CHAPTER 4

DESIGN AND DEVELOPMENT OF PREGNANCY FALL DETECTION AND ALERT SYSTEM

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4.1 INTRODUCTION

Falls are a serious global public health hazard, accounting for the second highest cause of unintentional injury fatalities globally. Falls kill roughly 684,000 people per year, with more than 80% of those deaths happening in low- and middle-income nations. Adults aged 60 [1][2] and over are more susceptible, emphasizing the necessity for comprehensive preventative actions. Non-fatal falls also have serious repercussions, causing approximately 37.3 million severe injuries each year and contributing to widespread disability and financial hardships [3].

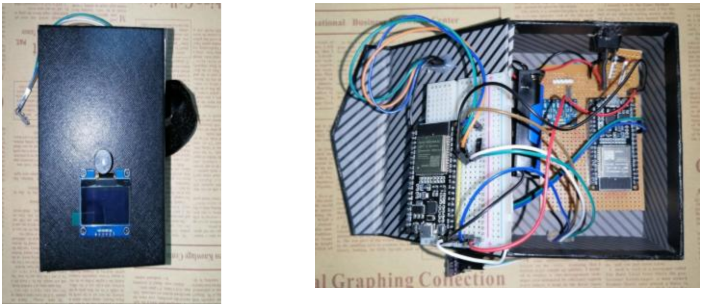
This study addresses the risk factors associated with falls, including age, gender, occupation, socioeconomic status, and health conditions, and emphasizes the importance of preventive interventions. The propose a fall detection system designed for pregnant women, a group at high risk for miscarriage due to falls. The system uses electronic components and sensors to provide real-time monitoring and alerts via an IoT platform and ESP32 microcontroller. The detection mechanism employs a 3-axis gyroscope and a 3-axis accelerometer to monitor motion and orientation changes, offering real-time data for accurate fall detection. This active sensor system surpasses passive alternatives like infrared or capacitive sensors, providing a reliable solution for preventing fall-related injuries.

4.2 METHODOLOGY

4.2.1 HARDWARE DESIGN

Figure 4.1 shows the project's hardware configuration is intended to detect falls and monitor the heart rate and blood oxygen saturation (SpO2). The project is attached to a strap to be worn on the wrist for the fall detection part while the MAX30100 is attached to the body by using a tape for the monitoring part. The initial phase of the hardware design incorporates the MPU6050 sensor, which consists of a 3-axis gyroscope and a 3-axis accelerometer, connected to the ESP32 microcontroller. The MPU6050 is employed to detect falls by continuously monitoring motion and orientation changes. The ESP32 microcontroller processes the data from the MPU6050 to identify fall incidents. Upon detecting a fall, the ESP32 triggers a buzzer to emit an audible alert and simultaneously sends a notification via the Telegram messaging platform. This configuration ensures immediate alerting and response to fall events, facilitating timely assistance and intervention.

The subsequent phase of the hardware design involves the integration of the MAX30100 sensor, responsible for monitoring heart rate and blood oxygen saturation levels, with the ESP32 microcontroller. The MAX30100 sensor transmits data to the ESP32, which then processes and displays the information on an OLED screen for real-time visualisation. Additionally, the ESP32 transmits the sensor data to the Blynk application for continuous remote monitoring by the caregiver. This setup enables persistent health monitoring, allowing the tracking of vital signs and prompt attention to any irregularities. The integration with the Blynk platform provides an intuitive interface for caregivers to monitor the health status of the individual in real-time.



(a) (b)

Figure 4.1: Project configuration (a) Final prototype and (b) Hardware circuit design

4.2.2 FALL DETECTION AND MONITORING SYSTEM

The fall detection and alert system employs the ESP32 microcontroller to process data from the MPU6050 sensor, which integrates a 3-axis accelerometer and gyroscope. The primary function of the MPU6050 sensor is to detect sudden movements and orientation changes that indicate a fall. When such an event is detected, based on pre-set amplitude thresholds and angle orientation, the system triggers a buzzer to alert the individual and surroundings [4][5]. Additionally, the ESP32 uses its Wi-Fi capability to send an immediate notification via Telegram to designated caregivers, ensuring prompt assistance. This system can be seen in Figure 4.2, where the process starts with initializing all components, reading data from the sensors, and executing the alert mechanism when necessary.

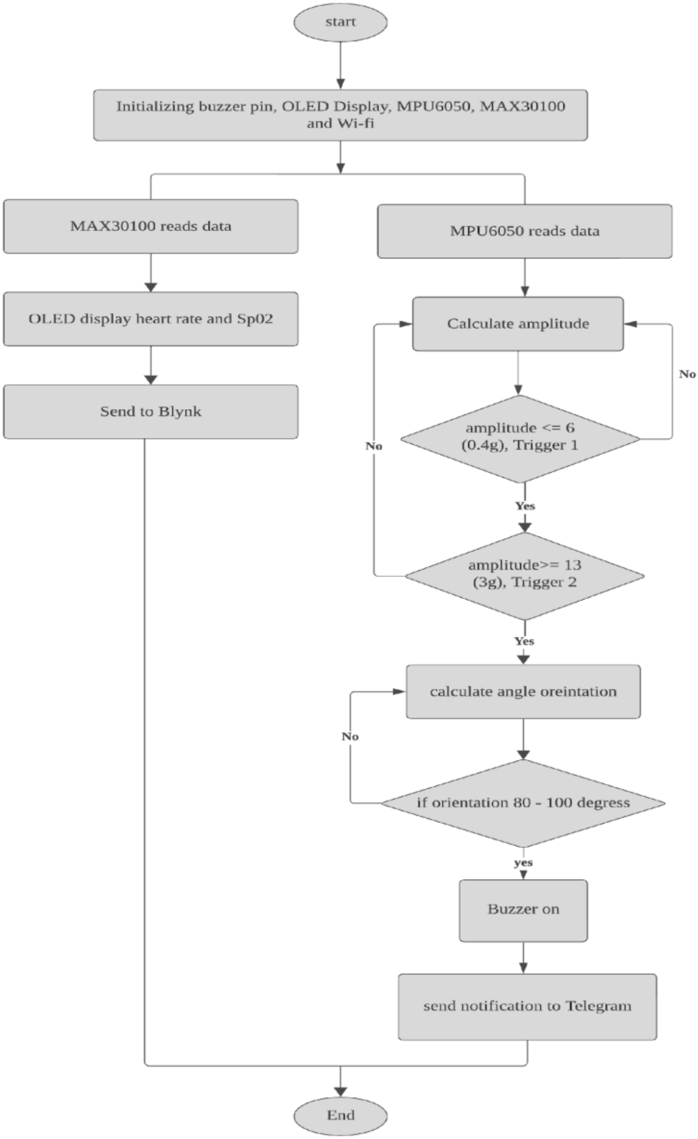


Figure 4.2: Flowchart of the project

The health monitoring aspect of the project leverages the MAX30100 sensor to measure heart rate and blood oxygen saturation (SpO2) levels. This sensor is connected to the ESP32 microcontroller, which processes the data and displays the real-time values on an OLED screen for immediate reference. Moreover, the system is integrated with the Blynk IoT platform, allowing continuous remote monitoring via a mobile application. The ESP32 sends updated sensor readings to the Blynk app at regular intervals, enabling caregivers to track vital signs consistently. Figure 4.3 illustrates this setup, showing how the ESP32 acts as a central hub, interfacing with the MAX30100 sensor, OLED display, and the Blynk app for comprehensive health monitoring.

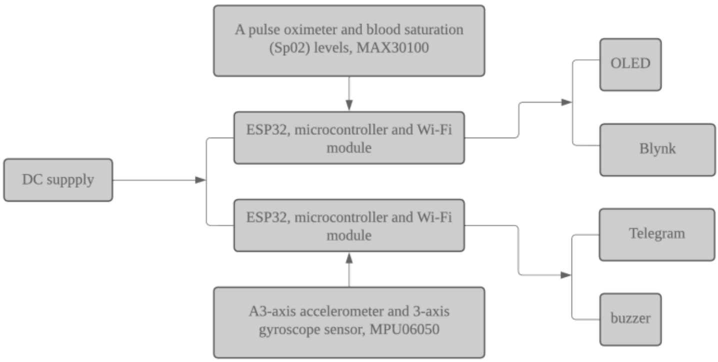


Figure 4.3: Block Diagram of the project

4.3 RESULTS AND DISCUSSION

This section presents the experimental validation and performance analysis of a fall detection prototype designed to be worn on various body parts—wrist, arm, and waist. Key metrics evaluated include precision and false negative rates (FNR) to assess detection accuracy across different placements.

4.3.1 RESULT OF THE EXPERIMENTS

The fall detection prototype was evaluated across three body placements: wrist, arm, and waist. Each experiment aimed to assess the prototype's ability to detect falls from various directions such as backwards, forward, left, and right by using accelerometer and gyroscope data. The thresholds for fall detection triggers were set based on accelerometer sensitivity specifications, ensuring accurate activation upon fall detection.

The experiments have three trials for each of the wrist, arm and waist. Based on Table 4.1, there are ten total falls detected for the wrist and the arm has 5 total which is the second highest that is suitable for the prototype to be placed. However, the waist only has two total positives of the falls and has the highest results of fall negatives which also means the number of non fall detected.

Table 4.1: Results of the experiments

	Falls				True positives (TP)	False Negatives (FN)
	Backwards	Forward	Left	Right		
Wrist	2	2	3	3	10	2
Arm	-	-	2	2	5	7
Waist	1	1	-	-	2	10

4.3.2 ANALYSIS

Precision and false negative rate (FNR) are critical metrics used to evaluate the performance of fall detection systems. Precision measures the proportion of correctly identified falls among all reported falls by the system, providing insight into the system's accuracy in detecting true positives. Conversely, the false negative rate indicates the percentage of actual falls that were missed by the detection system, highlighting the system's ability to avoid false negatives, which are crucial for ensuring timely assistance in fall-related incidents.

The precision of the fall detection prototype was evaluated across three body placements which are wrist, arm, and waist, to assess its accuracy in identifying falls from various directions. The wrist placement demonstrated the highest precision at 83.33%, correctly detecting 10 out of 12 falls. This result indicates effective sensor positioning and sensitivity on the wrist, crucial for reliable fall detection in both forward and lateral directions. In contrast, the arm placement exhibited a lower precision of 41.67%, accurately identifying 5 falls out of 12. This lower precision suggests challenges in maintaining consistent detection performance, particularly for lateral falls, potentially influenced by sensor placement dynamics and movement variability as shown in Eq. (1).

$$\text{Precision} = \left(\frac{\text{True Positives}}{\text{True Postives} + \text{False Negatives}}\right) \times 100\% \tag{1}$$

$$\text{False Negative Rate (FNR)} = \left(\frac{\text{False Negatives}}{\text{False Negatives} + \text{True Positives}}\right) \times 100\% \tag{2}$$

The false negative rate (FNR) provides insights into the prototype's ability to detect all actual falls. The wrist placement recorded an FNR of 16.67%, indicating that 16.67% of falls were missed by the detection system. Conversely, the arm placement had a higher FNR of 58.33%, highlighting significant missed detections, particularly for lateral falls. The inconsistency highlights limitations in sensor place and algorithmic sensitivity on the arm, affecting overall detection reliability, as shown in Eq. (2).

4.3.3 DISCUSSION

The experimental results demonstrate that the fall detection prototype achieves optimal performance when worn on the wrist, with a precision of 83.33% and a false negative rate (FNR) of 16.67%. This high level of precision indicates that the wrist placement effectively detects various fall directions, suggesting that the sensor positioning, and sensitivity are good for this location. In comparison, the arm placement recorded a precision of 41.67% and an FNR of 58.33%, indicating significant challenges in detection accuracy. The lower precision and higher

FNR at the arm may be attributed to the dynamic movements and varying sensor positioning that affect the reliability of fall detection.

However, the waist placement exhibited the lowest precision at 16.67% and the highest FNR at 83.33%, underscoring substantial difficulties in accurate fall detection from this position. The high rate of missed falls suggests that the sensor's effectiveness and placement at the waist are suboptimal, particularly for detecting lateral falls. These findings highlight the critical importance of optimal sensor placement and algorithm refinement to enhance the overall accuracy of the fall detection system. The superior performance of the wrist placement indicates its potential for reliable real-world application, while future improvements should focus on addressing the detection challenges associated with the arm and waist placements to ensure comprehensive and reliable fall detection across all body positions.

4.4 CONCLUSION

This project successfully utilized the MPU6050 sensor for fall detection and the MAX30100 sensor for measuring blood oxygen saturation and heart rate, integrated with an ESP32 microcontroller to deliver real-time alerts through the Telegram app. The system met monitoring requirements by allowing mothers to view data on an OLED display and caregivers to use the Blynk application for continuous monitoring. The wrist position demonstrated the highest precision at 83.33%, making it the most effective placement for fall detection. However, it also had a false negative rate (FNR) of 16.67%, indicating room for improvement. The arm and waist placements showed lower accuracies of 41.67% and 16.67%, respectively, with higher FNRs, highlighting challenges in these positions due to sensor placement and sensitivity issues. These findings emphasize the importance of optimizing sensor placement and refining detection algorithms to enhance the reliability and effectiveness of fall detection systems, ensuring timely assistance and improved safety for pregnant individuals.

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