Design and Evaluation of a Low-Cost Edge IoT System for Elderly Fall Detection

Hanim Abdul Razak[1*], Hazura Haroon[1], Anis Suhaila Mohd Zain[1], Siti Khadijah Idris@Othman[1], Fauziyah Salehuddin[1], Muhammad Shaiful Azim Redzuan[1], Muhamad Fuad Abdul Karim[2]

[1]Centre for Telecommunication Research & Innovation (CeTRI), Fakulti Teknologi dan Kejuruteraan Elektronik dan Komputer (FTKEK), Universiti Teknikal Malaysia Melaka, 76100, Durian Tunggal, Melaka, Malaysia

[2]Universiti Teknologi MARA, Cawangan Negeri Sembilan, Kampus Seremban 3, Persiaran Seremban Tiga 1, Seremban 3, 70300 Seremban, Negeri Sembilan, Malaysia

***Corresponding Author**

DOI: https://doi.org/10.47772/IJRISS.2026.100700396

Received: 18 July 2026; Accepted: 24 July 2026; Published: 03 August 2026

ABSTRACT

This paper presents the design and controlled experimental evaluation of a low-cost, edge-based elderly health and safety monitoring system implemented on an ESP32 microcontroller. The system integrates a DS18B20 temperature sensor and an MPU6050 inertial measurement unit (IMU) to perform real-time temperature monitoring and threshold-based fall detection. Unlike cloud-dependent approaches, the proposed architecture performs on-device processing to enable low-latency emergency alerting while simultaneously transmitting data to the ThingSpeak cloud platform for remote monitoring. Experimental validation was conducted under controlled simulated fall and activities-of-daily-living (ADL) scenarios. Temperature measurements demonstrated a mean absolute error (MAE) of 0.05°C compared to a clinical reference thermometer. Fall detection performance achieved 85.56% sensitivity, 90.67% specificity, and an overall accuracy of 88.48%. The computed precision and F1-score were 91.67% and 88.48%, respectively. The average fall-to-alert response latency was 0.20 seconds, confirming the effectiveness of real-time edge processing. While the system is validated under controlled conditions, results demonstrate the feasibility of low-cost embedded architectures for rapid emergency detection in home-based monitoring scenarios. The study provides practical performance benchmarking and highlights design trade-offs in threshold-based fall detection on resource-constrained IoT nodes.

Keywords: Edge computing, fall detection, IoT health monitoring, low-cost embedded system

INTRODUCTION

The rapid growth of the global elderly population has intensified the demand for reliable and scalable health monitoring systems, particularly for continuous monitoring of elderly individuals who are vulnerable to health emergencies and accidents. According to the World Health Organization, the proportion of individuals aged 60 years and above is expected to nearly double by 2050, significantly increasing the risk of age-related health complications and fall incidents [1]. Falls are one of the major health risks among elderly individuals and often lead to severe injuries, hospitalization, and long-term disability if immediate assistance is not provided [2], [3]. Timely detection of fall events is therefore critical in reducing adverse outcomes and enabling prompt emergency response. Traditional monitoring methods rely heavily on manual supervision by caregivers, which is often impractical for continuous observation and rapid emergency response in home environments [4].

Recent advances in Internet of Things (IoT) technologies have enabled the development of smart healthcare monitoring systems capable of continuously collecting physiological and motion data from wearable sensors [5], [6]. Wearable sensors such as accelerometers and gyroscopes are widely used in fall detection systems due to their ability to capture sudden motion changes and body orientation during fall events [7]. IoT-based architectures allow real-time remote monitoring through cloud platforms, enabling caregivers or family members to observe the health status of elderly individuals from remote locations [8], [9]. While such approaches provide advanced analytical capability, they introduce potential latency due to network transmission delays and server-side processing overhead [10]. In time-critical applications such as fall detection, these delays may compromise responsiveness and reliability.

Edge computing offers an alternative paradigm in which sensing, data processing, and decision-making are performed locally on embedded devices. By eliminating dependence on remote servers for primary inference, edge-based systems can achieve deterministic response times and improved operational robustness under limited connectivity conditions [11]. This architectural approach is particularly suitable for low-power microcontroller platforms deployed in wearable monitoring devices.

Fall detection techniques generally fall into two broad categories: threshold-based and machine learning-based methods. Threshold-based approaches classify fall events by comparing acceleration or angular velocity measurements against predefined limits, offering computational simplicity and predictable execution time. In contrast, machine learning-based methods rely on trained models to differentiate falls from normal activities, typically achieving higher classification performance at the cost of increased computational requirements and implementation complexity [12]. However, many existing systems rely on computationally intensive machine learning models that may not be suitable for low-power embedded devices commonly used in IoT healthcare applications [13].

The main contribution of this work lies in the development of a lightweight IoT-based elderly monitoring system that integrates fall detection and physiological monitoring within a single embedded platform. Unlike many existing approaches that rely on computationally intensive machine learning models, the proposed system employs a threshold-based fall detection algorithm implemented directly on the ESP32 microcontroller following an edge computing paradigm. This approach enables real-time fall detection with minimal computational overhead while reducing dependence on continuous cloud processing [14].

In addition, the system integrates temperature monitoring using the DS18B20 sensor to provide continuous health observation alongside motion-based fall detection. The collected sensor data are transmitted to the ThingSpeak cloud platform, enabling caregivers to remotely monitor the user’s condition through real-time dashboards.

The combination of edge-based fall detection, multi-sensor monitoring, and cloud-enabled visualization provides a scalable framework for real-time elderly healthcare monitoring.

LITERATURE REVIEW

Recent developments in wearable sensing technologies and Internet of Things (IoT) architectures have significantly advanced the design of fall detection systems for elderly healthcare monitoring. These systems commonly employ wearable sensors such as accelerometers and gyroscopes to capture motion patterns associated with sudden body movements. The collected sensor data are then analyzed using various detection algorithms to determine whether a fall event has occurred. Such approaches enable continuous monitoring and rapid emergency response, which are essential for improving the safety and quality of life of elderly individuals living independently [15], [16].

Several studies have explored IoT-based fall detection frameworks that integrate wearable sensors with cloud-based monitoring platforms. For example, Al-Kababji et al. proposed an IoT-enabled fall monitoring framework that utilizes wearable sensors and cloud communication to provide real-time fall detection and remote monitoring capabilities [1]. Similarly, Rathore et al. developed an edge-computing-based healthcare monitoring system that processes sensor data locally to reduce communication latency and improve response time in emergency situations [10]. These studies demonstrate the potential of IoT technologies in enabling continuous health monitoring for elderly individuals.

Various algorithmic approaches have been proposed for fall detection. Machine learning-based methods have been widely investigated due to their ability to classify complex motion patterns and improve detection accuracy.

For instance, Mekruksavanich and Jitpattanakul applied deep learning techniques to classify fall events using wearable inertial sensors, achieving improved detection performance compared to traditional rule-based approaches [20]. However, such techniques often require substantial computational resources and training datasets, which may limit their suitability for resource-constrained embedded devices.

In contrast, threshold-based fall detection algorithms remain widely used due to their simplicity and low computational requirements. These algorithms typically analyze acceleration magnitude derived from three-axis accelerometer data to identify sudden spikes associated with fall events. Because of their lightweight implementation, threshold-based approaches are particularly suitable for embedded platforms such as microcontrollers used in IoT monitoring systems [21], [22].

Edge computing has also emerged as an important paradigm in IoT healthcare applications. Instead of transmitting raw sensor data to remote servers for processing, edge computing enables data processing directly on the embedded device. This approach reduces network latency, minimizes bandwidth consumption, and allows faster response during critical situations such as fall detection events [19]. Consequently, integrating edge processing with IoT cloud platforms provides a balanced architecture that supports both real-time detection and remote monitoring.

Table 1 summarizes several recent studies related to IoT-based fall detection and elderly monitoring systems, highlighting the sensing technologies, detection approaches, and key characteristics of each study.

Table 1 Previous research on fall detection system

Study	Method	Sensor	Key Findings
Al-Kababji et al. [1]	IoT fall monitoring	Accelerometer	Real-time monitoring
Rathore et al. [10]	Edge-based fall detection	Wearable sensors	Low latency
Li et al. [18]	Wearble fall detection	Accelerometer+ gyroscope	High detection accuracy
Mekruksavanich et al.[20]	Deep learning fall detection	Wearable IMU	Improved classification
Torres-Sospedra et al. [21]	Wearable activity recognition	Accelerομeer	Lighweight fall detection method
Yang et al.[23]	IoTelderly monitoring system	IoT sensors	Remote monitoring

SYSTEM ARCHITECTURE

The proposed elderly monitoring system adopts an edge-based Internet of Things (IoT) architecture implemented on the ESP32 microcontroller platform. The system integrates multiple sensing components to monitor both motion activity and physiological conditions in real time. An MPU6050 inertial measurement unit (IMU) is utilized to capture three-axis acceleration data for fall detection, while a DS18B20 digital temperature sensor is incorporated to monitor body temperature as an additional health indicator.

The overall system architecture follows a three-tier IoT model to ensure modularity and clear functional separation, as illustrated in Fig. 1. The first tier is the sensing layer, which consists of the physical sensors responsible for acquiring environmental and physiological data. In this layer, the MPU6050 sensor captures motion-related acceleration signals, while the DS18B20 sensor continuously measures body temperature.

The second tier is the processing and communication layer, where the ESP32-WROOM-32 microcontroller functions as the central processing unit of the system. In this layer, sensor data are acquired and processed locally by the microcontroller. The fall detection algorithm is executed directly on the ESP32, following the edge computing paradigm where data processing and decision-making occur on the embedded device rather than relying on remote cloud servers. This approach minimizes communication delays and enables rapid response during emergency situations. The ESP32 also manages local alert mechanisms such as the buzzer and handles wireless data transmission.

The third tier is the cloud visualization and alert layer, which is implemented using the ThingSpeak IoT platform.

This layer receives the transmitted monitoring data and provides real-time graphical dashboards for remote observation. Through this interface, caregivers or family members can monitor the condition of the elderly individual from any location with internet connectivity, thereby completing the end-to-end monitoring framework. This layered architecture allows sensing, local processing, and remote monitoring functions to be managed independently while maintaining low system latency.

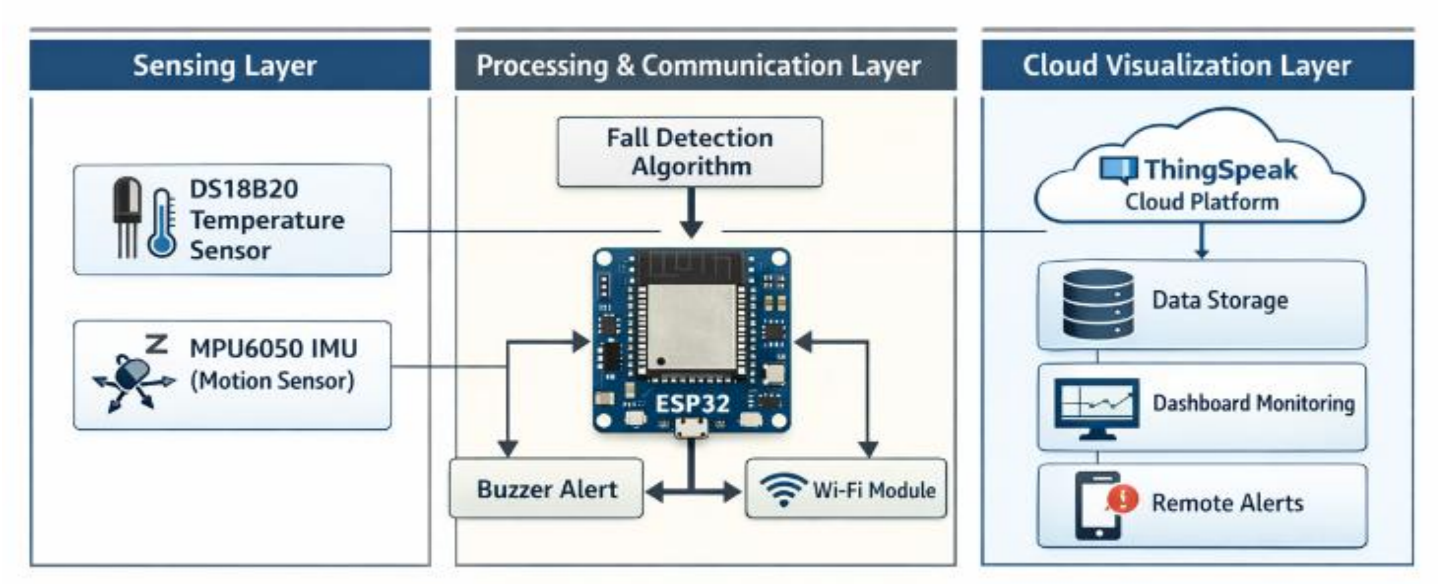

Fig 1: System architecture of the elderly health monitoring

FALL DETECTION ALGORITHM

The fall detection mechanism implemented in this study is based on a threshold-driven acceleration magnitude analysis. Acceleration measurements are continuously obtained from the MPU6050 sensor along three orthogonal axes corresponding to the x, y, and z directions. These measurements are used to compute the resultant acceleration magnitude, which reflects the overall motion intensity experienced by the device.

The acceleration magnitude, A_{mag} is calculated using the Euclidean norm expressed as:

$$(1)\ A_{mag} = \sqrt{a_x^2 + a_{y+}^2 a_z^2}$$

where a_x, a_y and a_z represent the acceleration components along the three axes.

Under normal daily activities such as walking, sitting, or bending, the resultant acceleration magnitude typically remains within a moderate range. However, during a fall event, a sudden and significant change in acceleration occurs due to the impact with the ground. The proposed system detects such events by comparing the calculated acceleration magnitude with a predefined threshold value.

When the computed magnitude exceeds the specified threshold, the system classifies the event as a potential fall and immediately triggers an alert through the buzzer module. The threshold value was determined empirically through multiple experimental trials involving both simulated fall events and normal daily activities. This approach ensures that the detection algorithm remains computationally efficient while maintaining reliable performance in distinguishing falls from routine movements [7],[22].

OPERATIONAL FLOW OF THE PROPOSED IOT-BASED ELDERLY MONITORING SYSTEM.

The operational process of the proposed fall detection algorithm is summarized in Fig. 2. The system continuously monitors motion data obtained from the MPU6050 inertial measurement unit (IMU) while simultaneously recording temperature readings from the DS18B20 sensor. These sensor values are periodically sampled and processed by the ESP32 microcontroller.

At each sampling interval, the acceleration components along the x, y, and z axes are retrieved from the MPU6050 sensor. The system then calculates the resultant acceleration magnitude using the Euclidean norm to determine the overall intensity of movement. This calculated value is subsequently compared with a predefined threshold that represents a potential fall event.

If the computed acceleration magnitude exceeds the threshold value, the system classifies the event as a fall. Once a fall is detected, the ESP32 immediately activates the buzzer module to generate a local alert. At the same time, the system transmits the corresponding sensor data and alert status to the ThingSpeak cloud platform for remote monitoring.

If the threshold condition is not satisfied, the system continues normal monitoring and periodically updates the cloud dashboard with the latest sensor readings. This continuous monitoring process ensures that both fall detection and physiological monitoring can be performed in real time while maintaining efficient resource utilization on the embedded platform.

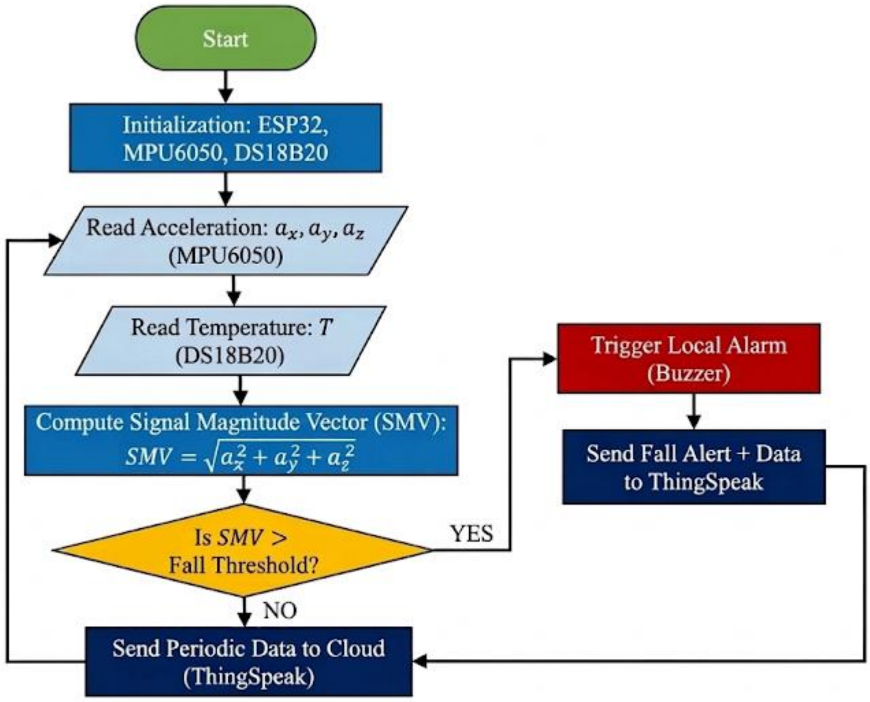

Figure 2: Operational flow of the proposed IoT-based elderly monitoring system

To evaluate fall detection performance, a series of controlled experiments were conducted involving both simulated fall events and activities of daily living (ADL). Simulated falls were performed to represent typical fall scenarios, while ADL activities such as walking, sitting, bending, and standing were carried out to examine the system’s ability to distinguish normal movements from fall events.

A total of 90 simulated fall events and 75 ADL activities were recorded during the testing phase. The classification results obtained from these experiments were used to construct the confusion matrix and calculate performance metrics such as sensitivity, specificity, precision, and F1-score. In addition, temperature measurement accuracy and system alert latency were also evaluated to assess the overall functionality of the proposed monitoring system.

CONFUSION MATRIX ANALYSIS

The proposed fall detection system was evaluated through controlled experiments involving simulated fall events and activities of daily living (ADL). A total of 90 fall events and 75 non-fall activities were conducted to assess the system’s detection capability. The classification outcomes obtained from the experiments are summarized in the confusion matrix shown in Table 2.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

Table 2 Confusion Matrix for Fall Detection Performance

	Actual Fall	**Actual Non-Fall**
Detected as Fall	77 (TP)	7 (FP)
Detected as Non- Fall	13 (FN)	68 (TN)

As presented in Table 2, the system successfully detected 77 out of 90 fall events, while 13 fall events were not detected. For normal daily activities, the system correctly classified 68 out of 75 activities as non-fall events, while 7 instances were incorrectly classified as falls.

FALL DETECTION PERFORMANCE METRICS

The performance of the proposed fall detection system was evaluated using several standard classification metrics commonly employed in activity recognition and health monitoring systems. These metrics include sensitivity, specificity, precision, and F1-score. The evaluation is based on the confusion matrix derived from the experimental results.

Sensitivity, also referred to as recall, measures the ability of the system to correctly identify actual fall events. It is defined as the ratio between correctly detected falls and the total number of fall events:

$$(2)\ Sensitivity = \frac{TP}{TP+FN}$$

where TP represents true positives and FN represents false negatives.

Specificity evaluates the capability of the system to correctly classify normal activities as non-fall events. This metric is calculated as:

$$(3)\ Specificity = \frac{TN}{TN+FP}$$

where TN denotes true negatives and FP denotes false positives.

Precision measures the proportion of detected fall events that correspond to actual falls and is expressed as:

$$(4)\ Precision = \frac{TP}{TP+FP}$$

Finally, the F1-score is used to provide a balanced evaluation of the detection performance by combining precision and recall through their harmonic mean:

$$(5)\ F1 = \frac{2\ x\ Precision\ x\ Recall}{Precision+Recall}$$

These metrics collectively provide a comprehensive assessment of the system’s ability to detect fall events accurately while minimizing false alarms during normal daily activities [3],[18].

Based on the confusion matrix, several evaluation metrics were calculated to assess the detection performance of the proposed algorithm. The results are summarized in Table 3.

Table 3 Performance Evaluation Metrics

Metric	**Value**
Sensitivity	85.56%
Specificity	90.67%
Precision	91.67%
F1-score	88.48%

The sensitivity of 85.56% indicates that the majority of fall events were correctly identified by the system.

Meanwhile, the specificity of 90.67% demonstrates the system's capability to distinguish normal activities from fall events with relatively low false alarm rates. The precision value of 91.67% suggests that most detected fall events correspond to actual fall incidents, while the F1-score of 88.48% provides a balanced measure of overall detection performance.

TEMPERATURE MONITORING ACCURACY AND STABILITY

In addition to fall detection, the proposed system also incorporates body temperature monitoring using the DS18B20 digital temperature sensor. The accuracy of the temperature measurement was evaluated by comparing the sensor readings with reference temperature measurements.

The performance of the temperature monitoring component was assessed using the Mean Absolute Error (MAE) metric, which measures the average absolute difference between the measured and reference temperature values. The MAE is defined as:

(6) $MAE = \frac{1}{N}\sum_{i=1}^{n} |Tmeasured - Treference|$

where $T_{measured}$ represents the temperature value recorded by the sensor and $T_{reference}$ represents the corresponding reference temperature.

The DS18B20 temperature sensor's performance was evaluated over 20 consecutive trials against a certified clinical thermometer. The results, summarized in Table 4, demonstrate high accuracy and consistency. The absolute error between the sensor reading and the reference value never exceeded 0.1°C, with a calculated Mean Absolute Error (MAE) of 0.05°C. The recorded temperatures showed minimal fluctuation, with a standard deviation of less than 0.1°C across trials. The experimental evaluation indicates that the DS18B20 sensor provides reliable temperature measurements for health monitoring applications. The relatively small error value demonstrates that the temperature monitoring component can provide sufficiently accurate physiological data for continuous elderly monitoring systems.

Table 4: Temperature Measurement Results (Sample of 20 Trials)

Trial	Reference Thermometer (°C)	DS18B20 Reading (°C)	Absolute Error, E (°C)
1	36.6	36.5	0.1
2	36.6	36.6	0.0
3	36.6	36.6	0.0
4	36.6	36.5	0.1
5	36.6	36.6	0.0
6	36.6	36.6	0.0
7	36.6	36.5	0.1
8	36.6	36.6	0.0
9	36.6	36.6	0.0
10	36.6	36.5	0.1
11	36.7	36.6	0.1
12	36.7	36.6	0.0
13	36.7	36.7	0.0
14	36.7	36.6	0.1
15	36.7	36.7	0.0
16	36.7	36.7	0.0
17	36.7	36.6	0.1
18	36.7	36.7	0.0
19	36.7	36.7	0.0
20	36.7	36.6	0.1

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue VII July 2026

ALERT LATENCY PERFORMANCE

Another important aspect of the system evaluation is the response time required to generate an alert after a fall event has been detected. Alert latency refers to the time interval between the occurrence of a fall event and the activation of the alert mechanism.

In the proposed system, alert generation is performed locally on the ESP32 microcontroller as part of the edge-based processing framework. Once the acceleration magnitude exceeds the predefined threshold value, the system immediately activates the buzzer alert and transmits monitoring data to the cloud platform.

The time delay between a detected fall event and the activation of the local buzzer alarm was measured across 10 trials. The results, shown in Table 5, indicate a consistent and low-latency response. The average fall-to- alert response time was 0.20 seconds, with a narrow range from 0.17 to 0.23 seconds and a standard deviation of 0.02 seconds.

This relatively short response time demonstrates the advantage of performing detection directly on the embedded device rather than relying solely on cloud-based processing. By minimizing communication delays, the system is able to provide rapid alerts that are critical for emergency response in elderly monitoring applications.

Table 5: Fall-to-Alert Response Time

Trial	t_event (s)	t_alert (s)	T_response (s)
1	10.000	10.180	0.18
2	20.000	20.220	0.22
3	30.000	30.200	0.20
4	40.000	40.190	0.19
5	50.000	50.210	0.21
6	60.000	60.170	0.17
7	70.000	70.230	0.23
8	80.000	80.200	0.20
9	90.000	90.190	0.19
10	100.000	100.220	0.22

IOT FUNCTIONALITY AND DATA TRANSMISSION

The IoT communication capability of the proposed system was also evaluated to verify the reliability of remote data transmission. During the experimental testing phases, the system successfully established a stable wireless connection between the ESP32 microcontroller and the ThingSpeak cloud platform.

Sensor data, including temperature readings and acceleration magnitude values, together with system status The consistent data transmission observed during the testing process confirms the effectiveness of the selected IoT architecture, which integrates the ESP32 wireless communication capability with the ThingSpeak application programming interface (API). This architecture enables continuous remote monitoring without requiring additional gateway devices. From a practical perspective, the cloud visualization feature allows caregivers or family members to monitor sensor data trends and system status remotely through an internet-connected interface. Consequently, the proposed system extends its monitoring functionality beyond the local environment by providing remote accessibility and continuous observation of the elderly individual’s condition. indicators, were periodically transmitted to the cloud server through the integrated Wi-Fi module of the ESP32. The transmitted data were successfully received and visualized in real time through the designated cloud dashboard interface.

COMPARISON WITH EXISTING STUDIES

To further evaluate the effectiveness of the proposed system, the performance results obtained in this study are compared with several previously reported fall detection systems from recent literature. The comparison focuses on commonly used evaluation metrics such as sensitivity, specificity, and F1-score. These metrics are widely used in fall detection research to assess the reliability and accuracy of classification models [24], [25]. As shown in Table 6, the proposed system achieves comparable performance with several previously reported fall detection systems. Although machine learning-based methods may achieve slightly higher detection accuracy, the proposed threshold-based approach offers a significant advantage in terms of computational efficiency and suitability for embedded IoT platforms. By implementing the detection algorithm directly on the ESP32 microcontroller, the system can perform real-time fall detection while maintaining low computational complexity. This lightweight design makes the system more practical for continuous elderly monitoring applications in home environments.

Table 6: Comparison of Fall Detection Performance with Existing Studies

Study	Method	Sensor	Sensitivity	Specificity
Li et al. [18]	Wearable fall detection using motion sensors	Accelerometer+ gyroscope	88%	91%
Mekruksavanich et al. [20]	Deep learning-based fall detection	Wearable IMU	92%	94%
Torres-Sospedra et al. [21]	Activity recognition using wearable sensors	Accelerometer	84%	89%
Yang et al. [23]	IoT-based health monitoring system	Wearable sensors	86%	90%
Proposed system	Threshold + Edge processing	MPU6050 IMU +DS18B20 Temperature sensor	85.56%	90.67%

CONCLUSION

This study presented the design and implementation of an IoT-based elderly monitoring system capable of detecting fall events and monitoring body temperature in real time. The system integrates the ESP32 microcontroller with the MPU6050 accelerometer and gyroscope sensor for fall detection, as well as the DS18B20 temperature sensor for physiological monitoring. Sensor data are processed at the edge device and transmitted to the cloud platform for remote visualization and monitoring.

Experimental evaluation was conducted using multiple simulated fall scenarios to assess the effectiveness of the proposed system. The results demonstrated that the system achieved a fall detection sensitivity of 85.56% and a specificity of 90.67%, indicating reliable performance in distinguishing fall events from normal daily activities. In addition, the temperature monitoring component produced a mean absolute error (MAE) of approximately 0.05°C when compared with reference measurements, confirming acceptable accuracy for continuous health monitoring. The system also achieved an average alert latency of approximately 0.20 seconds, enabling timely notification for potential emergency situations.

The integration of edge-based fall detection with cloud-enabled monitoring provides a practical and low-cost solution for continuous elderly care in home environments. By utilizing a lightweight threshold-based algorithm implemented directly on the ESP32, the system reduces computational complexity while maintaining real-time responsiveness. Furthermore, the use of the ThingSpeak platform enables caregivers to remotely monitor sensor data through an accessible and user-friendly interface.

For future work, the system can be further enhanced by incorporating additional physiological sensors, such as heart rate or blood oxygen monitoring, to provide more comprehensive health assessment. In addition, machine learning-based approaches may be explored to improve fall

detection accuracy and reduce false alarms under complex real-world conditions. Future studies may also involve larger-scale testing with real users to further validate the reliability and usability of the proposed system in practical elderly care applications.

ACKNOWLEDGMENT

The authors would like to thank Universiti Teknikal Malaysia Melaka (UTeM) and Ministry of Higher Education Malaysia (KPT) for the support on the research

Corresponding Author: Dr Hanim Abdul Razak, FTKEK, UTeM,

E-mail: hanim@utem.edu.my

REFERENCES

1. Al-Kababji A., Amira A., Bensaali F., Jarouf A., Shidqi L., Djelouat H., An IoT-based framework for remote fall monitoring, Biomedical Signal Processing and Control, 67 (2021), 102532
2. Igual R., Medrano C., Plaza I., Challenges, issues and trends in fall detection systems, BioMedical Engineering OnLine, 12 (2013), No.66
3. Özdemir A.T., Barshan B., Detecting falls with wearable sensors using machine learning techniques, Sensors, 14 (2014), No.6, 10691–10708
4. Mubashir M., Shao L., Seed L., A survey on fall detection: Principles and approaches, Neurocomputing, 100 (2013), 144–152
5. Noury N., Fleury A., Rumeau P., Bourke A.K., Laighin G.O., Rialle V., Lundy J.E., Fall detection – Principles and methods, Proceedings of the IEEE Engineering in Medicine and Biology Society, (2007), 1663–1666
6. Yuce M.R., Khan J., Internet of Things (IoT) in Healthcare Systems, Springer, 2021
7. Gjoreski H., Luštrek M., Gams M., Accelerometer placement for posture recognition and fall detection, Sensors, 14 (2014), 6317–6345
8. Kangas M., Konttila A., Lindgren P., Winblad I., Jämsä T., Comparison of low-complexity fall detection algorithms for body attached accelerometers, Gait & Posture, 28 (2008), 285–291
9. Hossain M.S., Muhammad G., Cloud-assisted industrial internet of things (IIoT) enabled framework for health monitoring, Future Generation Computer Systems, 101 (2019), 563–573
10. Rathore H.K., Ahmad A., Paul A., Jeon G., IoT-based fall detection system for elderly care using edge computing, IEEE Internet of Things Journal, 9 (2022), No.4, 2718–2728
11. Kumar S., Tiwari R., Zymbler M., Internet of Things is a revolutionary approach for future technology enhancement: A review, Journal of Big Data, 6 (2019), No.111
12. Rahman A.M., Hossain M.S., Muhammad G., Edge computing-based smart healthcare monitoring system, IEEE Access, 8 (2020), 146089–146101
13. Patel M., Wang J., Applications, challenges, and prospective in emerging body area networking technologies, IEEE Wireless Communications, 17 (2010), No.1, 80–88
14. Wang L., Zhang Y., Liu J., Wearable sensor-based fall detection using machine learning algorithms, Sensors, 20 (2020), No.3, 789
15. Patel S., Park H., Bonato P., Chan L., Rodgers M., A review of wearable sensors and systems with application in rehabilitation, Journal of NeuroEngineering and Rehabilitation, 9 (2012), No.21
16. Stankovic J.A., Research directions for the Internet of Things, IEEE Internet of Things Journal, 1 (2014), No.1, 3–9
17. Hossain M.S., Muhammad G., Cloud-assisted healthcare monitoring using IoT technologies, Future Generation Computer Systems, 66 (2017), 1–10
18. Li Q., Stankovic J.A., Hanson M.A., Barth A.T., Lach J., Zhou G., Accurate, fast fall detection using gyroscopes and accelerometer-derived posture information, Proceedings of the IEEE International Workshop on Wearable and Implantable Body Sensor Networks, (2009), 138–143
19. Mukherjee A., Misra S., Raghuwanshi N.S., A survey of IoT cloud-based healthcare monitoring systems, IEEE Internet of Things Journal, 6 (2019), 5949–5965
20. Mekruksavanich K., Jitpattanakul A., Deep learning-based fall detection using wearable sensors, Sensors, 22 (2022), No.10, 3621
21. Torres-Sospedra J., Montoliu R., Trilles S., Fall detection using wearable sensors: A review, Sensors, 20 (2020), 4755
22. Gjoreski H., Luštrek M., Gams M., Accelerometer-based human activity recognition and fall detection, Sensors, 16 (2016), 2063
23. Yang G., Deng J., Pang G., An IoT-enabled fall detection system using wearable sensors, IEEE Access, 8 (2020), 165229–165239
24. Sucerquia A., López J.D., Vargas-Bonilla J.F., Real-life fall detection using triaxial accelerometers, Sensors, 17 (2017), 223
25. Gjoreski H., Luštrek M., Gams M., Context-based fall detection and activity recognition using inertial and location sensors, Journal of Ambient Intelligence and Smart Environments, 6 (2014), 419–433