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IoT-Based Smart Walking Assistant for Fall Detection in the Elderly

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Abstract - *Falls are a major health risk for elderly individuals, leading to injuries, hospitalization, and reduced independence. Traditional walkers provide physical support but lack intelligence for fall monitoring and alerting. This work proposes an **IoT-enabled smart walking assistant** equipped with accelerometer– gyroscope sensors for fall detection, along with heart rate, SpO_2, body temperature, obstacle detection, and live caregiver alerts. The system uses ESP32 and LoRa communication to support **real-time tracking and emergency notification**, aiming to reduce injury severity and improve elderly safety.*

Key Words: Smart walking assistant, elderly safety, internet of things, fall prevention, physiological sensors.

1.INTRODUCTION

The global elderly population is growing rapidly, with the number of individuals aged 60 and above projected to reach 2.1 billion by 2050 [1]. While increased longevity is a positive societal achievement, it also presents significant challenges, especially in the realm of healthcare. Among these challenges, falls represent one of the most severe risks for the elderly. Statistics show that one in ten falls leads to an injury that causes older adults to limit their activities for at least a day or seek medical attention [2].

The global elderly population (60+ years) is expected to reach **2.1 billion by 2050**, increasing the risk and impact of falls. One in ten falls results in injury requiring medical support. Wearable and ambient systems have helped, but discomfort, privacy issues, and indoor limitations restrict usability. IoT-based health solutions enable **continuous remote monitoring** and timely alerts. This paper presents a smart walking assistant that improves mobility, detects Falls instantly, and notifies caregivers through a mobile app.

2. LITERATURE REVIEW

The rapid advancement of fall detection technologies has led to a wide array of methods aimed at enhancing elderly safety and reducing healthcare burdens. The literature generally categorizes fall detection methods into many types [3], [4], [5]. Each method offers unique benefits and faces specific challenges, as discussed below. Fall-detection systems employ several methods, each with distinct advantages and limitations. Wearable sensor–based approaches offer high accuracy and enable precise motion tracking, but they often face challenges related to user compliance. Ambient sensor systems eliminate the need for wearable devices, making them more comfortable for users; however, they are typically limited to indoor environments and raise privacy concerns. Vision-based methods provide very accurate pose estimation and fall recognition, yet they require costly camera setups and also involve significant privacy issues. More recently, machine learning combined with IoT has enabled intelligent fall prediction and faster emergency response by automatically sending alerts to caregivers, although this approach relies heavily on cloud infrastructure and large volumes of data. While machine learning significantly improves motion classification accuracy, its performance strongly depends on the diversity and quality of the training dataset.

2.1 Wearable sensor- based fall detection.

Wearable sensors such as accelerometers and gyroscopes are the most commonly used tools for fall detection due to Their portability and ability to capture real-time motion data [6]–[11]. Studies show that combining these sensors enables accurate discrimination between falls and normal movements. For example, Wu et al. [12] achieved high accuracy using quaternion-based motion analysis, while Siregar et al. [13] reported 93.75% accuracy with an Arduino-based alerting system. Ahn et al. [14] demonstrated 100% sensitivity in pre-impact fall detection using angular velocity and trunk inclination.

Machine learning techniques further improve performance. Albert et al. [18] achieved 98% fall-type classification accuracy using SVM and logistic regression. Kalman filtering enhances signal reliability by reducing noise [15]. Rakhmani et al. [20] obtained 93.3% accuracy using smartphone-based classifiers, and ensemble/data-fusion methods also help minimize false alarms [16]. However, despite high accuracy, user compliance remains a challenge as these systems require continuous wearing for reliable monitoring.

2.2 Ambient sensor-based fall detection.

Ambient fall detection systems utilize environmental sensors such as pressure mats, microphones, and infrared or proximity sensors to detect fall events without requiring users to wear devices [17], [21]. Vallabh and Malekian [8] showed that these systems can differentiate falls from regular daily activities, but they are limited by high installation and maintenance costs and lack portability. Mozaffari et al. [22] demonstrated that vibration and sound-based sensing can trigger alerts via IoT networks, making them suitable mainly for indoor environments.

Key advantages include non-intrusive monitoring and zero user interaction. However, they are prone to high false positives caused by pets, moving objects, or common household activities. To improve reliability, Ambient Assisted Living (AAL) systems integrate multiple environmental sensors for continuous monitoring and faster caregiver response [23]. Despite improvements, outdoor usability and accuracy remain ongoing challenges.

2.3 Vision-based fall detection.

Vision-based fall detection relies on cameras and computer vision algorithms to analyze human posture and detect abnormal movements [24]. Due to advances in artificial neural networks and CNN-based pose recognition, these systems offer high detection accuracy even under partial occlusions. Mrozek et al. [25] demonstrated that edge- cloud processing enables real-time fall identification while reducing local computational load.

However, continuous video monitoring raises privacy concerns, and performance can degrade under poor lighting or camera angle variations. Additionally, limited dataset diversity affects robustness in real-world environments. While primarily suitable for controlled indoor areas, hybrid solutions that combine camera data with wearable or ambient sensors can improve accuracy and reliability in dynamic settings [24].

2.4 Machine learning and IoT integration in fall detection.

Machine learning has significantly improved the performance of wearable and vision-based fall detection systems by identifying complex patterns that threshold- based methods often misclassify [19], [22], [25],[28]. Rakhmani et al. [20] showed that decision trees and neural networks applied to smartphone sensor data can reliably distinguish falls from daily activities with reduced false alarms. Integrating machine learning with IoT further enhances fall detection efficiency. Wu et al. [13] proposed a cloud- connected system combining wearable sensors and analytics for real-time monitoring. IoT frameworks using **edge–fog–cloud layers** support scalable data processing, reduce latency, and minimize network load, enabling faster and more accurate emergency response [22].

3. MATERIALS AND METHODS

The smart walking assistant is designed as an IoT-based safety system that continuously monitors the elderly user's health and movement while detecting hazards and falls.

3.1 System architecture

The system incorporates sensors to measure heart rate, SpO_2, body temperature, and motion across X, Y, and Z axes for fall detection. A distance sensor identifies nearby obstacles and triggers audible warnings for safe navigation. During normal operation, the device displays real-time health data, while emergencies automatically prompt alerts to caregivers. If abnormal vital signs or a fall is detected and the user does not respond, the system immediately sends an alert to caregivers containing the event time, user location, and last recorded posture. This ensures **quick assistance** and reduces risks from delayed intervention.

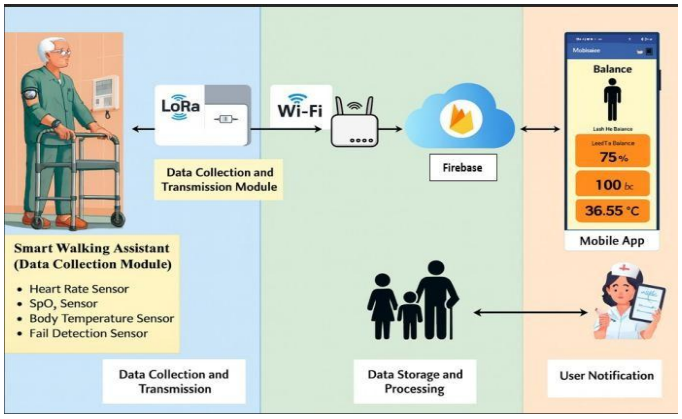

Fig. 1. The architecture of the smart walking assistant system

3.2 System components

The smart walking assistant consists of two modules:
(1) a data collection module and
(2) a data reception and transmission module, enabling continuous monitoring and real-time alerts.

Data Collection Module, is built around an ESP32 microcontroller, which reads physiological and environmental data from multiple sensors and displays the information on a TFT LCD screen. It includes a MAX30102 sensor for heart rate and SpO_2 measurement, a GY-906 infrared sensor for non-contact body temperature monitoring, a VL53L0X distance sensor for obstacle detection, and an MPU6050 accelerometer–gyroscope for distinguishing routine movements from falls. In emergencies, a PAM8403-powered speaker provides audible alerts. The module also integrates a GY-NEO- 6MV2 GPS for transmitting the user's precise location when a fall occurs. All collected data are sent to the receiver module using a LoRa SX1278 wireless module, ensuring long-range, low-power communication for efficient remote caregiver monitoring and assistance.

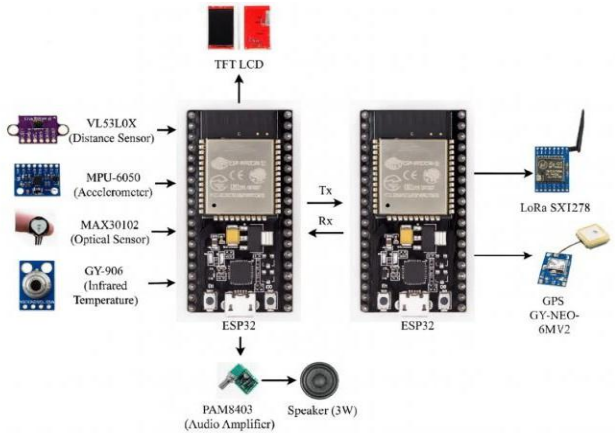

Fig. 2. The data collection module

The data reception and transmission module, based on an ESP32 controller, receives sensor data via a LoRa receiver, processes it, and uploads it to the Firebase cloud using Wi-Fi for real-time monitoring. Caregivers can view vital signs, fall alerts, and the user's location through a mobile app, ensuring rapid response during emergencies. The system uses a three-tier IoT architecture with dual ESP32 units handling sensing and cloud communication in parallel. FreeRTOS scheduling enables continuous sensor monitoring and communication, while a decision-tree algorithm classifies fall events. A 10,000 mAh rechargeable battery provides up to 120 hours of operation, supported by low-battery alerts and visual indicators. The modular design allows easy component replacement, and the user interface is optimized with large displays and simple controls for elderly users, requiring minimal technical involvement.

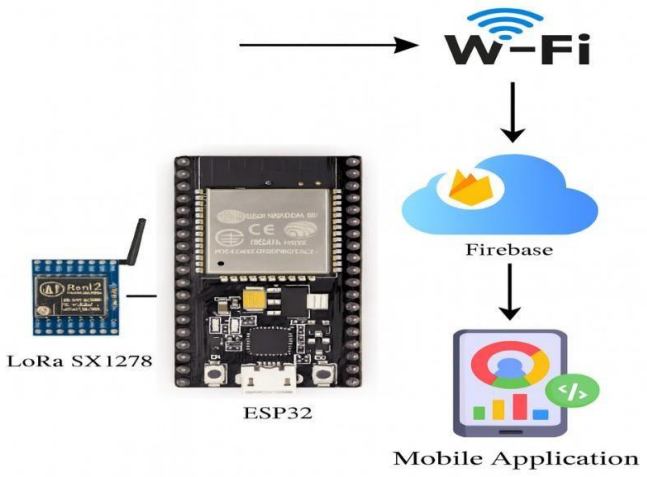

Fig. 3. Data reception and database transmission module

3.3 Hardware design and implementation

The hardware setup uses two compact PCBs: one for data collection and one for data reception and transmission. These modules are enclosed in a lightweight control box (12 × 17.5 × 5.25 cm) that mounts directly onto a walking aid, ensuring easy installation and usability for elderly individuals.

Figure 4 shows the internal/external arrangement of the data collection module and the design of the receiver unit, while Figure 5 displays the completed control boxes with power and Wi-Fi status indicators integrated into the walking assistant. This streamlined layout supports reliable communication between modules and seamless real-world usage.

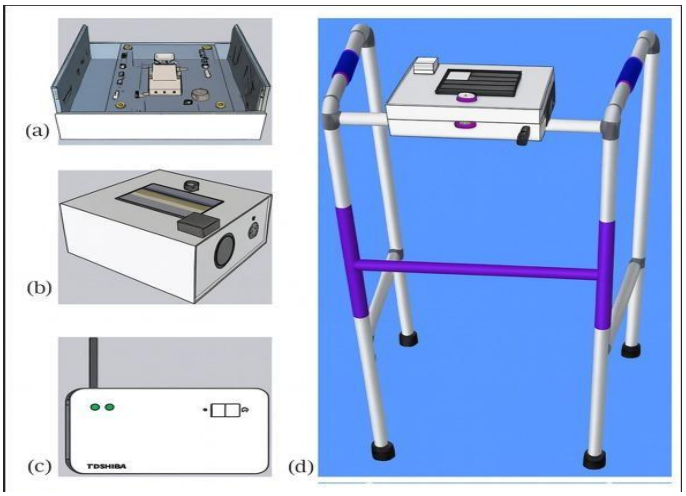

Fig. 4. Hardware design and integration of the smart walking assistant system: (a, b) internal and external layout of the data collection module,

(c) designed box of data reception and transmission module, and
(d) Integration with walking aid.

3.4 Data processing and analysis

The ESP32 microcontroller continuously analyzes sensor data to detect health abnormalities and fall events in real time. Heart rate, SpO_2, and body temperature are compared against predefined safe thresholds tailored for elderly users, triggering alerts when abnormal values are detected. Fall detection uses motion features from the MPU6050—acceleration and angular velocity—evaluated with threshold rules and a decision-tree classifier to distinguish normal activities from

forward, backward, or lateral falls. When a critical event occurs, the system immediately sends alerts to caregivers via Firebase, including the user's location, time, and last posture, while storing the data for future monitoring and medical analysis.

3.5 Experiment design

The system's performance was evaluated with 10 healthy volunteer students (aged 18–23) under controlled laboratory conditions. Tests were conducted to measure heart rate, SpO_2, body temperature, motion, obstacle detection, and fall detection accuracy. Heart rate and SpO_2 readings were taken while participants remained seated, body temperature was measured from a fixed 10 cm distance, and fall detection was simulated in forward, backward, and lateral directions. Obstacle detection was tested at distances of 300 mm, 500 mm, 700 mm, and 900
mm. Each measurement was calibrated and repeated three times for reliability, and all results were recorded for analysis.

4. RESULTS

4.1 Monitoring of physiological parameters and obstacle detection.

The smart walking assistant was evaluated for its accuracy in measuring key physiological parameters, including heart rate, blood oxygen saturation (SpO_2), and body temperature, as well as its ability to detect obstacles effectively, as shown in Figure 5. Data were collected under controlled laboratory conditions with a sample of 10 young, healthy participants. The average results of these measurements, along with the threshold ranges and observations, are summarized in Table 1.

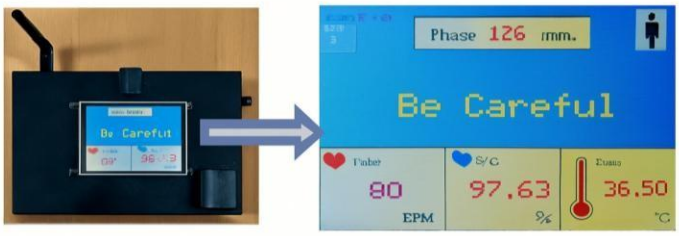

Fig. 5. Results capturing physiological parameters and obstacle detection performance

Table 1. Average results of physiological parameters and obstacle detection measured in 10 participants

Parameter	Average Value	Threshold Range	Observation
Heart Rate(bpm)	78.3	60-100 bpm	Within normal range
Blood Oxygen Saturation	97.3%	>94%	Within normal range
Body Temperature (°C)	36.6	36.1-37.5	Within normal range
Obstacle Detection(mm)	300-900	<900 mm	Within normal range

4.2 Fall detection and emergency alerts

To evaluate the fall detection capabilities of the smart walking assistant, controlled falls were simulated in multiple directions, including forward, backward, and lateral movements. Evaluate fall-detection performance, controlled forward, backward, and lateral fall scenarios were conducted, and the system accurately detected all events using acceleration and angular-velocity data from the MPU6050, triggering immediate alerts. Once a fall was confirmed, the user's posture, time, and GPS location were automatically sent to the mobile app for caregiver response. The Android-based app provides two modes: a normal monitoring view displaying real-time heart rate, SpO_2, and temperature, and a fall-alert view indicating emergency status and location to ensure rapid assistance.

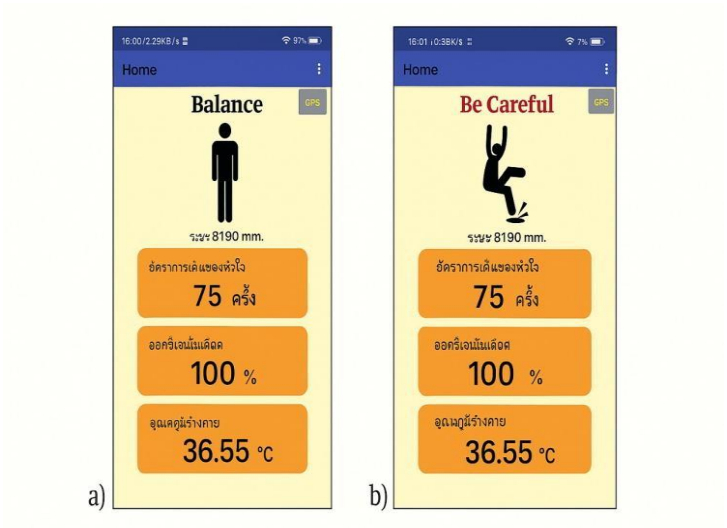

Fig 6. Mobile application interface: (a) Normal status, (b) Fall detection status

5. DISCUSSION

The smart walking assistant provides a more comprehensive solution than existing systems by combining accurate fall detection using the MPU6050 with continuous vital sign monitoring, obstacle avoidance, and real-time caregiver alerts with location tracking via Firebase, improving safety and response time. While this enhances user support compared to prior fall-only or health-only systems, its reliance on fixed thresholds limits personalization, indicating a need for machine-learning- based adaptation in future designs. Practical challenges such as smartphone dependency and alert fatigue must also be addressed through alternative notification channels like SMS or automated calls. The system is cost-effective by potentially reducing fall-related healthcare expenses, but further improvements in data security and large-scale testing with elderly users in real environments are required, as current validation involved only young participants.

6. CONCLUSION

The IoT-based smart walking assistant successfully provides real-time health monitoring, accurate fall detection, and instant caregiver alerts, improving elderly safety and independence. Testing confirmed reliable performance in detecting abnormal conditions and fall events. Future work includes machine-learning integration and real-world evaluation with elderly users to improve adaptability and usability. Overall, the system shows strong potential as an effective assistive technology.

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