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Research Article

IoT-Based System for Real-Time Fall Risk Assessment and Health Monitoring

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Abstract: Real-time fall risk assessment and continuous health monitoring are critical components in enhancing elderly care and preventing fall-related injuries. This study presents an IoT-based system designed to provide real-time fall risk assessment and monitor health parameters using wearable sensors. The system integrates the MPU6050 sensor with IoT technology for efficient data collection and analysis. A Random Forest algorithm is employed to process the complex health data, offering precise and reliable fall detection models. The algorithm demonstrates high sensitivity, precision, and accuracy, making it well-suited for processing sensor data to detect falls. The study identifies the waist as the optimal sensor placement, achieving up to 97.9% accuracy, 95.0% precision, and 95.4% sensitivity in detecting mild falls while standing. The wrist sensor performs well in detecting sudden falls, while the leg sensor shows lower accuracy, highlighting challenges in identifying specific fall types. Model validation with Support Vector Machine (SVM) and Random Forest (RF) reveals that the RF model outperforms the SVM, confirming its superiority for fall detection tasks. The system's adaptability and potential for personalized risk assessment promise significant improvements in fall prevention strategies. These findings highlight potential applications that go beyond elderly care, involving at-risk individuals in future research, including those with neurological disorders, sports injuries, or disabilities.

Keywords: real-time fall risk assessment, health monitoring system, IoT devices, random forest algorithm, sensor data analysis

1. Introduction

Falls are a significant social and economic issue since they are widespread among the rapidly growing "elderly" and "elderly" populations, and each fall has immediate and indirect effects. Every year, 28–35% of people aged 65 and up die, while the number of people over 70 rises to 32–42% (WHO, 2008).

That being said, falls among elderly persons are frequently cause for concern. Older people are more vulnerable to injury than young children and athletes who frequently fall [1]. This is because they are fragile, unsteady, and slow to react. An estimated 40–60% of falls reported by older persons result in injuries, with 30–50% minor and 5–6% fractures. Twenty percent of hip fractures caused by falls are fatal within a year, and the majority of older adults who break after a fall do not entirely heal. In Australia, a catastrophic fall involving a person over 65 may cost the health system $1049 (Hendrie et al., 2003), or $3611 [1].

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Falls can be causing harm to one's health, particularly as one grows older. Distinguishing falls, and especially preventing falls through a fall risk assessment, may help to avoid unfavorable health outcomes. Fall risk assessment and recognition have been carried out using a variety of approaches, and a blooming topic in wearable technology. Fall hazard management plans are customizable [2].

Falls in the elderly have been detected using smart home upgrades, camera systems, cell phone sensors, and other non-contact and wireless approaches such as monopulse Doppler radar [3]. Furthermore, portable technologies cannot address the limitations of traditional laboratory-based activity monitoring systems, such as the inability to monitor in unfamiliar settings, large-scale arrangements, or the effects of monitoring on natural walking when the user is aware of it [4].

Inertial estimation units (IMUs) are often used in portable systems to collect data from accelerometers and spinners. IMUs can be distributed throughout the body to collect motion data that can then be processed, assembled, and analyzed. Insoles are wearable frameworks designed to identify and evaluate fall risk. Installed below the sole, instrument-based frameworks frequently gather information on the strain appropriation of the sole.

Wearable systems are sensors and devices that can be attached to the human body to gather data. Wearable systems consist of several components, such as magnetometers, gyroscopes, accelerometers, and IMUs. The primary advantage of wearable devices is that they can collect data outside of a lab environment. Consequently, these technologies can be used to study fall detection data or prevent falls while doing ADLs. Because these sensors are commonly integrated into cellphones, data collection is possible without the need for additional hardware expenditures. In comparison to non-wearable devices, they also provide greater privacy. However, the processing power of wearable technologies is restricted with time. Furthermore, in order to make decisions, the wearable data must be further processed using statistical or machine learning methods [5].

Figure 1 provides an overview of the general fall risk assessment diagram.

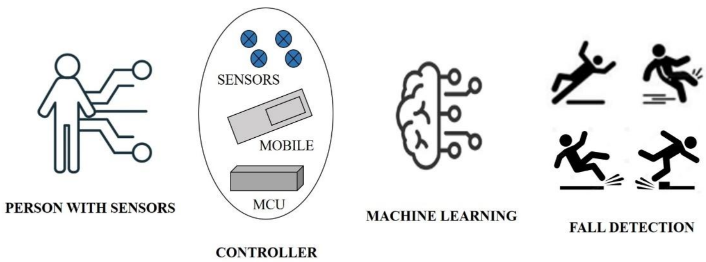

Figure 1. An overview of general fall risk assessment diagram [5]

The purpose of this paper is to provide an overview of research efforts that utilize machine learning techniques to identify and prevent falls. The main contributions of this study are as follows:

- An overview of both wearable and non-wearable fall detection and prevention systems is provided.
- It provides significant machine learning algorithms for fall detection and prevention.
- The most recent cutting-edge research is thoroughly discussed. The analysis includes participants, ML algorithms, acquisition sensors, datasets, and placements.
- It assesses performance metrics for various arrangements of sensors, ML algorithms, and measuring accuracy, precision and sensitivity.
- It offers a thorough examination of current and emerging technologies for fall detection and prevention.

This section provides an outline of the remaining content of the article. Section 2 contains a summary of the literature. Section 3 focuses on the problem statement and deals with methods. Section 4 offers the experimental data, which are then analyzed in terms of hardware and machine learning classification. Section 5 expresses the conclusion.

2. Literature survey

The research article titled “Wearable sensors for remote health monitoring” Mondal T, Majumder S, and Deen M [6] identify an issue caused by an aging population, underlining the need for novel approaches to meeting healthcare and social welfare demands. Faisal AI, Majumder S, Subramaniam S, and Deen MJ [7] describe a health monitoring system that builds on existing solutions and research.

Tracking the health of your feet, particularly irregularities in plantar pressure, activity, and gait, can aid in disease identification and rehabilitation. Visvanathan R. and Khow KSF [8] documented cases of falls among elderly people. Assesses current understanding of falls, with a focus on fast screening, evaluation, and community fall prevention activities [9].

Fievez D, Jojczyk L, Grenard R, Buisseret F, Catinus L, and Bar Vaux V [10] used wearable inertial sensors in timed up-and-go and six-minute walking tests to predict the fall risk of senior nursing home residents. Mun J, Kim B, Kim H, Heo H, Sim T, and Cates B [11] suggested a novel detection model and its optimum characteristics for categorizing falls in daily activities with low and high acceleration utilizing an insole sensor system.

Bresciani, Bihl, and Dubois A. [12] employ machine learning algorithms and a depth sensor to monitor daily activities at home and predict fall risk. In the course of computerized dynamic posturography, Whitney et al. [13] compared accelerometry to center of pressure data during computerized dynamic posturography.

The Table 1 shows the literature survey comparative study based on base paper references.

Table 1. Literature survey of the research project of fall risk assessment

Author	Paper	Year	Findings
Mondal T, Majumder S, and Deen M	Wearable sensors for remote health monitoring	2017	Expanding aging population, emphasizing the need for new ways to meet healthcare and social welfare demands.
Faisal AI, Majumder S, Subramaniam S, and Deen MJ	Insole-based systems for health monitoring: current solutions and research challenges Sensors	2022	Present a health monitoring system based on existing solutions and research. Tracking the health of your feet, especially any abnormalities in plantar pressure, activity, and gait, can help with early disease detection and recovery.
Visvanathan R. and Khow KSF	Falls in the Aging Population	2017	Evaluates current knowledge of falls, with a focus on quick screening, evaluation, and community fall prevention initiatives
Fievez D, Jojczyk L, Grenard R, Buisseret F, Catinus L, and Bar Vaux V	Timed up and go and six-minute walking tests with wearable inertial sensor: one step further for the prediction of the risk of fall in elderly nursing home people. Sensors	2020	Use wearable inertial sensors in timed up-and-go and six-minute walking tests to estimate senior nursing home residents’ fall risk.
Mun J, Kim B, Kim H, Heo H, Sim T, and Cates B	A novel detection model and its optimal features to classify falls from low- and high-acceleration activities of daily life using an insole sensor system	2018	An innovative detection model and its ideal characteristics for categorizing falls in daily activities with low and high acceleration using an insole sensor system.
Bresciani, Bihl, and Dubois A.	Identifying Fall Risk Predictors by Monitoring Daily Activities at Home Using a Depth Sensor Coupled to Machine Learning Algorithms	2021	Use Machine Learning Algorithms and a Depth Sensor to Track Daily Activities at Home and Determine Fall Risk Predictors
Whitney, S., Roche, J., Marchetti, G., Lin, C., Steed, D., Furman, G., Musolino, M. C., and Redfern, M. S. A	Comparison of accelerometry and center of pressure measures during computerized dynamic posturography:	2011	Compare accelerometry with center of pressure data. The table 1 shows the literature survey comparative study based on base paper references

2.1 *Fall detection and prevention systems*

Compact health care monitoring frameworks are available in a range of configurations, including completely integrated versatile, non-coordinated convenient, phone-based non-convenient, and remote non-versatile frameworks. Non-integrated systems are frequently costly, difficult to use, and inappropriate for long-term usage, despite the fact that they allow for extensive and continual monitoring. Fully coordinated flexible frameworks, on the other hand, are less expensive, more modest, and more suited to long-term use [14].

Inertial sensor systems and insole-based sensor frameworks are usually fully integrated, they are extremely valuable for assessing long-term user fall risk. Wearable technology frequently uses a number of sensors, including strain and inertial sensors, to analyze walking parameters. These gadgets measure a person's walking style and flexibility in order to detect slips, find falls, and determine fall risk.

2.1.1 *Objectives*

The primary purpose of fall risk assessment and health monitoring efforts is to transform healthcare by implementing standardized procedures and cutting-edge technology. This research aims to create standardized evaluation procedures for evaluating fall hazards in a variety of healthcare settings. The incorporation of cutting-edge technology, such as real-time data collection and user-friendly interfaces, is a vital goal for improving uptake and use.

Another important goal is to address privacy and security concerns, as well as to create robust safeguards for sensitive health data. The ultimate goal of improving data accuracy through calibration methods and boosting user participation is to provide healthcare professionals with reliable information so that they may make informed judgments and interventions based on trustworthy data.

2.2 *Problem statement*

The following are just a few examples of how IoT-based healthcare systems and its applications improve people's lives:

i. *Remote healthcare*: Wireless Internet of Things (IoT) technologies can detect falls in elderly patients, rather of relying on post-mortems. IoT-based sensors safely collect data, which is subsequently evaluated by a machine learning algorithm and distributed to medical specialists for relevant recommendations [15].

ii. *Limited Real-time Monitoring*: Certain health monitoring systems may not provide real-time data updates. Delayed or infrequent monitoring may result in a lack of prompt intervention for persons at risk, limiting the system's effectiveness in preventing falls. The accuracy of wearable devices. During different activities, the device measures the knee joint's acceleration, angular velocity, skin temperature, muscle pressure, and perspiration rate [9]. The study tackles problems related to optoelectronic stereo photogrammetric data interpretation and reconstruction of in vivo skeletal system kinematics [16, 17].

iii. *Adoption Challenges in Vulnerable Populations*: The elderly and those with particular health conditions, who are typically the target group for fall risk assessment, may struggle to adopt and use monitoring devices consistently [18]. Certain demographic groups may be unable to profit from these solutions owing to factors such as digital literacy, discomfort with wearable's, or cognitive disability.

2.3 *System overview*

Recently developed wearable devices, utilizing either foot or gyroscope sensor systems, are illustrated in Figure 2. These devices collect data from various sections, which is analyzed in the Sensor Systems segment to predict fall risk. Machine learning techniques are integrated for fall risk assessment. The hardware components are employed to detect falls, forming a collaborative hardware-software approach for evaluating fall risk.

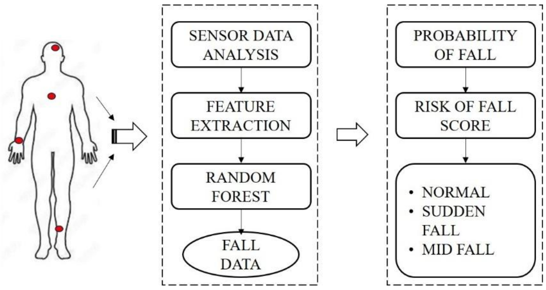

Figure 2. Block diagram of fall detection and prevention system [5]

The development of a fall detection system shows great promise for the relatively new technology known as the Internet of Things (IoT). This emerging technology could provide data processing, communication pathways, and smart sensors for the development of fall detection systems [16]. An Internet of Things device, such as a wearable or mobile phone, may monitor its surroundings, collect, process, and transfer data. The smartphone application can automatically inform emergency services, caregivers, or family members if the targeted person falls after a predetermined amount of time. The sensor data has been transferred to a cloud-based data center.

2.3.1 *Significance*

Regardless of their possible goals and relevance, machine learning-based fall risk assessment and health monitoring systems encounter challenges that must be properly addressed [19]. The seamless integration of ML algorithms with wearable devices and healthcare systems is important for accurate data analysis. Addressing user acceptance concerns, particularly among vulnerable populations, requires targeted education on the advantages of ML-powered health monitoring. Privacy concerns necessitate the development of transparent and ethical machine learning models, with an emphasis on explainability and interpretability. Interdisciplinary collaboration is still a key factor in addressing the challenges of fragmented care coordination and guaranteeing a comprehensive strategy for fall prevention and health monitoring [20]. Furthermore, efforts should be directed toward developing scalable and cost-effective ML solutions to enable greater access, particularly among underrepresented populations [21]. Successfully overcoming these barriers is crucial to the overall effectiveness and impact of fall risk assessment and health monitoring operations in healthcare.

3. Methodology and design

The development of the IoT-based Fall Risk Assessment and Health Monitoring System employs a multidisciplinary approach, integrating concepts from IoT, machine learning, and sensor technology [3]. This study starts with an in-depth review of existing literature, covering advancements in wearable sensors, environmental monitoring, and health tracking, specifically for elderly care. As shown in Figure 3, the proposed methodology's block diagram is designed to facilitate smooth connectivity between different components, ensuring compatibility and efficient data transmission.

The device incorporates a microcontroller (NODE-MCU ESP8266) along with various sensors, including a gyroscope, temperature sensor, sweat sensor, respiration sensor, and an SPO2 heart rate oximeter. These sensors are designed to gather health-related data, such as body temperature, heart rate, respiratory rate, and skin moisture. This information is utilized for both real-time monitoring and for conducting statistical analysis to track health trends over time. Health monitoring sensors, specifically, play a crucial role in gathering data for statistical evaluations. The microcontroller transmits data wirelessly over the internet, where it is received by a web server. The server processes, filters, and aggregates the incoming data, performing tasks like feature extraction and initial data analysis.

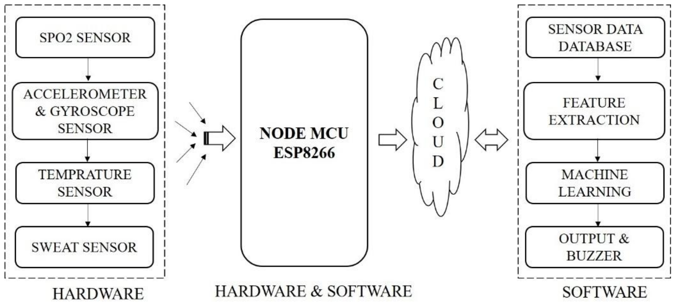

Figure 3. Proposed methodology of block diagram for the fall detection system

Table 2 lists the hardware peripherals that are currently in use along with the ratings that go with them.

Table 2. Hardware peripherals and current rating (mA) [17, 19]

Hardware peripherals	Current rating (mA)
ESP8266	250
SPO2 sensor, 400 nm–1100 nm	0.5
Accelerometer MPU-6050	0.5
Gyroscope sensor MPU-6000	3.6
Human Body Temperature Sensor MAX30205	0.6
Wearable Sensor	0.4
HDMI port	50
Wi-Fi connection	250
Keyboard	100
Mouse	100
Total current consumption	**755.6**

When the system is operational, sensors such as the accelerometer, gyroscope, sweat, and temperature sensors detect body movement and other physiological inputs. The microcontroller transmits this data to a web server, where it undergoes processing, filtering, feature extraction, and initial analysis. A communication module, equipped with Wi-Fi access points in the IoT-Multi-Sensor unit, links the device to an IoT platform accessible through a PC browser. Typically, the person remains within a 50–60 m range of the Wi-Fi point. Server-hosted machine learning models analyze sensor data to identify patterns suggesting an increased risk of falls. Indicators like posture changes, sudden gyroscope fluctuations, or unusual physiological data can prompt alerts for caregivers or medical personnel.

The Proteus circuit diagram in Figure 4 depicts a complex circuit diagram that incorporates numerous sensors. Wearable sensors, edge computing devices, a central server, and an easy-to-use mobile app are the system's key components.

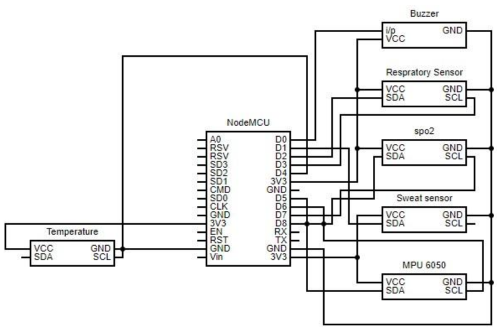

Figure 4. Proteus circuit diagram

The limitations of the methodology of IoT-based Fall Risk Assessment and Health Monitoring System include the following:

- Sensor sensitivity and battery life constraints in wearable devices can affect the consistency and duration of monitoring, especially for continuous health data collection.
- Potential issues with data accuracy due to sensor misalignment or motion artifacts, along with strategies to minimize false positives and negatives in fall detection.
- Given the sensitivity of health data, we address privacy measures such as anonymization and secure data storage to protect patient information and ensure compliance with healthcare regulations.

3.1 *Machine learning testing and training*

During the testing stage of fall risk assessment and health monitoring with machine learning, the model's performance is evaluated using a variety of metrics such as accuracy, precision, and sensitivity (also known as recall). These metrics demonstrate various aspects of the model's performance in detecting episodes that are neither falls nor non-falls.

Accuracy: One basic statistic used to evaluate the overall validity of the model's predictions is accuracy. It is calculated by dividing the total number of instances in the testing dataset by the number of correctly anticipated cases.

$$Accuracy = \frac{Total\ number\ of\ Predictions}{Number\ of\ Correct\ Predictions} = \frac{TP+TN}{TP+FP+FN+TN} \tag{1}$$

Precision: The precision of positive predictions is defined as the ratio of correctly predicted positive cases to the total number of cases predicted to be positive. In the context of fall risk assessment, precision quantifies the number of expected falls that are true or false.

$$Precision = \frac{True\ Positives}{(False\ Positives + True\ Positives)} = \frac{TP}{TP+FP} \tag{2}$$

Sensitivity (Recall)**:** Sensitivity, or recall, evaluates how well the model can identify every positive occurrence. It is the proportion of actual positive instances to all positive cases. Sensitivity in fall risk assessment relates to how accurately the model captures real falls.

$$Sensitivity = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives} = \frac{TP}{TP+FN} \tag{3}$$

F1-Score: The F1-Score is a performance indicator for classification models. It is the harmonic mean of Precision and Recall (Sensitivity), dealing with imbalanced datasets.

$$F1-Score = 2 - \frac{(Precision * Sensitivity)}{(Precision + Sensitivity)} \tag{4}$$

In the context of facial recognition model:

TP: it recognizes a person's face accurately by the model.

TN: non-face region is accurately rejected by the model.

FP: non-facial region is mistakenly identified as a face by the model (False Alarm).

FN: model is unable to recognize a face in the picture.

When these indicators are combined, they provide a comprehensive assessment of the model's performance, accounting for both accurate and inaccurate falls as well as non-fall event predictions. It is crucial to strike a balance between these KPIs based on the application's specific requirements, as optimizing one may jeopardize the other. Monitoring these indicators on a regular basis and updating the model as appropriate guarantees that it remains reliable and useful in fall risk assessment and health monitoring.

3.1.1 *Random forests (RF)*

Random forest is a supervised classification technique that consists of a huge number of decision trees. A decision tree relies on training data, which produces considerable changes in the overall tree structure. As a result, random forest belongs to the group of methods for determining the best prediction class for the model. This multilayer classifier employs motion classification logic to improve the accuracy of fall detection.

The Figure 5 illustrates a Random Forest Classifier-based Decision-Making Process for fall detection. Here's a brief explanation:

1. Feature Extraction: The input data undergoes feature extraction, where it is categorized into different motion states:

- Standing
- Non-Standing
- Falling
- Non-Falling

2. Training Data Preparation: The extracted features are used to form multiple sets of training data, labeled as "Training Data '1'", "Training Data '2'", and so on up to "Training Data 'N'".

3. Random Forest Classifier: Each set of training data is processed using a separate Random Forest model. A Random Forest consists of multiple decision trees, and the final output is determined based on the majority voting of these trees.

4. Classifier Layer: The output from each Random Forest model is passed to corresponding classifiers ("Classifier '1'", "Classifier '2'", etc.), which make predictions based on the learned patterns.

5. Testing and Result Prediction: Test data is provided to the classifiers, and the result for each classifier is generated ("Result '1'", "Result '2'", ..., "Result 'N'"). These results help in making the final decision regarding the motion state (fall or non-fall).

In summary, this process uses a multi-layer Random Forest classification approach to enhance the **accuracy of fall detection** by leveraging multiple decision trees trained on distinct subsets of the data.

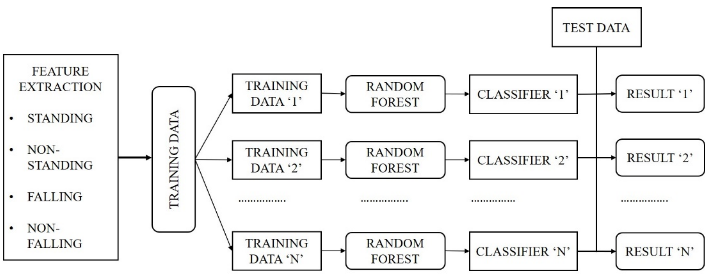

Figure 5. Random forest classifier-based decision-making process [22]

4. Result and analysis

The IoT-based Fall Risk Assessment and Health Monitoring System is designed to provide a comprehensive solution for monitoring users' movements, detecting falls, and assessing fall risk through a combination of advanced hardware and machine learning algorithms. The system aims to offer proactive health monitoring, especially for elderly individuals and patients with mobility issues, by integrating multiple sensor modules and leveraging the power of the IoT for real-time data processing and analysis.

The IoT-based fall risk assessment and health monitoring system that employs machine learning has been successfully developed. Figure 6 demonstrates the integration of wearable sensors, environmental monitors, and health tracking devices, which results in a comprehensive system that collects and analyzes data on users' movements and vital signs.

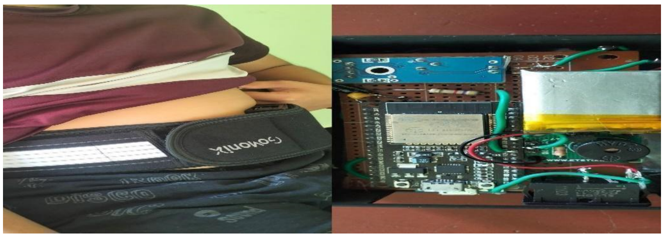

Figure 6. Proposed device implementation

Figure 7 provides a clear and intuitive visualization of heart rate patterns throughout the day, showcasing a waveform plot of BPM (beats per minute) levels over time. The graph seems to capture fluctuations in heart rate levels, likely correlating with the user's physical activities. The early morning spikes may be indicative of wake-up movements or potential fall events if this data is part of a fall detection study. The flat line in the middle hours could be due to a period of inactivity (e.g., sleep) or a temporary loss of signal, which should be investigated further for data integrity.

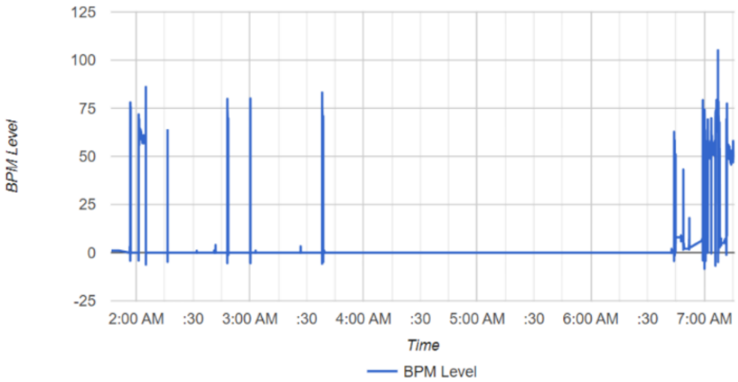

Figure 7. BPM level waveform of heart rate

Machine learning models that have been meticulously developed and trained on labeled datasets are effective in assessing fall risks and monitoring health problems. The system's deployment enables real-time prediction and decision-making, as well as immediate alerts and notifications in the event of a potential issue.

Table 3 shows data from the various sensor locations used in a fall detection system. Here is an explanation for each location. It facilitates in evaluating the efficacy of the fall detection system across several sensor locations, indicating its ability to detect falls.

Table 4 illustrates the waist sensor data. An evaluation of a waist-mounted sensor system for fall detection yielded exceptional results. The system achieves a high accuracy of 97.9% for abrupt falls while walking, with a precision of 95.0% and a sensitivity of 95.4%, indicating strong ability to correctly recognize positive events. The system performs even better for light falls while standing, with an accuracy of 99.4%, an extremely high precision of 99.6%, and a sensitivity of 99.2%. These findings highlight the system's endurance and potential effectiveness in real-world fall detection scenarios, particularly when detecting minor falls while standing, which could greatly improve safety and health monitoring efforts.

Table 3. Different location sensor data

SENSOR LOCATION	TP	TN	FP	FN
WAIST;				
1.SUDDEN FALL (WALKING)	209	773	11	10
2.MILD FALL (STANDING)	244	220	1	2
WRIST				
1.SUDDEN FALL (WALKING)	116	635	3	7
2.MILD FALL (STANDING)	229	473	11	10
LEG:				
1.SUDDEN FALL (WALKING)	275	166	51	23
2.MILD FALL (STANDING)	255	275	45	45

Table 4. Waist sensor data

WAIST	Accuracy	Precision	Sensitivity	F1-Score
1. SUDDEN FALL (WALKING)	97.9%	95.0%	95.4%	96.6%
2. MILD FALL (STANDING)	99.4%	99.6%	99.2%	99.3%

Figure 8 depicts an assessment of waist sensor data, emphasizing on accuracy, precision, and sensitivity. It offers higher accuracy and precision values for detecting sudden falls while walking than for moderate falls when standing, with somewhat higher sensitivity for mild falls.

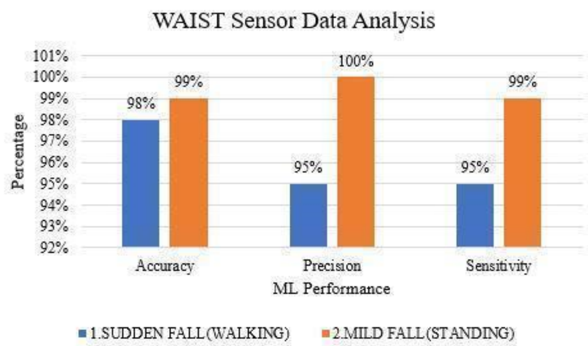

Figure 8. Waist sensor data analysis for sudden and mild fall

Table 5 appears to contain model evaluation metrics, most likely associated with wrist-related activities such as sudden falls when walking or mild falls while standing. The metrics available for each action are accuracy, precision, and sensitivity. The model has 98.69% accuracy and precision for abrupt falls while walking, as well as 94.31% sensitivity.

Table 5. Wrist sensor data

WRIST	ACCURACY	PRECISION	SENSITIVITY	F1-SCORE
1. SUDDEN FALL (WALKING)	98.69%	98.69%	94.31%	96.4%
2. MILD FALL (STANDING)	94.46%	96.55%	97.83%	96.1%

In the case of mild falls while standing, the accuracy is slightly lower (94.46%), but the precision and sensitivity are better (96.55% and 97.83%), respectively. These metrics demonstrate that the model correctly finds and classifies occurrences of each activity, with higher values indicating better performance.

Figure 9 depicts an analysis of wrist sensor data, focusing on accuracy, precision, and sensitivity. It has greater values for accuracy and precision in detecting sudden falls while walking than for moderate falls when standing, while sensitivity is slightly higher for mild falls.

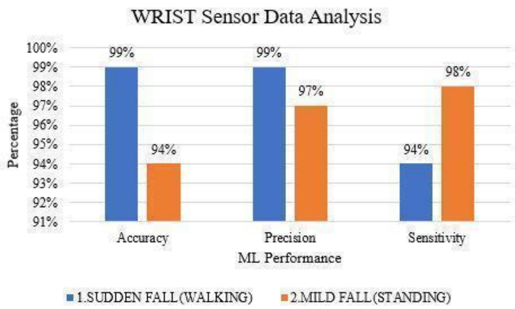

Figure 9. Wrist sensor data analysis for sudden and mild fall

Table 6 highlights the performance factors for two types of leg falls: sudden falls while walking and gentle falls while standing. The model's results revealed that it was 85.6% accurate overall, 84.4% precise (i.e., predicted the fraction of genuine positives among all positives), and 92.3% sensitive. For minor falls while standing, the model performed marginally better, with an accuracy of 87.4%, a precision of 85.5%, and a sensitivity of 94.3%.

These results highlight the model's strong ability to differentiate between sudden and minor falls, with higher sensitivity for low-impact falls, making it effective for comprehensive fall risk assessment.

Table 6. Leg sensor data

LEG	ACCURACY	PRECISION	SENSITIVITY	F1-SCORE
1. SUDDEN FALL (WALKING)	85.6%	84.4%	92.3%	88.8%
2. MILD FALL (STANDING)	87.4%	85.5%	94.3%	90.7%

Phase on accuracy, precision, and sensitivity. It performs better in identifying sudden falls when walking than in detecting moderate falls while standing, with slightly higher sensitivity for mild falls.

Figure 10 depicts a study of LEG sensor data processing that focuses on accuracy, precision, and sensitivity. It has higher values for accuracy, precision, and sensitivity in detecting light falls, however it has moderate fall accuracy, precision, and sensitivity when walking.

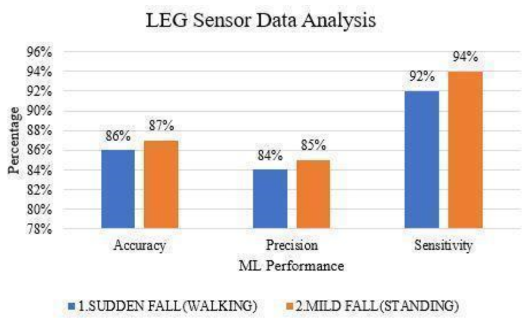

Figure 10. Leg sensor data analysis for sudden and mild fall

Table 7 presents a detailed analysis of mild fall detection during standing scenarios. It focuses on different body regions and evaluates the system's performance using key metrics: accuracy, precision, and sensitivity. The results provide insights into how sensor placement affects the effectiveness of detecting mild falls in standing situations.

Table 7. Data on standing situation

STANDING	ACCURACY	PRECISION	SENSITIVITY	F1-SCORE
1. WAIST MILD FALL	99.4%	99.6%	99.2%	99.3%
2. WRIST MILD FALL	94.46%	96.55%	97.83%	96.1%
3. LEG MILD FALL	87.4%	85.5%	94.3%	90.7%

In standing conditions, the accuracy ranges between 87.4% for leg mild fall detection and 99.4% for waist mild fall detection. The precision values vary between 85.5% for leg mild falls and 99.6% for waist light falls. Sensitivity, which measures the ability to correctly identify affirmative instances, ranges from 94.3% for leg mild falls to 99.2% for waist mild falls. These measurements provide information on the detection system's efficacy across different body areas, with waist detection showing the best overall performance.

Figure 11 depicts the data analysis for standing scenarios, focusing on accuracy, precision, and sensitivity. It shows how waist, wrist, and leg sensors detect tiny falls while standing. The waist sensor is the most accurate and precise, while the wrist sensor is the most sensitive.

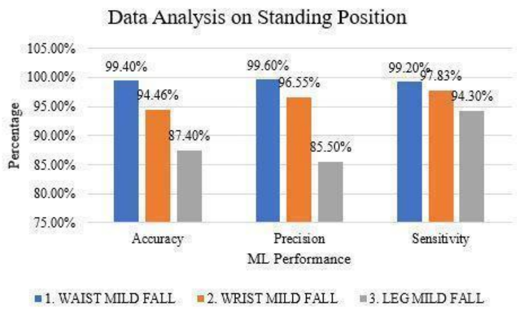

Figure 11. Data analysis on standing situations for waist, wrist and leg

Table 8 displays performance data for multiple types of moderate falls detected by various sensors while walking. The "Waist Mild Fall" detection is 97.9% accurate, 95.0% precise, and 95.4% sensitive.

Table 8. Data on walking situation

WALKING	ACCURACY	PRECISION	SENSITIVITY	F1-SCORE
1. WAIST MILD FALL	97.9%	95.0%	95.4%	96.6%
2. WRIST MILD FALL	98.69%	98.69%	94.31%	96.4%
3. LEG MILD FALL	85.6%	84.4%	92.3%	88.8%

Meanwhile, "Wrist Mild Fall" detection was somewhat more accurate and precise (98.69% each), with a sensitivity of 94.31%. However, the "Leg Mild Fall" detection did comparably poorly, with an accuracy of 85.6%, a precision of 84.4%, and a sensitivity of 92.3 percent. These measurements demonstrate how well different sensor locations detect moderate falls during walking activities, with wrist sensors performing somewhat better than waist sensors and leg sensors performing slightly worse.

Figure 12 shows the data analysis for walking conditions, with a focus on accuracy, precision, and sensitivity. It demonstrates the usefulness of waist, wrist, and leg sensors in detecting small falls while standing. The waist sensor has the highest accuracy and precision, whilst the wrist sensor is the most sensitive.

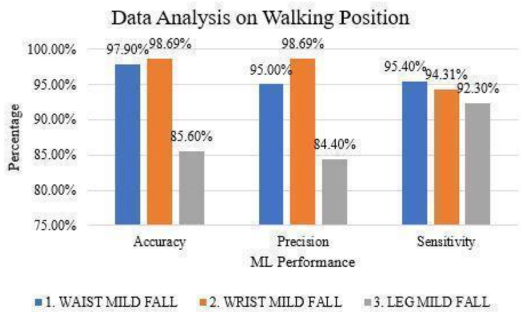

Figure 12. Data analysis on walking situations for waist, wrist and leg

Table 9 depicts a confusion matrix, a commonly used machine learning tool for assessing the performance of a classification model. The confusion matrices show the precise findings of random forest models for identifying frail and non-frail participants within each subgroup. Each column displays the instances in an actual class, whereas each row displays the instances in a predicted class. It helps with performance analysis by exposing places where the model is confused or making errors. The numbers in the cells represent the number of occasions. Evaluating a model's ability to recognize the waist, wrist, and leg categories. Random forest algorithms were employed in a large-scale feasibility study to characterize fall and non-fall histories in the elderly.

Table 9. Confusion matrix of waist, wrist, and leg

SENSOR LOCATION	TP	TN	FP	FN
WAIST 1. SUDDEN FALL (WALKING)	209	773	11	10
WAIST 2. MILD FALL (STANDING)	244	220	1	2
WRIST 1. SUDDEN FALL (WALKING)	116	635	3	7
WRIST 2. MILD FALL (STANDING)	229	473	11	10
LEG 1. SUDDEN FALL (WALKING)	275	166	51	23
LEG 2. MILD FALL (STANDING)	255	275	45	45

Confusion matrices representing the performance of the frailty state classifiers are displayed for each subgroup. A: Waist-1, B: Waist-2, C: Wrist-1, D: Wrist-2, E: Leg-1, F: Leg-2.

Further the system was evaluated using sensors placed at the Waist, Wrist, and Leg. The tabulated summary of the different location of sensor data and its analysis is shown in Table 10.

Table 10. Summarizes the performance tabulated data

SENSOR LOCATION	TP	TN	FP	FN	ACCURACY	PRECISION	SENSITIVITY	TOTAL SAMPLES
WAIST;								
1. SUDDEN FALL (WALKING)	209	773	11	10	97.9%	95.0%	95.4%	1003
2. MILD FALL (STANDING)	244	220	1	2	99.4%	99.6%	99.2%	467
WRIST								
1. SUDDEN FALL (WALKING)	116	635	3	7	98.69%	98.69%	94.31%	761
2. MILD FALL (STANDING)	229	473	11	10	94.46%	96.55%	97.83%	723
LEG								
1. SUDDEN FALL (WALKING)	275	166	51	23	85.6%	84.4%	92.3%	515
2. MILD FALL (STANDING)	255	275	45	45	87.4%	85.5%	94.3%	587

The table summarizes the performance of fall detection sensors placed at the Waist, Wrist, and Leg across three scenarios: Sudden Fall (Walking), Mild Fall (Walking), and Mild Fall (Standing).

Waist Sensor:

- Achieved the highest accuracy (99.4%) and sensitivity (99.2%) for mild fall (standing).
- Good performance across all scenarios, with accuracies above 97%.

Wrist Sensor:

- High accuracy (98.69%) for sudden falls (walking) with strong precision (98.69%).
- Good sensitivity for mild falls (97.83%).

Leg Sensor:

- Lower accuracy (85.6% for sudden falls, 87.4% for mild falls).
- Shows reduced performance compared to waist and wrist sensors.

Overall, the waist sensor shows the best performance, followed by the wrist, while the leg sensor is less effective, highlighting the impact of sensor placement on the system's performance.

For training the model, two machine learning algorithms model were used: Support Vector Machine and Random Forest [23]. The data was subsequently separated into training and test sets at a ratio of 70:30. The findings from the two algorithms are presented in Table 11.

Table 11. ML algorithm architecture used

ML ARCHITECTURE USED	ACCURACY	PRECISION	SENSITIVITY	F1-SCORE
Support Vector Machine model	94%	93.54%	93%	93.26%
Random Forest Algorithm model	97.9%	95.0%	95.4%	96.60%

Based on the performance metrics, the RF algorithm consistently surpassed the SVM across all evaluation criteria. Moreover, the F1-Score results confirmed that the Random Forest model was significantly more effective, showcasing its enhanced capability in fall detection tasks when compared to the SVM.

5. Conclusions

The integration of health monitoring and fall risk assessment in this study demonstrates a promising pathway for future healthcare solutions aimed at elderly care. By using sensors and an application dashboard, we were able to accurately capture health status data, with the MPU6050 sensor effectively detecting changes associated with fall risks. Among the machine learning methods evaluated, the Random Forest algorithm exhibited superior performance, demonstrating high sensitivity, precision, and accuracy. This highlights its robustness and versatility in handling complex, diverse datasets, making it a strong candidate for future fall detection applications.

Our findings show that the waist sensor achieved up to 97.9% accuracy, 95.0% precision, and 95.4% sensitivity in detecting mild falls while standing. The wrist sensor showed excellent results with 98.7% accuracy and high sensitivity for sudden falls, while the leg sensor exhibited lower accuracy (85.6%), indicating challenges in reliably detecting certain fall types. Thus, we conclude that the waist is the optimal sensor placement for assessing fall risk with this method.

Future studies will focus on comprehensive trials involving elderly participants to evaluate the comfort, usability, and long-term acceptance of the wearable sensors. Additionally, advancements in technology could enable even more sophisticated systems capable of real-time data processing and creating personalized risk profiles, enhancing the effectiveness of fall prevention strategies for elderly care.

Conflict of interests

There is no conflict of interest declared by the authors.

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