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PAPER

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

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ABSTRACT

This study introduces the design, development, and evaluation of a smart walking assistant tailored to enhance the mobility, safety, and independence of elderly individuals. The system integrates an ESP32 microcontroller to interface with multiple sensors, including the MAX30102 for monitoring heart rate and blood oxygen saturation, the GY-906 infrared sensor for body temperature measurements, and the MPU6050 accelerometer and gyroscope for precise motion tracking and fall detection. A compact and modular control unit, seamlessly integrated into the walker, enables real-time data collection and wireless transmission using LoRa and Wi-Fi technologies. This connectivity facilitates the delivery of alerts to caregivers through a user-friendly mobile application. Rigorous testing, including simulated fall scenarios and physiological parameter measurements, validated the system's accuracy, reliability, and responsiveness. The results demonstrated high precision in detecting obstacles, falls, and physiological anomalies, while the system's integration with IoT-based communication platforms ensures timely intervention. The smart walking assistant offers a comprehensive and effective solution, promoting safety and quality of life for elderly users.

KEYWORDS

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].

Falls in older adults often lead to serious injuries, hospitalizations, reduced mobility, and, in severe cases, death. Beyond the physical impact, falls can have

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lasting psychological effects, including fear of falling again, which may lead to decreased independence and social isolation. Moreover, falls place a substantial burden on healthcare systems globally, contributing to rising costs and increased demand for long-term care facilities [3].

In response to these challenges, researchers and engineers have been developing various technological solutions to aid fall prevention and detection. Traditional fall prevention devices, such as walkers and canes, offer physical support but lack the ability to detect falls or alert caregivers in real time. Recent innovations, including wearable sensors and ambient detection systems, have provided some advancements; however, they come with limitations. Wearable sensors, while effective in monitoring physiological signals and movement, may be uncomfortable or cumbersome for elderly individuals to wear consistently. Ambient systems, on the other hand, rely on environmental sensors and cameras, which can raise privacy concerns and are often limited to indoor use. Furthermore, both approaches may fall short in detecting subtle balance issues or pre-fall conditions that could help prevent falls from occurring in the first place.

The integration of the Internet of Things (IoT) in healthcare has opened new pathways to address these limitations by enabling real-time monitoring and caregiver notification systems [4], [5], [6]. An IoT-based smart walking assistant leverages sensors such as accelerometers, gyroscopes, and pressure sensors to continuously monitor the user's movements and detect potential fall risks. This technology can transmit data to connected devices such as smartphones or tablets, providing caregivers with timely alerts and valuable insights into the user's mobility patterns. Real-time monitoring and immediate notifications enable rapid intervention, which can be critical in reducing the consequences of falls. Moreover, IoT-based systems can collect and store data on user activity over time, allowing healthcare providers to analyze patterns and adjust care plans based on individual needs.

This paper presents an IoT-based smart walking assistant designed to prevent falls among the elderly. The system is intended to overcome the limitations of existing fall prevention methods by providing continuous, real-time monitoring and a responsive alert mechanism. Through this innovative approach, the smart walking assistant aims to improve the quality of life for elderly individuals, reduce healthcare burdens, and support aging populations in maintaining independence and safety.

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 [7], [8], [9]. Each method offers unique benefits and faces specific challenges, as discussed below.

2.1 Wearable sensor-based fall detection

Wearable sensors, particularly accelerometers and gyroscopes, are among the most widely used tools in fall detection due to their portability and ability to capture movement data in real time [10], [11], [12], [13], [14], [15]. Studies such as Wu et al. [13] demonstrated that wearable devices combining accelerometers with gyroscopes could effectively differentiate falls from normal activities by analyzing body movements using quaternion algorithms, achieving high accuracy in identifying sudden drops in acceleration typical of falls. Additionally, Siregar et al. [16] implemented a system using Arduino with accelerometers and gyroscopes, reporting an accuracy of 93.75% in fall detection and alerting caregivers immediately. Another study by Ahn et al. [17] explored pre-impact fall detection using inertial sensors, finding that angular velocity and trunk inclination were critical indicators. The study reported 100% sensitivity, underscoring the high potential of these algorithms for real-time fall prevention in elderly care.

The adoption of machine learning techniques has further enhanced the capabilities of wearable sensors. Albert et al. [18] employed support vector machines and logistic regression to classify fall types with 98% accuracy, showing that wearable sensors can capture nuanced fall dynamics when paired with robust algorithms. Kalman filters are also applied to preprocess sensor data, reducing noise and improving reliability, as noted by He et al. [19]. Rakhmani et al. [20] used accelerometer and gyroscope data with machine learning classifiers, achieving 93.3% accuracy in distinguishing falls from normal daily activities. Ensemble-based classifiers and data fusion approaches have also shown promise, combining multiple sensors to improve accuracy and reduce false positives, as illustrated by Saha et al. [12]. Despite these advancements, challenges remain in terms of user compliance, as continuous usage is required for reliable fall detection.

2.2 Ambient sensor-based fall detection

Ambient systems employ environmental sensors such as pressure mats, microphones, and proximity sensors to monitor fall events without requiring users to wear devices [17], [21]. Vallabh and Malekian [8] reviewed ambient sensor systems that use vibration and passive infrared sensors to distinguish falls from activities of daily living (ADLs) but noted the systems' limitations in portability and cost due to required installation and maintenance. Mozaffari et al. [22] highlighted the use of such sensors in detecting fall-related changes in the environment, such as vibrations or sound upon impact, which can trigger alerts to caregivers via IoT networks. These systems are particularly suitable for confined areas such as homes, but they are less effective outdoors or in environments where installation is limited. Despite these limitations, ambient systems offer certain advantages. Unlike wearable devices, they require no active engagement from the user. However, ambient systems are often prone to false positives due to interference from environmental factors, such as pets or moving objects, which may trigger alerts erroneously. Moreover, ambient sensors often suffer from high false-positive rates, as they can misinterpret routine household activities as falls. Ambient intelligence (AAL) in IoT-based systems has been proposed to enhance the fall detection process by integrating environmental sensors within a smart home setup. Al-Khafaji et al. [23] emphasized that AAL allows for a continuous and non-intrusive monitoring system, supporting early intervention and reducing the need for constant manual monitoring.

2.3 Vision-based fall detection

Vision-based systems utilize cameras and computer vision algorithms to monitor human posture and detect falls [24]. Gutiérrez et al. [24] reviewed the progress in vision-based fall detection, noting that these systems often achieve high detection accuracy due to advancements in computer vision and artificial neural networks, which help mitigate issues related to poor lighting or occlusions. These systems, however, present privacy concerns as they continuously capture video data, which some users may find intrusive. Mrozek et al. [25] conducted a study using edge and cloud computing for fall detection, finding that real-time video analysis can effectively identify falls while offloading data processing to cloud servers. Such systems benefit from advanced machine learning algorithms, particularly convolutional neural networks (CNNs), which can accurately recognize human poses and detect abnormal postures associated with falls. Nevertheless, datasets used to train these systems often lack real-world diversity, potentially limiting their robustness when deployed outside controlled environments.

While effective in controlled environments, vision-based systems raise privacy concerns and are susceptible to variations in lighting and occlusions. They are also limited by the need for stable camera setups, making them less adaptable to outdoor settings or highly dynamic environments. Nevertheless, vision-based systems have shown potential in hybrid setups, where camera data is augmented with wearable or environmental sensor data for improved accuracy and robustness.

2.4 Machine learning and IoT integration in fall detection

Machine learning techniques, particularly in wearable and vision-based systems, have enhanced fall detection accuracy [19], [22], [25], [26], [27], [28]. Traditional threshold-based methods detect falls based on fixed parameters, but they are prone to high false-positive rates due to movement variations. In contrast, machine learning algorithms can learn complex patterns and improve classification accuracy by recognizing subtle differences between falls and ADLs. Rakhmani et al. [20] demonstrated that combining machine learning with smartphone accelerometer and gyroscope data yielded reliable detection, especially when using classifiers such as decision trees and neural networks.

The integration of IoT and machine learning has been instrumental in advancing fall detection technology. Wu et al. [13] demonstrated an IoT-based architecture that combines wearable sensors with cloud analytics, enabling real-time monitoring and analysis of falls. IoT infrastructure, utilizing edge, fog, and cloud layers, has allowed for scalable systems capable of processing large datasets and supporting numerous devices. Edge computing, in particular, is beneficial in reducing latency and minimizing the volume of transmitted data, thereby enhancing the efficiency and responsiveness of fall detection systems [22].

3 MATERIALS AND METHODS

This section details the development, hardware structure, and operational design of the smart walking assistant device, which aims to enhance fall prevention and support for elderly individuals. The device integrates a range of sensors to continuously monitor physiological parameters, detect potential hazards, and transmit real-time alerts to caregivers or family members.

3.1 System architecture

The smart walking assistant was developed as an IoT-based system to improve safety for elderly users by monitoring vital signs and environmental conditions. The device's functionality is illustrated in Figure 1. The smart walking assistance device integrates multiple advanced functionalities to ensure user safety, support, and independence. It measures the distance to surrounding obstacles using precise sensing technology, issuing an audible alert to the user when hazards are detected, thereby enabling safe navigation in various environments. The device monitors motion along the X, Y, and Z axes to capture comprehensive movement data, allowing the detection of abnormal patterns and ensuring accurate differentiation between routine activities and potential falls.

Under normal operation, the system collects and displays real-time data from heart rate, blood oxygen level, and body temperature sensors. Additionally, when obstacles are detected, the device issues an audible alert to the user. In cases where physiological parameters such as heart rate, blood oxygen saturation, or body temperature deviate from normal levels, or if a fall occurs and the user is unable to respond, the system sends a notification to designated caregivers. This alert includes information on the time, location, and the user's last recorded posture, facilitating timely assistance and reducing the risks associated with delayed intervention.

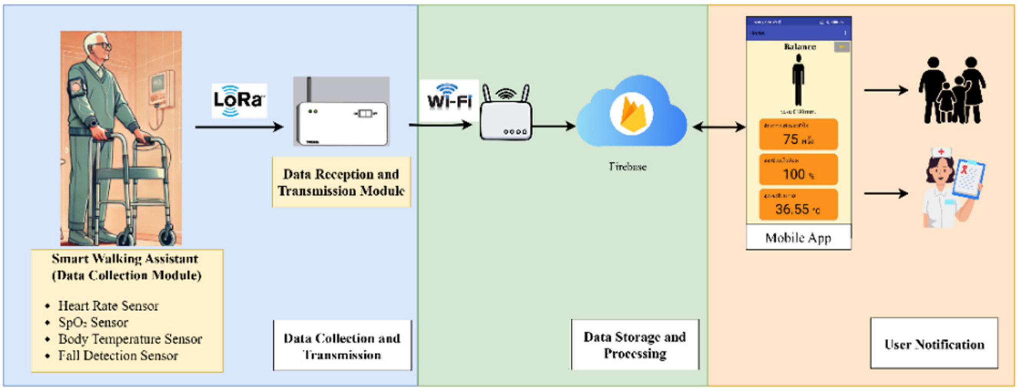

Fig. 1. The architecture of the smart walking assistant system

3.2 System components

The system structure of the smart walking assistant is composed of two main modules: the data collection module and the data reception and transmission module. Together, these modules enable continuous monitoring of the user's health and environment, supporting real-time alerts and remote caregiver access.

Data collection module. The core of the collection module is the ESP32 microcontroller, which manages a set of sensors to monitor essential physiological and environmental parameters. Data from these sensors is continuously displayed on the integrated TFT LCD screen for the user's reference. In emergency scenarios, such as abnormal health readings or fall detection, the system generates an audible alert through a speaker. The ESP32 then transmits data via a LoRa transmitter to the receiver module, enabling real-time monitoring from a distance, as depicted in Figure 2.

- MAX30102 optical sensor measures heart rate and blood oxygen saturation (SpO_2) by analyzing reflected infrared and red light. Real-time readings are displayed on an LCD screen, enabling the user to monitor vital health metrics immediately.
- GY-906 infrared temperature sensor is designed for non-contact readings; this sensor captures the user's body temperature by detecting emitted infrared radiation. It enables continuous temperature monitoring and alerts caregivers if temperatures fall outside of safe ranges.

- VL53L0X distance sensor uses laser time-of-flight technology; this sensor detects the distance between the user and nearby obstacles. When hazards are within a certain proximity, the device emits an audible alert, enhancing user safety.
- MPU6050 accelerometer and gyroscope combines linear acceleration and angular velocity measurements to identify unusual motion patterns. By distinguishing between routine movements and sudden falls, it reliably triggers alerts to caregivers when necessary.
- GY-NEO-6MV2 GPS module: This GPS module provides precise location data in emergency situations. If a fall is detected, location coordinates are included in the alert, enabling caregivers to locate the user quickly, especially in outdoor settings.
- LoRa SX1278 long-range wireless module supports long-range wireless communication between the collection module and data reception module. This module utilizes LoRa technology to transmit data over extended distances with low power consumption.
- The PAM8403 audio amplifier module enhances audio output by amplifying alerts generated by the system. This module works with a speaker to ensure warning signals are loud and clear, effectively notifying users of potential hazards or health alerts.

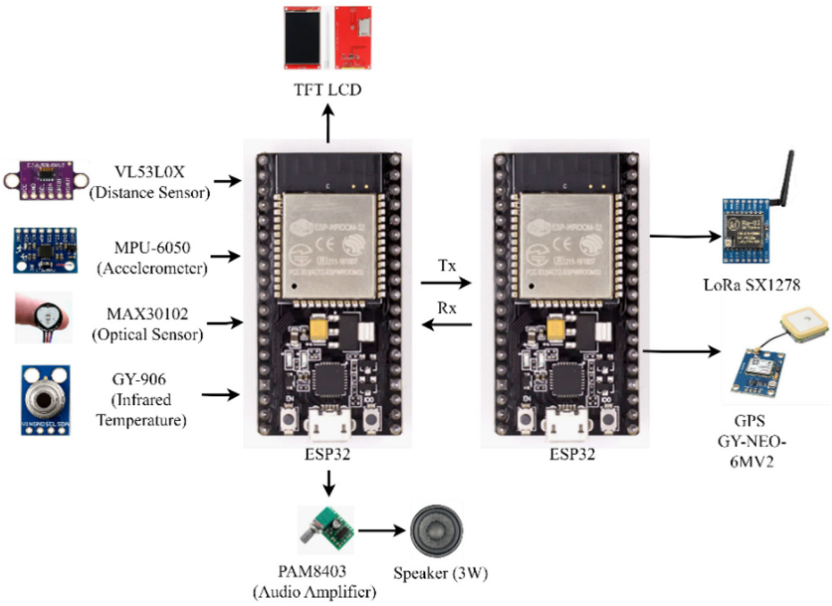

Fig. 2. Data collection module

Data reception and transmission module. The data reception and database transmission module, as illustrated in Figure 3, serves as a central component that receives, processes, and transmits user data to a cloud-based system. Built around an ESP32 microcontroller, it integrates a LoRa receiver and Wi-Fi connectivity to ensure reliable communication and data flow. The ESP32, equipped with Wi-Fi, processes the data and uploads it to the Firebase Cloud Database for real-time storage and synchronization. Through the Mobile Application Interface, caregivers can access data stored in Firebase, including vital signs, movement patterns, and emergency alerts such as fall detection. The app also provides real-time notifications and displays the user's last known location during emergencies, enabling rapid caregiver response. This integrated system ensures seamless data monitoring and enhanced safety for the user.

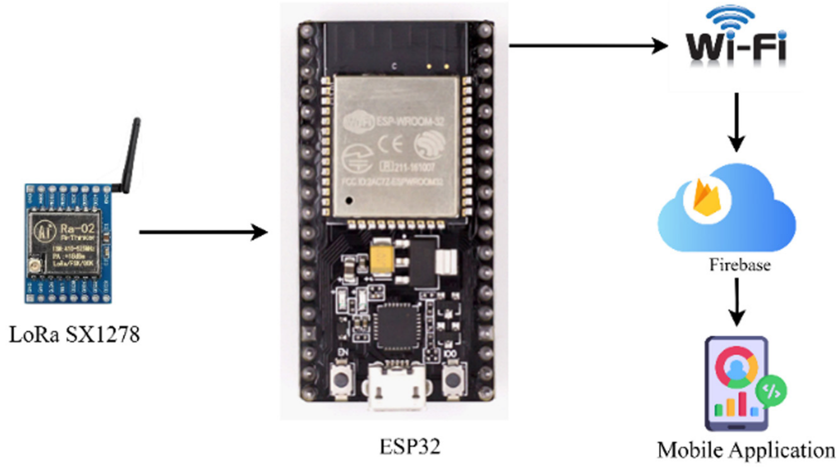

Fig. 3. Data reception and database transmission module

The smart walking assistant utilizes a sophisticated three-tier architecture that seamlessly integrates hardware, software, and communication protocols to create an effective monitoring and alert system for elderly care. At the hardware level, the system employs dual ESP32 microcontrollers that form the processing foundation of both the collection module mounted on the walking aid and the stationary reception module. The collection module incorporates multiple specialized sensors, including the MAX30102 for heart rate and blood oxygen monitoring, GY-906 for non-contact temperature measurement, VL53L0X for precise obstacle detection, and MPU6050 for motion tracking and fall detection. These sensors communicate with the ESP32 through optimized I²C and SPI bus configurations to ensure efficient data transfer.

The software architecture implements a layered approach with FreeRTOS managing task scheduling across the ESP32's dual cores, allowing critical monitoring processes to operate concurrently with communication tasks. The collection module's firmware handles sensor data acquisition, implements threshold-based anomaly detection algorithms, and employs a decision tree classifier for identifying fall events from motion data. The reception module functions as the intermediary between the collection unit and cloud database, validating and decoding incoming LoRa transmissions before transforming them into standardized formats suitable for cloud storage. During normal operation, the software maintains continuous Firebase database connectivity via Wi-Fi, transmitting real-time data through the MQTT protocol.

Power management is a crucial consideration for this assistive technology. The system operates on a rechargeable 10,000 mAh lithium-polymer battery selected for its optimal balance of capacity, weight, and longevity. Under standard operating conditions, the system provides approximately 120 hours of continuous operation between charging cycles. The control interface displays a color-coded battery indicator visible to both users and caregivers. When power levels decline to 30% capacity, the system activates low-battery notifications both on the device and through the caregiver's mobile application, ensuring sufficient time for recharging before power depletion occurs.

Despite the integration of multiple technologies, the system's modular design architecture significantly simplifies maintenance and troubleshooting for non-technical users. This approach enables isolated component testing and replacement without affecting overall system functionality. For instance, a malfunctioning heart rate sensor can be replaced independently without impacting the fall detection system. Visual status indicators provide clear information about power status, connectivity, and sensor operation, allowing users to identify basic issues without technical expertise.

The user interface follows universal design principles, featuring large displays and intuitive controls to accommodate elderly users who may find new technology challenging. The system is designed for single-time setup by caregivers or family members, requiring minimal technical understanding from elderly users during regular operation.

3.3 Hardware design and implementation

An adaptor printed circuit board (PCB) is designed in ensuring reliable communication and integration across the smart walking assistant system's various modules. The hardware system comprises two primary PCB. Figure 4. shows the hardware design and integration of the smart walking assistant system. Figure 4a and 4b shows the internal and external layout of the data collection module. The module is contained within a compact control box measuring 12 × 17.5 × 5.25 cm. Figure 4c shows the designed box of data reception and transmission module. Figure 4d shows the integration with walking aid, this design allows for flexible installation on a wide range of walking aids, enhancing the device's adaptability for diverse user needs. The control box's streamlined design promotes ease of use and facilitates seamless integration with various walking devices, ensuring that elderly individuals can benefit from enhanced support and safety.

The completed control box, as shown in Figure 5, incorporates all essential components for the smart walking assistant system. Figure 5a highlights the data collection control box, featuring a user-friendly interface that displays real-time data, including health parameters and alerts. Figure 5b showcases the data reception and transmission box, equipped with connectivity features such as power and Wi-Fi indicators. Figure 5c illustrates the final hardware assembly, demonstrating its seamless integration with a standard walking aid.

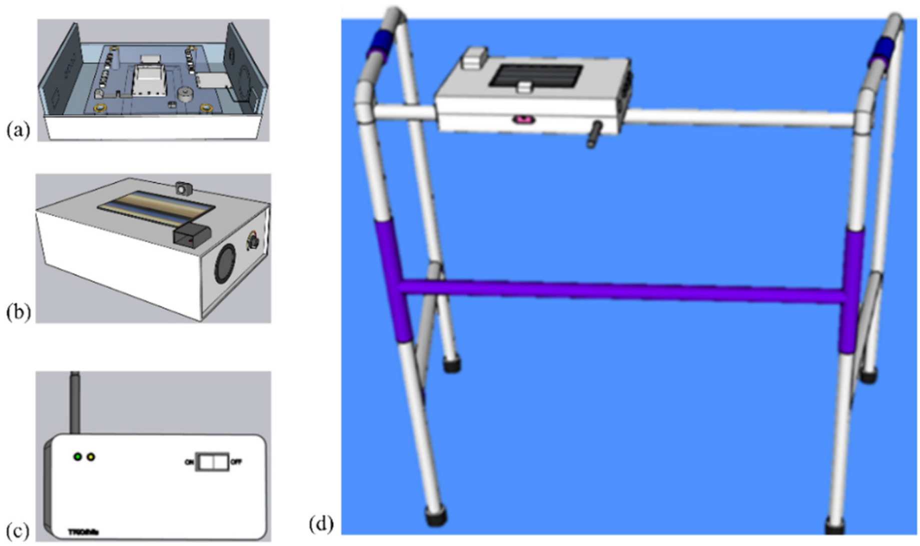

Fig. 4. Hardware design and integration of the smart walking assistant system: (a, b) internal and external layout of the data collection module, (c) designed box of data reception and transmission module, and (d) Integration with walking aid

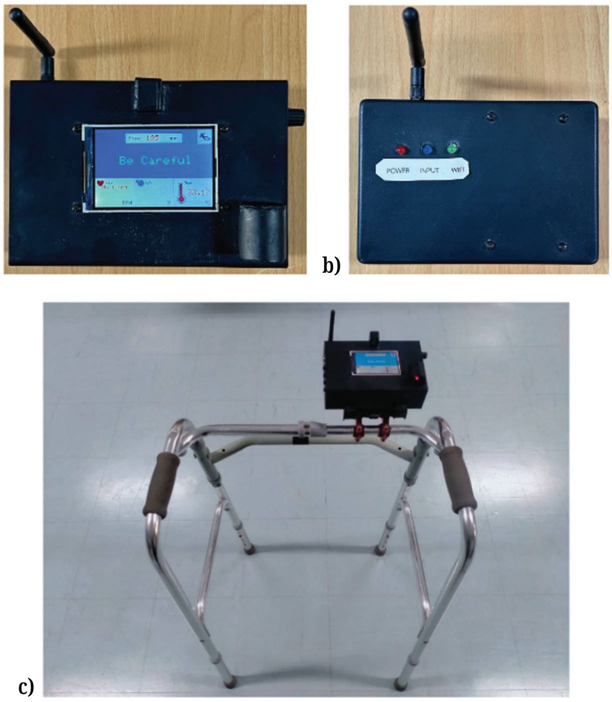

Fig. 5. Completed control box: (a) Data collection control box, (b) Data reception and transmission box, and (c) Integration with a standard walking aid

3.4 Data processing and analysis

The data processing and analysis framework of the smart walking assistant is designed to provide real-time monitoring of sensor outputs, ensuring timely and accurate detection of falls and health abnormalities. The ESP32 microcontroller serves as the core processing unit, employing advanced algorithms to analyze data from various sensors, including motion, heart rate, blood oxygen, and body temperature sensors.

Anomaly detection. The system monitors physiological parameters that are heart rate, blood oxygen saturation (SpO_2), and body temperature using predefined thresholds tailored to elderly individuals. These thresholds are designed to identify deviations indicative of potential health risks, allowing for early intervention. Each parameter is continuously evaluated against safe ranges, as defined in Table 1. Alerts are triggered whenever a parameter exceeds or falls below its respective threshold, signaling a potential health anomaly. The system employs threshold-based algorithms to identify health anomalies in real time. When an anomaly is detected, the system immediately classifies it as a critical event, prompting the next stage of processing and notification.

Table 1. Specific threshold values for each physiological parameter

Measurement Type	Sensor Used	Threshold
Heart Rate	MAX30102	60–100 bpm
SpO_2	MAX30102	> 94%
Body Temperature	GY-906	36.1–37.5°C
Obstacle Detection	VL53L0X	< 900 mm

Fall detection. Fall detection is a critical capability of the smart walking assistant, designed to address one of the primary causes of injury among elderly individuals. The system employs the MPU6050 accelerometer and gyroscope to monitor acceleration and angular velocity, enabling the capture of motion patterns indicative of falls.

Key features are extracted from the accelerometer and gyroscope readings, including the magnitude of acceleration and angular displacement. These features are essential for distinguishing routine movements from fall events. Specific threshold values, derived from experimental data, are applied to detect falls in various directions, including forward, backward, and lateral movements, ensuring comprehensive coverage of potential scenarios. To classify fall events, the system utilizes a decision tree classifier, which processes the extracted features to determine whether the detected motion qualifies as a fall. The classifier threshold values were determined through iterative testing under controlled laboratory conditions, achieving a balance between sensitivity and specificity in fall detection. Once an event is classified as a fall, the system immediately generates an alert containing critical information, such as the user's final recorded position. This alert is transmitted to caregivers, enabling prompt and informed responses to assist the user effectively.

Real-time data transmission and alert mechanism. Real-time communication is a key feature of the smart walking assistant, enabling caregivers to receive immediate alerts through Firebase for fall events or health anomalies, including critical details such as event type, timestamp, user location, and sensor readings. Additionally, the system stores data in a Firebase database, allowing caregivers to access both real-time and historical health information for trend analysis and informed medical decision-making.

3.5 Experiment design

To assess the accuracy and performance of the sensors integrated into the smart walking assistant, an evaluation was conducted involving 10 students enrolled in the Electrical Engineering program at Nakorn Pathom Rajabhat University, Thailand. The participants, aged between 18 and 23 years, were selected based on the absence of any known health conditions. The experiment involved measuring each participant's heart rate, blood oxygen saturation (SpO_2), body temperature, motion detection, obstacle detection, and fall detection under controlled conditions to ensure consistency and reliability in the data collected. The following sensors and measurement criteria were employed to evaluate the functionality of the smart walking assistant under controlled conditions.

1. Heart rate and SpO_2 were conducted over a 15-second duration. Participants remained seated and were instructed to place a finger on the sensor to obtain accurate readings.
2. Body temperature was captured body temperature from a fixed measurement distance of 10 cm. Participants were required to remain stationary during the measurement to ensure reliability.
3. Fall detection was performed in forward, backward, and side directions to evaluate the system's ability to distinguish between routine movements and fall events.
4. Obstacle detection was placed at predetermined distances of 300 mm, 500 mm, 700 mm, and 900 mm to test the sensor's detection capability and alert triggering mechanism.

The procedure for the experiment involved preparing and calibrating the sensors to ensure accurate functionality. Measurements for each parameter were conducted with all 10 participants, with each test repeated three times to account for variability and enhance data reliability. The data collected were systematically recorded for subsequent analysis and interpretation.

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 6. 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 2.

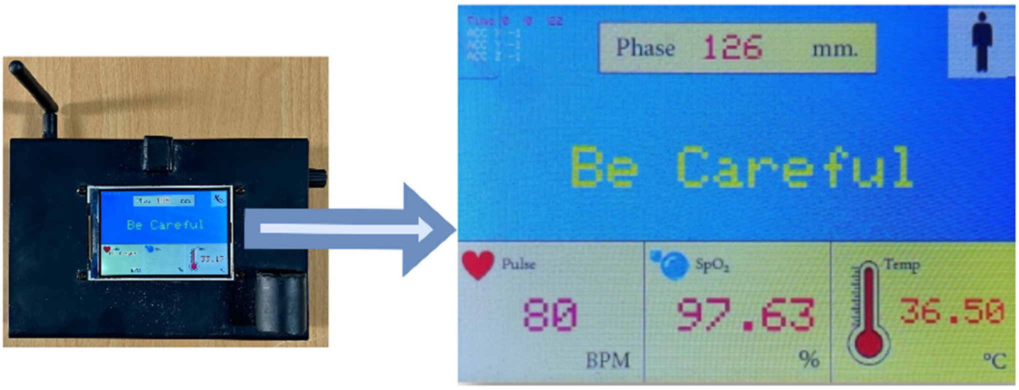

Fig. 6. Results capturing physiological parameters and obstacle detection performance

Table 2. 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°C	Within normal range
Obstacle Detection (mm)	300–900	<900 mm	All obstacles detected.

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, as shown in Figure 7. These tests assessed the system's classification algorithm, which utilizes data from the MPU6050 accelerometer and gyroscope to detect sudden changes in acceleration and angular velocity indicative of a fall. Calibration and threshold adjustments were iteratively performed to enhance accuracy and minimize false positives and false negatives. The system successfully detected all simulated falls and triggered the alert mechanism. Upon detecting a fall, the system transmitted critical information, including the user's last recorded posture, time of the event, and precise location, to a dedicated mobile application.

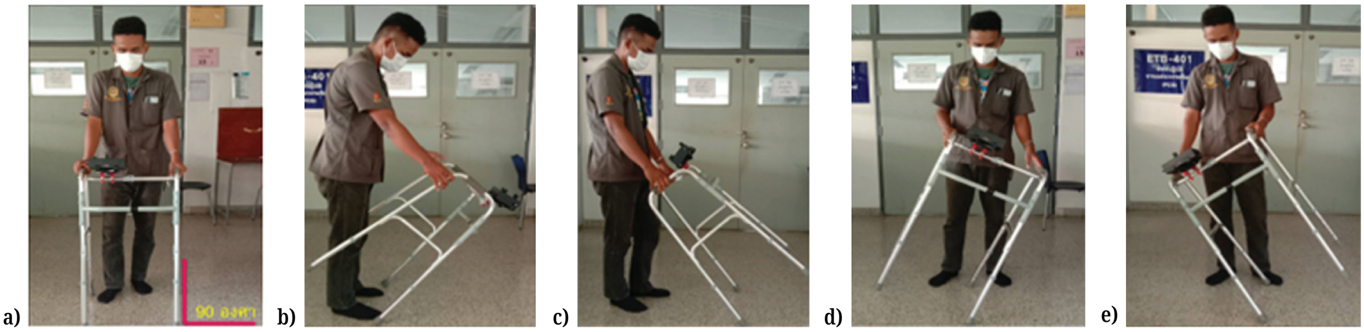

Fig. 7. Simulated fall detection scenarios with corresponding sensor readings: (a) Normal upright position, (b) Forward fall, (c) Backward fall, and (d, e) Lateral falls

The smart walking assistant's mobile application, developed using Kodular for the Android operating system, serves as a crucial interface for caregivers by providing real-time alerts and updates on the user's status. The application is designed with two primary operational modes to ensure comprehensive monitoring and timely intervention. The normal status (Figure 8a) is displayed when no abnormal events are detected. This status provides real-time information on the user's current heart rate, blood oxygen saturation (SpO_2), and body temperature, allowing caregivers to monitor the user's physiological parameters continuously. The fall detection status (Figure 8b) is activated when the system detects a fall event. In this mode, the application displays a warning alongside critical health metrics such as heart rate, SpO_2, and body temperature. Additionally, it includes actionable information, such as the user's precise location and last recorded movement, enabling caregivers to respond immediately and effectively to the situation.

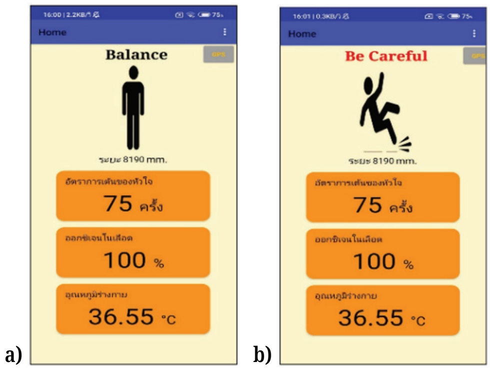

Fig. 8. Mobile application interface: (a) Normal status, (b) Fall detection status

5 DISCUSSIONS

The IoT-based smart walking assistant developed in this study demonstrates significant advancements compared to existing systems in the areas of fall detection, physiological monitoring, and caregiver communication. The system's use of the MPU6050 accelerometer and gyroscope achieved high accuracy in detecting simulated falls in various directions, including forward, backward, and lateral movements. These findings align with earlier studies, such as Rakhman et al. [20], but the proposed system incorporates additional calibration and threshold adjustments, reducing false positives and negatives while providing real-time location transmission, a feature lacking in many prior designs.

The integration of the MAX30102 sensor for heart rate and SpO_2 monitoring and the GY-906 infrared temperature sensor ensures accurate tracking of physiological parameters, consistent with findings from Wu et al. [13]. However, unlike previous systems focusing solely on physiological data, the smart walking assistant integrates additional features such as fall detection and obstacle detection, providing a more comprehensive solution for user safety. The use of Firebase for real-time data storage and notifications significantly enhances caregiver communication compared to SMS-based systems, such as Al-khafajiy et al. [23]. The proposed system ensures immediate transmission of critical information, including the user's location, event details, and vital metrics, enabling timely caregiver responses.

Additionally, the obstacle detection capability using the VL53L0X sensor offers reliable identification of obstacles within predefined ranges, improving user navigation safety. Unlike earlier systems such as Mozaffari et al. [22], which primarily focused on motion monitoring, the inclusion of obstacle detection adds an essential layer of environmental awareness, enhancing user safety during movement. Despite these advancements, the system's reliance on pre-defined thresholds for anomaly detection limits its adaptability to individual variations, as noted in studies such as Albert et al. [18]. Incorporating machine learning algorithms in future iterations could refine detection sensitivity and improve personalization for diverse users. Real-world validation in dynamic environments, such as crowded outdoor spaces, as emphasized by Karar et al. [26], would further enhance the system's reliability and applicability in broader scenarios.

Regarding mobile applications, several challenges exist with app-dependent alert systems in elderly care contexts. Many caregivers lack sufficient technological proficiency with smartphones, creating monitoring barriers. Continuous smartphone access is impractical, potentially causing notification gaps during sleeping or driving. The abundance of notifications on modern devices may produce "alert fatigue," where critical alerts are overlooked. To address these limitations, future development will implement alternative notification channels including SMS messaging, email alerts, and automated voice calls to landlines. Integration with smart home systems and wearable devices will further enhance alert delivery reliability regardless of caregiver technological preferences.

When evaluating the cost considerations of this innovation, affordability represents a critical factor for any assistive technology seeking widespread adoption. The smart walking assistant prototype was engineered with cost efficiency as a primary design consideration, carefully balancing advanced functionality with financial accessibility to ensure availability to users across various economic circumstances. From a healthcare economics perspective, this system offers potential cost advantages beyond its direct purchase price. The device's ability to prevent fall-related injuries could generate significant offset savings through reduced healthcare expenditures. Fall-related hospitalizations among elderly populations constitute substantial financial burdens for both individuals and healthcare systems. By effectively reducing fall incidence or severity and enabling more rapid emergency response, the smart walking assistant demonstrates potential cost-effectiveness that extends beyond its initial investment cost.

Regarding privacy considerations, our prototype implements basic security measures, but we recognize that medical data protection requires vigilant monitoring of evolving threats and regulations. Future iterations will enhance security through comprehensive encryption for all data, advanced authentication mechanisms, and granular access controls. Additionally, we will establish systematic security maintenance protocols, including regular updates and vulnerability assessments.

The smart walking assistant prototype shows potential for addressing elderly safety through its integration of monitoring and communication capabilities. While initial testing with young participants demonstrates technical feasibility, significant additional validation with elderly users in real-world environments is necessary before claims of robustness or advancement in assistive technology can be substantiated. This work represents a preliminary step that requires comprehensive evaluation with the target population.

6 CONCLUSION

This study presents the development and initial testing of an IoT-based smart walking assistant prototype intended to address mobility and safety challenges for elderly individuals. The system's integration of real-time monitoring, fall detection, and caregiver notifications addresses critical challenges in elderly care. Key features, including accurate physiological monitoring, reliable fall detection, and seamless data transmission via a mobile application, highlight the system's potential to improve the quality of life for elderly users.

The findings demonstrate the system's accuracy in measuring vital signs and detecting falls, ensuring prompt alerts to caregivers. These capabilities can reduce the risks associated with delayed intervention and enhance overall user safety. Future work could focus on incorporating adaptive machine learning algorithms to improve detection sensitivity and testing the system in diverse real-world settings. The IoT-based smart walking assistant holds significant promise as an assistive technology for the aging population, contributing to improved safety, independence, and healthcare outcomes.

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8 REFERENCES

[1] World Health Organization, "Ageing and health," 2024. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/ageing-and-health [Accessed: Oct. 3, 2024].

[2] Centers for Disease Control and Prevention, "Facts about falls," 2024. [Online]. Available: https://www.cdc.gov/falls/data-research/facts-stats [Accessed: Oct. 1, 2024].

[3] A. F. Ambrose, G. Paul, and J. M. Hausdorff, "Risk factors for falls among older adults: a review of the literature," *Maturitas*, vol. 75, no. 1, pp. 51–61, 2013. https://doi.org/10.1016/j.maturitas.2013.02.009

[4] B. G. Mohammed and D. S. Hasan, "Smart healthcare monitoring system using IoT," *Int. J. Interact. Mob. Technol.*, vol. 17, no. 1, pp. 141–152, 2023. https://doi.org/10.3991/ijim.v17i01.34675

[5] A. Adam, A. Abubakar, and M. Mahmud, "Sensor enhanced health information systems: Issues and challenges," *Int. J. Interact. Mob. Technol.*, vol. 13, no. 1, pp. 99–114, 2019. https://doi.org/10.3991/ijim.v13i01.7037

[6] H. Boudlal, M. Serrhini, and A. Tahiri, "A monitoring system for elderly people using WiFi Sensing with channel state information," *Int. J. Interact. Mob. Technol.*, vol. 17, no. 12, pp. 112–131, 2023. https://doi.org/10.3991/ijim.v17i12.36613

[7] S. Nooruddin, M. M. Islam, F. A. Sharna, H. Alhetari, and M. N. Kabir, "Sensor-based fall detection systems: A review," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 5, pp. 2735–2751, 2022. https://doi.org/10.1007/s12652-021-03248-z

[8] P. Vallabh and R. Malekian, "Fall detection monitoring systems: A comprehensive review," *J. Ambient. Intell. Human. Comput.*, vol. 9, no. 6, pp. 1809–1833, 2018. https://doi.org/10.1007/s12652-017-0592-3

[9] M. Cornacchia, K. Ozcan, Y. Zheng, and S. Velipasalar, "A survey on activity detection and classification using wearable sensors," *IEEE Sensors Journal*, vol. 17, no. 2, pp. 386–403, 2017. https://doi.org/10.1109/JSEN.2016.2628346

[10] E. Casilari, M. Álvarez-Marco, and F. García-Lagos, "A study of the use of gyroscope measurements in wearable fall detection systems," *Symmetry*, vol. 12, no. 4, p. 649, 2020. https://doi.org/10.3390/sym12040649

[11] M. I. Nari, S. S. Suprapto, I. H. Kusumah, and W. Adiprawita, "A simple design of wearable device for fall detection with accelerometer and gyroscope," in *2016 International Symposium on Electronics and Smart Devices (ISESD)*, Bandung, Indonesia, 2016, pp. 88–91. https://doi.org/10.1109/ISESD.2016.7886698

[12] J. Saha, C. Chowdhury, I. Roy Chowdhury, S. Biswas, and N. Aslam, "An ensemble of condition based classifiers for device independent detailed human activity recognition using smartphones," *Information*, vol. 9, no. 4, p. 94, 2018. https://doi.org/10.3390/info9040094

[13] F. Wu, H. Zhao, Y. Zhao, and H. Zhong, "Development of a wearable-sensor-based fall detection system," *International Journal of Telemedicine and Applications*, vol. 2015, pp. 1–11, 2015. https://doi.org/10.1155/2015/576364

[14] X. Fu *et al.*, "Remote monitoring system for livestock environmental information based on LoRa wireless ad hoc network technology," *International Journal of Agricultural and Biological Engineering*, vol. 15, no. 4, pp. 79–89, 2022. https://doi.org/10.25165/j.ijabe.20221504.6708

[15] R. Rucco *et al.*, "Type and location of wearable sensors for monitoring falls during static and dynamic tasks in healthy elderly: A review," *Sensors*, vol. 18, no. 5, p. 1613, 2018. https://doi.org/10.3390/s18051613

[16] B. Siregar, U. Andayani, R. P. Bahri, Seniman, and F. Fahmi, "Real-time monitoring system for elderly people in detecting falling movement using accelerometer and gyroscope," *J. Phys. Conf. Ser.*, vol. 978, p. 012110, 2018. https://doi.org/10.1088/1742-6596/978/1/012110

[17] S. Ahn, J. Kim, B. Koo, and Y. Kim, "Evaluation of inertial sensor-based pre-impact fall detection algorithms using public dataset," *Sensors*, vol. 19, no. 4, p. 774, 2019. https://doi.org/10.3390/s19040774

[18] M. V. Albert, K. Kording, M. Herrmann, and A. Jayaraman, "Fall classification by machine learning using mobile phones," *PLoS ONE*, vol. 7, no. 5, p. e36556, 2012. https://doi.org/10.1371/journal.pone.0036556

[19] J. He, S. Bai, and X. Wang, "An unobtrusive fall detection and alerting system based on kalman filter and bayes network classifier," *Sensors*, vol. 17, no. 6, p. 1393, 2017. https://doi.org/10.3390/s17061393

[20] A. Z. Rakhman, L. E. Nugroho, Widyawan, and Kurnianingsih, "Fall detection system using accelerometer and gyroscope based on smartphone," in *2014 The 1st International Conference on Information Technology, Computer, and Electrical Engineering*, Semarang, Indonesia, 2014, pp. 99–104. https://doi.org/10.1109/ICITACEE.2014.7065722

[21] K. Chaccour, J. Eid, R. Darazi, A. Hajjam el Hassani, and E. Andres, "Multisensor guided walker for visually impaired elderly people," in *2015 International Conference on Advances in Biomedical Engineering (ICABME)*, Beirut, Lebanon: IEEE, 2015, pp. 158–161. https://doi.org/10.1109/ICABME.2015.7323276

[22] N. Mozaffari, J. Rezazadeh, R. Farahbakhsh, S. Yazdani, and K. Sandrasegaran, "Practical fall detection based on IoT technologies: A survey," *Internet of Things*, vol. 8, p. 100124, 2019. https://doi.org/10.1016/j.iot.2019.100124

[23] M. Al-khafajiy *et al.*, "Remote health monitoring of elderly through wearable sensors," *Multimed. Tools. Appl.*, vol. 78, no. 17, pp. 24681–24706, 2019. https://doi.org/10.1007/s11042-018-7134-7

[24] J. Gutiérrez, V. Rodríguez, and S. Martin, "Comprehensive review of vision-based fall detection systems," *Sensors*, vol. 21, no. 3, p. 947, 2021. https://doi.org/10.3390/s21030947

[25] D. Mrozek, A. Koczur, and B. Małysiak-Mrozek, "Fall detection in older adults with mobile IoT devices and machine learning in the cloud and on the edge," *Information Sciences*, vol. 537, pp. 132–147, 2020. https://doi.org/10.1016/j.ins.2020.05.070

[26] M. E. Karar, H. I. Shehata, and O. Reyad, "A survey of IoT-based fall detection for aiding elderly care: Sensors, methods, challenges and future trends," *Applied Sciences*, vol. 12, no. 7, p. 3276, 2022. https://doi.org/10.3390/app12073276

[27] E. S. Kumar, P. Sachin, B. P. Vignesh, and M. R. Ahmed, "Architecture for IoT based geriatric care fall detection and prevention," in *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*, Madurai, 2017, pp. 1099–1104. https://doi.org/10.1109/ICCONS.2017.8250636

[28] P. Bhattacharjee and S. Biswas, "Smart walking assistant (SWA) for elderly care using an intelligent realtime hybrid model," *Evolving Systems*, vol. 13, pp. 265–279, 2022. https://doi.org/10.1007/s12530-021-09382-5

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