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An IoT-based Multi-sensory Intelligent Device for Bedridden Elderly Monitoring

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ABSTRACT

A significant responsibility of elderly caregivers is monitoring the health condition of the elderly. Health monitoring can become increasingly difficult for caregivers of bedridden older adults since they cannot lie in the same position for periods longer than two hours. Therefore, we used an artificial intelligence to alert caregivers and alleviating their workload. This work aims to develop a system to support the care of bedridden older adults using the SensorTag CC2650STK as a motion sensor. We used accelerometers and gyroscopes to generate the model for analyzing the lying position of older adults. The system can help caregivers by sending notifications when older adults have been lying in the same position for too long. We defined the lying position into four classes: sit, left, right, and back. Three machine learning models (K-NN, Decision Tree, and Naïve Bayes) were generated and evaluated in our work. We found that the decision tree could achieve the best classification results among these ML models, obtaining scores of 0.98, 0.97, and 0.97 for precision, recall, and F1 scores, respectively.

Article information:

Keywords: K-NN, Decision Tree, Naïve Bayes, Elderly, Activity Analysis, Low-pass Filtering

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1. INTRODUCTION

At present, Thailand's population is aging, with over 20 percent of the country's residents now aged 60 or older. Most elderly individuals in Thailand require assistance and are bedridden. Caring for a bedridden older adult is often challenging, as they cannot lie in the same position for periods longer than two hours. The main problems affecting the lives of bedridden elderly are the incidence of pressure ulcers and infections, which are significant causes of illness. Therefore, we used an artificial intelligence system as an aid in alerting caregivers and alleviating their workload.

Thus, this paper presents an artificial intelligence technology to develop a sleep posture analysis system for bedridden elderly individuals. Our work's significant contribution is developing of a system to support the care of bedridden older adults. We utilize the SensorTag CC2650STK from Texas Instruments as a motion sensor, along with accelerometers and gyroscopes, to generate a model for analyzing the lying position of older adult. Additionally, we have developed a mobile application to aid in the care of bedridden patients by notifying caregivers when the patient has been lying in the same position for an extended period. In the development phase, we employed artificial intelligence using three models: K-NN, Decision Tree, and Naïve Bayes. We used Flutter to develop the mobile application.

This paper consists of 5 sections: Section 1 is an introduction; Section 2 presents literature reviews; Section 3 covers implementation; Section 4 describes experimental results; and Section 5 offers discussions and conclusions.

2. LITERATURE REVIEWS

Assistive technology for older adults has been around for over a decade, ever since the world population began to transition into an aging society [1]. IoT (Internet of Things) and wearable technologies, such as activity recognition, fall detection, and health

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monitoring, are now integrated into mobile phones and smartwatches [1]. Figure 1 shows an example of assistive IoT-based technology designed to enhance the quality of life for older adults.

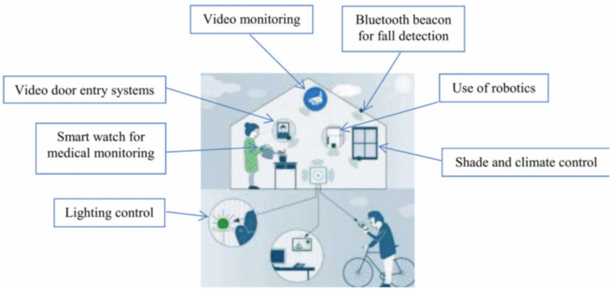


Fig.1: *IoT technologies for helping older adult to live independently [1].*

In [2], the research presented a comprehensive review of IoT and wearable technologies for elderly care. It introduced methods for capturing daily data to monitor the health conditions of older people. It also provided insights and opportunities for developing applications to support robotic and integrated technology in elderly healthcare.

Active and healthy aging were the key concepts explored in [3]. This study reviewed necessary IoT and interconnected sensing devices, wearable and in-room, to monitor, measure, and assess elderly health conditions using environmental parameters (e.g., room temperature, humidity, lighting). Fall detection, a primary function for elderly monitoring systems, was also introduced.

The investigation of Activities of Daily Life (ADLs) to support independent living for older people was the focus of [4]. Designing wearable sensors and IoT-based monitoring applications that are easy for the elderly to use and remotely accessible by their children is a significant challenge for those who live alone. The work also suggested future research directions for advanced sensors, wireless data collection, communication platforms, and usability.

In [5], the paper reviewed activity recognition for ambient assisted living in smart home technologies for older people. A gap was reported between emerging health care technologies (emotion recognition, occupancy, mobility, posture recognition, localization, fall detection, and generic activity recognition) and IoT robotic devices in terms of application development and deployment within varying socioeconomic and community contexts.

The work in [6] presented integrated wearable devices and sensors such as headband, camera clipper, sociometric badge, smart watch, and embedded sensors in clothing to assist with independent elderly living. It also proposed telemedicine, mobile healthcare services, and robotics for implementing IoT applications, specifically senior care. In [7], the paper proposed an enhanced monitoring with the integration of UHF (Ultra High Frequency) and RFID (Radio Frequency Identification) for elderly monitoring systems.

Intel Edison platform is a sophisticated IoT-based monitoring system [8]. The system integrated sensors to measure human vital signs, sleeping, and movement patterns. Output signals were transmitted to a central server to detect health abnormalities in older people. The system was robust against false alarms and could even call for help if older adult was in an emergency.

In [9], the emerging technology of ADLs recognition and Ambient Assisted Living (AAL) can help older people live independently. Using intelligent IoT and cloud activity monitoring via high-speed internet, these systems could help caregivers monitor older people in real time. Flexibility in wearable device types (e.g., chest band, badge, sleeping pad, and wristband) and focusing on applications like fall detection and health monitoring are vital aspects of the proposed system. The system also have the capability to connect directly to a doctor for real-time advice.

In [10] and [11], these works introduced multi-sensory devices and 5G technology into elderly care. They used three health sensors (heart pulse, body temperature, and galvanic skin response) to train an LSTM (Long Short-Term Memory) model in core cloud computing, prioritizing sensitive IoT data. This integration aimed to reduce hospital visits for older people and allow doctors to remote patient monitoring in real-time, ultimately reducing medical expenses.

In [12], it proposed ADLs classification using BPNN (Back Propagation Neural Network). It employed deep learning to classify activities of older people living independently. The work focused on identifying harmful activities performed when living alone. In [13], it integrated fall detection, prediction, and other features into the deep model. In [14], it used LSTM and low pass filtering to remove noise. The method can increase the robustness of ADLs classification.

Growing concerns about invasive monitoring and the loss of privacy for older people are also emerging issues [15]. Figure 2 illustrates the use of IP cameras to monitor the daily lives of older people.

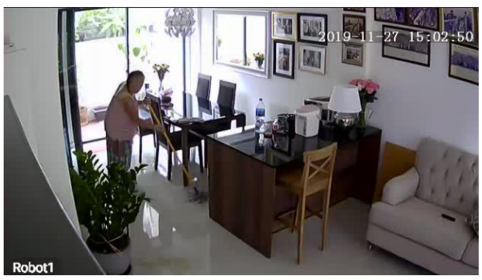


Fig.2: *The use of an IP camera to monitor older adult's activity [12].*

Low-cost IoT devices with multi-purpose usage were introduced in [16], [17], and [18] to reduce the expense of expanding the monitoring system. These studies combined PIR (Passive Infrared) sensors and blockchain technology for versatile use. They can tracked multiple signals with any number of health monitoring applications using cloud platforms.

In [19], the integration of LoRa (wireless modulation) and Message Queuing Telemetry Transport (MQTT) protocol in IoT aimed for high performance in machine-to-machine communication via real-time monitoring systems. LoRa and MQTT offer low energy consumption and a 6-kilometer communication range, providing an alternative solution for elderly care communities.

3. IMPLEMENTATION

We studied three Machine Learning (ML) techniques: K-NN, Decision Tree, and Naïve Bayes. Here is a brief description of each:

K-Nearest Neighbors (K-NN): This classification technique approximates functions locally and defers computation until evaluation. K-NN relies on distance measurements for classification. As a result, normalizing training data can dramatically improve its accuracy if features represent different physical units or scales [20], [21].

Decision Tree: A simple representation for classifying examples. We assume all input features have finite discrete domains and a single target feature termed "classification." Each domain element of the classification represents a class. A decision tree is a tree-like structure where we label each internal (non-leaf) node with an input feature. And we label arcs leading from a node with possible values of the target feature. Alternatively, an arc may lead to a subordinate decision node on a different input feature [22], [23].

Naïve Bayes: A straightforward technique for constructing classifiers. Classifiers are models that assign class labels to problem instances represented as vectors of feature values drawn from a finite set. Naïve Bayes algorithms use a common principle: all assume feature values are independent of each other, given the class variable [24], [25], [26].

We also studied the sitting and lying positions of bedridden elderly individuals to prevent them from staying in the same position for prolonged periods. We determined that there is one type of sitting position and three types of lying positions:

1. Sit

For elderly individuals, maintaining good posture while sitting in bed is crucial for comfort and preventing health problems. It aims for an S-shaped spine supported by pillows, with head aligned and neck neutral. The older adult should bend knees and hips at 90 degrees, resting feet flat on the floor or using a footstool. To avoid slouching, crossing legs, and sitting for extended periods. The older adult can shift positions regularly and use assistive devices if needed. For elderly individuals' requirements, the older adult may consult a healthcare professional for personalized guidance on achieving optimal seated comfort and safety in bed. Figure 3(a) shows sitting in bed posture.

2. Supine

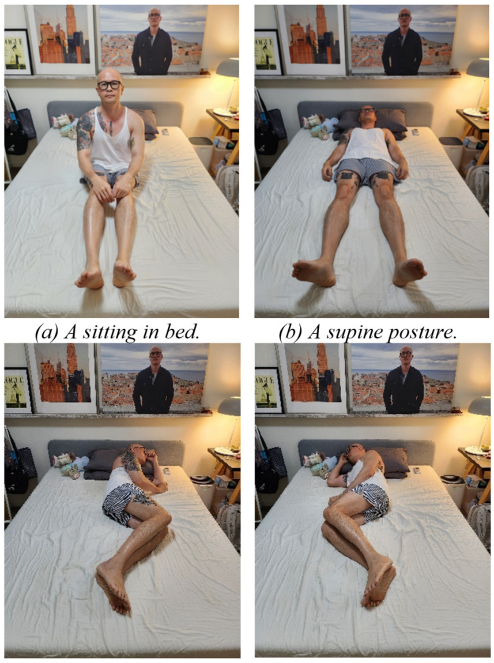
This posture is a common sleeping position for many people. It involves lying on back with arms either parallel to sides or extended. The prone position is beneficial for those without health problems, as it aligns the head, neck, and back in a neutral position. This posture can prevent neck and back pain while also helping to reduce acid reflux. Additionally, it's considered favorable for maintaining skin health and breast shape. Figure 3(b) shows a supine sleeping posture.

3. Lying on a Left Side

Lying on your left side promotes spinal health and improved sleep. It also benefits the digestive system by keeping the stomach and pancreas in natural positions, facilitating waste movement into the colon for morning elimination. This position can also relieve back pain. However, hugging a bolster and placing it between legs can prevent numbness from prolonged pressure on the left leg. Figure 3(c) shows a lying on left side sleeping posture.

4. Lying on a Right Side

This position supports heart function and promotes efficient food movement from the stomach into the small intestine. It also alleviates back pain. Figure 3(d) shows a right side sleeping posture.



(a) A sitting in bed. *(b) A supine posture.*

(c) A lying on a left side posture. *(d) A lying on a right side posture.*

Fig.3: *Positionings of an elderly person in bed.*

We used the purposive sampling method to select five elderly residents from the Premium Homecare Center for our experiment. Data collection occurred between 10:00 AM and 3:00 PM. We collected five data points per second. We categorized our data into four classes: sitting in bed, lying on the left side, lying on the right side, and supine. Table 1 shows the total data points collected from the five samples.

Table 1: *Data collection.*

Posture	**Number of data points**	**% of data collection**
Sit in bed	86,340	33.04
Lying on a Left Side	55,145	21.10
Lying on a Right Side	50,210	19.22
Supine	69,600	26.64
Total	261,295	100

We collected the dataset to train the three ML models mentioned earlier and subsequently compared their performances. After selecting the most efficient model, we embedded it in the bedridden sleeping pad and connected it to the application. The application allows the system to notify caregivers when the older person should change their sleeping position. Figure 4 shows the system architecture of our work.

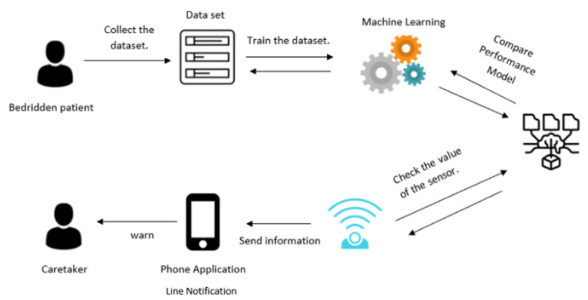


Fig.4: *The system architecture.*

Figure 5 shows the activity diagram of this work. The entire process consists of four steps:

1) The caregiver attaches the SensorTag to the patient's pampers.

2) SensorTag transmits raw data to the backend system.

3) Data processing using machine learning; notification sent.

4) The system displays a notification to alert the caregiver.

Tables 2-3 show the data collection used in our method. The data we used to train our model consists of acceleration in x-y-z and gyroscope in x-y-z.

To deploy our model, we used the SensorTag CC2650STK from Texas Instrument and Raspberry Pi 3B+ as the IoT devices in our experiment. SensorTag can be used immediately after inserting a

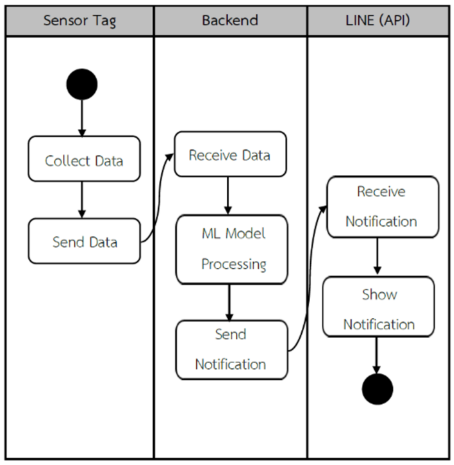


Fig.5: *The activity diagram of our work.*

Table 2: *Data collection.*

Date / Time Record	**Accel - X (g)**	**Accel - Y (g)**	**Accel - Z (g)**
21-10-21 02:15:20.30 PM	-0.655	0.814	-0.149
21-10-21 02:15:21.30 PM	-0.640	0.822	-0.168
21-10-21 02:15:22.30 PM	-0.650	0.780	-0.193
21-10-21 02:15:23.30 PM	-0.635	0.831	-0.173
21-10-21 02:15:24.68 PM	-0.634	0.814	-0.171
21-10-21 02:15:25.68 PM	-0.634	0.814	-0.171
21-10-21 02:15:26.68 PM	-0.634	0.814	-0.171
21-10-21 02:15:27.68 PM	-0.634	0.814	-0.171

Table 3: *Data collection.*

Date / Time Record	**Gyro – X (°/s)**	**Gyro – Y (°/s)**	**Gyro – Z (°/s)**
21-10-21 02:15:20.30 PM	-2.115	3.901	4.649
21-10-21 02:15:21.30 PM	-1.015	6.031	5.565
21-10-21 02:15:22.30 PM	0.565	4.160	6.366
21-10-21 02:15:23.30 PM	-0.328	4.664	6.321
21-10-21 02:15:24.68 PM	-3.992	6.191	4.756
21-10-21 02:15:25.68 PM	-3.992	6.191	4.756
21-10-21 02:15:26.68 PM	-3.992	6.191	4.756
21-10-21 02:15:27.68 PM	-3.992	6.191	4.756

CR2032-type battery and has a power button on the side. SensorTag transmitted the signal via Bluetooth Low Energy (BLE) to the receiver, the Raspberry Pi 3B+. We can view the Bluetooth address from the SensorTag specification. Figure 6 shows the SensorTag CC2650STK.

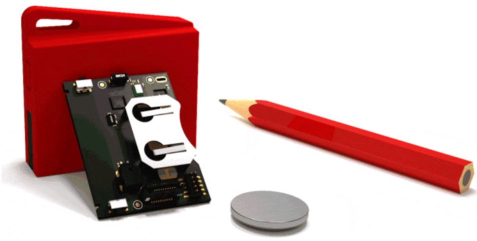


Fig.6: *The SensorTag CC2650STK.*

After connecting the Raspberry Pi to a power supply, we powered it on. For the initial setup, connect a monitor via an HDMI cable and establish a Wi-Fi connection. We enabled remote access via VNC Viewer for future use. Raspberry Pi communicated with the SensorTag using Bluetooth Low Energy (BLE). The system executed Python code that transmitted data to a Google Sheet. Figure 7 shows the Raspberry Pi 3B+.

Fig.7: *The Raspberry Pi 3B+.*

Figure 8 demonstrates our use of SensorTag and Raspberry Pi as an IoT device for bedridden individuals. We attached the SensorTag to the front of the diaper, designing it for easy removal when the caregiver needs to change it. In training and testing phases, we followed this reference procedure for data collection to ensure accurate sleep position classification. Figures 9 (a) and (b) illustrate data collection from the older people for class 1 (sitting on the edge of the bed) and class 4 (lying on the back, facing up). Table 4 shows the detail of the class label for the four elderly sleep positions.

Table 4: *Data collection.*

Class	Description
Sit	Sit on the edge of the bed
Left	Lying on the left side
Right	Lying on the right side
Back	Lying on back, turning face up

Fig.8: *IoT-based bedridden elderly monitoring.*

(a)

(b)

Fig.9: *Data collection of the older people.*

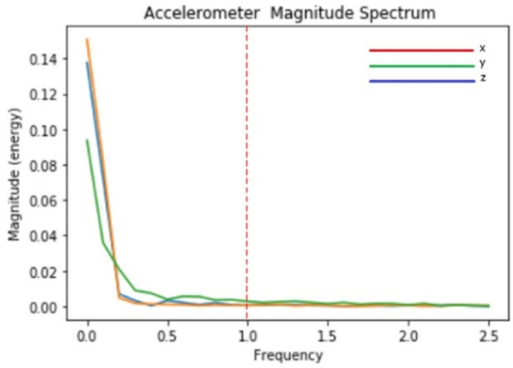
One last important step before using the collected data to train the machine learning models is signal smoothing. Since the signal transmitted from a high-frequency device to a lower-frequency one, noise can be typically generated during transmission in data captured from IoT devices. Therefore, noise removal is necessary before training the models.

We employed a low-pass filter technique to reduce high-frequency data (or energy). Low-pass filters eliminate unwanted frequencies or noise that frequently appear during transmission. The filtering process allows only low-frequency data to pass through, filtering out high-frequency data.

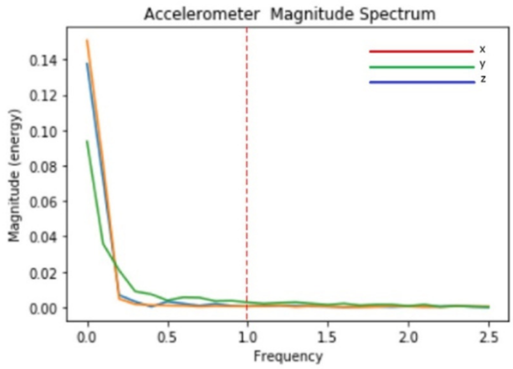
While the filtering process typically reduces the information within the signal, it also makes the data's layout and patterns more visible. The filtering process combined the high-frequency information within the low-frequency region. The high energy value (magnitude) resides in the frequency range from 0 to the cut-off frequency, with the remaining spectrum containing less energy as residue.

To accomplish this task, we segmented the signal captured from the SensorTag using a windowing technique. We used a window size of 10 seconds (or 50 data samples) with a 50% overlap between windows. Given a sample rate of 5 Hz (or one sample every 200 milliseconds), the method shifted the data by 5 seconds (or 25 data samples) for each window. Figure 10 provides an example of accelerometer data captured from a device, before and after the smoothing process.

The results of low-pass filtering process. The removal of high frequency data (in class Sit, Left and Back) is shown in Figure 11-13, respectively.

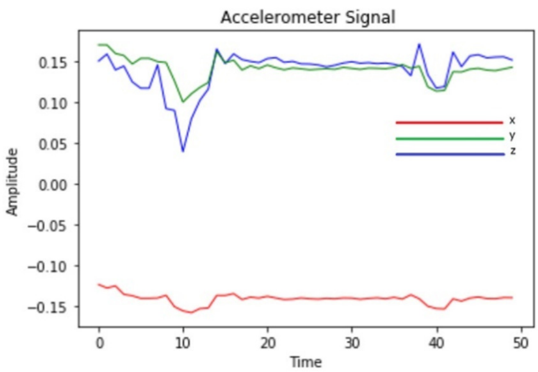


(a) Actual signal

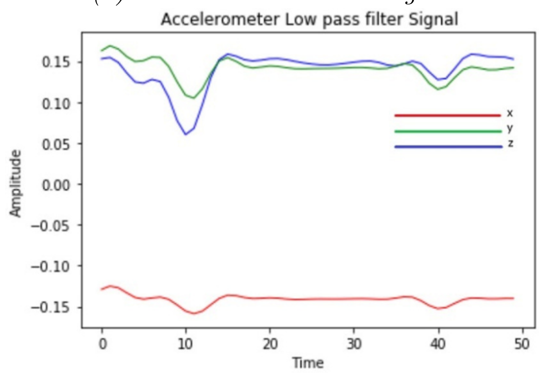


(b) Low-pass filtering

Fig.10: *An accelerometer raw data.*



(a) Actual accelerometer signal



(b) Accelerometer low pass filter signal

4. EXPERIMENTAL RESULTS

We deployed our models (K-NN, Decision tree, and Naïve Bayes) to the IoT hardware and collected the results in the testing state. We evaluated our classification models in terms of precision, recall, accuracy, and F1 score through equations (1)-(4):

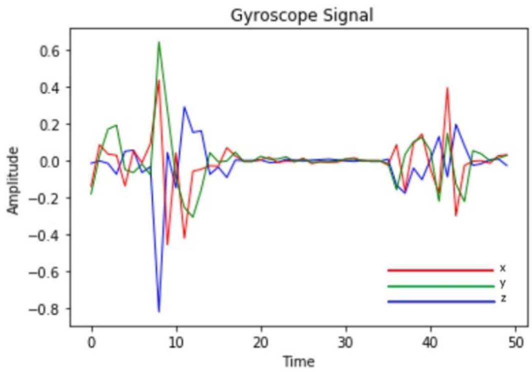
$$Precision = \frac{TP}{(TP + FP)} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

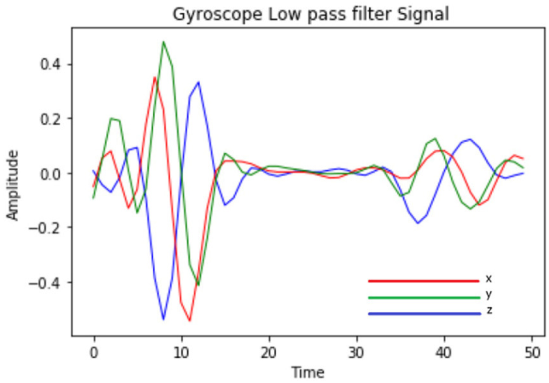
$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN} \tag{3}$$

$$F1\ Score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{4}$$

TP (true positive) is the correct classification. TN is true negative. FP is false positive. FN is false negative. Figure 14 shows the confusion matrix according to equation (1) to (4). Table 5 shows the classification results of the proposed method.

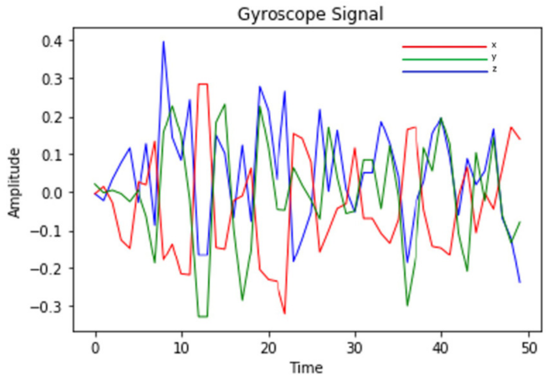


(c) Actual gyroscope signal

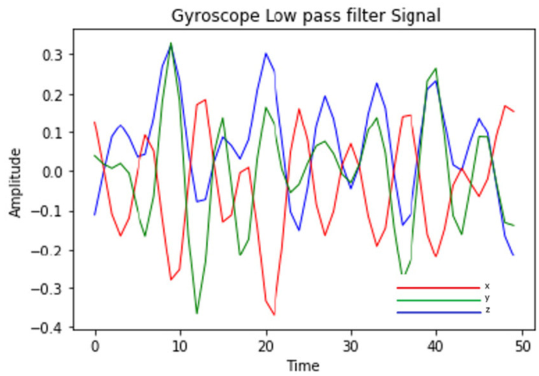


(d) Gyroscope low pass filter signal

Fig.11: *Low-pass filtering for class Sit data.*

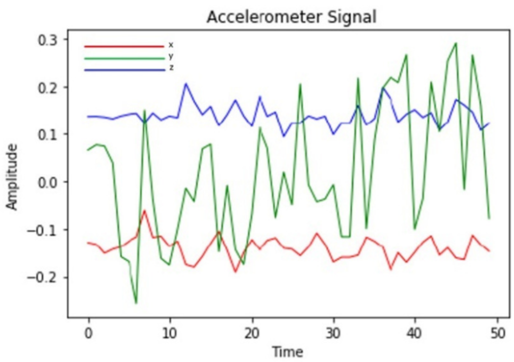


(c) Actual gyroscope signal

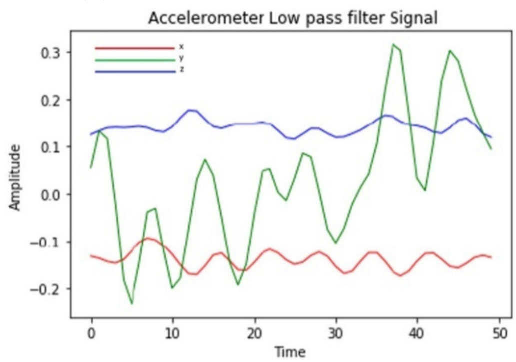


(d) Gyroscope low pass filter signal

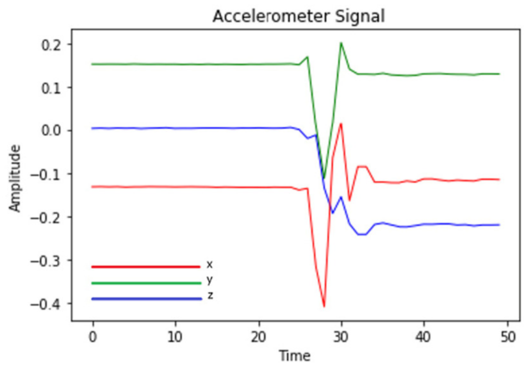
Fig.12: *Low-pass filtering for class Left data.*



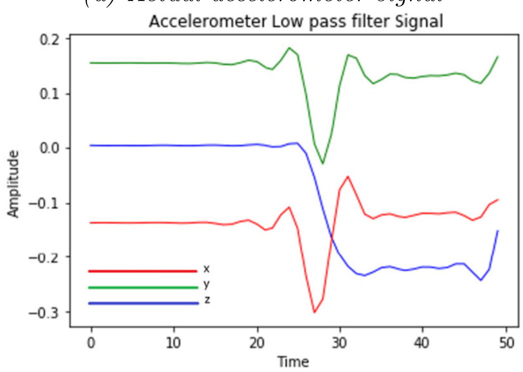
(a) Actual accelerometer signal



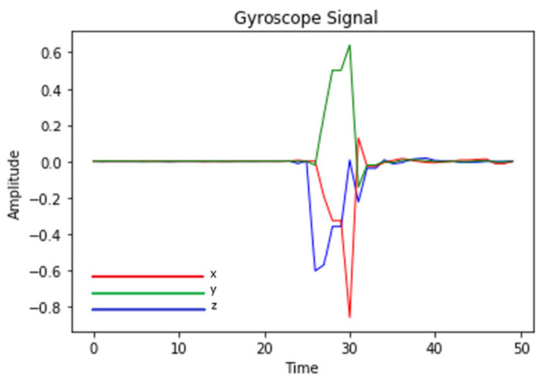
(b) Accelerometer low pass filter signal



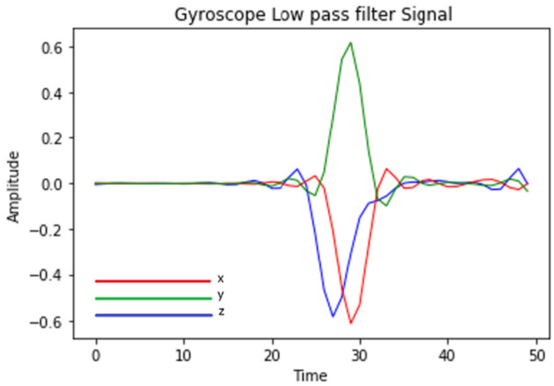
(a) Actual accelerometer signal



(b) Accelerometer low pass filter signal



(c) Actual gyroscope signal



(d) Gyroscope low pass filter signal

Fig.13: *Low-pass filtering for class Back data.*

Confusion Matrix

	Actually Positive (1)	Actually Negative (0)
Predicted Positive (1)	True Positives (TPs)	False Positives (FPs)
Predicted Negative (0)	False Negatives (FNs)	True Negatives (TNs)

Fig.14: *The confusion matrix.*

In Table 5, we found that the decision tree gave the best classification results among these ML models, which obtained the results of 0.98, 0.97, and 0.97 for precision, recall, and F1 scores, respectively. Our proposed method can identify the sleeping positions of the older people in bed accurately. We used the multi-sensory signal to evaluate performance (100 data of gyroscope x, y, z and acceleration values x, y, z). The criterion for measuring data accuracy is the average of the 15 previous data values. It shows the result as sleeping positions left, back, right, and sit.

After the end of the development of the proposed method, we report the results of each operation. We also report problems encountered during the development of the system.

1. Summary of the operating results:

The target group was older adults who were bedridden. We used Python and Flutter to write application programs. We coded the Python language for connecting to SensorTag and uploading data to Google Sheets. We coded the Flutter language to develop android application. In brief, the program has the following functions:

- The system notified caregivers of sleeping posture.

- Caretakers can see the values that the SensorTag measures out.

- There is a login system to access the application.

- Username and Password data are stored using Google Firebase.

- Connect SensorTag to Raspberry Pi by using BLE.

- Store the data that the SensorTag measures in Google Sheets.

- Connect to Google Sheets using Google Cloud APIs.

- Data are extracted from Google Sheets and analyzed using ML techniques.

- Alert for analytical sleep postures (it is time to change the sleep position).

2. Problems encountered in operation:

The connection of the Raspberry Pi and the SensorTag sometimes experienced instability because the transmitter and receiver were too far away. And There were obstacles that blocked the Wi-Fi signal.

3. Solution of problem:

We placed the Raspberry Pi and SensorTag in the right spot so there was no obstruction, and the distance was not more than 10 meters. We can place the Raspberry Pi in a halfway between the Wi-Fi router and the SensorTag.

Table 5: *The classification results.*

ML model	Class	Patterns	Precision	Recall	F1-Score
K-NN	1	Sit	0.99	0.91	0.95
	2	Left	0.66	0.98	0.79
	3	Right	1.00	1.00	1.00
	4	Back	0.99	0.99	0.99
	Weighted avg.		**0.97**	**0.96**	**0.96**
Decision tree	1	Sit	1.00	0.91	0.95
	2	Left	0.67	1.00	0.80
	3	Right	1.00	1.00	1.00
	4	Back	1.00	1.00	1.00
	Weighted avg.		**0.98**	**0.97**	**0.97**
Naïve Bayes	1	Sit	0.76	0.92	0.83
	2	Left	0.36	0.27	0.31
	3	Right	1.00	1.00	1.00
	4	Back	1.00	0.85	0.92
	Weighted avg.		**0.88**	**0.87**	**0.87**

5. DISCUSSION AND CONCLUSION

This work is mainly focused on three machine learning techniques: K-NN, Decision tree, and Naïve Bayes for classifying elderly sleeping posture. Our method is a sensible choice for several reasons:

1. Suitability for sensor data:

K-NN: This method excels in tasks where data points clustered naturally. Which is often the case with sensor data collected from wearable devices or SensorTag. It requires minimal feature engineering and works well with small datasets, which might be expected in initial deployments.

Decision tree: This algorithm is readily interpretable, allowing us to understand which sensor readings contribute most to classifying specific sleeping postures. The interpretability of this method is crucial in healthcare applications where understanding the reasoning behind predictions is critical.

Naïve Bayes: This simple yet effective method works well with categorical data (class labels related to sleeping postures), which sensor readings often translate to. This method also handles missing values gracefully, which can be an issue with real-world sensor data collection.

2. Additional considerations:

Computational efficiency: K-NN, decision tree, and Naïve Bayes algorithms are relatively lightweight and computationally efficient, making them suitable for real-time activity classification on edge devices or resource-constrained platforms (BLE platforms).

Ease of implementation: All three methods are commonly available in various machine learning libraries, making them easy to implement and experiment with.

We also have some guidelines for future development such as retraining machine learning models and augmenting data. Integrating the system to support multiple SensorTags at the same time is also recommended.

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Conceptualization, P. Visutsak; methodology, P. Visutsak and P. Vanijkachorn; software, W. Wudhiphan and T. Suthisoontrin; validation, W. Wudhiphan, T. Suthisoontrin and P. Vanijkachorn; formal analysis, P. Visutsak; investigation, P. Visutsak; data curation, P. Vanijkachorn; writing—original draft preparation, W. Wudhiphan and T. Suthisoontrin; writing—review and editing, P. Visutsak; visualization, P. Visutsak, P. Vanijkachorn, W. Wudhiphan and T. Suthisoontrin; supervision, P. Visutsak; funding acquisition, P. Visutsak. All authors have read and agreed to the published version of the manuscript.

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