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Wireless Sensor Networks for fall incident detection: a smart wearable approach using Kalman Filter and k-NN with LoRa WAN, Node Red, and Telegram integration

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Abstract—**Falls are a common problem in many environments and affect people of all ages. Although some people fall to be minor incidents, they can have serious consequences, especially for vulnerable groups like the elderly and stroke survivors. This study aimed to develop a system for detecting falls in patients using sensor fusion and machine learning methods to accurately identify the positions of the falls. The system combines data from accelerometers and gyroscopes using the Kalman filter to categorize falls into four types: supine, prone, left, and right. The system uses the k-Nearest Neighbors (k-NN) algorithm for threshold fall motion detection to reduce false detections. A fall detection triggers the system to send the position data via LoRaWAN communication, making the data accessible through Node-RED and Telegram. The system performance was evaluated through several tests: MPU6050 sensor measurement to calibrate and respond to the Euler accelerometer and gyroscope sensor, kalman filter measurement, threshold fall detection with the k-NN algorithm measurement, and performance LoRaWAN communication. The results showed that calibrating the MPU6050 sensor effectively minimized sensor drift and noise. The implementation of the kalman filter successfully reduced noise in the sensor readings, the k-NN algorithm provided optimal system values and performance, and data transmission via LoRaWAN to Node Red and Telegram was effective.**

Keywords—**WSN; Fall Incident; Kalman Filter; k-NN; LoRAWAN; IMU sensor; Node Red; Telegram**

I. INTRODUCTION

THE rapid advancement of technology in the field of wireless sensor networks (WSNs) has significantly enhanced health monitoring systems, particularly for fall detection among the elderly. WSNs consist of numerous low-cost, low-power sensor nodes that communicate wirelessly to monitor various health parameters, making them ideal for applications in elder care. These networks facilitate real-time data collection and analysis, which is crucial for timely intervention in health-related emergencies, such as falls[1]-[7]. One of the primary advantages of WSNs in health monitoring is their ability to provide continuous surveillance without the need for invasive procedures. For instance, wireless body area networks (WBANs) utilize small, wearable sensors to monitor physiological parameters such as heart rate, movement, and body temperatur [8]-[10]. These sensors can detect anomalies in a person's movement patterns, which is particularly useful for fall detection. The integration of advanced algorithms allows these systems to differentiate between normal activities and potential falls, thereby alerting caregivers or medical personnel when necessary [11], [12]. Moreover, the deployment of WSNs in health monitoring systems reduces the complexity and cost associated with traditional wired systems. The wireless nature of these networks eliminates the need for extensive cabling, which not only simplifies installation but also minimizes maintenance costs [13]. This is particularly beneficial in elder care facilities, where mobility and ease of access are paramount. The ability to monitor patients remotely also enhances the quality of care, as healthcare providers can receive real -time updates and respond promptly to any critical changes in a patient's condition[14]. The advancements in micro-manufacturing and wireless communication technologies have enabled the development of sophisticated sensor nodes that can operate in various environments, including those that are hostile or inaccessible to humans [15]. This capability is essential for monitoring the elderly, who may live independently and require constant surveillance to ensure their safety. Furthermore, the energy-efficient design of these sensor networks prolongs their operational life, allowing for sustained monitoring without frequent battery replacements procedures. For instance, wireless body area networks (WBANs) utilize small, wearable sensors to monitor.

This research purpose to integration of wireless sensor networks into health monitoring systems represents a significant leap forward in elder care. These technologies not only enhance the ability to detect falls and other health emergencies but also improve the overall quality of life for elderly individuals by providing them with a sense of security and independence. As technology continues to evolve, the potential applications of WSNs in health monitoring will likely expand, offering even more innovative solutions for elder care.

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II. Literature Review

This section discusses several research topics, such as hardware development, software development and communication, increasing accuracy, and determining device positions.

In recent years, the integration of advanced technologies for fall detection and monitoring of the elderly has gained significant attention. This literature review synthesizes various research studies focusing on hardware platforms, software development, machine learning algorithms, communication technologies, and the importance of accurate device positioning in enhancing fall detection systems.

Hardware development such as Arduino, Raspberry Pi, and ESP devices have emerged as popular platforms for developing fall detection systems. For instance, Raspberry Pi has been utilized in various applications due to its processing capabilities and flexibility. demonstrated that multithreading can significantly enhance detection performance on Raspberry Pi, achieving improved accuracy in monitoring applications [16]. Furthermore, developed an embedded system for human detection using Raspberry Pi, which integrates camera and sensor technologies to monitor movements effectively [17]. The versatility of these platforms allows for the integration of multiple sensors and communication modules, making them suitable for real-time monitoring of elderly individuals.

Software frameworks such as Node-RED and MQTT have been instrumental in developing efficient monitoring systems. proposed a cane-cased transmitter node that utilizes MQTT to send data regarding the elderly's position and health status, demonstrating the effectiveness of this protocol in real-time applications [18], [19]. Additionally, the integration of Node-RED allows for the visual programming of IoT applications, facilitating the development of user-friendly interfaces for monitoring systems. The combination of these software tools enhances the capability to process and visualize data, which is crucial for timely interventions in case of falls.

Machine learning techniques play a pivotal role in improving the accuracy of fall detection systems[20]-[24]. Algorithms such as k-nearest neighbors (KNN), random forests, and support vector machines (SVM) have been explored for their effectiveness in classifying fall events. For example, KNN has been successfully applied in various domains, including health monitoring, to classify events based on sensor data [25] The use of SVM in conjunction with Raspberry Pi has shown promising results in optimizing detection performance, as highlighted, These algorithms can be trained on diverse datasets to enhance their predictive accuracy, making them suitable for real-time fall detection.

Communication Technologies Low-power wide-area network (LPWAN) technologies such as LoRa[26]-[30], BLE[31], and Zigbee are critical for ensuring reliable communication in fall detection systems. emphasized the importance of LoRa technology in monitoring the health and residence conditions of elderly individuals, particularly in remote areas where traditional mobile networks may be inadequate [28] The ability of LoRa to transmit data over long distances with low power consumption makes it an ideal choice for continuous monitoring applications. Moreover, the integration of MQTT with LoRa enhances the system's responsiveness to fall events, allowing for immediate alerts to caregivers.

Accurate device positioning is essential for improving the effectiveness of fall detection systems. The placement of sensors and devices can significantly influence the system's ability to detect falls accurately. Research indicates that optimizing sensor placement and utilizing multiple sensors can enhance detection rates and reduce false positives [32]. Additionally, the use of advanced algorithms for data fusion from multiple sensors can further improve the accuracy of fall detection systems, ensuring that elderly individuals receive timely assistance when needed.

In conclusion, the integration of various hardware platforms, software development frameworks, machine learning algorithms, and communication technologies is crucial for advancing fall detection systems for the elderly. The ongoing research in these areas promises to enhance the safety and well-being of elderly individuals, particularly in smart city environments where technology can play a vital role in monitoring and care.

III. Materials and Methods

This study focused on developing a Smart Wearable Approach Using Kalman Filter and k-NN techniques with LoRAWAN, Node Red, and Telegram Integration. As shown in Fig. 1.

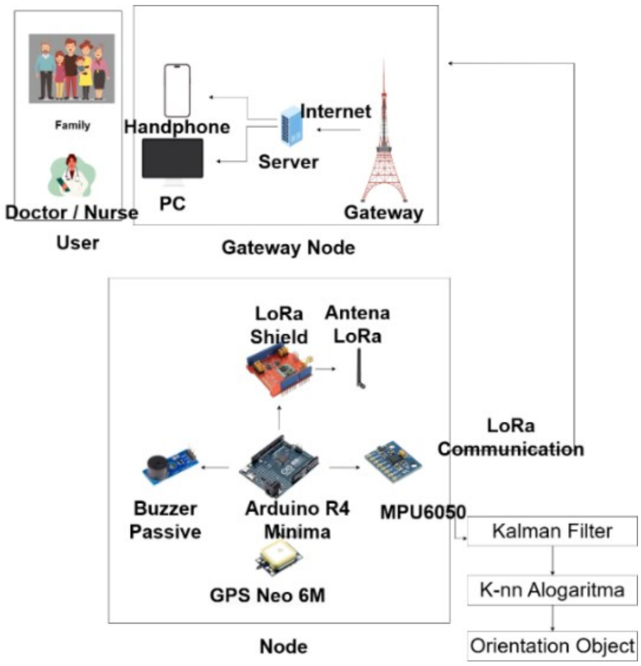

Fig 1. System Architecture Design.

A. Design Hardware and Materials

The mechanical design involves creating a casing and optimizing the layout of the electronic boards. This design aims to enhance the overall esthetics by crafting a protective case and efficiently arranging the electronic boards. The resulting mechanical design is expected to provide both structural integrity for the components and an organized configuration for enhanced electronic performance, as shown in Fig. 2.

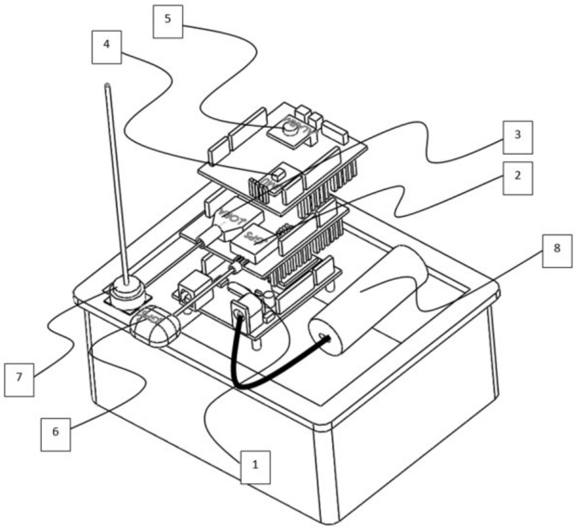

Fig 2. Design Hardware and Materials

The materials used in the Fig. 2 as follows:
1. Arduino Uno R4 Minima Microcontroller
2. GPS Neo 6M Module Sensor
3. Shield LoRa Module
4. MPU6050 Sensor Module
5. Passive Buzzer Module
6. Antenna GPS
7. Antenna LoRa
8. Battery 5 V DC.

B. *Orientation Estimation Computing Alogarithm*

The design of oreientation estimation to measureing position of object from data from the MPU6050 sensor, including the accelerometer and gyroscope data, involved several steps: reading the accelerometer and gyroscope data and applying the Kalman filter method, as shown in Fig. 3.

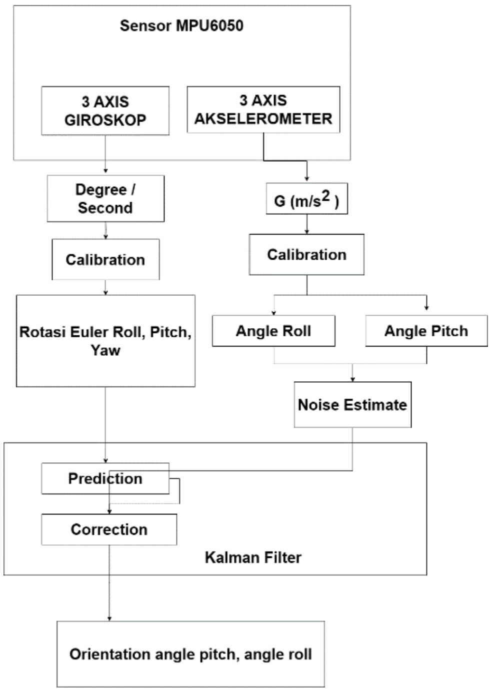

Fig 3. Design Method Kalman Filter.

Fig 3. illustrates the process of determining orientation angles (pitch and roll) using an MPU6050 sensor. The process begins with the MPU6050, which integrates a 3-axis gyroscope and a 3-axis accelerometer. The gyroscope measures the rotational speed around three axes in degrees per second, and this data is then calibrated to correct any biases. Simultaneously, the accelerometer measures acceleration along the three axes in units of gravitational force (G), and this data is also calibrated for accuracy. After calibration, the gyroscope data is used to calculate the Euler angles: roll, pitch, and yaw. Concurrently, the accelerometer provides direct estimates of the roll and pitch angles. To enhance accuracy, the system estimates the noise in the sensor data. The core of the process involves the Kalman Filter, which combines the gyroscope and accelerometer data. The filter uses the predicted orientation from the gyroscope and the actual measured orientation from the accelerometer to minimize noise and errors. This filtering process ensures that the final calculated angles are both accurate and stable. Finally, the output of the Kalman Filter provides the refined orientation angles: pitch and roll, which are crucial for orientation estimation.

C. *Embedded K-Nearest Neighbors (K-NN) on Microcontroller*

Designing of K-Nearest Neighbors (K-NN) machine learning algorithm involves a series of steps to comprehend and implement this method in the context of data analysis. The steps include data selection, preprocessing, training data, and evaluation. as shown in Fig. 4.

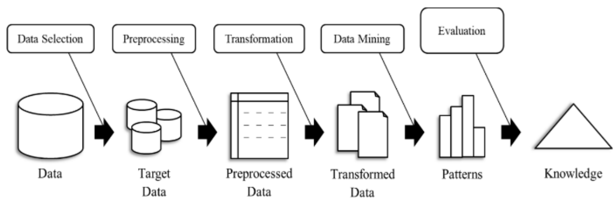

Fig 4. Design Processing K-NN.

Fig. 4 illustrates the process of transforming raw data into valuable knowledge through a series of structured steps. It begins with Data Selection, where relevant data is identified and chosen from various sources. This selected data becomes the Target Data. The next phase is Preprocessing, where the target data is cleaned and organized to remove any inconsistencies or errors, resulting in Preprocessed Data. Following this is the Transformation step, where the preprocessed data is transformed or normalized into a format suitable for analysis, producing Transformed Data. The transformed data is then subjected to Data Mining, where advanced techniques are applied to extract patterns and insights, yielding Patterns. Finally, in the Evaluation stage, these patterns are assessed to determine their usefulness, leading to the creation of Knowledge that can be used for decision-making and further application. This process is essential in data-driven environments for extracting meaningful insights from raw data.

D. *LoRaWAN Parameter*

For the design of LoRa WAN communication, parameter values are determined based on the literature. The steps involved in designing LoRa WAN communication include designing LoRa parameters and designing WAN parameters. In communication design, the communication variables are set up to transmit payload data to the LoRa WAN Gateway. Therefore, the node containing sensors sets the values of the variables to be used in the following Table I.

TABLE I.
SETUP PARAMETER LORA

Parameter	Value
Frequency	922.2 MHz
Spreading Factor	12
Bandwidth	12500 Hz
Coding Rate	4/5
Sync. Word	0x34
Preamble Length	8

The parameters for transmitting data using LoRa WAN communication play a vital role in determining the transmission performance and efficiency. In this scenario, the chosen frequency is 922.2 MHz, which is the operational frequency of LoRa WAN networks. A spreading factor of 12 indicates the level of spectrum spreading used by the LoRa module, which affects the transmission range and sensitivity. A bandwidth of 12500 Hz indicates the width of the band used for data transmission, which affects the data transfer rate. In addition, a coding rate of 4/5 represents the ratio between the data sent and the total number of sent data, which indicates the level of redundancy during transmission. The Sync Word with a value of 0x34 is the pattern used for synchronization between the transmitter and receiver to ensure accurate data reception. A preamble length of 8 indicates the initial signal length used for preparation and synchronization. The combination of these parameters is essential to achieve a balance between transmission range, data transfer rate, and power efficiency when delivering data using LoRa WAN technology. With the appropriate configuration, the system can provide optimal performance according to the application requirements and environmental conditions. The WAN configuration is implemented with the aim of establishing an internet connection for the backend/server application. This step is critical for ensuring Internet connectivity in the LoRa WAN communication system. The WAN setup is designed to facilitate seamless integration with the backend/server application, thereby enabling data exchange and communication over the internet. This configuration is essential for achieving the desired performance and aligning with specific application requirements.

E. Node Red and Telegram Interface

The software design phase includes planning for the creation of Node Red flows and the development of a bot, as well as setting up a Telegram channel. The design and creation of a Node-Red flow are performed to monitor GPS readings and patient position measurements. The following is the display of the created Node-Red flow, as shown in Fig. 5.

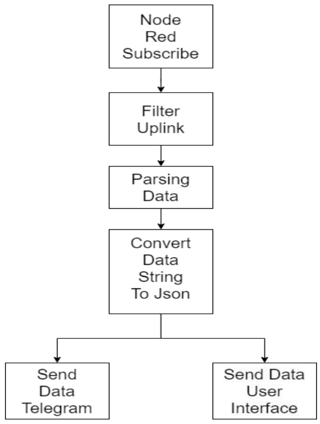

Fig 5. Design Flow Software.

IV. RESULTS AND DISCUSSION

A smart wearable prototype using Kalman Filter and k-NN with LoRaWAN, Node-RED, and Telegram integration was designed and developed to measure the orientation and GPS location of a patient. The development process for the MPU6050 sensor involves several critical stages to ensure optimal performance. Initially, the sensor is tested to measure its accuracy in providing Euler angles. This process involves monitoring the sensor's ability to deliver pitch, roll, and yaw values corresponding to the orientation of the object or device. Subsequently, calibration testing is conducted to correct any inaccuracies that may arise during measurements. The calibration process involves calculating offsets that are then applied to the sensor data to obtain more accurate angle readings, as shown in Fig. 6.

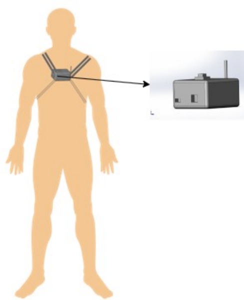

Fig 6. Position calibration device

The scenario involves applying a Kalman filter to the sensor data. This evaluates the Kalman filter's ability to suppress noise and disturbances in the sensor data, ultimately producing stable and accurate estimate orientation.

1. *MPU6050 Measurement*

The experiment sensor was conducted on the MPU6050 sensor with a focus on four aspects: calibration gyroscope, and accelerometer.

In quiet conditions, during the engineering process, the expectation is that the sensor provides a stable and consistent output close to zero. However, in practice, the sensor output may not always precisely approach zero under idle conditions.

Various factors, such as offset and drift, can cause deviations from the expected values. Therefore, the calibration process is crucial for ensuring that the sensor delivers outputs in line with actual conditions. Calibration values are established when the device is first powered on, and the device must remain stationary for the first 2 s. During this period, the program records sensor values that serve as references for forming calibration data. This testing compares data from the sensor without calibration with those that have undergone calibration. The test results revealed significant differences between the two datasets, with the calibrated data exhibiting better stability. This confirms that the calibration process successfully corrected the offset, thereby enhancing the sensor accuracy for subsequent data processing. This is evident in the following Fig.7

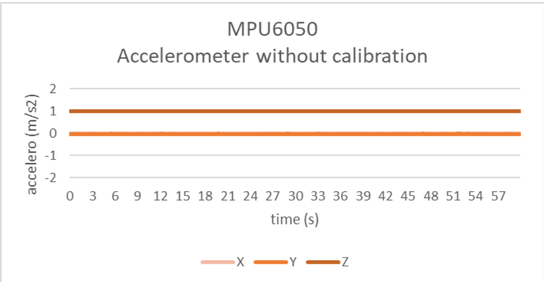

Fig 7. Accelerometer without calibration

Displaying the output of the accelerometer sensor on three axes (X, Y, and Z) before undergoing the calibration process. In this graph, it is evident that the Z-axis line from the accelerometer data is far from the value 0. The absence of proximity to 0 in this line indicates an offset or deviation that must be addressed.

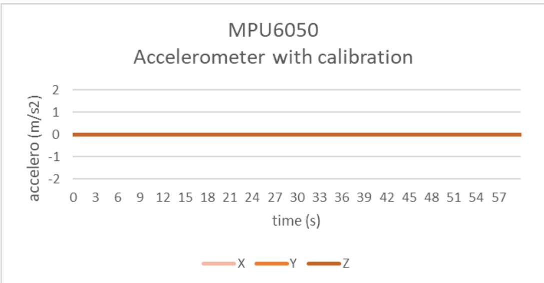

Fig 8. Accelerometer calibration

Fig. 8 illustrates the output of the calibrated accelerometer sensor. Note that after calibration, the lines of the accelerometer data on all three axes were closer to a value of 0. This outcome indicates that the calibration process successfully corrected the offset or deviation in the previous accelerometer data.

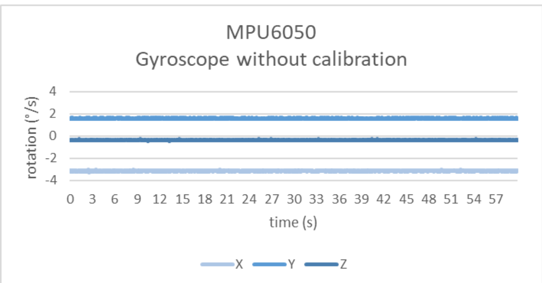

Fig 9. Gyroscope without calibration

Fig.9 Displays the output of the gyroscope sensor on three axes (X, Y, and Z) before calibration. In this graph, all curves are far from 0, indicating the presence of offsets or deviations that may affect the accuracy of the sensor data.

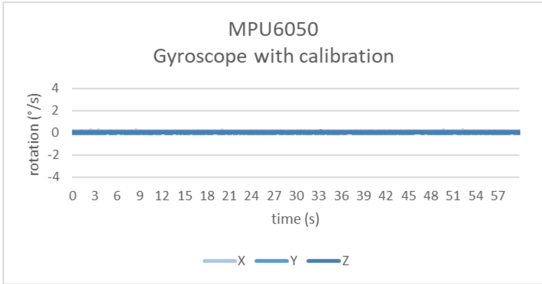

Fig 10. Gyroscope with calibration

Fig. 10 shows the output results from the gyroscope sensor after the calibration process. Post-calibration, it is noticeable that the gyroscope data curves on each axis approached the value of 0 significantly. This change indicates the successful calibration of the gyroscope sensor.

2. *Kalman filter measurements*

Kalman filter testing examines the sensor's ability to combine data from the accelerometer and gyroscope to produce more accurate orientation information.

A. *Noise reduction by the Kalman filter*

Noise reduction testing was conducted at the roll and pitch angles when the device was stationary and in motion. The main objective of this testing was to evaluate the effectiveness of the Kalman Filter in reducing noise or fluctuations that may occur when the device is either stationary or in motion. During the testing phase, the device is worn by the user, who is then instructed to sit still for 2 minutes, followed by standing still for another 2 min.

Fig 11. Angle Pitch Before and After Noise Reduction

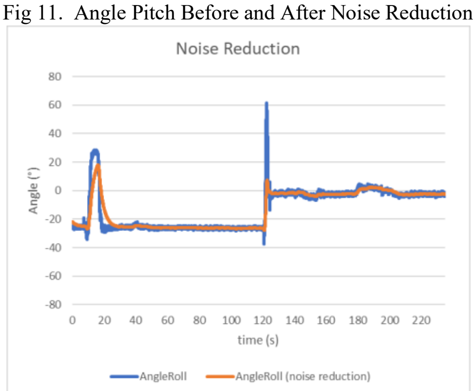

Fig 12. Angle Roll Before and After Noise Reduction

Fig.11 and 12 show the roll and pitch-angle graphs before and after the Noise Reduction process. In the time range of 0-2 minutes, it indicates the sitting position, while in the time range of 2-4 minutes, it indicates the standing position. It is noteworthy that the very high fluctuations that occur during position changes are effectively mitigated by the implementation of the Kalman Filter. If left unmitigated, these fluctuations would compromise the accuracy of the classification process. Therefore, the application of noise reduction techniques, such as the Kalman filter, is crucial to ensure the accuracy and reliability of sensor data.

3. ***KNN Classification Algorithm***

Testing the KNN classification algorithm was conducted to assess the algorithm's capability in classifying user positions. Testing all k-NN parameters based on the results obtained from the parameter testing above revealed the following data: the optimal value for the k parameter is 3, the optimal number of data is 300, and the weighting method used is without weighting.

TABLE II.
TABEL CONFUSION MATRIX

Confusion Matrix						
Actual \ Prediction	Non Fall	Semi Fall	Fallin Right	Falling Left	Falling Supine	Falling Prone
Non_ Fall	998	2	0	0	0	0
Semi_ Fall	0	1000	0	0	0	0
Falling_ Right	0	0	1000	0	0	0
Falling_ Left	0	0	0	1000	0	0
Falling_ Supine	33	0	0	0	967	0
Falling_ Prone	0	606	0	0	0	394

Actual=Prediction	5358
Count Data	6000
Accuray	89.30%

Table II the confusion matrix provided offers a detailed evaluation of a classification model's performance in predicting various types of fall and non-fall events. The matrix consists of rows representing the actual events and columns representing the predicted events, including categories such as "Non-Fall," "Semi-Fall," "Falling Right," "Falling Left," "Falling Supine," and "Falling Prone." The green cells along the diagonal indicate correct predictions made by the model, such as 998 Non-Fall events accurately predicted as Non-Fall, 1000 Semi-Fall events correctly identified as Semi-Fall, and so on. However, the red cells highlight areas where the model misclassified events, such as predicting 33 Falling Supine events as Non-Fall and 606 Falling Prone events also as Non-Fall. Overall, the model correctly predicted 5358 out of 6000 events, resulting in an accuracy of 89.30%. While this indicates a generally strong performance, the misclassifications, particularly in the "Falling Supine" and "Falling Prone" categories, suggest areas where the model could be improved for better accuracy.

4. *LoRaWAN Experiment*

In communication testing, the aim is to evaluate predetermined settings of the device designed to assess LoRa communication performance. Communication testing is divided into several stages: frequency testing, RSSI value testing, and air testing.

A. Frequency Device Measurement

In frequency testing, it was determined that the device configuration aligned with the programed settings, transmitting LoRa signals at a frequency of 922.2 MHz, as confirmed by measurements conducted using a spectrum analyzer. as shown in the Fig.13 below.

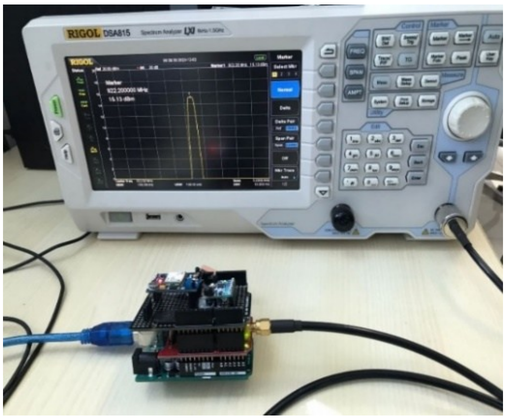

Fig 13. Testing Frequency using Spectrum Analyzer

B. RSSI Measurement

Measurement of RSSI (Received Signal Strength Indication) values against elevation is conducted with the aim of understanding how the received signal strength may change with variations in the elevation angle from the signal source or transmitting device.

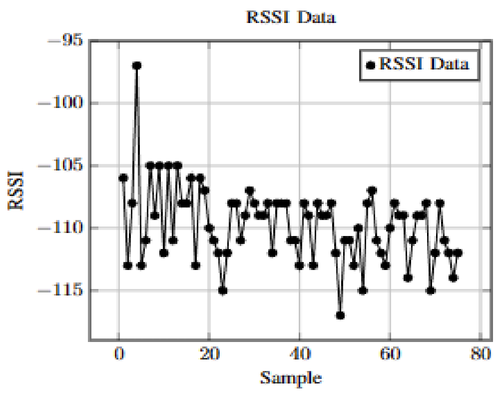

Fig 14. Graphic RSSI Data

From Fig.14 An analysis of the effect of altitude on LoRa RSSI values revealed changes in RSSI values, indicating that changes in node altitude significantly affect received signal quality. Increasing altitude tends to increase RSSI values because physical obstacles, such as buildings or terrain surfaces, can block or dampen the signal decrease. During testing, the

RSSI values stabilized around 115 dBm. This phenomenon occurs because the lack of obstacles allows LoRa signals to reach the antenna more effectively and with minimal attenuation. However, it should be noted that the impact of altitude is not always linear, and other factors, such as signal propagation and interference, can still affect RSSI variability. Therefore, when designing or optimizing LoRa networks, careful field evaluation and testing are necessary to thoroughly understand how altitude can be optimized to achieve optimal communication performance. Strategic implementations, such as repeater and gateway placements, should also be considered to ensure maximum coverage and improved signal quality under various altitude conditions.

5. *User Interface Node Red and Telegram*

User Interface display for the Fall Detection Movement monitoring system using a website. This interface provides real-time tracking and alerts for any detected fall movements. Users can easily access and interpret the data, facilitating efficient monitoring of patient safety and well being. as shown in the fig.15

Fig 15. User Interface

The Telegram bot is used for monitoring and informing physicians and nurses and the patient's family when the measurement parameters exceed or fall below predefined threshold values. This bot system consists of a single channel, namely the "Monitoring of Air Quality, Vital Signs, and Patient Movement" channel. The creation of a Telegram bot involves using the bot creation service BotFather provided by Telegram. To create a new bot, the command'/newbot' is sent to BotFather, followed by entering the desired bot name and creating a username for the bot ending with the word 'bot' to obtain a token. The token generated by BotFather is as follows. as shown in the Fig.16

Fig 16. Telegram interface

V. Conclusion

This study explores the development of a patient movement detection system using an optimized Kalman filter method to reduce false detections, supplemented by a machine learning approach using the k-nearest neighbor (k-NN) algorithm to determine patient positions and orientations. Data communication uses LoRaWAN technology, providing an efficient framework. System testing included MPU6050 sensor calibration, Euler accelerometer and gyroscope testing, and patient fall position determination using MPU6050 IMU sensor fusion and Kalman filter techniques. The k-NN testing resulted in an accuracy of 89.30% with the optimal parameters of k = 3 and no weighting method. LoRaWAN communication parameter testing revealed that a frequency of 922.2 MHz, Spreading Factor 7, and bandwidth yielded the best results with an RSSI stabilization of approximately 115 dBm and ToA around 1-2s. Overall, the integration of Kalman filtering, machine learning, and LoRaWAN communication provides a solid foundation for a reliable patient movement detection system with significant potential to enhance monitoring and response to critical medical events.

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