Elderly Care Assistance with Fall Detection and GPS Tracking

Mr. P. R. Kulkarni[1], Mr. Om Shinde[2], Mr. Virendra Shinde[3], Ms. Maitree Shirsat[4], Ms. Sejal Sonawane[5]

[1]Assistant Professor, Computer Engineering, GCOERC, Nashik
[2,3,4,5]Students, Department of Computer Engineering, GCOERC, Nashik

Abstract:
Falls are one of the leading causes of serious injuries among elderly individuals, especially those living alone. In many cases, delayed medical attention after a fall increases the risk of complications and even mortality. To address this issue, this paper presents a smart elderly fall detection and assistance system based on a wearable device integrated with a web-based platform. The proposed system continuously monitors user movement to identify fall events and automatically triggers an emergency response mechanism.When a fall is detected, a 10-second verification window is provided, allowing the user to cancel the alert in case of a false trigger. If no response is received, the system confirms the emergency and sends alert notifications to pre-registered guardians via email along with the user's live location. The wearable device also includes an SOS button for manual emergency activation and a medicine reminder feature to support daily healthcare management. A web dashboard is developed to configure medicine schedules, manage guardian details, and monitor alert history.By combining real-time fall detection, location tracking, automated alerts, and health assistance features, the proposed system aims to improve elderly safety, enable faster emergency response, and support independent living through reliable and technology-driven care.

Key Words: Elderly Care, Fall Detection System, Smart Wearable Device, Emergency Alert, Live Location Tracking, Medicine Reminder, SOS System, Web Dashboard, Assistive Technology, Remote Health Monitoring.

I. INTRODUCTION

The global elderly population is increasing rapidly, and with advancing age, the risk of falls, medical emergencies, and mobility-related accidents also rises significantly. Falls are among the most common causes of serious injuries in older adults and often lead to long-term health complications, loss of independence, and in severe cases, death. The situation becomes more critical for elderly individuals living alone, as immediate assistance may not always be available. Delays in emergency response after a fall can greatly worsen health outcomes, highlighting the need for reliable and continuous monitoring solutions.[1]

Traditional elderly care methods mainly depend on manual supervision, periodic medical check-ups, or the presence of caregivers. While these approaches are helpful, they do not provide continuous real-time monitoring and may fail to detect emergency situations instantly. In recent years, advancements in wearable technology, Internet of Things (IoT), and cloud-based systems have opened new possibilities for building smart healthcare solutions. Wearable sensors can continuously track motion patterns and activity levels, making it possible to automatically detect abnormal events such as sudden falls. At the same time, web-based platforms enable remote monitoring and instant communication with family members or caregivers.[4]

A smart elderly fall detection and assistance system can bridge the gap between conventional care and modern technology-driven support. By integrating wearable devices with intelligent alert mechanisms and online management platforms, such systems can ensure timely emergency response, reduce dependence on constant physical supervision, and improve overall safety. The objective of this project is to design and develop a wearable-based system that detects falls in real time, verifies emergencies to avoid false alerts, shares live location details, and provides additional support features such as SOS alerts and medicine reminders. The system aims to enhance elderly safety, promote independent living, and provide peace of mind to family members and caregivers through reliable and automated monitoring.

II. BACKGROUND

A. Traditional and Technology-Based Elderly Care and Fall Monitoring

Elderly care has traditionally relied on family members, caregivers, or medical staff to observe daily activities and respond to emergencies. Common methods include periodic health check-ups, home visits, and manual supervision to identify unusual behavior, injuries, or mobility issues. In many households, elderly individuals living alone depend on phone calls or scheduled visits, which do not guarantee immediate help during sudden incidents such as falls. These approaches are largely reactive and depend heavily on human presence and attention.

With advancements in technology, basic electronic and sensor-based solutions have been introduced to support elderly monitoring. Emergency call buttons, basic motion sensors, and CCTV-based observation systems have been used to provide limited remote assistance. More recently, wearable devices equipped with accelerometers and gyroscopes have enabled continuous tracking of body movement and posture. These devices make it possible to detect abnormal motion patterns that may indicate a fall. The emergence of the Internet of Things (IoT) has further improved elderly monitoring by allowing wearable devices to transmit real-time data to servers and web platforms. This enables caregivers and family members to remotely monitor activity and receive alerts. However, many existing solutions still focus mainly on simple motion detection or manual emergency triggering, offering limited intelligence and minimal integration with daily healthcare support features. [5]

B. Limitations of Existing Systems

Although current elderly monitoring systems and fall detection solutions have improved safety compared to purely manual care, several limitations still remain. Many traditional systems depend on panic buttons or manual emergency calls, which are ineffective if the elderly person becomes unconscious, confused, or physically unable to press a button after a fall. This reduces the reliability of such systems during serious emergencies.

Some wearable-based fall detection systems rely mainly on fixed threshold values for acceleration or orientation change. While this approach is simple, it often leads to false alarms during normal activities such as sitting quickly, lying down, or dropping the device. On the other hand, overly strict thresholds may fail to detect slow or partial falls. As a result, existing solutions often struggle to maintain a balance between sensitivity and accuracy. Another major limitation is the lack of integrated support features. Many systems only focus on fall detection and alerting, without addressing daily healthcare needs such as medicine adherence or regular status monitoring. Several platforms provide alerts but do not include location sharing, making it difficult for caregivers to quickly reach the elderly person. In addition, some solutions offer limited data storage and minimal user management, which restricts long-term monitoring and personalized care.[6]

Issues related to usability, device comfort, battery life, and system reliability also affect real-world adoption. Complex interfaces can be difficult for elderly users to operate, and unstable network connectivity can delay alert delivery. These limitations highlight the need for a more reliable, accurate, and user-friendly elderly assistance system that combines fall detection with emergency handling and daily care support.

C. Domain and Context Dependency Challenges in Elderly Fall Detection and Care Systems

Elderly fall detection and health assistance systems are highly context-dependent because physical conditions, mobility patterns, and daily routines vary significantly from one individual to another. A movement pattern that is normal for one elderly person may indicate a potential fall risk for another. Factors such as age, body strength, medical history, use of walking aids, and living environment strongly influence how sensor data should be interpreted. Systems that apply uniform thresholds or generalized models often fail to accurately distinguish between daily activities and real emergency situations.[7]

Environmental context also plays a critical role. Indoor surfaces, furniture layouts, lighting conditions, and outdoor surroundings can affect how falls occur and how sensors respond. For example, slow slips, supported falls, or collapsing onto furniture may not generate strong motion signals but can still be dangerous. Without contextual understanding, systems may either ignore such incidents or incorrectly trigger alarms during routine movements like sitting, lying down, or bending. Another challenge lies in integrating emergency detection with everyday care needs. Elderly users require systems that not only identify critical events but also support regular activities such as medication adherence and safety reassurance. A lack of personalization and adaptive behaviour often results in reduced system effectiveness and user trust. Therefore, an effective elderly fall detection and assistance system must account for individual behaviour patterns, allow flexible configuration, and combine emergency handling with continuous supportive care[8]

III. LITERATURE SURVEY

Sowmya and Pillai (2021) presented a wearable fall detection system using accelerometer and gyroscope data combined with machine learning algorithms. Their work focused on extracting motion features and training classifiers to distinguish falls from daily activities. The study demonstrated that wearable sensors are effective for real-time fall detection, but performance strongly depends on sensor placement and data quality.

Ferreira de Sousa et al. (2022) proposed a wearable pre-impact fall detection system using a 3D accelerometer and subject-specific parameters such as height. Their approach aimed to identify falling motion before ground impact. The results showed improved response time and potential for reducing injury severity. However, the system required careful calibration and personalization for different users.

Ponce et al. (2020) analysed sensor placement strategies and showed that body location significantly affects detection accuracy. Their study highlighted that waist and chest positions provide more reliable fall patterns than wrist-mounted devices, which are more affected by random hand movements.

Chen et al. (2022) proposed an elderly fall detection system based on an improved YOLOv5 network. Their method detected human posture changes and classified fall events from video frames. The system achieved high accuracy in controlled indoor environments but depended heavily on lighting conditions, camera placement, and unobstructed views.

Chang et al. (2021) introduced a pose-estimation-based fall detection system using edge AI computing. Their work focused on extracting skeletal features and analyzing posture transitions to identify falls. This approach improved robustness over simple motion detection but still faced limitations related to privacy, camera coverage, and occlusion.

Wang et al. (2017) developed RT-Fall, a real-time fall detection system using commodity Wi-Fi devices. By analyzing channel state information (CSI), the system detected motion disturbances caused by falls. The study demonstrated that Wi-Fi-based detection can work without wearables, but performance varied with room layout, interference, and the presence of multiple people.

Li et al. (2022) proposed a real-time fall detection system using mm Wave radar. Their approach captured fine-grained motion signatures and achieved promising indoor results. However, radar systems require careful deployment and are sensitive to environmental noise.

Summary of Reviewed Studies

From the reviewed literature, it is evident that:

- Wearable systems are the most practical and widely adopted, but they suffer from false alarms and personalization challenges.
- Vision-based systems provide detailed posture analysis but are limited by privacy concerns and environmental constraints.
- Contactless approaches remove the need for devices but depend heavily on surroundings and infrastructure.
- Pre-impact models improve response time but require subject-specific tuning.

Most existing systems focus primarily on detection accuracy, with limited integration of user verification mechanisms, daily healthcare support features, and multi-channel alerting frameworks. Few systems combine fall detection with false alarm handling, SOS support, medicine reminders, and live location-based alerts in a single platform.

These gaps strongly motivate the proposed elderly fall detection and assistance system, which integrates wearable fall detection with a verification window, emergency handling, caregiver notification, and daily support features through a unified web-based platform.

IV. THEORETICAL BACKGROUND

A. Wearable-Based Motion Sensing Framework

The system is primarily based on a wearable sensing framework that continuously monitors the physical movement of the elderly user. Inertial sensors such as accelerometers and gyroscopes capture linear acceleration and angular velocity of the body. These signals reflect daily activities such as walking, sitting, lying down, as well as abnormal motion patterns such as slips, sudden impacts, or loss of balance.

The wearable device acts as the data acquisition layer, where raw sensor signals are sampled, digitized, and buffered. Basic signal conditioning techniques, such as noise filtering and smoothing, are applied to reduce random fluctuations and sensor drift. This theoretical layer ensures that physical motion is converted into reliable digital data that can be used for further analysis.[9]

By enabling continuous and non-intrusive monitoring, wearable-based sensing forms the foundation of real time fall detection.

B. Fall Pattern Recognition and Event Classification

Fall detection is treated as a pattern recognition and classification problem. Human motion can be represented as time-series data, where falls exhibit distinctive characteristics such as sudden high acceleration peaks, rapid orientation changes, and short free-fall phases followed by impact.

The theoretical model assumes that motion windows extracted from sensor streams can be analysed to differentiate between Activities of Daily Living (ADLs) and fall events. Feature extraction methods derive meaningful attributes such as signal magnitude, variance, posture change, and impact duration. These features are then evaluated using decision logic or trained machine learning classifiers to classify the event as “normal activity” or “potential fall.”

This framework allows the system to move beyond simple thresholding and toward intelligent discrimination between true falls and routine movements.

C. Intelligent Alert Verification and Emergency Handling

One of the major theoretical aspects of the system is the concept of alert verification. Instead of immediately issuing emergency alerts after detecting a fall pattern, the system introduces a short verification interval. During this window, the user is given the opportunity to cancel the alert in case the event was accidental or non-critical.

This mechanism is theoretically motivated by human cantered system design, which aims to reduce false positives while preserving high sensitivity. The integration of a manual cancel option and an SOS trigger enables both automated and user-initiated emergency handling. The system thus supports three emergency states: automatically detected falls, user-confirmed emergencies, and false alarm cancellations.[10]

D. Location-Aware Assistance and Notification Framework

Another theoretical component is the location-aware alerting framework. When an emergency is confirmed, the system retrieves the user’s real-time geographic coordinates through a positioning module. Location information is combined with the emergency status and transmitted to caregivers through communication services such as email.

This framework ensures that alerts are not only timely but also actionable. Providing live location significantly reduces response time and enables caregivers to reach the user more efficiently. The notification layer thus acts as a bridge between automated detection and real-world intervention.

E. Summary

The theoretical structure of the proposed system combines wearable motion sensing, intelligent fall recognition, verified alert handling, location-aware notification, and continuous care support. Together, these components provide a unified framework that enables reliable detection, minimizes false alarms, supports daily health routines, and ensures rapid emergency response.

V. SYSTEM OVERVIEW

The system architecture represents the high-level structural design of the proposed elderly fall detection and assistance system. It illustrates how hardware components, software services, and user interfaces are organized and how they interact with each other.

At the bottom of the architecture is the **Wearable Device**, which acts as the primary data acquisition and user interaction unit. It consists of an accelerometer and gyroscope to monitor body movement, a GPS module to obtain live location, a cancel button to stop false alerts, a buzzer/display for notifications and medicine reminders, and a microcontroller (ESP32) to control all operations. The wearable continuously senses motion data and detects abnormal patterns that may indicate a fall. It also allows the user to manually trigger or cancel emergency events.

The wearable device communicates with the system through **Wi-Fi/Internet connectivity**, sending sensor data, emergency events, and location information to the backend infrastructure.

The **Backend Server** functions as the central processing and control unit of the system. It hosts the fall detection engine, which analyzes incoming sensor data to identify fall events. The false alarm handler manages the 10-second verification timer, allowing the user to cancel alerts before they are confirmed. The SOS and event manager processes manual emergency triggers and system-generated incidents. The notification controller coordinates alert delivery, while API services enable communication between all system components.

Connected to the backend is the **Database**, which stores user profiles, guardian contact details, medicine schedules, and emergency logs. This layer supports long-term data storage, event tracking, and system configuration.

The **Alert Services** module is responsible for delivering emergency notifications. When a fall or SOS event is confirmed, this module sends email alerts to registered guardians and includes the user's live location so that immediate assistance can be arranged.

At the top of the architecture is the **Web Dashboard**, which provides a user interface for caregivers or administrators. Through this dashboard, guardians can schedule medicines, manage contact details, and view alert history and system logs. The dashboard communicates with the backend server to retrieve data and update system settings.

Overall, the architecture demonstrates a layered and modular design where the wearable device handles sensing and user interaction, the backend manages intelligence and decision-making, the database ensures reliable data storage, the alert services handle emergency communication, and the web dashboard supports monitoring and configuration. This structure ensures scalability, reliability, and efficient real-time response for elderly safety and assistance

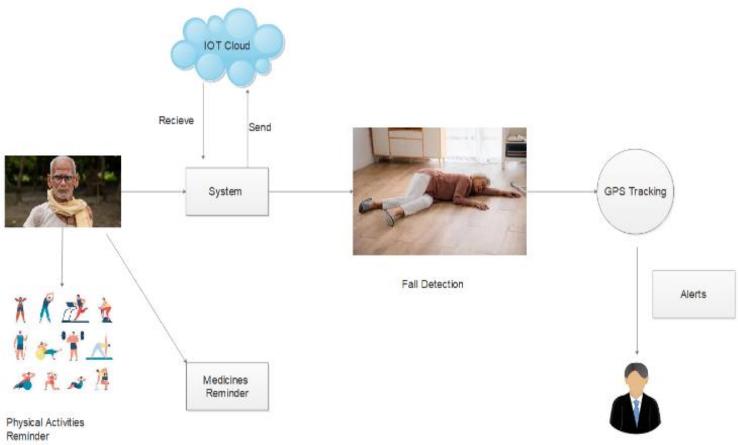


Figure 1.1 : System Architecture

Technology Suite Used
The system is built using a modern and scalable technology stack:

- **Embedded Development:** Arduino IDE for programming the ESP32 microcontroller, handling motion sensors, buttons, buzzer, GPS, and wearable device control.
- **IoT Hardware:** ESP32 with accelerometer and gyroscope for fall detection, GPS module for live location, SOS and cancel buttons, and buzzer/display for alerts and medicine reminders.
- **Backend Framework:** Django (Python-based) for fall detection processing, false-alarm handling, event management, user control, and API services.
- **Database:** Firebase for storing user profiles, guardian details, medicine schedules, emergency logs, and alert history.
- **Frontend:** HTML, CSS, Bootstrap, and JavaScript for developing a simple, user-friendly web dashboard to manage medicines, users, and alerts.
- **Communication:** Wi-Fi and HTTP/REST APIs for real-time data transmission between the wearable device, backend server, and web dashboard.

This combination ensures strong performance, easy scalability, and smooth integration for future system expansion.

VI. METHODOLOGY

The methodology diagram illustrates the functional working framework of the proposed elderly fall detection and assistance system. It explains how sensor data and user inputs are transformed into intelligent decisions and emergency services.

The process begins with the Motion Sensors and Signal Processing module, where accelerometer and gyroscope sensors continuously capture body movement. The raw signals are passed through basic signal processing techniques such as filtering and normalization to remove noise and prepare the data for reliable analysis.[11]

The processed signals are then forwarded to the Fall Detection and Pattern Analysis module. This unit analyzes motion patterns to identify abnormal movements that may indicate a fall. It differentiates between routine activities and potential fall events based on extracted motion characteristics.[12]

In parallel, the SOS / Cancel Button Module allows direct user interaction. The SOS button enables the elderly user to manually trigger an emergency at any time, while the cancel button allows the user to stop a false fall alert. These inputs are linked to both the fall analysis and validation stages, ensuring that user actions can override or confirm system decisions.

Detected fall events are passed to the Event Validation module, which implements the 10-second timer logic. This unit waits for a short confirmation window, during which the user can cancel the alert. If no cancellation occurs, the system confirms the emergency.[13]

Confirmed events are handled by the Emergency Manager, which acts as the central control unit for fall and SOS situations. It coordinates system responses, triggers emergency workflows, and activates supporting services.

The Location Unit (GPS Module) supplies real-time geographic coordinates when an emergency is confirmed. This location data is combined with the emergency event and forwarded to the backend.

At the same time, the Medicine Reminder Unit operates alongside emergency handling, delivering scheduled medicine alerts and supporting daily healthcare management.[14]

The Backend Services module manages data storage, system coordination, and control operations. It stores emergency logs, user information, and event details, and acts as the bridge between the wearable device and external services.

Finally, the Alert and Interface layer delivers system outputs. Emergency notifications are sent to registered guardians via email along with live location information, and all events and settings are made available through the web dashboard for monitoring and configuration.[15]

Overall, the methodology framework demonstrates how the system integrates motion sensing, intelligent fall detection, user verification, emergency management, location tracking, and healthcare support into a unified elderly assistance solution.

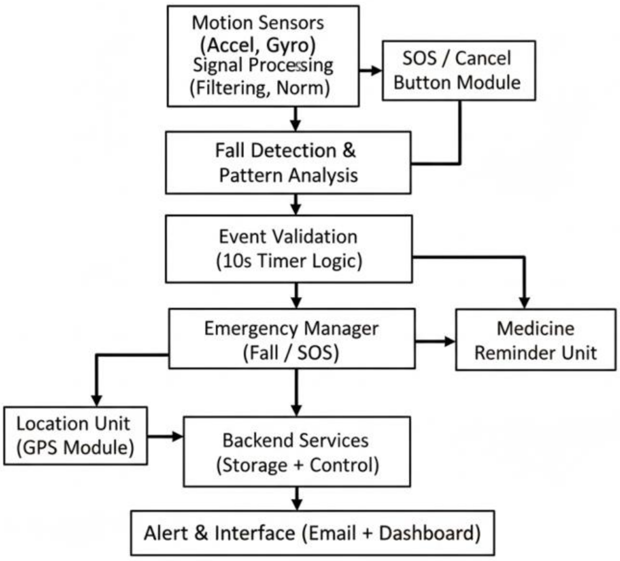


Figure 1.2: System Flow

VII. MATHEMATICAL MODEL OF THE SYSTEM

The proposed elderly fall detection and assistance system can be mathematically represented as a structured system that accepts sensor and user inputs, processes them through defined functions, and generates emergency and support outputs.

1. System Representation

The complete system S can be represented as:

$$S = \{I, P, O\}$$

- **I** → Input set (sensor data)
- **P** → Processing functions
- **O** → Output set

2. *Input Set*

The system input consists of real-time sensor data and user interactions:

I={A,G,Bsos,Bcancel,L}

Where:

- **A=** Accelerometer data
- **G=** Gyroscope data
- $\mathbf{B_{sos}}$= SOS button input
- $\mathbf{B_{cancel}}$= Cancel button input
- **L=** Location (GPS coordinates)

Sensor signal vector at time t:

$$\boldsymbol{X(t) = [a_x(t), a_y(t), a_z(t), \omega_x(t), \omega_y(t), \omega_z(t)]}$$

3. *Preprocessing Function*

Raw sensor data is filtered and normalized:

$$\boldsymbol{X_p(t) = f_{pre}(X(t))}$$

Where:

$\boldsymbol{f_{pre}}$= noise filtering and normalization function

$\boldsymbol{X_p(t)}$= processed motion signal

4. *Feature Extraction*
From processed signals, motion features are extracted:

$$F(t) = f_{feat}(X_p(t))$$

Where:
$F(t)$= feature vector (magnitude, variance, posture change, impact level)

5. *Fall Detection Function*
Fall classification is performed as:

$$D(t) = f_{fall}(F(t))$$

Where:

$$D(t) \in \{0, 1\}$$

0 → Normal activity
1 → Possible fall detected

6. *Event Validation (10-second Logic)*
Emergency confirmation is defined as:

$$E(t) = \begin{cases} 1, & \text{if } D(t) = 1 \text{ and } B_{cancel} = 0 \text{ for } T \geq 10s \\ 1, & \text{if } B_{sos} = 1 \\ 0, & \text{otherwise} \end{cases}$$

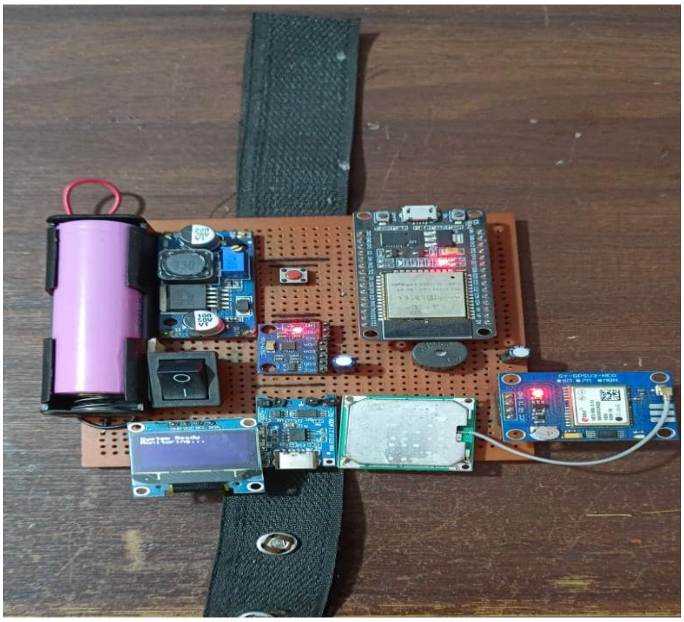
Where:
$E(t)$= confirmed emergency event
T= validation timer

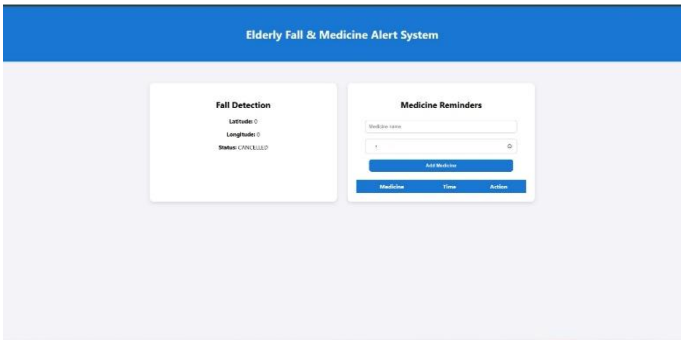
G. Output Set
The final output is:

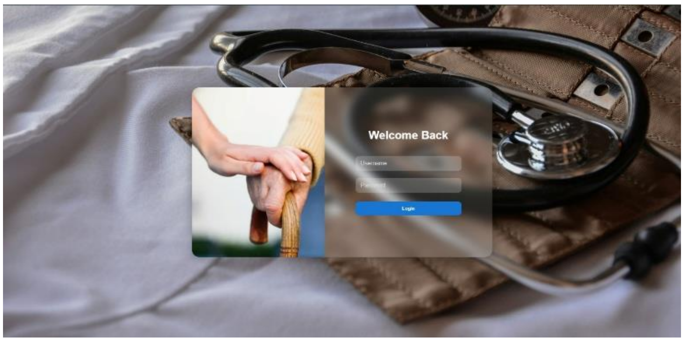
$$O = \{Alert, Location, Reminder, Log\}$$

Where:
- **Alert** = Email notification to guardian
- **Location** = Live GPS position
- **Reminder** = Medicine alert
- **Log** = Stored emergency record

VIII. RESULTS







IX. CONCLUSION AND FUTURE WORK

This paper presented an elderly fall detection and assistance system that combines a smart wearable device with a backend server and web-based platform to improve elderly safety. The system continuously monitors body movements to detect falls, provides a verification mechanism to reduce false alerts, and supports manual emergency triggering through an SOS button. When an emergency is confirmed, alert notifications along with live location details are sent to registered guardians. In addition, the system includes medicine reminders and a web dashboard for monitoring and management. The proposed solution aims to support independent living, enable faster emergency response, and provide reliable assistance for elderly individuals.

Future Scope

In the future, the system can be enhanced by integrating more advanced sensors to monitor additional health parameters such as heart rate, blood pressure, or oxygen levels. Machine learning and deep learning models can be introduced to improve fall detection accuracy and personalize detection based on individual behavior patterns. Mobile applications can be developed to provide easier access for guardians and healthcare professionals. The system can also be extended to include direct emergency service integration, voice assistance, and long-term health analytics, making it a more comprehensive elderly care platform.

REFERENCES:

[1] A. Sowmya and A. S. Pillai, “Human Fall Detection with Wearable Sensors Using Machine Learning Algorithms,” *2021 2nd International Conference on Smart Electronics and Communication (ICOSEC)*, 2021, pp. 1–6.

[2] F. A. S. Ferreira de Sousa, R. Escriba, and J. M. Lanza-Gutiérrez, “Wearable Pre-Impact Fall Detection System Based on 3D Accelerometer and Subject’s Height,” *IEEE Sensors Journal*, vol. 22, no. 8, pp. 7421–7432, Apr. 2022.

[3] T. Chen, Z. Ding, and B. Li, “Elderly Fall Detection Based on Improved YOLOv5s Network,” *IEEE Access*, vol. 10, pp. 92145–92156, 2022.

[4] W.-J. Chang, C.-H. Hsu, and L.-B. Chen, “A Pose Estimation-Based Fall Detection Methodology Using AI Edge Computing,” *IEEE Access*, vol. 9, pp. 134629–134640, 2021.

[5] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, and S. Li, “RT-Fall: A Real-Time and Contactless Fall Detection System with Commodity WiFi Devices,” *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 511–526, Feb. 2017.

[6] M. Mubashir, L. Shao, and L. Seed, “A Survey on Fall Detection: Principles and Approaches,” *IEEE Signal Processing Magazine*, vol. 30, no. 2, pp. 76–86, Mar. 2013.

[7] P. Vallabh and R. Malekian, “Fall Detection Monitoring Systems: A Comprehensive Review,” *IEEE Sensors Journal*, vol. 18, no. 15, pp. 6059–6072, Aug. 2018.
[8] S. Abbate, M. Avvenuti, G. Cola, P. Corsini, J. Light, and A. Vecchio, “Recognition of False Alarms in Fall Detection Systems,” *IEEE Consumer Electronics Magazine*, vol. 4, no. 3, pp. 79–87, July 2015.
[9] A. Casilari, M. Álvarez-Marco, and F. García-Lagos, “A Study of the Use of Gyroscope Measurements in Wearable Fall Detection Systems,” *IEEE Sensors Journal*, vol. 16, no. 19, pp. 6674–6683, Oct. 2016.
[10] J. Kangas, I. Korhonen, J. Vikman, M. Nyberg, and P. Korpelainen, “Sensitivity and Specificity of Fall Detection in People Aged 40 Years and Over,” *IEEE Journal of Biomedical and Health Informatics*, vol. 13, no. 2, pp. 184–191, Mar. 2009
[11] M. Bagala, C. Becker, A. Cappello, L. Chiari, K. Aminian, J. M. Hausdorff, and W. Zijlstra, “Evaluation of Accelerometer-Based Fall Detection Algorithms on Real-World Falls,” *PLoS ONE*, vol. 7, no. 5, pp. 1–9, May 2012.
[12] L. N. Sucerquia, J. D. López, and J. F. Vargas-Bonilla, “Real-Life/Real-Time Elderly Fall Detection with a Triaxial Accelerometer,” *Sensors*, vol. 18, no. 4, pp. 1–18, Apr. 2018.
[13] K. Wild, E. Boise, J. Lundell, and A. Foucek, “Unobtrusive In-Home Monitoring of Cognitive and Physical Health: Reactions and Perceptions of Older Adults,” *Journal of Applied Gerontology*, vol. 27, no. 2, pp. 181–200, Apr. 2008.
[14] A. Igual, C. Medrano, and I. Plaza, “Challenges, Issues and Trends in Fall Detection Systems,” *Biomedical Engineering Online*, vol. 12, no. 1, pp. 1–24, 2013.
[15] Y. Lee and S. Lee, “Activity Recognition and Fall Detection Using Smartphone Sensors,” *International Journal of Distributed Sensor Networks*, vol. 2014, pp. 1–8, 2014.
[16] S. Kwolek and M. Kepski, “Improving Fall Detection by the Use of Depth Sensor and Accelerometer,” *Neurocomputing*, vol. 168, pp. 637–645, Nov. 2015.
[17] N. Noury, T. Hervé, V. Rialle, G. Virone, E. Mercier, G. Morey, A. Moro, and T. Porcheron, “Monitoring Behavior in Home Using a Smart Fall Sensor and Position Sensors,” *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 837–844, July 2003.
[18] J. Perry, S. Kellog, S. Vaidya, J. Youn, H. Ali, and M. Sharif, “Survey and Evaluation of Real-Time Fall Detection Approaches,” *IEEE International Conference on Technologies for Homeland Security*, 2009, pp. 158–164.
[19] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, “Robust Video Surveillance for Fall Detection Based on Human Shape Deformation,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 21, no. 5, pp. 611–622, May 2011.
[20] D. Anderson, J. Keller, M. Skubic, X. Chen, and Z. He, “Recognizing Falls from Silhouettes,” *IEEE International Conference on Engineering in Medicine and Biology Society*, 2006, pp. 6388–6391.