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Fall Detection Tool for Vertigo Patients Using The Artificial Neural Network Backpropagation Method With Telegram Notifications

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ABSTRACT

In this research, a fall detection tool was developed using a backpropagation artificial neural network (ANN) algorithm, especially for patients who are at risk of experiencing vertigo and syncope with telegram notifications. This research aims to design and implement a fall detection system for six different movements, namely sitting, walking, bending, falling sideways, falling backward, and bending using ANN Backpropagation as a decision-making system from previous research which used thresholds. The research stages were carried out by processing data and solving problems to determine the position of the accelerometer sensor, activities carried out during data collection, and characteristics of fall conditions. Data collection consisted of 120 training data and 60 test data. The results of the research show whether the recognition of falling movements has been tested using the backpropagation method at two iteration stages, namely at 10,000 epochs, and 17,000 epochs. The best results were obtained at 17,000 epoch iterations with an accuracy rate of 94%, while in the 10,000-epoch iteration the accuracy level obtained was 92%, whereas without using the method, the accuracy was 85%. The HTTP protocol was used for data communication between the device and the database server in 17 seconds so that in 1 minute 4 data is collected.

1.0 Introduction

The balance system is a system that is important for human life. The balance system allows humans to be aware of their position in the surrounding space. Balance is an integrated system, namely the visual, vestibular, proprioceptive, and cerebellar systems. Disturbances in the balance system will cause various complaints, including a spinning sensation which is often called vertigo. Vertigo is a complaint that is often encountered, described as a spinning sensation, a feeling of swaying, unsteadiness (Fancello et al., 2023), and dizziness (Nguyen-Huynh, 2012). Vertigo is a real health problem in society. Patients have difficulty expressing the onset of symptoms.

In Indonesia, case data at R.S. Dr. Kariadi Semarang said that vertigo cases rank as the fifth most common condition treated in the neurological ward. The effect of vertigo on a person is a sudden loss of nerve function and experiencing spinning sensation which a person may fall and faint. Not only vertigo, the cause of fainting, or in the medical world is called syncope can be caused by low blood pressure or dilated blood vessels, irregular heartbeat, hypoglycemia, and neurological diseases (Pascual et al., 2023). Because the symptoms of vertigo and syncope appear suddenly, action is needed in the form of supervision for someone who has experienced this, because if action is not promptly initiated, it can cause more severe symptoms such as stroke and even death (Müller-Barna et al., 2021). This supervision is crucial to prevent unwanted outcomes. The closest family member must always be available to accompany and supervise whatever they do. So that if something happens, it can be treated immediately to avoid fatal consequences.

Research related to monitoring patients at risk of vertigo and syncope has been carried out using methods or algorithms according to sensors. Simple algorithms usually use threshold values (Razum et al., 2018). This algorithm is usually modified by adding an upper or lower threshold, it is found that the accelerometer sensor can detect falling conditions correctly by 83%. Apart from using threshold algorithms, data mining is also widely applied, such as K-Near Neighbors (KNN) (Gunale & Mukherji, 2016), Support Vector Machine (SVM) (Iazzi et al., 2018), the average accuracy of fall detection tools is 91 .23%. Based on these problems, in this research, we developed an IoT-based intelligent system to supervise and monitor patients at risk of vertigo and syncope whether falls occur or not. The fall detection approach developed is based on wearable sensors used for cost efficiency, installation, and design arrangement which are not complicated. The research aims to implement an IoT-based intelligent fall detection system as a decision-making system. In this research, the MPU6050 sensor was used as a fall detection sensor, to detect falling conditions using Backpropagation to differentiate between daily activities and falling conditions.

2.0 Research Methodology

The general architecture for a fall detection monitoring tool for patients at risk of vertigo is shown in Figure 1. The system consists of a device section, a server section, and a Backpropagation Artificial Neural Network.

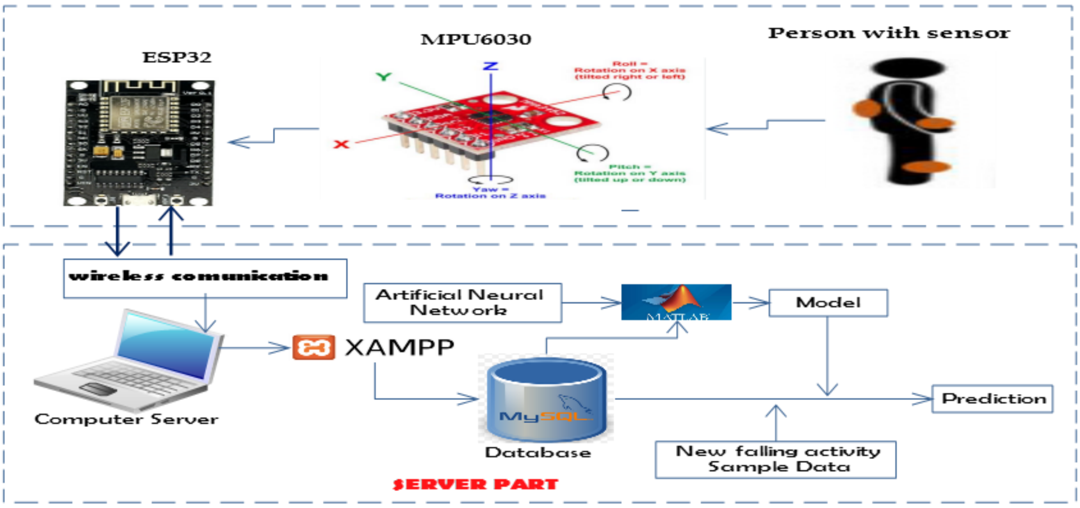
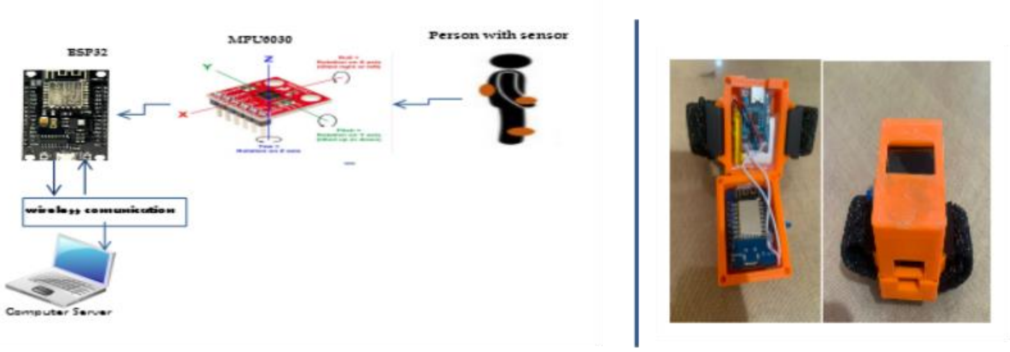


Figure 1: Block diagram of a tool for monitoring patients at risk of vertigo and syncope using Backpropagation

2.1 Device Section

This circuit consists of tilt angle detection using the MPU6050 accelerometer (Burgos et al., 2020) (Yulastri et al., 2023), ESP32 functions as a microcontroller to collect the input data (Md Hussin et al., 2023) from the person with sensor. The MPU6050 accelerometer sensor is connected to pins A4, and A5 on the microcontroller to detect the tilt of the patient's position which is placed on the patient's hand, when experiencing changes in position which are divided into several conditions. Next, the data from the sensor is sent to the server computer via wireless communication. Figure 2a shows the device section of an IoT-based fall detection tool for vertigo patients using Artificial Neural Network Backpropagation, and Figure 2b shows the prototype of the tool that has been created.



(a) (b)

Figure 2: (a) the device section of an IoT-based fall detection tool for vertigo patients using Artificial Neural Network Backpropagation, (b) the prototype of the tool that has been created

2.2 Server Section

The server section is for storing and processing data from sensors sent to the server using the HTTP protocol. In this section, PHP programming is used to send data from the device section. XAMPP to run a web server on a local host to manage databases using MySQL. The sensor data stored in the database is then displayed in MATLAB software and used as input data for the fall-type identification process. The identification procedure is achieved through the application of ANN backpropagation (Susanti et al., 2023). Figure 3 shows the server section of the system.

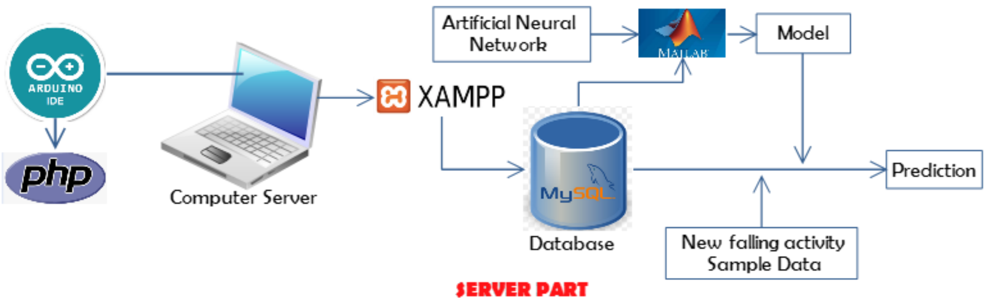


Figure 3. Server section

2.3 Artificial Neural Network Architecture Design

The artificial neural network architecture consists of three parts, namely the input layer, hidden layer, and output layer, as shown in Figure 4.

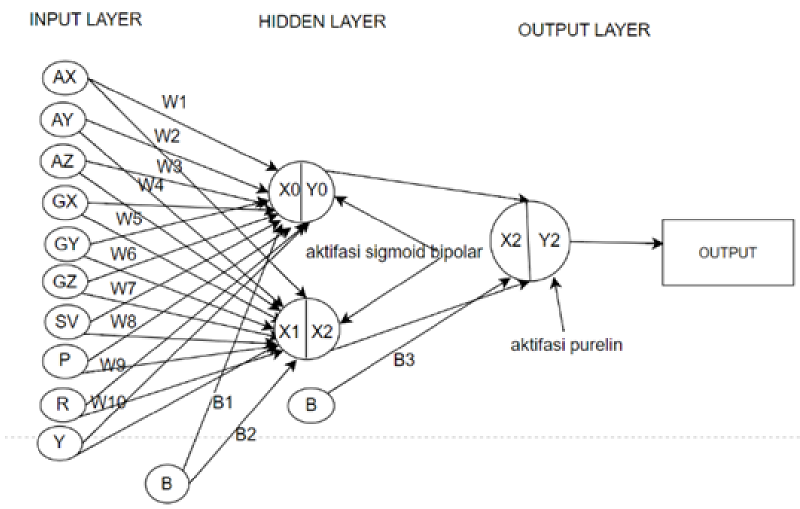
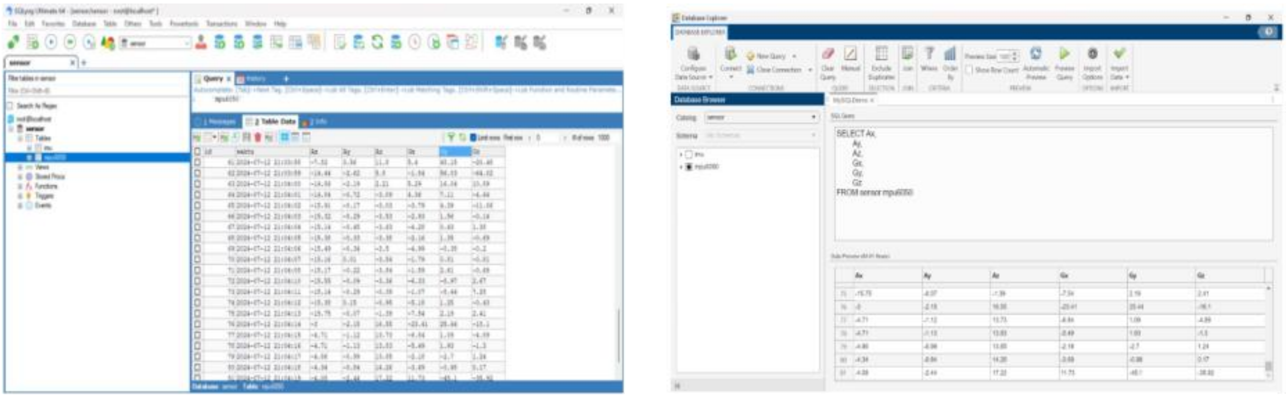


Figure 4: Artificial neural network architecture

The input layer consists of 10 neurons that receive output from the MPU6050 sensor. The hidden layer has 2 neurons that calculate the sum result of multiplying the input neurons by the input network weights and take into account the bias. On the other hand, the output layer holds the multiplication result of the hidden neurons with the weights of the output network and takes into account the bias. For hidden layer activation, a bipolar sigmoid function is used, while the output layer uses a pure line activation function.

3.0 Results and Discussion

In this tool, the data is processed to produce a model of 120 activities with 20 activities for each category consisting of sitting, walking, bowing, falling backward, falling sideways, and falling forwards. Figure 5 is a dataset stored in a SQL database and sent to MATLAB using the JDBC connector. The equation must be labeled below:



(a) (b)

Figure 5: The dataset

The ANN training process uses the backpropagation method with a total of 300 testing data, as shown in Figure 6.

Figure 6: ANN backpropagation in training MATLAB

The results of MATLAB training with ANN Backpropagation for all categories are shown in Figure 7.

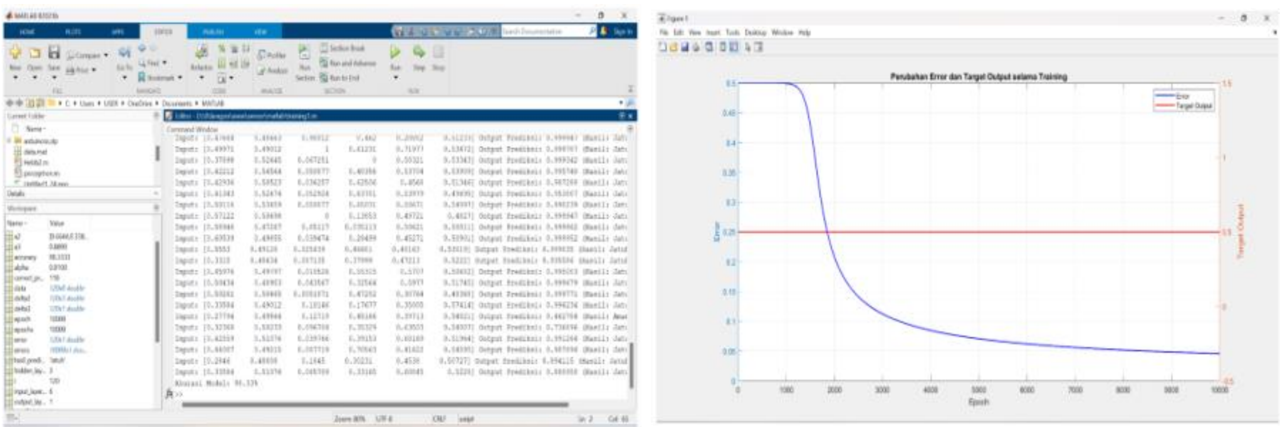


Figure 7: Errors and Target output in the training data process

Based on Figure 7, the model accuracy for all categories is 98.3%. The next stage was movement testing for all categories with 60 test data. Movement recognition using backpropagation was carried out 2 times. The first experiment uses 10,000 epoch iterations and the second experiment uses 17,000 epochs. Backpropagation accuracy results with 10,000 epoch iterations are shown in Table 1 and Table 2.

Table 1: Backpropagation accuracy by iteration 10.000 epoch

No.	Movement	The amount of data	Identification results	% Accuracy
1.	sitting	10	8	90%
2.	walking	10	9	95%
3.	bowing	10	9	95%
4	falling backward	10	8	90%
5	falling sideways	10	9	95%
6	falling forward	10	8	90%

Identification results:

Accuracy = (number of true predictions) / (total number of predictions) x 100 % [1]

The motion of sitting $Accuracy\ = \frac{8}{10}$ x 100% = 90%

The motion of Falling backward $Accuracy\ = \frac{8}{10}$ x 100% = 90%

The motion of Falling sideways $Accuracy\ = \frac{9}{10}$ x 100% = 95%

Table 2: Backpropagation accuracy by iteration 17.000 epoch

NO	**Movement**	**The amount of data**	**Identification results**	**% Accuracy**
1.	sitting	10	10	100%
2.	walking	10	9	95%
3.	bowing	10	9	95%
4	falling backward	10	8	90%
5	falling sideways	10	9	95%
6	falling forward	10	8	90%

Identification results:

Accuracy = (number of true predictions) / (total number of predictions) x 100 % [2]

The motion of sitting $Accuracy\ = \frac{10}{10}$ x 100% = 100%

The motion of Falling backward $Accuracy\ = \frac{8}{10}$ x 100% = 90%

The motion of Falling sideways $Accuracy\ = \frac{9}{10}$ x 100% = 95%

Based on Table 1 and Table 2, it can be explained that the calculation with 10,000 epoch iterations is still not close to the results of each movement. The sitting movement still gets an accuracy of 90% from pattern recognition using backpropagation at 10,000 iterations, namely from 60 data that can be tested, it can be identified according to the movement of 95% percent accuracy of movement recognition using backpropagation at 10,000 iterations is 92.50%. Next is pattern recognition with 17,000 iterations. The motion recognition results are already close. Of the 60-test data that can be identified according to the movement, the accuracy of motion recognition using backpropagation at 17,000 iterations is 94.10%. After testing the accuracy of each movement, notification testing is then carried out if the patient falls or does not fall using the Telegram application. Figure 8 is the result of notification testing.

Figure 8.: The result of notification testing

The model created was successful in categorizing six activities and distinguishing between falls and non-falls. The HTTP protocol used for data communication between the device and the database server is 17 seconds so that in 1 minute 4 data is collected. Meanwhile, the delivery time from the database to the notification is predicted to be the same.

4.0 Conclusion

Based on experiments conducted, the fall detection tool for patients at risk of vertigo and syncope was successful in categorizing six levels of activity. Namely sitting, walking, bowing, falling backward, falling sideways and falling forward. Motion recognition using the backpropagation method has an accuracy rate of 95%. The notification system can be sent using the Telegram application when the patient falls and does not fall.

The results of this research have not reached the maximum level expected. Therefore, further development is needed, both in the hardware aspect and in data mining techniques. It is important to increase the variety of movements covered in the study. The more diverse the movements tested, the better the sensitivity of the proposed product. Apart from that, it is necessary to pay attention to making devices that have efficient sizes so that they can be produced and used appropriately for the public, especially the elderly. For future research, there is potential to use features based on transient data from movement as input for machine learning.

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Author Contributions

Era M.: Conceptualization, Methodology, Software, Writing- Original Draft Preparation, Data Curation, Formal Analysis; **Indri A. U.**: Data Curation, Validation, Supervision; **Efrizon**: Software, Validation, Resources; **Yulastri**: Project Administration; **Anggara N.**: Project Administration.

Conflicts of Interest

The manuscript has not been published elsewhere and is not being considered by other journals. All authors have approved the review, agree with its Submission, and declare no conflict of interest in the manuscript.

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