Nat. Volatiles & Essent. Oils, 2021; 8(5): 8269- 8285

NVEO
Natural Volatiles &
Essential Oils

Smart Band For Elderly Fall Detection Using Machine Learning

[1]C. Ranjeeth Kumar, [2]M. Kaleel Rahman, [3]E. Derrick Gilchrist, [4]R. Lakshmi Pooja, [5]C. Sruthi

[1]AssistantProfessor(sr.gr),[2] [3] [4] [5]Student,
Department of Information Technology,Department of Information Technology,,
Sri Ramakrishna Engineering College,NGGO Colony,Sri Ramakrishna Engineering College,NGGO Colony,
Coimbatore, Tamil Nadu - 641022, IndiaCoimbatore, Tamil Nadu - 641022, India ,

[1]ranjeeth.chandran@srec.ac.in, [2]kaleelrahman.1805019@srec.ac.in , [3]derrickgilchrist.1805019@srec.ac.in, [4]lakshmipooja.1805050@srec.ac.in, [5]sruthic.1805144@srec.ac.in

Abstract—
Fall is a common issue for senior citizens, as they are weak and need assistance. A fall could result in serious injury or perhaps death. So giving proper attention as soon as possible will reduce the impact of the fall. The main goal of this research is to perceive the appropriate machine learning algorithm for the scenario and illustrate the deployment of the fall detection system. So if the person is under fall, the system detects it immediately and intimate the concerned person by sending a message through SMS along with the person's current location as a google map link. So that they can arrive at that spot and help them before the situation gets out of hand. It is a wearable device that should be worn in order to detect a person's fall. The hardware and software are combined in the design and implementation to detect and report the elderly's collapse in a seamless manner.

Index Terms—*Supervised learning; Medical wearable sensors; Internet of things; Care notification system.*

I. INTRODUCTION

Falling is a huge issue for the elderly, as they are physically weak, it can result in serious injuries or even death. So proper attention should be provided immediately. It is not a problem if someone is available to take care after the individual. However, if the person is alone, they will be unable to help themselves. So they need care as soon as possible. So a system that detects fall and intimates the concerned people immediately. We use the domain wearable technology and machine learning for the fall detection system.

Instead of relying on patterns and conclusions computer systems use Machine Learning. It is a scientific study of algorithms and statistical models. Machine learning algorithms use sample data, referred as "training data," to create a mathematical model that can make predictions or judgments without needing to be explicitly programmed.

The wearable device detects factors such as the person's pulse rate and body acceleration. The parameters are trained using supervised machine learning classification. This supervised classification model determines whether or not a person is in danger of falling. This model is a binary classification model which gives output as either fall or not.

II. LITERATURE REVIEW

Various researches have been done for Wearable devices for elderly. This research helped in understanding the various methods that were used in wearable and external devices for healthcare monitoring. It also helped to identify the benefits and drawbacks of the existing system and how to improvise it.

Adults above the age of 65 are the ones who have the most deadly falls. Every year, 37.3 million falls are severe enough to necessitate medical attention. Fall-related injuries
may be fatal or non-fatal though most are non-fatal [1]. The rates of HIT use decreased from 32.2% in the age group 65 to 74 to 14.5% in the 75-84 age group, and 4.9 percent in the 85-plus age group. However,attending or talking to a medical specialist, eye doctor, or physical therapist/occupational therapist (PT/OT) was only marginally linked with HIT usage in older males, whereas seeing or talking to a mental health professional was only slightly associated with HIT use in older women [2]. Fall detection and prevention are 2 common studies, and both aim to improve people's lives by utilising pervasive computing [3]. Despite the fact that the field of human activity recognition (HAR) has been discussed continuously, there are still critical factors that, if addressed, would result in a dramatic shift in how people interact with mobile devices [4]. Elderly individuals are eager to live alone in their homes, despite the fact that they are mentally strong but not physically strong. Using two or more of the following phases of a fall event: beginning of the fall, falling velocity, fall impact, and posture after the fall, three distinct detection algorithms with increasing complexity were tested [5]. Artificial Neural Networks (ANN) have a low computing cost, making them easier to deploy on a mobile device. They also increase fall detection accuracy by bypassing standard threshold-based fall detection approaches [6]. The wearable has the ability to communicate with a cell phone within a 100-foot range. When the wearable device senses a fall, it sends a notification to the phone [7]. There is a need for continuous monitoring of health using wearable and other IOT devices. There are a variety of health-monitoring options for the elderly with specific issues as well as general issues such as falls. When

technology for the elderly is offered, human comfort must be addressed [8]. There are various technologies available in monitoring systems for the elderly. The technologies are also divided into three groups: vision-based recognition, radio-based recognition, and sensor-based recognition. In sensor-based recognition systems accelerometers and gyroscopes are used together. Sensor-based recognition outperforms other categories for geriatric monitoring systems [9]. When the aged people meet any sudden critical situation, a multi-information fusion-based geriatric care system is capable of sending a GPRS notification to the elderly person's family members. The concept of a band can be simplified into a product that is easy to carry and wear all of the time [10].

SVM builds a non-probabilistic binary linear classifier. Fractional Gradient Descent reduces the training time but also the precision of the support vector machine algorithm [12]. Combined with cloud computing, machine learning is used for various health care applications like health monitoring and risk of disease analysis from medical profiles. Some of the commonly used classifiers for health care are Decision tree and random forest classifier [13]. A wireless sensor is widely used to collect vital information and pass it to a cloud service where it is stored and analyzed. The features are passed in to K Means classifier [14]. Advancements in the medical field have increased the application of machine learning algorithms.The various toolkits used for machine learning are pandas, NumPy, matplotlib and scikit-learn [15].

Various types of sensors like motion sensors and vital sensors can be used for monitoring the health of an elderly. Different methodologies are used for health monitoring using wearable devices. Both motion tracking and vital sensors can be used for better applications [16]. The elderly face many difficulties alone when the caretaker is not present. Smart systems are very helpful for their medical conditions or in critical situations. The accelerometer based approach produces better accuracy than acoustic based approach [17]. Emergency alert systems which use IOT and Machine Learning are proved to be an enhanced system compared with their predecessors [18]. Accelerometers can be used to detect the acceleration of the body. GPS is used to get the location of the elderly for various applications like providing the location of the elderly in a case of emergency [19]. The health care system contains wearable devices such as smart cloth, smart watch and body tag which detects the users health parameters. These parameters are stored into the database and then converted into the person's health analysis report. The care system will check if the parameter values health-enhancing physical activity and a healthy lifestyle. Everyday activities such as walking, jogging, and cycling are classified. Artificial neural networks, custom decision trees, and automatically generated decision trees are all used [22]. A Machine Learning-assisted Integrated Data-driven Framework (MLA-IDDF) that can acquire signal features based on personalised characteristics from older patients to increase compressive sensing performance with fewer measurements for a more precise model. MLA-IDDF creates semantic models that characterise patient situations and decision-making mechanisms based on the interpretation of acquired data, allowing for accurate observations of elderly patients [23]. A multi-sensor integrated measurement system (IMS) for monitoring physical activity that is worn on the body. To improve battery power efficiency while lowering energy consumption, an adaptive-scheduling system was developed.Experiments on humans have revealed that the multi-sensor IMS is more successful in detecting activities of varying intensity [24]. A Wireless Sensor Network (WSN) is made up of a large number of sensor nodes that are placed in an unattended and remote location to monitor a few physiological parameters. People tend to forget things as they become older, which might pose a threat to their safety.So for fire detection, gas leakage detection, and determining whether a door is closed or open, sensors such as temperature sensors, LPG sensors, and contact sensors are used [25].

III. SYSTEM ANALYSIS

The research is about fall detection using Supervised Machine Learning Classification Algorithms. The purpose of a wearable gadget is to detect pulse rate and body acceleration. These parameters are given as input to the Machine Learning model that predicts whether the fall has occurred or not. If fall occurs, the location of the person under fall is being detected and a message is sent to the concerned person stating that he/she has collapsed and they require immediate attention.

IV. MACHINE LEARNING ALGORITHMS

A. *Naive Bayes Algorithm*

Naive Bayes classification algorithm is applied to binary and multi-class classification problems.The classifiers calculate the probability of a given input sample to be of a certain category, based on prior knowledge. They employ the Naive Bayes Theorem, which states that the influence of one feature of a sample is unaffected by the effects of other features.

P (Class | Features) = P (Class | Features) . P (Class)

differ from the threshold value [20].

The global community is currently experiencing issues related to a variety of factors, one of which requires our attention is the ageing society. Healthcare sectors do not yet have viable solutions to the aforementioned issues. The Elder Care System (ECS) is a device that monitors the behaviour of older patients who are confined to a bed with a specially built system. A notification system, an in-bed position prediction system, and a real-time monitoring system are all part of the system [21]. Automatic classification of daily activities can be used to encourage

P(Features)

B. *Stochastic Gradient Descent Algorithm*

In simple words, gradient means the slope of a surface. As a result, gradient descent entails descending a slope to the lowest point on the surface [11]. It is an iterative process that starts at a random point on a function and gradually descends its slope until it reaches the function's lowest point [12].

C. Support Vector Machine Algorithm

Support Vector Machine is a supervised machine learning algorithm . It can be used to solve classification and regression problems. The SVM algorithm's purpose is to find the optimum line or decision boundary for categorising n-dimensional space into classes so that additional data points can be readily placed in the correct category in the future. A hyperplane is the name for the optimal choice boundary.

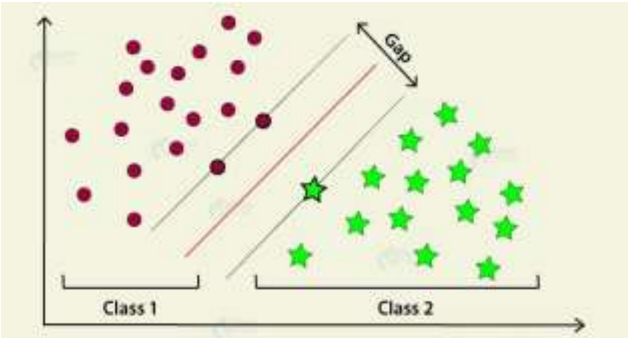


Fig. 1 Visualization of Support Vector Machine Algorithm's working

D. **Decision Tree Algorithm**

In this supervised learning algorithm, we start from the root of the tree to forecast a class label for a record. The root and record attributes are compared. The Decision Node and the Leaf Node are the two nodes of a Decision tree [13]. Decision nodes have multiple branches which are used to make any decision and Leaf nodes do not contain any further branches which are the output of those decisions.

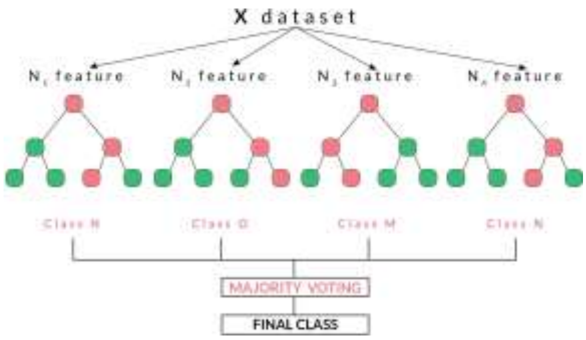
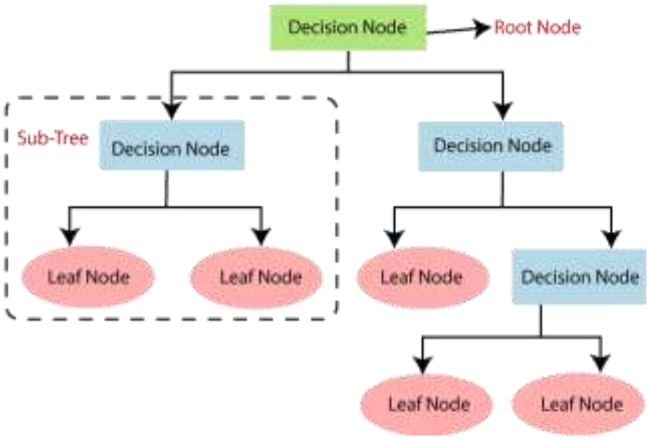


Fig. 2 Visualization of Decision Tree Algorithm's working

E. Random Forest Algorithm

A Random Forest algorithm is obtained by ensembling various individual decision trees. In the random forest each tree produces a class prediction. The class which has secured the most votes becomes the model's prediction. Random Forest is a classifier that combines a number of decision trees on different subsets of a dataset and averages the results to increase the dataset's predicted accuracy. The bigger the number of trees in the forest, the more accurate it is and the problem of overfitting is avoided.



3 Visualization of Random Forest Algorithm's working

Table 1 : Training and testing accuracies for various machine learning algorithms

Serial No.	**Machine Learning Algorithm**	**Train Accuracy**	**Test Accuracy**
1	Naive Bayes algorithm	94.30397%	92.75362 %
2	Stochastic Gradient Descent	91.40506%	88.50724 %
3	Support vector machine	96.83544%	94.20289 %
4	Decision Tree Classifier	100.0%	98.2456%
5	Random Forest Algorithm	99.4117%	96.4912%

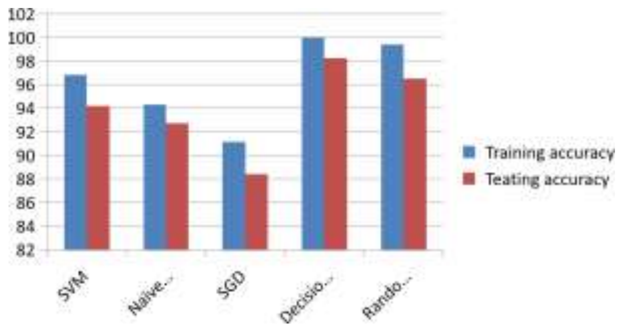


Fig. 4 Accuracy comparison graph of different models

The above graph illustrates the different test and train accuracy obtained from 5 different machine learning algorithms (Naive Beye, Stochastic Gradient Descent, Support Vector Machine, Decision tree classifier, Random Forest). Overall, The random forest algorithm produced the highest training and testing accuracy whereas the stochastic gradient descent produced the least accuracy. The training accuracy of the decision tree leads the random forest algorithm's accuracy with nearly 0.6%, the same trend is applied to the test accuracy where the decision tree stays superior to the Random forest with around 2%. The naive bayes algorithm produced the second least amount of accuracy. The SVM algorithm's testing and training accuracy are approximately 94% and little more than 94%.

V. MODULES

There are 4 modules involved in this project. The first module is data collection which is followed by data preprocessing. Using the preprocessed data on the next module 5 different machine learning models are trained. From that the model with highest accuracy is chosen and deployed in the prototype.

A. *Data Collection*

Arduino UNO board is used for data collection. The data was collected in real time by connecting the pulse rate sensor and tri-axial accelerometer sensor to the person's wrist. The data is collected with the different movements of the person like walking, standing, running, sitting, falling etc.

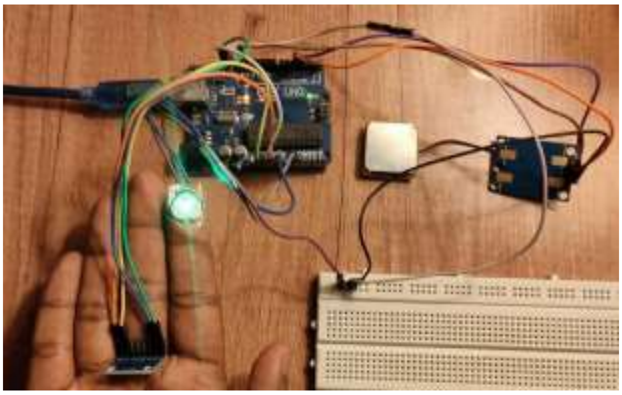


Fig. 5 Data Collection Using Arduino UNO

The activity fall is labelled 1 and all the other activities other than fall are labelled as 0. The collected data is stored into a csv file. The csv file has 5 columns i.e BPM(pulse rate), X (X–coordinate), Y (y-coordinate), Z(Z-coordinate), LABEL(fall or not).

Fig. 6 Real time Data collection

Here are some of the pulse rate and triaxial sensor values which are recorded in Arduino IDE.

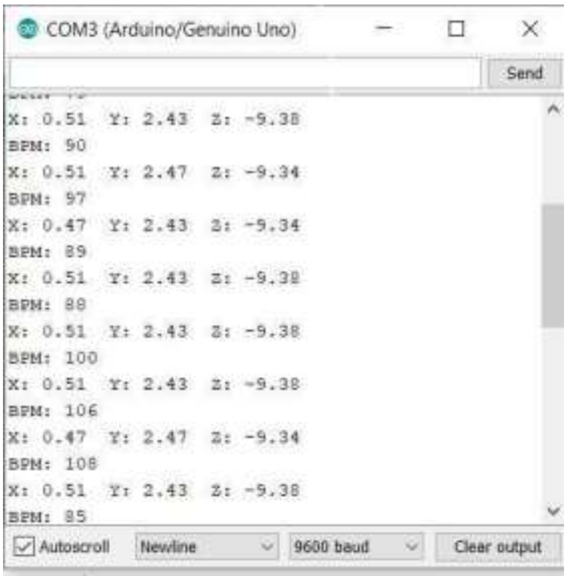


Fig. 7 pulse rate And Acceleration Values

B. Dataset Preprocessing

The Data which is collected from different actions of various persons is then divided into training data and testing data. The ratio between train and test data split is 70:30. The data set is labelled into fall or not fall. For fall the label is set to 1 and for not fall the data is set to 0.

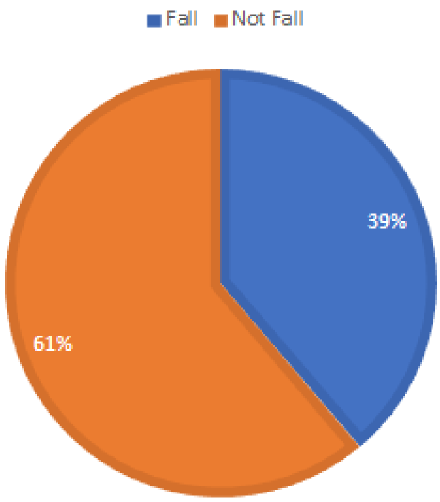


Fig. 8 Fall and Not Fall total data ratio

The total data values collected is around 1900. Out of which 730 data values are fall which is labelled as 1 and rest 1150 data values are not fall which is labelled as 0.

17	170	11.45	-8.55	-5.06	1
18	155	8.59	-4.51	-1.37	1
19	131	9.96	2.55	-4.31	1
20	97	3.26	3.3	-8.9	1
21	218	-8.63	3.84	-4.35	0
22	218	-7.45	5.57	-3.61	0
23	202	3.26	4.67	-5.37	0
24	46	-9.38	1.22	-1.45	0

Fig. 9 Preprocessed Data

C. *Model Development*

Support vector machine (SVM), Naive bayes algorithm, Random Forest algorithm, Decision Tree algorithm, and Stochastic Gradient Descent algorithm are among the machine learning algorithms that are trained using the preprocessed data [15]. They produce different training and testing accuracy. When compared with all trained models the decision tree algorithm produced better accuracy. The nodemcu esp8266 is connected with the sensors that detects the essential data from the elderly. The arduino requires code to read the input value from the sensor. This value is sent as input to the decision tree machine learning model. If the model predicts 'fall' then the location of the elderly person is detected using a GPS module. Then the alert message which is attached with the location of the elderly person is sent to the caretaker and emergency services.

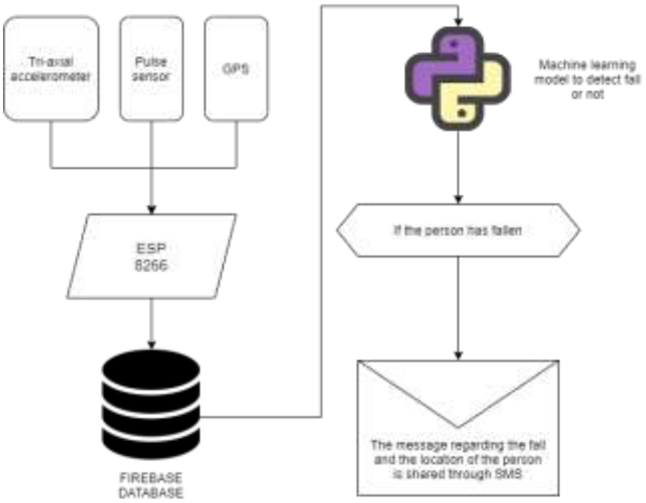


Fig. 10 Flow Chart

D. *Implementation and deployment*

The system consists of 3 main sensors namely NEO 6M GPS, ADXL345 triaxial accelerometer and Pulse sensor. The pulse rate sensor which is used is a plug and play type sensor which operates in +5V or +3.3V. This pulse rate sensor can be placed directly in the veins for example on a person's finger tip or on the ear tipsor on the wrist.The Tri-axial accelerometer which is used is ADXL345 which operates in 1.8V- 3.6V. Its bandwidth measure of the X and Y axis ranges from 0.5HZ to 1600HZ. Z axis ranges from 0.5HZ to 550 HZ bandwidth. The NEO 6M GPS operates on voltage between 3.3V – 6V. These sensors are connected to the nodemcu esp8266 module, the ports and the corresponding functionality are configured in Arduino IDE.

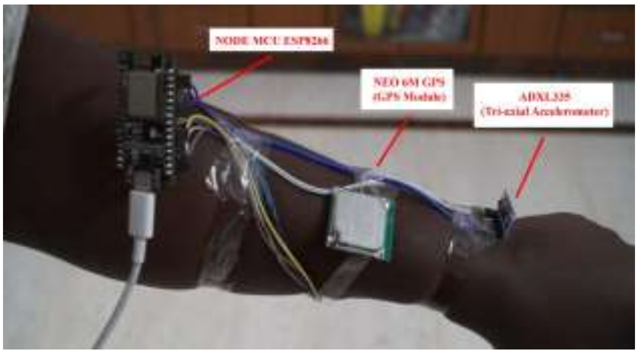


Fig. 11 Component Configuration (1)

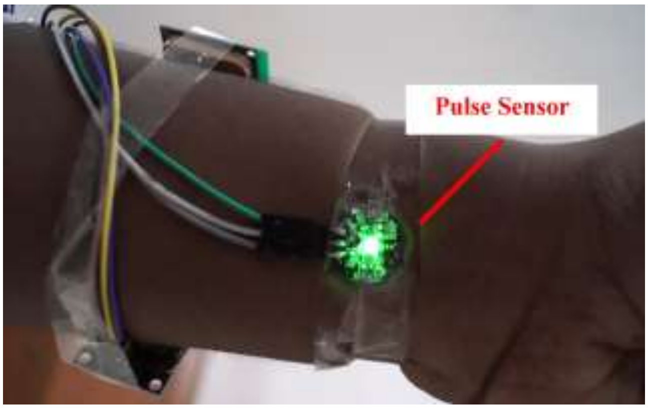


Fig. 12 Component Configuration (2)

The BPM value from the pulse sensor, the X,Y,Z coordinate values from the Triaxial sensor, and the latitude and longitude values from the GPS sensor are displayed in the Arduino IDE's serial monitor. All the BPM and X,Y,Z values are recorded in a time interval of 300 millisecond(ms). Nearly three data values are recorded per second. But the latitude and longitude values are recorded in a time interval of 3 seconds(s).

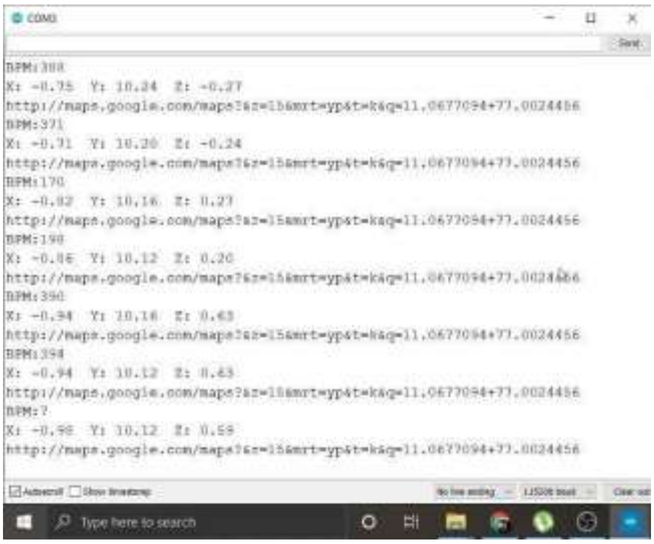


Fig. 13 Sensor output displayed in serial monitor

The pin configuration for the connection of node mcu esp8266 module along with Pulse sensor, ADXL345 Tri-axial accelerometer sensor and NEO 6M GPS sensor are shown in the Figure. 19.

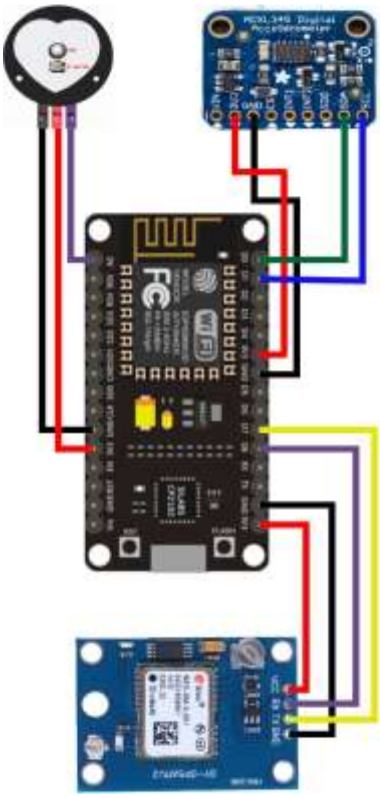


Fig. 14 Pin Configuration

The data from the sensor is uploaded to a cloud database [14]. Here, Google Firebase is utilised to construct a realtime database, which is then connected to nodemcu using the database's api credentials. Thus all the sensor values are passed instantly from the nodemcu esp8266 module to Google's firebase. The green coloured data entry can be seen in Figure 18, Which denotes the live feed of data values into the database.

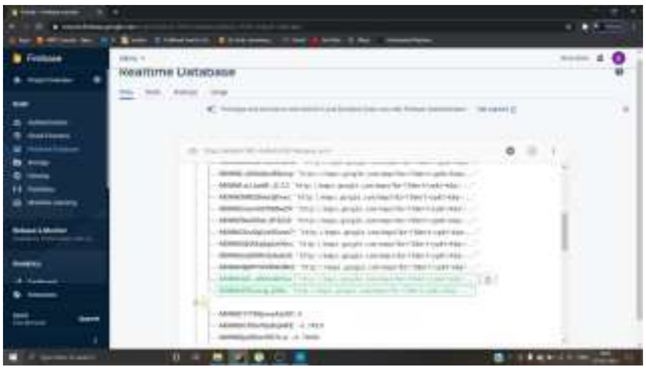


Fig. 15 Realtime data feed in Firebase

The sensor values from this Firebase are passed to Google Colab seamlessly as soon as the data is received from the nodemcu. The google colab has the decision tree machine learning model which is already trained and ready to predict whether there is fall or not by getting the data values. This model uses live feeded inputs from the firebase to estimate whether or not the person's condition would collapse. It has been programmed to send an alert message to the local hospital as well as the caretaker along with the person's location as a google map link, if any falling motion is predicted.

VI. EXPERIMENTAL RESULT AND DISCUSSION

The goal of this project is to efficiently monitor a person's pulse rate and acceleration. This model determines whether a person has fallen by inferring sudden falling propensity or a change in pulse rate. If the above circumstance exists, it sends a message to the concerned person.

Different Machine Learning models like Naive Bayes classifier, Random Forest Classifier, Stochastic Gradient Descent, Decision Tree Classifier have been used but the highest test and train accuracy is gained by Decision Tree Classifier Algorithm.

When the model classifies the input value as fall an alert message is sent along with a google map link which holds the person's location [7][18]. The person's location will be displayed in Google Maps when the link is clicked.

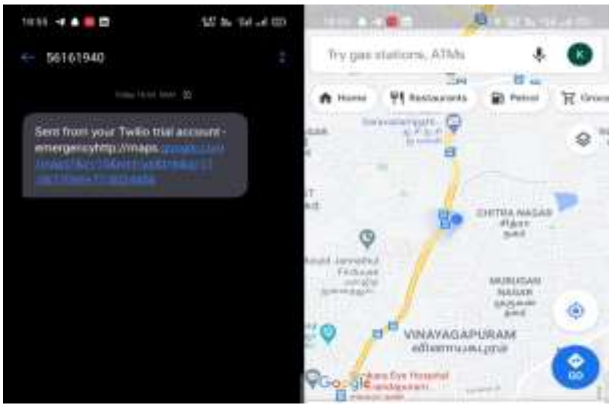


Fig. 16 Alert message received with location link

A. *Merits*

1) Monitor the health of the elderly people who are weak and are more prone to falls.
2) Monitors vulnerable Patients.
3) Give proper attention to the person under fall.
4) The cost of the wearable device is cheap.

B. *Demerits*

1) Battery life of the wearable device is less and it needs to be recharged regularly.
2) Maintenance is also difficult.
3) Many old people would not like to wear devices all the time [19].

CONCLUSION

As a result, our project assists older individuals who are in particular emergency situations in order to save them from the consequences of their falls. The project was built on a low cost compenents so that people from all walks of life are capable of affording it. This project can also benefit persons who are blind, autistic, intellectually retarded, with walking problem, or paralysed. The proposed method can be enhanced in the future by transforming the wrist band-based product into a simpler form that is easier to carry and wear all the time.

REFERENCES

[1] "Falls",World Health Organization, 26 April 2021.[Online]. Available: http://www.who.int/mediacentre/factsheets/fs344/en/

[2] Choi N, Relationship Between Health Service Use and Health Information Technology Use Among Older Adults: Analysis of the US National Health Interview Survey J Med Internet Res 2011;13(2):e33 doi: 10.2196/jmir.1753

[3] Delahoz, Y.S.; Labrador, M.A. Survey on Fall Detection and Fall Prevention Using Wearable and External Sensors. *Sensors* 2014, *14*, 19806-19842. https://doi.org/10.3390/s141019806.

[4] O. D. Lara and M. A. Labrador, "A Survey on Human Activity Recognition using Wearable Sensors," in IEEE Communications Surveys & Tutorials, vol. 15, no. 3, pp. 1192-1209, Third Quarter2013, doi: 10.1109/SURV.2012.110112.00192.

[5] Maarit Kangas, Antti Konttila, Per Lindgren, Ilkka Winblad, Timo Jämsä, Comparison of low-complexity fall detection algorithms for body attached accelerometers, Gait & Posture, Volume 28, Issue 2, 2008, Pages 285-291, ISSN 0966-6362, https://doi.org/10.1016/j.gaitpost.2008.01.003.

[6] M. Vallejo, C. V. Isaza and J. D. López, "Artificial Neural Networks as an alternative to traditional fall detection methods," 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2013, pp. 1648-1651, doi: 10.1109/EMBC.2013.6609833.

[7] J. Santiago, E. Cotto, L. G. Jaimes and I. Vergara-Laurens, "Fall detection system for the elderly," 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), 2017, pp. 1-4, doi: 10.1109/CCWC.2017.7868363.

[8] Stavropoulos, T.G.; Papastergiou, A.; Mpaltadoros, L.; Nikolopoulos, S.; Kompatsiaris, I. IoT Wearable Sensors and Devices in Elderly Care: A Literature Review. *Sensors* 2020, *20*, 2826. https://doi.org/10.3390/s20102826.

[9] Wang Z, Yang Z, Dong T. A Review of Wearable Technologies for Elderly Care that Can Accurately Track Indoor Position, Recognize Physical Activities and Monitor Vital Signs in Real Time. Sensors (Basel). 2017 Feb 10;17(2):341. doi: 10.3390/s17020341. PMID: 28208620; PMCID: PMC5336038.

[10] He Z, Lu D, Yang Y, Gao M. An Elderly Care System Based on Multiple Information Fusion. J Healthc Eng. 2018 Jan 15;2018:4098237. doi: 10.1155/2018/4098237. PMID: 29599947; PMCID: PMC5823425.

[11] Deepa, N., Prabadevi, B., Maddikunta, P.K. *et al.* An AI-based intelligent system for healthcare analysis using Ridge-Adaline Stochastic Gradient Descent Classifier. *J Supercomput* 77, 1998–2017 (2021). https://doi.org/10.1007/s11227-020-03347-2

[12] Puspita Hapsari, Dian ; Utoyo, Imam ; Wulan Purnami, Santi, " Text Categorization with Fractional Gradient Descent Support Vector Machine", Journal of Physics: Conference Series, Volume 1477, Issue 2, article id. 022038 (2020), doi: 10.1088/1742-6596/1477/2/022038

[13] David J. Wu, Tony Feng, Michael Naehrig, Kristin Lauter, "Privately Evaluating Decision Trees and Random Forests",

[14] Sareen S, Sood SK, Gupta SK. An Automatic Prediction of Epileptic Seizures Using Cloud Computing and Wireless Sensor Networks. J Med Syst. 2016 Nov;40(11):226. doi: 10.1007/s10916-016-0579-1. Epub 2016 Sep 15. PMID: 27628727.

[15] Mahabub, A. A robust voting approach for diabetes prediction using traditional machine learning techniques. *SN Appl. Sci.* 1, 1667 (2019). https://doi.org/10.1007/s42452-019-1759-7

[16] Haghi, M., Thurow, K., & Stoll, R. (2017). Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices. *Healthcare informatics research*, *23*(1), 4–15. https://doi.org/10.4258/hir.2017.23.1.4

[17] Kobkiat Saraubon, Keattisuk Anurugsa, and Adichart Kongsakpaibul. 2018. A Smart System for Elderly Care using IoT and Mobile Technologies. In Proceedings of the 2018 2nd International Conference on Software and e-Business (ICSEB '18). Association for Computing Machinery, New York, NY, USA, 59–63. DOI:https://doi.org/10.1145/3301761.3301769

[18] P. Pandey and R. Litoriya, "Elderly care through unusual behavior detection: A disaster management approach using IoT and intelligence," in IBM Journal of Research and Development, vol. 64, no. 1/2, pp. 15:1-15:11, 1 Jan.-March 2020, doi: 10.1147/JRD.2019.2947018.

[19] Ehrler, Frederic & Lovis, Christian. (2014). Supporting Elderly Homecare with Smartwatches: Advantages and Drawbacks.. Studies in health technology and informatics. 205. 667-671.

[20] P. Huang, C. Lin, Y. Wang and H. Hsieh, "Development of Health Care System Based on Wearable Devices," 2019 Prognostics and System Health Management Conference (PHM-Paris), 2019, pp. 249-252, doi: 10.1109/PHM-Paris.2019.00049.

[21] G. Pongthanisorn, W. Viriyavit, T. Prakayapan, S. Deepaisam and V. Somlertlamvanich, "ECS: Elderly Care System for Fall and Bedsore Prevention using Non-Constraint Sensor," 2020 International Electronics Symposium (IES), 2020, pp. 340-344, doi: 10.1109/IES50839.2020.9231781.

[22] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola and I. Korhonen, "Activity classification using realistic data from wearable sensors," in *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 119-128, Jan. 2006, doi: 10.1109/TITB.2005.856863.

[23] Tao Ba, Shan Li, Yangyang Wei, A data-driven machine learning integrated wearable medical sensor framework for elderly care service, Measurement, Volume 167, 2021, 108383, ISSN 0263-2241, https://doi.org/10.1016/j.measurement.2020.108383.

[24] Liu, Shaopeng & Gao, Robert & Freedson, Patty. (2010). Design of a wearable multi-sensor system for physical activity assessment. IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM. 254 - 259. 10.1109/AIM.2010.5695932.

[25] R. S. Ransing and M. Rajput, "Smart home for elderly care, based on Wireless Sensor Network," 2015 International Conference on Nascent Technologies in the Engineering Field (ICNTE), 2015, pp.1-5, doi:10.1109/ICNTE.2015.7029932.

00 International Distinguished Educators -Green ThinkerZ awards 2020 & Outstanding Faculty Mentor Award from Novel Research Academy, Puducherry. Has completed a sabbatical research program in NVIDIA Bennett Research Centre on Artificial Intelligence under leadingindia.ai at Computer Science Engineering Department, Bennett University, Greater Noida. NVIDIA Deep Learning Institute certified him as Deep Learning Instructor, University Ambassador and IBM certified Artificial Intelligence Practitioner-Instructor. He had published papers in reputed International Journals, presented papers in International/National Conferences and attended various Faculty Development Program, Seminars & Workshops. He published two patents under his name. He served as reviewer for International Journal of Machine Learning and Computing and Journal of Supercomputing, Springer. He has been mentoring students for Hackathons/project contests. He is a life member of CSI, ISTE, IAENG and IACSIT.He has successfully passed the BEC preliminary certification examination and completed online certification courses in NPTEL and