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DEVELOPMENT OF A WEARABLE FALL DETECTION SYSTEM USING ML AND IOT FOR THE ELDERLY

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Abstract. *One of the greatest health risks for the elderly is falling. The effect of a fall can be reduced, and prompt medical aid can be given. This study suggests a wearable system that employs sensors built into an Arduino Nano 33 BLE device to gather information on patterns of falls by older people in various directions in real time. A neural network (NN) on Edge Impulse is used to assess the sensor output data in order to train the machine learning (ML) model. Notifications are transmitted via a smartphone connected to an implanted device via the Internet of Things (IoT) system. The results of testing different falling postures revealed that the system has an accuracy of 100%, 100%, 90%, and 95% for falling forward, falling backward, falling to the left, and falling to the right, respectively. Testing machine learning algorithms revealed that the neural network (NN) was accurate at 90.6%.*
Keywords: Fall detection, Machine learning, Neural networks, Edge Impulse, Internet of Things

1. Introduction.

Falls are a major public health problem. It is the second leading cause of death among accidental injuries, secondary to injuries from road accidents. Falls include falling on the floor, slipping, taking a wrong step, and being hit or pushed by others. This includes falls involving chairs, beds, wheelchairs, furniture, etc. This often happens to the elderly, and patients with muscle weakness. Falls cause more than 1,000 deaths per year. For Thailand, the population survey found that the population aged 60 years over more than 10% is likely to increase continuously. In 10 years, there will be an increase of 2,500,000 elderly people, and it is projected to reach 20% by 2025 [1]. Elderly people are calling and using hotline 1669 for the cause of falls more than 50,000 times per year. Most of the 65% will fall outside the house and 31% will fall inside the house. However, a fall determines the type of injury that occurs, for example, falling forward or backward. Those who fall will have to use their hands to maintain their weight, breaking their wrists in the process. Also, rushing out of bed will make it difficult for the lower body to maintain good balance, which can lead to falls in all directions and possible hip fractures.

The main problem is not falls and bone fractures but is the consequence of treatment such as Osteoporosis and other physiological healing time. Furthermore, discomfort and

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the psychological effects on the elderly that followed because they view falls as a natural part of aging or fear being hospitalized or restricted in their activities.

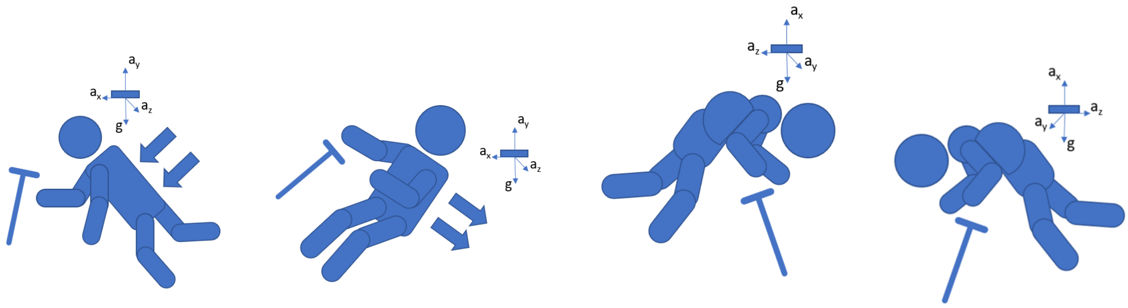
Nowadays, the technology is employed to care for the elderly and patients with muscular weakness as well as to identify and alert in the case of a fall. The popularity of applications in the form of IoT is more than before. This makes it easier to detect falls in the elderly. Accelerometers and gyroscopes or cameras [2] can be used to improve fall detection. For example, use mobile phones to detect falls in the elderly. They used the smartphone's accelerometer sensor to assess the value acquired as a fall and compute acceleration. However, if the elderly does not carry their phones, detection can be challenging. Yet, there is a method that uses a camera [3,4] and image processing that is practical for senior people. When an elderly person falls into an accident, the camera detects the falling motion and alerts the caregiver later and in detecting the falling motion by using shapes and body posture [5]. However, there is still a limit to detecting falls, that is the camera position and where to install the camera. As technology becomes more prevalent in daily life, fall detection may potentially be employed on body-mounted forms or wearable gadgets for the elderly [6]. Wearable systems for fall detection come in a variety of applications. Either a wearable system that displays the results of falls through an application on a mobile phone or a wearable system that utilizes an accelerometer sensor and gyroscope is connected to the microcontroller communicates via a wireless system [7] that is installed along the body. Another wearable system will use embedding a recurrent neural network (RNN) or artificial neural networks (ANNs) in a wearable system on a microcontroller unit (MCU) [8,9], and the crash data is stored on the board. For user convenience, the majority of wearable fall detection devices are wirelessly connected. A wide range of applications employ machine learning nowadays. It is not difficult to use AI to fall detection by employing computers to make predictions and choices rather than human beings. For example, having a computer judge if a fall is caused by data provided by an accelerometer and gyroscope installed on a wearable device [10,11], the installation device needs to be so tiny that the elderly feels comfortable. The cost increases as more development equipment are employed. A wearable fall alarm employing an Arduino Nano 33 with a built-in accelerometer was recently developed using Google TensorFlow to produce a notification model fall warning [12]. Nevertheless, in this work, only falling, walking, and running actions were gathered in the model procedure. Due to this inability to distinguish between lying and falling, no data is sent to the IoT system for monitoring purposes.

In addition to earlier work evaluating the literature, this study offers a concept for developing a system. The proposed system makes use of edge's artificial intelligence (AI) IoT architecture, which processes data from the 3D gyroscope and accelerometer, among other sensors, on the Arduino Nano 33 BLE. Edge Impulse is used to train the model for falling backward, falling forward, falling to the left, and falling to the right using the TensorFlow library. Moreover, the suggested solution would send data to caregivers via an IoT system on cellphones in order to inform and monitor them.

2. **Principles and Methods.**

2.1. **Working principles of accelerometer and gyroscope for fall detection.**

Health wearable devices require low power consumption and small devices, so the accelerometer and gyroscope integrated into the Arduino Nano 33 BLE board for processing provide this intelligence. The coordinates produced by the accelerometer and gravity vector are shown in Figure 1. This fall detection system's algorithm is based on real-world data. Figure 2 displays an illustration of the sensor output in a forward fall simulation when a fall happens in all dimensions.



(a) Forward fall (b) Backward fall (c) Left fall (d) Right fall

FIGURE 1. The 3-axis accelerometer and gyroscope for fall detection

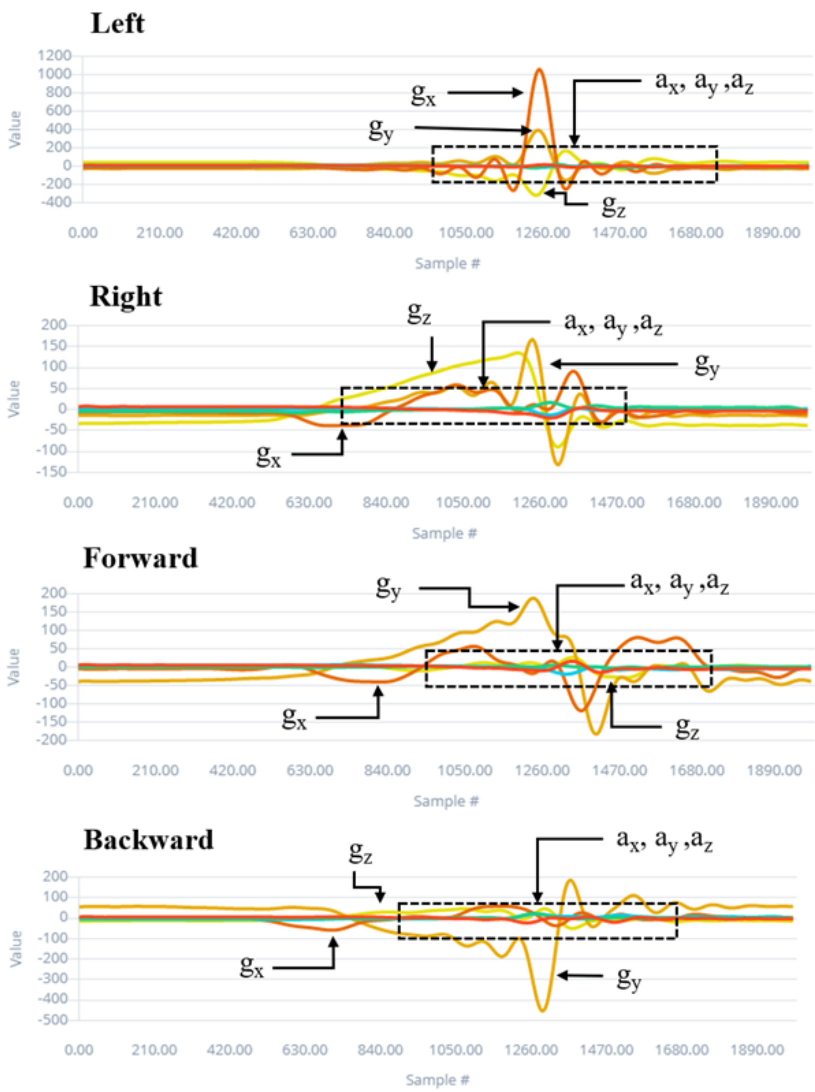


FIGURE 2. Graph accelerometer in a square frame and gyroscope of falling in left, right, forward, and backward

According to Figure 2, the output of the accelerometer and gyroscope will be significantly different from normal events if there is a fall in either direction.

2.2. **Machine learning for the fall detection system.** Machine learning technology plays an important role in fall detection applications [13]. In this research, machine learning was used to train models on Edge Impulse using the TensorFlow library. The resulting model was embedded in an Arduino Nano 33 BLE to predict fall events. The structure of the proposed system is shown in Figure 3. From Figure 3, the data collection uses the LSM9DS1 sensor installed inside the Arduino Nano 33 BLE, where accelerometer and gyroscope are in 4 falling patterns (fall forward, fall backward, fall to the left, and fall to the right) along the X, Y, and Z axes. The collected data is then taken to training and testing data on the Edge Impulse platform. This section relies on two types of signal processing: IMU Syntiant processing and Spectral features. Details of the analysis are as follows. The IMU Syntiant rescales raw data to 8 bits values to match the NDP 101 chip input requirements. The Spectral features extract frequency and power characteristics of a signal. Low-pass and high-pass filters can also be applied to filtering out unwanted frequencies. It is great for analyzing repetitive patterns in a signal, such as movements or vibrations from an accelerometer, and the Spectral features are shown in Figure 4.

The basic idea is that a neural network classifier will take some input data, and output a probability score that shows how probable it is that the input data belongs to a given class. The neural network consists of a number of layers, each of which is made up of

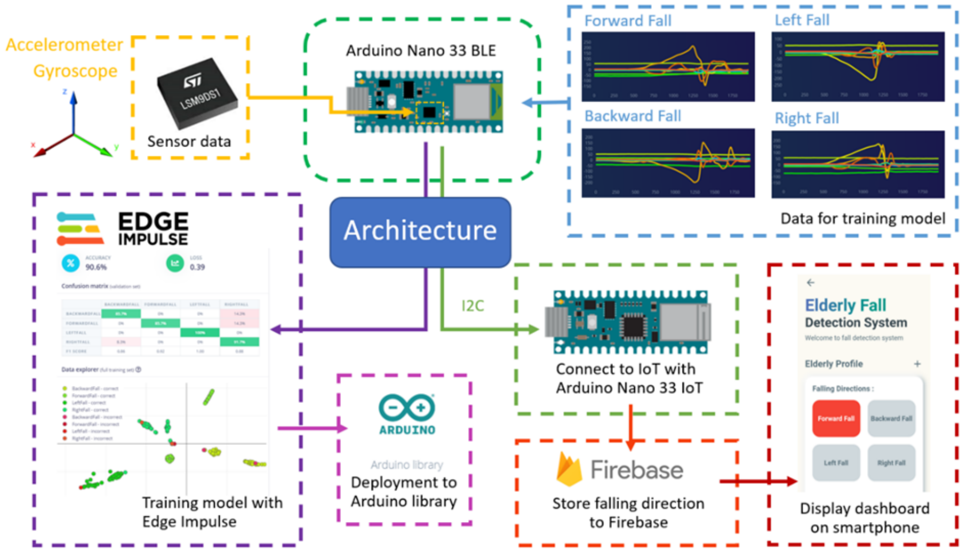


FIGURE 3. Fall detection system architecture

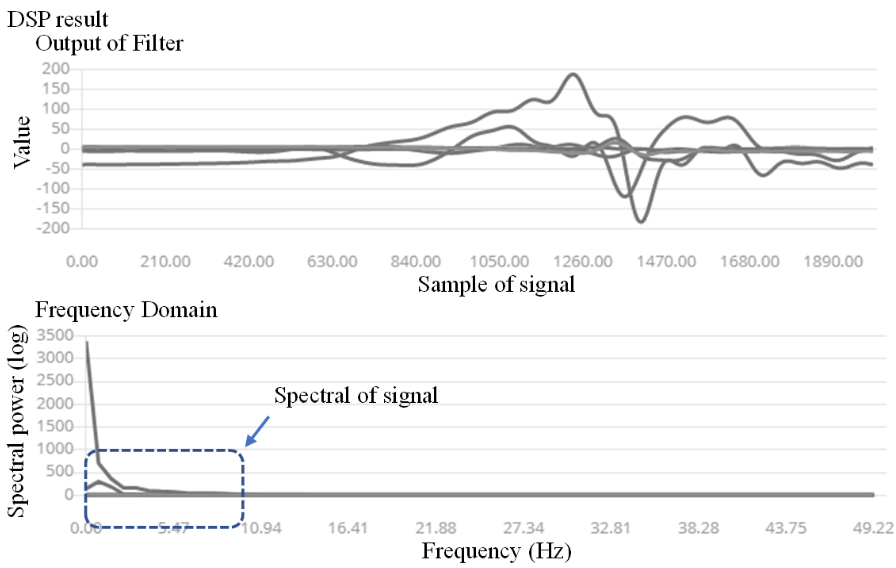


FIGURE 4. Digital signal processing in the analysis of fall detection system

a number of neurons. The neurons in the first layer are connected to the neurons in the second layer, and so on. The weight of a connection between two neurons in a layer is randomly determined at the beginning of the training process. The neural network is then given a collection of training data, which is a set of instances that it is expected to predict. The output of the network is compared to the correct response, and the weights of the connections between the neurons in the layer are changed as a result. This procedure is performed several times until the network has developed the ability to anticipate the right response for the training set of data. In this paper, an ANN architecture was adopted with four input variables (fall forward, fall backward, fall to the left, and fall to the right), neurons in the hidden layer, and one output layer (falling patterns). The best data sets are shown in Figure 4. The dataset used in this research is obtained from signal synthesis through IMU Syntiant and Spectral features of impulse design in edge impulse program. The data is divided into three sets, such as training, validation, and testing. The results of an ANN learning process show a group of falling patterns posture data as shown in Figure 5.

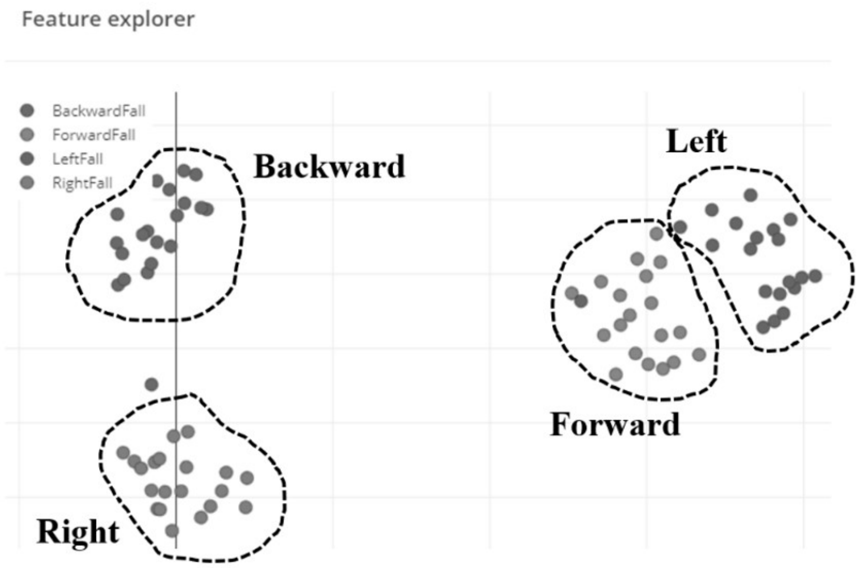


FIGURE 5. The feature data are shown in 3D model

In the training process, the validation is set to 20%, and the main parameters of the neural network architecture are set by the number of training rubrics (EPOCHS) and the Batch size (BATCH SIZE) of 500 and 1, respectively. Where the Batch size will cause LOSS to decrease. For the development of a mathematical model for data prediction, the simulated ANN was transformed into a mathematical equation that relies on the input variables with the output variable, based on the weights and biases extracted from the model in conjunction with the transfer function. The overall equation can be written as follows:

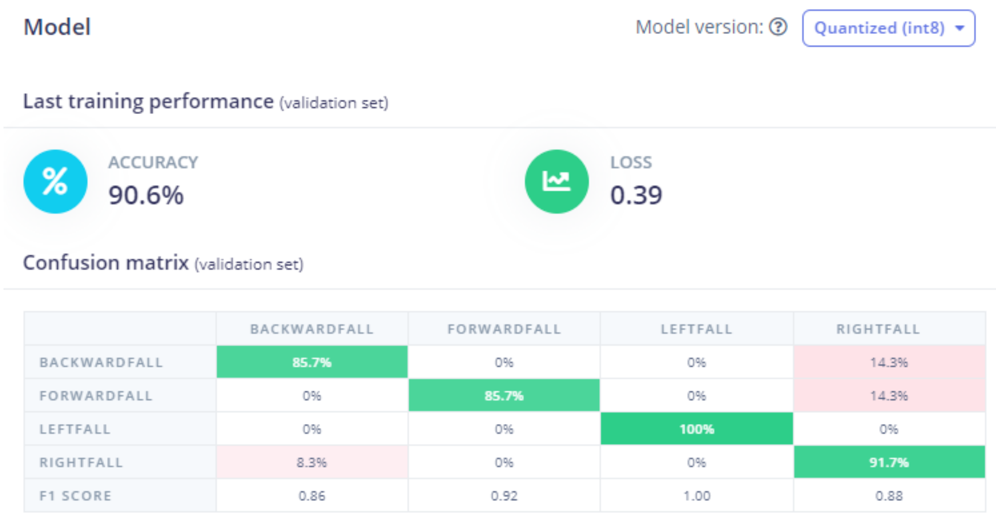
$$y = b_0 + \sum_{k=1}^{n} \left[w_k \times f_{sig} \left(b_{nk} + \sum_{i=1}^{m} w_{ik} \times X_i \right) \right] \tag{1}$$

where b_0 is the bias in the output layer, n is the number of neurons in the hidden layer, w_k is the connection weights between the hidden and output layers, f_{sig} is the transfer function, b_{nk} is the bias at each neuron in the hidden layer, m is the number of neurons in the input layer, w_{ik} is the connection weights between the input and hidden layers, X_i is the normalized input data, and y is the normalized output data.

3. Experimental Results and Discussion.

3.1. Experimental design process. The Arduino Nano 33 BLE was used in this study's design and development of a fall detection system as embedded artificial intelligence by being fastened to a strap around the user's waist. The test subject will have to fall 20 times in four distinct positions. To be more specific, in this study, activities were added to include lying down, standing up, sitting on a chair, sitting on the ground, and falling forward, backward, left, and right. In addition, the system also provides notification of these daily activities. The information obtained will be sent to caregivers via IoT, which will be displayed on and informed by mobile phones.

3.2. Model training results and testing the model. From training the data according to the setting with 60% training, 20% testing, and 20% validation, the machine learning teaching results are shown in Figure 6. The accuracy is up to 90.6% and the tolerance is 0.39. Then, a test model is used which uses the collected data to divide it into BACKWARD FALL, FORWARD FALL, LEFT FALL, RIGHT FALL, and other events. And in the part of the model test, the results are shown in Figure 8. From Figure 8, it can be seen that the results obtained from the test model have an accuracy of 95%.



	BACKWARDFALL	FORWARDFALL	LEFTFALL	RIGHTFALL
BACKWARDFALL	85.7%	0%	0%	14.3%
FORWARDFALL	0%	85.7%	0%	14.3%
LEFTFALL	0%	0%	100%	0%
RIGHTFALL	8.3%	0%	0%	91.7%
F1 SCORE	0.86	0.92	1.00	0.88

FIGURE 6. Data training results

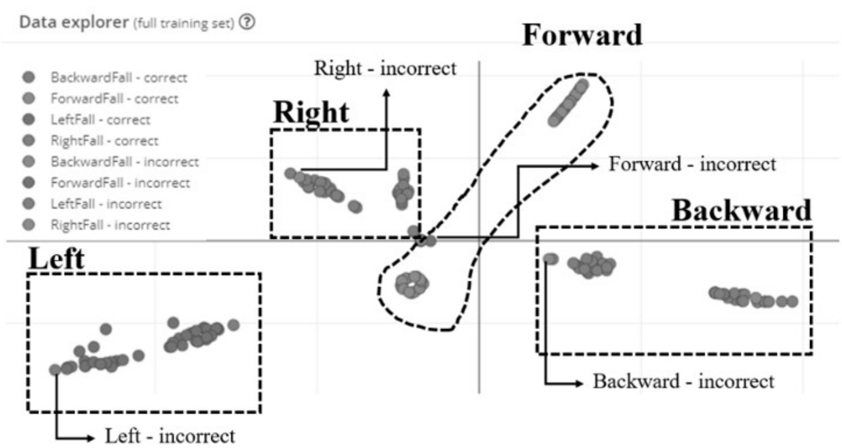
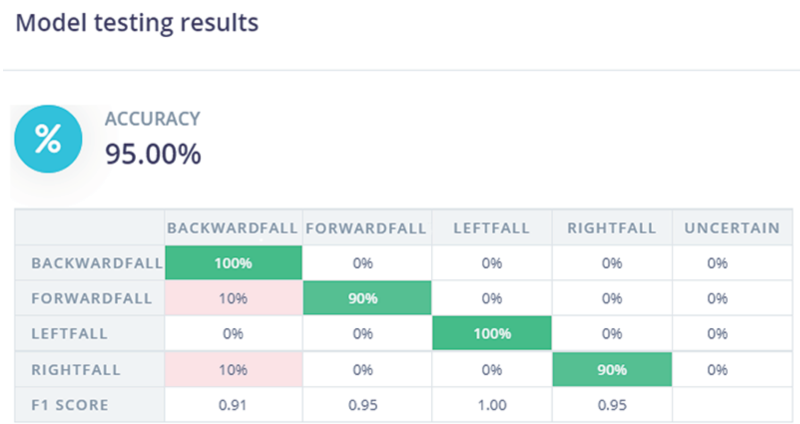


FIGURE 7. Model 3D training results



Model testing results

ACCURACY
95.00%

	BACKWARDFALL	FORWARDFALL	LEFTFALL	RIGHTFALL	UNCERTAIN
BACKWARDFALL	100%	0%	0%	0%	0%
FORWARDFALL	10%	90%	0%	0%	0%
LEFTFALL	0%	0%	100%	0%	0%
RIGHTFALL	10%	0%	0%	90%	0%
F1 SCORE	0.91	0.95	1.00	0.95	

FIGURE 8. Data testing results

3.3. **Experimental result.** The test results from real users performing the fall test 20 times are shown in Table 1 and Table 2 will show the fall detection test with daily activities. Daily activities include ground sitting, laying down, standing up, and sitting on a chair. Testing the fall detection system, the system should only detect 4 types of falling patterns, as shown in Table 2. The system detects 6 falls out of 20 tests in the ground sitting activity, so the fall detection accuracy is 70%.

TABLE 1. Fall detection test

Falling directions	Number of falls	Number of detected falls	Accuracy
Forward fall	20	20	100%
Backward fall	20	20	100%
Left fall	20	18	90%
Right fall	20	19	95%

TABLE 2. Falls detection test with activities

Activity	Number of activities	Detected as fall	Accuracy
Ground sitting	20	6	70%
Laying down	20	2	90%
Standing up	20	2	90%
Sitting on a chair	20	0	100%

The display of the application is depicted in Figure 9. The application will display fall information when the elderly person has fallen in different directions, and a notification will be delivered to the caregiver's smartphone.

4. **Conclusions.** A wearable fall detection and prediction device with an on-board accelerometer and gyroscope is constructed using an Arduino Nano 33 BLE. To train the data on Edge Impulse in this system, machine learning is used. It was discovered that the training model's fall test accuracy was 90.6% and the model test's fall test accuracy was 95%. The accuracy of falling forward, falling backward, falling left, and falling right are equivalent to 100%, 100%, 90%, and 95%, respectively, according to the findings of the experiment with all 4 types of falls. The suggested system may alert caregivers of all 4 types of falls on their smartphones because it has also been designed to interact with them via IoT. In the future, the development of fall detection systems in medical technology can be developed to use AI and ML or detect activity for monitoring the daily activity of

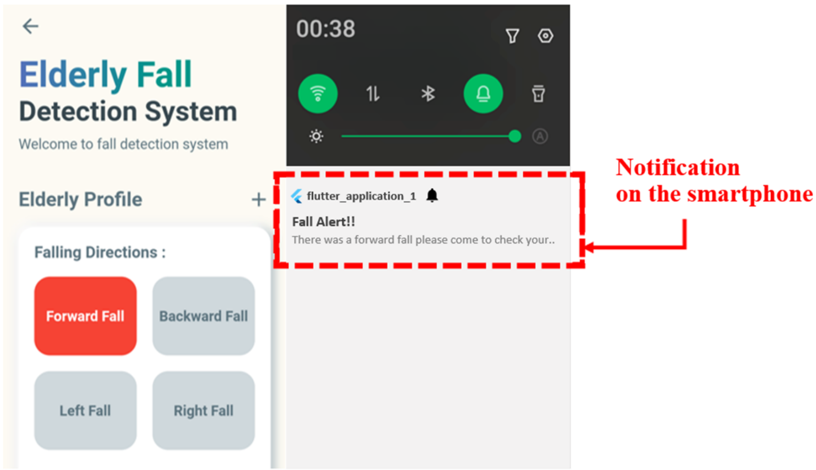


Figure 9. Display and notification on smartphone

patients. AI and ML now play a big role in our daily lives, such as AI that can answer patient questions. Furthermore, the system can develop more accurate fall predictions, and can identify other activities or use a chatbot to check the elderly status when fell and contact followers via chatbot. Confirm that there are symptoms, and if there is no reaction, call an ambulance, etc.

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