Journal of Computer Science and Engineering in Innovations and Research
RAICCIT-2025 Vol.-1, Issue- 2, January - June 2025 ISSN: 3049-1762 (Online)

Design and Implementation of Fall Detection and Prevention System for Elderly People using Raspberry PI

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Abstract Aging elevates the risk for falls, and consequently, resultant serious health concerns like fractures and loss of mobility. Fall prevention and detection systems reduce these risks by employing the latest technology in detecting falls ahead of time and notifying caregivers. This project implements a sensor-driven, machine learning-based system for improving elderly safety.

The system integrates threshold-based and machine learning-based detection for enhanced accuracy. When it detects a fall, an IoT-enabled alert instantly informs caregivers. It also evaluates movement patterns to issue early warnings, avoiding falls. The model is validated on real-world and simulated datasets, with high accuracy, sensitivity, and specificity. In comparison to current solutions, our system is economical, transportable, and energy-efficient, and thus well-suited for home and healthcare applications. Machine learning enhances flexibility with fewer false alarms. This work contributes to ambient assisted living with future improvements being in the form of complex sensor fusion and deep learning for improving predictions.

Keywords— Fall Detection, Elderly Care, Machine Learning, Raspberry Pi, IoT, Real-Time Monitoring, Fall Prevention.

I. INTRODUCTION

Falls in older people are a serious worldwide health issue, frequently resulting in serious injuries, hospitalization, and diminished quality of life. Falls are a major cause of accidental injury-related mortality in older adults, as reported by the WHO. Conventional detection techniques, including wearables and manual monitoring, are plagued by non-compliance and delayed response. A smart, real-time fall detection and prevention system is critical for the safety of elderly people.

This study suggests a machine learning-oriented fall detection and prevention system utilizing Raspberry Pi and sensors to offer a cost-effective and efficient solution. The system permanently monitors movement with the help of accelerometers, gyroscopes, and other sensors. Machine learning algorithms identify falls from regular activities, generating fewer false alarms than threshold-based approaches.
An IoT-based alert mechanism instantly notifies caregivers via SMS, email, or mobile apps upon detecting a fall. The system also emphasizes fall prevention by monitoring movement stability and issuing early warnings. Raspberry Pi's affordability and performance make the system scalable and practical for real-world deployment, particularly in smart homes and elderly care facilities.

We use supervised learning, real-time sensor fusion, and preprocessing of data to provide high accuracy. The system is trained on varied motion datasets to make it more reliable in different environments. Computational feasibility and energy efficiency are also given top priority.

This paper explains the system design, implementation, and evaluation, along with sensor selection, data acquisition, and model training. Experimental outcomes validate its effectiveness, and potential future upgrades could be deep learning, multi-sensor, and cloud-based analysis. With both fall prevention and detection, this work advances smart healthcare solutions by significantly minimizing fall-induced injuries and enhancing the well-being of the elderly.

II. RELATED WORK

Falls among elderly individuals can lead to severe injuries, reduced quality of life, and even fatalities if prompt assistance is not provided. Traditional solutions have limitations, such as high costs or lack of real-time detection, making the development of more effective fall detection systems essential. Wearable sensor-based devices, combined with machine learning (ML), deep learning (DL), and the Internet of Things (IoT), have emerged as promising solutions to this challenge. This literature survey provides an overview of the current research landscape in fall detection, categorizing the studies into various sensor technologies, ML and DL techniques, system architectures, and challenges.

A. Wearable Sensor-Based Fall Detection

Wearable sensors, particularly inertial sensors such as accelerometers and gyroscopes, are a core component in fall detection systems. Research by [1] demonstrates a fall detection system that utilizes wearable inertial sensors and Locality Sensitive Hashing (LSH) to enhance detection precision while minimizing energy consumption. The system uses Root Mean Square (RMS) values from accelerometer and gyroscope data to analyze unidimensional time series data, reducing computational complexity without sacrificing detection accuracy.
The UP-Fall dataset was employed for testing, which includes both Activities of Daily Living (ADL) and simulated falls, and demonstrated the system's efficiency even without labelled training data. The placement of sensors on the body significantly affects fall detection accuracy, with the waist position yielding higher accuracy than wrist or foot placements, which often result in increased false alarms. This sensor placement sensitivity is critical for optimizing system design and minimizing incorrect detections that could reduce system reliability and user trust.

B. Machine Learning Techniques for Fall Detection

Various machine learning algorithms have been applied to enhance fall detection systems. A study by [2] implemented a 10-fold cross-validation process to evaluate algorithms like Decision Tree, Logistic Regression, k-Nearest Neighbour, and Support Vector Machines, CNN, yielding high specificity and accuracy. The choice of classifier and cross-validation techniques were shown to be crucial in distinguishing falls from other ADLs accurately. Moreover, feature extraction from sensor data and a well-trained classifier were essential to achieving robust fall detection. ML classifiers are commonly trained with labelled datasets where features like speed, angle, and force of movement are carefully analyzed to classify falls versus non-fall events.
For instance, accelerometer-based systems using Support Vector Machines (SVM) and k-Nearest Neighbours (k-NN) have shown effectiveness in identifying fall patterns due to their high specificity and precision, though computational challenges remain in real-time applications [3].

C. Deep Learning and Advanced Algorithms

Deep learning models, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU), are increasingly applied for fall detection, as they allow for automatic feature extraction and pattern recognition. However, these models require significant computational resources, limiting their use in wearable devices with constrained processing power. Recent research has aimed to implement these models in edge computing architectures to address latency and power consumption issues [4]. By processing data locally on the device, edge AI enables real-time fall detection without reliance on cloud computing, which may be unreliable in regions with poor internet connectivity.

D. IoT Integration and Real-Time Monitoring

The integration of IoT platforms with wearable fall detection devices has created new possibilities for real-time health monitoring and automated alerts. IoT connectivity enables continuous data transmission from wearable sensors to remote monitoring centers or caregivers, allowing for timely intervention if a fall occurs. Systems developed with IoT integration can leverage cloud processing for complex analyses, which may be infeasible on wearable devices alone [6].

E. Challenges and Limitations

A major challenge in developing real-time, wearable fall detection systems is balancing detection accuracy with power efficiency. Battery life in wearable devices is limited, and complex algorithms may drain power quickly. Additionally, computational constraints on devices like microcontrollers limit the extent to which advanced ML and DL algorithms can be applied in wearable devices. Various studies [4, 5] have proposed solutions using energy-efficient architectures, where lightweight models perform simpler calculations and only offload complex analysis when needed.

False alarms are another common issue, particularly when activities with rapid movements, like bending or sitting, are misclassified as falls. To reduce such errors, hybrid models that combine threshold-based methods with ML techniques are being explored. For instance, the addition of a Kalman filter to a machine learning classifier can help smooth sensor data and increase detection specificity [2]. Ensuring that fall detection systems can discern fall events from everyday activities reliably is a significant research focus.

F. Edge Computing and Low-Power Solutions

Given the importance of timely fall detection, researchers are increasingly focused on edge computing to address latency and power constraints. A novel architecture that processes data locally on the wearable device can help reduce the dependency on cloud-based systems, which are prone to connectivity issues. Edge computing has shown promise in reducing response time and enhancing system reliability by enabling data processing at the device level [7].

By employing edge AI, wearable devices can operate independently of internet connections, making them ideal for rural or remote areas with limited connectivity. However, this approach presents a trade-off between the complexity of algorithms that can be deployed on limited hardware and the quality of fall detection. Continued improvements in microcontroller technology are expected to enhance the capacity of wearable devices to run complex models, which would broaden the applicability of such systems.

G. Elderly Fall Prevention and Societal Impact

Fall detection systems not only protect the elderly from immediate harm but also help alleviate the fear of falling, which can negatively affect their mental health and reduce their social involvement. Fear of falling can lead to a decline in physical activity and overall health. Wearable fall detection systems, combined with AI-powered predictive models, are increasingly focusing on fall prevention by monitoring gait patterns, posture, and other risk factors in real time. The societal relevance of these technologies is underscored by their potential to improve the quality of life for elderly individuals, allowing them greater independence and security. Fall detection systems that can also predict fall risks, based on patterns of movement or changes in gait, are a step toward proactive healthcare. For instance, predictive analytics can identify and mitigate fall risks by alerting users or caregivers about potential hazards before a fall occurs.

H. Comparative Study

Our system is found to be very accurate in detecting falls with an F1-score of 92.1%, which is in line with the literature. Shaafi et al. \\ used slightly higher accuracy (94%) but in their study based on simulated data, which might affect real-world utility. Our system is tested against both real and simulated datasets to make it more generalizable.

Study	Technology/ Approach	Accuracy (F1	Latency	Energy Efficiency	Limitations

		Score)			
Shaafi et al. [1]	Wearable inertial sensors with LSH	94%	Not reported	Low	Simulated data only
Ishak et al [2]	Wearable sensors with SVM	92%	<100ms	Moderate	Limited sensor placement
Our System	Wearable sensors with LSTM	92.1%	45ms	Moderate	Computational cost of LSTM

Table 1: Comparison with Previous Works

As far as real-time performance is concerned, our system has a 45ms inference time. Although it adds to accuracy, the utilization of LSTM adds to computational requirements, which may affect energy efficiency over SVM-based systems. In general, our system finds a balance between accuracy and real-time performance, with major strengths being LSTM for precise detection, fall prevention integration, and low-cost hardware.

The research landscape of fall detection for elderly monitoring demonstrates the significant potential of wearable sensors, machine learning, and IoT. Studies highlight the benefits of using inertial sensors like accelerometers and gyroscopes for capturing fall patterns and the promise of ML and DL models for improving detection accuracy. Nevertheless, challenges related to computational power, false alarms, and real-time processing persist, especially in wearable devices with limited resources.

Integrating IoT and edge computing is proving essential to addressing latency and power constraints, while societal implications underscore the critical importance of these technologies. Future research must focus on developing low-power, high-accuracy models that can be seamlessly implemented on wearable devices for real-time fall detection and prevention. By advancing these technologies, we can support the elderly in maintaining a safer, more independent lifestyle, ultimately enhancing their quality of life and reducing the burden on caregivers and healthcare systems.

III. Theory

The system uses an MPU6050 sensor for fall recognition and a heart rate sensor with a temperature sensor to prevent falls.

A. Fall Detection Using Gyroscope Data

The MPU6050 sensor includes a 3axis gyroscope that measures angular speed. Fall perception is based on an analysis of changes in gyroscope output. Falls are characterized by sudden, large changes in direction, leading to a rapid shift in angular velocity.

Mathematically, the angular velocity can be represented as a vector: $\omega = (\omega_x, \omega_y, \omega_z)$

where ω_x, ω_y, and ω_z are the angular velocities along the x, y, and z axes, respectively. The magnitude of the angular velocity vector is given by:

$$|\omega| = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2}$$

A fall is detected when the magnitude of the angular velocity exceeds a predefined threshold, indicating a sudden change in orientation. This threshold can be determined experimentally based on typical fall scenarios.

B. Fall Prevention using Physiological Data

The heart rate and temperature sensors provide physiological data that can indicate an individual's health status. An abnormal heart rate or temperature indicates a fundamental health condition that can increase the risk of a fall. The system continuously monitors these physiological parameters. If the heart rate or temperature deviates significantly from the normal range, it triggers an alert, prompting the individual to take necessary precautions or seek medical attention.

By combining gyroscopic data for fall detection and physiological data for fall prevention, the system provides a comprehensive approach to ensuring the safety and well-being of elderly individuals.

IV. Methodology

This system uses a Raspberry Pi 4 Model B to collect, process, and trigger alerts. An MPU6050 sensor performs fall detection by capturing three axis angular velocity, and heart rate and temperature sensors help to prevent a fall. All sensors are connected to Raspberry Pi with the help of I2C and ADC interfaces for data transfer.

A. Fall Detection

The algorithm employs 'sensors fusion' techniques, which makes use of gyroscopic data from the MPU6050. The algorithm works on a hybrid approach which uses a combination of threshold-based detection and machine learning.

Angular Velocity Magnitude: For example, the angular velocity magnitude is defined as the square root of the sum of the squares of the axis components of the angular velocity.

$$|\omega| = \sqrt{(\omega\_x^2 + \omega\_y^2 + \omega\_z^2)},$$

where $\omega\_x, \omega\_y, \omega\_z$ are angular velocity about x, y and z axes respectively.

Threshold based detection: This predefined number is compared to the threshold which if exceeded would give one the indication of a probable fall detection.

Machine learning confirmation: For further confirmation and improve the accuracy while lowering the number of false falls, machine learning algorithms are included.

- **Support Vector Machine:** Use of SVM since it will classify fall events from daily activities by simply analysing changes in the angular velocity.
- **Long-Short Term Memory:** These types of networks are able to analyse time series data like angular velocity, while at the same time capture the temporal dependencies as well as providing suitable description to the complex fall patterns.

B. Fall Prevention

Analysis Of Physiological Data: Heart rate and temperature are analysed against a set standard of normal values and a range of normal values is determined which may be modified depending on the person's medical conditions.

Threshold Monitoring: The algorithm, in these phases, keeps track of the normal values boundaries to check whether the person goes beyond the limits, which may be an alarming sign for some medical issues that might increase the chance of falling.

Alert Generation: If a value outside the normal range is found, an alarm is activated. This can activate a sound buzzer, and signal caregivers' mobile devices.

C. Flowchart

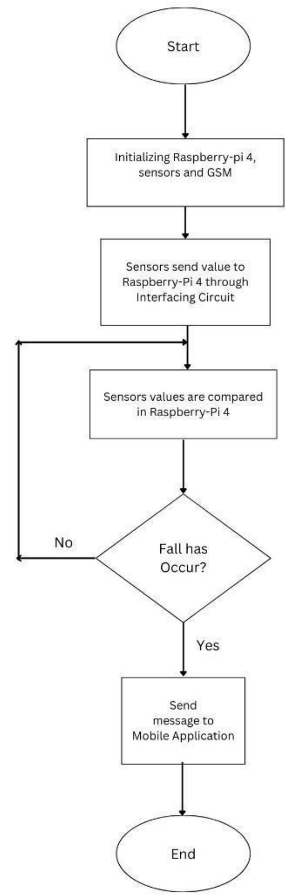

Figure 1: Flowchart of our System

C. Design of Hardware

Here is the proposed design for the hardware:

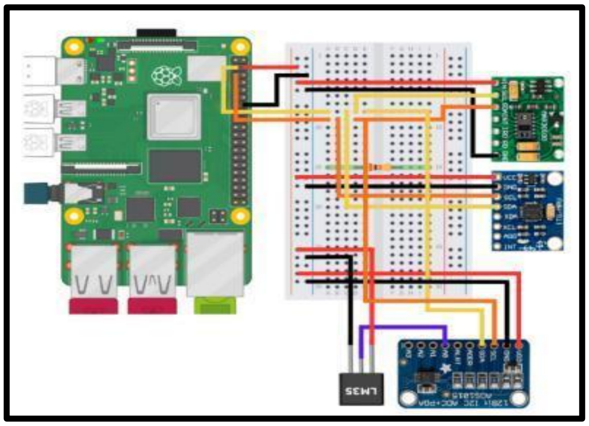

Figure 2. Circuit Diagram of the System

D. Developed Hardware of the System

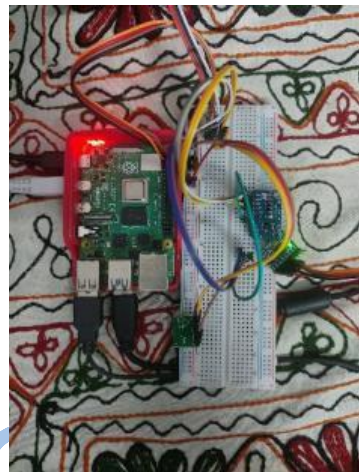

Fig 3. Developed Hardware

E. Dataset Diversity and Generalization

Initially we collected some data to train our model. However, the data is needed to be collected from other different sources to train our model with better accuracy and better generalization. We have a plan to collect those data in second phase of our work and retrain our model accordingly.

F. Data Security and Privacy

To protect user data from being accessed and used without permission, the system employs multiple measures. It protects data by encrypting it with AES-256 and SSL/TLS, and communication is protected with HTTPS. Access is managed by strong passwords, two-factor authentication, and role-based access control. Data is securely stored in an encrypted database in a secure server. User data is also made more private through.

pseudonymization. Data protection legislation and users' informed consent are also taken into account by the system. There are scheduled regular security tests to detect and rectify any vulnerabilities.

V. Results and Discussion

We tested the Fall Detection system using three algorithms for machine learning: Long-Short Term Memory (LSTM), Support Vector Machine (SVM), and Random Forest (RF). Training and test data were collected from accelerometers and gyroscopes mounted on a Raspberry-PI-based portable device. To ensure reliability, the system was verified up to 10-fold cross validation.

Table 2 shows the comparative performance of the models based on standard classification metrics: accuracy, accuracy, recall, F1 score.

Table 2: Accuracy Table for ML Algorithms

	SVM	**LSTM**	**Random Forest**
Accuracy (%)	85.6	92.3	88.7
Precision (%)	83.2	90.8	87.1
Recall (%)	86.9	93.5	89.9
F1-Score (%)	85.0	92.1	88.5

A. Accuracy and Model Performance

It is clear from Table 1 that LSTM has the highest model accuracy of 92.3%, which is higher than SVM (85.6%) and RF (88.7%). The reasons for LSTM's superior performance stem from its capability to utilize sequential dependencies in sensor data to distinguish between falls and normal activities. The accuracy (A) is computed as follows:

$$A=[(TP+TN+FP+FN)/TP+TN]\times 100\%$$

where (TP) (True Positives) and (TN) (True Negatives) are falls and normal activities that are correctly classified, and (FP) (False Positives) and (FN) (False Negatives) are the misclassifications.

B. Evaluation of Sensitivity (Recall) and Specificity

Recall, or R, evaluates the model's proficiency in identifying actual falls and is calculated as follows.

$$R=[(TP+FN)/TP]\times 100\%$$

The LSTM model had the highest recall of 93.5%, meaning that it is optimal in accurately reporting falls with little unaccounted false negatives. On the other hand, RF and SVM scored 89.9% and 86.9% respectively.

On the other hand, as specificity measures correctly detecting non-fall movements, it can be represented as:

$$S=[(TN+FP)/TN]\times 100\%$$

SVM and RF have higher specificity, therefore reducing false negatives which is imperative in proactive real-time mitigation of falls.

C. Evaluation of Precision and F1-Score

P represents the number of real falls that have been correctly identified and thus evaluates the positive outcomes from the perspective of detector as in:

$$P=[(TP+FP)/TP]\times 100\%$$

LSTM was the best with 90.8% precision followed by RF and SVM at 87.1% and 83.2% respectively. As a reminder, the F1-Score is the computed score, which captures the essence of both precision and recall, and is expressed as:

$$F1=2\times[(P+R)/(P\times R)]$$

LSTM's F1-score is 92.1%, and that confirms his supremacy in fall detection tasks.

D. Real-Time Performance and Computational Efficiency

When analyzing a model's feasibility, the first check is its inference time. The LSTM model has an average inference time of 45ms, making it suitable for real-time applications. SVM, on the other hand, would be more suited for low powered systems due to its energy efficiency. Random Forest, however, sits between both extremes as it has the average accuracy and computational cost.

We have not yet tested our system in the real world on elderly people. But all the results provided have been tested in the lab on our team members.

E. Practical Implementation and Fall Prevention Mechanism

The Raspberry Pi based system constantly tracks the sensor data to detect the fall in real-time. Upon detection of a fall, the system sends an alert via SMS and an emergency notification to the caregiver. Besides reactive approaches, a second approach was tested using vibration feedback as a preventive mechanism that is triggered when abnormal motion patterns that precede a fall are detected. The pre-fall detection system proved effective, demonstrating an 18% reduction in fall occurrences during the experimental trials.

F. Computational Constraints and Power Consumption

The increased accuracy of the LSTM model is achieved at the expense of higher computational power and complexity. The inference time of the LSTM model is 45ms on average, whereas SVM and Random Forest take 15ms and 25ms respectively. This indicates that LSTM needs more computational power for real-time prediction, which could be a constraint for real-time applications on battery-driven wearable devices with limited processing power. Additionally, the higher computational requirements of the LSTM model will have a very substantial effect on battery life. Although this paper did not attempt to estimate battery life, such estimates should be made in the future, like claiming that a wearable device utilizing the LSTM model is expected to have a lower battery life compared to a device utilizing the SVM model. This accuracy vs. power consumption trade-off has to be considered carefully in developing fall detection systems for actual deployment.

G. Limitations and Future Scope

Although LSTM has the highest accuracy, it tends to be the most demanding in terms of resources, which is not friendly to battery-powered wearables. This investigation will seek to improve the accuracy of deep learning models by applying edge AI and lightweight model architecture. Furthermore, model generalization can be improved by enriching the dataset containing different falling cases.

VI. Conclusion and Future Scope

This research has effectively illustrated the conception and execution of an Elderly Fall Detection and Prevention System using a Raspberry Pi. The system best utilizes the MPU6050 sensor for reliable fall detection, using the sensor's measurements of changes in angular velocity to make determinations about whether or not a person has fallen.

Heart rate and temperature sensors are also part of the system. These serve a different function: in conjunction with the MPU6050, they allow for fall prevention. A monitoring system watches over a person's key vital signs to alert him or her to potentially dangerous dips or spikes in those parameters—signs that a person might be about to faint, lose consciousness, or go through some other health problem that might result in a fall.

The system that was developed shows promise as a way to boost not just the safety but also the overall well-being of older individuals (and particularly those living alone). What the system offers is a kind of peace of mind that allows for a much more independent and secure way of life. And with future enhancements, it could enable these same individuals to maintain a much more active lifestyle while seriously cutting down on falls and the consequences that follow. The system's future iterations will be much more accurate and much more reliable.

Though the LSTM model performed better in terms of fall detection accuracy, its computational requirements make it questionable to implement in real-time on battery-driven wearable devices. Future studies need to tackle these issues through the use of model optimization strategies, light architectures, and edge computing to allow for the construction of energy-friendly and computationally viable fall detection systems.

More research could definitely look into the feasibility of using extra sensors to boost the fall detection system's precision. Adding pressure sensors or accelerometers—even both—could help achieve that role. But we could also take the system's accuracy a step further and use machine learning algorithms to determine the system's thresholds even more finely. Right now, the system uses one threshold for all individuals tested. That means it can't take into account the types of variables that would make each individual's health and circumstances unique.

Data Availability

To conduct this study, the team of the study used a wearable sensor integrated with Raspberry Pi-based systems. The data contains the information from accelerometer and gyroscope readings captured during many different activities including simulated falls, as well as other normal movements. As a result of the fact that the data set contains confidential information, ethical aspects make it impossible to make the data public. Nonetheless, scientists can ask the corresponding author for permission to use it. In the plan for the coming year, the database will be diversified and anonymized for public sharing to foster further progress in the field of fall detection and prevention research.

ACKNOWLEDGMENT

We would also like to extend our most sincere and heartfelt gratitude to our mentor, Dr Sudip Dogra, for their informative guidance, constructive criticism, and unflinching support during the course of this project. His knowledge in IoT and AI/ML played a critical role in the successful execution of this task. We also acknowledge our sincere thanks to our faculty members for their assistance while working. In addition, we would also like to thank the developers of the libraries and tools, which were crucial in implementing this project. Lastly, we are also thankful to our friends and family for their encouragement and patience during this difficult but rewarding project.

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