
Epoch 62/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1267 - a
ccuracy: 0.9434 - val_loss: 0.4071 - val_accuracy: 0.9135
Epoch 63/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1210 - a
ccuracy: 0.9472 - val_loss: 0.3611 - val_accuracy: 0.9121
Epoch 64/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1117 - a
ccuracy: 0.9502 - val_loss: 0.3111 - val_accuracy: 0.9186
Epoch 65/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1132 - a
ccuracy: 0.9521 - val_loss: 0.3706 - val_accuracy: 0.9169
Epoch 66/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1533 - a
ccuracy: 0.9423 - val_loss: 0.4784 - val_accuracy: 0.8996
Epoch 67/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1489 - a
ccuracy: 0.9460 - val_loss: 0.3952 - val_accuracy: 0.9080
Epoch 68/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1182 - a
ccuracy: 0.9525 - val_loss: 0.3491 - val_accuracy: 0.9101
Epoch 69/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1204 - a
ccuracy: 0.9513 - val_loss: 0.3071 - val_accuracy: 0.9189
Epoch 70/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1177 - a
ccuracy: 0.9512 - val_loss: 0.3403 - val_accuracy: 0.9097
Epoch 71/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1128 - a
ccuracy: 0.9535 - val_loss: 0.3318 - val_accuracy: 0.9128
Epoch 72/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1124 - a
ccuracy: 0.9570 - val_loss: 0.3738 - val_accuracy: 0.9158
Epoch 73/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1100 - a
ccuracy: 0.9532 - val_loss: 0.3994 - val_accuracy: 0.9111
Epoch 74/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1124 - a
ccuracy: 0.9529 - val_loss: 0.4262 - val_accuracy: 0.9108
Epoch 75/100

7352/7352 [=====] - 26s 4ms/step - loss: 0.1068 - a
ccuracy: 0.9551 - val_loss: 0.4459 - val_accuracy: 0.9053
Epoch 76/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1075 - a
ccuracy: 0.9531 - val_loss: 0.4066 - val_accuracy: 0.9141
Epoch 77/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1168 - a
ccuracy: 0.9520 - val_loss: 0.3940 - val_accuracy: 0.9128
Epoch 78/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1093 - a
ccuracy: 0.9567 - val_loss: 0.3772 - val_accuracy: 0.9165
Epoch 79/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1112 - a
ccuracy: 0.9539 - val_loss: 0.3633 - val_accuracy: 0.9179
Epoch 80/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1064 - a
ccuracy: 0.9581 - val_loss: 0.3295 - val_accuracy: 0.9158
Epoch 81/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1074 - a
ccuracy: 0.9551 - val_loss: 0.3802 - val_accuracy: 0.9155
Epoch 82/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1050 - a
ccuracy: 0.9580 - val_loss: 0.3834 - val_accuracy: 0.9209
Epoch 83/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1011 - a
ccuracy: 0.9558 - val_loss: 0.3930 - val_accuracy: 0.9162
Epoch 84/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1151 - a
ccuracy: 0.9543 - val_loss: 0.3322 - val_accuracy: 0.9206
Epoch 85/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1063 - a
ccuracy: 0.9547 - val_loss: 0.3533 - val_accuracy: 0.9209
Epoch 86/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1057 - a
ccuracy: 0.9559 - val_loss: 0.3469 - val_accuracy: 0.9145
Epoch 87/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1100 - a
ccuracy: 0.9539 - val_loss: 0.3275 - val_accuracy: 0.9131
Epoch 88/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1137 - a
ccuracy: 0.9524 - val_loss: 0.3467 - val_accuracy: 0.9223
Epoch 89/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1101 - a
ccuracy: 0.9559 - val_loss: 0.5188 - val_accuracy: 0.9125
Epoch 90/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1130 - a
ccuracy: 0.9553 - val_loss: 0.5026 - val_accuracy: 0.9091
Epoch 91/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1141 - a
ccuracy: 0.9532 - val_loss: 0.3782 - val_accuracy: 0.9209
Epoch 92/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1107 - a
ccuracy: 0.9561 - val_loss: 0.4357 - val_accuracy: 0.9128
Epoch 93/100
7352/7352 [=====] - 26s 3ms/step - loss: 0.1074 - a
ccuracy: 0.9576 - val_loss: 0.5562 - val_accuracy: 0.9070
Epoch 94/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1097 - a
ccuracy: 0.9555 - val_loss: 0.4038 - val_accuracy: 0.9240
Epoch 95/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1141 - a
ccuracy: 0.9529 - val_loss: 0.3881 - val_accuracy: 0.9209

```
Epoch 96/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1170 - a
ccuracy: 0.9504 - val_loss: 0.5715 - val_accuracy: 0.8989
Epoch 97/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1187 - a
ccuracy: 0.9532 - val_loss: 0.4648 - val_accuracy: 0.9118
Epoch 98/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1075 - a
ccuracy: 0.9566 - val_loss: 0.4258 - val_accuracy: 0.9196
Epoch 99/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1032 - a
ccuracy: 0.9555 - val_loss: 0.4230 - val_accuracy: 0.9165
Epoch 100/100
7352/7352 [=====] - 26s 4ms/step - loss: 0.1358 - a
ccuracy: 0.9510 - val_loss: 0.4273 - val_accuracy: 0.9172
```

Out[142]: <keras.callbacks.callbacks.History at 0x15d483e3e08>

```
In [143]: score = model.evaluate(X_test, Y_test)
score
```

```
2947/2947 [=====] - 14s 5ms/step
```

Out[143]: [0.42743501546085205, 0.917203962802887]

Observation ...

3. Divide and Conquer method

refer: <https://www.mdpi.com/1424-8220/18/4/1055>

refer: <https://github.com/heeryoncho/sensors2018cnnhar>

From paper:

"Our approach is similar to [36] in that we perform a two-stage classification where we classify abstract activities (e.g., dynamic and static) first and then classify individual activities (e.g., walking, standing, etc.) next. However, we build one binary 1D CNN model at the first stage and two multi-class 1D CNN models at the second stage. More importantly, we introduce test data sharpening in between the two-stage HAR, selectively at the prediction phase only, and this differentiates our approach from the rest of the two-stage HAR approaches."

```
In [34]: # refer: https://www.mdpi.com/1424-8220/18/4/1055
# refer: https://github.com/heeryoncho/sensors2018cnnhar

from IPython.display import Image
Image(filename='divide and conquer.PNG')
```

Out[34]:

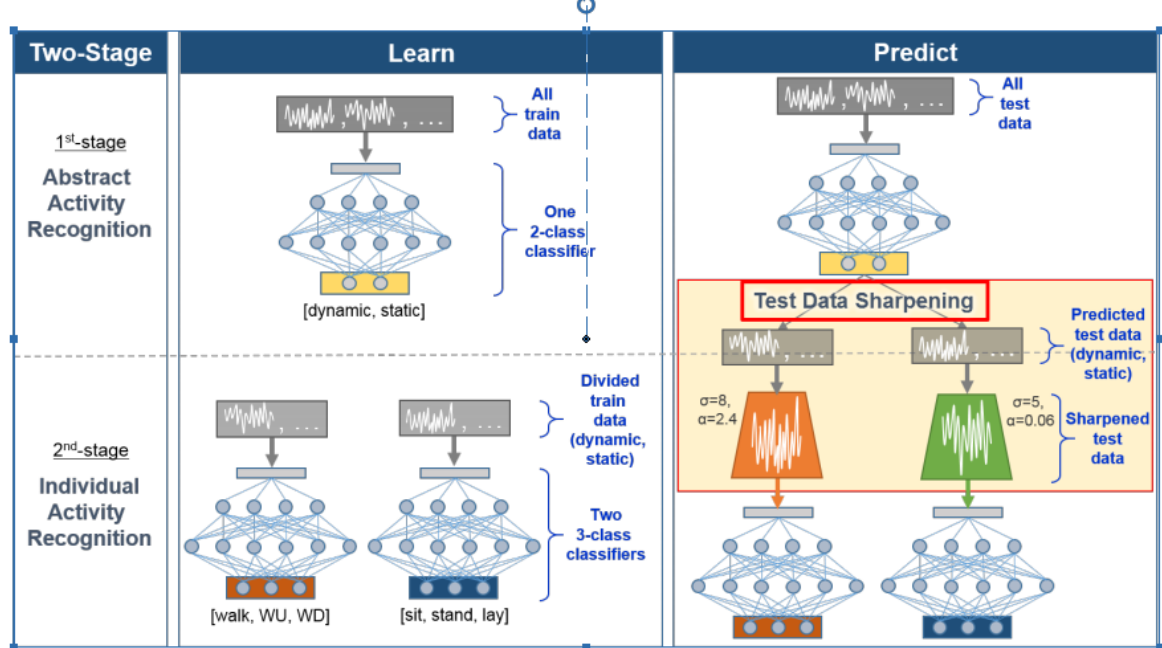


Figure 2. Overview of our divide and conquer-based 1D CNN HAR with test data sharpening. Our approach employs two-stage classifier learning during the learning phase and introduces test data sharpening during the prediction phase.

```
In [35]: #utility function
# decoding y_train(6 class) into {0,1,2,3,4,5,9}
def amax(num):
    return (np.argmax(num))

y_train_decode=pd.DataFrame(Y_train).apply(amax,axis=1)
y_test_decode=pd.DataFrame(Y_test).apply(amax,axis=1)

print("Before: ")
print(Y_train)
print("\nAfter: ")
print(y_train_decode)
```

Before:

```
[[0 0 0 0 1 0]
 [0 0 0 0 1 0]
 [0 0 0 0 1 0]
 ...
 [0 1 0 0 0 0]
 [0 1 0 0 0 0]
 [0 1 0 0 0 0]]
```

After:

```
0      4
1      4
2      4
3      4
4      4
```

```
..
7347    1
7348    1
7349    1
7350    1
7351    1
```

Length: 7352, dtype: int64

The current behaviour of 'Series.argmax' is deprecated, use 'idxmax' instead.
The behavior of 'argmax' will be corrected to return the positional maximum in the future. For now, use 'series.values.argmax' or 'np.argmax(np.array(values))' to get the position of the maximum row.

```
return getattr(obj, method)(*args, **kwds)
```

```
In [36]: # utility function
def binary_decode(num):
    if np.argmax(num)<3:
        return 0
    else:
        return 1
```

3.1 Model for static and dynamic binary classification

```
In [37]: # model for static and dynamic binary classification
def train_2_class_classification():

    # mode configuration
    model = Sequential()
    model.add(Conv1D(128, 3, input_shape=(128, 9), activation='relu'))
    model.add(Conv1D(64, 3, activation='relu'))
    model.add(Flatten())
    model.add(Dense(2, activation='softmax'))
    model.add(Dropout(0.50))

    model.compile(loss='mean_squared_error', optimizer='adam', metrics=['accuracy'])

    # Summarize layers
    print(model.summary())
    return model

train_2_class_classification()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv1d_9 (Conv1D)	(None, 126, 128)	3584
conv1d_10 (Conv1D)	(None, 124, 64)	24640
flatten_5 (Flatten)	(None, 7936)	0
dense_5 (Dense)	(None, 2)	15874
dropout_5 (Dropout)	(None, 2)	0
Total params: 44,098		
Trainable params: 44,098		
Non-trainable params: 0		
None		

Out[37]: <keras.engine.sequential.Sequential at 0x2da5b4c8188>

```
In [38]: # preparing data for static and dynamic binary classification

# this will convert y_train and y_test into {0,1}
y_train_binary= pd.DataFrame(Y_train).apply(binary_decode,axis=1)
y_test_binary= pd.DataFrame(Y_test).apply(binary_decode,axis=1)

# one hot encoding of decoded y_train and y_test
y_train_static_dynamic_oh = keras.utils.to_categorical(y_train_binary)
y_test_static_dynamic_oh = keras.utils.to_categorical(y_test_binary) # one hot
encoding of decoded y_test

# Training static and dynamic binary classification
binary_model = train_2_class_classification()
binary_model.fit(X_train, y_train_static_dynamic_oh,
                 batch_size=32, epochs=15, verbose=2, validation_data=(X_test,y_test_static_dynamic_oh) )
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
conv1d_11 (Conv1D)	(None, 126, 128)	3584
conv1d_12 (Conv1D)	(None, 124, 64)	24640
flatten_6 (Flatten)	(None, 7936)	0
dense_6 (Dense)	(None, 2)	15874
dropout_6 (Dropout)	(None, 2)	0

=====
Total params: 44,098
Trainable params: 44,098
Non-trainable params: 0
=====

None

Train on 7352 samples, validate on 2947 samples

Epoch 1/15

- 2s - loss: 0.3890 - accuracy: 0.6094 - val_loss: 0.0746 - val_accuracy: 0.9969

Epoch 2/15

- 1s - loss: 0.3816 - accuracy: 0.6158 - val_loss: 0.0745 - val_accuracy: 0.9973

Epoch 3/15

- 1s - loss: 0.3803 - accuracy: 0.6100 - val_loss: 0.0634 - val_accuracy: 0.9969

Epoch 4/15

- 1s - loss: 0.3737 - accuracy: 0.6243 - val_loss: 0.0735 - val_accuracy: 0.9959

Epoch 5/15

- 1s - loss: 0.3781 - accuracy: 0.6117 - val_loss: 0.0671 - val_accuracy: 0.9990

Epoch 6/15

- 1s - loss: 0.3767 - accuracy: 0.6124 - val_loss: 0.0768 - val_accuracy: 0.9959

Epoch 7/15

- 1s - loss: 0.3768 - accuracy: 0.6163 - val_loss: 0.0770 - val_accuracy: 0.9946

Epoch 8/15

- 1s - loss: 0.3727 - accuracy: 0.6306 - val_loss: 0.0796 - val_accuracy: 0.9956

```

0.9936
Epoch 9/15
  - 1s - loss: 0.3768 - accuracy: 0.6158 - val_loss: 0.0526 - val_accuracy:
0.9976
Epoch 10/15
  - 1s - loss: 0.3773 - accuracy: 0.6106 - val_loss: 0.0764 - val_accuracy:
0.9990
Epoch 11/15
  - 1s - loss: 0.3800 - accuracy: 0.6113 - val_loss: 0.0718 - val_accuracy:
0.9936
Epoch 12/15
  - 1s - loss: 0.3776 - accuracy: 0.6089 - val_loss: 0.0737 - val_accuracy:
0.9976
Epoch 13/15
  - 1s - loss: 0.3776 - accuracy: 0.6128 - val_loss: 0.0615 - val_accuracy:
0.9986
Epoch 14/15
  - 1s - loss: 0.3806 - accuracy: 0.5996 - val_loss: 0.0545 - val_accuracy:
0.9980
Epoch 15/15
  - 1s - loss: 0.3760 - accuracy: 0.6133 - val_loss: 0.0644 - val_accuracy:
0.9990

```

```
Out[38]: <keras.callbacks.callbacks.History at 0x2da5ad6ce88>
```

```
In [39]: binary_model.evaluate(X_test,y_test_static_dynamic_oh)

2947/2947 [=====] - 0s 74us/step
```

```
Out[39]: [0.06440044102560151, 0.9989820122718811]
```

3.2 Model for Dynamic HAR

```
In [40]: # refer: https://www.mdpi.com/1424-8220/18/4/1055
# refer: https://github.com/heeryoncho/sensors2018cnnhar

from IPython.display import Image
Image(filename='dynamic model.PNG')
```

```
Out[40]:
```

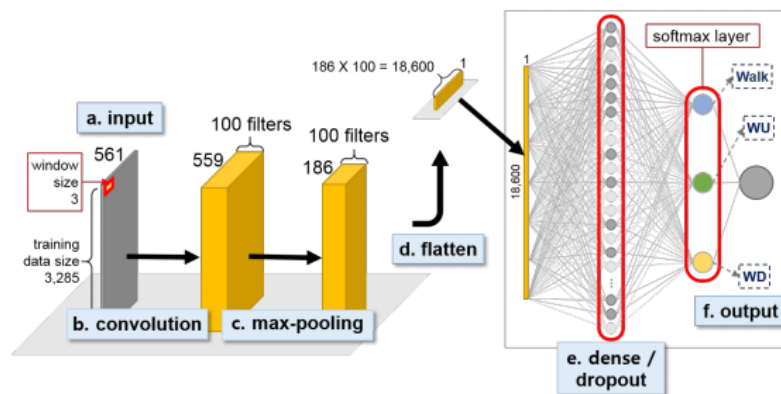


Figure 10. Second-stage 1D CNN for classifying dynamic activity, i.e., Walk, WU, and WD, for UCI HAR dataset.

```
In [41]: # 1d CNN for dynamic HAR
def train_dyanamic():
    model = Sequential()
    model.add(Conv1D(100, 3, input_shape=(128, 9), activation='relu'))
```

```

model.add(keras.layers.MaxPooling1D(3))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
model.add(Dropout(0.5))

adam = keras.optimizers.Adam(lr=0.0004, beta_1=0.9, beta_2=0.999, epsilon=
1e-08, decay=0.0)
model.compile(loss='mean_squared_error', optimizer=adam, metrics=['accurac
y'])

model.summary()

return model

```

```

In [42]: # preparing traning data for dynamic 3-class classification

# Index of dynamic activity
dynamic_0=np.where(y_train_decode==0)[0]
dynamic_1=np.where(y_train_decode==1)[0]
dynamic_2=np.where(y_train_decode==2)[0]

dynamic_index=np.concatenate((dynamic_0,dynamic_1,dynamic_2),axis=0)

x_train_dyanamic=X_train[dynamic_index]
y_train_dynamic=y_train_decode[dynamic_index]
print("Total number of dynamic_traning data:",dynamic_index.shape[0])

# preparing test data
# Index of dynamic activity
dynamic_0=np.where(y_test_decode==0)[0]
dynamic_1=np.where(y_test_decode==1)[0]
dynamic_2=np.where(y_test_decode==2)[0]

dynamic_index=np.concatenate((dynamic_0,dynamic_1,dynamic_2))

x_test_dyanamic=X_test[dynamic_index]
y_test_dynamic=y_test_decode[dynamic_index]
print("Total number of dynamic_testing data:",dynamic_index.shape[0])

# Convert to one hot encoding vector
y_train_dynamic_oh = keras.utils.to_categorical(y_train_dynamic)
y_test_dynamic_oh = keras.utils.to_categorical(y_test_dynamic)

Total number of dynamic_traning data: 3285
Total number of dynamic_testing data: 1387

```

```

In [43]: # Early Stopper callback
early_stopper = EarlyStopping(monitor='val_loss',min_delta=1e-4,patience=10,ve
rbose=1,
                                mode='auto',baseline=None,restore_best_weights=T
rue)

dynamic_model=train_dyanamic()
dynamic_model.fit(x_train_dyanamic, y_train_dynamic_oh,
                  batch_size=32, epochs=50, verbose=2, validation_data=(x_test_dyan
amic,y_test_dynamic_oh),callbacks=[early_stopper] )

Model: "sequential_7"

```

Layer (type)	Output Shape	Param #
conv1d_13 (Conv1D)	(None, 126, 100)	2800
max_pooling1d_2 (MaxPooling1D)	(None, 42, 100)	0
flatten_7 (Flatten)	(None, 4200)	0
dense_7 (Dense)	(None, 3)	12603
dropout_7 (Dropout)	(None, 3)	0

Total params: 15,403
 Trainable params: 15,403
 Non-trainable params: 0

Train on 3285 samples, validate on 1387 samples

Epoch 1/50

- 1s - loss: 0.3150 - accuracy: 0.4180 - val_loss: 0.1867 - val_accuracy: 0.6496

Epoch 2/50

- 1s - loss: 0.2827 - accuracy: 0.4919 - val_loss: 0.1606 - val_accuracy: 0.6792

Epoch 3/50

- 1s - loss: 0.2632 - accuracy: 0.5163 - val_loss: 0.1412 - val_accuracy: 0.7952

Epoch 4/50

- 1s - loss: 0.2478 - accuracy: 0.5379 - val_loss: 0.1274 - val_accuracy: 0.8472

Epoch 5/50

- 1s - loss: 0.2516 - accuracy: 0.5193 - val_loss: 0.1209 - val_accuracy: 0.8385

Epoch 6/50

- 1s - loss: 0.2425 - accuracy: 0.5382 - val_loss: 0.1129 - val_accuracy: 0.8832

Epoch 7/50

- 1s - loss: 0.2423 - accuracy: 0.5279 - val_loss: 0.1118 - val_accuracy: 0.8717

Epoch 8/50

- 1s - loss: 0.2388 - accuracy: 0.5467 - val_loss: 0.1071 - val_accuracy: 0.9084

Epoch 9/50

- 1s - loss: 0.2368 - accuracy: 0.5428 - val_loss: 0.1039 - val_accuracy: 0.9142

Epoch 10/50

- 1s - loss: 0.2350 - accuracy: 0.5482 - val_loss: 0.1064 - val_accuracy: 0.9048

Epoch 11/50

- 1s - loss: 0.2310 - accuracy: 0.5629 - val_loss: 0.1043 - val_accuracy: 0.9293

Epoch 12/50

- 1s - loss: 0.2347 - accuracy: 0.5440 - val_loss: 0.1026 - val_accuracy: 0.9279

Epoch 13/50

- 1s - loss: 0.2361 - accuracy: 0.5425 - val_loss: 0.1002 - val_accuracy: 0.9200

Epoch 14/50

- 1s - loss: 0.2381 - accuracy: 0.5333 - val_loss: 0.1000 - val_accuracy: 0.9380

Epoch 15/50

- 1s - loss: 0.2341 - accuracy: 0.5479 - val_loss: 0.1005 - val_accuracy:

0.9358
Epoch 16/50
- 1s - loss: 0.2314 - accuracy: 0.5473 - val_loss: 0.0986 - val_accuracy:
0.9329
Epoch 17/50
- 1s - loss: 0.2299 - accuracy: 0.5549 - val_loss: 0.0993 - val_accuracy:
0.9337
Epoch 18/50
- 1s - loss: 0.2258 - accuracy: 0.5659 - val_loss: 0.1000 - val_accuracy:
0.9409
Epoch 19/50
- 1s - loss: 0.2319 - accuracy: 0.5479 - val_loss: 0.0974 - val_accuracy:
0.9344
Epoch 20/50
- 1s - loss: 0.2340 - accuracy: 0.5333 - val_loss: 0.0962 - val_accuracy:
0.9452
Epoch 21/50
- 1s - loss: 0.2330 - accuracy: 0.5425 - val_loss: 0.0946 - val_accuracy:
0.9466
Epoch 22/50
- 1s - loss: 0.2295 - accuracy: 0.5565 - val_loss: 0.0945 - val_accuracy:
0.9438
Epoch 23/50
- 1s - loss: 0.2348 - accuracy: 0.5279 - val_loss: 0.0970 - val_accuracy:
0.9438
Epoch 24/50
- 1s - loss: 0.2337 - accuracy: 0.5382 - val_loss: 0.0942 - val_accuracy:
0.9488
Epoch 25/50
- 1s - loss: 0.2315 - accuracy: 0.5452 - val_loss: 0.0971 - val_accuracy:
0.9301
Epoch 26/50
- 1s - loss: 0.2319 - accuracy: 0.5425 - val_loss: 0.0936 - val_accuracy:
0.9531
Epoch 27/50
- 1s - loss: 0.2326 - accuracy: 0.5385 - val_loss: 0.0950 - val_accuracy:
0.9394
Epoch 28/50
- 1s - loss: 0.2253 - accuracy: 0.5565 - val_loss: 0.0956 - val_accuracy:
0.9452
Epoch 29/50
- 1s - loss: 0.2308 - accuracy: 0.5406 - val_loss: 0.0943 - val_accuracy:
0.9466
Epoch 30/50
- 1s - loss: 0.2286 - accuracy: 0.5434 - val_loss: 0.0944 - val_accuracy:
0.9546
Epoch 31/50
- 1s - loss: 0.2265 - accuracy: 0.5671 - val_loss: 0.0939 - val_accuracy:
0.9488
Epoch 32/50
- 1s - loss: 0.2339 - accuracy: 0.5336 - val_loss: 0.0918 - val_accuracy:
0.9546
Epoch 33/50
- 1s - loss: 0.2292 - accuracy: 0.5498 - val_loss: 0.0930 - val_accuracy:
0.9539
Epoch 34/50
- 1s - loss: 0.2293 - accuracy: 0.5446 - val_loss: 0.0919 - val_accuracy:
0.9539
Epoch 35/50
- 1s - loss: 0.2251 - accuracy: 0.5580 - val_loss: 0.0946 - val_accuracy:
0.9560
Epoch 36/50

```

- 1s - loss: 0.2304 - accuracy: 0.5425 - val_loss: 0.0926 - val_accuracy:
0.9539
Epoch 37/50
- 1s - loss: 0.2274 - accuracy: 0.5495 - val_loss: 0.0898 - val_accuracy:
0.9640
Epoch 38/50
- 1s - loss: 0.2245 - accuracy: 0.5586 - val_loss: 0.0929 - val_accuracy:
0.9603
Epoch 39/50
- 1s - loss: 0.2207 - accuracy: 0.5714 - val_loss: 0.0942 - val_accuracy:
0.9495
Epoch 40/50
- 1s - loss: 0.2256 - accuracy: 0.5574 - val_loss: 0.0939 - val_accuracy:
0.9531
Epoch 41/50
- 1s - loss: 0.2274 - accuracy: 0.5479 - val_loss: 0.0922 - val_accuracy:
0.9560
Epoch 42/50
- 0s - loss: 0.2285 - accuracy: 0.5482 - val_loss: 0.0931 - val_accuracy:
0.9488
Epoch 43/50
- 0s - loss: 0.2303 - accuracy: 0.5346 - val_loss: 0.0922 - val_accuracy:
0.9582
Epoch 44/50
- 0s - loss: 0.2287 - accuracy: 0.5528 - val_loss: 0.0933 - val_accuracy:
0.9560
Epoch 45/50
- 0s - loss: 0.2306 - accuracy: 0.5412 - val_loss: 0.0935 - val_accuracy:
0.9510
Epoch 46/50
- 0s - loss: 0.2289 - accuracy: 0.5446 - val_loss: 0.0945 - val_accuracy:
0.9539
Epoch 47/50
- 0s - loss: 0.2311 - accuracy: 0.5373 - val_loss: 0.0933 - val_accuracy:
0.9517
Restoring model weights from the end of the best epoch
Epoch 00047: early stopping

```

Out[43]: <keras.callbacks.callbacks.History at 0x2da5ac96e48>

```

In [44]: dynamic_model.evaluate(x_test_dyanamic,y_test_dynamic_oh)

1387/1387 [=====] - 0s 58us/step

```

Out[44]: [0.08977583711181257, 0.9639509916305542]

3.3 Model for static HAR

```

In [45]: # refer: https://www.mdpi.com/1424-8220/18/4/1055
# refer: https://github.com/heeryoncho/sensors2018cnnhar

from IPython.display import Image
Image(filename='static model.PNG')

```

Out[45]:

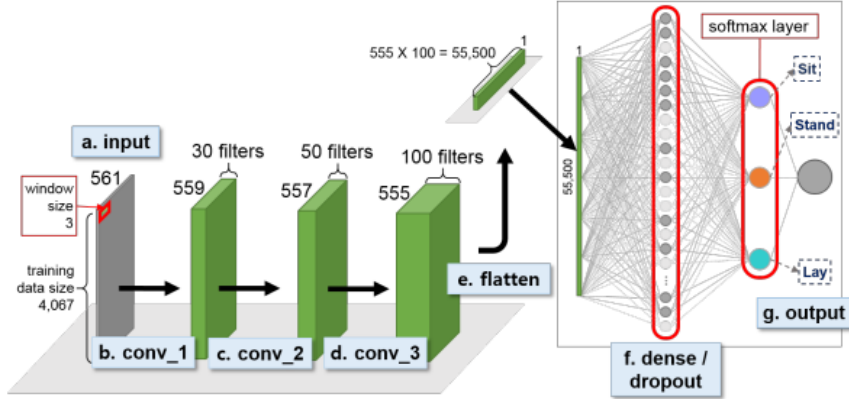


Figure 11. Second-stage 1D CNN for classifying static activity, i.e., Sit, Stand, and Lay, for UCI HAR dataset.

```
In [46]: # model for static HAR
def train_static():

    model = Sequential()
    model.add(Conv1D(30, 3, input_shape=(128, 9), activation='relu'))
    model.add(Conv1D(50, 3, activation='relu'))
    model.add(Conv1D(100, 3, activation='relu'))
    model.add(Flatten())
    model.add(Dense(3, activation='softmax'))
    model.add(Dropout(0.50))

    adam = keras.optimizers.Adam(lr=0.0001, beta_1=0.9, beta_2=0.999, epsilon=
1e-08, decay=0.0)
    model.compile(loss='mean_squared_error', optimizer=adam, metrics=['accurac
y'])

    # Summarize layers
    print(model.summary())
    return model
```

```
In [47]: # preparing data for STATIC 3-class classification

# Index of static activity train data
static_0=np.where(y_train_decode==3)[0]
static_1=np.where(y_train_decode==4)[0]
static_2=np.where(y_train_decode==5)[0]
static_index=np.concatenate((static_0, static_1, static_2),axis=0)

# X_train_static, y_train_static
x_train_static=X_train[static_index]
y_train_static=y_train_decode[static_index]
print("Total number of static_training data:",static_index.shape[0])

# Index of static activity test data
static_0=np.where(y_test_decode==3)[0]
static_1=np.where(y_test_decode==4)[0]
static_2=np.where(y_test_decode==5)[0]
static_index=np.concatenate((static_0, static_1, static_2) )
print("Total number of static_training data:",static_index.shape[0])

# X_test_static, y_test_static
x_test_static=X_test[static_index]
y_test_static=y_test_decode[static_index]
```



```
# labeling class_lables from {3,4,5} to {0,1,2} for training
y_train_static=y_train_static.map({3:0, 4:1, 5:2})
y_test_static=y_test_static.map({3:0, 4:1, 5:2})

# Convert to one hot encoding vector
y_train_static_oh = keras.utils.to_categorical(y_train_static)
y_test_static_oh = keras.utils.to_categorical(y_test_static)
```

Total number of static_training data: 4067
Total number of static_training data: 1560

```
In [48]: # Early Stopper callback
early_stopper = EarlyStopping(monitor='val_loss',min_delta=1e-4,patience=10,verbose=1,
                                mode='auto',baseline=None,restore_best_weights=True)

static_model=train_static()
static_model.fit(x_train_static, y_train_static_oh,
                 batch_size=32, epochs=50, verbose=2, validation_data=(x_test_static,y_test_static_oh) ,callbacks=[early_stopper] )
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
conv1d_14 (Conv1D)	(None, 126, 30)	840
conv1d_15 (Conv1D)	(None, 124, 50)	4550
conv1d_16 (Conv1D)	(None, 122, 100)	15100
flatten_8 (Flatten)	(None, 12200)	0
dense_8 (Dense)	(None, 3)	36603
dropout_8 (Dropout)	(None, 3)	0

Total params: 57,093
Trainable params: 57,093
Non-trainable params: 0

```
None
Train on 4067 samples, validate on 1560 samples
Epoch 1/50
- 1s - loss: 0.2748 - accuracy: 0.4773 - val_loss: 0.1040 - val_accuracy: 0.8603
Epoch 2/50
- 1s - loss: 0.2473 - accuracy: 0.5213 - val_loss: 0.0995 - val_accuracy: 0.8603
Epoch 3/50
- 1s - loss: 0.2414 - accuracy: 0.5331 - val_loss: 0.1016 - val_accuracy: 0.8788
Epoch 4/50
- 1s - loss: 0.2473 - accuracy: 0.5055 - val_loss: 0.0971 - val_accuracy: 0.8641
Epoch 5/50
- 1s - loss: 0.2451 - accuracy: 0.5151 - val_loss: 0.0921 - val_accuracy: 0.8821
Epoch 6/50
- 1s - loss: 0.2437 - accuracy: 0.5225 - val_loss: 0.0919 - val_accuracy:
```

```
0.8769
Epoch 7/50
  - 1s - loss: 0.2453 - accuracy: 0.5100 - val_loss: 0.0975 - val_accuracy:
0.8769
Epoch 8/50
  - 1s - loss: 0.2451 - accuracy: 0.5085 - val_loss: 0.0920 - val_accuracy:
0.8833
Epoch 9/50
  - 1s - loss: 0.2428 - accuracy: 0.5144 - val_loss: 0.0937 - val_accuracy:
0.8712
Epoch 10/50
  - 1s - loss: 0.2408 - accuracy: 0.5279 - val_loss: 0.0963 - val_accuracy:
0.8769
Epoch 11/50
  - 1s - loss: 0.2401 - accuracy: 0.5195 - val_loss: 0.0993 - val_accuracy:
0.8737
Epoch 12/50
  - 1s - loss: 0.2395 - accuracy: 0.5220 - val_loss: 0.0940 - val_accuracy:
0.8692
Epoch 13/50
  - 1s - loss: 0.2427 - accuracy: 0.5181 - val_loss: 0.0942 - val_accuracy:
0.8724
Epoch 14/50
  - 1s - loss: 0.2414 - accuracy: 0.5225 - val_loss: 0.0958 - val_accuracy:
0.8692
Epoch 15/50
  - 1s - loss: 0.2415 - accuracy: 0.5183 - val_loss: 0.0947 - val_accuracy:
0.8788
Epoch 16/50
  - 1s - loss: 0.2425 - accuracy: 0.5200 - val_loss: 0.0901 - val_accuracy:
0.8853
Epoch 17/50
  - 1s - loss: 0.2428 - accuracy: 0.5164 - val_loss: 0.0910 - val_accuracy:
0.8833
Epoch 18/50
  - 1s - loss: 0.2414 - accuracy: 0.5141 - val_loss: 0.0954 - val_accuracy:
0.8827
Epoch 19/50
  - 1s - loss: 0.2361 - accuracy: 0.5368 - val_loss: 0.0967 - val_accuracy:
0.8731
Epoch 20/50
  - 1s - loss: 0.2443 - accuracy: 0.5095 - val_loss: 0.0956 - val_accuracy:
0.8827
Epoch 21/50
  - 1s - loss: 0.2405 - accuracy: 0.5183 - val_loss: 0.0972 - val_accuracy:
0.8853
Epoch 22/50
  - 1s - loss: 0.2425 - accuracy: 0.5151 - val_loss: 0.0952 - val_accuracy:
0.8897
Epoch 23/50
  - 1s - loss: 0.2396 - accuracy: 0.5272 - val_loss: 0.0970 - val_accuracy:
0.8865
Epoch 24/50
  - 1s - loss: 0.2363 - accuracy: 0.5301 - val_loss: 0.0938 - val_accuracy:
0.8910
Epoch 25/50
  - 1s - loss: 0.2427 - accuracy: 0.5149 - val_loss: 0.0947 - val_accuracy:
0.8897
Epoch 26/50
  - 1s - loss: 0.2396 - accuracy: 0.5213 - val_loss: 0.0908 - val_accuracy:
0.8737
Restoring model weights from the end of the best epoch
```

Epoch 00026: early stopping

Out[48]: <keras.callbacks.callbacks.History at 0x2da54126ac8>

```
In [49]: static_model.evaluate(x_test_static,y_test_static_oh)
1560/1560 [=====] - 0s 60us/step
```

Out[49]: [0.09011286143691112, 0.8852564096450806]

Testing

```
In [50]: # Execute this after executiong binary, static and dynamic classification training is complete
def testing(x_test, y_test):

    # Binary class prediction
    predict_y_test_binary=binary_model.predict_classes(x_test)

    # Static 1-D CNN 3-class prediction
    static_prediction_index = np.where(predict_y_test_binary==1)
    predict_y_test_static = static_model.predict_classes(x_test[static_prediction_index]) # for static
    predict_y_test_static = pd.Series(predict_y_test_static).map({0:3,1:4,2:5})

    # Dynamic 1-D CNN 3-class prediction
    dynamic_prediction_index = np.where(predict_y_test_binary==0)
    predict_y_test_dynamic= dynamic_model.predict_classes(x_test[dynamic_prediction_index]) # for dynamic

    # Modify the value of prediction od dynamic and static activity
    y_test_pred_generated = np.zeros((x_test.shape[0]))
    y_test_pred_generated[static_prediction_index] = predict_y_test_static
    y_test_pred_generated[dynamic_prediction_index] = predict_y_test_dynamic

    # converting final value to one hot encoding
    y_test_pred_generated_oh = keras.utils.to_categorical(y_test_pred_generated)

    # accuracy score
    accuracy = accuracy_score(y_test, y_test_pred_generated_oh)

    return accuracy
```

```
In [51]: print("Train accuracy: ",testing(X_train,Y_train))
print("Test accuracy: ",testing(X_test,Y_test))
```

Train accuracy: 0.9610990206746464
Test accuracy: 0.9219545300305395

Test Sharpening

```
In [52]: # refer: https://www.mdpi.com/1424-8220/18/4/1055
# refer: https://github.com/heeryoncho/sensors2018cnnhar
```

```
from IPython.display import Image
Image(filename='test sharpening.PNG')
```

Out[52]:

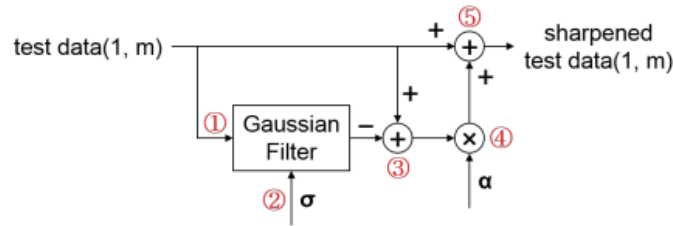


Figure 4. Test data sharpening using a Gaussian filter. Test data is first denoised using a Gaussian filter (①) using the σ parameter (②), and the denoised result is subtracted from the test data to obtain sharpened details (③). The sharpened details are then amplified to some degree using α parameter (④) and added to the original test data to obtain sharpened test data (⑤).

$$\text{Denoised}(1, m) = \text{GaussianFilter}(\text{TestData}(1, m), \sigma) \quad (1)$$

$$\text{Detailed}(1, m) = \text{TestData}(1, m) - \text{Denoised}(1, m) \quad (2)$$

$$\text{Sharpened}(1, m) = \text{TestData}(1, m) + \alpha \times \text{Detailed}(1, m) \quad (3)$$

```
In [53]: def sharpened(data, sig=1, al=1):

    sharpen_data = []
    for i in (range((data.shape[0]))):

        x_t=data[i]
        denoised_data = scipy.ndimage.gaussian_filter(input=x_t , sigma=sig)
        detailed_data = x_t - denoised_data
        after_sharpend = x_t + (al*denoised_data)

        sharpen_data.append(after_sharpend)

    return np.array(sharpend_data)
```

```
In [54]: # refer: https://www.mdpi.com/1424-8220/18/4/1055
# refer: https://github.com/heeryoncho/sensors2018cnnhar
```

```
from IPython.display import Image
Image(filename='after sharpening.PNG')
```

Out[54]:

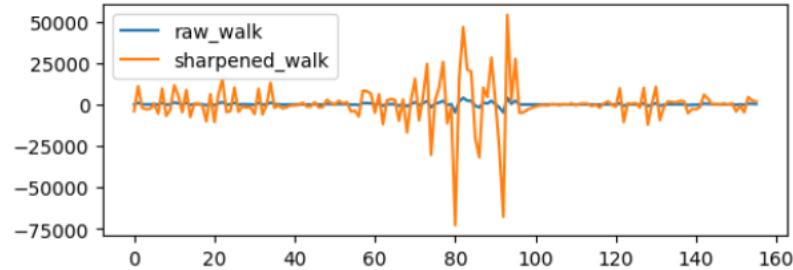


Figure 5. A sample activity data describing walking activity. Each number in the horizontal axis indicates various statistical features such as mean, standard deviation, minimum and maximum calculated from a fixed length time series data collected from multiple sensors. The blue line indicates data before sharpening and the orange line indicates data after sharpening.

```
In [55]: X_test_sharpened=sharpened(data=X_test, sig=0.1, al=0.1)

testing(X_test_sharpened ,Y_test)
```

Out[55]: 0.9219545300305395

Finding right value of sigma and alpha for Test sharpening

```
In [56]: # finding right value of sigma and alpha for Test sharpening
sigma_range = np.arange(5,10,1)
alpha_range = np.round(np.arange(0.01,0.31,0.01),3)

result_daframe = pd.DataFrame(np.zeros((sigma_range.shape[0],alpha_range.shape
[0])),index=sigma_range,columns=alpha_range)

for sig in sigma_range:
    for al in alpha_range:
        X_test_sharpened = sharpened(data = X_test, sig=sig , al=al )
        result = testing(X_test_sharpened,Y_test)

        result_daframe.loc[sig][al]=result
```

```
In [57]: result_daframe
```

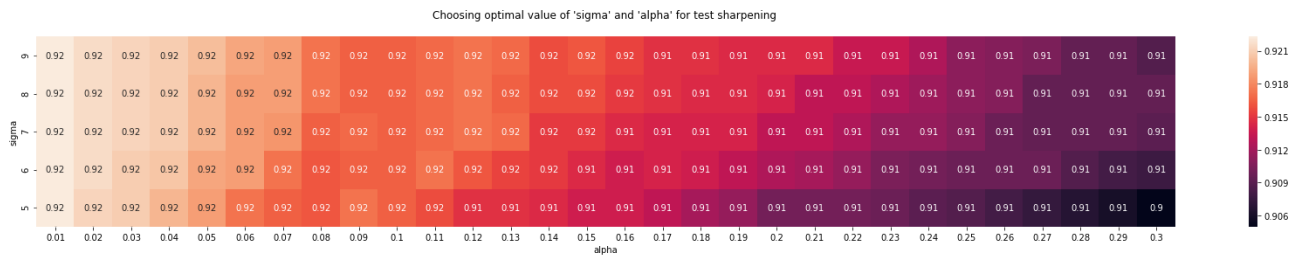
Out[57]:

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10
5	0.922294	0.921276	0.920937	0.919919	0.918901	0.917204	0.916525	0.916186	0.917204	0.916525
6	0.922294	0.921615	0.920937	0.920597	0.919240	0.918901	0.917204	0.916186	0.916525	0.916525
7	0.922294	0.921615	0.921276	0.920937	0.919919	0.918901	0.918561	0.916525	0.916865	0.916525
8	0.922294	0.921615	0.921276	0.920937	0.919919	0.918901	0.918901	0.917204	0.916525	0.916525
9	0.922294	0.921615	0.921276	0.920937	0.920258	0.919240	0.918901	0.917204	0.916525	0.916525

5 rows × 30 columns

```
In [59]: import seaborn as sn
import matplotlib.pyplot as plt
```

```
plt.figure(figsize=(30,4))
sn.heatmap(result_daframe,annot=True,square=True)
plt.title("Choosing optimal value of 'sigma' and 'alpha' for test sharpening
\n")
plt.ylabel("sigma")
plt.xlabel("alpha")
plt.ylim(0,len(result_daframe.index))
plt.show()
```



```
In [69]: np.where(result_daframe==result_daframe.max(axis=0).max(axis=0))
```

```
Out[69]: (array([0, 1, 2, 3, 4], dtype=int64), array([0, 0, 0, 0, 0], dtype=int64))
```

```
In [72]: # testing using optimal sigma and alpha value
X_test_sharpened=sharpened(data=X_test, sig=8, al=0.01)
testing(X_test_sharpened ,Y_test)
```

```
Out[72]: 0.9222938581608415
```

4. LSTM using keras callbacks

```
In [9]: from keras.callbacks import EarlyStopping, CSVLogger, TensorBoard,ReduceLROnPl
ateau

# reduce_learning_rate callback
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.01,patience=10, min
_lr=0.001)

# CSVLogger callback
csv_log=CSVLogger(filename = "training_log.csv")

# Early Stopper callback
early_stopper = EarlyStopping(monitor='val_loss',min_delta=1e-4,patience=10,ve
rbose=1,
                                mode='auto',baseline=None,restore_best_weights=T
rue)
```

```
In [10]: n_hidden=150

model = Sequential()
model.add(LSTM(n_hidden, kernel_initializer='glorot_normal',input_shape=(128,
9)))
model.add(Dropout(0.5))
model.add(Dense(6, activation='softmax'))
model.summary()

# Compiling the model
model.compile(loss='categorical_crossentropy',
```

```
optimizer='adam',  
metrics=['accuracy'])
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
=====	=====	=====
lstm_1 (LSTM)	(None, 150)	96000
dropout_1 (Dropout)	(None, 150)	0
dense_1 (Dense)	(None, 6)	906
=====	=====	=====
Total params: 96,906		
Trainable params: 96,906		
Non-trainable params: 0		
=====		

```
In [11]: # Training the model  
model.fit(X_train,Y_train,  
          batch_size=100,validation_data=(X_test, Y_test),epochs=100,callbacks  
          =[early_stopper, csv_log])
```

WARNING:tensorflow:From C:\Users\family\Anaconda3\lib\site-packages\keras\backend\tensorflow_backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Train on 7352 samples, validate on 2947 samples

Epoch 1/100

7352/7352 [=====] - 15s 2ms/step - loss: 1.3167 - accuracy: 0.4498 - val_loss: 1.0624 - val_accuracy: 0.5684

Epoch 2/100

7352/7352 [=====] - 14s 2ms/step - loss: 1.0655 - accuracy: 0.5563 - val_loss: 0.9930 - val_accuracy: 0.6322

Epoch 3/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.7310 - accuracy: 0.7130 - val_loss: 0.8851 - val_accuracy: 0.6837

Epoch 4/100

7352/7352 [=====] - 15s 2ms/step - loss: 0.8096 - accuracy: 0.6825 - val_loss: 0.7926 - val_accuracy: 0.6787

Epoch 5/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.7330 - accuracy: 0.6994 - val_loss: 0.6850 - val_accuracy: 0.7418

Epoch 6/100

7352/7352 [=====] - 15s 2ms/step - loss: 0.5707 - accuracy: 0.7807 - val_loss: 0.5850 - val_accuracy: 0.7665

Epoch 7/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.6064 - accuracy: 0.7865 - val_loss: 1.1314 - val_accuracy: 0.6071

Epoch 8/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.9855 - accuracy: 0.6072 - val_loss: 0.7015 - val_accuracy: 0.7472

Epoch 9/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.6435 - accuracy: 0.7614 - val_loss: 1.7106 - val_accuracy: 0.4635

Epoch 10/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.7652 - accuracy: 0.7334 - val_loss: 0.5634 - val_accuracy: 0.7913

Epoch 11/100

7352/7352 [=====] - 15s 2ms/step - loss: 0.4615 - accuracy: 0.8392 - val_loss: 0.5001 - val_accuracy: 0.8263

Epoch 12/100

7352/7352 [=====] - 14s 2ms/step - loss: 0.4161 - accuracy: 0.8517 - val_loss: 0.4931 - val_accuracy: 0.8256
Epoch 13/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.3306 - accuracy: 0.8845 - val_loss: 0.4509 - val_accuracy: 0.8347
Epoch 14/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.3069 - accuracy: 0.9021 - val_loss: 0.3356 - val_accuracy: 0.8921
Epoch 15/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.2328 - accuracy: 0.9215 - val_loss: 0.3051 - val_accuracy: 0.8941
Epoch 16/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.1974 - accuracy: 0.9324 - val_loss: 0.3013 - val_accuracy: 0.8918
Epoch 17/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.1633 - accuracy: 0.9406 - val_loss: 0.3015 - val_accuracy: 0.8958
Epoch 18/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.1456 - accuracy: 0.9465 - val_loss: 0.3337 - val_accuracy: 0.8951
Epoch 19/100
7352/7352 [=====] - 14s 2ms/step - loss: 0.1625 - accuracy: 0.9399 - val_loss: 0.3177 - val_accuracy: 0.8972
Epoch 20/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.1664 - accuracy: 0.9411 - val_loss: 0.3400 - val_accuracy: 0.8938
Epoch 21/100
7352/7352 [=====] - 15s 2ms/step - loss: 0.1491 - accuracy: 0.9430 - val_loss: 0.3109 - val_accuracy: 0.9023
Epoch 22/100
7352/7352 [=====] - 9s 1ms/step - loss: 0.1593 - accuracy: 0.9404 - val_loss: 0.3561 - val_accuracy: 0.8972
Epoch 23/100
7352/7352 [=====] - 8s 1ms/step - loss: 0.1533 - accuracy: 0.9483 - val_loss: 0.2875 - val_accuracy: 0.9040
Epoch 24/100
7352/7352 [=====] - 8s 1ms/step - loss: 0.1579 - accuracy: 0.9372 - val_loss: 0.3630 - val_accuracy: 0.8870
Epoch 25/100
7352/7352 [=====] - 13s 2ms/step - loss: 0.7281 - accuracy: 0.7926 - val_loss: 1.5556 - val_accuracy: 0.4717
Epoch 26/100
7352/7352 [=====] - 13s 2ms/step - loss: 0.9578 - accuracy: 0.7088 - val_loss: 0.5580 - val_accuracy: 0.8334
Epoch 27/100
7352/7352 [=====] - 10s 1ms/step - loss: 0.3733 - accuracy: 0.8894 - val_loss: 0.4334 - val_accuracy: 0.8744
Epoch 28/100
7352/7352 [=====] - 8s 1ms/step - loss: 0.3367 - accuracy: 0.8853 - val_loss: 0.4983 - val_accuracy: 0.8252
Epoch 29/100
7352/7352 [=====] - 8s 1ms/step - loss: 0.3492 - accuracy: 0.8551 - val_loss: 0.3980 - val_accuracy: 0.8717
Epoch 30/100
7352/7352 [=====] - 8s 1ms/step - loss: 1.1440 - accuracy: 0.6158 - val_loss: 1.4484 - val_accuracy: 0.4181
Epoch 31/100
7352/7352 [=====] - 8s 1ms/step - loss: 1.5720 - accuracy: 0.4026 - val_loss: 1.3622 - val_accuracy: 0.4544
Epoch 32/100
7352/7352 [=====] - 8s 1ms/step - loss: 1.1757 - accuracy: 0.5257 - val_loss: 1.0895 - val_accuracy: 0.5758


```
Epoch 33/100
7352/7352 [=====] - 8s 1ms/step - loss: 1.5048 - ac
curacy: 0.3747 - val_loss: 1.3143 - val_accuracy: 0.4754
Restoring model weights from the end of the best epoch
Epoch 00033: early stopping
```

```
Out[11]: <keras.callbacks.callbacks.History at 0x1d54b93fd48>
```

```
In [12]: model.evaluate(X_test,Y_test)
```

```
2947/2947 [=====] - 5s 2ms/step
```

```
Out[12]: [0.2874682506673262, 0.9039701223373413]
```

Query:

I have tried various LSTM Architecture and also the architecure suggested by appliedAI team but still I am not getting desire result .

Shall I submit abover model`s result ?

```
In [ ]:
```

```
In [ ]:
```