Wearable Sensor and Machine Learning Model based Fall Detection System for Safety of Elders and Movement Disorders

Sejal Badgujar [1], Anju S Pillai [2], Sujatha Krishnamoorthy[3]

[1,2]Department of Electrical and Electronics Engineering,

Amrita School of Engineering, Coimbatore

Amrita Vishwa Vidyapeetham, India.

s_anju@cb.amrita.edu, bsejalnil@gmail.com

[3]Assitant Professor, Department of Computer Science

Wenzhou Kean University, China

krishnsu@kean.edu

Abstract: Due to different working culture of people, elderly people's health gets neglected as they live alone at home. With the rising population, there is a pressing demand for the evolution of fall identification systems. People with age greater than 65 are suffering from highest number of fatal falls. Some of the difficulties and challenges faced by the elders and mobility disordered people can be over passed by implementing algorithms able to anticipate falls. It is possible to have a good to great quality of life for the affected, by providing living assistance through automatic fall detection and alarming systems. We propose implementation of a fall recognition system for real-time tracking of elderly people. The proposed system has wearable sensor unit for detecting falls and alert mechanism to intimate the concerned and the care takers in case of falls by means of messages. The acceleration data is collected by the system using tri-axial accelerometer and uses machine learning algorithms to detect the falls upon various feature calculations. Extensive computations are carried out to compare the performance of different machine learning algorithms with varying features and the algorithm giving the highest accuracy with optimal features is identified. The system gains an accuracy up to 99% by using random forest algorithm with 10-fold cross validation. Thus, with a secure and reliable fall detection and alarming system, one could reduce the fatal falls, improving social integration, productivity and quality of life.

Key words: Fall detection, fall alarming, activity of daily living, elderly people assistance, movement disorders, machine learning, wearable sensors, fall forecast.

1. Introduction

Parkinson's disease (PD) is a chronic progressive neurodegenerative disorder which prominently impacts the older population. Despite this, due to aging, people get lot of difficulties for moving around and around four million people worldwide are living with this condition. The diagnosis is clinical and is complex, while the cause remains largely unknown. While Parkinson’s itself is not malignant, disease intricacy can be acute. Under such circumstances, fall detection system plays an important role. In times of emergency, elderly people require immediate attention in their homes or care centers. In most cases, they are not able to ask for help as they do not have access to technology, many live-in rural areas, also few may have physical limitations. According to the survey conducted by World Health Organization (WHO), the second leading cause of accidental or unintentional injury deaths worldwide are falls [1]. To improve quality of life of elderly people, people with movement disorders and to ensure wellbeing of our family member, use of automatic fall detection system is crucial.

This paper proposes, a real-time fall detection system to monitor elderly people and people with movement disorders. The system has wearable sensor unit for detecting falls and alerting the concerned person in case of falls by means of messages. It also provides living assistance to elderly people. The system consists of tri-axial accelerometer and uses machine learning (ML) algorithms to detect the falls after calculating various features. Six machine learning algorithms are tested for its performance and the most accurate algorithm is identified. The system models are trained by using existing SisFall dataset [8] and tested. It consists of 19 types of daily life activities and 15 types of falls performed by participants. Out, of a set of ML algorithms tested, random forest algorithm is found to give best accuracy up to 99%.

The paper is arranged as follows: the detailed literature survey is presented in section 2 and the system overview and methodology is explained in third section. The details of extensive simulations and hardware implementation are illustrated in section 4 and the conclusions and future research directions are summarized in section 5.

2. Related Work

In the literature, there are ample of research works which focuses on human activity classification, fall detection and fall forecast which is a hot research topic [20-21]. Due to the advancements in the technology, especially sensor system developments, IoT and deep learning; the support extended to improve the life of human has increased sufficiently [7]. The literature shows a large variety of methods adopted to identify human falls and efforts to reduce the false alarms and increase the fall identification accuracy. The broad categories of design of fall detection system is using three types of sensors: vision-based devices, ambient devices and wearable devices [18].

In vision-based fall detection, cameras fitted in the room allows monitoring of the elderly or the affected [2-3]. Different image processing algorithms are used to detect the fall. Mostly, in this case, simulation data set is used but, on an average 24% of the falls remain unexplored and the presence of false alarms are high. In ambient based fall detection [4][19], various sensor such as: vibration and passive infrared sensors are incorporated in the fall detection system for identifying the falls, identifying the person, identification of footstep, motion detection and uncommon inactivity detection. Thus, with the support of ambient sensors, falls are identified [19].

In general, the wearable fall detection systems have buttons incorporated with the fall detection system, so that in case of a not harmful fall, the person can push the button to sending emergency message [18]. Mostly such devices wear like a necklace and the subject need to be careful during the occurrence of fall to press the button. The other possible versions were a Bluetooth enabled pendant connected to mobile phone. The system enables a communication between the person and the mobile phone; but the phone needs to be within 100 meters range of the pendant. The overhead of such device includes: activities such as bending towards front are not identified properly due to false reading of falls.

In one of the implemented systems, six wireless sensor units were tightly connected to the subjects' head, chest, waist, right wrist, right thigh, and right ankle. The data set consists of data acquired from 14 healthy adult volunteers and various features are selected and employed feature reduction using principal component analysis (PCA). In their proposed research, six different ML learning classification algorithms were used for fall identification [13][17]. The major difficulty faced with the system is presence of large number of sensors to be attached to the elder's body, which is inconvenient [5]. Another method presented is a wearable device attached on human's waist which analyzes the acceleration data to identify the fall [6][14-15]. Upon, fall detection, messages are sent to the care takers by sharing the geographic position. This enables the elderly people to get timely help and reduces the negative influence. The system uses a threshold-based algorithm and thus, accurate identification of threshold is vital in this case. Based on the threshold, the accuracy of the system fluctuates. The literature also supports IoT and big data-based fall detection methods. The system consists of four main components: a wearable device [9-10], a wireless communication network, a smart IoT gateway and cloud services. In their proposed system architecture, data gets stored for further big data analysis but the installation is costly. Few of the implemented systems, uses a threshold-based mechanism to detect the fall but, generates high false alarms.

3. System overview and methodology

We propose to solve this problem with machine learning (ML). The system for identifying the human activities of daily life (ADL) are implemented using various datasets: WISDM accelerometer dataset [16] and SisFall [8]. Here we propose continuous monitoring of user activities based on Gait analysis through the body sensors attached to the subject via a wearable waist belt.

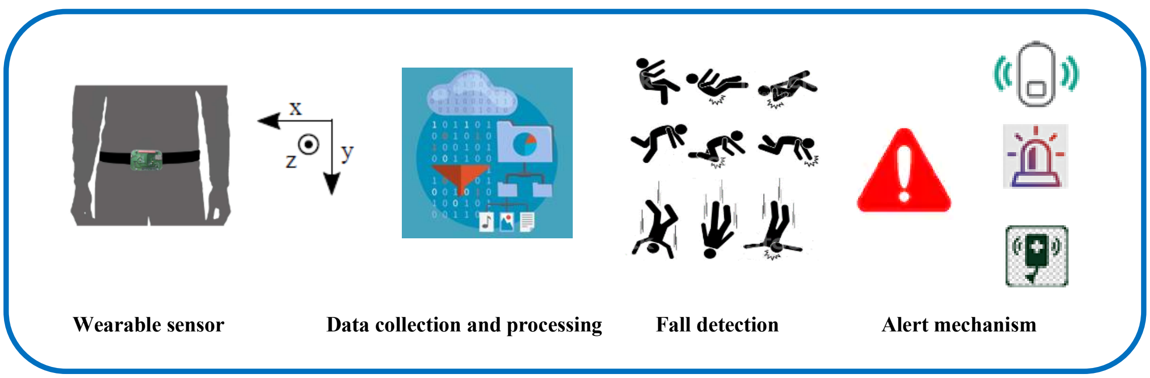

Fig. 1 Proposed Fall Detection System Overview

The proposed system consists of wearable waist belt with micro-controller and tri-axial accelerometer sensor. The methodology can be explained in five stages as in Fig. 1. The first stage is data acquisition where acceleration data is collected using tri-axial accelerometer and in second stage, data preprocessing is carried out. Data processing is done on the collected data to filter it out. In the succeeding stage, features are extracted from the filter data followed and the processed sensor data is fed as input to the ML model which consists of various ML algorithms to classify the activities as fall or not fall. Finally, alert messages or alarm signals are sent to the concerned person or care takers to intimate the fall occurrence.

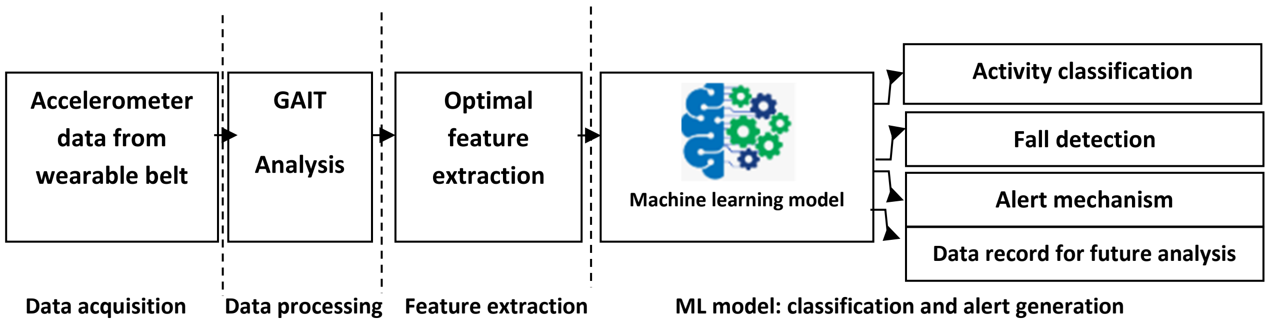

Fig. 2 Implementation of Proposed Fall Detection System

4. Algorithm Implementation

Fall detection system has ML algorithm incorporated which is implemented in two stages: training and testing. The machine learning model is trained using SisFall dataset [8] consisting of 1546456 data points and analyzed by using 10-fold cross validation. The highest accuracy exhibiting model is taken into account and saved. The saved model is used for testing.

Training	Read the sensor data from the dataset
	Data pre-processing and filtering
	Feature computation
	Training machine learning model with algorithms
	Save and test the model
	Analyze the model for fall identification

Testing	Read the sensor data from the dataset
	Data pre-processing and filtering
	Feature computation
	Test the model
	Save and test the model
	Analyze the model for fall identification

Fig. 3 Steps of Algorithm Implementation

4.1 Machine Learning Model Training

4.1.1 Sensor Data Procurement

To train the machine learning model, the model is inputted with accelerometer data. The input data is acquired from the waist band, which is available in SisFall dataset. The tri-axial accelerometer used is ADXL345 which gives acceleration values along x, y and z axis. The accelerometer provides larger span with low energy. The Dataset consists of 23 young adults (11 male and 12 female) and 15 elderly people (8 and 7 male and female respectively). 19 daily life activities and 15 fall activities are carried out by the young adults whereas, only one participant has performed fall in the elder's group. The data is collected with the sampling rate of 200Hz.

4.1.2 Data handling

Before the sensor data can be fed as an input to the machine learning model, the unwanted glitches and noise need to be removed. This is accomplished with 4th order Butterworth filter with cutoff frequency of 5Hz. The filter selection is confirmed as it was capable of generating similar outputs which other sophisticated filters such as: FIR and IIR produces and is simple to construct [12]. In [12], analysis off filters at different cutoff frequencies are performed and concluded that 4th order Butterworth filter is most effective. The original sample data and filtered data are plotted as shown below. The data has been smoothened after filtering.

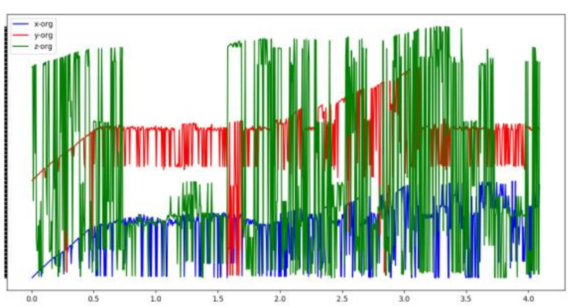

Fig. 4a Acceleration data points before filtering

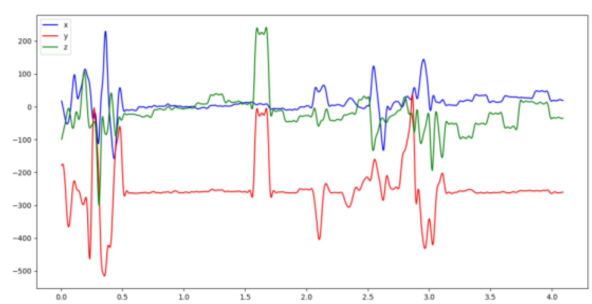

Fig. 4b Acceleration data points after filtering

4.1.3 Feature extraction

The features are calculated on the entire SisFall dataset. It consists of 19 daily life activities and 15 fall activities. One or more trials are taken for each activity. For every trial, all the six features along three axes are calculated. Overall, 1789 ADL and 1452 falls exists. Total feature count for ADL class is 1789X 3 axes and fall feature count is 1452 X 3axes. Overall, 1546456 feature points are calculated. Using these features machine leaning models are trained to detect the fall. The features that are considered with formula are presented in Table 1.

Table 1. Features calculated with its formulae and meaning

Type	Code	Feature	Equation	Meanings
Amplitude	M1	Maximum amplitude	$\max(a[k])$	It is maximum of the amplitude along x-axis, y- axis and z-axis
	M2	Minimum amplitude	$\min(a[k])$	It is minimum of the amplitude along the three axes.
	M3	Mean Amplitude	$\mu = \frac{1}{N}\sum a[k]$	It is mean of the amplitude along the three axes.
Statistical	M4	Variance	$\sigma^2 = \frac{1}{N}\sum (a[k]-\mu)^2$	It is variance of the amplitude along the three axes.
Skewness	M5	Measure of asymmetry	skewness: $g_1 = m_3 / m_2^{3/2}$ $m_3 = \sum(x-\bar{x})^3 / n$ and $m_2 = \sum(x-\bar{x})^2 / n$	It is measure of asymmetry of distribution curve along the three axes.
Kurtosis	M6	Measure of tailedness	kurtosis: $a_4 = m_4 / m_2^2$ $m_4 = \sum(x-\bar{x})^4 / n$ and $m_2 = \sum(x-\bar{x})^2 / n$	It is measure of tailedness of distribution curve along the three axes.

4.1.4 Fall detection algorithm

The vital module of the fall detection system is the machine learning model. Various machine learning algorithms are used to test and compare the fall detection accuracy. The algorithms include: K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Naive Bayes, Neural Network, Logistic Regression, Decision Tree and Random Forest. 10-fold cross validation is used to detect the accuracy. For the extended testing, the model that exhibits highest accuracy is saved. The major advantage of using machine learning algorithms is it allows detection of different falls with higher accuracy, identify patterns, incompleteness anomalies and also can detect patterns in the signal [11]. This conforms the superior performance of ML algorithms compared to the threshold-based algorithms. But this demands large data for training of ML algorithms along with high computational complexity.

4.1.5 Alert mechanism

In case of falls, alert messages are sent to the concerned person and care takers as emergency support. Every time when a fall occurs, it's important to alert the concern person in terms of message or call so that immediate actions can be taken to save the life of the person or do any immediate actions to safe guard the person. In the proposed system, SMS is sent by using Twilio, as soon as fall occurs. Amazon web services are used to provide HTTP connectivity and public switched telephone network and formed API called Twilio, which is a web service to send and receive messages and calls.. To protect against wrong outage, it has architectural design principles. Twilio can be used to develop open source software.

4.2 Hardware implementation

The test algorithm is used in Raspberry pi3 which is communicated with ADXL345 by serial communication (I2C communication). Sampling rate i.e data collection rate from ADXL is 200Hz i.e. every sec 200 samples of accelerometer from all three axes X, Y, Z are fetched. The acceleration fetched is in 'g' unit which needs to be converted to 'm/sq. sec'.

$$Accerleration\ data = \frac{Accerleration[g] * 2^{Resolution}}{2 * Range} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

5 Evaluation Parameters

The performance of different trained ML models is compared on the basis of different parameters. The parameter includes: training and prediction time, confusion matrix, accuracy, sensitivity and specificity. The details of these parameters are given below.

5.1 Sensitivity

Sensitivity is a measure of the actual positive cases that are predicted as positive i.e. true positive. Sensitivity is also called as Recall. Sensitivity gives the proportion of all correctly predicted data points to that of all correct and incorrect predictions (True positive and false negative).

$$Sensitivity\ (SE) = \frac{TP}{TP+FN} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

5.2 Specificity

By definition, specificity is a measure of the actual negative cases that are predicted as negative i.e. true negative. Specificity gives the proportion of all correctly predicted data points to that of all correct and incorrect predictions (False positive and true negative).

$$Specificity(SP) = \frac{TN}{TN+FP} \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

5.3 Accuracy

Accuracy is the fraction of predictions our model got right.

$$Accuracy\ (AC) = \frac{SE+SP}{2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

5.4 10-fold cross validation

While training the model, data set needs to be divided into training and testing sets and the performance of the model is assessed based on the accuracy of the model. As accuracy varies with various divisions of dataset, this method is not reliable. Therefore, K-fold cross validation is used to divide data into k folds. Every time one-fold acts as test and remaining fold data acts as training set. In the proposed system, 10-fold cross validation is used. Total considered data is divided in to 10-folds and every time one of the fold acts as test and all other as train.

6. Results

6.1 Implementation of ML algorithms

The different ML algorithms are fed with the SisFall data set and used 10-fold cross validation to calculate the accuracy. Improved results are obtained and is tabulated in Table 2 showing a maximum accuracy of 99.18% using random forest algorithm.

Table 2. Accuracies with training time and prediction time

Algorithms	Accuracy	Training Time	Prediction Time
KNN (K=15)	91.54	0.031 s	0.39 s
SVM	60.09%	4.259 s	3.76 s

Naïve Bayes	96.89%	0.016 s	0.016 s
Neural Network	75.01%	4.742 s	0.07 s
Logistic Regression	96.36%	9.995 s	0.08 s
Decision Tree	97.00%	0.125 s	0.06 s
Random Forest	99.18%	1.154 s	0.047 s

The Fig. 5 is a comaprison plot of different machine learning algorithms for accuracy with 10-fold cross validation. Form the box plot, it is evident that random forest algorithm gives the best accuracy for fall identification when tested with SisFall dataset.

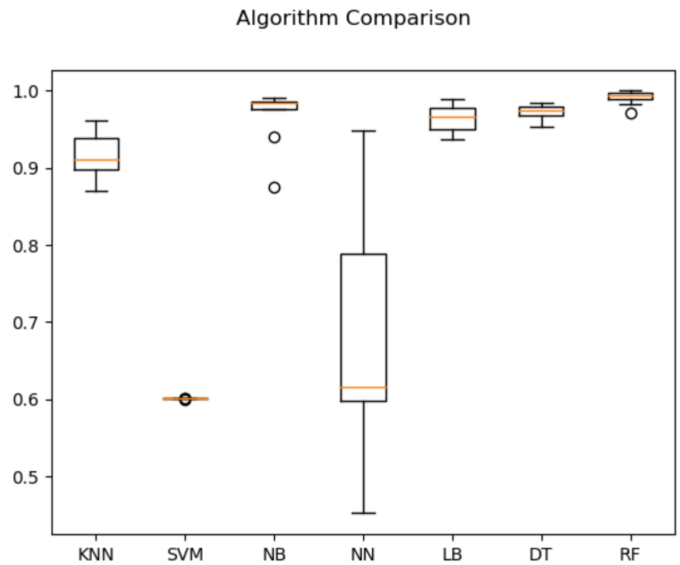

Fig. 5 Accuracy comparison of different machine learning algorithms

6.2 Hardware Prototype

The hardware prototype is shown in Fig. 6 with positioned sensor and waist belt.

Fig. 6 Hardware Prototype

The user will be in upright position when there is no fall and this state is checked and readings are taken using VNC server. The result is shown in Fig. 7.

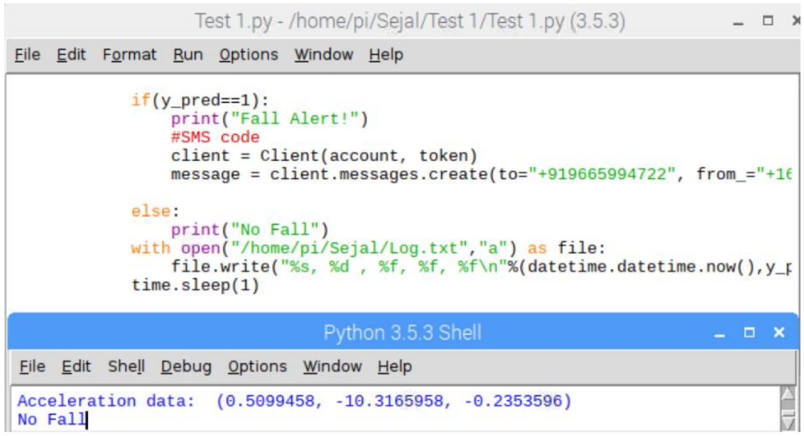

Fig. 7 No fall condition output

The user will be in bending or lying position when there is fall. This condition is checked and readings are taken by using VNC server. Fig. 8 shows the respective output.

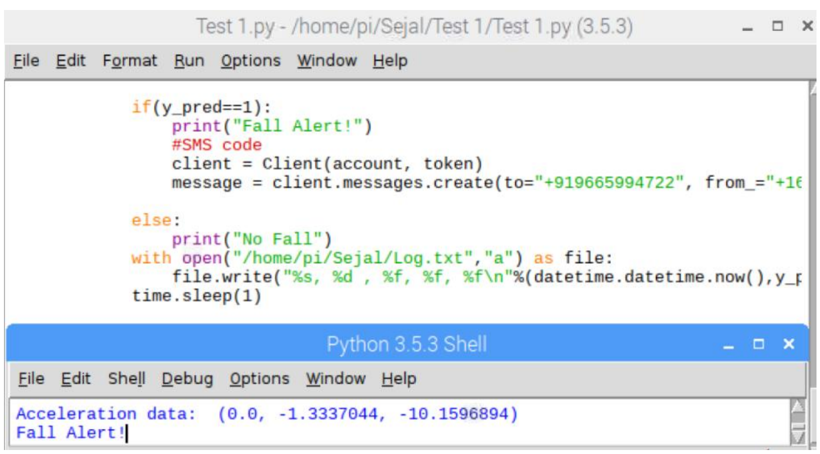

Fig. 8 Fall condition output

6.3 Time Analysis

Followed by the testing of the system at real-time, time and activity analysis are carried out for different sample sizes of 1, 1000 and 2000 for varying time duration of 5sec. and 10 sec. the obtained resulted are tabulated in Table 3.

Table 3. Time and activity analysis

Steps	For 1 sample	For 1000 sample (For 5 Sec)	For 2000 Sample (For 10 sec)
Collection	0.002 sec.	2 sec.	4 sec.
Conversion (g to m/sec2)	0.0 sec.	0 sec.	0 sec.
Saving to Data frame	0.017 sec.	17 sec.	34 sec.
Feature calculation		0.143 sec.	0.146 sec.
Prediction		0.12 sec.	0.12 sec.
Notification		4 sec.	4 sec.
Total Time		19 to 21 sec. (Without fall) 23 to 25 sec. (With Fall)	35 to 37 sec. (Without fall) 39 to 41 sec. (With Fall)

The analysis of the above results shows that, if data is collected for 5sec./10sec., saving that data to data frame takes more time 17sec./34sec. So even when the fall is detected on basis of acceleration data of 5sec./10sec., it takes more time to process and predict it. Overall, to complete one cycle, the system takes about 20 sec. for 5 sec. data collection and about 36 sec. for 10 sec. data collection. This time can be minimized by using faster microcontrollers.

7 Conclusion

In this paper, implementation of recognition and differentiation of fall activities and activities of daily living for the support of elderly and people with movement disorders is carried out. The proposed technique of fall identification includes a wearable sensor-based solution which is more suitable for the elderly due to the possibility to identify a fall in which environment the subject is, unlike a camera based or ambient based fall detection systems, which are confined to a particular room or indoor surrounding. In addition, the wearable sensor-based implementation is less costly when compared to that of camera or PRI sensors.

Falls are appropriately detected using various machine learning algorithms such as: KNN, SVM, naïve Bayes, neural network, logistic regression, decision tree and random forest using SisFall dataset. These ML models are trained and 10-fold cross validation is used to calculate the fall accuracy. The performance of the model is evaluated using significant parameters. Out the different tested ML models, random forest is found to give the highest accuracy of 99.18% for fall detection. But the time overhead associated with the proposed systems is found to be in the order of 20 sec. for 5 sec. data collection and in future, we intend to minimize the time using faster microcontrollers and incorporate methods to forecast a fall before its occurrence from the history of stored data. In future, we will try to addresses the complex scenarios of human ADLs to predict a fall with minimum response by determining suitable machine learning algorithms by modeling the human kinematics.

References

[1] World Health Organization, World Report on Ageing and Health, World Health Organization, Geneva, 2015.

[2] Glen Debard, Greet Baldewijns, Toon Goedem, Tinne Tuytelaars and Bart Vanrumste, “Camera-based fall detection using a particle filter Glen”, IEEE, 978-1-4244-9270-1, 2015.

[3] Rita Cucchiara, Andrea Prati, Roberto Vezzani, "A multi-camera vision system for fall detection and alarm generation”, Expert Systems, November 2007, Vol. 24, No. 5, 2007.

[4] Yazar A, Erden F, Cetin AE, “Multi-sensor ambient assisted living system for fall detection”, In: Proceedings of the IEEE international conference on acoustics, speech, and signal processing (ICASSP’14), 1–3, 2014.

[5] Ahmet Turan Özdemir and Billur Barshan, “Detecting Falls with Wearable Sensors Using Machine Learning Techniques”, Sensors, 14, 10691-10708; doi:10.3390/s140610691, 2014.

[6] Guilherme Gerzson Torres, Renato Ventura Bayan Henriques, Carlos Eduardo Pereira, Ivan Müller, An EnOcean Wearable Device with Fall Detection Algorithm Integrated with a Smart Home System, IFAC-PapersOnLine, Volume 51, Issue 10, 2018, Pages 9-14, ISSN 2405-8963, https://doi.org/10.1016/j.ifacol.2018.06.228.

[7] S. K. Bhoi et al., "FallDS-IoT: A Fall Detection System for Elderly Healthcare Based on IoT Data Analytics," 2018 International Conference on Information Technology (ICIT), Bhubaneswar, India, 2018, pp. 155-160, doi: 10.1109/ICIT.2018.00041.

[8] Angela Sucerquia, José David López, Jesús Francisco Vargas-Bonilla, "SisFall: A Fall and Movement Dataset", Sensors, 17, 198; doi:10.3390/s17010198, 2017.

[9] Gjoreski, Hristijan & Lustrek, Mitja & Gams, Matjaz. "Accelerometer Placement for Posture Recognition and Fall Detection", Proceedings – 2011, 7th International Conference on Intelligent Environments, IE 2011. 47 - 54. 10.1109/IE.2011.11.

[10] A. Sucerquia, J.D. López, J.F. Vargas-Bonilla, "Real-life/real-time elderly fall detection with a triaxial accelerometer", Preprints, doi:10.20944/11.0087, v3, 2018.

[11] Cong Zhang, Chin-Feng Lai, Ying-Hsun Lai, Zhen-Wei Wu, Han-Chieh Chao, "An inferential real-time falling posture reconstruction for Internet of healthcare things", Journal of Network and Computer Applications, Volume 89, 2017, Pages 86-95, ISSN 1084-8045, https://doi.org/10.1016/j.jnca.2017.02.006.

[12] Ozdemir, A.T., Barshan, B. "Detecting falls with wearable sensors using machine learning techniques", Sensors 14(6), 10691/10708, 2014.

[13] Jian, H., Chen, H. "A portable fall detection and alerting system based on K-NN algorithm and remote medicine", China Communications 12(4), 23/31,2015.

[14] Delahoz, Y.S., Labrador, M.A. "Survey on fall detection and fall prevention using wearable and external sensors", Sensors 14(10), 19806/19842, 2014.

[15] Aslan, M., Sengur, A., Xiao, Y., Wang, H., Ince, M.C., Ma, X. "Shape feature encoding via sher vector for efficient fall detection in depth-videos", Applied Soft Computing 37, 1023/1028, 2015.

[16] WISDM (Wireless Sensor Data Mining) Project. Fordham University, Department of Computer and Information Science, http://storm.cis.fordham.edu/~gweiss/ wisdm/

[17] A. Purushothaman, “Fall detection system using Artificial Neural Network”, in 2nd International Conference on Inventive Communication and Computational Technologies (ICICCT 2018), Hotel Arcadia, Coimbatore, 2018.

[18] R. K. Megalingam, G. Pocklassery, A. A. Thulasi, V. Jayakrishnan and G. Mourya, "MediSuit: Wearable health monitoring system for elders and bed-ridden patients," *2016 10th International Conference on Intelligent Systems and Control (ISCO)*, Coimbatore, 2016, pp. 1-6, doi: 10.1109/ISCO.2016.7727091.

[19] R. K. Megalingam, V. Radhakrishnan, D. C. Jacob, D. K. M. Unnikrishnan and A. K. Sudhakaran, "Assistive Technology for Elders: Wireless Intelligent Healthcare Gadget," *2011 IEEE Global Humanitarian Technology Conference*, Seattle, WA, 2011, pp. 296-300, doi: 10.1109/GHTC.2011.94.

[20] Ranjith, R., Pillai, A.S. “Classification of activities of daily living using smart phones,” International Journal of Recent Technology and Engineering, 2019, 8(3), pp. 2984-2988.

[21] S. Badgujar and A. S. Pillai, "Fall Detection for Elderly People using Machine Learning," 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2020, pp. 1-4, doi: 10.1109/ICCCNT49239.2020.9225494.