# ESWEEK IoMT Design Contest Project Report

# **Embedded Human Activity Recognition Design Contest**

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#### **Contents**

- 1 Introduction
  - 1.1Purpose of the Project
  - 1.2 Definitions
- 2 Tools have been used
- 3 Procedure
- 4 The Program and Results
- **5** Conclusion

## **Purpose of the Project**

As any other living being on this planet humans depend also on usage of their muscles. use different muscles in our body for different actions ranging from basic activities to hard workouts. The way things are going in the industry we might be inclined to ask that what can we do to maximize our muscle usage in terms of efficiency using the technologies available? The answer is wearable devices. Wearable devices can give us the opportunity to collect information about how muscles are working. These devices can also be used in human activity recognition. Human activity recognition makes it possible to use information obtained by subjects for specific purposes in certain wearable devices. Generally, these can be count as following; to make disabled people's lives easier, getting information from athletes and according to this information, setting-up daily workout training for individual athletes, to prevent possible injuries during sports activities and to minimize the recovery time of a patient receiving physiotherapeutic treatment.

In this project, we used wearable devices as a monitor of user activity. The purpose of the project is that recognize and define the current condition of the subject according to human activities. Subjects' information is stored in CSV files. These CSV files keep data of each subject's "Time(s)", "User", "Scenario", "Trial", "Window Number", "Stretch Value" and "Label" variables. Time(s) variable is showing milliseconds, Scenario is combinations of sequence of activities and Label is for current activity. With the provided data we started to turn the data to a data frame with the use of Jupiter notebook.

#### **Definitions**

A Decision Tree is a structure used to divide a data set containing a large number of records into smaller clusters by applying a set of decision rules. In summary it is a structure used by dividing large amounts of records into very small groups of records by applying simple decision-making steps.

Random Forest is result of multiple decision trees. During the classification process, it is aimed to increase the classification value by using more than one decision tree.

#### **Tools**

We have done classification on Jupyter Notebook with the help of the Python 3.7 language. Simplicities that provided to us by Jupyter notebook, we have turned the user data files from CSV format to Panda data frame. For several mathematical calculations, numpy was used. Graphs are made by matplotlib, seaborn, graphviz, pydotplus tools. Train and test data sets while creating Decision Tree are created with sklearn module.

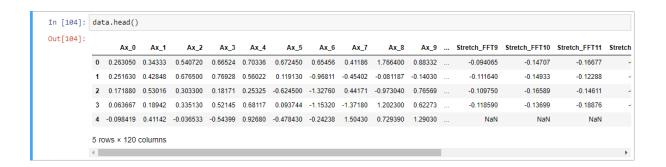
## **Procedure**

Files were in csv format. With Jupiter notebook which uses python, I turned CSV files into the data frames.

```
In [105]: my_list = data2["Label"].values
    new_list=[]
    dictionary={1:'Jump',2:'Lie Down',3:'Sit',4:'Stand',5:'Walk',6:'Stairs up',7:'Stairs down',8:'Transition'}
    for i in range(len(my_list)):
        new_list.append(dictionary[my_list[i]])
```

```
In [114]: features=['Ax_0', 'Ax_1', 'Ax_2', 'Ax_3', 'Ax_4', 'Ax_5', 'Ax_6', 'Ax_7', 'Ax_8', 'Ax_9', 'Ax_10', 'Ax_11', 'Ax_12', 'Ax_13', 'A
```

Decision Trees classifies the data according to the parameters in the list of features shown above and divides the data into the smallest units. In this way, we receive a summary of the data. That features list contains 120 values. These values keeps angle between muscles, stretch values, minimum stretch, maximum stretch data.



As seen we have NAN values which means empty for that specific column and row. To use dataframe modules accurately we have to drop these rows from the dataframe.

```
In [107]: data=data.dropna()
```

With that piece of code we easily can get rid off those unwanted rows.

# The Program and Results

After we get clear rows then we can move on with training and testing. At last we will get accuracy of the predictions of different classifiers.

```
In [110]: train,test=train_test_split(data,test_size=0.15)

In [111]: print ("Training size: {}; Test size:{}".format(len(train),len(test)))

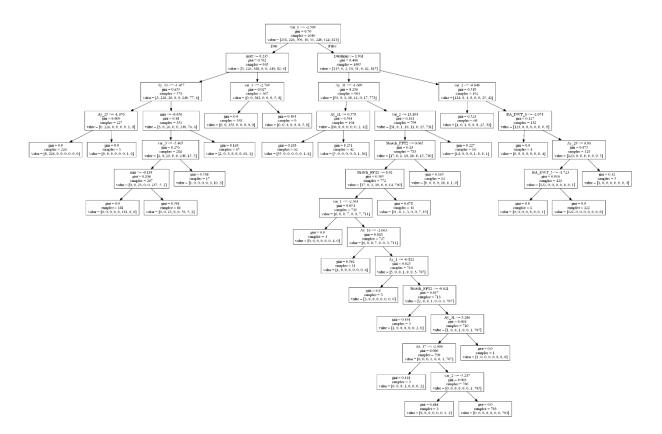
Training size: 2040; Test size:360

In [115]: x_train-train[features]
    y_train-train["Label"]
    x_test=test[features]
    y_test=test["Label"]

In [116]: dt=c.fit(x_train,y_train)

In [117]: def show_tree(tree,features,path):
    for i in range(100):
        foi.o.stringIO()
        export_graphv1z(tree, out_file=f, feature_names-features)
        pydotplus.graph_from_dot_data(f.getvalue()).write_png(path)
        ing=misc.imread(path)
        plt.rcParams["Figure.figsize"]=(20,20)
        pit.imshow(img)
```

#### And after all these we get decision trees as shown below



According Jupyter Notebook, accuracy of Decision Tree is 90.0 %. But if we want dou ble check we can use weka.

```
Feature set: 33,118,119,121
Time taken to build model: 3.97 seconds
=== Stratified cross-validation ===
=== Summarv ==
Correctly Classified Instances
                                     2006
                                                        83,5833 %
Kappa statistic
Mean absolute error
Root mean squared error
Relative absolute error
                                        0.1949
Root relative squared error
                                       63.1395 %
                                     2400
Total Number of Instances
=== Detailed Accuracy By Class ===
                TP Rate FP Rate Precision Recall
                                                     F-Measure MCC
                                                                          ROC Area PRC Area Class
                                                      0,854
                                                                 0,752
                 0,951
                         0,183
                                  0,775
                                            0,951
                                                                         0,954
                                                                                    0,921
                                                                                              Walk
                 0,418
                                  0,696
                                             0,418
                                                                 0,516
                                                                                    0,444
                                                                                              Transition
                         0,012
                                                                          0,880
                                  0,973
0,758
                 0,929
                         0,006
                                             0,929
                                                      0,950
                                                                 0,939
                                                                          0,992
                                                                                    0,976
                         0,021
                                                      0,630
                                                                 0,605
                                                                          0,913
                                                                                    0,659
                 0,539
                                             0,539
                                                                                              Jump
                                                                 0,802
                                                                                    0,855
                                                      0,922
0,000
0,632
0,827
                 0.900
                         0.007
                                  0.946
                                             0,900
                                                                 0,913
                                                                          0,988
                                                                                    0.947
                                                                                             Lie Down
                 0,000
                         0,000
                                  0,000
                                             0,000
                                                                 -0,001 0,756
                                                                                    0,009
                                                                                              Stairs down
                 0,500
                         0,000
                                             0,500
                                                                 0,653
                                                                          0,685
                                                                                    0,570
                        0.079
                                  0.835
                                                                 0.778
Weighted Avg.
                0.836
                                             0.836
                                                                          0.956
                                                                                    0.863
=== Confusion Matrix ===
```

Accuracy with weka is 83.5%. And this result is not that close to our result. So we can use now weka for Random Forest classifier.

```
=== Summary ===
```

Correctly Classified Instances 2294 95.5833 %

Kappa statistic 0.9417

Mean absolute error 0.0294

Root mean squared error 0.104

Relative absolute error 15.4029 %

Root relative squared error 33.6763 %

Total Number of Instances 2400

As we see accuracy of Random Forest is 95%. Which means for this data set Random Forest is good for the classifying.

## **Conclusion**

Taking everything into consideration, the main objective of the project is to show how human activity recognition can be used in different purposes. Our purpose was according to stretch and angle values, predict the current condition of user. For prediction, Decision Tree and Random Forest classifiers were used. To organize the data and use for our purposes we used Jupyter notebook. Through features that weka provide us, we can get accuracy and other information about data while classifying with Decision tree and Random Forest.