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A low-cost edge-AI smart floor mat using multi-point force sensors for real-time fall detection and elderly safety

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ABSTRACT

This study describes the creation of a smart floor mat (SFM) that integrates edge-based artificial intelligence (AI) processing on an embedded system to identify movements such as standing, sitting, and falling to improve the safety of the elderly. The design incorporates nine force sensitive resistor (FSR) sensors, an ESP32 microcontroller, and a multi-class support vector machine (SVM) algorithm to analyze the sensor data in real time or long-time immobility detection, the device will automatically switch on and activate alarms to alert tele-caregivers and helpers via Telegram Bot notifications, indicator lights, and speakers for immediate responses. Experimental results demonstrated that the classification accuracy was 93.33% in model evaluation and 88.33% on the embedded platform, respectively, with an F1-score of 0.82-0.83 and an utterly perfect fall event detection (100%). Data are automatically logged in Google Sheets through Wi-Fi for trend analysis and health monitoring. The proposed SFM is low-cost, foldable, portable, and capable of supporting real-time monitoring and proactive safety management in the elderly. This innovation contributes to the development of smart home healthcare systems and is in line with the goal of achieving a better quality of life.

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1. INTRODUCTION

The World Health Organization (WHO) reports that people aged 65 and over have a 28-35% risk of falling, increasing to 32-42% for those aged 70 and over. As a result, falls in older adults are a global health problem that significantly impacts quality of life and the ability to perform daily activities. The incidence of falls is 30–50% in the community and as high as 40% in nursing homes [1]. Previous research suggests that falls and related injuries are a major contributor to the decline in physical function [2]. In Thailand, the Department of Disease Control states that approximately one in three older adults, or approximately four million people, experience falls each year, with 20% of these injuries resulting in disability or death. This necessitates improvements in environmental safety, promotion of exercise to improve strength and balance, and health assessments to address risk factors [3]. Falls are often caused by both internal factors, such as muscle wasting. Falls are often caused by both intrinsic factors, such as muscle wasting, dementia, and chronic conditions, and extrinsic factors, such as uneven surfaces or insufficient lighting [4]. The area near the bed is considered a high-risk area for falls in the elderly. This is because transitioning from lying down to standing requires muscle stability and balance, which can be challenging without appropriate support devices. Therefore, the development of assistive technologies, such as smart mats or force-sensing floor systems, is crucial to detect, prevent, and reduce the severity of falls. Such technologies can significantly improve safety, promote independence, and improve the quality of life of the elderly. Currently, sensor technology plays a key role in intelligent electronic systems, particularly in human behavior monitoring and analysis [5]. Force sensors have received significant attention in health research due to their ability to continuously detect and assess movement patterns, which are useful for predicting potential health conditions in advance [6], [7]. Integrating sensor technology with the internet of things (IoT) and deep learning data processing has enhanced real-time health monitoring for the elderly [8]–[11]. Devices such as the ESP32, Raspberry Pi, and Arduino have been used to transmit health information to caregivers in a timely manner [12], [13]. Furthermore, the application of IoT technology combined with artificial intelligence (AI) has increased the accuracy of health data analysis, supported proactive medical decision-making, and enabled early detection of risk factors [14]–[16].

Current research focuses on developing fall detection and behavior tracking systems for the elderly using advanced sensor and data processing technologies to increase detection accuracy and reduce false alarm rates. Employed technologies include force sensors, accelerometers, smart floor systems, IoT platforms, and AI [17]–[19]. Force sensors and accelerometers have become popular due to their ability to efficiently detect abnormal movements. For example, Al-Dahan *et al*. [17] used an MPU6050 sensor coupled with an Arduino microcontroller to measure changes in orientation and acceleration, while Zitouni *et al*. [18] and Li *et al*. [19] developed a smart floor system equipped with force sensors to automatically classify elderly behavior. This significantly improves the accuracy of fall detection. Minvielle *et al*. [20] and Feng *et al*. [21] extended this approach by using a network of ground-based sensors to accurately detect the location of falls.

In AI, Lu *et al*. [22] work used 3D-convolutional neural networks (CNN) and long short-term memory (LSTM) models to analyze video to distinguish falls from normal motion, while Chan *et al.* [23] applied deep neural networks (DNNs) to process data from force and acceleration sensors. Furthermore, Wang *et al*. [24] used computer vision techniques to detect falls from camera images, and Ibrahim *et al.* [25] developed a body angle analysis algorithm to reduce the false alarm rate. Another line of research focuses on monitoring sleep behavior. Using force, strain, and vibration sensors, for example, Schrempf *et al*. [26] and Waltisberg *et al*. [7] used force sensors embedded in beds to detect sleep behavior in real time. Kutilek *et al*. [27] developed a strain sensor for analyzing patient movement, and Hamza *et al*. [28] used vibration sensors combined with machine learning techniques to classify movement behavior. In IoT technology, automated detection and alerting systems have been used to monitor the behavior of the elderly. For example, Saranan and Chaiyabut [29] used infrared sensors to detect falls in high-risk areas. Namkhun *et al*. [30] used wireless sensors to monitor bed getting out, while Cocconcelli *et al*. [31] developed an IoT-integrated smart floor system to measure user weight and movement.

From a literature review revealed that current research trends focus on the application of AI, machine learning (ML), and edge computing to enhance real-time data analysis and reduce the response time of automated alert systems. Researchers have therefore developed a system to support daily living at home, specifically smart floors or mats that respond to the behavior and needs of each elderly person. Such systems help reduce health risks, increase safety during movement, and shorten response times to emergencies such as falls or sudden falls, via real-time alerts to caregivers. This significantly improves the quality of life and overall efficiency of elderly care.

This research differs from previous studies that primarily focus on camera-based or wearable sensors for fall detection by presenting a cost-effective, foldable smart floor mat (SFM) that integrates nine force sensitive resistor (FSR) sensors and embedded AI processing support vector machine (SVM) directly on the ESP32 microcontroller. This edge-AI approach reduces reliance on cloud, ensuring low latency, high privacy, and real-time response. Furthermore, the integration of IoT alerts (Telegram Bot API) and automatic cloud data logging (Google Sheets) enables continuous behavior tracking, which is essential for developing a scalable, intelligent elderly safety system.

2. RESEARCH METHOD

2.1. Systems overview

This research is the development of a foldable smart floor plate, which integrates nine FSR sensors and embedded AI processing SVM directly on the ESP32 microcontroller. It can detect movement behavior and detect falls, sitting, or standing in the same position for an abnormally long time, which may be caused by muscle strain. The system will provide an audible alert and send a notification to the caregiver's smartphone via the Internet so that the elderly can receive timely assistance. The overall system is shown in Figure 1.

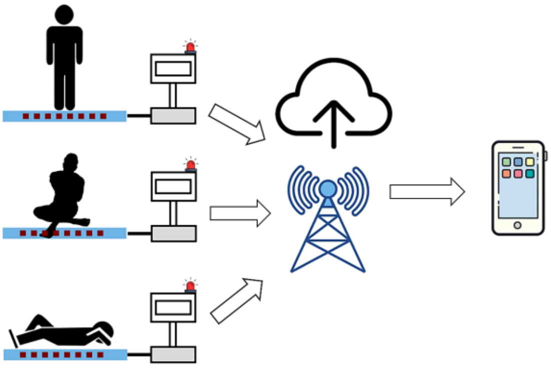


Figure 1. System overview

The SFM for the elderly is designed to detect, analyze and alert about potentially dangerous behaviors in real time. It works through three main parts: i) a rubber floor mat with a FSR sensor, ii) a control unit using ESP32 to process data with ML algorithm, and iii) a display and alert system via a display, Telegram Bot API and warning signal, as shown in Figure 2.

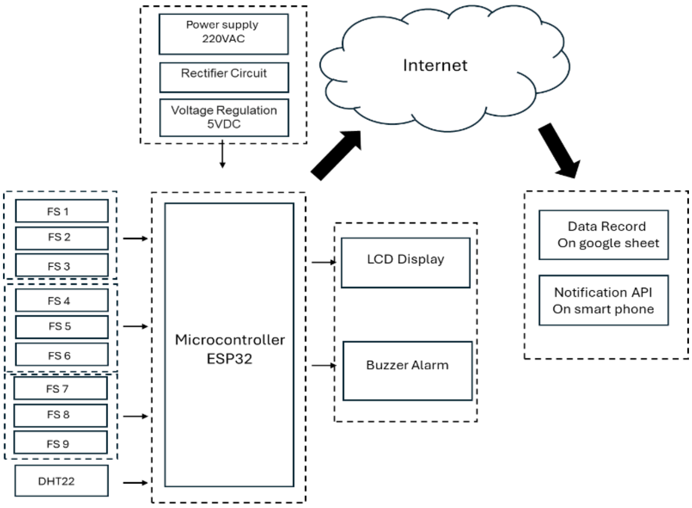
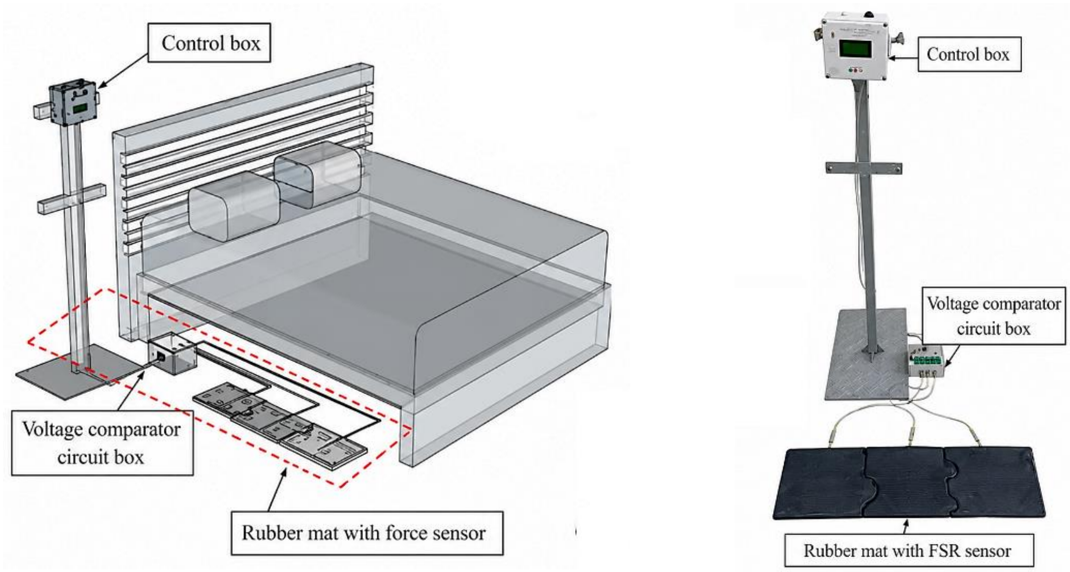


Figure 2. System diagram

The SFM detects the force generated by movement. Inside the mat are nine 1.5-inch FSR sensors, which are resistance sensors that can change their electrical value depending on the force applied. These sensors are positioned in strategic locations on the rubber floor mat to measure the force generated when standing, sitting, or falling. The detected values are sent to the control unit. The control unit then collects, analyzes, and processes the data received from the FSR sensors using AI algorithms on the ESP32, the main processor. It can analyze movement behaviors such as sitting, standing, or falling, and detect behaviors that may be signs of an emergency, such as falling without continuous movement or abnormal weight bearing. The control unit then sends the data to a display and notification system via a wireless network.

This system is installed next to the bed to detect the movement of the elderly person as they get out of bed. When the elderly person changes from lying down to standing, their body must adjust to immediately supply blood to the brain. If the circulatory system does not respond well, blood will flow down the legs, temporarily reducing blood flow to the brain, potentially causing dizziness or unconsciousness. This system is a prototype that detects movement behavior and alerts when the sensor detects force for a prolonged period. It is assumed that the elderly person may fall to the floor or experience spasticity and be unable to move when stepping on the floor. The system will send an alarm via a loudspeaker, buzzer, and Telegram Bot application to inform the elderly caregiver and provide timely assistance. The system consists of a rubber floor mat with an FSR sensor, a voltage comparator circuit box, and a control box, as shown in Figure 3.

Figure 3(a) shows a model of the system installation, consisting of a pressure-sensitive rubber pad with an FSR sensor, a pressure comparator circuit box, and a main control box. Figure 3(b) shows the actual prototype of the developed system. When an elderly person steps out of bed, the sensor detects the pressure and sends the data to the control unit to analyze the movement pattern. If continuous pressure is detected for an unusually long period, the system will send an alert signal via speaker, buzzer, and Telegram Bot to notify the caregiver for timely assistance.



(a) (b)

Figure 3. Structural design: (a) structural design of the proposed system and (b) prototype of the developed system

To assemble the SFM to support the nine FSR sensors, we designed a stable structure and efficient signal detection. Two carpet mats with a width of 24 cm, a length of 111 cm, and a thickness of 3 mm were prepared and assembled. Then, they were divided into three equal parts and cut into jigsaw puzzle pieces for easy connection. Three 1.5-inch FSR sensors were installed in these positions. In addition, the wires were placed in the center of the SFM, and they were connected to the voltage comparison circuit box with a 6-pin plug, as shown in Figure 4. Then, we placed a 1 mm thin acrylic sheet on the sensors to improve the force detection performance of the FSR sensors, as the thin acrylic sheet helps to distribute the force evenly.

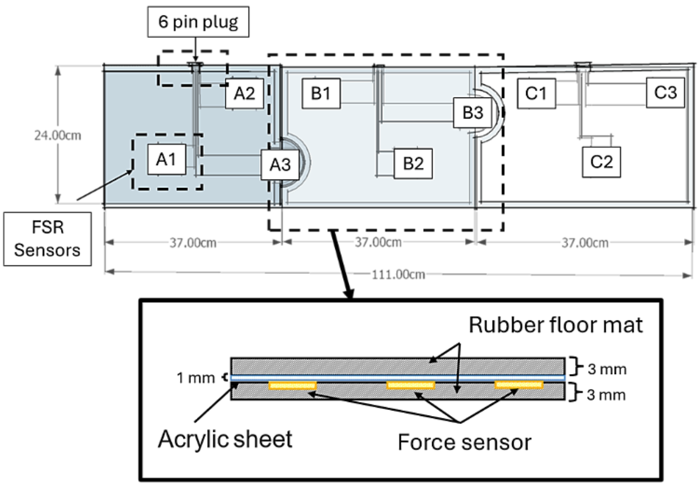


Figure 4. FSR sensor installed on rubber floor mat

The force data detected by the nine FSR sensors is transmitted to a voltage comparator box located at the end of the SFM, which converts the analog signals from the sensors into digital signals. Inside the box are nine voltage comparators designed using the IC LM393, a high-precision voltage comparator op-amp. The digital data is then sent to a processor in the control box to analyze and detect the elderly's movement using ML algorithms, such as abnormal weight distribution or possible falls. When such events are detected, the system will send an alarm via the monitor interface and Telegram Bot API to immediately notify the caregiver.

The researchers studied the response behavior of the FSR sensor when subjected to changing loads and evaluated the relationship between the force and the ADC signal level obtained from the voltage divider circuit. The experiments were performed by placing a pendulum weight ranging from 1 to 15 kilograms on the FSR sensor position and measuring the change in the ADC signal to understand the low force sensitivity and limitations of FSR. The response behavior of the FSR sensor from three repeated experiments is shown in Figure 5.

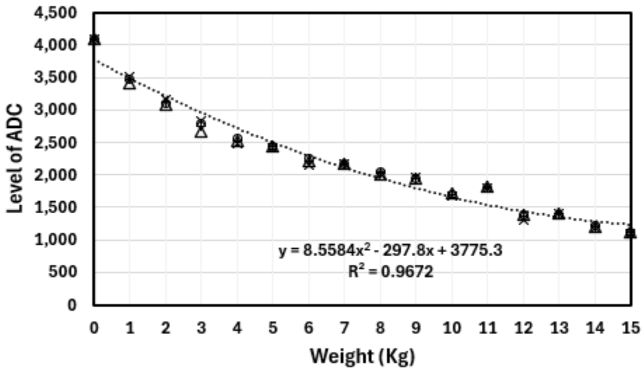


Figure 5. Relation of weight and level of ADC signal

Figure 5 shows that the ADC value decreases with increasing weight, with a nonlinear relationship consistent with the characteristic of FSR, which is low sensitivity to force and saturates with increasing force. The sensors can detect forces at different positions and convert the readouts into 12-bit analog signals ranging from 0 to 4095. At the position with the highest force, the analog signal value is the lowest, while at the position without force, the value is close to the highest (4095). This behavior reflects the limitations of the stability and accuracy of a single sensor in estimating the actual force. Therefore, research on SFM uses multiple measurement points together to generate force distribution patterns instead of relying on a single ADC value. This data supports edge-AI processing approaches that use spatial and temporal characteristics to increase the accuracy of detecting events such as falls.

2.2. Machine learning models development and implementation

In this research, researchers chose to develop a multiclass SVMs model for analyzing the movement behavior of the elderly. This is because SVMs are more suitable than other machine learning models because they clearly separate information and support high-dimensional data. They also perform efficiently even with a small amount of training data, which is consistent with the limitations of difficult data collection. Using SVMs allows for classifying different postures in a single model without the need to create multiple separate models, such as the one-vs-one or one-vs-rest methods in some algorithms. In addition, SVMs are more resistant to overfitting than models such as k-NN or decision trees when the data is noisy or complex, ensuring accurate and reliable behavior detection in real-world environments. Furthermore, SVMs are less complex and require less computing resources, making them suitable for application on microcontroller boards. Figure 6 shows the process of developing a multiclass SVMs model to classify three types of movement behaviors in the elderly: standing, sitting, and falling, based on the values measured by the FSR sensor.

From Figure 6, it starts with the data collection process to collect data and prepare the data to be transformed into a format suitable for training the SVMs model. Then, the results are put into the data transformation process to consider the relationship between the values measured by the sensors and the type of movement. The relationship obtained from this process will be used as data to create an ML model for predicting movement in the next SVMs modelling step. The resulting SVMs model will be embedded on the ESP32 microcontroller board for processing.

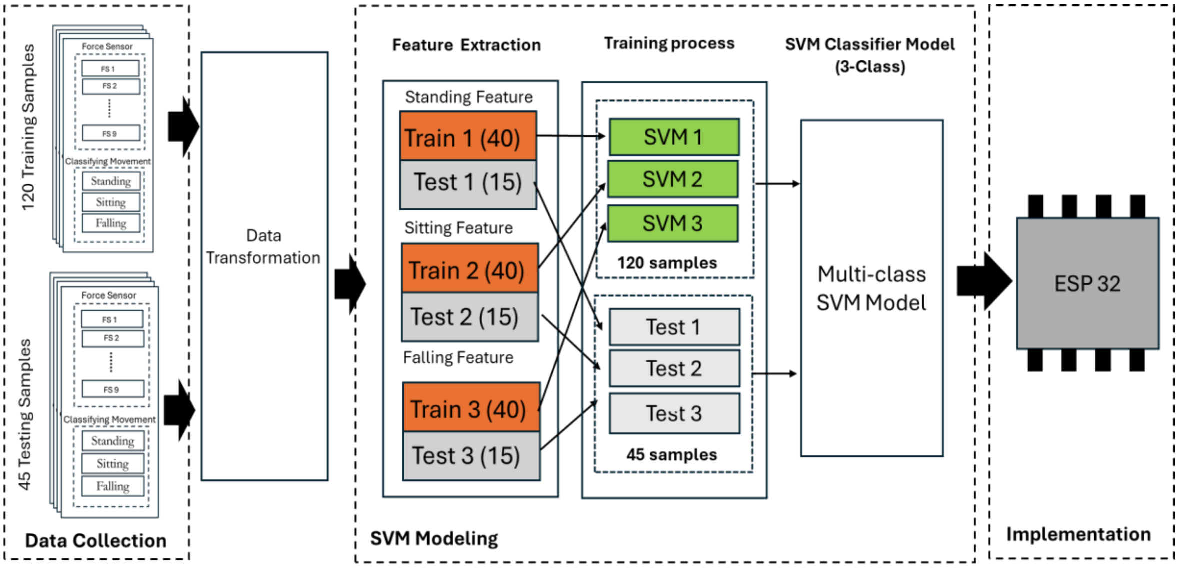


Figure 6. Multi-class SVMs modeling

2.2.1. Data collection

In this step, data was collected to evaluate the performance of the sensors and record movements. The three types of movement used to collect data: standing, sitting, and falling. Each category has 40 samples, for a total of 120 samples as shown in Figure 7. The red squares indicate the locations of the nine FSR sensors embedded within the Smart carpet. Different movements generate different pressure distribution patterns on the sensor array, which are recorded and used as input for training and evaluating the proposed edge-AI model.

Figure 7. Data collection group

By collecting force measurement data from three sensors in three postures from 120 testers, the spatial distribution of force across the nine FSR sensors revealed different patterns for each posture. In the standing posture, two sensors detected force, with an average ADC value of approximately 1527 and a standard deviation of approximately 495. In the standing posture, both sensors primarily receive force from both feet, resulting in high force detection. In the sitting posture, three sensors detected force, which is due to the wide force distribution in the sitting posture. The average ADC value from the sensors was approximately 2219 and a standard deviation of approximately 537. This indicates that in the sitting posture, more force is distributed to the sensors, each of which detects less force than in the standing posture. In the falling down posture, the force is distributed to more than 6 sensors simultaneously, resulting in an average ADC value of approximately 2856. This indicates that each sensor detects a low force compared to standing and sitting, as shown in force sensor profile of standing, sitting and falling in Figures 8-10, respectively.

These physical features provide strong discriminative properties for the SVM classifier and support the robustness of the edge-AI method for pose classification. This information, along with the associated motion annotations, is used to develop a mathematical model using the SVM algorithm for subsequent classification.

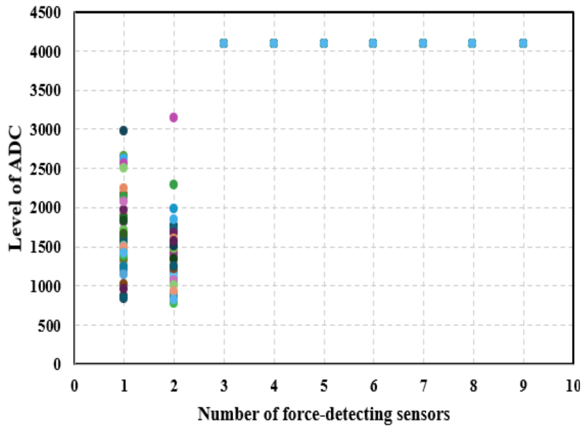


Figure 8. Force sensor profile of standing

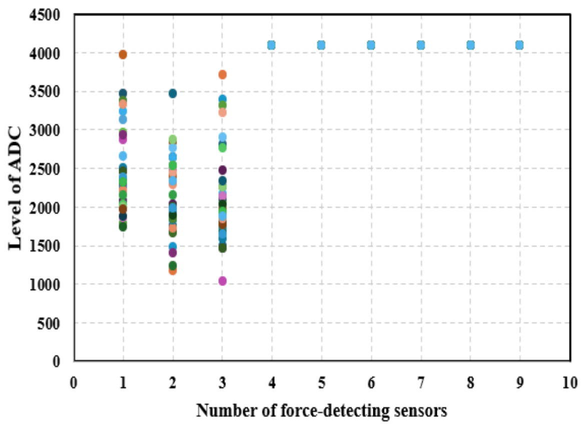


Figure 9. Force sensor profile of sitting

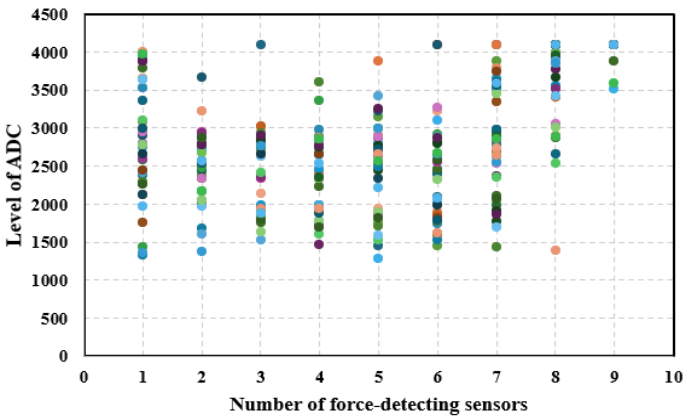


Figure 10. Force sensor profile of falling

2.2.2. Data transformation

In this step, the ADC signal levels obtained from the sensors were analyzed and prepared to develop a mathematical model for classification training. It was found that the physical behaviors of standing, sitting, and falling on the SFM affected the number of force sensors. Especially in the standing position, regardless of the position on the SFM, generally only 1-2 sensors could detect the force. In the sitting position, 2-3 sensors were triggered, while in the case of falling, more than 3 sensors responded. Therefore, the ADC values recorded from all sensors under these conditions were analyzed to calculate the mean and standard deviation as defined by (1) and (2), respectively, to consider the relationship between the sensor activities and the types of movement. The results are shown in Figures 11 and 12.

$$\bar{X} = \frac{\sum_{j=A}^{j=I} X_i}{n} \quad (1)$$

where n is the number of sensors.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \bar{X})^2}{N}} \quad (2)$$

where: X_i is the value of each data, $\bar{X}$ is the average of all data, and N is the total number of data.

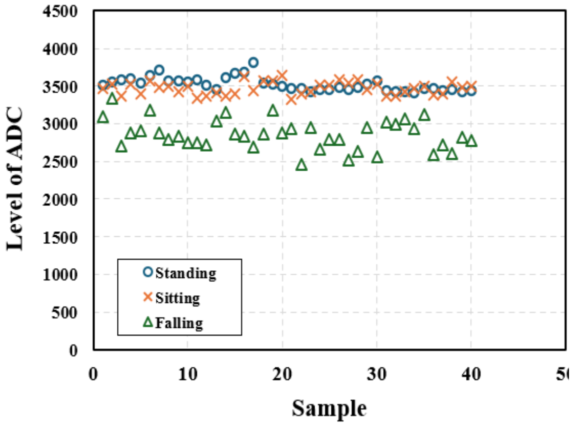


Figure 11. Average of ADC with movement behaviors

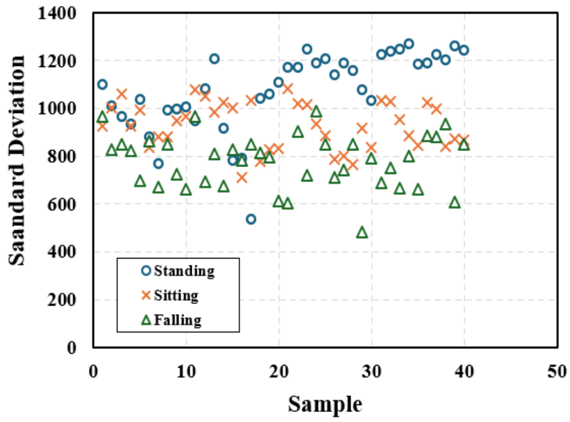


Figure 12. Standard deviation of the ADC with movement behaviors

Analysis of the mean and standard deviation of ADC signal levels obtained from sensor measurements revealed that the mean ADC levels corresponding to falling were significantly lower than those for standing and sitting, due to the higher number of sensors detecting force in the lying position compared to standing and sitting. In contrast, the mean ADC levels for standing and sitting were relatively similar, possibly due to the similar number of sensors detecting force in both cases. Furthermore, when examining the standard deviation of ADC levels, standing had the highest standard deviation, followed by sitting, while falling had the lowest standard deviation. This result indicates a more even distribution of force in standing and a more uniform distribution during falls. Therefore, the researchers analyzed the mean and standard deviation of ADC values obtained from all sensors to determine their relationship with movement in the cases of standing, sitting, and falling. It was found that there was a tendency to significantly distinguish movement, as shown in Figure 13.

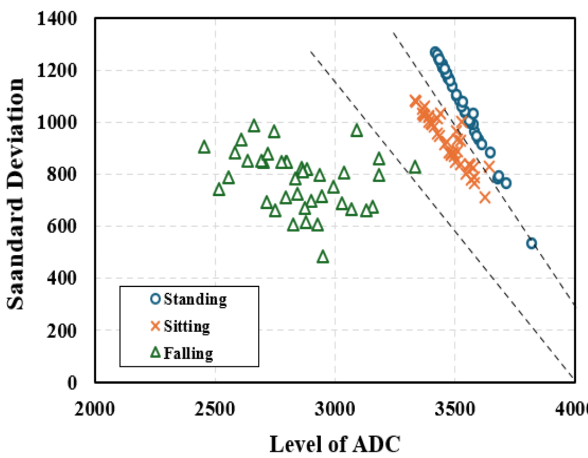


Figure 13. Relation of average and standard deviation with movement behaviors

2.2.3. Support vector machine modelling

From a total of 120 samples, it is a data set for learning to create a mathematical model. Then, the data set for learning is used to create a SVMs model using one-vs-one (OvO), which is used to classify 3 classes of data: Class 1 is standing behavior, Class 2 is sitting behavior, and Class 3 is falling behavior. From the SVMs model, 3 linear equations are obtained for grouping (decision boundary) between each pair of classes, where each SVMs equation represents the group boundary between two classes using the linear in (3).

$$F(x_1, x_2) = w_1, x_1 + w_2, x_2 + b = 0 \quad (3)$$

where: w_1, w_2 are the weights of the independent variables x_1, x_2, b is the constant (Bias), the point at which $F(x_1, x_2)$=0 is the group line, and the value of $F(x_1, x_2)$= tells which side of the group line the data lies on. From the learning data set to create a mathematical model, the SVMs equation is obtained as (4)-(6):

$$SVM\ 1: 2.061\ x_1 + 1.902\ x_2 - 0.432 = 0 \tag{4}$$

$$SVM\ 2: 1.627\ x_1 + 0.487\ x_2 - 0.803 = 0 \tag{5}$$

$$SVM\ 3: 2.128\ x_1 + 0.598\ x_2 - 1.084 = 0 \tag{6}$$

where SVM 1, 2, and 3 are linear equations that divide Class 1 and Class 2, Class 1 and Class 3, Class 2 and Class 3, respectively.

From SVM 1, SVM 2, and SVM 3, when the values of x_1 and x_2 are substituted into all three SVMs equations, if the calculated values are positive or zero, the classification analysis can be performed as follows: If SVM 1 is greater than or equal to 0, it is classified as Class 1; if it is less than 0, it is classified as Class 2. The same applies to the values calculated for SVM 2 and SVM 3.

When multiple SVMs equations are used, we compare the values of each function to determine which class the data falls into using a voting method. The results of the analysis from all three equations are used to determine the number of clustering results.

- If SVM 1 identifies as Class 1, SVM 2 identifies as Class 1, concluding that the data chooses Class 1.
- If SVM 1 identifies as Class 2, SVM 3 identifies as Class 2, concluding that the data chooses Class 2.
- If SVM 2 identifies as Class 3, SVM 3 identifies as Class 3, concluding that the data chooses Class 3.

Therefore, the researcher used the equations and conditions for class classification to write a program on ESP32 to classify data in real time using C/C++ language (Arduino IDE and ESP-IDF) and used the Voting Method to select the final class which is the end of the prediction.

3. RESULTS AND DISCUSSION

In this section, the research presents the experimental results and systematically analyzes the performance of the system. It starts with evaluating the SVM model in motion classification to reflect its accuracy on the training data. Then, the results of the real system testing are presented, divided into two parts: i) the prediction performance of the model and ii) the experimental results of the real system prediction, which show the system response to abnormal events and collect behavioral data for retrospective analysis.

3.1. Predictive performance of model

After obtaining a SVMs model for classifying the movement behavior of the elderly at 3 levels, namely, standing, sitting and falling, in this method, the efficiency of the model is tested with 45 samples, divided into 15 samples per level, with the test results as shown in Figure 14 and the results of the model efficiency analysis using confusion matrix as shown in Table 1.

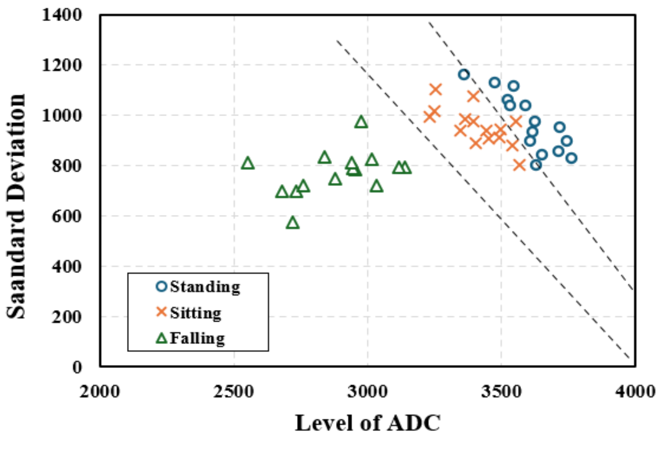


Figure 14. Predictive performance of SVMs multi-class model

Table 1. Confusion matrix of SVMs multi-class model

Actual\predicted	Standing	Sitting	Falling
Standing	13	2	0
Sitting	1	14	0
Falling	0	0	15

From this matrix, a comparison between the actual and predicted classes of the model is shown to evaluate its ability to classify the three categories, namely, standing, sitting, and falling. The model demonstrates high performance with an overall accuracy of approximately 93.33%. The analysis of the precision, recall, and F1-score of the confusion matrix is shown in Table 2.

Table 2. Results of confusion matrix analysis

Class	Precision	Recall	F1-score
Standing	0.9286	0.8667	0.8968
Sitting	0.8750	0.9333	0.9035
Falling	1.0000	1.0000	1.0000

From the table, the model's F1-score in all classes exceeds 0.89, which is considered an acceptable level for activity recognition research. The depressed class has perfect precision and recall of 1.0, which is of great academic significance in the case of detecting critical events (e.g., falls). The standing class and the sitting class have similar levels of precision and recall, indicating that the model is not biased towards any of the classes.

3.2. Experimental result on predicting of implemented system

3.2.1. Predictive performance of implementation system

In this step, the multi-class SVMs mathematical model is embedded in the ESP32 microcontroller to process the motion analysis in real-world applications. Then, its performance in gesture classification is tested with a total of 60 samples, divided into 20 samples per class. The results of the motion classification test are shown in Figure 15, and the performance analysis results using confusion matrix are shown in Table 3.

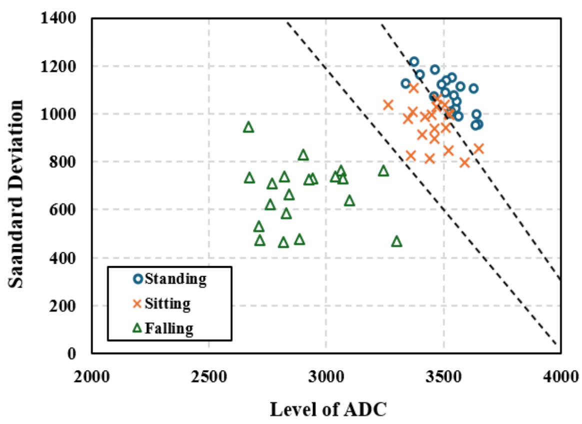


Figure 15. Predicting system performance

Table 3. Confusion matrix of implementation system

Actually\predicted	Standing	Sitting	Falling
Standing	16	4	0
Sitting	3	17	0
Falling	0	0	20

Analysis of the model's classification results using the confusion matrix revealed that the model could efficiently classify all three behaviors, namely, standing, sitting, and falling, with an overall accuracy of

88.33%, which is considered satisfactory in practice. Especially in the case of "falling", which is an important category in the context of safety and healthcare, the model could correctly classify all behaviors. The analysis of the accuracy, recall, and F1-score of the confusion matrix is shown in Table 4.

Table 4. Results of confusion matrix analysis of implementation system

Class	Precision	Recall	F1-score
Standing	0.8421	0.8	0.8203
Sitting	0.8095	0.85	0.8293
Falling	1	1	1

From the analysis table, it is found that the performance measurement of the system simulated with confusion matrix shows that the model has a high accuracy of 88.33% and can predict "falling" with 100% accuracy. In addition, there is confusion between "standing" and "sitting" resulting in an F1-score of approximately 0.82-0.83, which may require further improvement such as using more data or improving the model to be able to distinguish similar.

3.2.2. Notification results and data recording

In this research, the system was designed to alert and record the elderly's movement in real time, using the Telegram Bot as the primary communication channel. Whenever there is a change in posture, such as standing, sitting, or falling, the system immediately sends an alert message to the caregiver, enabling them to respond promptly. If pressure is detected but there is no continuous movement for more than 10 seconds, the system assesses whether the elderly may be in a state of stiffness, numbness, or immobility, and automatically sends an alert with the elderly's current status. Furthermore, all data is stored in Google Sheets via a Wi-Fi connection to the ESP32. The sensor values are then sent to Google Apps Script via HTTP requests. The data is then processed and recorded, with details such as recording time and sensor status, enabling efficient and systematic data storage and retrieval.

4. CONCLUSION

This research successfully demonstrates a practical and intelligent fall-detection solution through the integration of sensor technology, embedded AI processing, and IoT-based communication. The developed SFM achieved a high overall accuracy of 88.33% when implemented on the ESP32 microcontroller, with 100% accuracy in fall detection, confirming its reliability for real-world applications in elderly care. The edge-based SVM model effectively reduces computational latency and enhances privacy by processing sensor data locally, without reliance on external cloud computing. The integration with Telegram Bot API provides real-time caregiver alerts, while automated data logging to Google Sheets enables long-term monitoring and pattern analysis of elderly movements.

Although the system performs efficiently, its accuracy in distinguishing “standing” and “sitting” behaviors can be further improved by increasing the training dataset and integrating additional sensing modalities such as accelerometers or gyroscopic sensors.

In future work, the research will focus on extending the system’s usability testing with real elderly users, multi-person detection, and adaptation to various floor materials and body weights. The proposed system represents a cost-effective, scalable, and portable edge-AI solution for enhancing elderly safety, contributing to smart home healthcare.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sahapong Somwong	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
Chatree Homkhiew						✓	✓	✓		✓			✓	✓
Thanwit Naemsai			✓	✓		✓	✓	✓		✓				
Athirot Mano		✓		✓	✓	✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are presented within the article. Additional data related to this study are available from the corresponding author upon reasonable request.

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