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A Comparative Study of Body Motion Recognition Methods for Elderly Fall Detection: A Review

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***Abstract*— To maintain the welfare of the elderly, intensive and effective monitoring is needed to ensure their safety. Conventional elderly activity monitoring has several limitations (i.e., space and time) due to human abilities. This problem can be overcome by applying real-time monitoring methods using Wireless Body Area Networks (WBAN) and Artificial Intelligence (AI). Several methods have been used and tested, including artificial intelligence implementations from sensor data-based to computer vision-based pattern recognition for body motion classification. Several methods that have been studied show accurate results in classifying elderly body motions/gestures. However, the Human Activity Recognition (HAR) method performs better for elderly activity monitoring applications and makes fall classification more accurate.**

***Index Terms*— wireless body area networks; artificial intelligence; fall classification; pattern recognition; computer vision.**

I. Introduction

A fall is an accidental event that occurs at a fast pace that can result in a person's body lying on the ground or floor, or other lower levels [1], [2]. Fall-related injuries are categorized as fatal and non-fatal [3], [4]. Based on information released by the World Health Organization (WHO), it is estimated that around 684,000 fatal falls occur worldwide every year. The majority of victims of such incidents are individuals over the age of 60. The estimated number of cases makes it the leading cause of death from accidental injuries after traffic accidents. Falls are a significant public health problem for the elderly worldwide, with more than 80% occurring in low- and middle-income countries. Injuries sustained by older adults from falls have far-reaching repercussions for their families, healthcare institutions, and society [2].

One way to reduce the risk of fatal injuries due to falls in the elderly is to conduct intensive supervision [5]. Intensive supervision makes detecting falls and medical enforcement faster [6]. Elderly supervision is still carried out using conventional methods by human labor (volunteers/nurses) [7]. Manual supervision requires more time and limited human resources, while consistent monitoring must continue to detect emergency conditions and provide timely responses [8]. Therefore, new approaches are needed to improve the efficiency of elderly monitoring, provide early warning of changes in behavior or suspicious movements (risk fatal conditions), and reduce reliance on limited human supervision.

In recent years, the development of the Internet of Things (IoT), WBAN, and AI technologies has provided rapid progress in the health sector. Many studies have discussed methods of utilizing these technologies to automate monitoring in the elderly [9]–[11]. An example is the application of sensors installed on the body (around the neck, wrists, or waist) connected to the internet. The device is called a sensor node, a system for identifying and providing user notifications. If a user or individual falls, then the system will quickly activate an alarm to notify a supervisor [12].

In this paper, the authors present a comparative study of methods for detecting falls in the elderly. In addition, challenges and prospects for problems that can be solved through research in the future are also discussed. The contribution to this paper is to provide an accurate description of human activity classification algorithms to be further developed and applied to the real environment for fall recognition.

II. Methodology

Data collection in this paper comes from journals and proceeding articles between 2018 and 2022. The authors searched for references from the IEEE Explore, ScienceDirect, MDPI, and Google Scholar websites using the keywords "IoT", "elderly", "older adults", "motion recognition", "fall detection", and "machine learning". All journals used by the authors are based on relevance to the development and application of motion recognition technology for monitoring elderly activities, especially in fall conditions. Data collection methods can be seen in Fig. 1.

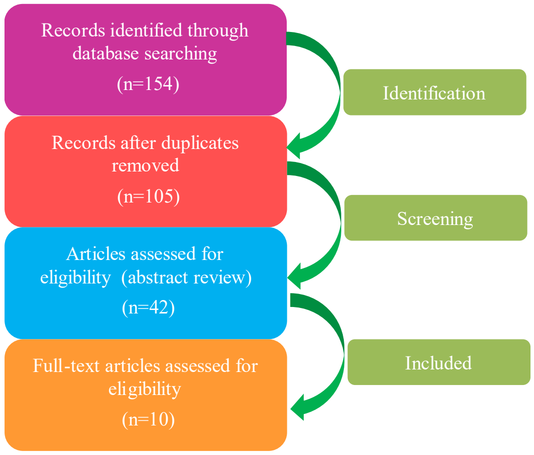

Fig 1. Literature Search Process Diagram

III. Result and General Overview

A. Literature Search Result

This study includes ten journal and conference articles published between 2018 and 2023. These studies come from nine countries, including Thailand [13], Germany [14], Canada [15], Malaysia [16], Spain [17], Portugal [18], Japan [19], India [20], and Indonesia [21]. Most of the research is the innovation and development of motion recognition methods using pattern recognition.

B. Body Motion Recognition Systems and Techniques

Motion recognition in humans can be done by installing sensor nodes on the human body combined with artificial intelligence algorithms or using computer vision method approaches. The method of installing sensor nodes connected to the network (WBAN) is described in subchapter 1. The artificial intelligence algorithm used to perform the fall classification is discussed in Subchapter 2.

1) Wireless Body Area Network

Wireless Body Area Network (WBAN) is a specific type of sensor network that uses wireless sensor nodes on a person's body to measure physiological parameters such as body temperature [22], blood pressure [23], blood glucose [24], heartbeat [25], and other parameters, which allows the patient's health to be monitored remotely [26]. WBAN can be wearable or implanted in a person's body [27]. WBAN aims to ensure individual health by intensively monitoring physiological information using sensors and sending the data to the server. It can help doctors continuously understand patients' health. In addition, WBAN can also significantly reduce patient care costs by monitoring data related to patients' vital signs for an extended period [28], [29].

Almost the same as wireless sensor networks in general, WBAN uses a star topology architecture but with a slightly different approach. In this topology, sinkholes are located in the body to collect information from sensor nodes [10], [30]. Details on the WBAN network architecture can be seen in Fig. 2. In this network, sensor nodes have access to limited energy resources. In physical sensor networks, sensors (such as motion sensors) are installed on the patient's body to observe the patient's vital signs or detect motions/gestures in real-time [31]. By doing this, WBAN can provide an instant response to users (medical personnel, volunteers, families), and the user can follow the patient's disease progression and take the necessary precautions relatively quickly [32]. The use of sensor energy in this network is crucial because if the energy source runs out, the duration of network life will be shorter [33].

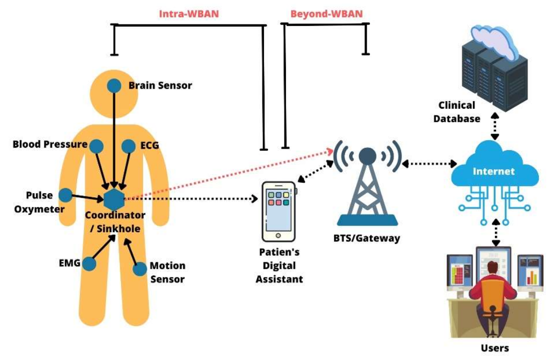

Fig 2. Architecture of WBAN

2) Artificial Intelligence Algorithm for Fall Classification

In detecting the motions or activities of the elderly, the authors found several artificial intelligence methods that can be used to classify human motions/gestures. Further explanation can be seen in Table 1.

C. Implementation of Body Motion Recognition Techniques in Elderly Monitoring

Pattern recognition is an approach to identifying specific patterns or characteristics in data to classify or identify objects or phenomena being observed. In body motion recognition, pattern recognition methods are used to classify body motions/gestures based on patterns identified in sensor or camera data [34]. Pattern recognition methods in body motion recognition involve training and testing using machine learning algorithms [35]. The training process involves stages to identify, analyze, and classify motions performed by objects or individuals [36]. Body motion recognition involves several steps, from collecting data to making classification decisions [37]. The training process of a machine learning algorithm model can be seen in Fig. 3. After the training process is complete, the moved pattern recognition model will be used to classify body motions in the

TABLE I. SUMMARY OF MOTION/GESTURE-RECOGNITION TECHNIQUES.

Method	Description	Pros	Cons
Artificial Neural Network (ANN) [3], [38]	• Computational models inspired by the workings of the biological nervous system in the human brain • ANN consists of a large number of simple processing units called neurons or nodes • There are several commonly used types of ANN architectures, including Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Temporal Convolutional Networks (TCN), and Long Short-Term Memory (LSTM).	• Can handle problems of high complexity, including pattern recognition, classification, and prediction. • It can learn from training data and adapt itself. • Can solve the problem of imperfect data (noise) • Can process data simultaneously.	• Requires a considerable amount of training data to produce accurate results. • Large amounts of data affect long computation times. • Lack of clear interpretation in making decisions. • Prone to overfitting.
Decision Trees [38]	• A pattern recognition method that uses a set of tree-based decision rules to classify data. • Decision trees generate a predictive model in the form of a tree structure, where each node in the tree represents a decision rule, and each branch represents the possible outcome of that decision.	• Humans can easily interpret and explain it due to simple tree-based decision rules. • Can overcome incomplete data or have missing values of various types and scales.	• Prone to overfitting if the tree is too complex and fits too much into the training data. • Sensitive to small changes in training data • Must discretize continuous attributes.
Support Vector Machines (SVM) [3], [38]	• Machine learning methods are used for classification and regression by separating data into two classes using a hyperplane (Separation space between 2 dimensions).	• Effective handling of high-dimensional data, even when the sample size is small. • Can separate data that cannot be separated linearly.	• Less efficient for large datasets. • Requires proper selection of parameters, such as kernel parameters, which can affect the performance and stability of the model.
Random Forest [3], [38]	• It uses a combination of several decision trees to perform classification or regression. • Each decision tree in a random forest is generated randomly and independently. Finally, the classification results are taken through voting or averaging all existing decision trees.	• Have good performance in terms of classification or prediction accuracy. • It can handle large datasets with different features, including numerical and categorical ones. • Can solve overfitting problems by using the ensemble concept	• When doing training, it takes relatively longer than simple models such as a single decision tree.
k-Nearest Neighbor (k-NN) [3], [13], [38]	• Non-parametric methods used for classification and regression based on proximity to training data known to the class • k-NN is an unsupervised learning method that falls into the category of lazy learning algorithms, which means that it does not perform complex training processes at an early stage. • Instead, k-NN stores all training data and performs the classification process directly when new data is classified.	• Easy to understand and implement. • It does not require complex training processes. • Effective in cases with high-dimensional data. • Suitable for data that does not have complex patterns	• Sensitive to irrelevant data or noise • Sensitive to different data scales.

testing process. Testing data not used in the training process will be provided to the model, and the model will identify patterns that match the observed body motions [37].

Several studies apply the gyroscopes and accelerometers (IMU) sensor that aim to analyze changes in acceleration vectors during falls and create fall recognition algorithms based on specific stages (such as the beginning of the fall, shock, aftershock, and body position), such as research in [15]. Research by [17] also discussed the development of pattern recognition methods by integrating an accelerometer into a smartwatch to recognize falls. When the detector device detects a fall event, the data will be sent via Bluetooth to the smartphone as a gateway. Then smartphone forwards (transmits) the data to the cloud server, then the cloud server sends a notification [17].

Another study by [16] has also conducted research on pattern recognition methods by applying IMU sensors, which are a combination of Gyroscope and Accelerometer sensors (MPU6050) installed on elderly bodies, and Bluetooth Low Energy (BLE) Beacon location sensors scanned using the Raspberry Pi module. The data generated by the IMU sensor is then acquired and analyzed using machine learning. Using Random Forest and SVM classification techniques, the accuracy results obtained were 97.69% in detecting motion and 97.25% in detecting the location of users or individuals. On the other hand, research by [39] had an average of 73.7% accuracy and 81.1% precision for older women's fall detection using the RF classification method. Furthermore, research by [40] used SVM to classify the fall events from IMU data and got a 99% accuracy rate.

Meanwhile, research by [15] proposes a configurable real-time motion pattern recognition framework using the same sensor (MPU6050). The classification method applied is the single-hidden-layer Feedforward Neural Network (FNN). This technique's training results showed an accuracy rate of 98.23% from as many trials (~207 thousand data points) or datasets. Similar trials have also been conducted using the k-NN classification technique. By selecting k = 3 with the same histogram feature and training test data points, the accuracy obtained was 97.66%. FNN slightly outperformed k-NN. These results can be improved by involving more subjects and (or) more IMU nodes. While FNN and k-NN provide similar results for large data sets, k-NN requires significant memory usage and experiences long latency, which makes it unfeasible for real-time execution.

Another study by [14] proposes classifying patterns using Temporal Convolutional Network (TCN). The matrix used for performance analysis is accuracy and F1 score using the proposed approach, then compared with baseline LSTM, bidirectional LSTM, residual LSTM, and deep residual bidirectional LSTM. The results showed that the proposed approach with TCN performed better than others, with 94.2% accuracy on the F1 score matrix. A high F1 score indicates the efficiency of the model.

Not only using IMU sensors, the study in [41] also uses RFID to detect fall events. The various classifier algorithms include XGBoost, Gated Recurrent Units (GRUs), RF, KNN, and Logistic Regression (LGR). The results show that the GRUs exhibit a 44% accuracy rate, the RF algorithm achieves a 43% accuracy rate, and XGBoost achieves a 33% accuracy rate. Meanwhile, KNN outperforms the others with a 99% accuracy rate.

In the context of accuracy, research using IMU sensors installed on individual bodies has proven effective and high-quality in monitoring the elderly. However, the research requires a relatively large number of sensor nodes, so other methods are needed to support or complement the performance of devices used to monitor the elderly more efficiently in terms of equipment quantity. In this case, the authors found a solution in a recent study, where visual sensors in the form of cameras were used to identify body motion [19]–[21]. This method can monitor the activities of the elderly using only cameras so that the quantity of equipment and installation will be more efficient.

The development of alternative WBAN methods to monitor the elderly has been carried out using visual sensors to identify motions combined with computer vision-based artificial intelligence technology. This method aims to produce accurate and detailed visual representations of body motions in three-dimensional space. In this method, Artificial Neural Network (ANN) is the most commonly used classification technique [36]. The reconstruction process begins with data capture from 3D camera sensors that can produce information about the position and depth of objects in space. Once the 3D data is collected, the next step is to build a 3D body motion model. This model can be a digital representation consisting of dots or a mesh (network) that describes the shape and position of the body in space. Such 3D models can be used to perform further analysis, such as feature extraction, motion tracking, or animation. This method is commonly called Human Activity Recognition (HAR) [19]–[21].

Research by [20] proposed motion recognition and fall detection systems using deep convolutional long short-term memory (ConvLSTM) networks, which involve the merging of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This study used geometric and kinematic features on the Depth Camera Kinect sensor to build features. Meanwhile, cross-entropy and softmax activation are used to obtain performance models and measures. This proposed model was evaluated on a video dataset (KinectHAR dataset), and results were obtained with an accuracy rate of 98.89%.

On the other hand, research by [21] also proposed a new motion recognition method involving motion feature extraction techniques to form windows of frames representing motion in a time series, which were then provided as input to the CNN model. This model was trained and tested using the Florence public dataset with 3D data from the positions of fifteen joints comprising 215 videos. Using the Kinect 3D camera sensor, the accuracy results obtained by the model were 99.3421%, the precision value was 100%, the recall value was 94.73%, and the F1 score was 97.29%.

In addition to using ANN to classify data from 3D camera sensors, some studies use SVM as a classification method. Research conducted by [19] proposed a method, namely motion recognition using the SVM technique in depth differences between two consecutive frames to determine whether motion has been detected in a video frame. Using the Depth Camera sensor, this feature extraction system shows that sitting/standing/lying down has a classification accuracy of 96.60%, 96.41%, and 95.35%, respectively. In addition, the overall accuracy of the system is 91.82%.

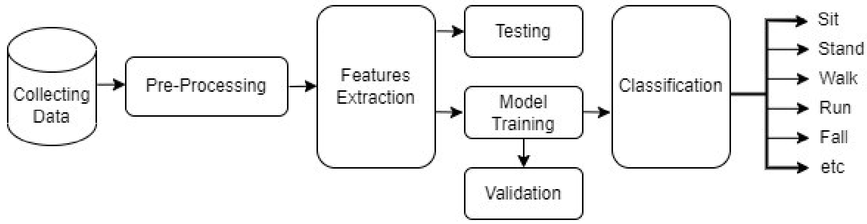

Fig 3. The learning process of the machine learning algorithm

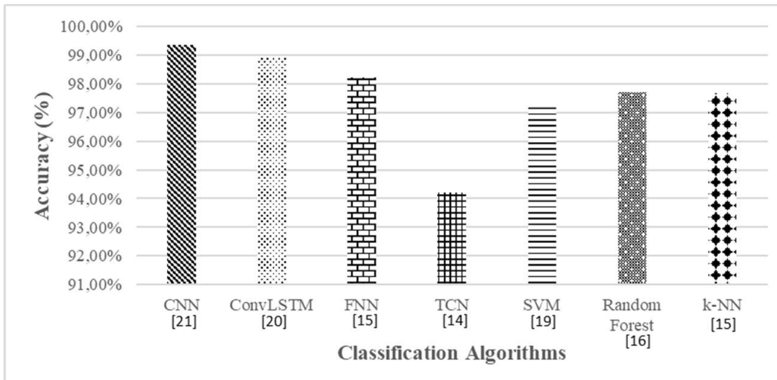

Fig 4. Accuracy comparison of body motion/gesture recognition techniques

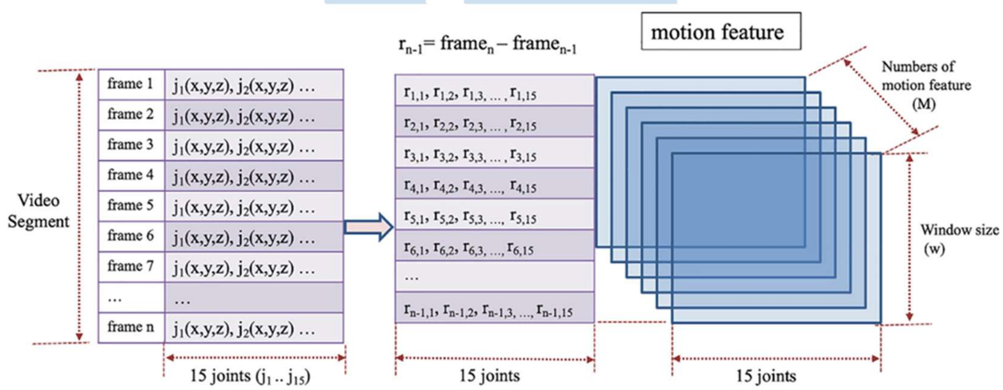

Fig 5. Feature Extraction Method [21]

IV. Discussion

A. Related Literature Review

Overall, various ANN methods have very accurate performance in studying complex patterns using large datasets. However, other classification techniques such as k-NN, SVM, and Random Forest also have a high degree of accuracy in studying these patterns, but in smaller, less complex datasets [42]. The authors compared the classification techniques studied in Fig. 4 to see the results more clearly.

CNN and ConvLSTM methods combined with 3D camera sensors have proven to be very effective in detecting and analyzing the body motion of subjects or objects. With high accuracy, it can be used to monitor activities carried out by the elderly at a distance in a quality and efficient manner without the need for many sensors installed on the body of the elderly or subject. The CNN method with the extraction of certain features is the best method to date that can be used to accurately detect various kinds of human movements or activities [21].

This study [21] uses the CNN method for extracting different features. The feature extraction technique used is the sliding window technique on time series data to construct motion features. Each video segment in the dataset consists of multiple frames. Next, the distance change will be calculated consecutively at each joint coordinate point or joint (fifteen joints) on the frame. Identification of features of motion is carried out through this process. The depiction of feature extraction techniques used in this study can be seen in Fig. 5.

In addition, the method used was also tried on other datasets, where the activities carried out by individuals include walking, sitting, standing, falling, and other motions. The experimental results showed a loss value of 0.1964 and an accuracy of 93.18%. So, it can be categorized that the model used can also classify different datasets with high accuracy [21].

B. Challenges

According to the existing research results that have been reviewed, Human Activity Recognition (HAR)-based Pattern Recognition has excellent results in identifying movements so that it can classify body motion with a high level of accuracy. 3D camera sensor or Depth Camera can be the latest application of the HAR method, where the results obtained are very accurate. However, this method can be improved again in a more varied dataset to provide validation, considering that this new method is more efficient regarding equipment quantity. That is a challenge that must be developed in the future so that the activities of the elderly can be known and monitored by caregivers and families of the elderly who are monitored. By combining computer vision with medical technology, this system can significantly improve the quality of health for the elderly. At the same time, this system can also reduce accident rates and maintenance costs. Nevertheless, on the other hand, the application of cameras also has limitations regarding installation in private areas, such as bathrooms and toilets.

C. Development Approach

In this comparative literature review, error detection/classification exists when using several models in other datasets. It can be reduced by converting depth maps into 3D Point Clouds by grouping and segmenting distance information of observed objects to improve analyzing patterns of daily activities and behavior using statistical models such as the Hidden Markov Model (HMM). Therefore, how to improve accuracy during observation and interaction between objects will be the subject of further research in the future. In addition, combining with WBAN will support the detection and classification accuracy of fall events by measuring the impulse response to the signal generated by the IMU sensor. Combining WBAN with computer vision systems will extend the monitoring range to private areas.

The HAR-based pattern recognition using a classification algorithm, especially for elderly fall detection in this review, performs well and can accurately recognize the fall, but it still has several limitations. In this literature review, the authors have not discussed other classification algorithms on multilabel classification methods and hierarchical decision making-based classification algorithms. Furthermore, only wearable device-based and vision-based methods are discussed in this study.

V. Conclusion

Human Activity Recognition (HAR) is one example of AI based on computer vision in the scope of wireless sensor networks. It is a new method that must be developed in the future in order to be useful in many fields, especially in terms of supervision or monitoring. Computer vision is a relatively inexpensive technological breakthrough with high classification accuracy. There have been many implementations of motion recognition methods using AI, and one example can be applied to monitor activities carried out by the elderly directly from a distance. Starting from daily activities, such as walking, sitting, standing, sleeping, and other involuntary activities (for example, falling), and can analyze the behavior of the elderly, such as sluggishness, confusion, and other signs of cognitive impairment. The latest development of existing methods is needed to optimize the quality of results and the quantity of tools used. So, this opens up opportunities for future research to find new ways or methods to carry out remote monitoring more efficiently and effectively.

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