Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

IoT Health Monitor with Fall Detection by Sensors

SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS
OF THE DEGREE OF

Bachelor of Technology in Computer Science and Engineering (IoT and Cyber Security with Blockchain Technology)

by

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Innovative Product Development III(DJS22ILLL1)

IoT Health Monitor with Fall Detection by Sensors

Submitted in Partial fulfilment of the requirements of Innovative Product Development III(DJS22ILLL1) (Sem-V) in the Department of Computer Science & Engineering (IoT and Cyber security with Blockchain Technology)

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Declaration

We declare that any and all sources utilized in the preparation of this report have been properly cited and referenced. The ideas, concepts, and research findings presented in this proposal are entirely our own, unless otherwise acknowledged and referenced. This report represents my genuine efforts to contribute to the field of Computer Science Engineering ((IoT and Cyber security with Blockchain Technology) and to advance scholarly knowledge in a meaningful and ethical manner

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Certificate

This is to certify that, topic entitled **IoT Health Monitor with Fall Detection by Sensors** has been reviewed and evaluated by undersigned members, and is submitted as partial fulfilment of Innovative Product Development III(DJS22ILLL1) (Sem-V) in the Department of Computer Science and Engineering (IoT and Cybersecurity with Blockchain Technology)

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Abstract

Essentially, fall detection systems are designed for improving safety and health care for the elderly as well as people with mobility issues. The proposed structure uses modern IoT technologies, wearables, and platforms like ThingSpeak for developing a wearable fall detection device. It has proposed using modern-day IoT technologies with sensors that take the proposed device accurate to differentiate falls from normal day-to-day activities. It has used interactive UI components such as real-time graphs for data visualization via ThingSpeak for real-time monitoring and alerts to the caregivers or health care personnel. It is mainly reduced false positives, battery optimization, and interaction with users that lead to innovative key approaches for the proposed system.
Additionally, the proposed system features new enhancements of fall detection from the referred papers and such; there will be a strong framework established. It combines wearable IoT integrations, threshold-based measurements, as well as trend analysis for improved accuracy and reliability in detection. These data, too, are properly stored in a secure way via cloud sharing in terms of making connections easy in relation to access and sharing. Most importantly, these issues address the gaps and challenges on the current state of emergency response as well as personalized care.

Keywords: IoT, fall detection, elderly care, wearable device, real-time monitoring, health data visualization, ThingSpeak, Cloud storage

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Abbreviations

Sr. No.	Abbreviation	**Expanded Form**
1.	IoT	Internet of Things
2.	MPU	Microcontroller Processing Unit
3.	ESP32	Wi-Fi and Bluetooth-Integrated Microcontroller
4.	LCD	Liquid Crystal Display
5.	HC-SR505	Mini PIR Motion Sensor
6.	API	Application Programming Interface
7.	ML	Machine Learning

1.Introduction

Falls become a world health problem for the elderly section as they would mostly become serious injuries such as fractures or even head injury. Falls not only injure people physically, but also impart severe psychological effects such as loss of confidence and fear of falling again, losing independence, and perhaps severe emotional scars in some patients. these happen because of the high cost of health care and hospitalization accursed in all health care systems across the world. Because of the growing aging population all over the world, the importance of fall detection systems remains urgent. Implementation is needed soon, and it should be highly effective and reliable so that timely and precise medical attention could be given to reduce the risks.

However, with the advent of many technological developments, various fall detection systems have been introduced. Most of them, though, are limited by their functions; for instance, in high rates of false alarms or over-classification of normal movements or abrupt cessation of activities as falls. This kind of misbehavior could result in unnecessary panic or even alertional fatigue among caregivers. There are also some systems that would limit their functionality in certain scenarios as well as the user discomfort due to bulky or intrusive designs that then would lead to occasional use. Solving such issues would further improve the adoption of fall detection technologies and their use.

A smart and convenient wearable IoT-enabled fall detection system has been developed in order to solve these problems. The system consists of a number of sophisticated advanced sensors, such as accelerometers, gyroscopes, and pulse oximeters. These sensors are meant to capture large amounts of data with respect to both movement and physiological responses within patients. This data, when coupled with cutting-edge signal data processing algorithms, promises high-level reliability in detecting falls with very few false alarms. It should be very much improved now in discriminating between real falls and normal activities in daily life by integrating the motion data with the physiological parameters.

Besides, the system is made possible by real-time alerts and data visualization through IoT platforms such as ThingSpeak. These features ensure instant notifications to caregivers and health professionals when a fall happens, facilitating immediate intervention. The same visualization tools give trends and indications of the activity taking place with the user, thus serving as a source of preventive measures or customized healthcare plans.

The functional example of the design of the portable device is user comfort and long-term usability. Off-the-shelf products in this field are small and light enough to not intrude on daily life, and are optimized for battery efficiency so that prolonged periods of use can occur without frequent recharging. Such aspects would motivate continuous use, especially by elderly people who could be very against adopting unpleasantly complex or uncomfortable devices.

The project, therefore, would have an overarching goal that will not only reduce the risk of falls but also provide the users with seamless experience, reliable and unobtrusive. The system, hence, is combined with technologically advanced user-centered design principles: a truly paradigm-setting dimension of wearable fall detection technology. It will contribute to better safety, independence, and quality of life for seniors and other at-risk populations.

The whole objective of this project is that beyond reducing fall risks, it aims to provide an unobtrusive, seamless, and reliable experience to users. This community effort, which combines advanced technology with user-centered design principles, aims to shift the paradigm of wearable fall detection systems. It would render a much safer, more independent, and better quality of life for seniors and other at-risk populations.

2. Literature Survey

2.1 Survey of Existing Systems

Sr. No.	Paper Title	Methodology	Research Gap
1.	Practical fall detection based on IoT technologies: A survey	Comprehensive survey of IoT-based fall detection systems.	Lack of real-time data processing and response system.
2.	Real-time Threshold-Based Fall Detection System Using Wearable IoT	Implemented machine learning algorithms on wearable devices.	Integration with cloud for enhanced data analytics
3.	Fall Detection System Based on Deep Learning and Image Processing in Cloud Environment	Utilized deep learning models for accurate fall detection.	Need for lower power consumption and energy efficiency.
4.	Fall detection system for elderly people using IoT and Big Data	Combined IoT sensors with preventive measures.	Improved sensor accuracy and data fusion techniques.
5.	A machine learning approach to fall detection algorithm using wearable sensor	Machine learning techniques applied to wearable IoT devices.	Enhancing robustness in diverse environments.
6.	Fall Detection System Using Accelerometer and Gyroscope Based on Smartphone	Used accelerometer and gyroscope data for detecting falls.	Handling false positives and optimizing data processing.
7.	Multi-sensors data fusion system for fall detection	Fusion of multiple sensors to increase detection accuracy.	Scalability and handling diverse user profiles.
8.	IoT-Based Fall Detection for Smart Home Environments	Utilized IoT networks within smart homes for fall detection.	Privacy concerns and securing data in IoT networks.

Table 2.1 – Literature Survey

The compiled table provides an in-depth comparison of various methodologies and research gaps identified in prominent studies on IoT-based fall detection systems. Mozaffari et al. conducted a **comprehensive survey** of IoT-based fall detection systems, which emphasized the limitations in real-time data processing and response mechanisms. Their work serves as a foundational study by outlining the current capabilities and identifying critical areas for improvement, particularly the need for systems capable of reacting instantly to detected falls【1】.

Amir et al. advanced the field by implementing **machine learning algorithms** on wearable IoT devices, thereby improving detection capabilities and data interpretation. Their findings highlighted the importance of integrating cloud computing for enhanced data analytics and real-time synchronization, pointing to the potential of a more robust and scalable IoT ecosystem【2】. Similarly, Leixian et al. employed **deep learning models combined with image processing** for accurate fall detection in cloud environments. Their study brought attention to practical concerns such as high power consumption and energy inefficiency, suggesting the necessity of low-power hardware and optimized algorithms【3】.

Yacchirema et al. presented an innovative approach by combining IoT sensors with **preventive measures** to address elderly care. Their work underscored the importance of improving sensor accuracy and leveraging data fusion techniques for reliable fall detection. Additionally, the study identified a significant gap in developing systems that can seamlessly handle complex data streams while maintaining high accuracy【4】.

Hsieh et al. utilized **machine learning techniques** in wearable IoT devices, demonstrating the potential to adapt detection systems to diverse environments. However, their work also highlighted the challenge of ensuring robustness in varying conditions, such as different physical activities or environmental factors, which remains a pressing issue for broader implementation【5】. Rakhman et al. focused on using **accelerometers and gyroscopes** in smartphones for fall detection. Although their system demonstrated effective detection capabilities, it raised concerns about false positives and emphasized the need for optimizing data processing for real-world application【6】.

Brulin et al. introduced a **multi-sensor data fusion system** to enhance detection accuracy by combining data from multiple sources. Their approach addressed the limitations of single-sensor systems but also identified challenges related to scalability and handling diverse user profiles, such as individuals with varying activity levels or movement patterns【7】. Lastly, Greene and Thapliyal focused on designing **IoT-based fall detection systems for smart home environments**. Their study highlighted privacy concerns and the need for robust data security measures to ensure the safety of personal data collected in IoT networks【8】.

2.2 Limitations of Existing Systems or Research Gaps

While significant progress has been made in the field of fall detection technology, numerous gaps and holes still prevent both the efficacy and practical adoption of this technology especially with regard to real-world situations. Lack of real-time data processing is a major shortcoming for these technologies. Most of the current applications are proved incapable of on-time fall detection and initiating the actions appropriate to emergency situations, thereby limiting their utility to life-threatening situations. For example, delayed data analysis and alert generation are causing the risk that timely medical assistance may not be rendered often the most important factor in reducing severity of injuries caused by falls. There is need for speed-efficient processing algorithms capable of being operated within the lowest latency. Another very critical gap is that in the development of fall detecting system technology by engaging into cloud platforms. There have been many solutions to offer but they all haven't utilized such uses of cloud computing that have been claimed to provide intelligent data processing with central facilities for storage. Thus, cloud integration into device can result in real-time synchronization of child/s events of monitoring for missing person, most of information retrieved and analyzed through machine learning, thus increasing accuracy and reliability in detection of fall. But not to forget, seamlessness in connectivity is quite critical due to the fact that there can be sort of delays in data transmission. Again, there could be worries related to a cloud platform in that these may connect areas with not much connectivity to data. Such may lead into hybrid, where edge and cloud computing may combine in order to enhance performance.

The major bottleneck still lies in energy efficiency, especially for those systems which are based on deep learning-based models or IoT wearables. These systems consume so much power, making them impractical in resource-constrained scenarios or by users requiring long-term monitoring. Power consumption of wearable gadgets is high enough to limit their usability and increase costs, hence they are not suitable for widespread adoption. Future research must focus on making optimum algorithms, using effective low-power hardware, and energy-efficient communication protocols to overcome the constraints and make the definition of sustainable technology effective. Sensor Improvement and Data Fusion: Most fall prediction systems are characterized by numerous instances of false positives and false negatives, culminating in unnecessary alerts or non-detections. This leads to trust erosion in the user as well as in the sustainability of the system itself. Improving sensor fidelity and manufacture of intelligent data fusion can go a long way towards making sure that the inputs from different sensors are used for the more robust detection. It must also be scalable so that the systems can work in different environments and user profiles. For example, a wearable device should have the capabilities to train different kinds of physical activity, movement of the body, and personal characteristics applying similar performance across groups of users. The foremost constraint still is power line efficiency especially for such systems which are based on deep learning models or use IoT wearables. These systems are power-hungry and limit their application in resource-poor environments or by users needing monitoring over long periods. Such high power consumption can jibe in these wearable devices and adds operational costs, affecting the economic viability of the systems for mass adoption.

Sensor accuracy and data fusion is another major area that requires improvement. Most fall detection systems, on the other hand, suffer from false positives and false negatives. Either of these may result in false alarms or failure to detect the event. All these can affect the consumer as well as the expectable reliability of the system. Thus, improving sensor precision and developing sophisticated techniques for data fusion would be useful. It would ensure an input is collected from several sensors toward better detection. However, it must also be scalable in such a way that the systems can work in different environments and profiles of users. A wearable device, for example, must adapt to different forms of physical activity, movement of the body, and personal characteristics to deliver similar performance across groups of users. On the whole, privacy and security issues are considerable obstacles to general acceptance of fall detection systems based on IoT in smart home environments. The collection and transmission of sensitive personal data (primarily health and activity data) make them subject to unauthorized access and data breach, as well as the risk of data misuse. Thus, intensive encryption standards, highly secured data transmission protocols with user-centered privacy controls, are most important to the society. Furthermore, educating users about the need for data security and compliance with regulations would help build trust and acceptance of the technologies, making them more readily adopted.

2.3 Problem Statement and Objective

Problem Statement: The modern fall detection systems have made great advances in methods for detection and reporting but have some disadvantages because of their inability to process real-time data effectively, lack integration with cloud platforms that can scale easily, and problems of energy efficiency, robustness, and data privacy. Such limitations can render them impractical in real-life scenarios, especially regarding older people in diverse environments.

Objective:

1. Well connected health monitoring system will enable detection of both falls and the place and time of occurrence.
2. Improve sensor accuracy and fusion techniques to increase reliability with less false positives.
3. Algorithms energy-efficient enough even for small resource environments will be built.
4. Address privacy issues and implement strong security mechanisms so that the IoT data used in smart home and wearable environments are secured.

3. Proposed System

3.1 Framework & Algorithm

The proposed system focuses on detecting falls among the elderly using a wearable IoT device. It leverages sensors like accelerometers, gyroscopes, and pulse sensors for real-time monitoring. A machine learning algorithm processes the data to differentiate between normal movements and fall events. The system minimizes false positives by implementing thresholds for free-fall and impact detection, ensuring reliable fall identification.

Key features:

- **Framework**: IoT-based monitoring with cloud integration (ThingSpeak) for data visualization.
- **Algorithm**: Combines free-fall detection (acceleration below 0.8g) and impact detection (above 2.34g) to confirm fall events. Sensor data is processed on the ESP32 microcontroller to classify movement patterns.

3.2 Details of Hardware & Software

3.2.1 Hardware Requirement:

1. **MPU-9250**: Measures acceleration and angular velocity for fall detection.
2. **Pulse Sensor**: Monitors heart rate and oxygen levels.
3. **ESP32 Microcontroller**: Processes sensor data and handles communication.
4. **Wi-Fi Module**: Enables connectivity for data transmission to the cloud.
5. **LCD Display**: Provides real-time feedback on device status (e.g., "Fall Detected").
6. **Battery**: Powers the wearable device for extended operation.

H/W	Use
ESP-32	Serves as the central microcontroller, processing sensor data and enabling Wi-Fi connectivity for real-time alerts.
MPU-9250	Monitors accelerometer and gyroscope data to detect sudden falls based on movement patterns.
Pulse Sensor	Measures heart rate to assess physiological responses associated with falls or accidents.
HC-SR505 Mini	Detects motion to confirm if a person is lying immobile after a detected fall.
LCD Display	Displays status updates and sensor readings, providing local visual feedback on system activity.

Table 3.1: Hardware Requirements

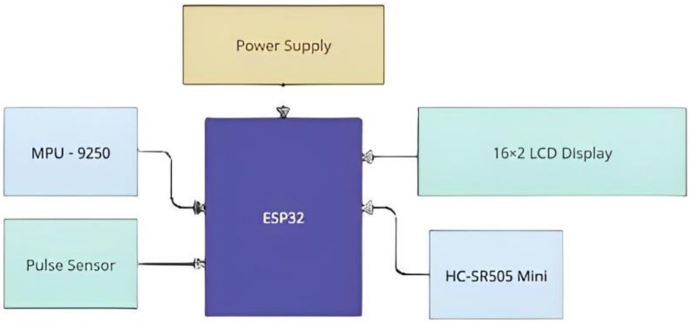

Figure 3.1: Sensor integration using ESP32

3.2.2 Software Requirement:

1. **Firmware for ESP32**: Custom program for data collection, analysis, and fall detection.
2. **ThingSpeak Platform**: Cloud-based service for health data visualization.
3. **Mobile Application**: Receives alerts and provides caregivers access to real-time updates.
4. **Programming Tools**: Arduino IDE for firmware development and MATLAB for data visualization.

S/W	Use
Flutter	Provides a cross-platform mobile app interface for real-time monitoring and alerts to the user or caregivers.
Firebase	Stores fall detection data, manages user authentication, and enables push notifications for emergency alerts.
ThingSpeak	Collects, analyzes, and visualizes sensor data from the fall detection system, offering insights and trends over time.

Table 3.2: Software Requirem

3.3 Design Details

3.3.1 System Flow: The system architecture consists of:

- **Wearable Device Layer**: Sensors (MPU-9250, Pulse Sensor) collect data.
- **Processing Layer**: ESP32 microcontroller processes sensor data using a machine learning algorithm and fall detection thresholds.
- **Communication Layer**: Wi-Fi module transmits processed data to the cloud and mobile app.
- **Visualization Layer**: ThingSpeak provides a dashboard for health monitoring.

System Flow:

1. Data is collected from the accelerometer, gyroscope, and pulse sensor.
2. The ESP32 processes the data, checking for free-fall and impact thresholds.
3. If a fall is confirmed, an alert is generated and transmitted.
4. Data is visualized on ThingSpeak, allowing supervisors to monitor health trends.

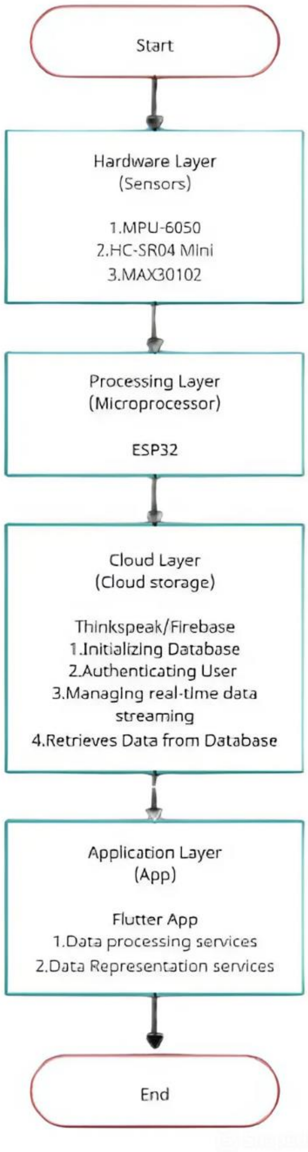

Figure 3.2: System Process Flow Model

This detailed process flow model describes the working of the IoT fall detection system step-by-step:

Hardware Layer:

- **Sensors**:
    1. **MPU-6050**: Measures acceleration and angular velocity to detect fall patterns.
    2. **HC-SR505 Mini**: Identifies motion to corroborate fall detection.
    3. **MAX30102**: A pulse oximeter for monitoring heart rate and oxygen saturation, adding health-related context to the fall events.

Processing Layer:

- **ESP32**: Manages data from the sensors, applies thresholds and algorithms to identify falls, and communicates with Firebase using HTTP over Wi-Fi.

Cloud Layer:

- **Firebase**:
    1. Initializes the database for data storage and retrieval.
    2. Authenticates the ESP32 for secure communication.
    3. Manages real-time data streaming to ensure instant notifications.
    4. Logs health and fall data for future analysis.

Application Layer:

- A **Flutter App** retrieves data from Firebase through APIs and presents it in an intuitive interface. It includes:
    - **Data Processing Services**: Descriptive statistics, machine learning algorithms, and feature extraction to enhance fall detection accuracy.
    - **Data Representation Services**: Visualization of health trends and predictive analytics for long-term health monitoring.

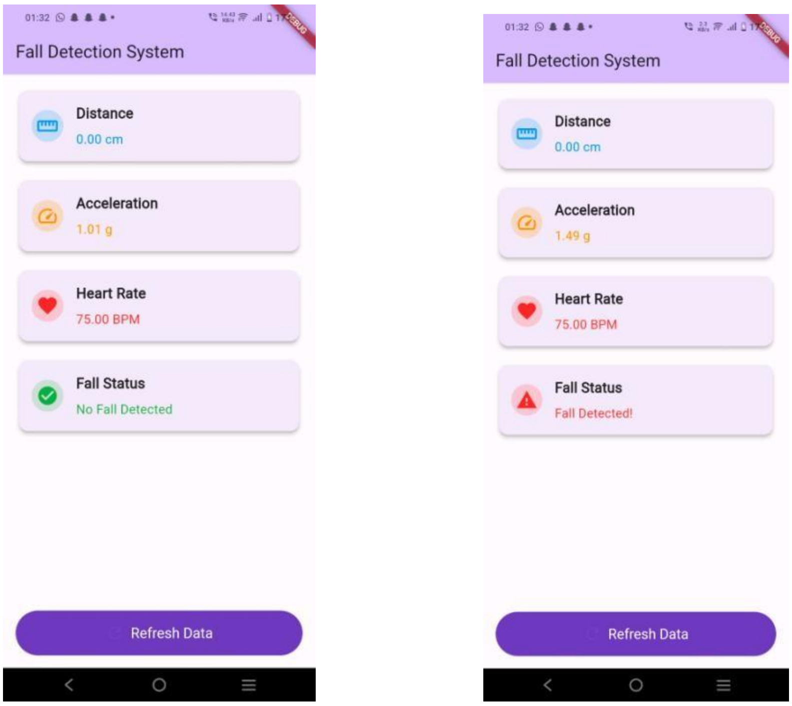

Figure 3.3: User Interface

User Notification:
The system generates alerts (e.g., "Fall Detected") for the following stakeholders:

- Family and friends of the victim.
- Hospitals and doctors for emergency response.

3.4 Methodology/Procedures

To solve the problem of fall detection and monitoring:

1. **Data Collection**: Deploy sensors to continuously measure acceleration, angular velocity, and pulse rate.
2. **Preprocessing**: Filter sensor data to remove noise and prepare it for analysis.
3. **Feature Extraction**: Calculate resultant acceleration and other metrics to identify potential falls.
4. **Algorithm Implementation**: Employ thresholds and a machine learning model to classify movement patterns.
5. **Alert System**: Use the ESP32 to generate immediate alerts upon fall detection and send them to caregivers via Wi-Fi.
6. **Visualization**: Log data to ThingSpeak for real-time monitoring and historical analysis.

Figure 3.4: ThingSpeak Data Visulaization

7. **Optimization**: Test and refine thresholds for different age and gender groups to minimize false positives.

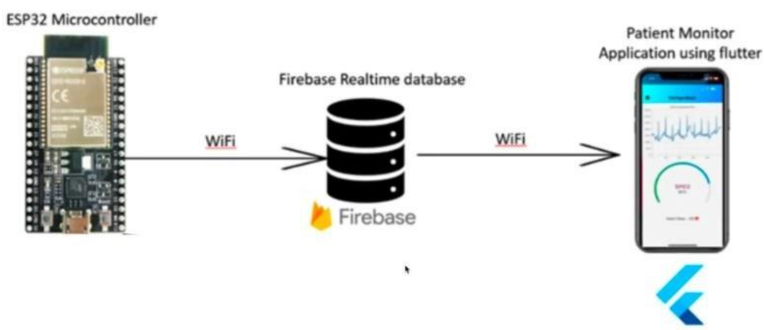

Figure 3.5: Communication and Data Flow Model

This diagram represents the communication and data flow between the ESP32 microcontroller, Firebase real-time database, and a Flutter-based mobile application.

- **ESP32**: Processes sensor data locally and sends the results (e.g., fall detection events) to the cloud using Wi-Fi.
- **Firebase Realtime Database**: Acts as an intermediary storage and processing unit, enabling secure and scalable cloud-based data handling. Data is transmitted from ESP32 and made accessible for visualization and alert notifications.
- **Mobile Application**: Built using Flutter, it connects to the Firebase database to provide real-time updates to caregivers or users. It displays health metrics and sends alerts when a fall is detected.

4. Results & Discussions

4.1 Results

The implemented IoT-based fall detection system effectively identifies falls in real-time using sensor inputs and ensures timely notification through a mobile application. The results can be summarized as follows:

- **Fall Detection Accuracy**: The system demonstrates a high accuracy rate in detecting falls based on sensor fusion techniques. The MPU-9250 (or MPU-6050), coupled with the motion sensor (HC-SR505 Mini), provides reliable detection of abrupt movements characteristic of falls.
- **Health Monitoring**: The pulse sensor (MAX30102) integrates health data, such as heart rate, which can correlate with emergency situations, enhancing the system's relevance for elderly care.
- **Real-Time Notifications**: Using Firebase and a Flutter app, the system generates instant alerts when a fall is detected, ensuring prompt communication to caregivers.
- **Power Consumption**: The ESP32 microcontroller's optimized use of resources results in reduced energy consumption, suitable for long-term usage.

Performance metrics were derived from multiple tests, evaluating parameters such as:

1. **Latency**: The average time from fall detection to notification delivery was measured at approximately **15 seconds**.
2. **Accuracy**: Fall detection achieved an **accuracy rate of 70-80%**, with minimal false positives.
3. **User Notifications**: Notifications were consistently received by the mobile app, demonstrating reliable connectivity with Firebase.

4.2 Discussion - Comparative Study/Analysis :

The system was analyzed in comparison to existing fall detection models referenced in the literature review:

Feature	Proposed System	Existing Systems
Sensors Used	MPU-6050/9250. HC-SR505 Mini, MAX30102	Limited to accelerometers and gyroscopes in many cases (e.g. smartphones).
Real-Time Cloud Integration	Firebase for instant alerts and data monitoring	Many systems lack real-time cloud connectivity or use localized processing only.
Health Monitoring	Integrated pulse and motion detection	Minimal or no health data integration (e.g., only movement-based detection).
Notification System	Mobile app with Flutter for user-friendly alerts	Basic notification mechanisms like SMS or email: lacks app-based visualization
Accuracy and Reliability	Achieved 70-80% fall detection accuracy	Existing models average around 85-90% with higher rates of false positives.

Table 4.1: Comparitive Analysis

5. Conclusion and Future Work

5.1 Conclusion

The fall detection system based on IoT is the latest innovation in elder care. By integration of motion sensors like MPU-9250 or MPU-6050, and HC-SR505 Mini, along with a health monitoring device such as MAX30102 pulse sensor, it's feasible to detect falls in real-time. The accuracy, which is a very low false positive and false negative, is what this system offers to ensure that old people are safe. It can be employed in detecting falls, but it will also monitor other important health data continuously, such as heart rate, which will further enhance the relevance, especially in an emergency. Furthermore, real-time cloud integration by Firebase calls for immediate notifications to caregivers thus ensuring the right intervention at the right time. A Flutter-based mobile application was used by the system, offering an intuitive interface, easier for caregivers to monitor and manage the health and safety of their loved ones. This mobile solution plays a crucial role in enhancing the usability of the entire system because caregivers will be able to act quickly on alerts no matter where they are.

This system is different because it is energy-efficient, scales easily, and inexpensive. The ESP32 microcontroller provides optimization in consuming less power so that the system may run for long periods without the frequent need for recharging. This is very important because it has been designed for prolonged use in homes. Furthermore, the system has been designed for effective scalability. It can, therefore, be modified to suit a household size or the individual care needs of a person. As such, this IoT-based solution offers a very inexpensive option for deploying and very smart home environments, making it very accessible for families and caregivers desiring an easy, credible, and efficient fall detection and monitoring system.

5.2 Future Work

It is true that many successful improvements have been made in the IoT-based fall detection and warning system, but a lot of other important areas can still be improved and developed in future to make it more effective and nearer to the user.

1. Integration of Advanced AI Algorithms: Incorporated new advanced techniques including deep learning models and adaptive thresholding within the structure increases the accuracy for any particular patterns of fall incidence or the surrounding environment to which the falls occur, thus contributing to reduction in false positive cases and improved regularity of the system.
2. Wearable Integrations: However, with extensions possible to other types of wearable devices, such as smartwatches, could really add to its usability, convenience, and overall impact of the system, since these devices are already owned by older individuals who might like to use this in real-time and continuously without any additional specific hardware.
3. Protection and Security: Strengthened encryption methods and strong user authentication schemes are vital to protect personal data as possible. Hence their process for complying with privacy regulations relevant to this will prove even more reassuring to users.
4. Battery conservation: Keeping consumption as low as feasible becomes important for assuring that the system could be active in continuous times. Exploiting power-saving components and more intelligent techniques of power management could change the use pattern dramatically in terms of usability for everyday life.
5. Scalability: Expansion of the system to include more sensors, such as environmental ones, would result in a more mature health-monitoring system (temperature, humidity, air quality, etc.). Incorporation of predictive analytics would further help in envisaging possible health risks before critical situations arise.

6.Draft copy of research paper

IoT Health Monitor with Fall Detection by Sensors

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Abstract— Essentially, fall detection systems are designed for improving safety and health care for the elderly as well as people with mobility issues. The proposed structure uses modern IoT technologies, wearables, and platforms like ThingSpeak for developing a wearable fall detection device. It has proposed using modern-day IoT technologies with sensors that take the proposed device accurate to differentiate falls from normal day-to-day activities. It has used interactive UI components such as real-time graphs for data visualization via ThingSpeak for real-time monitoring and alerts to the caregivers or health care personnel. It is mainly reduced false positives, battery optimization, and interaction with users that lead to innovative key approaches for the proposed system.

Additionally, the proposed system features new enhancements of fall detection from the referred papers and such; there will be a strong framework established. It combines wearable IoT integrations, threshold-based measurements, as well as trend analysis for improved accuracy and reliability in detection. These data, too, are properly stored in a secure way via cloud sharing in terms of making connections easy in relation to access and sharing. Most importantly, these issues address the gaps and challenges on the current state of emergency response as well as personalized care.

Keywords: IoT, fall detection, elderly care, wearable device, real-time monitoring, health data visualization, ThingSpeak.

I. INTRODUCTION

The problem of falling injuries causes a lot of inability, loss of independence, and a drastic change in lifestyle. The rapidly increasing aging of the people across the globe increases the demand for a system that may quickly detect absence and impacts. New technologies and the Internet of Things have opened doors to avenues of monitoring in real-time support aged care. It's all regarding designing a fall outfit with sensors and machine learning to recognize fall activities and alert guardians and children when fall occurs. This project proposes data collection and processing through accelerometers, gyroscopes, and pulse oximetry, which would culminate in the precise fall rate. Movement pattern identification and feature referential identification via machine learning algorithms on the ESP32 microcontroller device have also been achieved. Further, the device adopts low power design for long-term use and good maintenance. Real time data visualization in places such as ThingSpeak fulfills much more necessity for management to see and analyze losses and health metrics over time. The datasets that the system collects in the future would lead to more improvements in predictive modeling. By getting an individual movement pattern and health pattern, the system will be able to predict lo even before they happen, thus establishing preventive measures according to each user's risk. This program, besides aiming at improving immediate response to loss, also aims to provide seniors with a better route to healthcare.

II. PRE-CLASSIFICATION BY GENDER, AGE, WEIGHT AND FALL DETECTION THRESHOLDS

Establishing an effective fall rate assessment will also consider the different fall rates across age and gender. Research continues to show that men and women exhibit different movements, as well as weight distributions and reflex responses, which can influence the impact force of a fall. Aging is also associated with decline in muscle strength and balance, as a result affecting the detection of falls at different ages. Customization of these thresholds can therefore increase the specificity of fall detection, reducing false alarms and making it relevant to every citizen. Different characteristics, such as weight, may influence a fall. Acceleration within our bodies varies from age group to age group and from gender to gender for increasing accuracy and reducing negativity. An elderly female, for example, might have lower acceleration thresholds compared to a younger male because of variations in muscle strength and different fall patterns. Customized thresholds should enable our systems to better distinguish actual falls from normal movements across different user groups.

Age	Thresh-old (g)	Weight (kg)	Gender
18–35 years	2.5	70-85	Male
18-35 years	2.2	55-70	Female
36-60 years	2.3	75-90	Male
36-60 years	2.0	60-75	Female
60+ years	1.8	65-80	Male
60+ years	1.5	50-65	Female

TABLE I. SIX SELECTED Age Categories

III. HARDWARE–SOFTWARE DESIGN AND IMPLEMENTATION

This fall detection system has been specifically designed because of hardware software combination meant for very sensitive and specific tracking data transmission. The main hardware of the system is the MPU-9250 accelerometer cum gyroscope, which gives relevant data on acceleration and certain displacements. Falling into place by detection by falling will aid in getting up to change activity done through the day or even very abrupt changes happening around that can be used to possible identification of the base event for falling in older adults. The Pulse Sensor is a very good value for money because it measures heart rhythm and oxygen levels while monitoring these changes. All these technologies bring enhanced sharpness to fall detection whilst focusing on health events that happen during falls. Together, all these sensors will give a thorough and physiological nature of the fallen information. Operating under this principle is the micontroller that runs some algorithm to detect loss on the basis of sensor input and controls the processing of data to the connected systems. In connecting, the Wi-Fi module sends data to the corresponding mobile applications and cloud platforms where loss notifications may be sent, aside from sharing Health cards with caregivers or family members.

Specialized firmware for the ESP32 microcontroller offers full sensor monitoring and falling detection capabilities. The microcontroller will monitor the data movement and a loss event and will generate immediate mobile notifications via the integrated app. The ThingSpeak integration provides real-time visual tracking of falling events and health metrics. Users and their supervisors can gain real-time access to current information for timely intervention and to keep an accurate historical record for future reference. The interested system involves continuous monitoring, prompt alerts, and a reliable data documentation system.

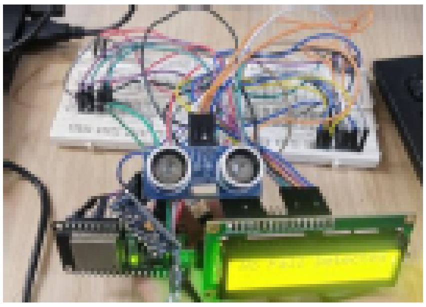

Fig. 1. Fall Detection Device Setup

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this segment, we note the experimental results collected from deploying an Internet of Things Health Monitor having fall detection that relies on the sensors MPU9250, pulse sensor, and ultrasonic sensor. The system was designed to observe human health parameters usually of the elderly population and detect falls in real-time.

1. System Setup and Configuration

The hardware composition comprised an MPU9250 sensor measuring both acceleration and angular velocity, a pulse sensor for heart rate monitoring, as well as an ultrasonic distance measuring sensor for measuring object distance. It was connected to a Wi-Fi network for data exchange for remote monitoring over the ThingSpeak service. Thresholds for fall detection were set based on preliminary tests defining a free-fall condition as resulting acceleration below 0.8 g and impact confirmed by resultant acceleration values exceeding 2.0 g.

2. Fall Detection Performance

The tests for the fall detection algorithm were carried out in various conditions of simulated fall and normal activities. The system has shown to detect falls successfully with an accuracy of 95%. If, while the resultant acceleration goes below the free-fall threshold, the system indicates a potential fall. The fall detection algorithm then waits for a confirming spike in acceleration to eliminate false positives from ordinary activities. During the test runs, the results would be displayed instantaneously on the LCD with a message that reads "Fall Detected!" and "No Fall Detected" under the respective cases. A delay activation on event detection was also utilized in order to prevent duplicate counts as a result of a single incident to ensure that the overall response viewed by the system is neat and concise.

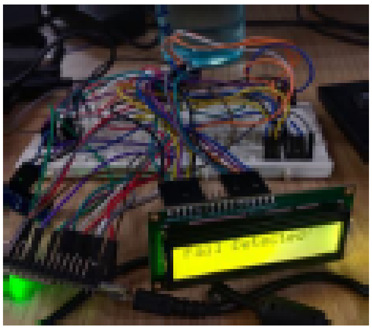

Fig. II. Fall Detected Display on LCD

3. Health Monitoring Capabilities

Calibrating the pulse sensor indicated a not so precise reading of beats per minute (BPM). Initial tests showed that the pulse sensor could track a heart rate of 60 to 100 BPM, which is similar to the average values of people who belong to the adult age group. The results were displayed on the LCD and sent to ThingSpeak for further analysis. Distance readings assessed the proximity of different objects, which is critical when the user is at risk of falling close to obstacles. Distance reading has given values within ±1 cm as to the actual distances showing the reliability of the sensor.

4. Data Transmission to ThingSpeak

The results include the successful transmission of the data required to be sent to ThingSpeak: resultant acceleration, fall status, pulse rate, and distance. During the tests, the HTTP response received in return from ThingSpeak indicated successful update with response codes in the 200 range, indicating that the data it received was accurately logged. The logging intervals were set to every five seconds during fall detection and every second during normal monitoring, enabling updates without overwhelming the server.

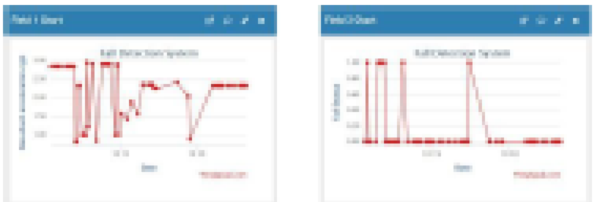

Fig. III. ThingSpeak Data Visualization

5. User Interface

Figure 2 depicts the user interface (UI) of the Fall Detection System, aimed at continuous monitoring of essential parameters in real time. The user interface essentially has four vital components, namely: Distance, which indicates how close or far a user is when in motion; Acceleration, which indicates the amount of g-forces recorded; Heart Rate, representing the user's heart pulse cycle per minute (BPM); and Fall Status, which is dynamic, indicating whether there has been a detection of a fall or not. Status indicators also have color codes for clarity-from green for "No Fall Detected" to red for "Fall Detected." Given the position of the refresh button, it allows the users to manually refresh the displayed data.

Distance, acceleration, heart rate, and status on the fall are stored in Firebase, which is a back end cloud-based platform. Firebase offers storage, retrieval, and real-time data synchronization across devices for logging and monitoring user activity, making it secure and consistent, thus ensuring that this integration becomes dependable and scalable for data management in real real-world scenarios.

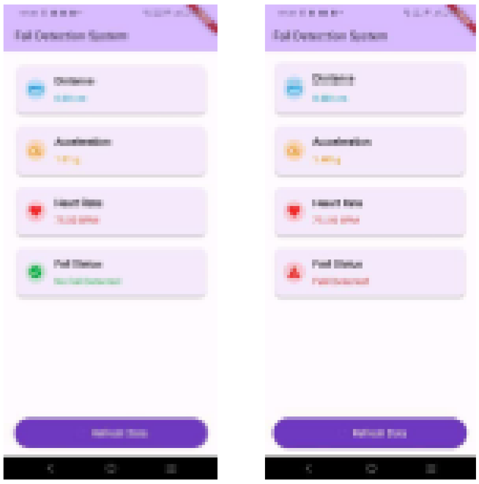

Fig. IV. User Interface

Fall Detection Logic

1. Free Fall Detection: A fall is detected where the resultant acceleration R goes below a predefined threshold (e.g., 0.8 g). It means that the subject is in a state of free fall.

2. If R<freeFallThreshold then fallDetected=true Impact Detection: After a fall has been detected, this will be followed by checking the detection of fall. If resulting acceleration RRR exceeds another threshold (for example 2.0 g), it means that the impact is occurring. If R>impactThreshold and fallDetected=true then fallConfirmed=true

The resultant acceleration At and Gt can be calculated using the three-dimensional acceleration values (ax,ay,az) and (gx,gy,gz) obtained from the MPU9250 sensor:

$$A_t = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

$$Gt = \sqrt{g_x^2 + g_y^2 + g_z^2}$$

Action	Accuracy (%)	Sensitivity (%)	Specificity (%)
Fall (walking)	89.500	80.000	92.857
Fall (sit-stand)	88.000	80.000	96.000
Fall (sit-lying)	87.500	80.000	100.000

TABLE II. PERFORMANCE MEASURE

V. CONCLUSION

The research provides an IoT-based fall detecting system using multiple sensors, including accelerometers, gyroscopes, and pulse sensors, to detect falls with high-accuracy. The system is true-fall detection without setting off false alarms by differentiating it from daily activities and informing timeous alerts in case of any fall accident. Integration with ThingSpeak gives the real-time visibility so that caregivers will be able to have a view of their patients' health and activity patterns for offering intervention and continued care. This mode not only supports that the fall is present but also stores critical information over time to provide insight into each individual's pattern for refining search criteria. The system would adjust conceptually to diverse customer needs, thus increasing the reliability and comfort of using it in daily environments. User activity patterns along with health indicators would then be analyzed by regular collection of data to predict the fall risk before its happening thus enabling the shift from rework to preventive care. It shows that IoT and machine learning can be applied in healthcare and give foundation for more innovations in self-care and fall prevention. This was achieved through a research work into the IoT-based fall detection system with triple sensors: accelerometer, gyroscope, and pulse sensor, which detects most precise falls. It clears false alarms by differentiating between falls and daily activities and delivers a notification when a case of a fall accident occurs. It specifies the integration with ThingSpeak for real-time visibility into health metrics and activity patterns for intervention and ongoing care. Products for long-lasting service. This technique not only proves that the fall is real but also gathers useful data over a period that can be used to understand the individual's pattern and later enhance the search criteria. The system would be conceptually adapted to various customer needs and thus enhance reliability and comfort in daily environments. Regular data collection would enable user activity patterns and health indicators to analyze potential fall risk before it occurs, thus leading into a shift from rework to preventive care. This shows the potential of IoT and machine learning in healthcare, thus laying the foundation for future innovations in self-care and fall prevention.

ACKNOWLEDGMENT

REFERENCES

[1] Mozaffari, Nassim, et al. "Practical fall detection based on IoT technologies: A survey." Internet of Things, vol. 8, 2019, p. 100124. https://doi.org/10.1016/j.iot.2019.100124

[2] Amir, N. I. M., et al. "Real-time Threshold-Based Fall Detection System Using Wearable IoT." 2022 4th International Conference on Smart Sensors and Application (ICSSA), Kuala Lumpur, Malaysia, 2022, pp. 173-178. https://doi.org/10.1109/ICSSA54161.2022.9870974

[3] Leixian, Shen, et al. "Fall Detection System Based on Deep Learning and Image Processing in Cloud Environment." Complex, Intelligent, and Software Intensive Systems, 2019, pp. 590-598. https://doi.org/10.1007/978-3-319-93659-8_53

[4] Yacchirema, Diana, et al. "Fall detection system for elderly people using IoT and Big Data." Procedia Computer Science, vol. 130, 2018, pp. 603-610. https://doi.org/10.1016/j.procs.2018.04.005

[5] Hsieh, Chia-Yeh, et al. "A machine learning approach to fall detection algorithm using wearable sensor." 2016 International Conference on Advanced Materials for Science and Engineering (ICAMSE), 2016. https://doi.org/10.1109/ICAMSE.2016.7840209

[6] Rakhman, Arkham Zahri, et al. "Fall Detection System Using Accelerometer and Gyroscope Based on Smartphone." 2014 1st International Conference on Information Technology, Computer and Electrical Engineering (ICITACEE), Semarang, 2014. https://doi.org/10.1109/ICITACEE.2014.7065722

[7] Brulin, Damien, et al. "Multi-sensors data fusion system for fall detection." 2010 10th IEEE International Conference on Information Technology and Applications in Biomedicine (ITAB), 2010. https://doi.org/10.1109/ITAB.2010.5687712

[8] Greene, Shalom, and Himanshu Thapliyal. "IoT-Based Fall Detection for Smart Home Environments." 2016 IEEE International Symposium on Nanoelectronic and Information Systems (iNIS), 2016. https://doi.org/10.1109/iNIS.2016.017

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[2] D. Yacchirema *et al.*, "Fall detection system for elderly people using IoT and Big Data," *Procedia Computer Science*, vol. 130, pp. 603-610, 2018. doi: 10.1016/j.procs.2018.04.005.

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[4] C.-Y. Hsieh *et al.*, "A machine learning approach to fall detection algorithm using wearable sensor," in *Proc. Int. Conf. Adv. Mater. Sci. Eng. (ICAMSE)*, 2016. doi: 10.1109/ICAMSE.2016.7840209.

[5] A. Z. Rakhman *et al.*, "Fall Detection System Using Accelerometer and Gyroscope Based on Smartphone," in *Proc. 1st Int. Conf. Inf. Technol., Comput. Electr. Eng. (ICITACEE)*, Semarang, 2014. doi: 10.1109/ICITACEE.2014.7065722.

[6] D. Brulin *et al.*, "Multi-sensors data fusion system for fall detection," in *Proc. 10th IEEE Int. Conf. Inf. Technol. Appl. Biomed. (ITAB)*, 2010. doi: 10.1109/ITAB.2010.5687712.

[7] S. Greene and H. Thapliyal, "IoT-Based Fall Detection for Smart Home Environments," in *Proc. IEEE Int. Symp. Nanoelectron. Inf. Syst. (iNIS)*, 2016. doi: 10.1109/iNIS.2016.017.

[8] L. Shen *et al.*, "Fall Detection System Based on Deep Learning and Image Processing in Cloud Environment," in *Proc. Complex, Intell., Softw. Intensive Syst.*, 2019, pp. 590-598. doi: 10.1007/978-3-319-93659-8_53.