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# GPS-based fall detection system for old and specially-abled people

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**ABSTRACT**

Falls are a serious public health concern for older people across the world. Modern telemedicine now depends heavily on remote monitoring of older patients and the ability to spot threats to human health. If a fall is not assisted in time, it can significantly reduce an older person's mobility, independence, and his/her quality of life. Older people who experience post-traumatic problems or mortality frequently do so because of falls. As a result, preventing falls consequences or providing essential help on time may depend on the early identification of falls. In this article, we propose an internet of things (IoT) based system that makes use of low-power wireless sensor networks, smart devices and cloud computing to detect falls and track positions for older and specially-abled people. The tracking is done by sending links of positions from the proposed system every 15 seconds to a specified google drive. On the other hand, an alert message will be delivered to the caregiver whenever a fall is happened. Thus, a MPU-6050 sensor and NEO-6M global positioning system (GPS) module are used with ESP32 microcontroller for the aforementioned purposes. A pilot study with several protocols was carried out to validate the cost-effective proposed system and achieved good results.



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## 1. INTRODUCTION

Most people suffer from physical challenges when they grow up. The world health organization (WHO) reported that between 2015 and 2050, the proportion of the world's population over 60 years will nearly double from 12% to 22% [1]. Therefore, many countries have adopted healthy aging policies for helping old people to be active and independent [2]. According to WHO statistics in October 2021, falls considered “the second cause of unintentional injury death”. Moreover, 684,000 people annually die from falls worldwide (80% of them are from low-middle income countries). People older than 60 years are the greatest number who suffer from fatal falls [3]. So, it is very important to provide proper care to those people.

On the other hand, workplace changes and younger generations mobility affect housing relationships. Thus, the average distances between family members is increased and consequently the chances of receiving vulnerably help from adult is significantly decreased in difficult situations (such as falls). Furthermore, lack of help for people in falling situation may lead to serious consequence called “long lie” when the person remains on the ground for a long time waiting for help [4]. Thus, serious health complications such as pneumonia, dehydration and hypothermia can be resulted from “long lie” and this probably leads to death within six months after fall. Therefore, falls can negatively impact independence and quality of life (QoL) of old people when not assisted in time [5]. All the aforementioned reasons necessitate applying technology solutions for ensuring quality care and self-efficiency for old people.

Falls cannot be fully prevented from daily life and activities. The simple identification of a fall is not enough to protect an older person from being hurt; the ideal option is to avoid them. However, prompt action and assistance after an incident can considerably reduce the negative consequences. For the aforementioned reasons, numerous fall detection methods have been developed. These methods can be classified into three categories according to the used device: systems that rely on wearable devices with various sensors, such as an accelerometer; systems that monitor a person using an external device, such as a camera; and systems that combine the two [5]. Dias *et al.* [6] an accelerometer is employed in a wearable Arduino-based prototype device. Mezghani *et al.* [7] proposed fall detection devices that use smart clothing with an embedded accelerometer. Miguel *et al.* [8] developed a pendant with accelerometer and gyroscope sensors that may send data directly to a smartphone. These solutions provide dedicated fall detection wearable devices. Several fall detection techniques mentioned in [9]–[11] were also created using external devices such as Microsoft Kinect, in which the monitored person is observed as well as posture recognition, movement tracking and falls detecting are enabled whenever they occur. Employed a dedicated, low-cost cameras in their study [8]. The smart carpet, monitors walking activity, detects falls, and alerts caregivers [12].

Fall detection technologies, such as [13]–[15], based on sensors incorporated in mobile devices, such as smartphones. The accelerometer is used as a sensor in the majority of smartphone-based fall detection solutions. Other fall detection systems, such as those described in [16], [17], detect falls by merging sensor data from smartphones and smartwatches. Local detection is performed by these solutions, which then alert a relative or caregivers. The developed methodologies may be divided into two categories in terms of the mechanism utilized to detect falls: (1) threshold-based techniques and (2) machine learning (ML) based techniques. A fall is recognized in the first category [18]–[21] when the measured signal from the sensor, generally an accelerometer, exceeds a specified threshold. The outcomes of these approaches for diverse groups of people being watched are prone to considerable fluctuation. They may require further parameter calibration in order to adapt to the fall detection method for those having specific characteristics.

Besides, For fall detection, ML-based methods, such as [15], [22], [23] based on the creation of a classification model (e.g., decision trees, artificial neural networks, support vector machines, and others) were used for fall detection. Parameters suitable for fall classification must be properly extracted and carefully selected when using ML-based methods. Moreover, the classification algorithm should be well trained using the collected data. Thus, both aforementioned types are highly successful in detecting falls, as measured by several metrics such as accuracy and precision, as described in [24]. Recent research in the field of fall detection and monitoring individuals using body area networks focuses on constructing massive monitoring centers to support these duties and collect data related to fall incidents and other risky circumstances [25], [26]. These solutions are focused on the ability to monitor large groups of older individuals at the same time, collect fall incidents and train large-scale classification algorithms. The system given in Liao *et al.* [27], where exhibited a system that detects falls using the support vector machines (SVM) model based on motion data from Microsoft Kinect sensors, is an example of this sort of solution.

Khalifeh *et al.* [28], on the other hand, used cloud database resources primarily to store and update the sensor streamed data from the fall detection module. However, no specific system design was provided. Ozdemir *et al.* [29] proposed an architectural strategy for an autonomic healthcare management system and demonstrated how to use it for autonomic fall detection. They used accelerometer readings and the machine learning-based k-nearest neighbor (k-NN) technique to identify falls, similarly to many other studies in this field. Yacchirema *et al.* [30] introduced a system that includes a smart IoT gateway for fall detection in the fog and makes use of cloud services to build and deploy a machine learning-based categorization model. Lastly, Mainali and Shepard [31] focused on inertial measurement unit (IMU)-based fall detection using cloud-based multi-party computation (MPC). However, preserving the secrecy of IMU data is the prime objective.

## 2. RESEARCH METHOD

This part will describe the methods of implemented an emergency response system which consist of two parts: fall detector and positioning tracker. The hardware components, programming and designing process of the implemented system. Which shown in Figure 1 will be discussed below in details.

### 2.1. Hardware structure

The key motivation of this system is to help older people to move independently. That is mean, they can continue their regular activities easy and being involved in the day-to-day without any direct support. Therefore, the system should be easy to use, comfortable to wear, small and light to carry in order to ensure the aims. This is done by using small hardware components which can be worked automatically and independently. The core component of the system is the accelerometer. A cost-effective with 6-Axis accelerometer and gyroscope is used to detect the fall by setting a specific threshold. The system is also including a global positioning system (GPS) sensor for tracking the subjects' positions during their walking or wheelchair moving. Both sensors are connected to a low-power system on a chip (SoC) microcontroller that is integrated with both Wi-Fi and dual-mode Bluetooth called ESP32 development board. These features of SoC will improve the functionality of the implemented system by monitoring the position of the person as well as sending fall notifications to his/her relative/caregiver remotely. The whole system is combined in one box attached to an elastic fabric band so it can be worn easily by the subject. The following figure shows all the aforementioned components and working principle of the whole system. Figure 2 shows the structure of the entire proposed emergency response system.

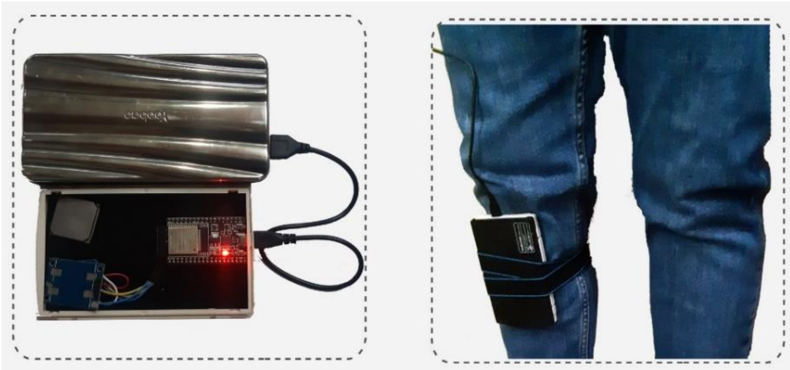

Figure 1. The implemented emergency response system

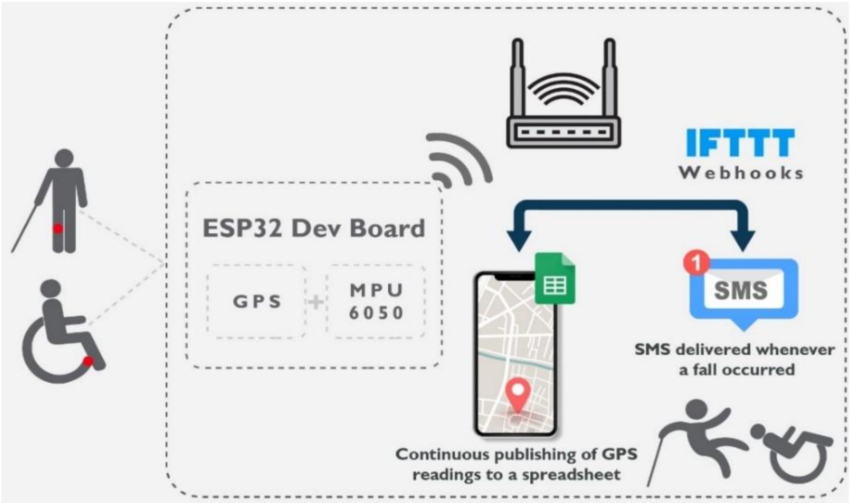


Figure 2. The structure of the entire proposed falling detection system

## 2.2. Wireless communication

In order to make the system communicate with the caregiver remotely and automatically. If-this-then-that (IFTTT) free web service is used for that task by programming and configuring ESP32 to send the required notifications whenever a fall is happened as well as publishing the position continuously. Arduino integrated development environment (IDE) is used for the programming part with necessary libraries for the used sensors. A threshold of the accelerometer is set according to multiple trials so the fall is detected accurately. Whenever a fall occurs, the system will directly send an email alert as well as a short message (SMS) to the caregiver. The GPS is programmed to send the subject's location every fifteen seconds and this timing can be adjusted according to the person requirements. The locations are stored in a spreadsheet as a Google Map link on Google drive which can be easily accessed from anywhere. The caregiver can access to these links and know the elderly location immediately whenever a fall is detected.

## 3. RESULTS AND DISCUSSION

Our proposed system evaluation comprises of two stages: the first stage is the GPS path visualization while the second stage is the sensitivity of detection the falls. Regarding the path, the GPS module is programmed to send the latitude and longitude of the subject to the cloud. The data is fed to a spreadsheet on Google drive every fifteen seconds and the time can be changed according to the requirements. The person who is responsible for monitoring can access that information easily and check the position of the monitored people. Moreover, they can check the path that is stored in the Google Map. The following figure shows a map that contain two paths which are drawn during the evaluation. We can see that the system is drawn a path line according to the subject's movement. Figure 3 shows the path of the monitored people during the evaluation stage.

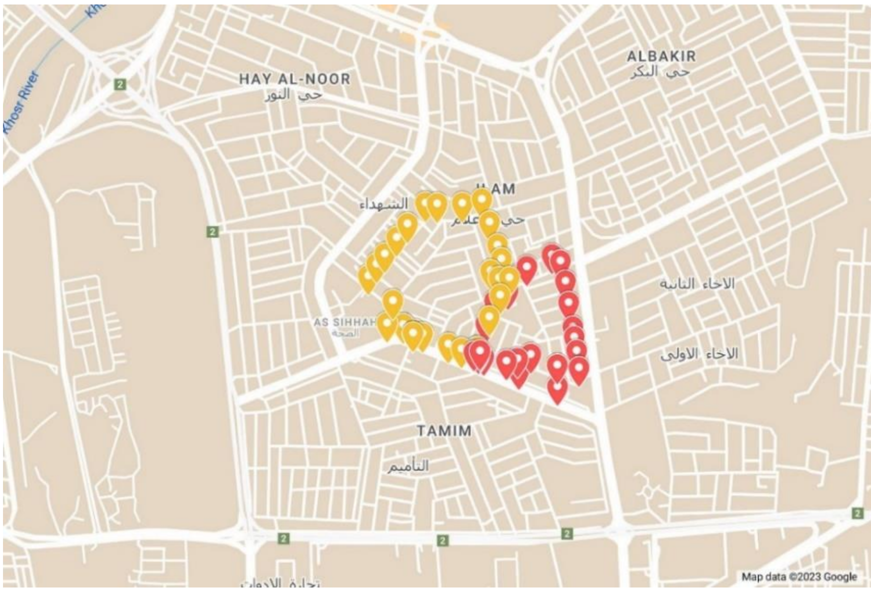


Figure 3. Path of the monitored people during the evaluation stage

Regarding the fall detection stage, as mentioned before, the accelerometer threshold is set according to multiple trials. Different experiments are carried out in order to evaluate the system accurately. The hardware is attached in two ways: directly to the subject or attached to the wheelchair. Five subjects have been participated in these experiments. According to Table 1, every single experiment has two sessions. In the First experiment, the system was attached to the wheelchair, and every subject was asked to sit and move the wheelchair through specific paths that were chosen to let a fall happened forwardly or backwardly (in two sessions). So, any received alerts specifically refer to the wheelchair fall and the caregiver can immediately move to the person's position by accessing the sent links. On the other hand, the system in the second experiment was directly attached to the subject, then, s/he was asked to do some fake falls (front/back in session one and left/right in session two). Thus, any received alerts refer to the subject's fall and an action may be required by the caregiver. The following table represents the experiments results.

Table 1. Fall detection succeeded alerts in both experiments

| Subject ID | Wheelchair | | Subject | |
|---|---|---|---|---|
| | Back-fall | Front-fall | Back-fall | Front-fall |
| S1 | ✓ | ✓ | ✓ | ✓ |
| S2 | ✓ | ✓ | ✓ | ✓ |
| S3 | ✓ | ✓ | ✓ | ✓ |
| S4 | ✓ | ✓ | ✓ | ✓ |
| S5 | ✓ | ✓ | ✓ | ✓ |

When combined, fall detection and GPS tracking can provide a comprehensive solution for individuals who are at risk of falls or getting lost. As mentioned earlier, the proposed system evaluation involves two stages

(GPS path visualization and sensitivity of detecting the falls). Regarding the GPS tracker, the two paths (red and orange) shown in Figure 2 represent the subjects' locations on google map during a two short trips of evaluation. Published readings from the spreadsheet (i.e. latitude and longitude every 15s) can lead the caregiver to the exact position of the person. However, the GPS module may not work properly in closed areas (indoor) due to the signal loss so it is highly recommended to use it outdoor for a precise tracking. On the other hand, the fall detection is evaluated in two different experiments. According to Table 1, all alerts (SMS) sent by the system were successfully delivered to the caregivers whenever falls happened. The challenge in detecting a fall accurately was the properly determination of MPU 6050 sensor threshold. Several values in many trials were set to evaluate the sensor before attaching it to subjects or wheelchairs so that the system can distinct the vibration from fall. Finally, the system achieved good results.

## 4. CONCLUSION

To sum up, GPS tracking and fall detection technology can be powerful tools for ensuring the safety and well-being of older and specially-abled people who may be at risk of falls or getting lost. By combining these technologies, a comprehensive solution can be provided by caregivers that offers peace of mind for both themselves and their loved ones. However, it's important to consider privacy concerns and ensure that the individual wearing the device is comfortable with it.

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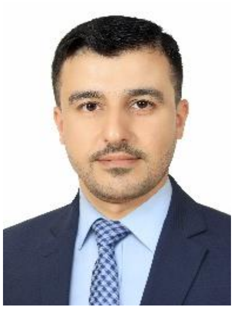

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