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Intelligent System for Fall Prediction Based on Accelerometer and Gyroscope of Fatal Injury in Geriatric

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A B S T R A C T

Methods of prevention and equipment to reduce the risk of falls based on accelerometer and gyroscope sensor have developed rapidly because its operations are cheaper than video cameras. Improved accuracy of detection and fall prediction based on accelerometer and gyroscope sensor is carried out by utilizing Artificial Intelligence (AI) to predict falling patterns. However, the existing fall prediction system is less responsive and also has a low level of accuracy, sensitivity and specificity. The current system does not have a notification system to care givers or doctors in the hospital. To overcome the above problems, this study proposes the development of smart fall prediction system based on accelerometer and gyroscope for the prevention of fractures in geriatric populations (JaPiGi) which are accurate and have high sensitivity and specificity. This study uses Fuzzy Mamdani to recognize movements falling forward, falling sideways, sitting, sleeping, squatting and praying. The total data tested was 100 data from 10 participants. The introduction of this movement is based on 6 input variables from data of accelerometer and gyroscope sensor. To calculate the accuracy, precision, sensitivity and specificity in this study using the equation Receiver Operating Characteristic (ROC). Motion recognition is carried out 3 times with an average accuracy of 90%.

INTRODUCTION

In Indonesia, falls have entered into the top five medical incidents besides medicine error and geriatric populations (people over 60 years [16]) who survived falling incidents. Vulnerable to decreased quality of life [15]. Fall prevention can be done by identifying risk factors, assessing balance and gait, providing flexibility exercise movements, physical balance training, and balance coordination, and improving environmental conditions that are considered unsafe [20]. Besides, technology has also played a role in mitigating, and monitoring falls against geriatrics, namely by creating a fall monitoring system [3][7][24][27]. Furthermore, a fall monitoring system has also been developed to predict fall events when walking or being active. In the current case, the fall prediction is able to predict up to one step before the fall event. This prevents fatal injuries to geriatrics [29][30][31]. Smart Health is one of the world's biggest challenges in the next few years, as shown in Figure 1.

Fall prediction sensors can be divided into three, namely: 1. video cameras, 2. acoustic and ambient sensors, and 3. kinematic sensors [12]. Of these three types of sensors, kinematic sensors based on the accelerometer and gyroscope are most widely used because the development costs are cheaper than others. However, the predicted threshold value will vary in value from one subject to another due to several factors such as age, weight, and so on [30]. Threshold An incorrect will reduce the accuracy of the fall prediction system [31].

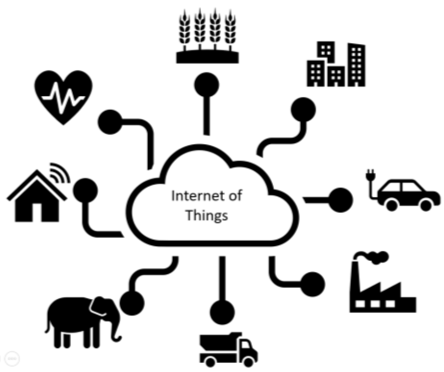

Figure 1. Internet of Thing Challenges 2019

Improved accuracy of detection and prediction of falls based on the accelerometer and gyroscope sensor has been carried out by utilizing Artificial Intelligence (AI) to predict falling patterns, such as using fuzzy systems [26], machine learning [14], neural networks [9][21] or support vector machines (SVM) [22][28]. However, the existing fall prediction system is less responsive, then has low accuracy, sensitivity, and specificity. For example, the prediction system by [30] can predict falls in young people,

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but not necessarily the same thing can be done for geriatrics. In addition, the current system does not have a notification system for caregivers or doctors in the hospital.

Based on the results of previous studies. Above, this research was carried out by integrating IoT and Fuzzy Mamdani. The conditions experienced by geriatrics are not sure to occur, so using the fuzzy mamdani method, which is one part of the Fuzzy Interference System, is helpful for making the best decisions in problems that are not sure [33]. This method is carried out by drawing conclusions that are most easily understood by humans so that according to (Salman, 2010) this method can produce the best decisions for a problem.

METHOD

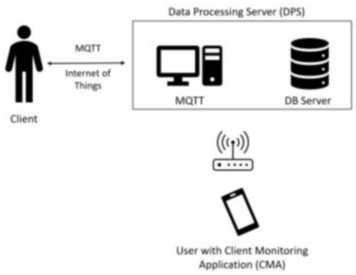

Figure 2 Japigi Architecture

Early planning for the development of the JaPiGi architecture can be seen in **Error! Reference source not found.**. This architecture is the basic architecture that will be explored and adjusted during the development of JaPiGi. As shown in **Error! Reference source not found.**, JaPiGi has three main components, namely Client Fall Detection System (CFDS), Data Processing Server (DPS), and Client Monitoring Application (CMA). Each component will be connected by the Internet of Things (IoT) technology. While the basic architecture of the prediction of falling patterns based on accelerometer data is as seen in Figure 3. For initial planning, kNN will be used as a classification technique for falling data as used by [10].

But in contrast to [10], to improve the accuracy of fall predictions, this study considers entering pre-processing data, as described in [8]. Besides this, feature extraction also uses different techniques. For data classification, SVM will differentiate between normal geriatric data and geriatric fall data. If the difference is too large, then the event will be classified as a fall event.

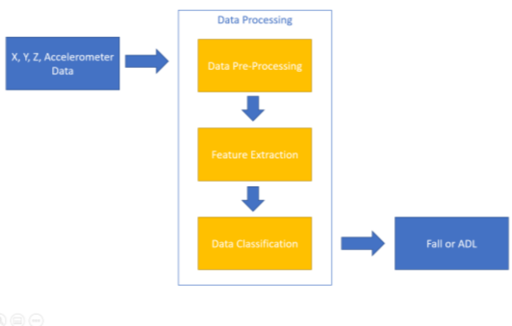

Figure 3. Fall Pattern Prediction based on SVM

The next step is to explore the feedback on the detection algorithm to minimize errors. Design ideas about this can be seen in Figure 4. By using this method the fall detection system is adaptive because it is able to learn from the results of the previous process.

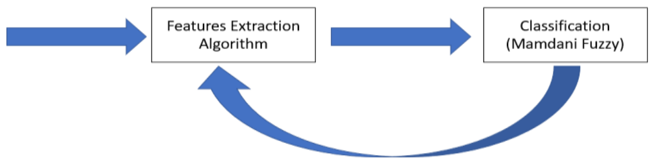

Figure 4. Classification Results Feedback

A. *Development of Data P rocessing Server (DPS) and Fall Prediction Algorithms*

This stage deals with the design of algorithms to predict falling patterns and distinguish them from ADL. Preliminary planning for the development of the algorithm uses techniques, as shown in Figure 4. As shown in the figure, there are several steps to predict falling patterns: data pre-processing, feature extraction, and data classification. Development of classification algorithms for SVM-based fall predictions will be carried out using MATLAB. The output of this stage is an a-based classification algorithm fuzzy to predict falling patterns that have accuracy, specificity, high sensitivity, which will be published in reputable international and accredited national journals.

B. *Development of Client Fall Detection System (CFDS)*

At this stage, CFDS software and hardware will be developed. CFDS hardware will consist of an accelerometer sensor, Global Positioning System (GPS), GPRS, and microcontroller. GPS is needed here because the initial design of the JaPiGi was used for outdoor conditions. The software developed will acquire data from sensors and send it using the internet using the MQTT protocol. The output of this stage is a compact and comfortable system for data retrieval of an accelerometer.

C. *Development of Client Monitoring Application (CMA)*

An-based application Android that can monitor geriatric conditions in real-time is the output of this stage. Besides this, CMA is also useful for visualizing alerts generated by falling prediction algorithms. This CMA must be installed by the next of kin, caregivers, or physiatrist of the geriatric who will be monitored.

D. *Integration and Evaluation*

At the Integration and Evaluation stage, a test of the overall system performance will be carried out. The main output of this stage is JaPiGi's performance based on metrics performance such as accuracy and proportion of service provided without error. The performance evaluation process is carried out by comparing the results of monitoring and falling detection by a prototype developed with monitoring direct physiatrists as a baseline. Thus the prototype is expected to replace the monitoring of the function and fall detection carried out by the physiatrist. The results of this evaluation will be written to be published in reputable international journals.

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RESULTS AND DISCUSSION

Experiments are a process carried out to assess whether the tools designed are following what is expected. This study also experimented with adjusting the sensor's output following the provisions—experiment by producing accelerometer sensor output on a smartphone. There are two types of experiments: experiments in a stationary position with a device mounted on the body. Experiments in this stationary position will be carried out by placing the smartphone, and the proposed device is driven the same and observed whether getting the same output. Installation of the device in the user's body with certain conditions. This provision is intended so that each data retrieval always gets the same value. The condition is that the position of the tool must be facing left. This means that the z-axis of the sensor will face the body, the x-axis to the left of the body, and the y-axis to the top left, as shown in Figure 5.

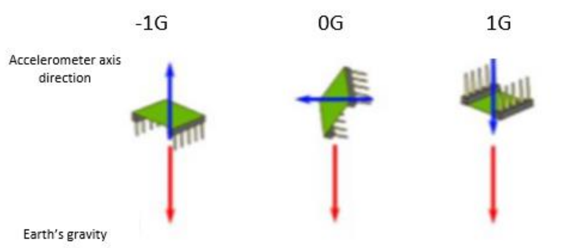

Figure 5. Accelerometer axis and the direction of Earth's gravity

Device testing is done by producing accelerometer output on a smartphone. The smartphones used are smartphones Redmi Note 8 and iPhone 6S +. The application used is the "Accelerometer" contained in the play store. For this test, the output of the accelerometer and gyroscope on the smartphone is due to having only the sensors accelerometer and gyroscope.

Tests in this research were carried out with several general conditions that might occur in daily activities, including when the device is idle, the position of a person sitting, standing, sleeping, falling to the right, falling to left, falling backward, falling forward, and bow. The results of the accelerometer test measurements are shown in Table 1.

Idle position testing is carried out using equipment and smartphones placed in a vertical plane. In this test, the Smartphone is placed on a flat table next to a fall detection device. In sitting position, participants tested sitting position using a chair shown in Figure 6. The device is turned on when the participant is in an idle sitting position, without any movement resulting in changes in sensor values.

Figure 6 Sitting Position

In standing position, participants carry outstanding position testing. The device is turned on when the participant is idle standing position, which results in no change in the sensor value. The purpose of testing in the sleep position is to see the results of the fall detection device so that when testing, the movement gets good results.

Table 1. Accelerometer Test Table

Position Testing	Accelerometer Axis		
	Ax(G)	Ay(G)	Az(G)
Idle	0,33	0,15	0,04
Sitting	0,25	0,51	0,45
Standing	0,022	0,023	0,0033
Sleep	0,79	0,14	0,06
Fall - to -Right	0,59	0,85	0,48
Fall - to -Left	0,25	0,13	0,12
Falling Backward	0,00074	0,0008	0,0098
Falling Forward	0,0002	0,0000072	0,002
Bow	0,31	0,2	0,95

Figure 7 describes the participant's position when testing the right/left-sided motion ideally. Participants in a standing position while facing right/left with a slope of 90 degrees. Falling Backward position testing is carried out on one participant paired with a fall detector and Smartphone shown in Figure 8. In Salah Position, participant's position when testing the salah movement ideally. Participants were in a standing position while facing the Qibla with a slope of 90 degrees. All tests were carried out with Smartphone is placed in the participant's pocket. Testing is carried out for 3 seconds.

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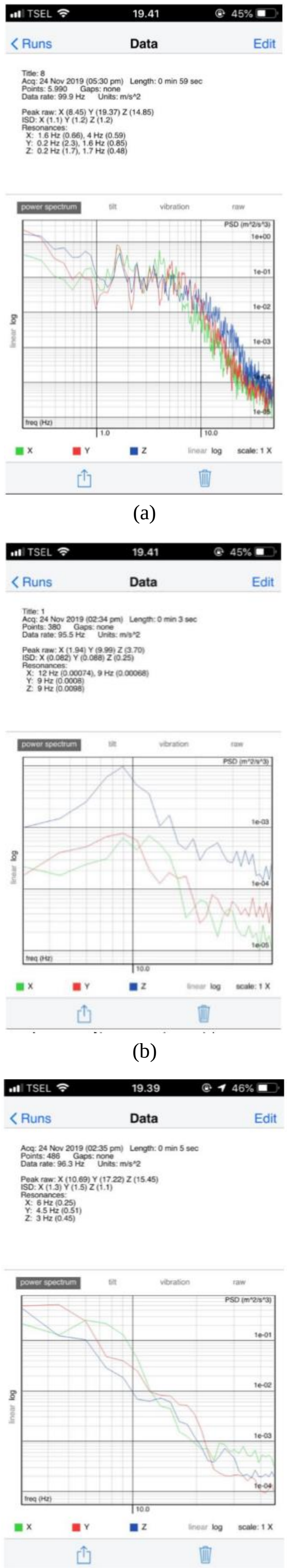
Figure 7. Fall to Right Position

Data collection by recording data on a smartphone is shown in Figure 9. The average data collection was carried out for 3 seconds in each condition. Based on the measurement results, it is known that all conditions of a person have different accelerometer assessment characteristics so that the training data processed using the Mamdani fuzzy intelligence system can detect someone falling or not.

Figure 8. Falling Backward Position

The smartphone will display a graph of data reading on the X, Y, and Z axes. Decision-making is done using fuzzy mamdani. Where the results on the smartphone are in the form of notifications if someone will experience a fall to anticipate unexpected events, so from the results of this experiment, it is known that utilizing the smartphones that we have and use in everyday life, will make it easier for geriatric families to monitor and anticipate unexpected events.



(a)

(b)

(c)

Figure 9. Recording Data Collection in Smartphone a) Falling Backward Position, b) Standing Position, c) Sitting Position

CONCLUSIONS

Based on the results obtained in this study, the falling movement has an accuracy of 90%, but the movement of daily activities has not gotten good accuracy, especially in the movement of falling forward and backward. Too much movement outside the core motion can damage the expected feature. In addition, procedures for data retrieval must also be considered.

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