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Human Activity Recognition System

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HUMAN ACTIVITY RECOGNITION SYSTEM

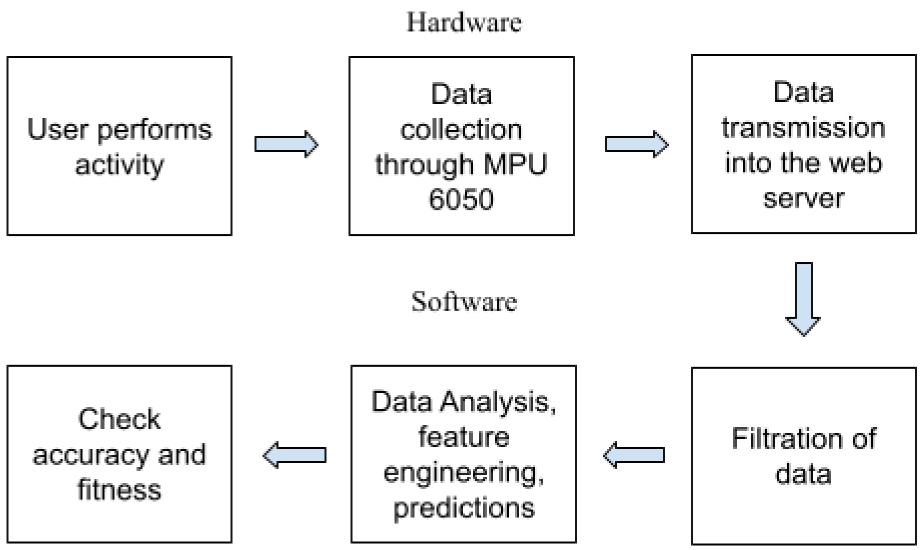
1. Abstract

In recent days the awareness of health and wellness care has become one of the important aspects in the modern world with the evolution of technology and many modern methods. The main objective of our project is to make a device and train a model for human activity recognition(HAR) based on a motion sensor to analyze different daily activities of an individual and classify into one of these i.e., walking, sitting, laying, standing, walking down or walking up the stairs. Our model uses 5 different passive learning methods to classify the activities performed by an individual, a) logistic regression b) support vector machine(SVMs) c) k-nearest neighbor algo d) random forest algo e) artificial neural networks. Finally, we compare the accuracies of our algorithms, use the ensemble approach on our best predictors and deploy in a real time device.

2. Introduction

In recent times, the health and wellness of an individual have become one of the most prominent factors with the evolution of various advanced technologies and more advanced methods which can track daily human activities so accurately. It is a significant computational task to provide the information regarding different human activities precisely and find the patterns. The modern advancements in Human Activity Recognition systems have countless applications in the modern world in various domains which include health and medical care (elder care, rehabilitation centers, diabetes and cognitive disorders), virtual reality, entertainment, advanced security etc., By using such human activity recognition systems a huge number of resources can be saved. These systems can monitor all the time and report any abnormal behavior without the help of any caretaker. So, in this project we use a motion sensor to get the data from different people performing different activities i.e., walking, sitting, laying, standing, walking down or walking up the stairs. We filter this data for any noise and then to differentiate different signals. We apply dimensionality reduction to extract different features from the sensory data. Then we train the model with this data using different learning methods to classify the activities accurately. We find the learning method with the most accuracy and test it on the test data.

3. Methodology



4. Hardware Implementation

4.1 Collection of data

The user is made to perform an activity among the six activities we want to analyse. It is tracked by using our hardware which is based on a MPU-6050 chip. The MPU-6050 chip is a Motion Tracking device. This device is a combination of a tri-axial gyroscope and a tri-axial accelerometer. Our objective of using this chip is to get information of the targeted object in the scope of 6 axis based motion discussion by means of its GyroScope and Accelerometer sensors. This information will serve as raw data for our time series model to be able to classify performed human activity in 6 different classes.

4.2 Data Transmission

Wifi Module (ESP8266) interfaced with Arduino Nano is used for data transmission.Arduino Nano acts as the main controller for directing our other components. It communicates with the MPU6050 chip to gather the required data and transmits it through the wifi module. The ESp8266 is a module used to communicate between our microcontroller and any other web based interface using its WiFI functionality. For this project we have chosen Firebase to act as a web server.

4.3 Components Used

MPU6050

Arduino Nano

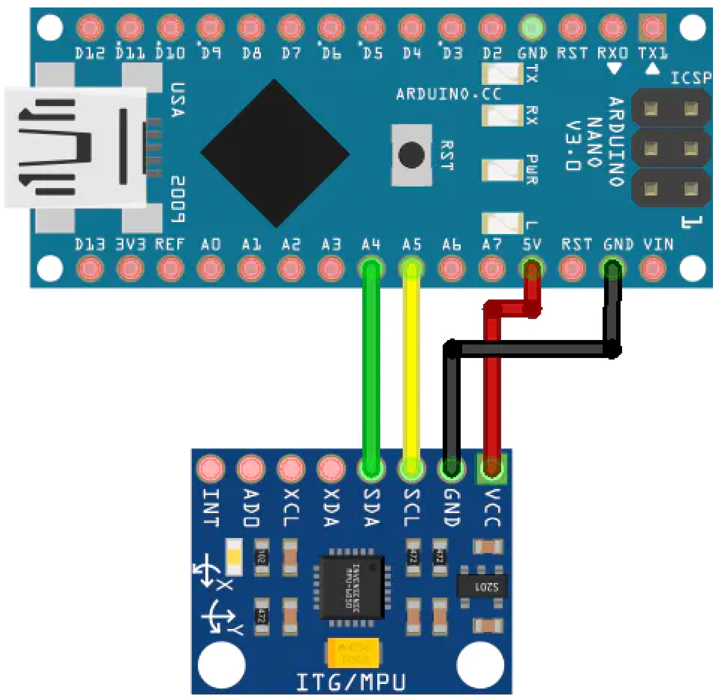
ESP8266-01

Wearable Band

Resistors,Switches,Battery,Connecting Wires,Jumping Cables.

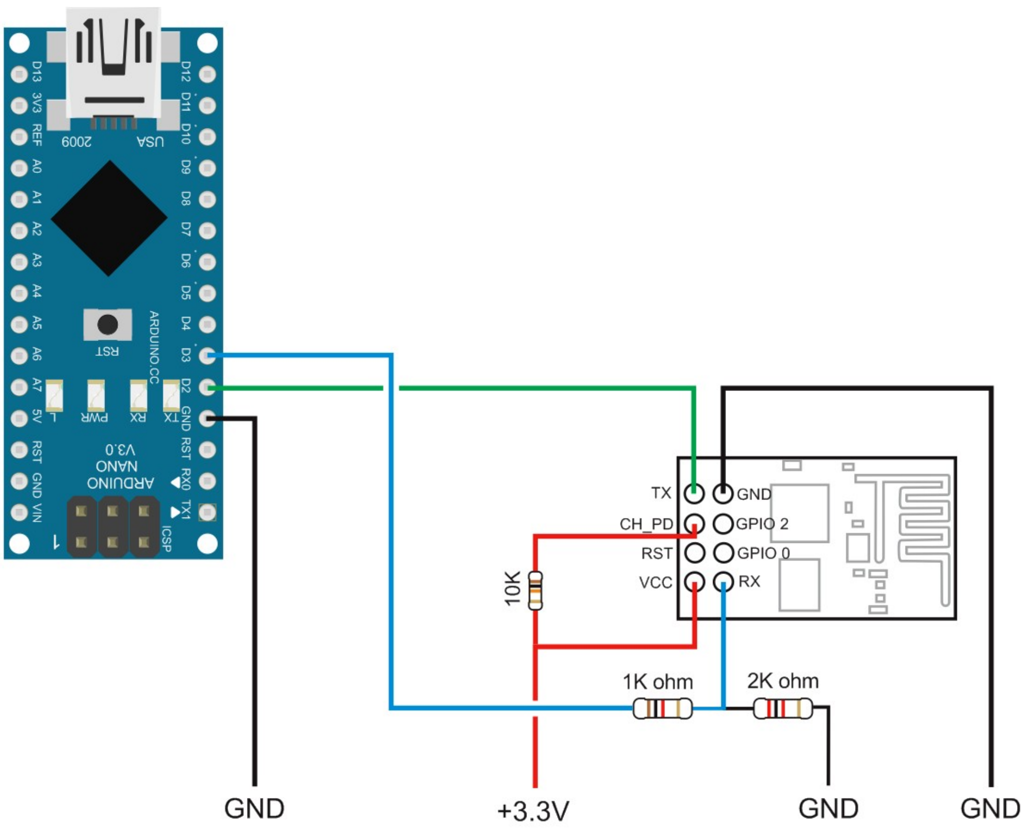
4.3 Circuit Diagram

4.3.1 MPU6050-Arduino Nano Interface



Arduino Nano	MPU6050
5v	Vcc
Gnd	Gnd
A5	SCL
A4	SDA

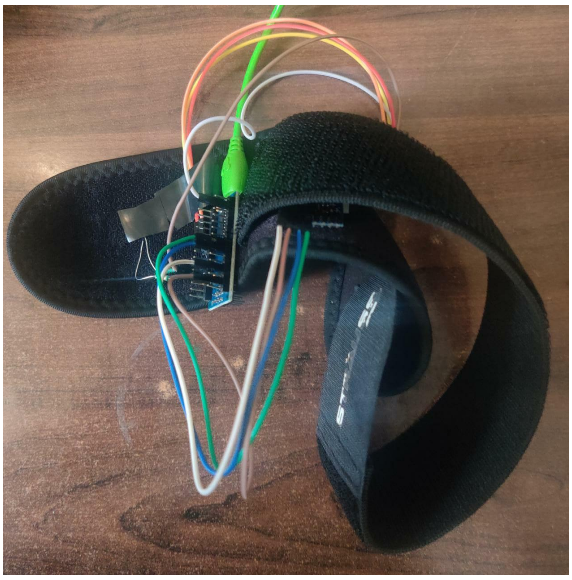
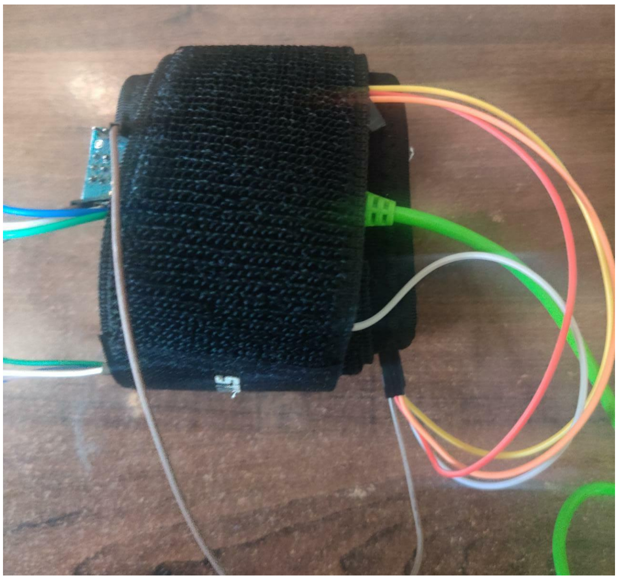
4.3.2 ESP8266-Arduino Nano Interface



Note: Since Rx(of ESP8266) accepts the maximum voltage of 3.6V whereas output voltage from Tx(of Arduino Nano) is around 5V so a resistor circuit must be placed in between of the connection as to divide up the voltage so that the chip doesn't get damaged. It is better for the ESP8266 to draw voltage from an eternal stable source since Arduino Nano isn't able to provide the current required constantly.

Arduino Nano		MPU6050
3.3	--	3.3
3.3	--	En
Gnd	--	Gnd
Tx	--	Rx
Rx	--	Tx

4.3.3 Wearable Band Circuit

5. Software Implementation

5.1 Filtration of Data

After taking the input from the hardware, a sensor signal of acceleration is produced, which has two main components a) body motion components b) gravitational components. To analyse the data those components have to be separated. The components of gravitational signal mostly consist of low frequency components, hence a low pass filter butterworth of cutoff frequency of 0.3Hz is used so as to derive those components from sensor acceleration signal. To remove the noise we use another butterworth low pass filter of cut off frequency 20 Hz. This data is then used for feature extraction and normalization.The time domain signals (prefix 't' to denote time) are sampled at a frequency of 50 Hz. Then we are using a 3rd order low pass Butterworth filter with a cutoff frequency of 20 Hz to remove noise along with a median filter which is available in scipy.signals library.

The acceleration signal was then divided into 2 different components - body acceleration signals and gravity acceleration signals along all the three axises. It is carried out by using a different low pass Butterworth filter with a cutoff frequency of 0.3 Hz.

5.2 Feature Engineering

The idea is to engineer as many features as possible and then apply dimensionality reduction techniques later to preserve only the most important features which are highly predictive and very uncorrelated with each other so as to maintain a perfect balance of bias and variance in our model.

We Specifically get 9 features after filtration > tGyro-XYZ + tBodyAcc-XYZ + tGravityAcc-XYZ

5.2.1 Deriving Jerk Signals

tGyro-XYZ (angular velocity of the body) and tBodyAcc-XYZ (linear acceleration of the body) are differentiated wrt time to calculate the Jerk (Impulse) signals in all three directions each. (tBodyAccJerk-XYZ and tBodyGyroJerk-XYZ)

5.2.2 Euclidean Norm

||L_2|| is carried out on our signals viz. >

tBodyAcc, tGravityAcc, tBodyAccJerk, tBodyGyro, tBodyGyroJerk to obtain their respective euclidean norms (magnitudes).

5.2.3 Fast Fourier Transform (FFT)

FFT is applied to these signals to correspondingly derive new respectively set as - fBodyGyro-XYZ fBodyAccJerkMag fBodyGyroMag fBodyGyroJerkMag fBodyAcc-XYZ fBodyAccJerk-XYZ

Although we had previously tried using FFT to engineer new features in the frequency domain, it turns out that those frequencies were purely complex numbers and hence cannot be utilized further on performing methods like mean,max, min,standard deviation to obtain more features.

5.3 Features obtained

We use the notation ‘XYZ’ to denote the X, Y and Z directions of 3-axial signals

5.3.1 Time Domain Signals

tBodyAcc-XYZ
tBodyGyroMag
tBodyAccJerk-XYZ
tBodyGyro-XYZ
tGravityAccMag
tBodyAccJerkMag
tBodyAccMag
tBodyGyroJerkMag
tGravityAcc-XYZ
tBodyGyroJerk-XYZ

5.3.2 Frequency Domain Signals

fBodyAcc-XYZ
fBodyGyro-XYZ
fBodyAccJerkMag
fBodyGyroJerkMag
fBodyAccJerk-XYZ
fBodyAccMag
fBodyGyroMag

5.4 Methods Calculated

5.4.1 For Time Domain

mean() is the mean value
std() is the Standard deviation
mad() is the absolute median deviation
iqr() is the Interquartile range
energy() denotes the energy measure which is obtained as Sum of the squares divided by the number of values.
max() gives the largest value in array
min() gives the Smallest value in array

5.4.2 For Frequency Domain

Frequency domain has some extra parameters
skewness() gives skewness of the frequency domain signal
kurtosis() gives the kurtosis of the frequency domain signal
maxInds() gives the index of the frequency component which is of the largest magnitude
meanFreq() gives the weighted average of the frequency components so as to obtain a mean frequency

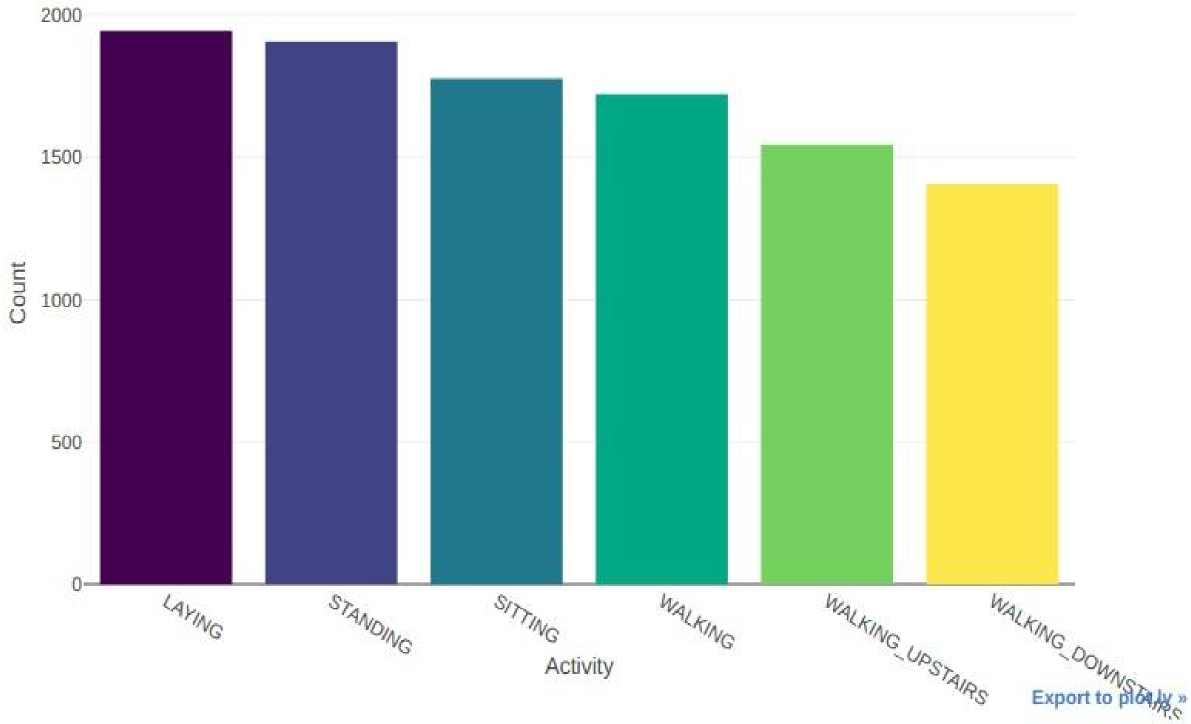
6. Observation

These observations were made while training our data model on test data

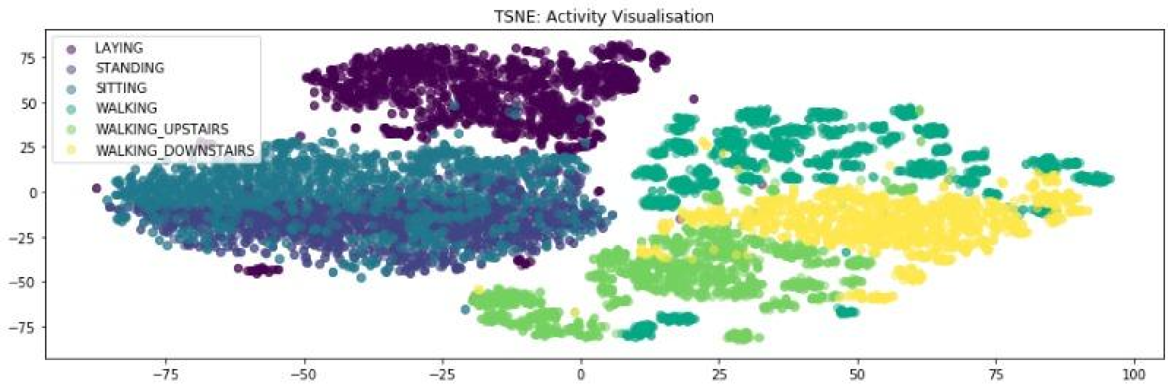
6.1 Dimensionality Reduction and EDA:

Final number of features after feature engineering have been reduced to 240 feature vectors from 561. For this, the feature selection was made from the above mentioned approaches viz. T-SNE and Random Forest Most Important Features. We also tried using PCA, but we found out that the model accuracy became way too low as we lost some of the most important features during PCA dimension reduction, hence we discarded that approach.

6.1.1 Balancing of Data :

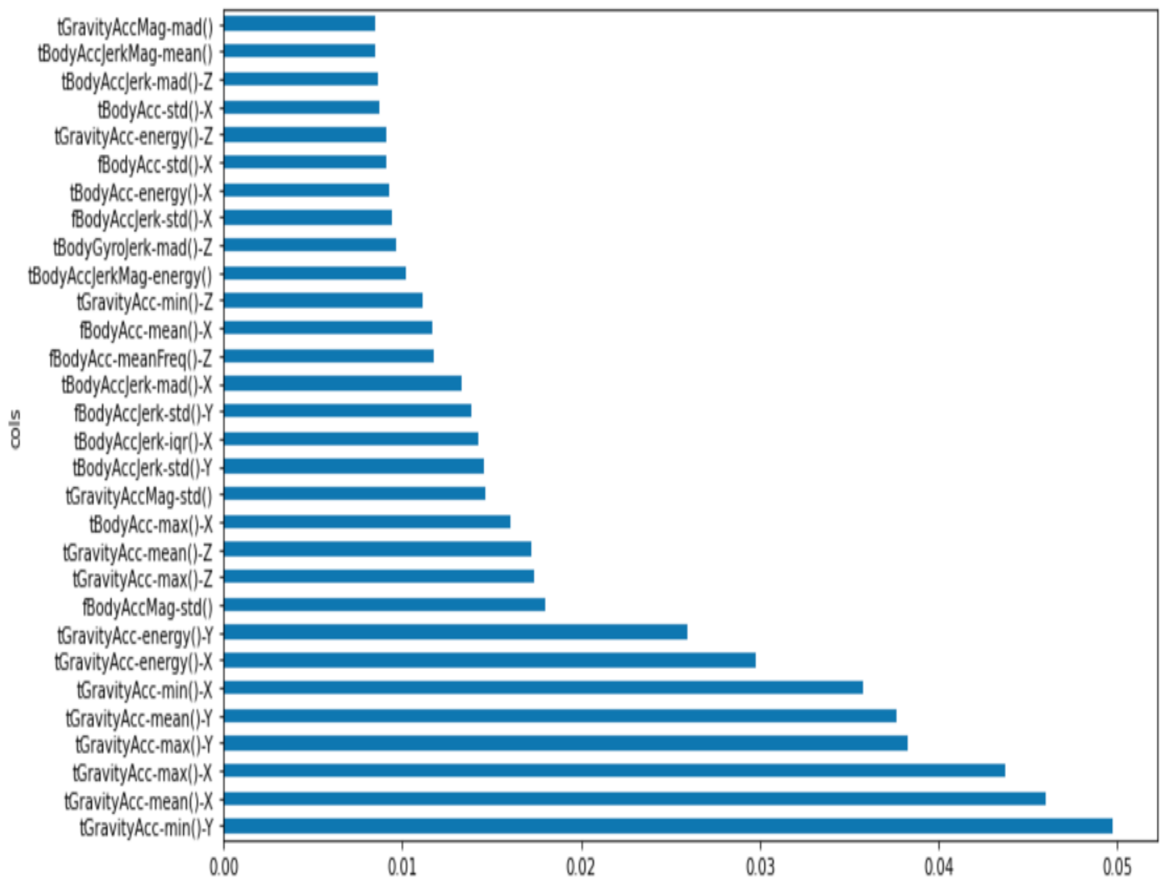


6.1.2 Activity Visualization



Inference : In this Plot, you can clearly see the activities are mostly separable.

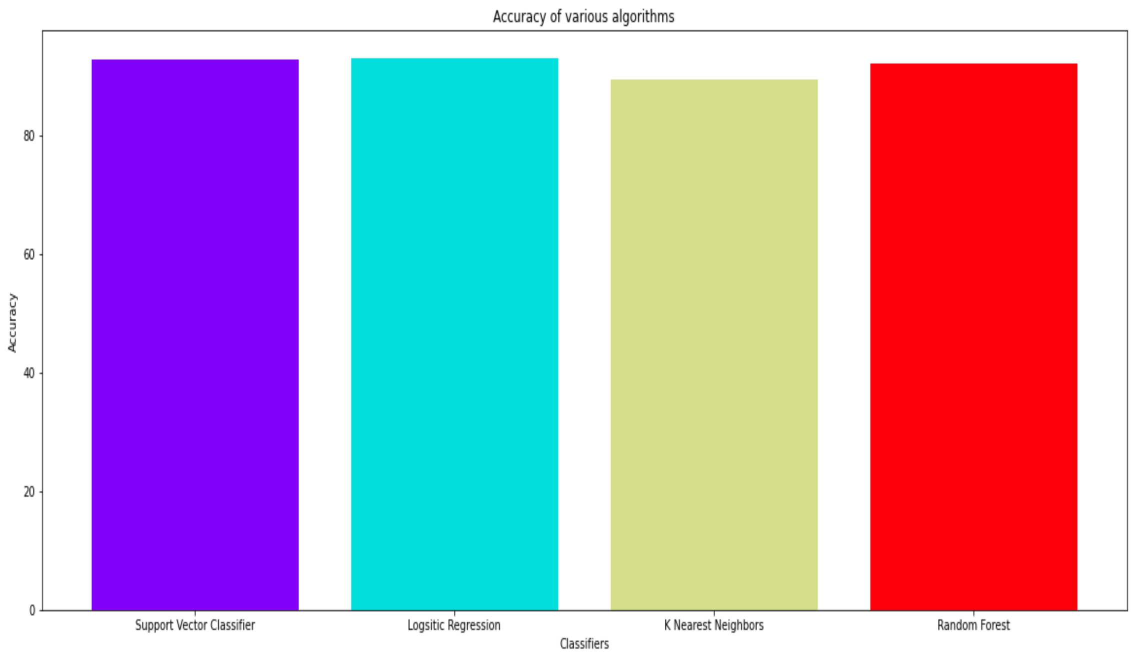
6.2 Feature Importance



6.3 Neural Network Accuracy :

epoch	train_loss	valid_loss	accuracy	time
0	1.287432	1.062707	0.443841	00:01
1	0.760734	0.711194	0.710892	00:01
2	0.518069	0.926899	0.694944	00:01
3	0.424878	0.433807	0.843909	00:01
4	0.371867	0.467676	0.819817	00:01
5	0.345518	0.625569	0.745165	00:01
6	0.311922	0.390711	0.880217	00:01
7	0.267359	0.350643	0.889718	00:01
8	0.253087	0.378833	0.882592	00:01
9	0.228431	0.369288	0.888022	00:01

6.4 Other Algorithms : SVM, Logistic Regression, KNN, Random Forest



Model	Accuracy on Validation Set
SVM Classifier	92.670512385547675%
Logistic Regression	93.07770614183916%
KNN Classifier	89.44689514760775%
Random Forest Classifier	92.05972175093315%

7. Output Results :

Each of the float variables represent a class
from [0.0,6.0] in

0.0 - LAYING
1.0 -SITTING
2.0 - STANDING
3.0 -WALKING
4.0 -WALKING_DOWNSTAIRS
5.0 -WALKING_UPSTAIRS

fBodyAccMag-meanFreq()	fBodyAccMag-skewness()	fBodyAccMag-kurtosis()	Activity	Activity_pred
-0.383094	1.198959	0.937951	5.0	2.0
-1.567831	0.398203	0.201232	1.0	1.0
-0.912775	0.775423	0.514118	1.0	2.0
0.100698	0.335375	0.087057	5.0	5.0
0.184162	0.177725	0.115336	3.0	3.0
0.141364	0.705120	0.747611	4.0	4.0
0.208487	0.783693	0.687241	2.0	2.0
-0.857988	0.940305	0.774108	0.0	0.0
0.964521	-1.073852	-0.839554	3.0	3.0

Sample Result Screenshot of Walking (Ground Truth) :

```
[21]  1 prediction(x1)

    SVM Prediction :  ['LAYING']
    Logistic Regression Prediction :  ['WALKING_DOWNSTAIRS']
    KNN Classifer Prediction:  ['WALKING_DOWNSTAIRS']
    Random Forest Prediction :  ['WALKING_UPSTAIRS']
    Tabular Neural Net Prediction :  SITTING
```

8. Conclusion

We have successfully implemented an automated human activity recognition system using MPU6050 sensor data based on optimal attribute selection, digital discrete signal processing and machine learning techniques. The real time model predicts the Human Activity based on a Wearable Sensor Motion Variables (3- (X,Y,Z) acceleration and 3- (X,Y,Z) Angular Velocity) which are used to classify the Human Activity in one of the classes as mentioned above.

9. Challenges Faced and Future Work

The future work mainly consists of researching and implementing the advanced noise reduction techniques and signal processing part which we found to be challenging and which can have a major impact on the model's accuracy as the signals are very sensitive to the motion of the sensor due to which noise occurs.

10. References

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[2] Mannini, A., Sabatini, A.M.: Machine learning methods for classifying human physical activity from on-body accelerometers. Sensors 10(2) (2010) 11541175

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