INDOOR POSITIONING AND MACHINE LEARNING BASED FALL DETECTION SYSTEM

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Abstract:—Falls that leads to fatal injuries have become a great challenge that cannot be neglected for elderly people. Hence, mechanisms to detect and avoid falls are necessary to improvise common living of aged people. An ambient-assisted Living applications will be developed in the near future having user positioning as ground technology: elderly tele-care, energy consumption, security and which are strongly based on indoor positioning information. Though many fall detection solutions were presented, few included wrist-wearable devices, mainly due to typical processing and classification challenges to achieve satisfactory accuracy. Considering the wrist as the most comfortable, discrete and acceptable place for an elderly wearable device, this work presents the development and evaluation of a wrist-worn fall detection solution, RFID based indoor positioning system and an android supported text to speech reminders. The fall alert sent to the care takers will be SMS which consists of location where the fall occurred. The sensors like accelerometer, gyroscope, and magnetometer are used to obtain, signals (acceleration, velocity, and displacement) which were combined and then the threshold-based and machine learning methods were applied in order to define the best approach for fall detection and monitoring. Machine learning gave a satisfactory accuracy when compared to threshold-based method.

IndexTerms - Fall Detection, Alzheimer's disease, Wearable device, RFID, Indoor Positioning System, Machine Leaning.

I. INTRODUCTION

Falls are the extensive problem among the elderly, causing momentous amount of injury, impermanence and use of health care services. Worldwide the number of elderly (people aged 65 years or older) is rising faster than any other age group; their stake was to 12 percent in 2014 and is predictable to reach 21 percent by 2050. Coarsely 28-35% of people ages of 65 and 32-42% aged over of 70 fall each year. In addition, the sector of the population aged 80 and over, particularly liable to fall, will denote the 20% of the elderly population in 2050.[1]

According to the latest unconfined fact sheet from the World Health Organization, almost 424,000 fatal falls occur each year, making them the second leading cause of unintended injury death, after road traffic injuries. Among the non-fatal falls recorded each year, approximately 37.3 million are severe enough to require medical attention, and are answerable for over 17 million DALYs (Disability-Adjusted Life Years) losses.[1]

During a fall a spontaneous change in position with or without loss of consciousness arises, instigating the victim to land on ground. Falls and subsequent injuries require medical attention and are often the cause of fractures, traumatic brain injuries and lacerations in the upper limbs inducing, in many cases, to the loss of independence or death. Often the elderly cannot return to upright position after a fall and there is a close relationship amid the delay in assisting to the injury and the mortality rate. Therefore, a hasty reporting of the fall can enable a fast help and avoid serious consequences.[6]

Alzheimer and Epilepsy are greatly increasing neurodegenerative diseases in the world. Alzheimer's disease roots hallucinations, wandering, falls and incidence of getting lost. On the other hand, Epilepsy annexations may occur at any time. Falls being one of the major health issue in world, should be detected and an immediate alert should be sent to the care takers. An alert SMS sent should consist of location where the fall occurred. Also a smart tracking system can aid to monitor and locate patients. Though global positioning systems are used in various tracking applications, their use is chiefly based on outdoor environments and they can provide satisfactory accuracy. However, patients mostly spent their time in indoor environments. Since global positioning system signals are interrupted and attenuated by materials between user and satellite, it is bit difficult to locate user in a building. Hence, there needs to be a different technology for tracking patients in indoor environment for both general and emergencies.[12]

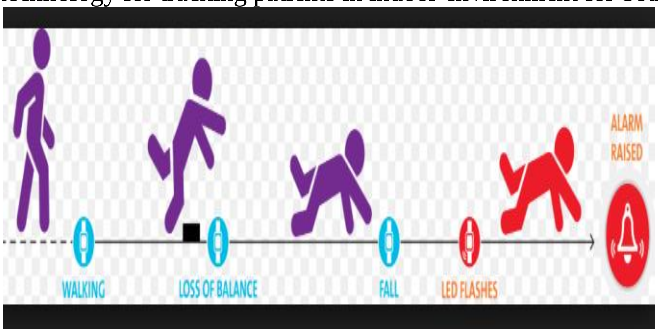

Fig.1: Working module

II. RELATED WORK

A waist mounted device was designed to detect possible falls in elderly people.Attitude and heading reference system provides data related to attitude of a system coming from a triaxial accelerometer, a triaxial gyroscope, a triaxial magnetometer, and a barometer sensor integrated into our device.Performance was low as there was no optimum threshold and uncomfortable to use as it was a waist mounted device.[2]

A fall detection system consisting of an inertial unit that includes triaxial accelerometer, gyroscope, and magnetometer and a barometer with efficient data fusion and fall detection algorithms. On placing the wearable sensor on the waist of the subject, the unit was able to achieve fall detection performance.The altitude signal, calculated by means of measurements coming from the barometer, contains huge amount of noise that makes it unsuitable for the application.Location of the wearable device was uncomfortable.[3]

A system called SPEEDY was presented, which was a fall detector in wrist watch which was easy to wear and offered full functionality of small transportable wireless alarm system. It comprised a fall detection alarm which would alert a call center after heavy fall and it occurs if wearer is unconscious or too agitated to press the alarm button himself. It gave low accuracy because of threshold used, which could be optimized based on long term tests. Power consumption was high due to high power accelerometer (ADXL202E) and barometer used.[5]

A Footwear-Based Methodology for Fall Detection presented a methodology for fall detection that relied on a pair of smart shoes, equipped with force sensors and a tri-axial accelerometer, able to detect the fall and notify it to a supervising system. Major drawback of this work was fall detection algorithm was completely dependent on roll and pitch threshold whereas yaw is completely neglected. Few hardware devices were placed outside the shoe which was not user friendly.[4]

A Fall Detection System for laborsafetywas aimed to design and construct a real-time system which could detect human fall and notify the concerned person on time to minimize the death-rate due to any mishap during building construction or industrial environment and embed the whole system into a wearable, rigid and low-cost gadget using a MEMS motion sensor (MPU-6050) along with GSM/RF protocol to transmit the data. The designed gadget would be installed at a location so that the system could detect the various changes in the subject's center of gravity and process and analyze the data to detect the type of fall on comparing from already stored database i.e. tested previously. But fall could not be detected if the person was away from the gadget installed at the location. It was limited to minimal distance.[11]

A short time min-max feature for improving fall detection performance based on the specific signatures of critical phase fall signal, acquired using a tri-axial accelerometer on a torso. This was validated by SVM that used cross validation. The short time min-max feature gives better performance, uses only one sensor for a body's position, does not require a fixed threshold for 100% sensitivity or specificity, and does not involve additional processing for a posture after a fall.[8]

Another approach proposed used low-cost Pi Camera mounted on Raspberry Pi to monitor and detect person's fall-like movements. Pi Camera being a smart camera could be easily fixed on windows and walls of living room. System will be watching keenly for fall detection and unexpected motion changes in targeted person. An unexpected abrupt change with peak in the system is treated as a fall. But the drawback was cameras could not be used in private areas and not a comfortable approach to monitor the patients/elderly person.[10]

III. PROPOSED WORK

Fall detection system is a wrist wearable device which is the most discrete and convenient to be used by elderly person or the patients. Fall detection is completely based on the IMU. In our work, we are using GY 80 IMU which comprises of accelerometer, gyroscope and magnetometer. IMU is mounted on the wearable band which measures the acceleration force, angle and movement estimation with respect to poles. A RFID tag is mounted to the doors in the entrance of every area at home. Indoor positioning is based on the RFID reader in the wearable device. Once the person taps the RFID reader to the tag whenever the person enters the new area at home, RFID reader receives the signal from the tag, decodes that signal and send it to the Arduino. Arduino is interfaced with the Node MCU to transmit the data to the server. Input data is compared with the dataset on applying the algorithms to differentiate between the fall and non-fall. The dataset is collected in prior from our testbed for both fall and non-fall activities from three people. Whenever the fall occurs, an alert will be sent to the caretaker. The alert message consists of the location where the fall occurred. The fall location will be either RFID based or GPS based location. Fig 2 represents the proposed system. The major advantages over current system are comfortable and reliable to use, provides accurate results because of Machine learning algorithm used, helpful in indoor tracking of the patients and an addon of text to speech reminder in patient's end.

Fig.2: Proposed System

IV. Methodology

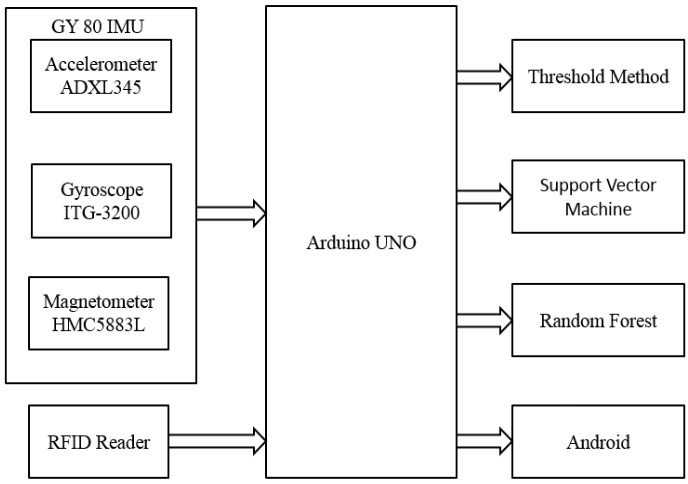

Fig.3: Architecture

Architecture of wrist wearable fall detection system is as shown in Fig 4. For the movement signals acquisition, the GY-80 IMU device designed for embedded system application was employed. This IMU is comprised of a Triaxial accelerometer (ADXL345 model), Triaxial gyroscope (L3G4200D model) and Triaxial magnetometer (HMC5883L model). The RFID reader is also used to read the tags and transmit the required info to the android mobile. The distance allowed between RFID tag and RFID reader was 50 mm, since we used passive tag in the form of card or key chain.

4.1Data Acquisition from Hardware

Data acquisition is the initial stage where the sensor data is read from the hardware used in the wrist-wearable device.The data obtained from the sensor i.e., GY80 IMU is continuously collected with the delay of 200ms and the sensor data is further cleansed in Arduino UNO to limit the decimal to two points. Then sent to the server through Node MCU. Similarly, the passive RFID tag info is sent to the reader and the same info is transmitted to the Arduino and then to the android on the caretaker's end.

The hardware components used in the device areas are: Arduino UNO, Node MCU, GY 80 IMU, RFID Reader and Tags.An Arduino UNO is an open-source microcontroller board based on the Microchip ATmega328P microcontroller and developed by Arduino.cc. This board is equipped with set of digital and analog input/output (I/O) pins that can be interfaced to various expansion boards (shields) and various circuits. Fig.4 represents the Arduino UNO used in our work.

Fig.4: Arduino UNO

The GY-80 Inertial Measurement Unit contains the following sensors such as L3G4200D,ADXL345 and HMC5883L. L3G4200D is a low-power three-axis angular rate sensor, the ADXL345 is a 3-axis accelerometer with high resolution (13-bit) measurement at up to ±16 g and a HMC5883L is the surface-mount, multi-chip module that is designed for low-field magnetic sensing with a digital interface.

Fig.5: GY 80 IMU

RFID is an acronym word form for "radio-frequency identification" and refers to a technology whereby digital information encoded in RFID tags or sensible labels square measure captured by a reader via radio waves. A frequency identification reader (RFID reader) could be a device, which will not gather information from associate RFID tag, that is employed to trace individual objects.

The RFID tag should be at intervals that various associate RFID reader that ranges from three to three hundred feet, so as to be scan. RFID technology permits many things to be quickly scanned and allows quick identification of a specific product, even once it's enclosed by many different things. RFID tags may be either passive, active or battery-assisted passive. An active tag has associate on-board battery and sporadically transmits its ID signal. A passive tag is cheaper and smaller as a result of it's no battery; instead, the tag uses the radio energy transmitted by the reader. However, to control a passive tag, it should be light with an influence level roughly one thousand times stronger than for signal transmission.

Fig.6: RFID Reader and tags

4.2 Threshold Based Method

A threshold-based method is the one in which the optimum threshold will be set and the fall will be detected based on the threshold value considered. The sensor readings obtained from the data acquisition stage will be used to detect fall. Dataset collected is based on the samples collected from the testbed with a particular group of experimental subjects. Threshold value for accelerometer, gyroscope, and magnetometer will be set and based on the threshold, fall will be detected. The threshold is set based on the mean value of the sensor dataset collected. Once the input from the wearable crosses the threshold, the value will be predicted as fall or non-fall.Threshold is calculated using the below formula:

TH' = (sum of column value)/(total number of rows)

Threshold = (Average of TH')

4.3 Machine Learning Methods

Machine learning being an application of artificial intelligence (AI) that provides system the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning emphases on the development of computer programs that can access data and use it to learn for themselves.

The classification process with MLM includes two stages: Dataset preparation and preprocessing, training and classification.

4.3.1 Dataset Preparation and Preprocessing:

Dataset is the basic unit for machine learning. Gathering the required amount of data plays a major role in machine learning. The dataset required for our project was collected from the testbed itself.

The raw data from the sensors were collected for different activities from 3 persons. The activities were the fall and non-fall, wherein the data for non-fall activities were for walking and clapping patterns. These data collected from the sensors would be in the raw data which in turn needs to be formatted and cleansed to get the required form of the data. The formatting and the cleansing of data are done in the preprocessing stage of the data. The preprocessing is involved in formatting the data from the accelerometer, gyroscope and magnetometer data initially. The formatted data will contain the row of tri-axial data from all the 3 sensors separated by the delimiter.

The cleansing of data involves removing the noise in data i.e., the data value for every axis is limited to two decimal points. The entire formatting and cleansing of data are done by the Arduino. This dataset is stored for further training.

4.3.2 Training and Classification

Training process entails "feeding" the algorithm with training data. An algorithm will process data and output a model that is able to find a target value (attribute) in new data — an answer you want to get with predictive analysis. The purpose of model training is to develop a model. The classification model used in our work is SVM and Random Forest.

- **Support Vector Machine:**

  A Support Vector Machine (SVM) is a classifier defined by a separating hyperplane. In other words, given alabelled training data (supervised learning), the algorithm aims to output an optimal hyperplane which categorizes new examples. In two-dimensional space, this hyperplane is a line dividing a plane two parts were in each class lay in either side. SVM classifies data by finding the hyperplane on the basis of best-fit margin and separates data point of one class from the other.

- **Random Forest:**

  Random forests or random decision forest is defined as an ensemble learning method for classification, regression and various tasks that functions by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes or mean estimation of the individual trees.

4.4 Indoor Positioning

For an indoor tracking, an RFID tag was carried by a user and continually read whenever he/she accessed a room while GPS was used mainly when the user was staying outdoor.For indoor area, an RFID reader was installed in each room and the user should tap his/her RFID tag in order to be identified. When the user tapped his/her RFID tag to the reader, UID would be validated by a database server. When it was valid, the RFID would display the position of the user in a smartphone. When the user got out from the room 3 meters away, the RFID would be off and GPS would automatically trace the position of the user. In our work, we have used passive tags for which tapping is required and can be further improvised by using active tags to automatically detect the in bit larger area. We have used 5 passive tags which are given with respective location name like kitchen, living hall, room and blocked area. Whenever the person enters the blocked area, and the alert saying the same will be sent to the caretaker. Also when the fall occurs, GPS will send the location along with alert and RFID can, in turn, provide the exact indoor position in case of big buildings.

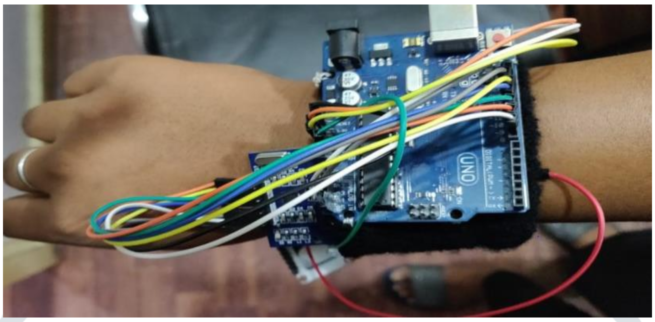

Fig.7: Wearable device

V. RESULTS AND DISCUSSION

The hardware designed for fall detection is as shown in the Fig.7and the sensors are provided with the power supply through batteries. The raw data collected from the hardware shown in Fig.8 is cleansed to get the required format represented in Fig.9. The tool used for the coding with respect to hardware is Arduino software. The raw data represented is the Arduino screen which represents the sensor values read with the delay of 200ms. Once the input sensor data is read from the hardware, algorithms are applied and the activity is predicted to be either fall or non-fall as represented in Fig.10 and if the activity is predicted to fall, the SMS based alert is sent to the care taker along with the location where the fall occurred. This SMS based alert is as shown in Fig.11. Runtime verification is carried out to validate the algorithm and the graph for same represented in Fig.12.

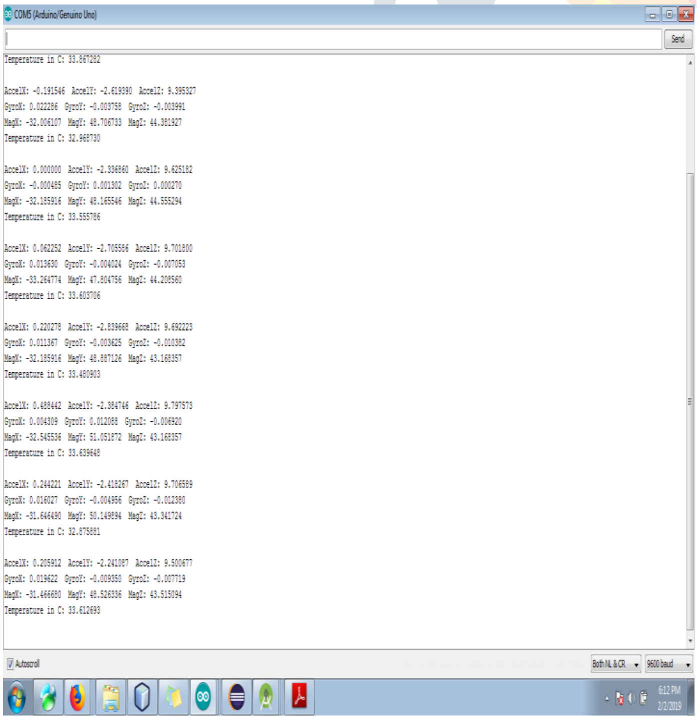

Fig.8: Raw data

```
-9.98@3.05@4.20#-0.83@1.38@0.41#-9.35@7.58@56.52
-10.66@3.28@-2.05#-0.53@-0.16@-0.10#16.90@46.18@75.59
-9.63@4.33@-5.18#0.95@-0.69@-0.64#8.63@34.64@79.40
-6.12@2.73@-8.72#2.03@-3.05@0.06#-11.51@38.97@77.32
-8.59@0.79@-6.31#3.21@-1.85@0.76#-10.61@30.13@75.41
-10.10@1.24@-3.66#2.79@-2.66@2.25#-14.38@9.74@57.21
-12.83@0.23@-0.46#0.54@0.15@1.52#-7.01@5.23@48.02
-10.97@-1.91@-2.48#-4.50@2.23@-3.06#-10.61@21.11@71.25
-8.42@3.93@2.10#-0.47@-0.36@-0.51#2.52@18.04@72.47
-8.88@3.63@2.10#-0.30@-0.02@-0.21#5.03@19.48@71.43
-8.96@3.39@2.40#-0.31@-0.08@-0.21#5.21@18.58@70.91
-9.30@2.89@2.07#-0.18@0.07@-0.68#6.29@18.94@72.99
-9.71@0.70@1.96#-0.08@-0.18@-0.10#14.20@33.73@77.50
-9.34@0.31@2.24#-0.24@-0.04@-0.13#15.46@33.91@77.32
-8.33@4.59@1.06#1.13@-0.59@0.03#17.98@50.51@76.97
-9.05@0.98@3.50#-1.94@0.44@0.73#20.32@31.57@74.37
-9.42@1.02@1.48#4.17@-2.80@0.23#-4.68@16.96@70.73
-11.61@-0.03@2.09#1.45@0.19@0.06#-3.06@12.45@64.32
-9.69@1.39@-0.05#-2.72@2.48@-1.31#5.57@38.78@80.62
-8.66@0.92@-6.29#0.79@-0.19@-0.26#0.00@49.79@80.44
-10.16@-0.74@0.72#1.35@-0.15@0.12#-1.26@11.73@63.63
-9.06@-0.27@2.49#-3.08@0.11@-0.84#6.83@44.74@81.14
-9.41@0.94@0.17#0.23@-0.19@-0.34#6.47@19.48@71.43
-4.31@9.21@4.11#-1.69@-2.37@-2.00#30.21@42.57@64.15
-9.52@0.96@0.65#-0.17@-1.09@-0.88#12.23@51.95@76.28
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-12.68@2.44@-0.55#-1.95@-0.82@-4.00#-15.46@44.38@76.97
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-10.32@-4.36@-1.14#-3.96@-0.46@-4.23#-5.39@71.80@58.25
-7.11@-10.57@-5.30#-3.45@-0.56@-2.21#6.65@66.57@30.69
-1.42@-13.67@-10.55#0.37@-0.47@0.36#2.88@66.02@27.05
```
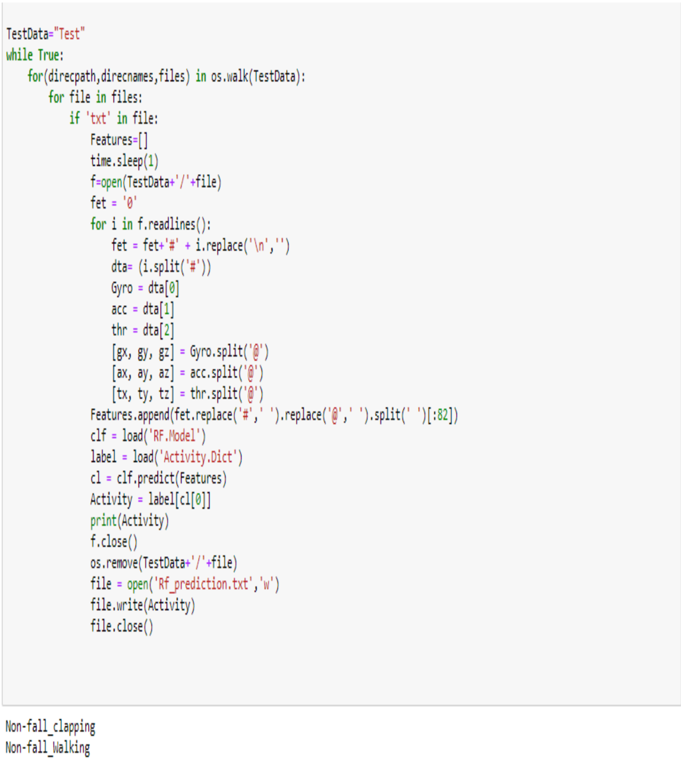

Fig.9: Cleansed data



```
TestData="Test"
while True:
    for(direcpath,direcnames,files) in os.walk(TestData):
        for file in files:
            if 'txt' in file:
                Features=[]
                time.sleep(1)
                f=open(TestData+'/'+file)
                fet = '0'
                for i in f.readlines():
                    fet = fet+'#' + i.replace('\n','')
                    dta= (i.split('#'))
                    Gyro = dta[0]
                    acc = dta[1]
                    thr = dta[2]
                    [gx, gy, gz] = Gyro.split('@')
                    [ax, ay, az] = acc.split('@')
                    [tx, ty, tz] = thr.split('@')
                Features.append(fet.replace('#',' ').replace('@',' ').split(' ')[:82])
                clf = load('RF.Model')
                label = load('Activity.Dict')
                cl = clf.predict(Features)
                Activity = label[cl[0]]
                print(Activity)
                f.close()
                os.remove(TestData+'/'+file)
                file = open('Rf_prediction.txt','w')
                file.write(Activity)
                file.close()

Non-fall_clapping
Non-fall_Walking
```

Fig.10: Predicted activity

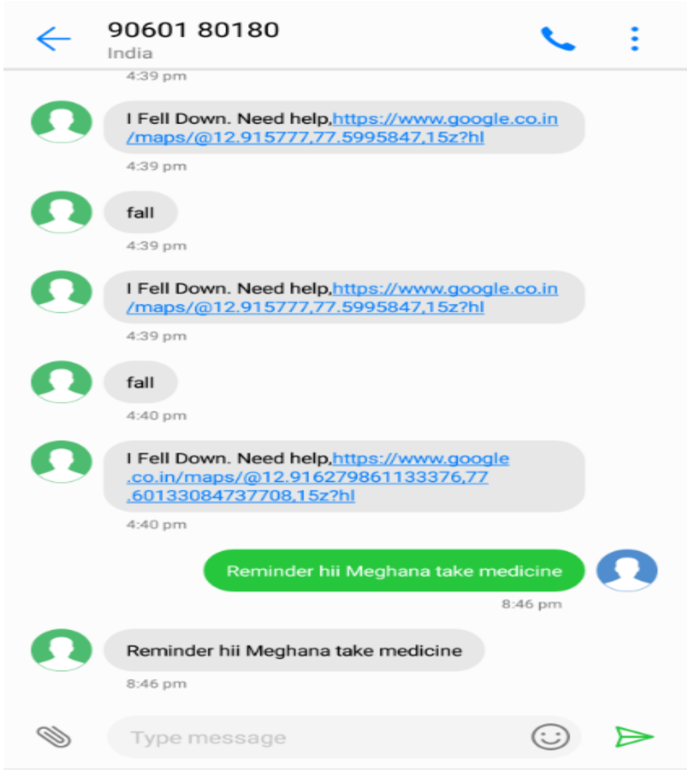


Fig.11: Fall Alert SMS

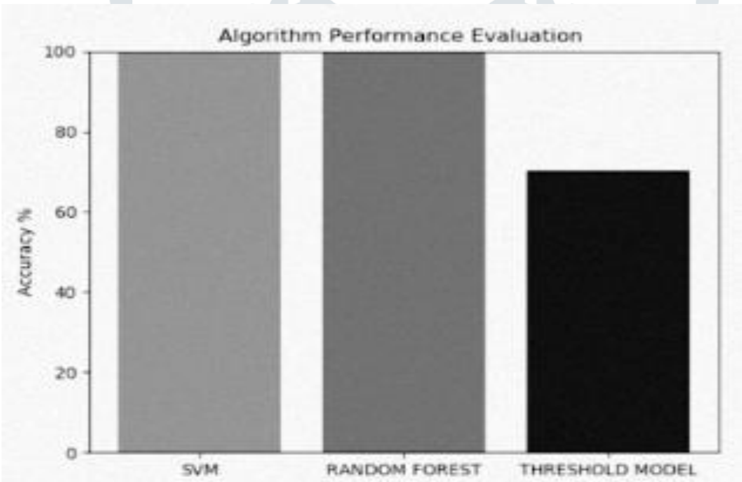


Fig.12: Graphical Representation

VI. CONCLUSION

This work proposed the development of a fall detection system based on a wearable system located at wrist. The wrist was chosen for being considered the most discrete and comfortable place to wear a device 24 hours a day. It may also be less associated to the stigma of using a health device, allowing a higher acceptance by users. In this sense, we presented two different approaches. The first was related to threshold-based algorithms and second the machine learning algorithms. Also RFID based indoor positioning is developed to track the person in both general and emergency situations. An additional feature of text to speech based reminders at the patient's end is designed to ensure an assistance for Alzheimer's patient. After evaluating these algorithm possibilities, this work concludes that machine learning approaches with the proposed movement decomposition are potentially able to achieve ideal results for a fall detection system based on a wrist-worn device. In future, dataset can be improvised and different techniques can be used to set an optimum threshold.Also, RFID passive tags can be replaced by active tags for the practical use.

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