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Development of a Wearable Fall Sensing Device for Enhanced Independent Living Among the Elderly

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Abstract

Unwitnessed falls among elderly people which consequently has resulted in cases of fatality before caregivers are alerted for prompt response, has been a call for concern. This was the motivation for this work. It integrates a motion sensors and Internet of Things (IoT) algorithms with a web application platform that alerts caregivers. The device would measure the wearer's physical parameters; movement speed and angular orientation through the sensors. The design makes use of two sensors; the accelerometer for measuring acceleration forces and the gyroscope for rotational motion. The adopted method includes component selection, sensor integration, data acquisition and processing, fall detection algorithm, wireless communication, user interface, power management, testing, and packaging. The test for fall sensor for elderly people was carried out by attaching the device to a mannequin to measure the accuracy of the device. The mannequin was pushed in various ways to check for accuracy when detecting various types of falls. The sensor's data were sent to the web server (ThingSpeak) at 15s intervals for visualization by the user and to enhance storage of data about fall incidences. The readings from the MPU6050 sensor had good data precision with an average movement speed of 8.37 m/s. The readings from the sensor showed an average trigger speed of 8.05 m/s and an average execution time of 2.4 s. There is a 90% accuracy in the detection of fall occurrences. The use of fall sensors for fall detection has greatly improved the detection of fall occurrences among elderly people, providing a safer approach to caring for elderly people.

Keywords: *Fall detection, sensors' integration, trigger-speed, execution-time, elderly-people.*

1.0 Introduction

A fall could be described as "an occurrence to a person, which could result in tumbling to a lower level involuntarily; this may exclude deliberate adjustment in position to rest on household upholstery, wall or other objects [1]. A direct association exist between falls and increased mortality, morbidity, and loss of functional ability. Falls often occur among the elderly, children, and athletes, and it is considered a major public health issue for the elderly, as they are major source of mortality from injury among a nation's citizen [2]. When fall occurs, victims may suffer diverse type of injuries such as broken bones, minor cuts, skin damage, connective and soft tissue impairment and loss of quality of life. The cost of providing medical attention may be significant. To address this issue, there is a need to develop a cost-effective fall detection device for the elderly.

A severe outcome of experiencing a fall is the occurrence of a '*long-lie*', which is laying low on the floor unwillingly for a longer-than-normal period after the fall. The '*long-lie'* is a usual incidence and studies have revealed that significant number of aged people often find it difficult to rise, sometimes from innocuous falls. It has also been revealed that half of those elderly who experience a '*long-lie'* die within six months, even if no direct injury from the fall has occurred, indicating a deterioration in general health. Thus, if an elderly person experiences a fall followed by a '*long-lie'* while living alone, the impact could be grave and possibly deadly.

Auto sensing of falls amongst the elderly will in no small measure, often greatly reduce the frequency of '*long-lie*' occurrence and also minimize the consequential damage, by enabling quicker fall detection, hence ensuring swifter arrival of medical attention. This fall detection system can be in the form of a wearable device, a technology that has the potential to detect falls in real-time [2].

The design of fall detection device will be based on motion sensors and enhanced with the use of machine learning algorithms. The product could be made user-friendly and easy for the aged to wear. The device itself will include sensors such as an accelerometer and/or gyroscopes to detect changes in movement or position, as well as software that can interpret the sensor data and ascertain if there is a fall. The goal of this project is the development of a device that is affordable for the elderly and their families, while also providing a high level of accuracy and reliability in fall detection, it could also include features such as a panic button. By providing a cost-effective solution for fall detection, the device aims to improve the safety and independence of older adults.

The existing fall detection systems are quite expensive, these could make them cost-prohibitive for the elderly and their families. Existing fall detection systems may not be as accurate and reliable as they need to be, leading to false alarms and reducing the system's overall effectiveness. The sensor should be user-friendly and easy for the

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elderly to wear, and should have the ability to differentiate falls from other types of movements. The aforementioned motivated the development of a wearable fall sensor adopting IoT.

2.0 Literature Review

The population of the elderly is growing rapidly, and with it, the incidences of falls are prevalent. Falls have been established to impact the quality of life of the elderly, resulting in loss of independence, hospitalization, and institutionalization [3]. Detecting falls as soon as they occur is critical to ensuring a prompt response and reducing the risk of further harm.

Fall sensors are often wearable devices that can detect a fall and trigger an alarm, alerting caregivers or emergency services to the situation. With advances in technology and miniaturization, fall sensors are becoming more affordable, convenient, and accessible, making them a promising solution for fall detection and prevention [4].

The working of fall sensors is based on the principle of acceleration, and the device measures the sudden change in acceleration during a fall. There are two main types of fall sensors: those that rely on accelerometers and those that use a combination of accelerometers and gyroscopes. Accelerometers measure a moving object's acceleration and can detect the frequency and intensity of human movement. Accelerometers are widely used in monitoring functional motor movement and have focused on measuring gait, posture, and tremor parameters, besides detecting falls. Body-worn accelerometers have also been utilized to classify activities in sitting, walking, standing, cycling, and lying positions, and have shown high accuracies in such studies [5]. When a person falls, the sudden change in acceleration is detected by the accelerometer and this information is processed and analyzed by the device's software. The software determines if the change in acceleration is consistent with a fall and if it is, an alarm or alert is triggered [6]. A gyroscope measures the rate of rotation around an axis. In a fall sensor, it can be used to detect the orientation of the device and the direction of the fall [7]. The gyroscope can detect the angular orientation of the device and can be used to determine if the device is falling or not. The gyroscope data is combined with accelerometer data to improve the accuracy of fall detection [8].

The accuracy of fall sensors can vary depending on the technology used and the conditions in which they are used. Factors that can affect the accuracy of fall sensors include the type of accelerometer or gyroscope used, the type of fall detection algorithm, and environmental conditions such as noise and interference and they offer a practical solution for fall detection and response.

A fall detection system that combines depth maps obtained from an RGB-D sensor with data from a wireless accelerometer was proposed in [9]. The system acquires data from a depth camera and a wireless accelerometer. The depth camera provides depth maps of the user's surroundings, while the accelerometer provides acceleration data of the user's movements. The depth maps and accelerometer data are pre-processed to remove noise and irrelevant information. The data is filtered and normalized to ensure that it is suitable for analysis. Relevant features are extracted from the pre-processed data, such as the height and velocity of the user, as well as the acceleration and orientation of their movements. An algorithm is developed to detect falls based on the extracted features. The algorithm utilizes a threshold value for the height of the user, as well as the acceleration and velocity of their movements, to differentiate between falls and other activities. The fall detection algorithm is implemented on an embedded platform, which is a small computer system that is designed for specific applications. The embedded platform is used to process the data in real-time and trigger an alarm when a fall is detected. Based on the output of the fall detection algorithm, the system determines whether a fall has occurred. If a fall is detected, an alarm is triggered to alert caregivers or emergency services. The system utilizes depth maps and a wireless accelerometer to provide accurate and reliable fall detection on an embedded platform.

Inertial measurement unit (IMU) for fall detection was employed in the work of [10]. The system created in the study is expandable and can add a large number of sensors. The data transferred from the IMU sensors placed on the patient to the Raspberry Pi is evaluated by software. A fall perception is created when sudden changes occur from the values determined as normal posture levels

In the article of [11], a real-time online activity recognition approach was proposed based on the genetic algorithm–optimized support vector machine classifier. A new sliding window-based feature representation technique enhanced by mutual information between sensors is devised. In addition, the genetic algorithm is used to automatically select optimal hyperparameters for the support vector machine model, thereby reducing the recognition inaccuracy caused by manual tuning of hyperparameters. Finally, a series of comprehensive experiments are conducted on freely available data sets to validate the effectiveness of the proposed approach.

In [12], a machine-learning approach for fall detection and daily living activity recognition was proposed. The sensors used measured acceleration and angular orientation in three dimensions. The collected data was processed and noise was eliminated in preparation for feature extraction and machine learning analysis. The system extracted features from the pre-processed data that represent the user's movement pattern. Statistical tools, such as mean and standard deviation, as well as time and frequency domain features were used to analyze the features.

Previous studies did not consider the impact of different environmental conditions, such as surfaces, on the accuracy of fall detection. The wrist-worn device used in some systems may not be suitable for individuals with physical limitations, such as limited wrist mobility. The decision tree classifier used in the fall detection algorithm may not perform well in complex or uncommon fall scenarios. The use of multiple sensors and the processing of depth maps can add complexity to the system, which may impact its performance and practicality. The experiments were conducted in a controlled environment, which may not fully reflect the real-world conditions in which the system would be used. The method was not compared with other fall detection systems, which would have provided a better understanding of the relative performance of the system compared to other methods. Hence, the need to develop a fall sensory device that takes into consideration, the aforementioned deficiencies.

3.0 Materials and Methods

The methodology adopted in this work was based on sensor-driven technology with inputs made of sensors mainly, while the microcontroller served as the brain of the system (processing unit), and the output comprised of OLED screen, API and the visual display of the mobile. The block diagram of the system is shown in Figure 1.

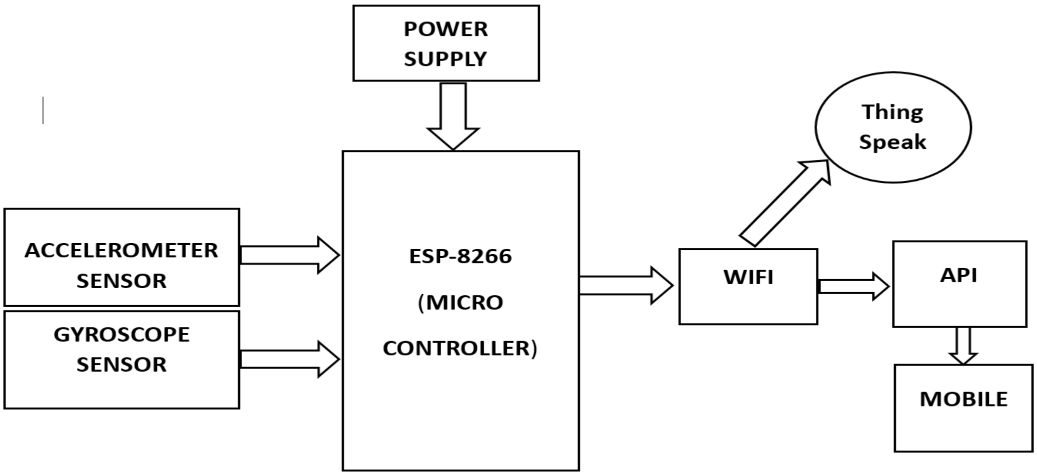

Figure 1: Block diagram of the fall sensor for elderly people

The developed wearable falls sensing device for enhanced independent living among the elderly was built with the following as integrated units: the input, the processing, and the output. The input comprised selected sensors, including the accelerometer and gyroscope, the processing unit with the interfaced ESP8266 microcontroller, while the output relays the detected falls signals.

Accelerometer and Gyroscope: MPU6050 component was employed for measuring acceleration forces and rotational motion; while ESP8266 microcontroller was used for the controlling function of the system. The complete circuit was powered with the Li-ion or Li-Po rechargeable battery, while TP4056 was integrated for battery charging. OLED screen displays the sensed falls signal in form of a message, while the buzzer generates the audio alert.

3.1 System Overview

Data collected by integrated sensors (gyroscope and accelerometer) in form of user's motion, acceleration, or orientation is linked to the microcontroller via the data port. The ESP8266 microcontroller processed the data using suitable algorithms to extract meaningful features for fall detection. A fall detection algorithm was developed and implemented on the ESP8266 microcontroller. Factors such as acceleration thresholds, motion patterns, and orientation changes were considered in the algorithm to differentiate falls from normal activities.

The microcontroller was programmed to establish a cellular connection using Wi-Fi, allowing the fall sensor to send alerts or notifications in case of a fall event via a third-party API. SMS messages were utilized to notify designated contacts about the fall incidence. The fall sensor incorporated a user interface to facilitate configuration and provide feedback. Buttons were included for user interaction, and an OLED screen was integrated to provide visual feedback, displaying relevant information such as system status or notifications. A rechargeable battery was incorporated to power the device. A charging circuit, such as the TP4056 was connected for auto-charging of the battery.

3.2 The Working of the Device

The device measures the physical parameters of the users, such as: movement speed and angular orientation through the sensors. The brain of the project is the ESP-8266, a microcontroller, interfaced with the sensors for input data processing. When the sensor parameters exceed a threshold value, the ESP-8266 is programmed to trigger the third-party API and sends a fall detection notification to a designated caregiver through SMS. The unit

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is designed as a system enabled to function as a portable and wearable unit, with which users' physical parameters are measured. The result is transmitted to a web page (ThingSpeak) to be accessed in real time.

The flowchart and the circuit diagram are shown in Figures 2 and 3 respectively.

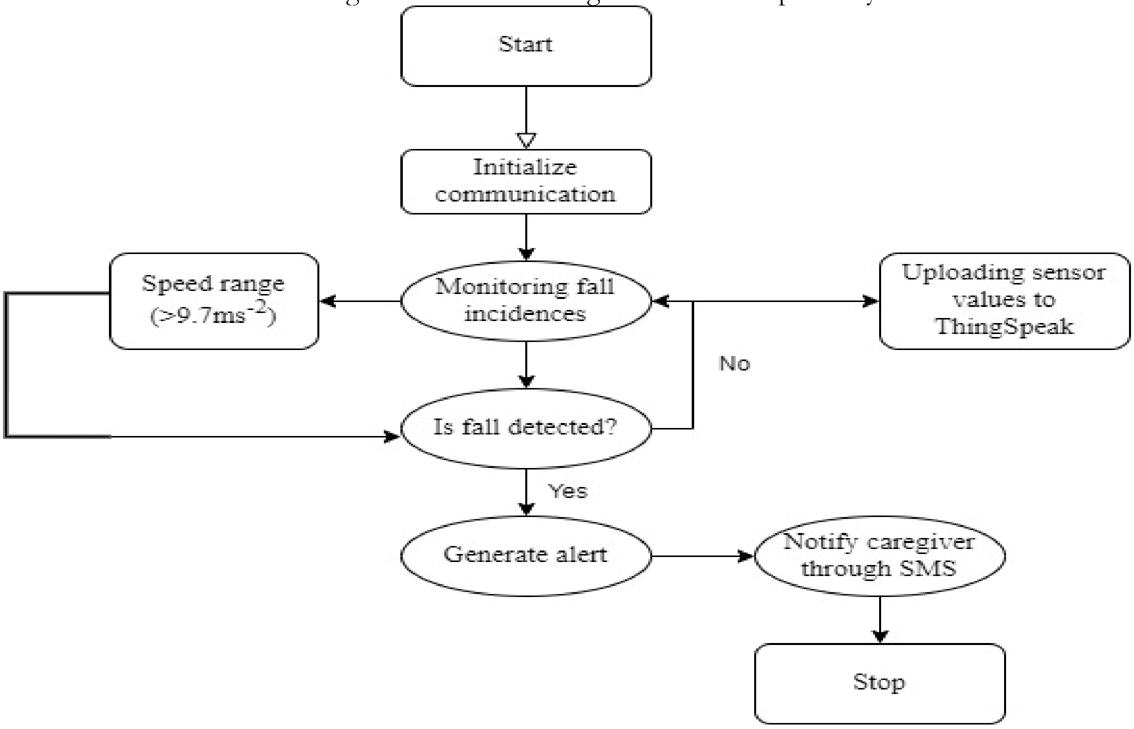

Figure 2: Flowchart of the system

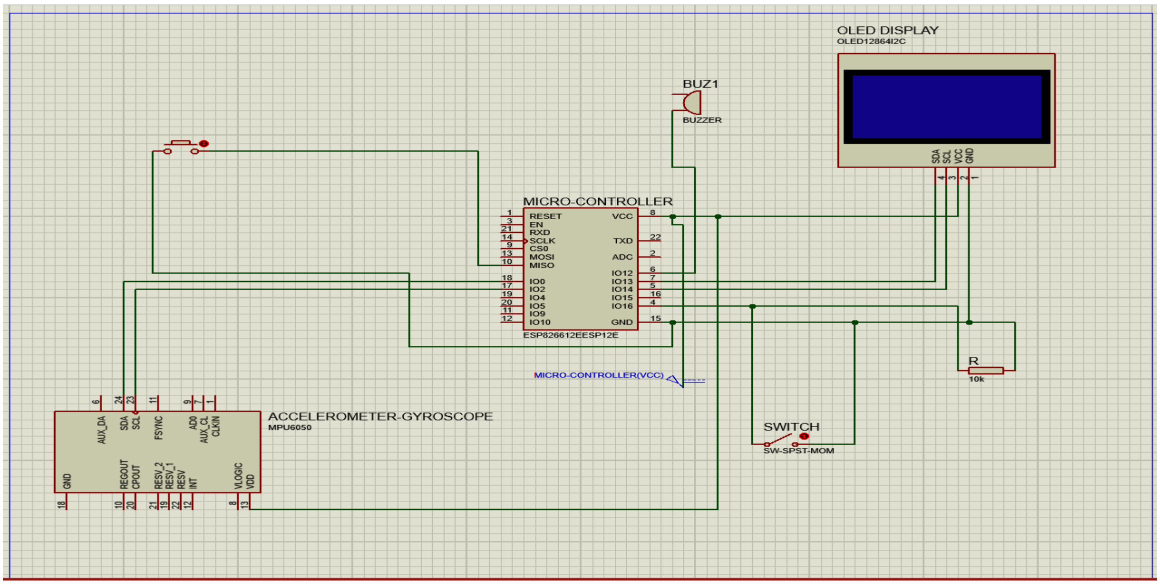

Figure 3: Circuit diagram of the system

3.3 System Evaluation

After completing all of the preliminary design and analysis, the project was implemented on a breadboard to observe the behavior of the sensors and to determine the functionality of the whole system. The implementation of this project involves:

- Writing and debugging of the software code on Arduino IDE
- Implementation of the whole project on the breadboard
- Uploading the code to the microcontroller (ESP8266NodeMCU)

The sensor was placed on the breadboard and connected to the microcontroller (ESP8266NodeMCU) and was tested by uploading the required code for each component to achieve respective functionality. Then the OLED was connected to the whole circuit to display the value of the sensors and the battery was connected with a DC-DC boost converter during this phase to serve as a power source that supplies 5V to the circuit on the breadboard.

After the whole components had been connected and their functionality had been confirmed, the Wi-Fi module on the ESP8266NodeMCU was activated by updating the with Wi-Fi connectivity code to send the sensor data value to a webserver (ThingSpeak) for visualization and real-time monitoring as shown in Figure 4.

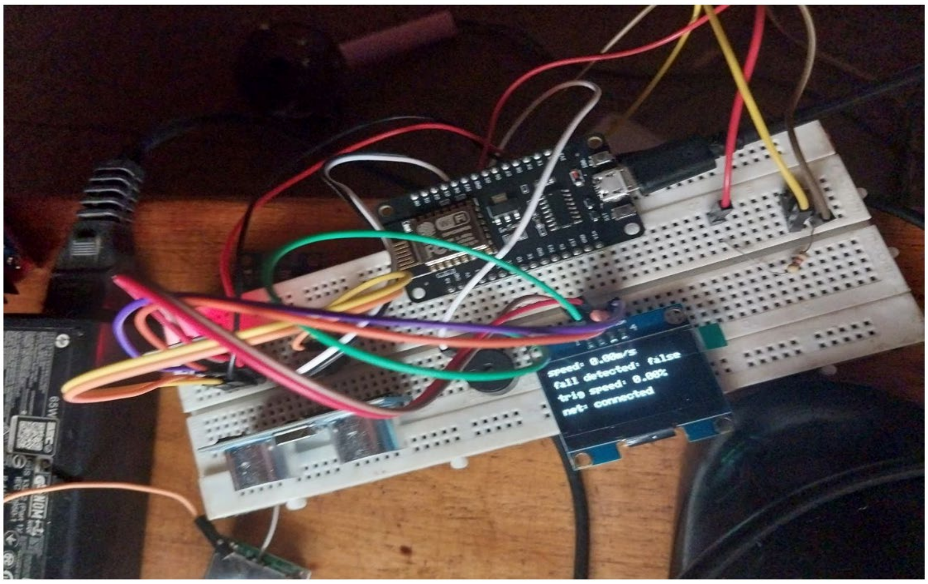

Figure 4: Implementation on the breadboard

4.0 Results and Discussion

The developed system was tested using a mannequin. Table **1** showed the varied movement speed and how it affected the trigger speed and execution time during the test. The movement speed is the speed at which the body falls, the trigger speed is the speed at which the set threshold has been exceeded. The execution time is the time taken to detect the fall.

Table 1: Test results of the device

Measurement	Movement speed (m/s)	Trigger speed (m/s)	Execution Time (s)
1	8.32	8.05	2.5
2	8.45	8.05	2.4
3	8.40	8.05	2.4
4	8.34	8.05	2.3
5	8.68	8.05	2.3
6	7.86	0	0
7	8.42	8.05	2.4
8	8.44	8.05	2.5
9	8.45	8.05	2.4
10	8.32	8.05	2.4

Source: Akinde *et al.* (2025)

From Table 1, it is established that, despite the varying speed of movement, the trigger speed was constant; this implied that the device only detected a fall when the set threshold was exceeded, it also indicted an average execution time of 2.4s. From the results, it was observed that the sensor consistently triggered at a speed of 8.05 m/s in almost all trials, regardless of the slight variations in the actual falling speed of the mannequin, which ranged from 8.32 m/s to 8.68 m/s. This showed that the device has a stable and well-defined threshold for detecting a fall event.

The execution time for detection was also found to be relatively consistent, ranging from 2.3 to 2.5 seconds. This indicated that once the threshold was exceeded, the device required about two to two and a half seconds to process and register the fall. The small variations in execution time may be attributed to minor processing or sensor delays, but overall, the detection response remained reliable and predictable. An exceptional case was noted in measurement 6, where the mannequin's movement speed was 7.86 m/s, below the set threshold. In this case, the device did not register a fall, with the trigger speed and execution time both recorded as zero. This suggests that the threshold is strict, ensuring that slower or less forceful movements, such as controlled sitting or lying down, are not mistakenly classified as falls. While this minimizes false alarms, it also highlights a potential limitation, as slower falls, which are often characteristic of elderly individuals—may not always be detected.

Figure 5 indicated the movement speed acquired by the MPU6050 sensor being uploaded to ThingSpeak at an interval of 15s, and with an average value of 8.37m/s. Figure 6 showed the trigger speed data acquired from MPU6050 being uploaded to ThingSpeak at an interval of 15s with an average trigger speed of 8.05m/s.

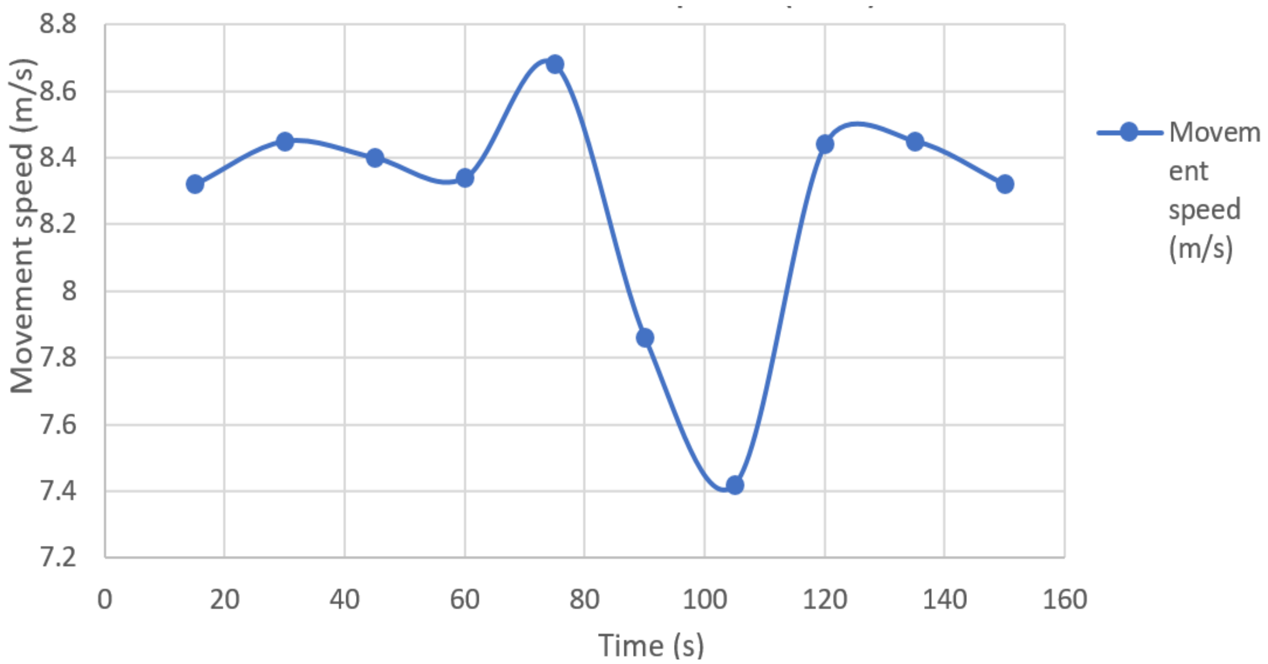

Figure 5: Motion speed data uploaded to ThingSpeak at intervals of 15s

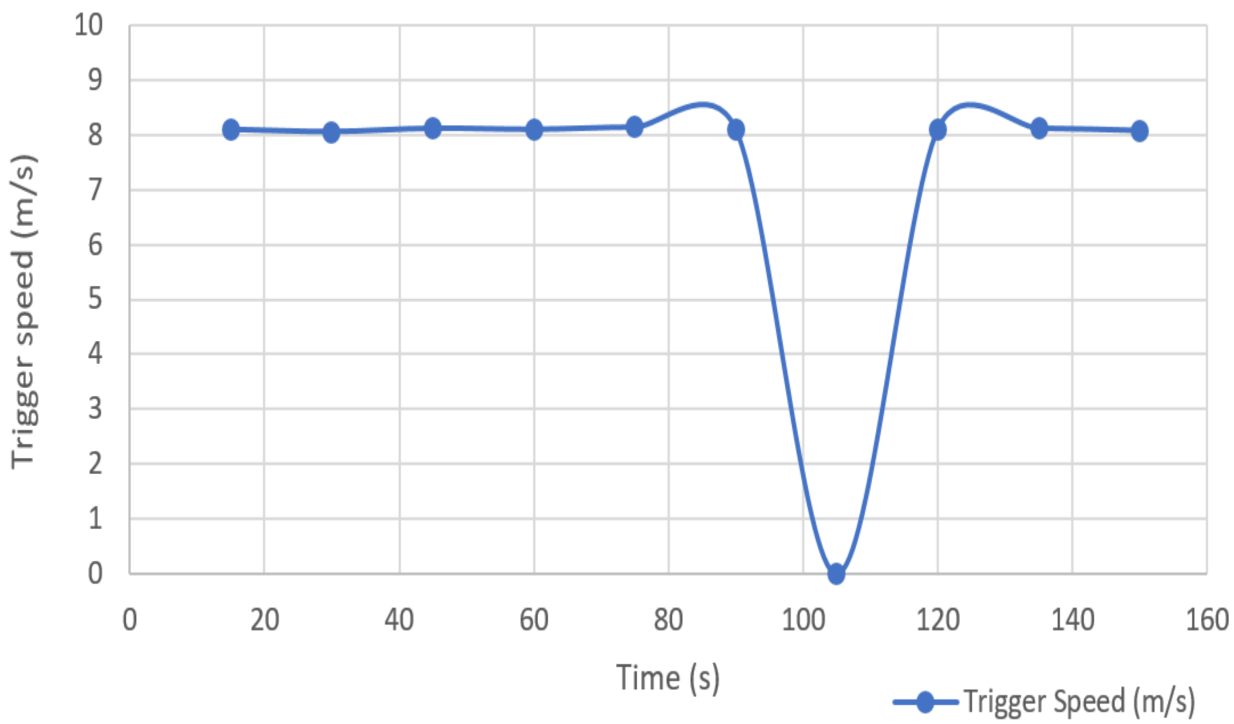

Figure 6: Trigger Speed data uploaded to ThingSpeak at intervals of 15s

The following tests were carried out to check for accuracy when detecting various types of falls of the developed device: the mannequin was pushed in different positions and directions: pushed behind(quick falls), pushed sideways(rotational falls), gradual lowering(slow falls). The sensor's data are sent to the web server (ThingSpeak) at 15s intervals for visualization by the caregiver and to enhance storage of data about fall incidences.

Figure 7 (a) and (b) are the screenshots of how the system sends notifications of fall occurrences to caregivers at both instances of tests with high movement speed.

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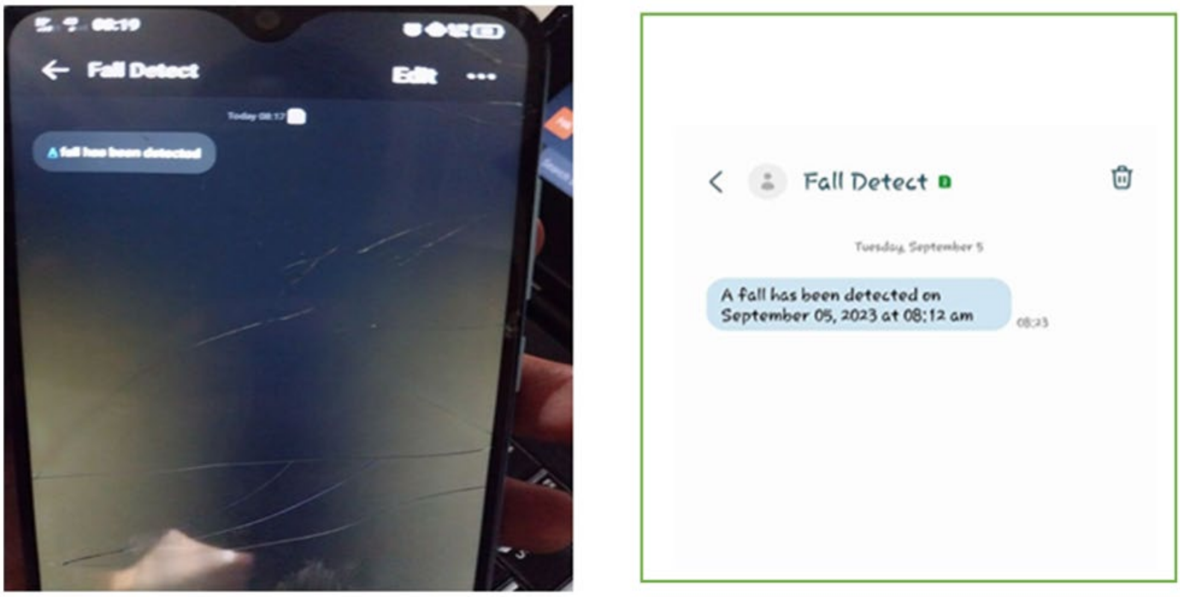

Figure 7(a) and (b): The fall occurrence messages sent to the caregiver

5.0 Conclusion

The development and testing of the wearable fall sensor demonstrated its potential as a reliable tool for enhancing independent living among the elderly. The device, which integrates accelerometer and gyroscope sensors with an IoT-based communication platform, consistently detected falls at a set threshold of 8.05 m/s with an average execution time of 2.4 seconds. The results showed a 90% detection accuracy, confirming that the system is effective in recognizing fast and rotational falls while minimizing false positives from slower, controlled movements.

By transmitting sensor data and fall alerts to a web server (ThingSpeak) and notifying caregivers in real time, the system addresses the risks associated with unwitnessed falls and the "long-lie" problem that often leads to severe health deterioration or fatalities among the elderly. Its low-cost design, portability, and ease of use make it a practical solution for elderly care, with significant potential to improve response times, reduce the consequences of falls, and ultimately enhance the quality of life and independence of older adults.

Future improvements should focus on refining the detection algorithm to better capture slower falls, which are more typical in real-life elderly scenarios, and further validating the device in real-world conditions beyond mannequin testing. With such refinements, the sensor could become a scalable and dependable fall detection solution for elderly healthcare and community deployment.

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