ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR HUMAN ACTIVITY RECOGNITION

Project report submitted in partial fulfillment of the requirement for the degree of

BACHELOR OF TECHNOLOGY

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

By

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UNDER THE GUIDANCE OF

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DECLARATION

We hereby declare that the work reported in the B.Tech Project Report entitled ‘’**Analysis of Machine Learning Techniques for HUMAN ACTIVITY RECOGNITION”** submitted at **Jaypee University of Information Technology, Waknaghat, India** is an authentic record of our work carried out under the supervision of **Dr. Sunil Datt Sharma**.We have not submitted this work elsewhere for any other degree or diploma.

Signature of Student

Adarsh

181029

This is to certify that the above statement made by the candidates is correct to the best of my knowledge.

Signature of the Supervisor

Dr. Sunil Datt Sharma

Date:

Head of the Department/Project Coordinator

ACKNOWLEDGEMENT

The completion of any project depends upon cooperation, coordination and combined efforts of several sources of knowledge. I grateful to my project guide **Dr. Sunil Datt Sharma** for his even willing to give me valuable advice and direction whenever I approached him with any problem.

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LIST OF ACRONYMS AND ABBREVIATIONS

1. HAR	Human Activity Recognition
2. IOT	Internet of Things
3. BP	blood pressure
4. GPS	Global Positioning System
5. ECG	electrocardiogram
6. PDA	personal digital assistant
7. IP	Internet Protocol
8. CNN	convolutional neural network
9. WI-FI	wireless fidelity
10. NN	neural network
11. KNN	k-nearest neighbors
12. HA	human activity
13 GDA	Generic data acquisition

LIST OF FIGURES

ABSTRACT

HAR has already shown to be a challenging task, and this would be completed. When used in conjunction with other technologies such as the IOT, it be used largely for senior healthcare care as a popular alternative(IoT). HAR can be created using sensors, mobiles, or images. In this project, we convey a few high-level methodologies and explain each and every one using literature search. Various data sets can be used for every process inwhich data is being collected in different ways like sensors, images,accelerometers, gyroscopes, the placing of such devices in different areas.One of most critical problems of machine learning is providing relevant and complete information regarding people's behavioral patterns. In medical,military, entertaining, and tactical circumstances, there are numerous applications that might be imagined. Fact that HAR has been a hot topic from long time, still some issues that is not addressed, might result in substantial shift people;s behavior when using mobile.This project examines the current state of wearable sensor-based HAR. At first, the overall structure is defined, as well as a summary of the essential parts of any HAR system. Furthermore, depending on the study method as well as response time, we propose a two-level classification. The proliferation of smart phones has greatly simplified the daily life of people.This project introduces analysis of the activity of the sensor in order to monitor human activity by smart phones.Human activities are a natural translation of nature and are organized into sections. The universal presence of smart phones and their ever-growing power of computers, networks, and sensory power they have changed the nature of HAR. In other things, job recognition, which takes the green learning sensation as embedded and predicting user movement. One of most intriguing areas for research is the study of HAR, which has continued in recent decades, the usage of ML approaches has increased.They had meanwhile, suffered as a result of producing the train database as well as increasing the number of occupations to be recognized. HAR classifies human activity that uses the affected sensory nerves from thedeparture of man. Both users and senses of smart phones are proliferating and users often manage their own smart phone with them. Various factors make HAR more significant. This project focuses on the HAR using smart phone’s sensors. Data got from mobiles accelerometer; gyroscope are available separated to identify HA. End Results for the methods are discussed for efficiency as well foundation.Provide

accurate and informative information to human activities and morals are one of the most important works on a full computer. Countless activity can be recognized for example medical field, security area for entertaining and time tactical. Without HAR since the field has been active for more than a decade, there is still a key feature that, if considered, will undergo major changes how people interact with mobile devices.

CHAPTER-1

INTRODUCTION

The goal of this project was to discover common human actions..Complicated activity recognition is a tough and active area of study,Moreover, the idea of human activity poses particular challenges. Human activity comprehension includes two parts: activity detection and activity pattern matching. The first is focused with accurately HAR using a predetermined activity model.HAR is a recently popular computer vision topic. Video surveillance, universal healthcare, and social contact are just a few examples of HAR uses. Novel approaches to HAR are continually emerging as imaging techniques evolve and camera devices improve.

- The need for HAR has increased especially in the fields of health as well as the care of senior citizens and people with cognitive problems.
- We can save a lot of money and time by analyzing the actions of any patient or his odd behavior utilizing mobile sensors.
- In regarding the health sector, Iot systems operate a variety of important tasks, such as security.

Mobile phones are extremely useful products in our everyday lives, and as technology advances, they gain additional abilities to satisfy client wants and expectations. Designers add new modules and components to the hardware to make these gadgets extra effective and powerful. Sensors play an important role in making cellphones more functional and comfortable,therefore most cellphones come with a variety of inbuilt sensors, allowing them to collect a vast quantity of data about the users daily life and activities.[1]These devices also include accelerometer sensor. All smart phone makers included an accelerometer as standard equipment. Accelerometers, as the name implies, measure speed conversion rather than speed itself. The accelerometer;s data can be analysed to allow for quicker alterations in mobility. A gyroscope, which measures shape using gravity, always was standard technology for smart phones. The shape and alignment of the fence can be determined by analysing the signs detected using a gyroscope.Because the signals from different sensors differ significantly, many features can be extracted from the sensory data to define the activity of the man in charge of a device. Signals from the accelerometer data of a smart phone were analysed using several machine learning algorithms while several men and women participated in various activities.As a result, detecting activities such as walking and running might assist caregivers provide feedback on patient behaviour. Similarly, for patient’s dimension and psychiatric pathologies can detect unusual objects and thus preventing unwanted results. In the case of tricks, specific information on military activities and It is highly advantageous in their performance as well as safety because of their locations as well as chronic illnesses. In both anti-training and pro-training scenarios, such knowledge is useful in supporting the decision to act.Human activity can be recognized in two ways: externally and through worn sensors. The devices are initially limited to pre-determined locations of interest, so task consideration is totally dependent on the user's voluntary contact with sensors. Finally, the user is connected to the gadgets.Wise homes model hearing. These systems can detect complexity activities because they rely on sensors data embedded in them it aims at things that people should engage with. Still, nothing can be done when the user is not where the sensors can reach or they do activities that do not require contact see. Addition repair and setup of sensors often cover high prise. External sensors are also utilized with cameras. Video sequences become the subject of research. Specially convenient for security (e.g., access discovery) and applications that are interactive. However, the video sequence is quite good problems in HAR. The first is secretive, as not everyone is hired on a permanent basis and is monitored by cameras. The second issue is congestion as a result of videotaping. It's tough to connect equipment on people in order to take photographs of their entire body while they go about their regular lives. Supervised individuals should remain within the perimeter, which outlines the cameralocation and power.The latter problem can be complicated; as the video is processed the techniques are costly. This fact prevents the real-time HAR system from being updated. [2]

Recognition of human activities is the basis of construction after these requests. It estimates enhance the experience behavior utilizing raw sensed data as feed. Many large streaming smart phones include sensors like as accelerometers, GPS, light sensors, temperature monitoring, gyroscopes, and leading indicators in a number of applications. These devices have turned into a valuable source of data for measuring numerous aspects of a users regular living. Walking, racing, and sitting are all common activities. Smart phones became the predominant human capital evaluation forum due to their lack of installation expenses and ease of use. Among the recent studies that focus on human-based activity awareness, The accelerometer research methodology is gaining the most traction. with many researchers choosing the waistline as a portable device for smart phones However portable gadgets (e.g., smart watch and smart band), smart phones are treated differently and uncertainly in daily living. We might put the camera in our jacket and pant pocket despite carrying it in our hand. The cable is always held above our arm, even when we are jogging or doing other sports. This could be one of the key reasons why detecting human activity with mobile phone sensors is difficult. [3]

This project proposed framework for HAR using a mobile phone accelerometer, as well as an examination of its performance, which can continuously detect the movement status of the user. Sensor data is collected when people performed certain normal and daily HA. We also investigatedhow sensory combinations would affect visual performance. Given that various functions are more likely to take place in a usersreal-world situation(e.g., having to walk, the jump occurs significantly less frequently in a personregular activities), we may learn about the impact of data balance here. This project major goal is to carry out a systematic analysis of reflex detection by mobile phones, and our approach is not the only however a systematic opportunity to boost the efficiency of sensory-based activity monitoring.

1.1 BACKGROUND AND RELATED WORK

This section gives an overview of HAR research. Next, we concentrate on detecting activity using mobile phone sensor information.

The purpose HAR is to detect people action patterns by analyzing movement dataset got by various sensorsHA monitoring has a variety of uses that can still supervise human activity(e.g., tracking, health care), and yet also aid in wide range of human activity (e.g., surveillance areas, unusual tasks). Work recognition methods are currently divided into two categories: vision-based as well as practical. The vision-based approach emerged before the sensory-based process. Its main stages of processing include pre-processing of data, object classification; feature extraction and classification. Despite many appropriate strategies suggested in the last several decades, vision-based HAR presents a concern: the viewer's position and angle, body and clothing size, background color and brightness will all affect accuracy. In general, functionality can be split into 2 groups: time - frequency, with SVM being one of the most frequently used division. [4], Neural Network, KNN and Hidden [5]. Markov model. [6]

1.2 HAR by Smartphone Sensors

Hearing and computer skills are now standard in modern smart phones, and researchers use the Cellphone as either a staging post to establish sensory-based feature identification**.** Table 1 summarises one of most prevalent detectors found on widely known cell devices. The accelerometer as well as gyroscope are the two most significant moving sensors in this project. Mobile phone activity recognition had also faced many problems as well as challenges when especially in comparison to processes that use portable sensor nodes. One of its most significant matters is the location of the cellphone. The phone may be held in the hand, and it may be carried in a pocket. The device can be kept in one's arm or decided to carry in one's pocket. Some other concern is that HA is always a complicated phenomenon involving lower - extremity spinning and muscle and nerve function; however, without any other sensors, we would only get each portion of body motion information at a time, trying to make Mobile phone recognition a tough challenge. [7]. However, because of the cost limit, sensory accuracy is often poor. To improve the efficiency of their methods, research has centered on nose removal, function design, location and sensory selection, and the use of a detector.

COMMON SENSORS IN POPULAR SMARTPHONES

Sensor	Sony Xperia Z5	iPhone6	Samsung Galaxy S6
Accelerometer	√	√	√
Gyroscope	√	√	√
Light	√	√	√
Proximity	√	√	√
Barometer	√	√	√
GPS	√	√	√

1.3 GENERAL STRUCTURE OF HAR SYSTEMS

Work recognition, like some other ML tools, needs two stages: training as well as testing phase. During the initial training stage, a time - series data of evaluated characteristics from individuals who do either every task is required. Time series are splitted in windows of time to allow the domain name feature to extract valuable information in clean signals. Reading processes are being used to generate an activity identification system out from feature extraction database. Correspondingly, during evaluation, data is taken throughout a time frame that is being used to item wise. A collection of these functions was examined in front of a skilled learning method, that also generates a forecasting work tag. We however still recognised a basic data collection layout utilising HAR systems, as shown in Figure1. To begin, the customisable sensor is connected to the person's body throughout order to assess nice characteristics. like movement, temperature, ECG, among others. These sensors must be connected to the connecting device, which can be a mobile phone, a PDA, a portable computer, or a customized embedded system. [8]

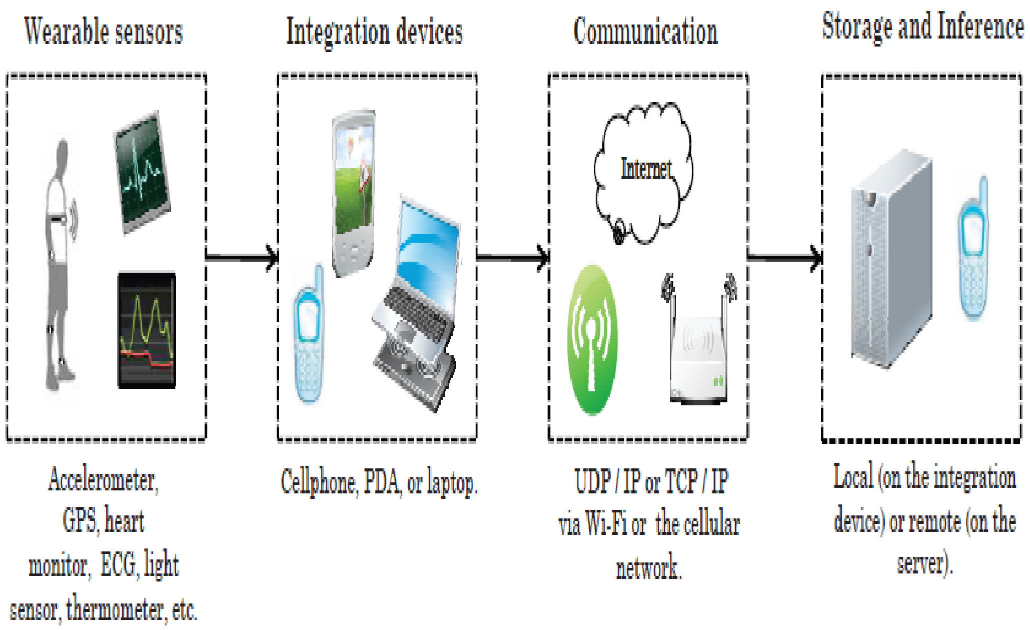


FIG-1.1 GDA architecture for HAR

The essential duty of ID would be to interpret information out of its sensing devices as well as, in certain cases, to send it all to the platform for actual tracking. Visual and analytics server.

1.4 DESIGN PROBLEMS

I have identified 7 important problems involved recognition of a person's work, i.e., Sensor selection, obtrusiveness, data gathering procedure, identification efficiency, energy consumption, computation, and flexibility.

1.4.1 Recognition performance

Many factors influence the HAR system's performance, like set function, a level training data, feature removal method, and learning algorithm. First, each set of tasks presents the problem of recognizing a unique pattern. Like, discriminate against running, moving, and trying to stand, it represent that it is easy installing a lot difficult activities like TV watching, food, climbing, and decline. Second, it should have been enough training set that should also be the normal test data. At the end, a comparative study a few testing styles are interesting as every set of information shows various factors that can be beneficial or harmful by the way. A really connection among both sets of data as well as training methods could be tricky to potentially examine, highlighting the importance of venture reading. [9]

1.5 Why is HAR important?

HAR is critical in human interaction Also in social communication. It is difficult to extract data from it because it contains information on a person's identity, personality, and psychological state. HAR refers to the difficulty of expecting a person's activity obtained from the sensors data, such as an accelerometer in a smart phone. A sliding window technique divides sensor data streams into subsequences called windows, each of which is associated with a larger action.

Fig. 1.2 Different human activities

LST memory connections as well as neural systems, as well as the combination of the two, are most suited to extracting characteristics from raw sensor data and anticipating movement.

1.6:-Why HAR Is Challenging?

- Background "clutter" – Other items or people in video recording or in image.

- Different people variation:

  (i) Humans vary in size as well as in shape.
  (ii) Various sorts of action variation were carried out. Etc.

1.7:-Sensing Activity

Despite the fact that there really is countless equipment that is widely used in HAR and way of measuring various attributes including vitals, body movement, and climate signal.

a. Accelerometer: The accelerometer is a device that measures how snappily an object moves it is commonly used mostly for operational dimensions such as resonance, kinetic energy in elevated automobiles, and large roadways, amongst many others.

b. Gyroscope: A gyroscope is an analyzer which can provide visibility details, except with less accuracy. It really is widely used in a variety of processes such as navigation systems, standing automobiles for stabilization expansion, and electrical gadgets (e.g. Smartphone, game console etc).

FIG-1.3 Sensors in phone

CHAPTER-2

LITERATURE REVIEW

S.NO	Name Of Paper	Author Name	Year	Journal

1	**Human activity recognition using smart phones**	**Erhan Bulbul Ibrahim Alper Dogru Aydin Cetin**	**2018**	***International symposium on* multidisciplinary *studies***
2	**Human activity recognition using accelerometer data from smart phones**	**AkramBayat MarcPomplun Duc A.Tran**	**2014**	**Procedia Computer Science**
3	**Human activity recognition and pattern discovery**	**Kim, Eunju, Sumi Helal, and Diane Cook**	**2009**	***IEEE pervasive computing***
4	**Human activity recognition and embedded application based on convolutional neural network.**	**Xu, Yang, and Ting Ting Qiu**	**2021**	***Intelligence and Technology***
5	**Human activity recognition from 3D data: A review**	**Aggarwal, Jake K., and Lu Xia**	**2014**	***Pattern Recognition Letters***

2.1 Human Activity Recognition using smart phones:-It is critical to gather precise health - related data in sequence to have more complicated quality healthcare. One significant field of study for acquiring relevant data is HAR, which has developed in recent decades through the application of supervised learning methodologies. Previous research, on the other hand, has struggled to get a training data and expand no. of actions that may detect. To get a fresh result that overcomes these drawbacks. Without having to manually construct training datasets, the results of our technique, we believe, provide a mechanism for automatically determining an optimized k value for event detection that maximizes accuracy. [11]

2.2 Human activity recognition using accelerometer data from Smart phones:-

This paper demonstrates how and where to detect a variety of human physical activities utilizing acceleration data from a participant's phone. We offer a method for separating the gravity and body acceleration components in raw data using a unique digital low-pass filter. The structure has been trained and checked on human volunteers inside an experiment. To evaluate a range of classifiers, several statistical features were used. The data was divided into low - and high components. We chose five classifiers that each performed well in our collection of action and looked into how to combine them to create a great set of classifiers.

Most probabilities as the fusion approach resulted in a 91.15 percent overall accuracy rate. [12]

2.3 Human activity recognition and pattern discovery:-

This paper aimed at examining basic human tendencies. Acknowledging sophisticated exercises is a challenging and continuous topic of research, as well as the nature of the human actions introduces unique challenges. HAR consists of two main components: action recognition as well as pattern matching. The first one is involved with appropriately detecting HA using a predefined exercise is designed. An analyst who analyses activity first begins to develop a universal system, after which discusses sensor data to discover patterns of activity. This Activity detection has the potential to bring considerable societal advantages, especially in real-world, human-centered uses like caring for the elderly and health services. [13]

2.4. Human activity recognition from 3D data: A review

This survey article summarizes the ways for identifying human activity from 3D data. Pay special attention to recent advances in deep data-based human activity detection algorithms. Characteristics are used to categories algorithms into different types. The benefits and drawbacks of the algorithms in every location are discussed.

In last decade, 3D data collection method had also rapidly progressed. This study summarizes the main methods in HAR from 3D data, with a concentrate on approaches that use depth information. The use of various features allows for the identification of different types of algorithms. [14]

2.5 Human activity recognition and embedded application based on convolution neural network

In this article, CNN methods are used in deep learning to retrieve forms of human health-related activities. The CNN parameters are improved using a stochastic gradient approach. This article describes how NN can be used on portable systems to identify six common human activities. The acceleration sensor is utilized to identify the proper aspects of the task. The network structure of CNN's built-in model is which includes input layer, two-layer integration and two-layer integration. The finest model has been selected by saying the measured precision of every training case with the testing dataset of the model found in it. [15]

CHAPTER-3

DATA SET

All the data set is taken from Kaggle, the Human Activity Recognition dataset was developed with records of 30 participants in the study executing ADL when wearing a phone with gyroscope and accelerometer sensors attached to their waist. The goal is to categories each activity into those 6 actions. The experiments were carried out from a set of 30 participants varying ages as 19 to 48 yr. Every participants performed major activities despite having a mobile over their waist. We recorded acceleration and velocity at the steady level of 50Hz by using device's internal accelerometer and gyroscope. This same experiment was recorded so that the data could be manually labelled.The data set is divided into two categories train and test sets. 70% peoples are getting training data and 30% getting test data. The sensor information was pre-processed utilizing sound detectors before ever being captured in 2.56sec. A Butterworth low-pass filter had been used to divide the horizontal and human mobility portions of the detector accelerometer data in body Because it is assumed that the force of gravity only has lower frequencies elements, a filtering with such a frequency response of 0.3 Hz was utilized. Calculating factors from of the frequency and time domain produced vectors of features from each frame.

3.1 DATASET FOR ACTIVITIES RECORDED NUMBER OF TIMES

Graph shows how many times each activity is being performed

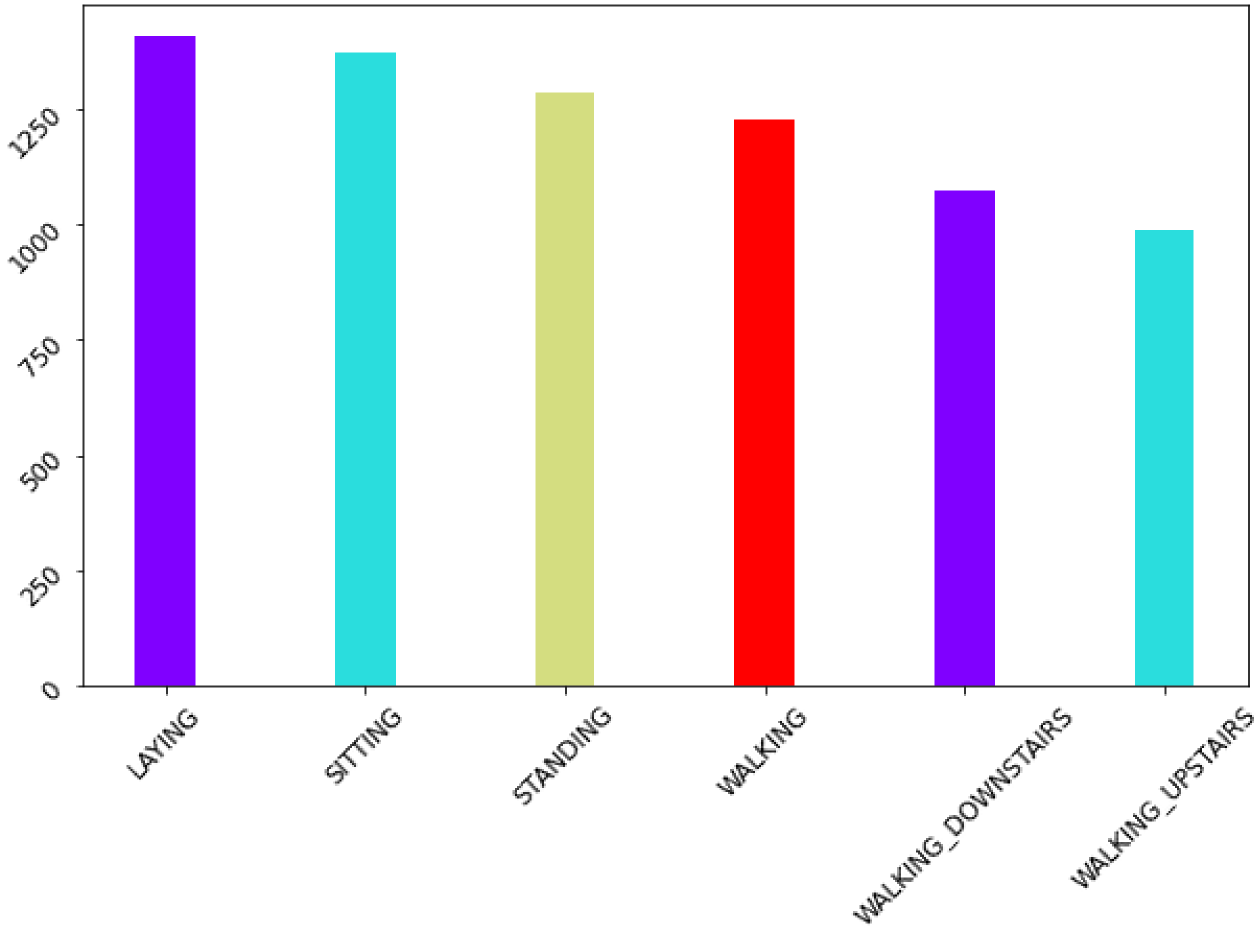


FIG-3.1

3.2 PERCENTAGE OF DATA FOR EACH ACTIVITY

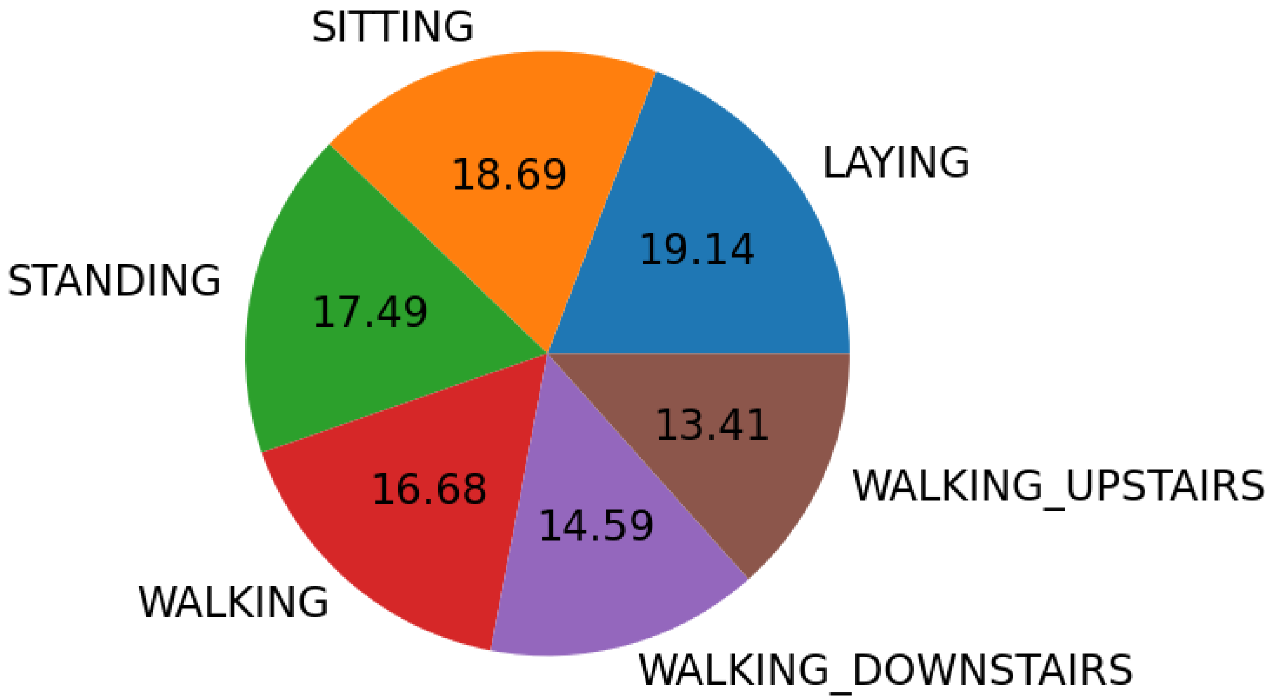

SITTING
LAYING
18.69
19.14
STANDING
17.49
13.41
WALKING_UPSTAIRS
16.68
14.59
WALKING
WALKING_DOWNSTAIRS

FIG-3.2

3.3 DATA COLLECTED FROM GYROSCOPE, ACCELEROMETER AND OTHER VALUES

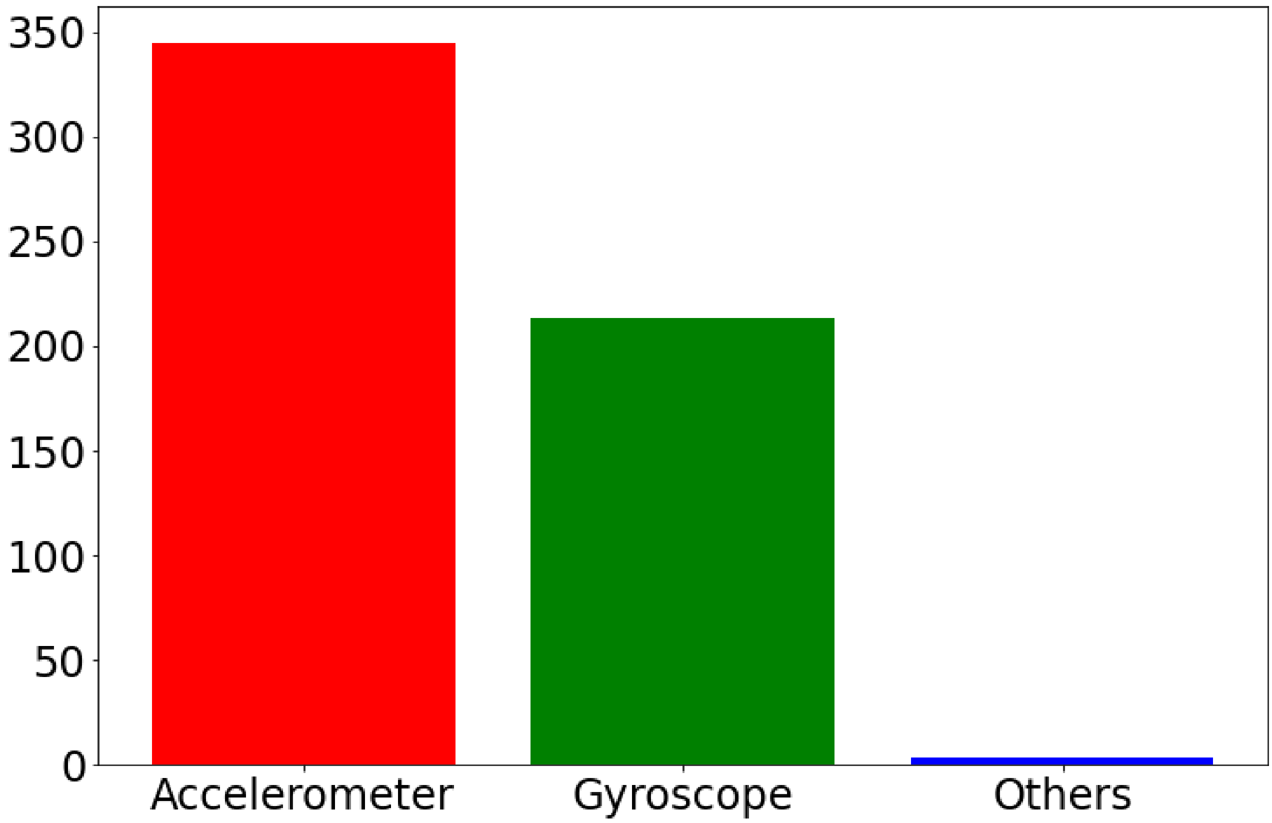


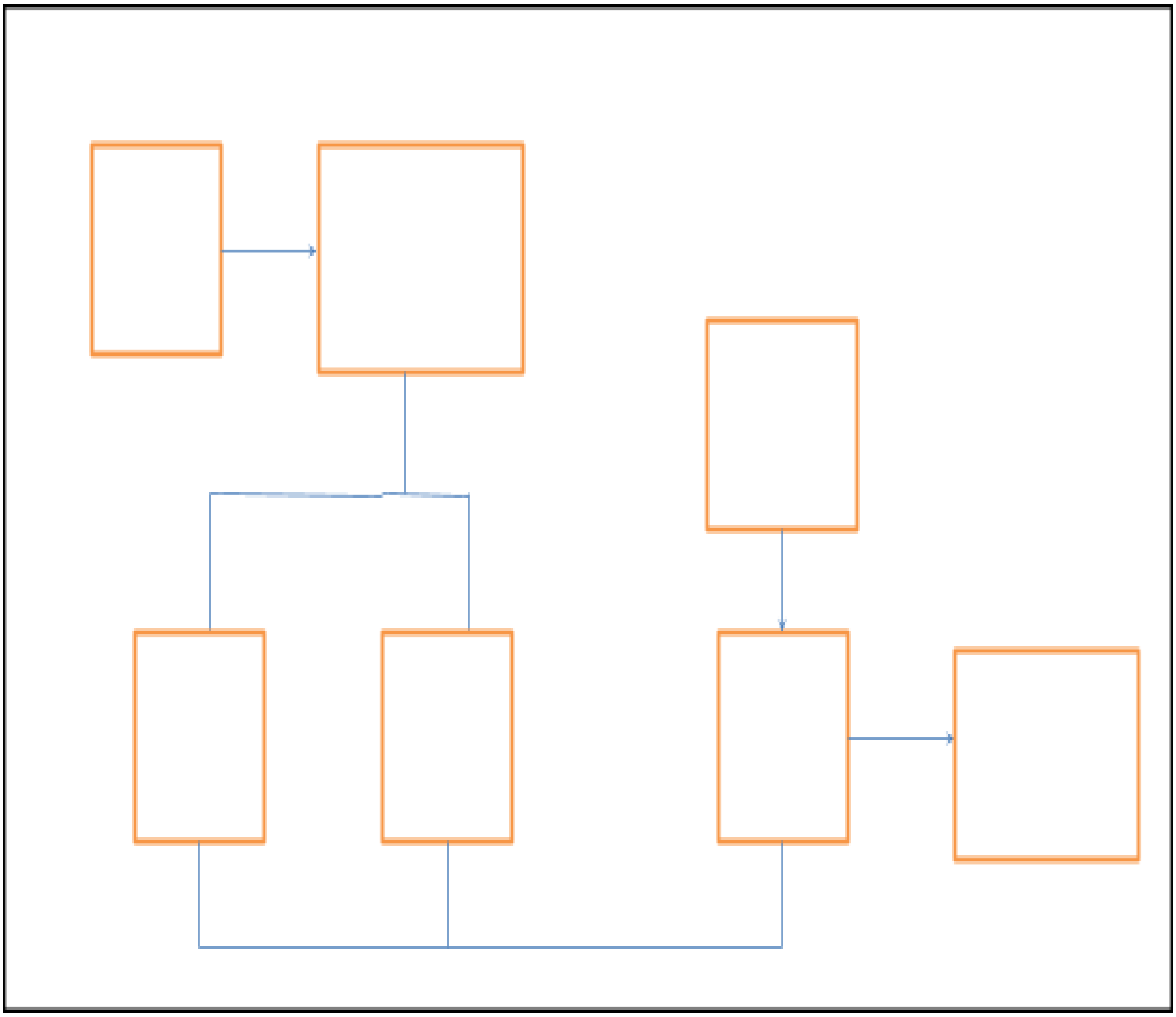
FIG-3.3

As we can see that most of the data is collected with the help of accelerometer

CHAPTER -4

ANALYSIS OF HAR ALGORITHIMS

4.1 HAR ALGORITHIMS



A. Data set- Firstly we collect the data from data set from the accelerometer and gyroscope of the smart phone.

B. Data Processing- then second step is data pre processing in which we pre process the data by removing unnecessary data from that like those activity that are repeating ,background clutter, empty frames. So this is good for us to reduce the amount of data .now we divide this pre processing data into two sets train set and test set. If we train and test the model in same data set we will always get the same output. we need to check that output we are getting is determined by model.

C. Train Set- We take the training the set and train the model, th emodel is trained for some time.

D. Test Set- Test set is used to check if the output that is actuaky required by model is same as the output of the model,and if output is same we say yhat the model has been designed accuratelyan d has high accuracy and itb can detect the action that we want to detect from set of six action (walking,laying,walking upstais ,walking downstais,sitting and standing).

So for each of these activity we have train and test set and model is trained for each of these activties together.

CHAPTER 5
CLASSIFIERS

Following classifiers have been analyzed in this work and their description is given below:

5.1Support Vector machine

It is a ML model for two-group classification issues that employs classification techniques. SVM classifiers can also be used to reconizing handwriting.

5.2 Logistic regression

It is a ML classification approach for predicting a target variable's probability.

5.3 KNN algorithm

It is ML method that can address regression and classification problems. It's simple to set up and comprehend, but it has the problem of being noticeably slower as the amount of data in use grows.

5.4 Random Forest

It is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset.

CHAPTER-6

RESULT ANALYSIS

6.1 FOR STANDING

- Support Vector Classifier accuracy:95.04%
- Logistic Regression accuracy: 95.82%
- K Nearest Neighbors Classifier accuracy: 90.02%
- Random Forest Classifier accuracy: 92.60%

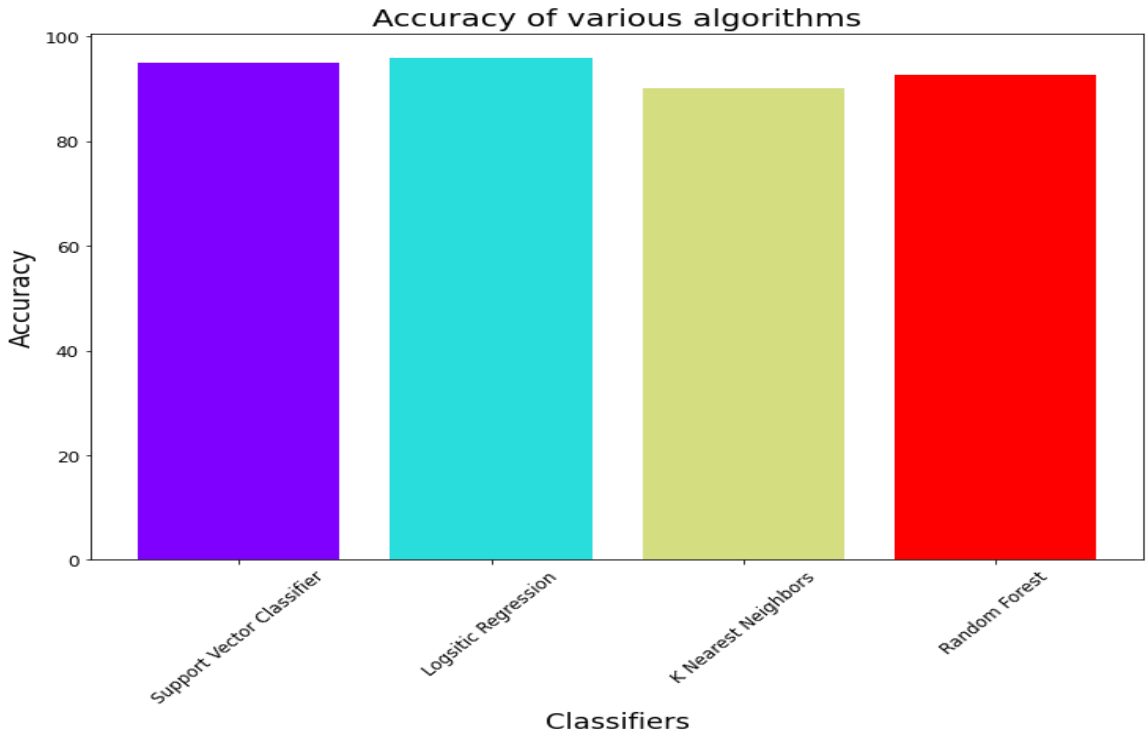


FIG-6.1 Accuracy of various algorithms for STANDING

6.2 FOR WALKING

- Support Vector Classifier accuracy: 95.04%
- Logistic Regression accuracy: 95.82%
- K Nearest Neighbors Classifier accuracy: 90.02%
- Random Forest Classifier accuracy: 92.43%

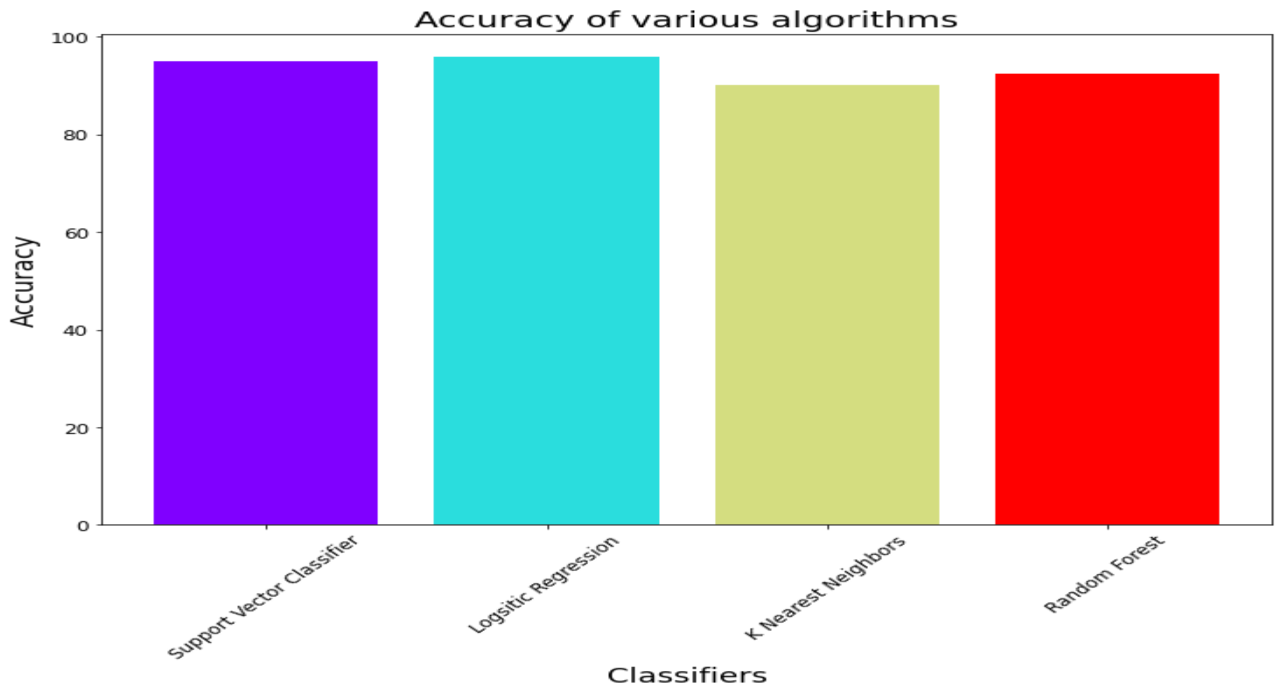


FIG-6.2 Accuracy of various algorithms for walking

6.3 FOR LAYING

- Support Vector Classifier accuracy: 95.04580929759076%

- Logistic Regression accuracy: 95.82626399728538%
- K Nearest Neighbors Classifier accuracy: 90.02375296912113%
- Random Forest Classifier accuracy: 93.21343739395996%

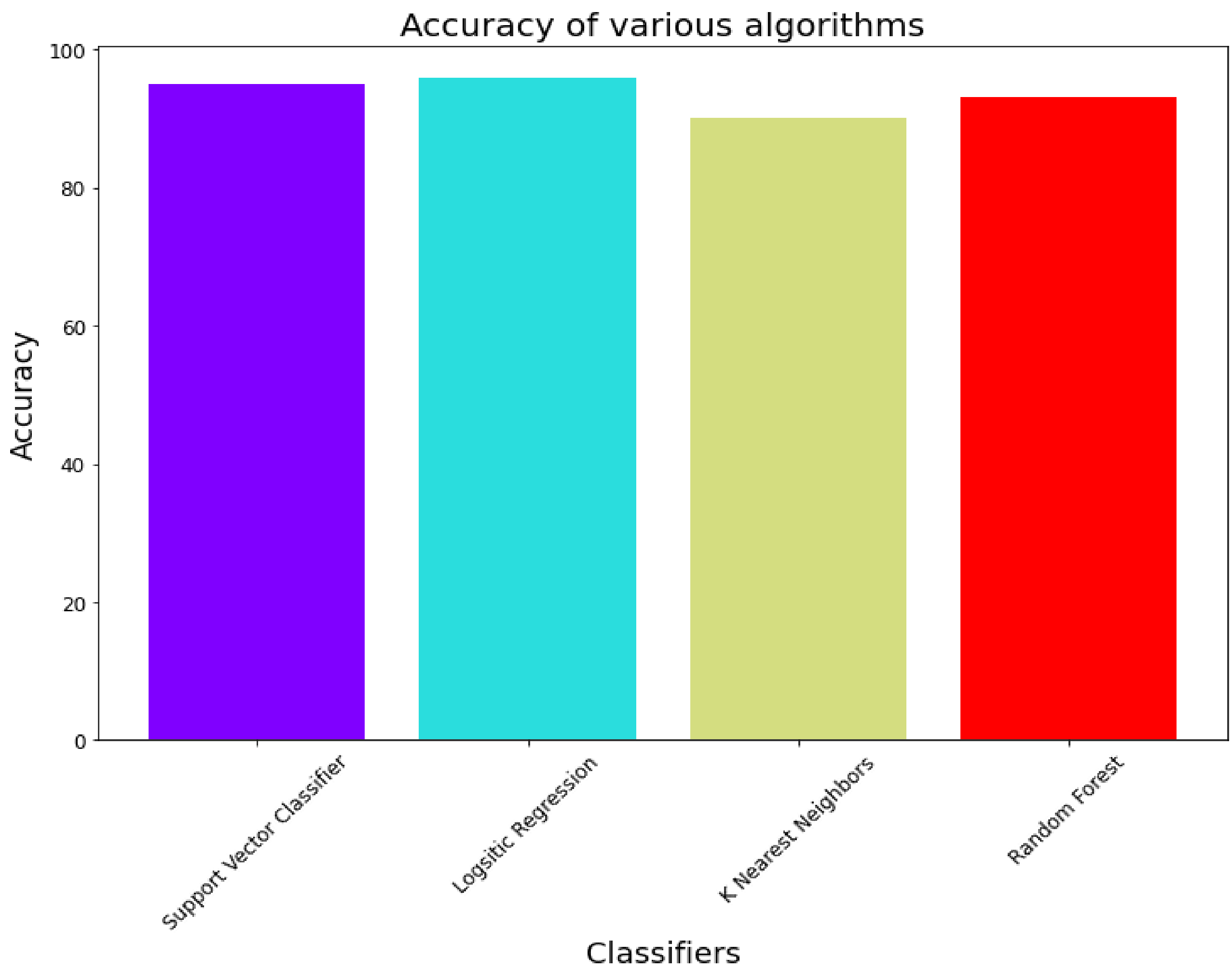


FIG-6.3 Accuracy of various algorithims for laying

6.4 FOR WALKING UPSTAIRS

- Support Vector Classifier accuracy: 95.04%
- Logistic Regression accuracy: 95.82%
- K Nearest Neighbors Classifier accuracy: 90.02%
- Random Forest Classifier accuracy: 92.05%

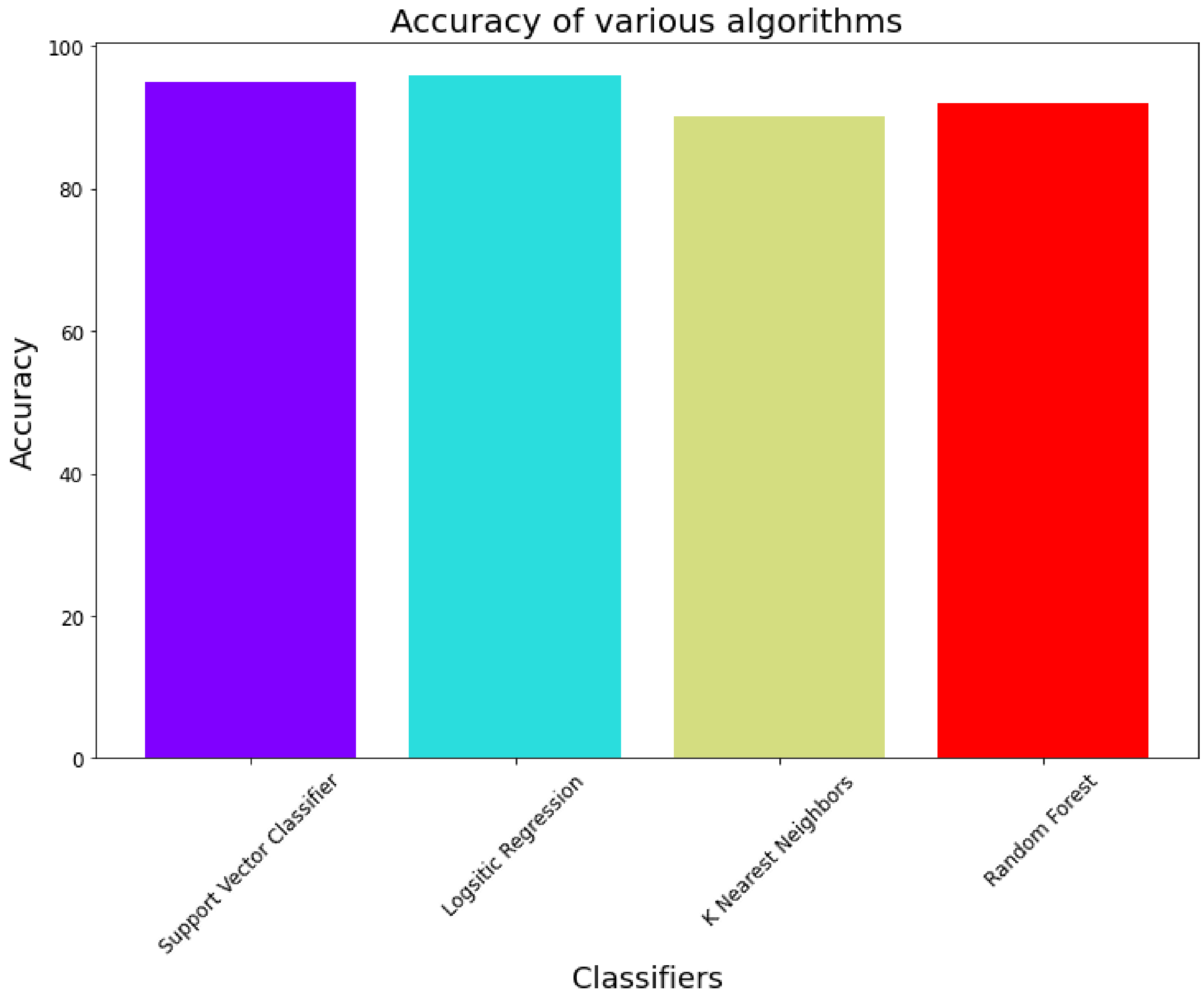


FIG-6.4 accuracy of various algorithms for walking upstairs

6.5 FOR WALKIN DOWNSTAIRS

- Support Vector Classifier accuracy: 95.04%
- Logistic Regression accuracy: 95.82%
- K Nearest Neighbors Classifier accuracy: 90.02%
- Random Forest Classifier accuracy: 92.67%

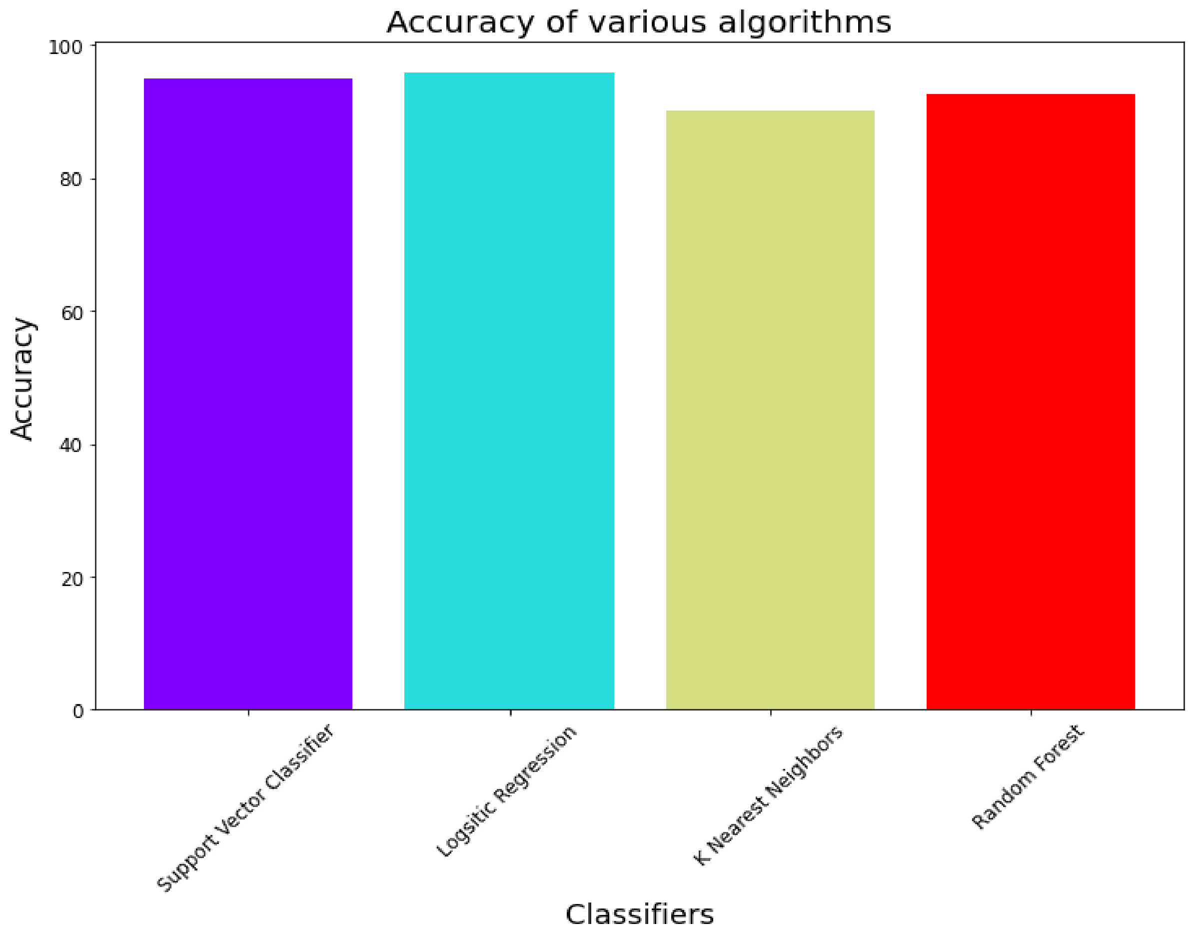


FIG-6.5 Accuracy of various algorithms for walking downstairs

6.6 FOR SITTING

- Support Vector Classifier accuracy: 95.04%

- Logistic Regression accuracy: 95.82%
- K Nearest Neighbors Classifier accuracy: 90.02%
- Random Forest Classifier accuracy: 92.90%

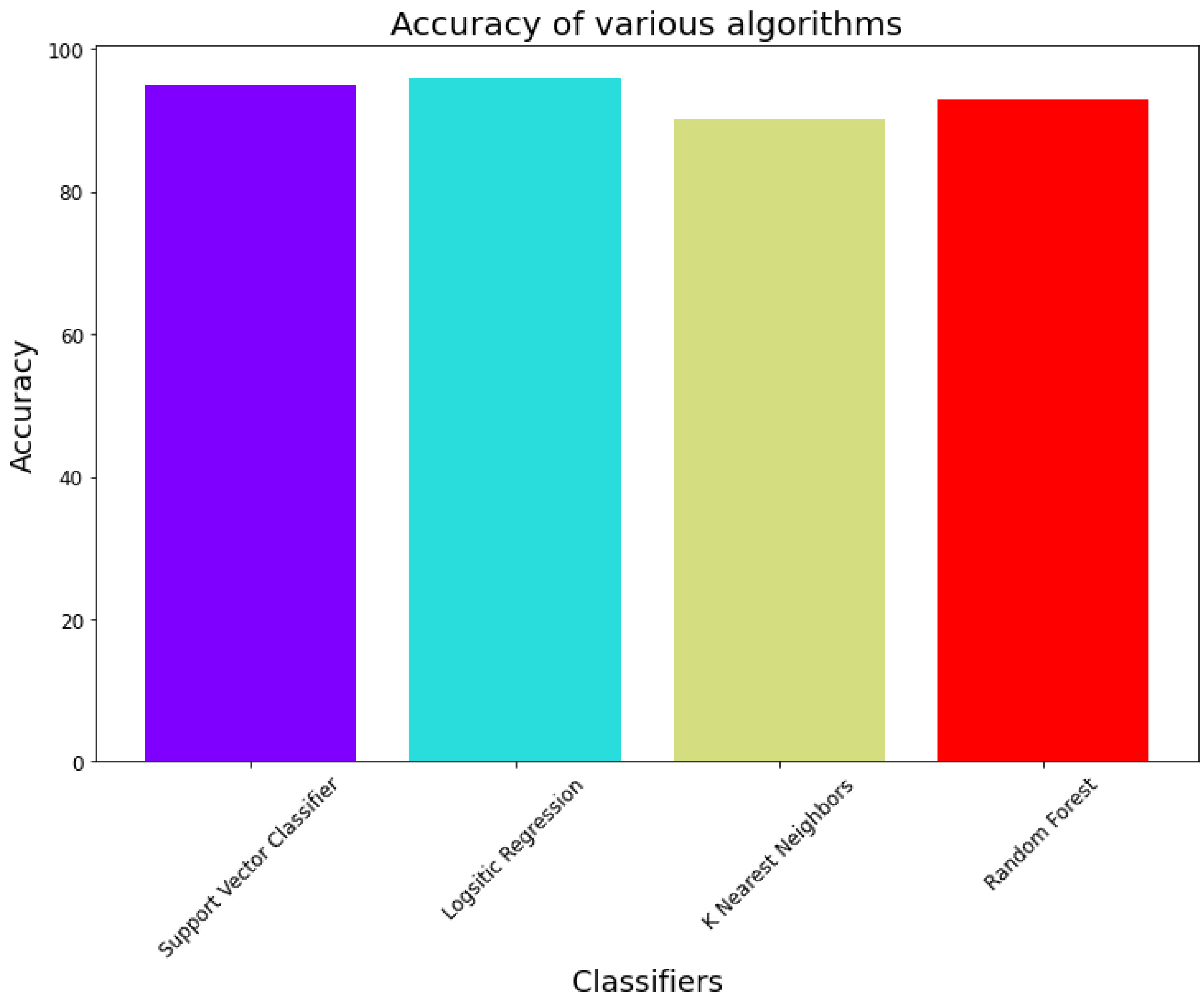


FIG-6.6 Accuracy of various algorithms for sitting

CHAPTER-7

CONCLUSION

In this project four classifiers used for evaluation. Recognition accuracy of all algorithms is above 90% for all six activities. But accuracy of Logistic Regression is higher than other classifiers. The collected data in this research is made up entirely of accelerometer and gyroscope signals. Naturally, the smart phone has evolved into an ideal platform HAR. Because of its impact on wellbeing, human activity recognition does have a broad array of applications and has really become a critical tool in combating obesity and eldercare. In this project we have seen how mobile phone's sensors can help in human activity recognition in our daily life.

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APPENDIX

APPENDIX 1:

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import matplotlib.cm as cm
%matplotlib inline

from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score
```

```
training_data = pd.read_csv('/content/drive/MyDrive/DATA SET/train.csv.zip')
testing_data = pd.read_csv('/content/drive/MyDrive/DATA SET/test.csv.zip')
training_data.head()
```

APPENDIX 2:

```
X_train = training_data.drop(columns = ['Activity', 'subject'])
y_train = training_data["Activity"]


y_test = testing_data['Activity']
X_test = testing_data.drop(columns = ['Activity', 'subject'])
```

```
[9] count_of_each_activity = np.array(y_train.value_counts())
    activities = sorted(y_train.unique())
    colors = cm.rainbow(np.linspace(0, 1, 4))
    plt.figure(figsize=(10,6))
    plt.bar(activities,count_of_each_activity,width=0.3,color=colors)
    plt.xticks(rotation=45,fontsize=12)
    plt.yticks(rotation=45,fontsize=12)
```

APPENDIX 3:

```
[10] plt.figure(figsize=(16,8))
     plt.pie(count_of_each_activity, labels = activities, autopct = '%0.2f')
```

```
[ ] Acc = 0
    Gyro = 0
    other = 0

    for value in X_train.columns:
        if "Acc" in str(value):
            Acc += 1
        elif "Gyro" in str(value):
            Gyro += 1
        else:
            other += 1

    plt.figure(figsize=(12,8))
    plt.bar(['Accelerometer', 'Gyroscope', 'Others'],[Acc,Gyro,other],color=('r','g','b'))
```

APPENDIX 4:

```
[ ] training_data['subject'].unique()
    standing_activity = training_data[training_data['Activity'] == 'STANDING']

    standing_activity = standing_activity.reset_index(drop=True)
    time = 1
    index = 0
    time_series = np.zeros(standing_activity.shape[0])
    print(time_series)

    [0. 0. 0. ... 0. 0. 0.]

[5] from google.colab import drive
    drive.mount('/content/drive')

    Mounted at /content/drive
```

```
for row_number in range(standing_activity.shape[0]):
    if (row_number == 0
        or standing_activity.iloc[row_number]['subject'] == standing_activity.iloc[row_number - 1]['subject']):
        time_series[index] = time
        time += 1
    else:
        time_series[index] = 1
        time = 2
    index += 1


time_series_df = pd.DataFrame({ 'Time': time_series })
standing_activity_df = pd.concat([standing_activity, time_series_df], axis = 1)

colors = cm.rainbow(np.linspace(0, 1, len(standing_activity_df['subject'].unique())))


id = 0
for subject in standing_activity_df['subject'].unique():
    plt.rcParams.update({'figure.figsize': [40, 30], 'font.size': 24})
    plt.plot(standing_activity_df[standing_activity_df['subject'] == subject]['Time'],
             standing_activity_df[standing_activity_df['subject'] == subject]['angle(X,gravityMean)'],
             c = colors[id],
             label = 'Subject ' + str(subject),
             linewidth = 4)
    plt.xlabel('Time',fontsize=28)
```

APPENDIX 5:

```
[11] accuracy_scores = np.zeros(4)


clf = SVC().fit(X_train, y_train)
prediction = clf.predict(X_test)
accuracy_scores[0] = accuracy_score(y_test, prediction)*100
print('Support Vector Classifier accuracy: {}%'.format(accuracy_scores[0]))


clf = LogisticRegression().fit(X_train, y_train)
prediction = clf.predict(X_test)
accuracy_scores[1] = accuracy_score(y_test, prediction)*100
print('Logistic Regression accuracy: {}%'.format(accuracy_scores[1]))


clf = KNeighborsClassifier().fit(X_train, y_train)
prediction = clf.predict(X_test)
accuracy_scores[2] = accuracy_score(y_test, prediction)*100
print('K Nearest Neighbors Classifier accuracy: {}%'.format(accuracy_scores[2]))

# Random Forest
clf = RandomForestClassifier().fit(X_train, y_train)
prediction = clf.predict(X_test)
accuracy_scores[3] = accuracy_score(y_test, prediction)*100
print('Random Forest Classifier accuracy: {}%'.format(accuracy_scores[3]))
```

```
plt.figure(figsize=(12,8))
colors = cm.rainbow(np.linspace(0, 1, 4))
labels = ['Support Vector Classifier', 'Logsitic Regression', 'K Nearest Neighbors', 'Random Forest']
plt.bar(labels,
        accuracy_scores,
        color = colors)
plt.xlabel('Classifiers',fontsize=18)
plt.ylabel('Accuracy',fontsize=18)
plt.title('Accuracy of various algorithms',fontsize=20)
plt.xticks(rotation=45,fontsize=12)
plt.yticks(fontsize=12)
```