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A WEARABLE DEVICE FOR FALL DETECTION IN THE ELDERLY

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ABSTRACT

In this study, fall detection was developed for the elderly or patients with balance problems who require monitoring all the time to reduce the impact of a greater fall. The system tracks the movement of the human body, identifies falls from normal daily activities by calculating acceleration and orientation, and then sends requests for help to nurses or their families via. Telegram messages and fall locations using the Blynk application. The results show that the system can distinguish between normal activities and falls. The system can detect falls forward, backward, and sideways to the left and right with an accuracy of 95%, 80%, 100%, and 75%, respectively.

Keywords: fall detection, wearable device, blynk, telegram.

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1. INTRODUCTION

In general, the elderly or people with balance disorders need to be always monitored for their condition, both under normal conditions and when they fall. People over the age of 65 are 25% more likely to fall. The likelihood of falling increases with age, as does the severity of the injury [1], [2]. The problem is how to distinguish the normal condition that befell that person. Falls can be recognized by sudden changes from normal conditions such as sitting, lying down, walking, jumping, and running. Falls can occur anytime and anywhere; therefore, it is necessary to monitor their condition at any time for people who have problems with their balance. so that action can be taken immediately.

Several previous studies on fall detection have been conducted including; the purpose of the literature review was to systematically assess the current state of fall detection device design and implementation [2],fall detection using the difference vibration method at each step has been carried out by [3], pattern recognition of falling people with the camera sensor using the Yolo3 algorithm [4], a wrist device with a machine learning algorithm for online Fall detection [5], The IR array sensor measures temperature distribution and detects falls based on temperature change [6], A lidar sensor with the K-nearest neighbor algorithm and random forest algorithms is used to detect falls [7], Radar-based fall detection in indoor environments using deep neural networks developed by [8], a method to detect falls using images from a standard video camera instead of environmental sensors was developed [9], a fall detection system based on body acceleration data by using recurrent autoencoders to distinguish between normal activities of daily living and falls[10].

In previous studies using artificial intelligence algorithms that required the introduction of the learning process by recognizing falling patterns, which of course takes quite a long time, we now offer an easier method, namely by using a combination of several sensors to find out the difference between daily activities and falls. Furthermore, the previous study only worked indoors. In this study, we propose to use wearable devices that can be used both indoors and outdoors. The wearable devices are mainly based on a single accelerometer and gyroscope sensor, a GPS module, and a microcontroller with built-in Wi-Fi. Furthermore, the devices use an efficient fall detection algorithm with less resources and power consumption.

2. THE METHOD

2.1 Block Diagram

The block diagram of the proposed method is shown in Figure-1. A wearable device is wrapped around a person's upper arm. Wi-Fi is required for this device's connection in order for Telegram and the Blynk App to communicate. The system can identify geriatric falls by using a microcontroller to calculate acceleration and orientation. Then, using GPS to determine the elderly person's location, it will send a fall alert to caregivers via Telegram message with detailed information about the patient's condition and location. The caregiver may also keep an eye on the patient using the Blynk App. Finally, if an elderly person suddenly feels in danger or needs quick medical attention, they can request assistance by pressing a panic button. So that the elderly can receive early assistance to mitigate the negative effects.

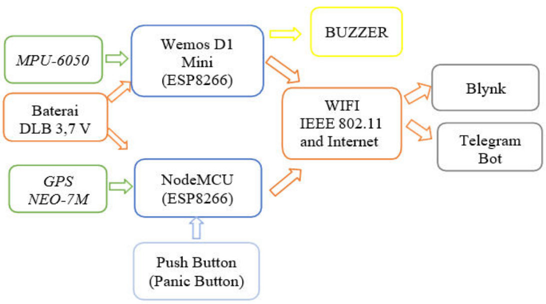

Figure-1. Block diagram of falls monitor devices.

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2.2 Flowchart

The monitoring of the proposed system is shown in Figure-2. The Wemos microcontroller searches for a network that can be connected to a Wi-Fi network. MPU accelerometer sensor will continue to operate in "measured" mode while the device is connected to the network and will be active when a fall takes place. The device would send an emergency notification to Telegram and the Blynk App if there was no response after a certain amount of time, and the buzzer would then continue to be active until the contact in question deactivated it by clicking the reset button. As soon as the location is obtained, the data will continue to be acquired by the other microcontroller from the GPS module.

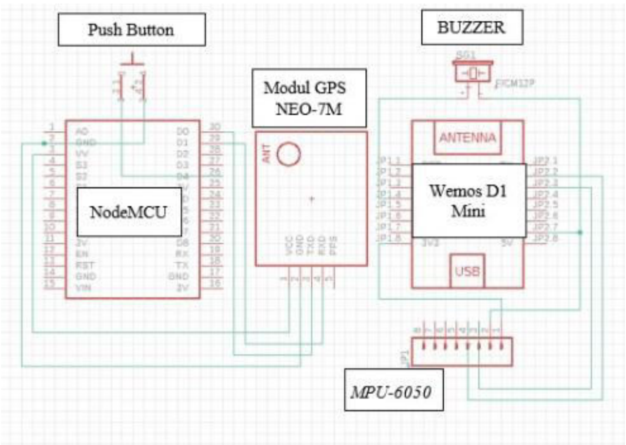

Figure-2. Flowchart of the proposed system.

2.3 Schematic Diagram

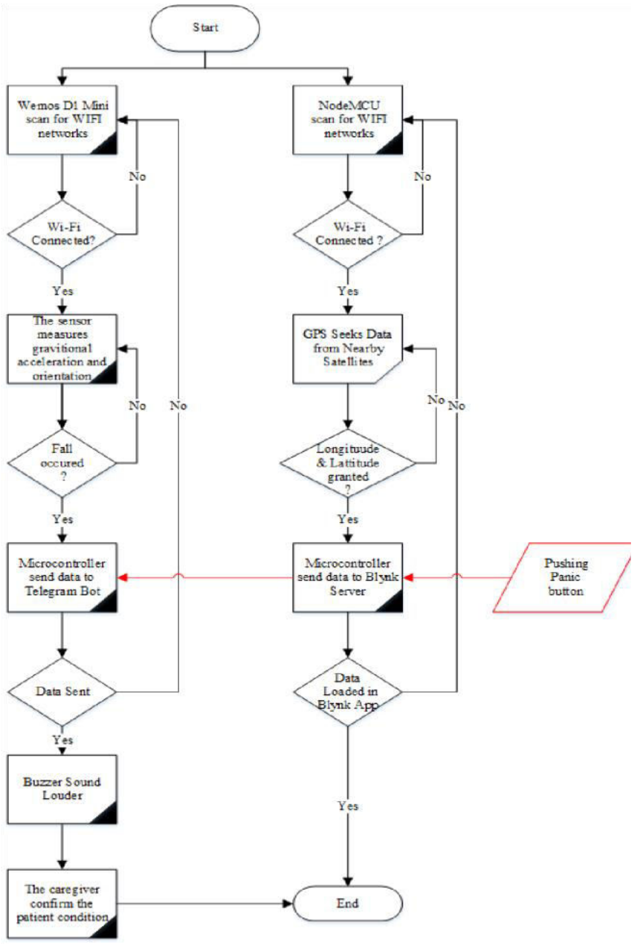

Figure-3. Schematic diagram of falls detecting.

Figure-3 shows a schematic diagram of the proposed system having 2 control centers: the NodeMCU is connected to the GPS module, and the push button is used to check location when the button is active, while the Wemos is connected to the accelerometer sensor, and the buzzer is used to check the condition of the patient and sound the alarm.

2.4 Algorithm Falls Detecting

At the same time, the other microcontroller will continue to get the location from the GPS module. Once the location is obtained, the data is immediately sent by the Blynk App, and in the other option, when the panic button is pushed, the microcontroller will immediately interrupt the process and then send the current condition and location both to telegram and the Blynk App. The caregiver could then check the patient's condition, as well as monitor where the patient is or what the patient's condition is using the Blynk app, so if the patient gets lost or goes somewhere without saying anything, the caregiver could still possibly know where the patient belongs. At the same time, the other microcontroller will continue to get the location from the GPS module. Once the location is obtained, the data is immediately sent by the Blynk App, and in the other option, when the panic button is pushed, the microcontroller will immediately interrupt the process

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This algorithm is based on the concept that when falling, a person experiences a momentary change and a large spike in acceleration to a change in orientation. The flowchart for the algorithm is given in Figure-4. The initial stage is to detect changes in acceleration from the MPU sensor, namely sensors that measure changes in acceleration and orientation. Based on previous experience, the threshold for changes in acceleration and changes in orientation is 5 seconds for a 0.5-second threshold. If there is a very significant change in acceleration below the threshold of 0.5 seconds and the orientation does not change within 5 seconds, it means that a fall has occurred.

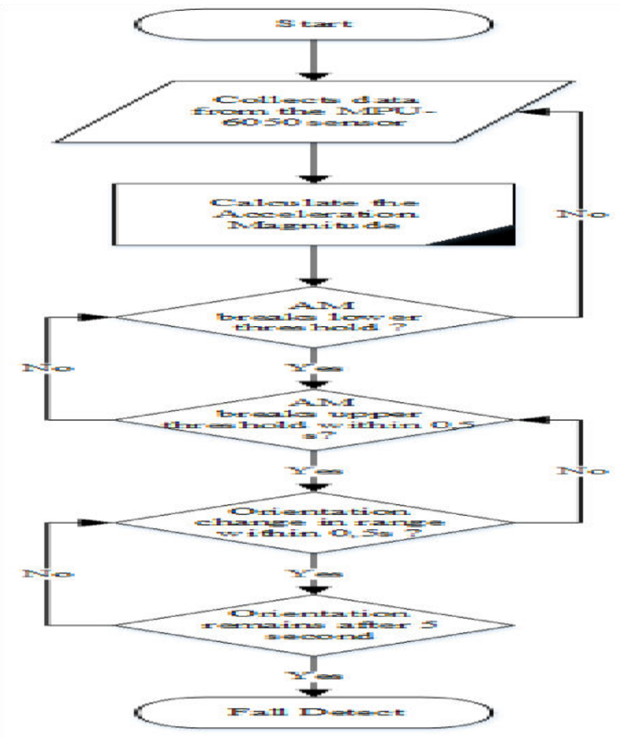
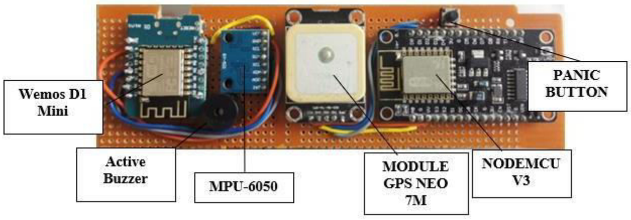


Figure-4. Algorithm for falls detecting.

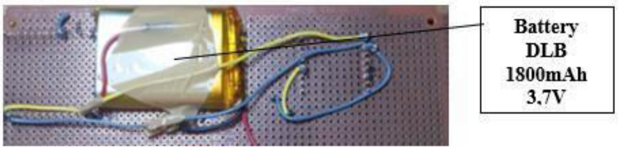
3. RESULTS AND DISCUSSIONS

3.1. Implementation of Wearable Device

Figure-5 shows the wearable device. In the wearable device, there is a MPU-6050 sensor as a measure of the value of changes in acceleration and orientation [11], the GPS Module NEO-7M, which functions to provide data in the form of latitude and longitude values [12], the NodeMCU and Wemos D1 Mini Microcontroller, which function as the brain for the processing of the system [13][14], the passive buzzer [15] as a direct notification, the push button as a response from both the patient and the contact whose details have been described in the previous discussion, a DLB Li-Po 3.7 V battery as a power supply unit.



(a)



(b)

Figure-5. Implementation of devices shown in: (a) Front (b) Back.

3.2 Device Placement Position

Figure-6. The device placement position is on the upper arm.

The placement of the device is very important to determine its effectiveness, and based on the test results, it can be concluded that the best area to place the device is on the arm, both the upper arm and forearm. Figure-6 shows the device placement position on the upper arm.

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3.3 The Result

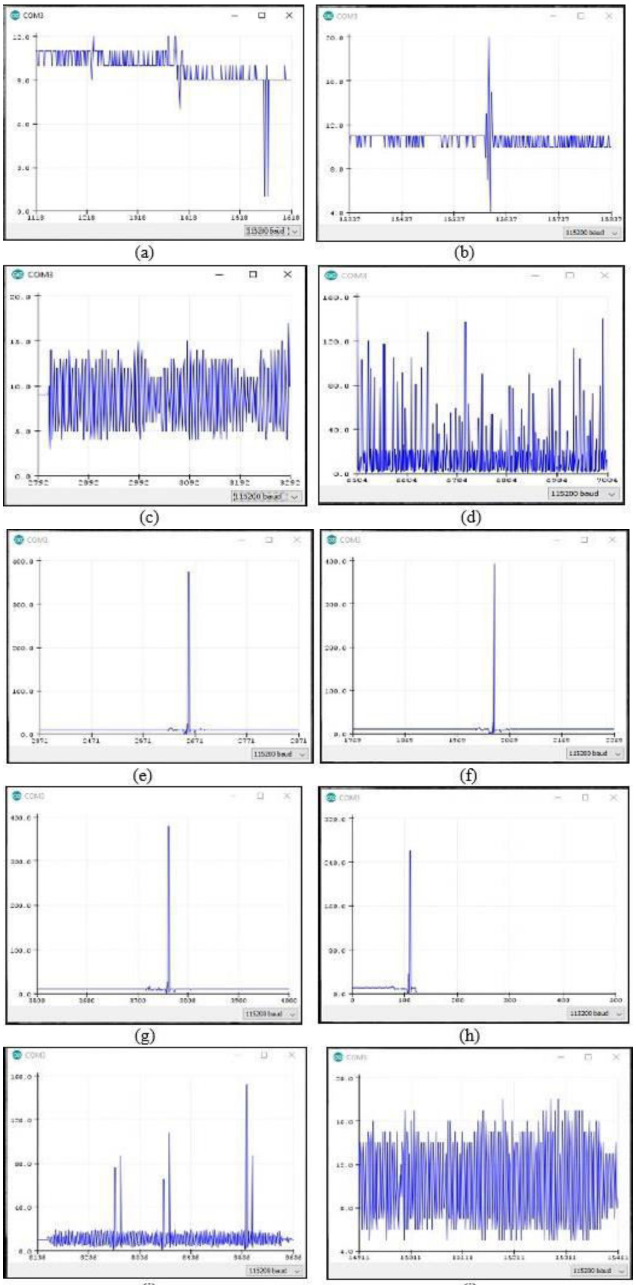

Figure-7. (a) Lie on a bed (b) Sit in a chair (c) Walk (d) Run (e) Falling in Front (f) Falling behind (g) Falling to the Left (h) Falling to the Right (i) Downstairs (j) Jumps.

The sensor detection plots under normal conditions of lying in bed, sitting in a chair, and walking and running positions are shown in Figure-7 (a)-(d), respectively. The graph of fall detection is shown in Figure-7. (e)-(g), from the graph plot the difference between normal and fall conditions is as follows: in normal conditions, the graph does not show a peak, and in fall conditions, there is a peak. Furthermore, the condition of the stairs going up is shown in Figure-7. (i) There are several regular periodic peaks indicating normal conditions; also, as in Figure-7. (j), when jumping, there are no peaks that exceed the limit.

Table-1. Test results severe activity with 20 repetitions.

Activity	Fall Detect
Front Falling	19
Behind Falling	18
Fall to Right	20
Fall to Left	15
Walking	0
Brisk	0
Running	0
Sit on Chair	0
Get up from the chair	0
Sit on the bed	0
Lie on the bed	0
Get up of bed	0
Jump	0
Down the stairs	0
Take the stairs	0
Muslim Prayer	0

From Table-1, it can be concluded that several conditions fall forward, fall backward, fall to the left, and fall to the right, and in 20 trials there were 19, 18, 20, or 15 fall detections respectively; in other words, the system has an accuracy in detecting falls in the condition of falling forward, falling backward, falling to the left, and falling to the right of 95%, 80%, 100%, and 75%, respectively.

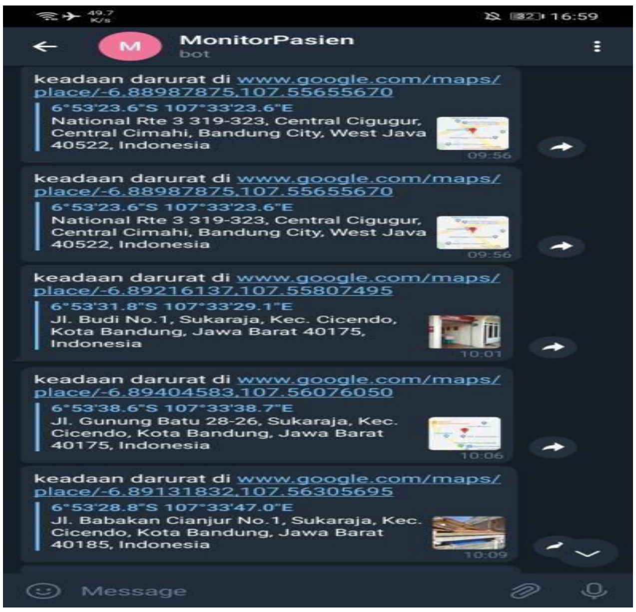

Figure-8. Notification on Telegram App.

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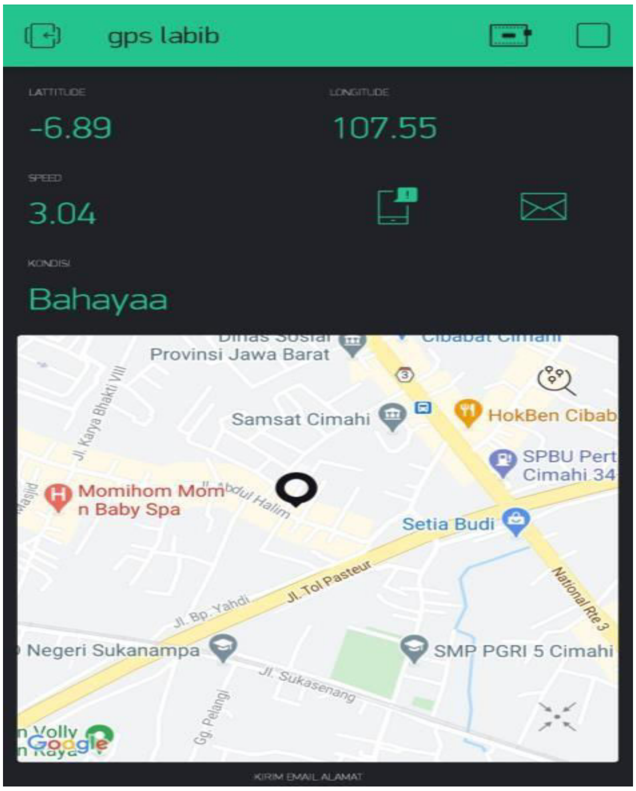

Figure-9. Blynk App Interface.

Figure-8 shows the appearance of the Telegram app when the device detects a fall at that time and sends it directly via the Telegram application. Figure-9 shows the coordinates of the patient's fall, detected by the GPS sensor, and sent to the Blynk app and displayed in map form.

4. CONCLUSIONS

This research designs wearable gadgets with sensors (accelerometer, gyroscope, and GPS) mounted on the body to track falls. From the results, it can be proven that this tool is effective for detecting people falling anywhere, both indoors and outdoors. The gyroscope sensor is able to detect fall conditions, which are marked by a graph that plots the difference between normal conditions and a person's fall as follows: In normal conditions, the graph does not show peaks or peaks that are visible continuously and do not exceed a certain limit. On the other hand, in a falling condition, there is a peak that exceeds the limit and appears only once. In several conditions of falling forward, falling backward, falling left, and falling right, in 20 trials, there were detection failures of 1, 2, 0, 5 or 95%, 80%, 100%, and 75%. Furthermore, this system also sends the coordinates of the position when he/she falls on the map via the Bynk application and the time it falls directly via the Telegram application.

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