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IMU Sensor Based Expandable Fall Detection System Design

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Abstract

Falls and their consequences pose significant health problems affecting individuals of various age groups. Aging individuals are generally weaker, less stable, and slower to react, increasing the likelihood of falls and injuries. Falls are a serious concern, have a significant impact on mobility and quality of life. They also have a significant financial impact on healthcare systems worldwide. The effects of a fall can range from minor bruises, injuries, life-threatening fractures, and even fatal conditions. For these reasons, continuous monitoring of the activities of elderly and disabled people has become one of the main goals of telemedicine, and wearable devices have become widespread. The main goal of this study is to develop a system that allows for precise and automatic detection and monitoring of falls. This approach will generate timely alerts and notifications to quickly inform caregivers or medical doctors. 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. Bending and falling are separated. Taking this into account, various falling variations are detected.

Keywords: elderly people, fall detection, remote patient monitoring, IMU sensor, Raspberry Pi

IMU Sensör Tabanlı Genişletilebilir Düşme Tespit Sistemi Tasarımı

Öz

Düşmeler ve sonuçları, çeşitli yaş gruplarındaki bireyleri etkileyen önemli sağlık sorunlarını ortaya çıkartır. Yaşlanan bireyler genellikle daha güçsüz, daha dengesizdir ve daha yavaş tepki verirler, bu da düşme ve yaralanma olasılıklarını artırır. Düşme ciddi bir endişe kaynağıdır, hareket ve yaşam kalitesi üzerinde önemli bir etkiye sahiptir. Ayrıca dünya çapında sağlık sistemleri üzerinde önemli bir finansal etkiye sahiptir. Bir düşmenin etkisi, küçük morluklar, yaralanmalar, hayatı zorlaştıran kırıklar ve hatta ölümcül olabilen durumlara kadar değişebilir. Bu nedenlerle yaşlı ve engelli kişilerin aktivitelerinin sürekli olarak izlenmesi tele-tıbbın temel amaçlarından biri haline gelmiş ve giyilebilir cihazlar yaygınlaşmıştır. Bu çalışmanın temel amacı, düşme durumlarının hassas ve otomatik olarak algılanmasına ve izlenmesine imkan tanıyan bir sistem geliştirmektir. Bu yaklaşım, bakıcıları veya tıp doktorlarını hızlı bir şekilde bilgilendirmek için zamanında uyarılar ve bildirimler üretecektir. Çalışmada oluşturulan sistem, geliştirilebilir özellikte olup çok sayıda sensör eklenebilmektedir. Hastanın üzerine yerleştirilen IMU sensörlerden, Raspberry Pi'ye aktarılan veriler yazılımla değerlendirilmektedir. Normal duruş seviyeleri olarak belirlenen değerlerden ani değişiklikler meydana geldiğinde düşme algısı oluşturulur. Eğilme ve düşmeler ayrıştırılır. Bu durum göz önüne alınarak çeşitli düşme varyasyonları tespit edilir.

Anahtar Kelimeler: yaşlı insanlar, düşme tespiti, uzaktan hasta izleme, IMU sensör, Raspberry Pi

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Introduction

Up to 30% of people over the age of 60 are at risk of falling. This can lead to injuries, worsening of pre-existing conditions, and even death (Cedeno-Moreno et al., 2024). It causes serious injuries, especially when the person who falls remains on the ground for a long time without assistance (Zurbuchen et al., 2021). Elderly and frail patients have difficulty walking and are at higher risk of falling (Ruiz-Ruiz et al., 2021). The lack of appropriate care support for elderly people living alone increases the risk of falls (Seneviratne et al., 2024; Mohan et al., 2024). In the last few years, automated systems have emerged to monitor people and improve their quality of life (Galvao et al., 2021; Seneviratne et al., 2024; Santiago et al., 2017). Such e-health technologies are of critical importance, especially for the care of elderly people living alone (Mohan et al., 2024). Early intervention for people who have fallen is important to eliminate the leading cause of death and disability in older adults. Developed warning systems reduce the costs of falls to healthcare systems (Qian et al., 2022; Nooruddin et al., 2022; Xueyi et al., 2020; Villa et al., 2024). The systems facilitate access to patient data and provide high-quality care at low costs (Malche et al., 2022). It reduces the risk of loss of life, injury, and related healthcare expenses by quickly transporting individuals who have fallen to emergency services (Gharghan et al, 2024).

Fall risk assessment and fall detection are crucial for preventing adverse and long-term health outcomes (Sophini et al., 2022). Monitoring falls to assess fall risk in daily life can provide important information to prevent future falls (Ferreira et al., 2022; Kim et al., 2022; Xiaoqun et al., 2021). It is thought that the information necessary to address the risk of falls in advance can be obtained by monitoring near-fall situations (Kim et al., 2022). In the context of sitting-to-standing transitions, sitting-to-standing transition tests are performed on subjects. Thus, non-invasive tools are developed to assess the risk of postural instability, contributing to fall prevention efforts (Lee et al., 2025). Wearable sensor systems are used to assess fall risk and detect falls, while also providing additional information on gait characteristics such as stride duration and walking speed (Ruiz-Ruiz et al., 2021; Sophini et al., 2022). Thus, it is possible to automatically identify abnormal gait (Chen et al., 2022). The large-scale dataset and benchmark algorithms created can provide valuable data and references for researchers and practitioners to develop new technologies and strategies for pre-impact fall detection and proactive injury prevention for the elderly (Xiaoqun et al., 2021).

There are differences in detection methods, system architecture, wireless communications, sensor types, performance measurements, difficulties and limitations among existing fall detection systems (Gharghan et al., 2024; Abdulmalek et al., 2022). Fall risk assessment methods performed in the scientific literature using wearable sensors are versatile (Ferreira et al., 2022). Devices consist of sensors combined with other components. These components are usually: transistors, resistors, capacitors, relays, buzzer, integrated circuits to detect falls and transmit information to emergency caregivers, and various alert mechanisms (Archibald et al., 2024). A fall detection system that monitors an older adult in real time has two main components: a wearable device and a mobile phone. When the wearable device detects a fall, the mobile phone sends an alert to emergency contacts defined by the user (Santiago et al., 2017). Fall detection systems are divided into two main categories in terms of sensor density: single-sensor and multi-sensor-based fall detection systems. While single-sensor-based systems mostly detect falls accurately, multi-sensor-based systems are more sensitive (Nooruddin et al., 2022). Combining multiple sensor signals increases the robustness of fall detection systems, while producing higher accuracy and fewer false alarms (Xueyi et al., 2020; Xefteris et al., 2021). Wearable systems have been developed by combining sensors, sensor fusion, and combining several types of sensors (Fula et al., 2024; Ruiz-Ruiz et al., 2021; Xueyi et al., 2020; Yu et al., 2021; Nahian et al., 2021).

Some systems consist of Inertial Measurement Unit (IMU) devices that provide an embedded algorithm and real-time fall detection (Fernandez-Bermejo et al., 2024). A single IMU device worn on the waist is used to obtain acceleration and angular velocity signals using accelerometer and gyroscope sensors (Kim et al., 2022). IMUs are wearable devices that are an excellent option for analyzing human gait parameters in health monitoring applications due to their accuracy, portability, and low price. Different IMU-based methods have been developed to analyze gait parameters to assess the risk of weakness or falls (Ruiz-Ruiz et al., 2021). Commonly used IMUs can be placed at various locations on the body (waist, ankle, foot, etc.) to obtain motion data that can be better analyzed and interpreted. In addition, pressure sensor data placed under the sole of the foot is also added to the systems (Garcia et al., 2022; Sophini et al., 2022). Systems are being designed that collect data using low-energy and inconspicuous sensors attached to patients' bodies and beds, and transmit it by connecting to a smart gateway. These systems can transfer data to an electronic health record system. Thus, healthcare professionals can easily access relevant patient data (Fama et al., 2022).

The rapid development of sensor networks, the Internet of Things (IoT), machine learning (ML), and artificial intelligence techniques (AI), including deep learning (DL) models, has led to the emergence of healthcare systems that monitor patients remotely. These developments have paved the way for real-time, accurate, and rapid detection of fall accidents in elderly patients (Abdulmalek et al., 2022; Karar et al., 2022; Xefteris et al., 2021; Vimal et al., 2021; Zhang et al., 2024). The emergence of technological developments such as artificial intelligence, the Internet of Things, wearable devices, and smartphones make it possible to design fall detection systems for smart home care (Vaiyapuri et al., 2021). IoT-based systems are proposed to detect falls in elderly people indoors using low-power wireless sensing networks, big data, cloud computing, and smart devices (Kulurkar et al., 2023). To achieve high efficiency in fall detection, the data read from the sensors are processed and analyzed. If a fall is detected, an alert is generated and the system automatically responds by sending notifications to the groups responsible for the care of elderly people (Yacchirema et al., 2018). The systems also include a user interface for healthcare professionals developed based on cloud technology and server-client architecture (Qian et al., 2022). AI-IoT technology has been developed by combining the Internet of Things and Artificial Intelligence with other emerging technologies. It is envisaged that such systems will be the best solution for fall prevention in real-time and long-term monitoring without human intervention (Mohan et al., 2024). Most researchers use their own datasets to develop fall detection algorithms (Xiaoqun et al., 2021). Machine learning models are used to monitor the patient's activities such as running, sleeping, walking, and exercise, as well as vital signs such as body temperature, heart rate, and breathing patterns (Malche et al., 2022; Yu et al., 2021). Artificial intelligence techniques including machine learning and deep learning methods are used to detect elderly falls (Gharghan et al., 2024). Deep learning models combine sensors such as pressure sensors, three-axis gyroscopes, and three-axis accelerometers. Such real-time systems can classify activities performed as falls or daily living activities (Campanella et al., 2024; Galvao et al., 2021; Zurbuchen et al., 2021; Nahian et al., 2021). Artificial intelligence-based deep convolutional neural networks are used to analyze the cause of falls (Zhang et al., 2024; Vimal et al., 2021). To determine the applicability of computer vision and machine learning computation in distinguishing different gait patterns associated with falls from level ground (Chen et al., 2022).

To define a robust and reliable method, sensor fusion and multi-point measurements are required. Therefore, in order to avoid false alarms, it may be necessary to combine the analysis of signals captured by the smartwatch with signals collected by another low-power sensor placed at a point closer to the body's center of gravity (e.g., waist) (Gonzalez-Canete et al., 2021). The availability of different sensor types such as gyroscopes and accelerometers in smartwatches is a step towards realizing successful Fall Detection Systems (FDS) (Karar et al., 2022). In addition, smartwatch-based Fall Detection Systems are becoming widespread due to their widespread acceptance, ergonomics, and low cost (Gonzalez-Canete et al., 2021). In other designs, technologies that combine IMUs with Hearing Aids (HA) are being developed. Hearing aids are being transformed into hearing, headphones, and fall detection technologies with embedded sensors and artificial intelligence methods (Steenerson et al., 2025).

Night monitoring systems are being developed to provide a safe environment for the elderly and to relieve caregiver burden. Remote sensors placed in spaces are used for such systems. In addition, pressure sensors and infrared fence systems have been designed for bed-exit scenarios (Cheung et al., 2021). Non-contact radar systems are also being created to detect elderly falls (Arnaoutoglou et al., 2024). Fall detection robots have been developed to reduce the risk of falls. The robot can detect three basic types of falls: slipping, tripping, and fainting (Seneviratne et al., 2024). Wearable device-based fall detection systems use wireless transmission methods for data transmission. Short-range technologies such as Bluetooth or network connections such as LPWAN interfaces are used (Villa et al., 2024).

One of the most important problems in fall detection systems based on wearable devices is that the fall motion is simulated under unrealistic conditions. For this reason, a large number of datasets containing acceleration samples captured during the emulation of falls and ordinary movements are obtained and artificial intelligence algorithms are trained with this data. Thus, the designed systems can distinguish real falls from daily activity movements (Silva et al., 2024, Fula et al., 2024). Human fall motions are captured with multiple cameras to create skeletal models with modeling software and human motions are created (Tang et al., 2024).

In our study, an IMU sensor-based extensible patient monitoring system was developed using Raspberry Pi-4 as a control unit. Fall detection was performed using two sensors in the prototype. By evaluating the positions of the sensors; bending, walking and falling were detected. The system was designed to communicate with a large number of sensors. The situations are directed to the specified persons via SMS.

Material and Method

In the fall detection system we designed; motion information coming from IMU sensors placed on various parts of the body is evaluated using a single Raspbery PI. I2C Multiplexer is used to select the sensors, thus creating a system that can connect 64 sensors. In the first application, two sensors are used to evaluate the operation of the system. However, while developing the system, the number of sensors will be easily increased to evaluate the patient's movements in more detail and more sensitive detections will be made by evaluating multiple sensor data. The scheme of the designed system is shown in Figure 1. The detected situation is sent to the relevant persons as a short message using an SMS service.

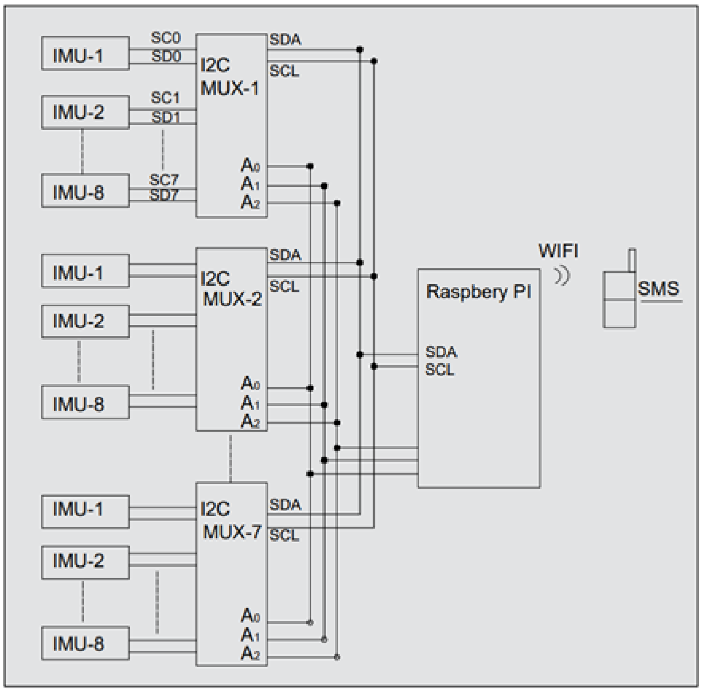

Figure 1. Schematic of the Developed Fall Detection System

Technology Used for the Designed System

Raspberry Pi: It runs a customized version of the Linux operating system. However, it also supports other operating systems such as Ubuntu, Windows 10 IoT Core, and RISC OS. Raspberry Pi supports many programming languages such as Python and Scratch as the main programming languages. There are many different operating systems and programming languages that you can run on Raspberry Pi. It is affordable, low-power, small-sized, and accessible. Raspberry Pi, shown in Figure 2, is a Single Board Computer. It can expand its capabilities with various add-on cards and accessories such as cameras, screens, and sensors. Raspberry Pi; It can be used in many areas such as simple coding exercises, home automation, web server, file server, healthcare, and automotive. Electric motor control, IP camera design, LED applications, robotic projects, device on and off projects can be done. It can turn into a computer with a keyboard, screen, and a mouse. Raspberry Pi is an ideal platform for IoT projects. Despite its small size, it is quite powerful and has a wide range of processor, memory, and storage options (Raspberry Pi OS, 2025).

Figure 2. Raspberry Pi-4 (Raspberry Pi OS, 2025)

IMU Sensor: Inertial Measurement Unit (IMU) is a sensor that combines multiple sensors including accelerometer, gyroscope and magnetometer to measure orientation, velocity and gravitational forces. IMUs are used to determine the motion and orientation of an object in 3D space. The 10DOF IMU sensor card, which includes a 3-axis gyroscope, accelerometer, magnetometer and BMP10 barometric pressure sensor, is shown in Figure 3. Using the I2C serial communication interface, all connections can be established with the microcontroller without requiring too many pins. (Inertial measurement unit (IMU), 2025).

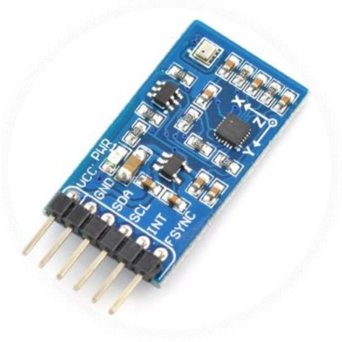

Figure 3. 10-DOF IMU (MPU-9255) Sensor Board [Inertial Measurement Unit (IMU), 2025[.

When installed inside a robot, the IMU can measure various factors such as the robot's speed, acceleration, direction, angular rate, inclination, and orientation. In the case of a magnetometer, the IMU can also measure the magnetic fields surrounding the robot. It helps with the robot's GPS positioning systems. Each component in the IMU is responsible for measuring different parameters. Accelerometer: Measures speed and acceleration. Gyroscope: Measures degrees of rotation and rate of rotation. Magnetometer: Measures magnetic fields and determines direction. Figure 4 shows the data measured by the IMU sensor.

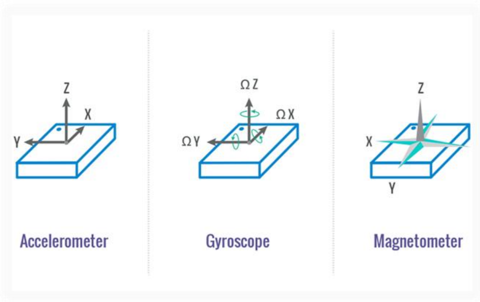

Figure 4. Measurement Parameters within the 10-DoF IMU (Robotics for Beginners, 2021).

I2C Multiplexer (TCA9548A): The I2C Multiplexer circuit board shown in Figure 5 is designed to use multiple devices (up to 8) using the same address. If there are 2 or more devices (sensors) with the same address, it will be possible to use these devices together with the multiplexer circuit. The multiplexer acts as a gatekeeper. It brings and takes commands in the I2C set selected by the applied command. The multiplexer itself comes at the I2C address (0x70) as standard. It can be placed between (0x70-0x77) to reach different MUX devices with I2C. The integrated circuit works in the (3.3V-5V) logic signal range. Dimensions: 30.6mm x 17.6mm x 2.7mm and weight: 1.8gr (TCA9548A datasheet, 2024).

Figure 5. I2C Multiplexer (TCA9548A) (TCA9548A I2C Multiplexer, 2025)

In our study, the address selection lines of the MUX (A0 A1 A2) are connected to the ground (000) and the MUX is placed at address (0x70). In order to increase the number of accessible sensor-like devices in the system, 8 separate addresses can be created between (0x70)-(0x77) with the codes (000)2-(111)2, as shown in Table 1., 8 different MUX devices can be used by changing these addresses.

Table 1. MUX Address Change

A0	A1	A2	Address
0	0	0	0x70
0	0	1	0x71
0	1	0	0x72
0	1	1	0x73
1	0	0	0x74
1	0	1	0x75
1	1	0	0x76
1	1	1	0x77

Fall Detection Method

Raspberry Pi-4 was determined as the control unit of the created system. Raspberry Pi-4 was used to detect the change data from IMU sensors and to run the software required to detect falls. IMU sensors measure movement and orientation and transmit it directly to Raspberry Pi-4. When the person wearing the wearable system moves or falls, the IMU sensor detects changes in acceleration and orientation and transmits it to Raspberry Pi-4 for analysis. This setup allowed Raspberry Pi-4 to receive real-time data from IMU sensors. Our study tested the two-sensor system.

The analysis software loaded onto the Raspberry Pi-4 was created in Python. In order to start reading sensor data, communication was established with the MPU-9255 IMU sensors via the microcomputer's I2C interface. The read sensor data (acceleration and gyroscope values) was adjusted to provide accurate measurements, thus increasing the reliability of fall detection. The created software calculates the Amplitude Vector (AM) representing the overall movement intensity using the accelerometer data. As shown in Figure 6, one of the IMUs is connected to the waist and the other to the upper leg. The system distinguishes walking, bending and falling. The number of sensors in the expandable system can be increased up to 64. Various combinations of sensor changes to be placed in different parts of the body will provide much more accurate fall detection.

Figure 6. Location of Sensors

Circuit Connection Diagram

A connection can be established with Rasppery Pi-4 via I2C. The data lines coming to each MUX input (SDO..SD7) are connected to the sensor (SDA) line by looking at the command sent. The code sent from the SCL line determines which line the data will be sent. With this selection, Rasppery Pi-4; SDA, SCL lines are connected to the SDA, SCL lines of the desired IMU sensor. The circuit connection diagram and its application on the board are shown in Figures-7 and 8. The IMU sensor is connected to the microcomputer system via "GPIO pins" (General Purpose Input/Output pins). SD0, SC0 sends a command, channel-0 becomes active (sensor-1) is read. Similarly, for SD1 and SC1; channel-1 becomes active (sensor-2) is read.

bus.write_byte(0x70, 0b00000000) → Channel 0 (Sensor 1) is activated.

bus.write_byte(0x70, 0b00000010) → Channel 1 (Sensor 2) is activated.

bus.write_byte(0x70, 0b00000111) → Channel 7 (Sensor 8) is activated.

The first part of the code sent selects the MUX address. The second part activates the channels. If new sensors were added to the system with more than one MUX, the following commands would be used.

bus.write_byte(0x71, 0b00000000) → 2.MUX, Channel-0 is activated.

bus.write_byte(0x72, 0b00000011) → 3.MUX, Channel-3 is activated.

bus.write_byte(0x77, 0b00000101) → 8.MUX, Channel-5 is activated.

Figure 7 shows the circuit connection diagram of the expandable system.

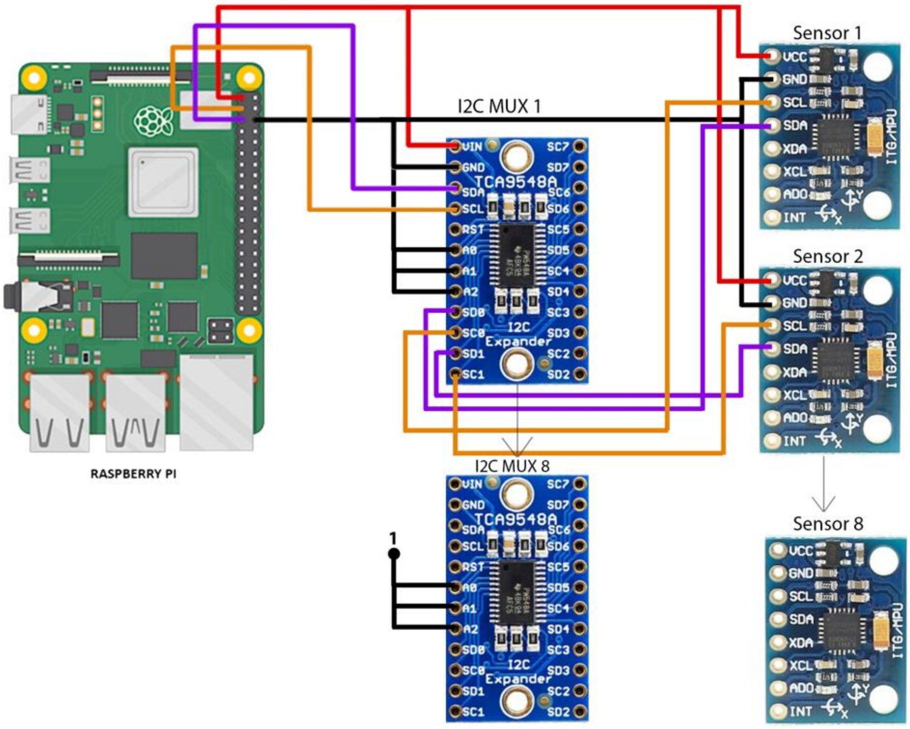

Figure 7. Circuit Connection Diagram of the Expandable Fall Detection System

Figure 8 shows the circuit connection of the two IMU sensor fall detection system.

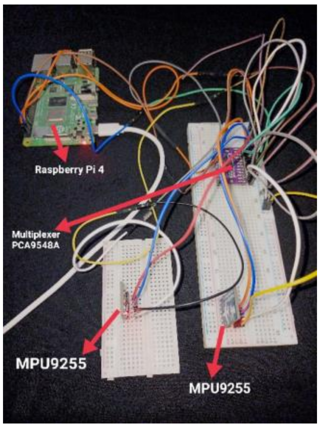

Figure 8. Circuit Connection of the Fall Detection System with Two IMU Sensors

Results

With the created software, the accelerometer and gyroscope values (x, y, z) coordinate data from IMU sensors are normalized for processing. Then, the amplitude vector is calculated for three axes. A decision is made about the patient's position according to the value ranges of the obtained result.

From the variables defined in the software;

trigger1; It is activated when the amplitude vector exceeds a lower threshold and shows a significant movement.

trigger2; It is activated when a large change in direction is detected by the gyroscope indicating a potential fall.

trigger3; If trigger2 remains active for a certain period of time, it confirms a fall indicating a continuous change in orientation. Based on the activation of trigger3, it detects a fall event indicating the characteristic change in orientation associated with falls.

When a fall is detected, the system sends an SMS to inform caregivers or take preventive measures. A message indicating the movement status is also created on the screen image during the operation of the circuit. Example fall situations and messages are shown in Figure 9. Similarly, the message generated on the computer screen for different states of the sensors and the SMS sent to the desired person are seen. As a result of falls; "falling backwards, forwards, right, left detected" message is generated.

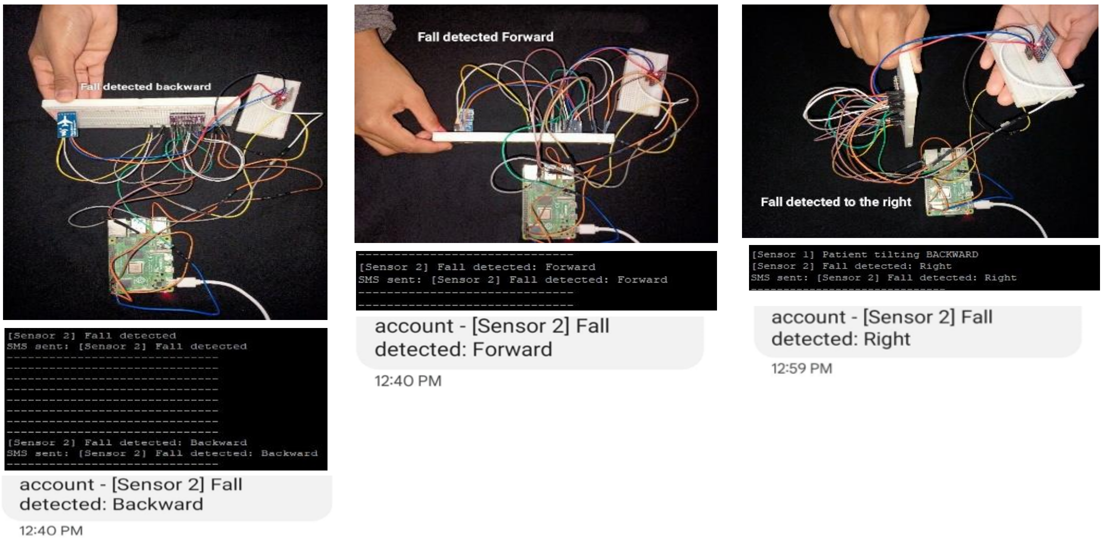

Figure 9. Examples of Situations where the "Patient has fallen" Message Occurs

Similarly, we perceive the left or right leaning from the X axis (ax) values. The situation of being below or above a certain set value constitutes this evaluation. Z axis (az): Measures the forward and backward leaning. The situation of being below or above a certain set value constitutes this evaluation. Examples for leaning situations are shown in Figure 10.

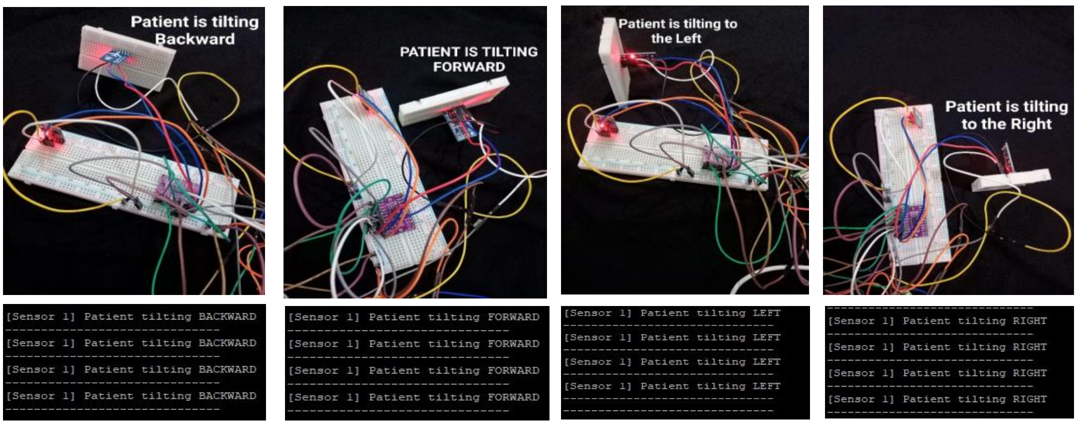

Figure 10. Bending Messages

Discussion, Conclusion and Recommendations

Many fall detection systems have been studied in the literature. Our study is an embedded system software and sensor-based study. In the study, fall and bending detection was performed with two IMU sensors. The designed system can be improved by adding many sensors. Bending and falling situations are distinguished with two sensors. The detected situation is transmitted to the relevant people via SMS. Detection accuracy will be improved by using more IMU sensors. As many sensors as necessary will be added for the most accurate detection. A more ergonomic, easy-to-carry system will be designed. More sensitive fall detections will be made by adding more sensors to the system and associating the sensors. A panic button that can be used to warn emergency persons in case the user feels that there may be a fall will be added to the system. In addition, pressure sensors to be placed under the floor will contribute to the detection sensitivity. System accuracy should be tested with real fall situations. The portability of the developed system, when the sensors to be placed in certain places of the leg, waist, back and chest are evaluated together; walking, sitting, bending movements can be distinguished from falling actions. In addition, a pressure sensor to be placed under the sole of the foot can be integrated into the same system and the accuracy of the system can be increased. When compared to the studies in the literature, its most important difference is its flexibility. Fall detection and notification are made without being too complicated. Although the detection accuracy of the system is seen from the data received in response to the movements on the two-sensor prototype applied. This analysis will be measurable after multiple sensor connections. It is planned to add new hardware and analysis software to the developed system. The system will be developed with artificial intelligence, machine learning and internet of things support over fall models with decision support software.

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Author Contribution

Ahmet Turan and Duaa Warille determined the topic and followed the process. *Duaa Warille,* performed the data collection and statistical analysis. The authors wrote, read and approved the article together.

Ethics Statement

There are no ethical issues related to the publication of this article.

Conflict of Interest

The authors declare that they have no conflict of interest.

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