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ORIGINAL RESEARCH ARTICLE

WEARABLE MULTISTAGE FALL DETECTION AND EMERGENCY ALERT SYSTEM FOR ASSISTED-LIVING OLDER ADULTS

O.E. Agwu[1*], K.O. Odo[1], D.E. Iniobong[2]

[1]*Department of Electrical/Electronic Engineering, Michael Okpara University of Agriculture, Umudike, Nigeria*
[2]*Central Emerald State Research Community, MOUAU, Nigeria*
[*]*Corresponding author's Email: agwu.ekwe@mouau.edu.ng*

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ABSTRACT

Falls are becoming increasingly serious issues for elderly people. In fact, one out of three individuals aged 65 and older will sustain at least one fall per year. Unfortunately, existing fall detection systems still have to overcome problems of false alarms and sensitivity in order to be effectively employed. This article introduces a new smart wearable device with an advanced multi-stage fall detection algorithm that successfully distinguishes between falls and ordinary actions. This system is based on the ESP32 DevKit V1 microcontroller, MPU6050 inertial measurement system (accelerometer and gyroscope), SIM800L GSM module, buzzer, pushbutton, and LED indicator, powered by 3500 mAh rechargeable battery. The fall detection system works by sequentially analyzing free-fall, impact, orientation change, inactivity after fall, and final standing position with regard to the user-calibrated reference. The results show that the accuracy of readings in tests reached 96.0%, with false alarms rate equal to 4.0% based on 150 simulated experiments. In addition, it was observed that system could send emergency SMS alerts within 12 seconds of confirming a fall. Another benefit is that the Wi-Fi dashboard facilitates remote management of contacts as well as monitoring contacts in real time. This inexpensive prototype offers an innovative means for ensuring a high level of safety among the elderly and providing them with an independent lifestyle, with the future upgrades in plans, such as the addition of GPS and memory capabilities for storing contacts.

1.0 Introduction

Population ageing is one of the major demographic changes of the 21st century, with a growing number of elderly people in both developed and developing countries. Age-related reductions in muscle strength, balance, and reaction time increase the risk of falls (Tanwar *et al.*, 2022). Falls affect approximately one-third of people aged 65 years and above annually, while the rapidly increasing global population of adults over 60 highlights the need for intelligent technologies for fall monitoring and assistance (Tanwar *et al.*, 2022; Gorce and Jacquier-Bret, 2025).

Falls can result in physical injuries as well as psychological and social consequences. Prolonged periods spent on the floor after a fall, known as a "long lie," can increase the risk of complications and mortality, while fear of falling may restrict daily activities and accelerate frailty (Flor-Unda *et al.*, 2025). Consequently, fall-detection and assisted-living systems incorporating sensors, communication technologies, and intelligent algorithms have been developed to enable continuous monitoring and rapid caregiver notification (Broadley *et al.*, 2018). Such systems can automatically transmit alerts through SMS, mobile applications, or IoT platforms, thereby reducing response time and potentially limiting the consequences of falls (Li *et al.*, 2023).

Recent advances in wearable sensors, IoT infrastructure, and artificial intelligence have significantly transformed fall-detection research (Li *et al.*, 2025). Wearable accelerometers and gyroscopes can continuously monitor movement, while machine-learning and deep-learning techniques enable more sophisticated recognition of fall patterns beyond conventional threshold-based methods (Flor-Unda *et al.*, 2025; Florence *et al.*, 2018; Pannurat *et al.*, 2020; Casilari *et al.*, 2020). Various approaches have been reported, including threshold-based wearable systems, smartphone-based applications, inertial-sensor systems using support-vector machines, and deep-learning models. However, these approaches have limitations such as false alarms, dependence on users carrying smartphones, poor specificity, high computational requirements, and the need for large training datasets (Abbate *et al.*, 2020; Sposaro and Tyson, 2019; Vidal *et al.*, 2020; Chen *et al.*, 2021; Zhang *et al.*, 2024).

Vision-based systems can achieve high accuracy but are affected by occlusion, lighting conditions, and privacy concerns, while hybrid systems combining wearable and ambient sensors often increase system cost and complexity (Flor-Unda *et al.*, 2025). Similarly, conventional threshold-based detectors may misclassify activities such as jumping or sudden sitting as falls while missing less pronounced events, whereas machine-learning approaches may be unsuitable for low-cost wearable devices because of their computational and data requirements (Flor-Unda *et al.*, 2025; Casilari *et al.*, 2020; Zhang *et al.*, 2024). Furthermore, nearly half of older adults who experience falls may be unable to summon assistance, making timely automatic notification particularly important (Li *et al.*, 2023; Abbate *et al.*, 2020). Therefore, there is a need for a reliable, affordable, and autonomous fall-detection system capable of distinguishing falls from normal activities while providing timely alerts without requiring user intervention. This study addresses this need by developing a low-cost wearable device incorporating a multi-stage algorithm to reduce false alarms and improve fall-detection reliability.

2. Materials and Method

2.1 System Architecture

The given system is a wearable device which is developed for the detection of falls with four major subsystems, which include sensing, processing, communication, and power. This device works continuously and collects motion data and analyzes it to detect the fall incidence. When a fall is detected, the device immediately sends alarm signals. The heart of this system is the ESP32 DevKit V1 microcontroller, chosen based on its high processing capability, efficiency, and variety of communication means, including Wi-Fi. The MPU6050 IMU is responsible for motion detecting, combining three-axis accelerometer and three-axis gyroscope to deliver accurate motion information (InvenSense, 2011). The SIM800L GSM/GPRS module provides emergency communications. Other device's components include buzzer fortified with audio signals, a push button designed for interacting with a user, and LED signifying the state of the system. The device functions using a strong 3500 mAh 18650 lithium-ion battery combined with 5 V boost converter.

Figure 1 shows the block diagram of the system. The sensor data is sent from the MPU6050 to the ESP32 using I^2C, whereas the GSM module uses UART for communication. The buzzer, button, and LED are each connected to GPIO pins. All of the components are properly assembled on a Veroboard in accordance with the circuit schematic presented in Figure 2.

2.2 Hardware Implementation

In building the hardware, we put all the components on a Veroboard according to the schematic shown in Figure 2. Communication between the MPU6050 and the ESP32 is carried out using the I^2C protocol on the SDA and SCL lines. The SIM800L module is connected via a serial UART port. In addition, we connected the push button, buzzer, and LED components to certain GPIO pins while ensuring that the appropriate pull-up and limiting currents resistors were installed. The circuit is powered by a 18650 battery which is controlled by a 5V power booster providing power to ESP32 (3.3V) and GSM with a constant voltage of 4 volts. It is very important to keep in mind the supply of electricity so that maximum demand (up to 2 amps at the peak) of SIM800L during data transmission does not ruin the whole system.

2.3 Multi-Stage Fall Detection Algorithm

In an effort to enhance trustworthiness and minimize false alarms, a multi-step event-confirmation approach was established. This method necessitates the accomplishment of a precise order of requirements before a fall can be identified. It is based on the following limits that have been established by means of scientific testing:

i. Free-fall threshold: $A_{ff} = 0.5g$
ii. Impact threshold: $A_{impact} = 2.5g$
iii. Orientation tolerance: $D_{threshold} = 0.4$

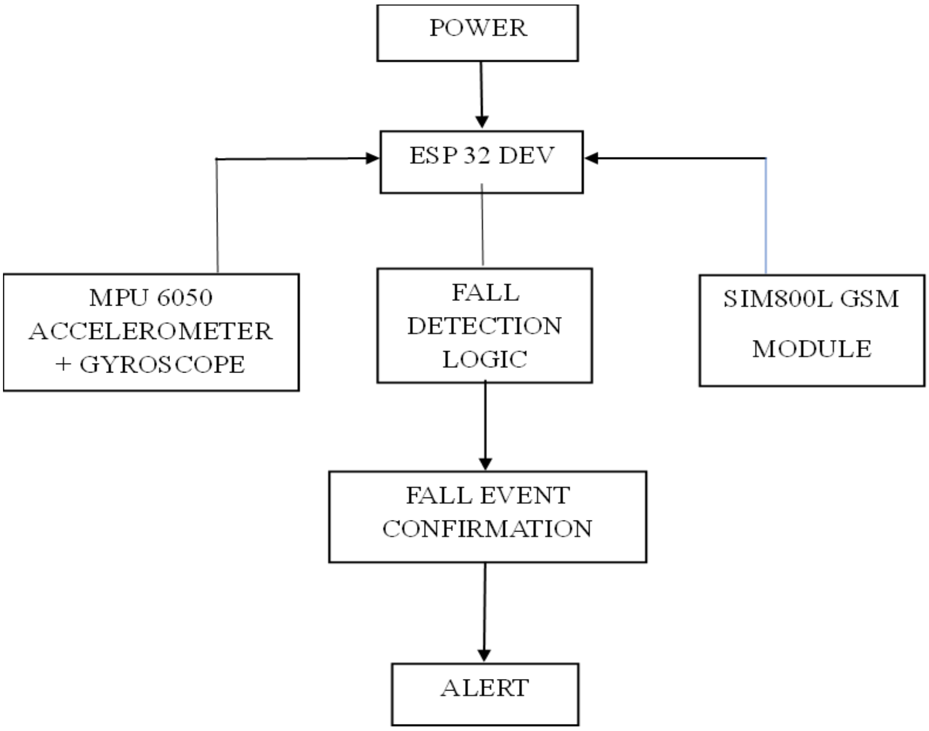

Figure 1: System block diagram (illustrative components interconnected with flow arrows)

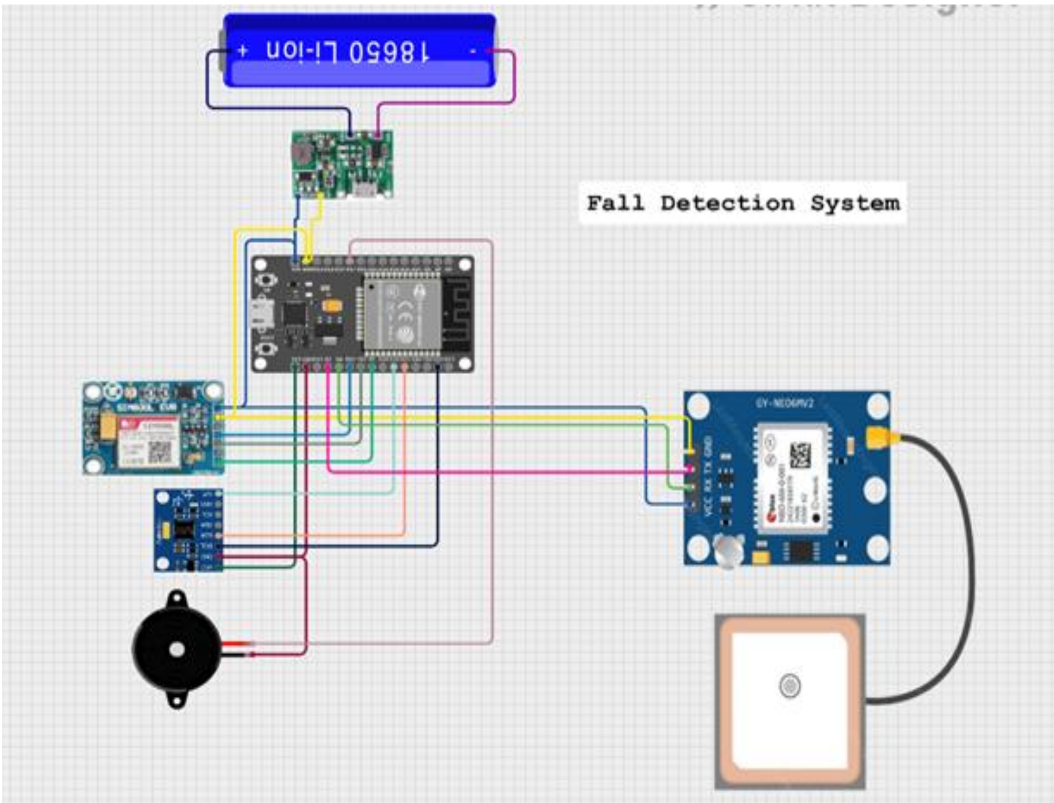

Figure 2: Circuit schematic diagram (showing ESP32, MPU6050, SIM800L, and peripheral connections)

iv. Inactivity delay: configurable (~2 seconds of minimal acceleration change)
v. Standing reference vector (X_r, Y_r, Z_r) obtained from a one-time calibration.

The algorithm proceeds as follows:

i. Data Acquisition: The ESP32 gathers raw acceleration data (x, y, z) and gyroscope information from the MPU6050 registers using the I2C protocol. To calculate the overall acceleration magnitude (A), we apply the Euclidean norm:

$$A = x^2 + y^2 + z^2 \quad (1)$$

where x is the horizontal or first-axis component, y is the depth or second-axis component and z is the vertical or third-axis component.

ii. Free-Fall Detection: A fall is suspected when the acceleration magnitude drops significantly, indicating weightlessness.

Condition: $A < A_{ff}$, where $A_{ff} = 0.5g$ (experimentally determined).

iii. Impact Detection: Following a free fall, the system checks for a sudden, sharp increase in acceleration due to impact with the ground.

Condition: $A > A_{impact}$, where $A_{impact} = 2.5g$.

iv. Orientation Change Analysis: The system compares the current posture vector against a calibrated standing reference vector (X_r, Y_r, Z_r). The Euclidean distance (D) is calculated as:

$$D = \sqrt{(x - X_r)^2 + (y - Y_r)^2 + (z - Z_r)^2} \quad (2)$$

v. The orientation change will be regarded as significant if D exceeds D_threshold (tolerance = 0.4).
vi. Monitoring for Inactivity: Following the impact and the orientation change, the system then monitors for notable activity for the predetermined time frame (for example, 2 seconds). If no activity is observed, the system will indicate inactivity as long as the difference in acceleration between two consecutive points remains below a certain value, Δ.
vii. Verification of Final Standing Position: At this stage, we are able to distinguish between real falls and activities like jumping, where the user is able to return to a standing position. If the last position is within tolerable limits (D ≤ D threshold), the warning is cancelled. If there are considerable deviations (D > D threshold), a fall is confirmed and the alert sequence is activated.
viii. Establishing the standing position: In the procedure of set-up, one-time calibration is performed. The individual remains in a vertical posture during the time when the device collects data from the sensors during certain sampling time to determine the reference vector. For example, the data could be the following: X_r = 0.07, Y_r = -0.97, Z_r = 0.10.

The algorithm is presented in Figure 3, and pseudo-code for it can be found in Algorithm 1.

Algorithm 1: Multi-Stage Fall Detection Pseudo-code

Algorithm: MultiStageFallDetection()

Input: Raw acceleration data (x, y, z) from MPU6050

Output: fallConfirmed (Boolean)

Constants:

FF_THRESH = 0.5g

IMPACT_THRESH = 2.5g

ORIENT_TOL = 0.4

INACTIVITY_DELAY = 2.0 seconds

```
    DELTA = 0.1g

Initialization:

    standingRef = CalibrateStandingPosition()

    fallConfirmed = FALSE

Main Loop:

    while system is ON:

        x, y, z = ReadAccelerometer()

        A = sqrt(x² + y² + z²)

        // Stage 1: Free Fall Detection

        if A < FF_THRESH:

            startImpactTimer()

            // Stage 2: Impact Detection

            if A > IMPACT_THRESH within impactWindow:

                // Stage 3: Orientation Change

                D = DistanceToStandingRef(x, y, z)

                if D > ORIENT_TOL:

                    // Stage 4: Inactivity Monitoring

                    if inactivityDuration > INACTIVITY_DELAY:

                        // Stage 5: Final Standing Verification

                        finalOrient = ReadAccelerometer()

                        D_final = DistanceToStandingRef(finalOrient)

                        if D_final > ORIENT_TOL:

                            fallConfirmed = TRUE

                            TriggerEmergencyAlert()
```

Once a fall is established as valid, the ESP32 goes into action initializing the SIM800L module via AT commands. Next, it checks for network registration with AT + CREG? and confirms signal quality using AT + CSQ. After that, it proceeds to switch the SMS to text mode using the command AT + CMGF = 1. A predefined emergency message will be subsequently sent to a specified contact number. If you wish to cancel the alert, you only need to triple-click on the pushbutton within a certain time window. On the contrary, holding the button pressed for 3 seconds will trigger the emergency alert manually without going through the usual detection mechanism.

The ESP32 also acts as a web server using the Wi-Fi connection and implements a web dashboard (see Figure 4) built with HTML/CSS and JavaScript. The user will be able to connect to the SSID called "FallDetector" to check out the status of the system and find out the emergency contact number. The dashboard is updated in real-time using AJAX functionality, and there is a form for updating the contact number.

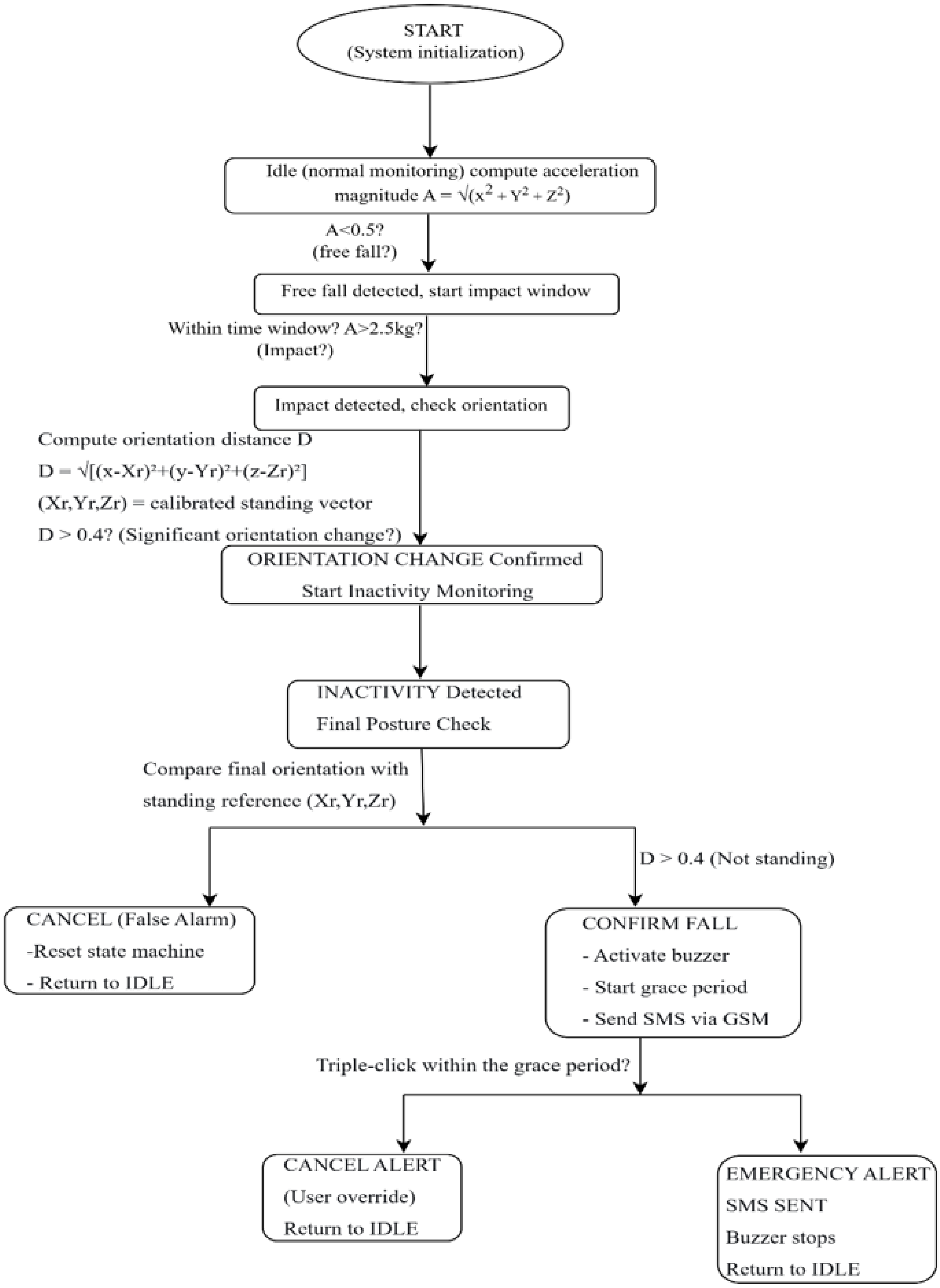

Figure 3: Flow diagram of the multi-stage fall detection algorithm (showing decision nodes for free-fall, impact, orientation change, inactivity, and final standing check)

2.4 Performance Metrics

To quantitatively evaluate the system, we used the following metrics:

i. Accuracy: $\frac{TP+TN}{TP+TN+FP+FN} \times 100\%$
ii. Sensitivity (Recall): $\frac{TP}{TP+FN} \times 100\%$
iii. Specificity: $\frac{TN}{TN+FP} \times 100\%$
iv. False Positive Rate (FPR): $\frac{FP}{FP+TN} \times 100\%$

v. False Negative Rate (FNR): $\frac{FN}{TP+FN} \times 100\%$

where TP = true positives, TN = true negatives, FP = false positives, FN = false negatives.

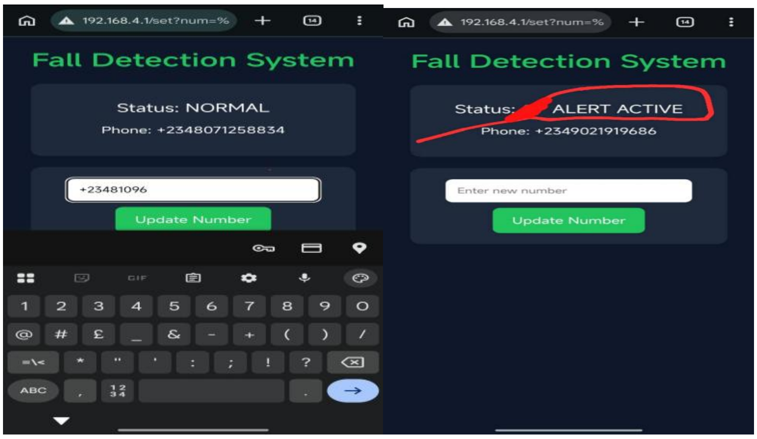

Figure 4: Mobile dashboard interface (showing real-time status, alert log, and contact configuration form)

2.5 Experimental Setup

The prototype was systematically assembled and examined in a smart laboratory environment. Ten participants, aged from 22 to 35 years with an average height of 1.72 m, went through a total of 150 trial runs, which were broadly classified into two groups:

i. Falls (75 trials): This consisted of 25 forward falls, 25 backward falls, and 25 sideways falls onto a crash mat.
ii. Non-fall activities (75 trials): Participants performed 20 vertical jumps, 20 sudden sitting movements, 25 walking and bending activities, and 10 slow lying-down movements.

In order to achieve accurate results, the participants wore the gadget tightly to their waists using a flexible belt. The information was collected via serial detection and confirmations of alerts: The results were recorded in the form of SMS notifications. The responses of the system were defined as true positive (TP), true negative (TN), false positive (FP), or false negative (FN) regarding already known types of activities.

3. Results and Discussion

3.1 Performance Evaluation

The results are summarized in Tables 1, 2 and Figure 5. The multi-stage algorithm worked very effectively, detecting 72 from 75 falls and showing sensitivity equal to 96.0%. Also, the system correctly detected 72 from 75 non-fall activities. Therefore, a specificity of 96.0% was demonstrated. In general, the accuracy is highly impressive and equals 96.0%.

Table 1: System response to different activities

Activity	Free-Fall Detected	Impact Detected	Orientation Change	Inactivity Monitored	Final Standing Position	Alert Triggered	Correct / Total
Forward fall	Yes	Yes	Yes	Yes	No (not standing)	Yes	25/25
Backward fall	Yes	Yes	Yes	Yes	No (not standing)	Yes	24/25
Sideways fall	Yes	Yes	Yes	Yes	No (not standing)	Yes	23/25
Jumping	Yes	Yes	No (transient)	No	Yes (returned)	No	20/20
Sudden sitting	No	Maybe	Yes	No	Yes	No	20/20
Walking / bending	No	No	No	No	Yes	No	25/25
Lying down slowly	No	No	Yes	No	No	No	10/10

Table 3: Overall Performance Metrics

Metric	Value
True Positives (TP)	72
True Negatives (TN)	72
False Positives (FP)	3
False Negatives (FN)	3
Accuracy	96.0%
Sensitivity	96.0%
Specificity	96.0%
False Positive Rate	4.0%
False Negative Rate	4.0%

It typically required approximately 12 seconds to transmit an SMS once a fall was detected, particularly in areas with good GSM connectivity. Once the fall was detected, the alarm was triggered immediately. The results indicated that the emergency button being manually pressed (long pressed) and the ability to cancel triggering (quickly pressing three times) worked exceptionally well in all tests conducted.

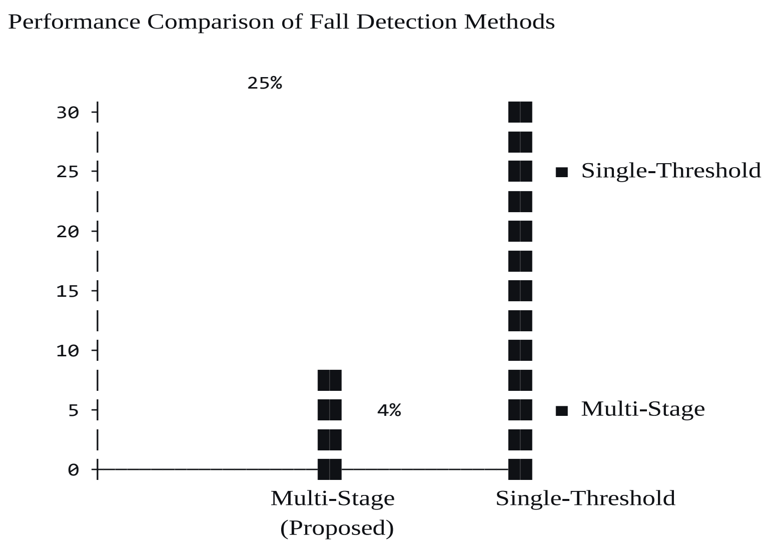

Figure 5: Performance comparison with single-threshold methods (bar chart showing false alarm rates: 25% for single-threshold vs. 4% for our multi-stage approach)

The results demonstrated the efficiency of our multi-stage algorithm in terms of minimizing false alarms since the percentage of misidentified events is way below that of any single-threshold method. The experiments showed that the single-threshold method based solely on the magnitude of the impact would have resulted in false alarms in around 25 percent of cases during such activities as jumping or sitting down. In contrast, the multi-stage algorithm successfully eliminated these activities from consideration by checking the final standing position, which is responsible for reducing the number of false alarms by more than 84 percent.

The final standing position verification turned out to be very important since otherwise the falls would have been classified as jumps. The comparison of the final standing position to the calibrated standing position allows the system to differentiate between really fallen and fleeting events.

The prototype costs less than $50 and includes easily accessible parts, making it suitable for regions with limited resources lacking proper health facilities. The availability of the Wi-Fi dashboard makes using the device easier as there is no need to have a mobile application.

Nevertheless, the system has some limitations as it depends on GSM network to function properly. This may be an issue in some regions having weak network coverage since SMS alerts won't be sent. Also, GPS is not available, and that information is crucial while sending emergency telegrams. The emergency number is saved in temporary memory and needs to be saved again due to loss of power. Moreover, the device consumes a lot of power while transmitting the information which may cause it to restart.

In spite of these problems, the system is an efficient option for fall detection with performance that meets if not exceeds those of other costly and more complicated solutions.

Corresponding author's email address: agwu.ekwe@mouau.edu.ng

4. Conclusion

In this study, a wearable fall detection system specifically tailored for elderly users, presenting its design, development, and testing results was carried out. The main advantage is an innovative algorithm with several stages that detects free fall, impact, orientation change, absence of movement, and standing position with respect to the user initialized parameters. The system has reached the efficiency of 96% and was able to minimize the false alarms to only 4% in 150 experiments. The hardware, consisting of ESP32 microcontroller, MPU6050 IMU, and SIM800L GSM module, has shown the performance of fall monitoring, fall reporting, and organization of emergency calls in less than 12 seconds. The system has an intuitive design with a possibility of emergency notification registration or cancellation and the remote access through the Wi-Fi dashboard, contributing to its usability. The invention is low-cost and may be used for increasing safety and independence of elderly people at home.

Looking ahead, future work will focus on overcoming the current limitations by integrating a GPS module to transmit the user's location in emergency SMS messages for quicker responses, adding non-volatile memory (EEPROM) to permanently store emergency contacts and prevent data loss after power outages, incorporating battery monitoring and deep-sleep modes to extend battery life and improve power management, developing a companion mobile application with features such as fall history tracking, caregiver notifications, and remote monitoring, and conducting field trials with elderly participants in assisted-living facilities to evaluate real-world performance and gather user feedback.

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Corresponding author's email address: agwu.ekwe@mouau.edu.ng