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International Journal of Combinatorial Optimization Problems and Informatics, 15(4), Nov 2024, 42-60. ISSN: 2007-1558.
https://doi.org/10.61467/2007.1558.2024.v15i4.497

Fuzzy Logic and Machine Learning Algorithms for Detection and Classification of Falls and Activities of Daily Living

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Abstract. This article analyses the movements of young and elderly people using data collected from an accelerometer and a gyroscope. This study proposes Type I fuzzy logic (FL) and several machine learning (ML) algorithms for the detection and classification of daily life movements and falls. The results obtained demonstrate that a fuzzy logic system can efficiently integrate data from an accelerometer and a gyroscope to classify falls and movements in daily life with 97.4% accuracy. When ML classifiers are used, the performance across several algorithms is also very high.

Keywords: Falls, Activities of Daily Living, Accelerometer, Gyroscope, Fuzzy Logic, Artificial Neural Network.

Article Info
Received Jul 22, 2024
Accepted Sep 11, 2024

1 Introduction

People frequently fall, especially those who are elderly. The World Health Organization (WHO) reports that 30% of seniors need medical attention after falling (Mushtaq et al., 2024). The population most vulnerable to experiencing falls includes older adults, young children and babies, people with physical or cognitive disabilities, and people working in critical environments (construction sites or any place with slippery or unstable surfaces). Especially in the elderly population, due to factors such as decreased muscle strength, loss of balance, vision problems, and chronic medical conditions that can significantly affect mobility and may accelerate their quality of life, such as wounds, fractures, fear of falling, and diminishment of physical activity, among others.

Falls can have negative consequences for both individuals and the healthcare system, including healthcare costs, health consequences, impact on quality of life, emotional and social burden, and global economic impact. Preventive measures such as improving home safety, maintaining physical activity, and reviewing medication can help reduce the risk of falls.

Monitoring Activities of Daily Living (ADL) using technologies such as accelerometers and gyroscopes can significantly enhance the detection and classification of falls in adults. These advanced technologies offer an interesting approach to healthcare by continuously tracking movements and patterns in real-time. By analyzing data from these sensors, subtle changes in motion indicative of a fall can be swiftly identified and responded to, potentially reducing the severity of injuries or medical complications resulting from falls.

The movements of the activities that an older adult performs in daily life are generally slow, and if they are associated with a type of muscular dystrophy, weakening of the joints, or even a type of degenerative disease, these can become even slower. This represents a computational challenge to be able to correctly detect and classify these movements of daily life, including the different types of falls. The above is because the change in acceleration during an adult's walk will not be very noticeable using an accelerometer or a gyroscope.

Accelerometers can detect sudden changes in the acceleration of body movement in a person, which may indicate a possible risk of falling or a fall in development. For fall detection, accelerometers record acceleration on the three axes of space (X, Y, and Z). When a person falls, the sudden downward movement, followed by an impact or sudden stop, generates a characteristic acceleration pattern that the accelerometer can detect.

A slight change in acceleration could be reflected in a negative acceleration on the Z axis, which would indicate that the person is suffering a fall. Once the person has fallen to the ground, the accelerometer records a change in the form of a spike in the accelerometer's Y-axis signal. This peak indicates the instant in which the person's body has touched the ground or has hit a nearby object. Once on the ground, the person generally remains motionless and exhibits some micromovement due to the impact of the fall. This immobility can be detected as a constant or close to zero acceleration in the three axes, depending on the body position in which the accelerometer has been left, whether it is the hand, the neck, or the abdomen.

A gyroscope measures angular velocity along one, two, or three axes (X, Y, and Z). In literature, the gyroscope is commonly used to detect abrupt alterations in the orientation angle of a device monitoring an individual's daily activities. This can indicate an unforeseen rotational motion that occurs during a fall. The gyroscope provides additional information about the orientation and direction of movement, thus complementing the acceleration information from the accelerometer. To take advantage of the advantages of both sensors (accelerometer and gyroscope), the fusion of the two sensors is proposed in this article. The above involves combining the data readings from both sensors to obtain a more precise estimate of the state of the device's movement. This fusion is proposed to detect rapid and significant changes in linear acceleration, which may indicate a fall.

The article organizes its subsequent sections as follows: Section 2 provides a brief overview of the recent existing literature. Section 3 provides a full description of the database used to detect activities of daily living (ADL) and falls. Section 4 presents two proposed models: a fuzzy logic approach and five machine learning algorithms with experimental findings. Section 5 contains the conclusions.

2 Related work

The following articles reported in the literature were examined to identify falls and Activities of daily life on elderly population: The authors (Pierleoni et al., 2015) proposes a fall detection method based on a 3-axis accelerometer, gyroscope, and magnetometer unit to detect the position of the fall. The algorithm was tested in different scenarios where volunteers experienced falls and daily exercises. By placing a portable sensor on the subject's abdomen, this device can detect falls better than other sensors proposed in the literature. The results obtained are very satisfactory in terms of accuracy, sensitivity, and specificity.

An approach based on fuzzy logic is reported by authors (Er & Tan, 2018), where falls are detected using an accelerometer and a sound sensor. To avoid misinterpretation of some activities of daily living and classify them as falls, they propose a fuzzy logic-based fall system to classify signals obtained from the accelerometer and sound sensor. This allows inferring whether the event is a fall or an ADL.

In (Webber & Rojas, 2021), a comparison of three types of data fusion collected from an accelerometer and a gyroscope is conducted to analyze human activity. This analysis was performed on four public databases using four machine learning classifiers during result validation. The reported results indicate that their fusion model outperforms some other algorithms proposed in the literature; however, the computational load is excessive during training and classification. This proposal's outcomes serve as a comparative basis for other data fusion techniques applied in human activity recognition.

This paper (Campanella et al., 2024) presents a deep learning model for edge devices with fall detection capabilities, combining a wearable sensor with a three-axis accelerometer, gyroscope, and pressure sensor. The system operates in real time, recognizing actions as routine daily activities or falls. The method achieves 99.38% accuracy.

This survey reported by (Hu et al., 2024) explores different radar-based fall detection methods. It highlights the need for precise fall definitions and detection standards. The survey provides an overview of radar signal processing principles and technology, highlighting current research gaps and potential future strategies. The survey examines 74 research articles since 2000.

The authors (Ordoñez et al., 2024) use a machine learning method to forecast human falls using accelerometer and gyroscope data. Six models were trained and evaluated, with the Random Forest waist model achieving the highest accuracy rate of 97.22% in a 5-s window.

This paper reported by (Singh & Malarvizhi, 2024) presents a novel approach to multi-class fall detection using the FallAllD dataset and machine learning technologies, demonstrating its effectiveness in practical settings. The CNN-based 5-class classifier can identify falls 99.24% of the time.

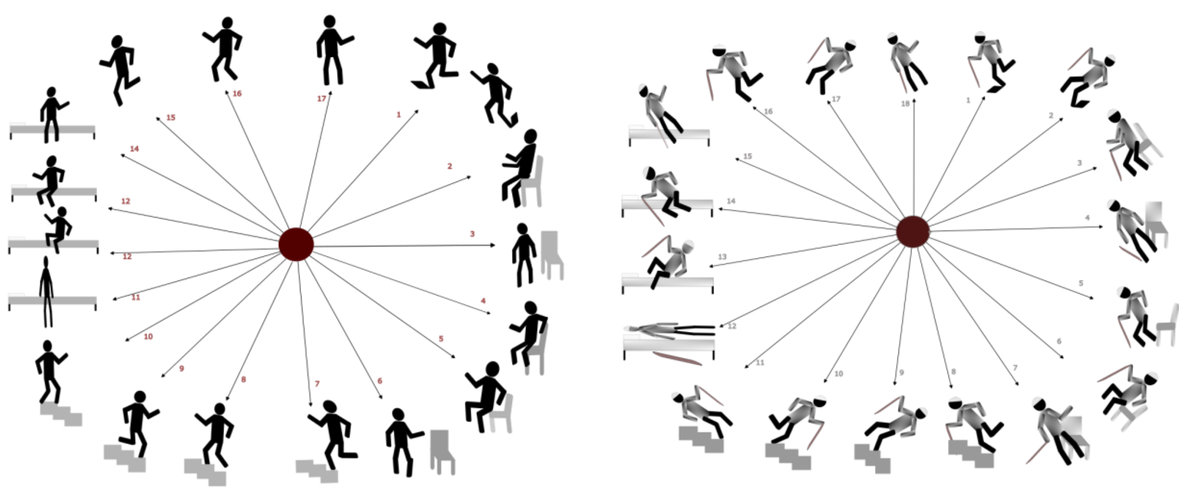
In (Wang et al., 2024) is reported a new drop location strategy for wearable frameworks uses threshold-based screening and machine learning models to address the lopsidedness between daily activities and real drop events. The strategy outperforms existing methods on open-source IMU datasets, with accuracy rates of 99.55%, 99.68%, 99.76%, and 99.52%, respectively. The key highlight extraction also reduces model execution by fourfold, demonstrating wearables' potential for high-precision drop discovery.

This paper (Purwar & Chawla, 2024) surveys papers on drop discovery frameworks (FDS) for elderly individuals from 2017-2023, focusing on wearable, non-wearable, and crossover frameworks. It highlights the importance of FDS in maintaining elderly wellbeing and explores how modern advancements like deep learning, computer vision, IoT, and big data can enhance existing systems.

This article (Tian et al, 2024) focuses on developing a low-power drop detection sensor for elderly at-risk individuals to anticipate and identify falls. The system uses a Convolutional Neural Network (CNN) and an ST Microelectronics LSM6DSOX inertial estimation unit (IMU) sensor. It is reported an accuracy of 94.5% in software and 83.5% in hardware.

3 Database

To carry out the experiments, the SisFall database was used (Sucerquia et al., 2017). This database includes 15 distinct fall types and 19 Activities of Daily Life (ADL). All ADLs, including falls, were performed by 23 young participants. This dataset was collected using a gyroscope and two accelerometers. Figure 1(a) and Figure 1(b) shows this information.



a) ADL b) Fall

Fig. 1. Database SisFall. a) Activities of Daily Living, b) Type of falls for elderly people, performed by young people.

4 Methodology

The proposed model uses a movement base available on the internet and widely referenced in the literature. Figure 2 shows the block diagram of the model.

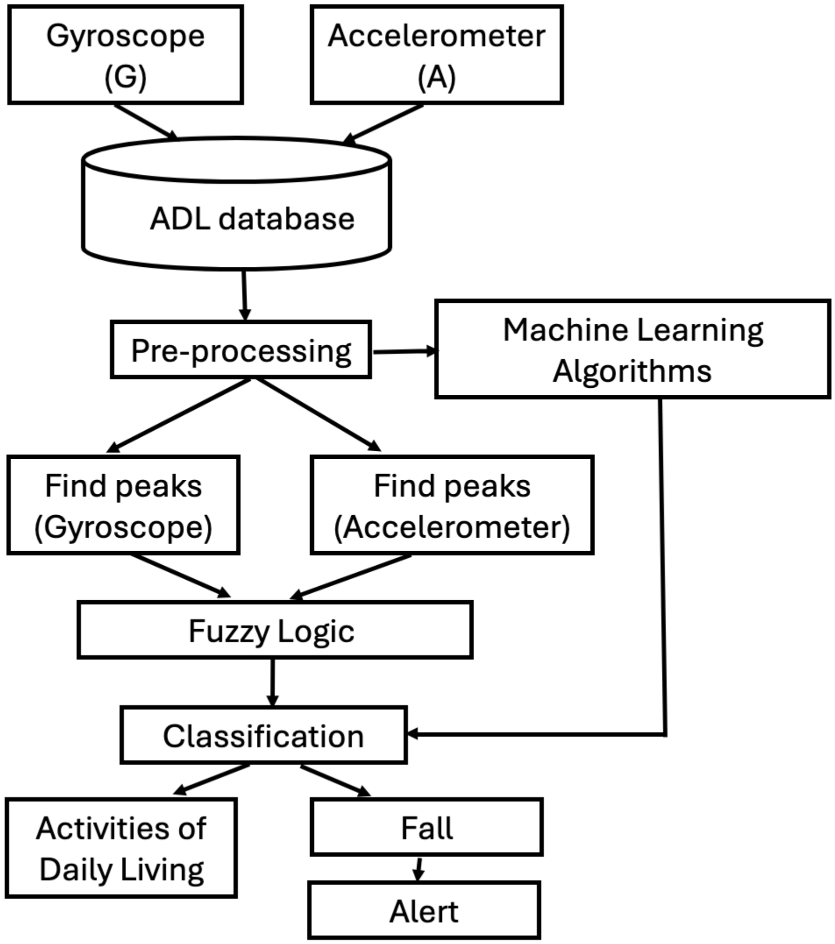


Fig. 2. Fuzzy Logic and Machine Leaning algorithms proposed for the detection and classification of falls and ADL.

Accelerometer and gyroscope magnitudes

An accelerometer is a device that quantifies linear acceleration along the three axes (*x*, *y*, and *z*). The procedure for detecting falls using readings is defined as follows:

$$a_x, a_y, a_z \quad (1)$$

The total acceleration magnitude is calculated using the Euclidean norm as follows:

$$a_{total} = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (2)$$

where: a is the acceleration in the 3 axes and a_{total} is the total magnitude of the acceleration recorded by the accelerometer. This magnitude represents the total acceleration experienced by the device in all directions to detect a possible fall or ADL.

The gyroscope's angular velocity is done in the axes: roll (left-right horizontal rotation), pitch (forward-backward rotation) and yaw (rotation around the vertical axis). Readings process to detect falls and ADL is like accelerometer:

$$\omega_x, \omega_y, \omega_z \tag{3}$$

where ω_x is the roll, ω_y is the pitch and ω_z is the yaw, respectively. The total acceleration magnitude for gyroscope is defined as follows:

$$\omega_{total} = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2} \tag{4}$$

where: ω_{total} is the sum of the 3 axes of the gyroscope over time, better known as magnitude. This magnitude represents thus, the total rotation speed measured by the gyroscope to detect an ADL or fall.

Reducing gravity component

To reduce the effects of gravity on accelerometer and gyroscope signals, the method used was to eliminate the average value of their signals. In this way, it removes the very low and very high frequencies produced by the effects of movement (Batista et al., 2010; Ohkawara et al., 2011). The above is so that a classification system does not give false positives for falls if they are movements of daily life such as sitting, going up or down stairs, or lying down. The following equations are defined for an accelerometer and gyroscope, respectively:

$$a_{grav} = a_{total} - \overline{a_{total}} \tag{5}$$

$$\omega_{grav} = \omega_{total} - \overline{\omega_{total}} \tag{6}$$

where: a_{grav} and ω_{grav} are the magnitudes of the acceleration vector of accelerometer and gyroscope, respectively. $\overline{a_{total}}$ and $\overline{\omega_{grav}}$ represent the accelerometer and gyroscope's mean magnitudes, respectively.

Pre-processing magnitudes

Normalizing the accelerometer and gyroscope readings is a good idea to ensure all magnitudes of ADL's and falls have a range of [0, 1]. This pre-processing step helps to improve the convergence speed and performance of machine learning algorithms, including fuzzy inference systems. We employ min-max normalization (Cichosz, 2022) for an accelerometer and a gyroscope as follows:

$$\Psi_a = \frac{a_{grav} - \min(a_{grav})}{\max(a_{grav}) - \min(a_{grav})} \tag{7}$$

and for gyroscope:

$$\Psi_\omega = \frac{\omega_{grav} - \min(\omega_{grav})}{\max(\omega_{grav}) - \min(\omega_{grav})} \tag{8}$$

where Ψ_a and Ψ_ω are the magnitude normalized for an accelerometer and gyroscope, respectively.

Finding peaks in accelerometer and gyroscope readings

We apply a function to identify the peaks in the normalized input signal of the accelerometer and gyroscope magnitude, yielding a vector that includes the local maxima, or peak values. To detect a peak, this function checks if the normalized magnitude exceeds the height threshold. To validate a threshold for the accelerometer or gyroscope, we verify that the magnitude signal exceeds its neighboring peaks by at least the threshold value, indicating a peak.

Spikes are generated in the order they appear as sudden changes in a person's movements. It is recommended to conduct an analysis to discover patterns and classify them based on the amplitudes of these peaks. The identified peaks signify stationary activities, a crucial feature of a peak detection algorithm for identifying falls and ALDs. If the distance between peaks occurs at regular intervals, it means that the person's walk is considered normal, otherwise, there is a possible anomaly that must be analyzed.

Generally, when a subject falls to the ground in an accelerometer, there is a high peak in their magnitude signal. It is proposed to use a threshold value of 0.995 for the accelerometer and a threshold value of 0.996 for the gyroscope, respectively, to distinguish between ADL and falls. These thresholds show that both the normalized acceleration magnitude and normalized angular velocity magnitude exceed the established values, potentially indicating a fall event; otherwise, it is an ADL. This criterion helps filter noise and reduce false positives in ADL and fall detection scenarios.

Figure 3 shows a simplified example of a fall using the magnitude normalized for an accelerometer. In this example, the signal indicates a fall while a person is walking. It also indicates the impact and maximum peak, and the normal movements preceding and after the fall.

It incorporates threshold-based peak detection into an accelerometer and gyroscope with normalized magnitudes to fuse into a fuzzy Inference System (FIS) to mitigate false positives in a fall detection system.

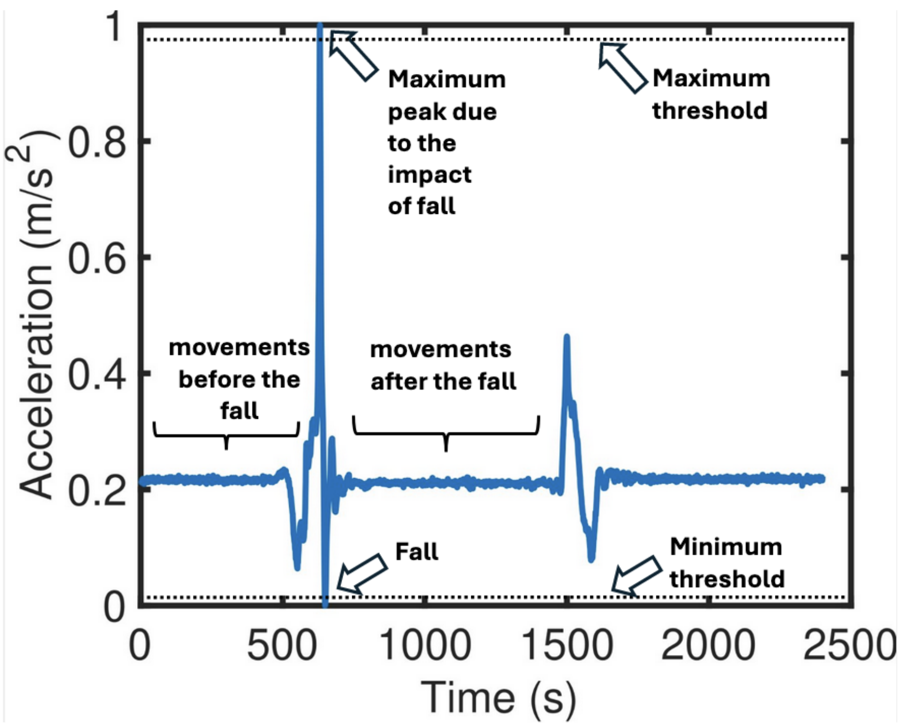


Fig. 3. Example of maximum magnitude detected of a fall.

Fuzzy Logic

The accuracy and reliability of fall detection and classification systems can be significantly improved by implementing intelligent algorithms to combine accelerometer and gyroscope readings. In this subsection, a fuzzy logic approach is defined to fuse accelerometer and gyroscope measurements. In figure 1 is shown the basic model of a fuzzy logic system.

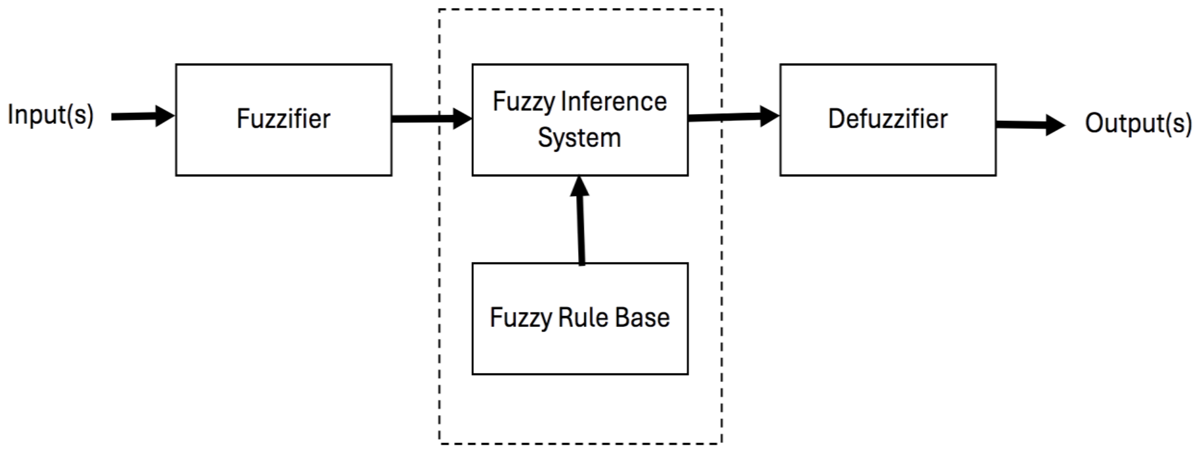


Fig. 3. Fuzzy logic architecture.

Fuzzification is the process of transforming input and output variables to calculate their membership or degree of membership in fuzzy sets (Ross, 2005; Peckol, 2021). The input variables are *accelerometer_peaks* and *gyroscope_peaks*. The output variable is *fall*. These variables are partitioned into three fuzzy sets according to the number of peaks obtained from the readings of the accelerometer and gyroscope magnitudes by using thresholds. In Figures 4 and 5, those partitions are shown.

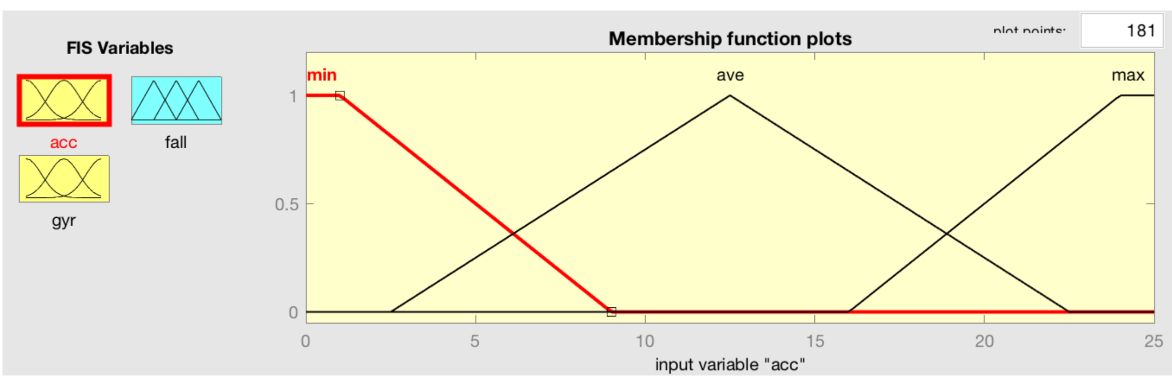


Fig. 4. Input: accelerometer_peaks.

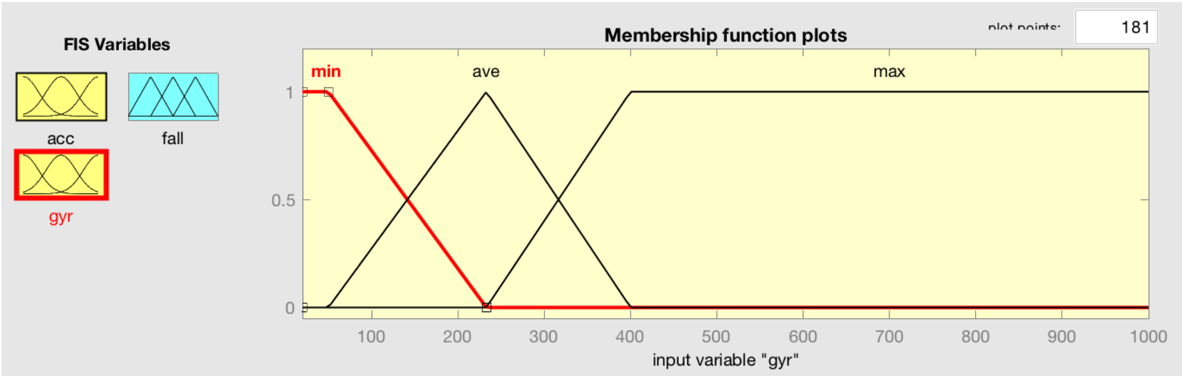


Fig. 5. Input: gyroscope_peaks.

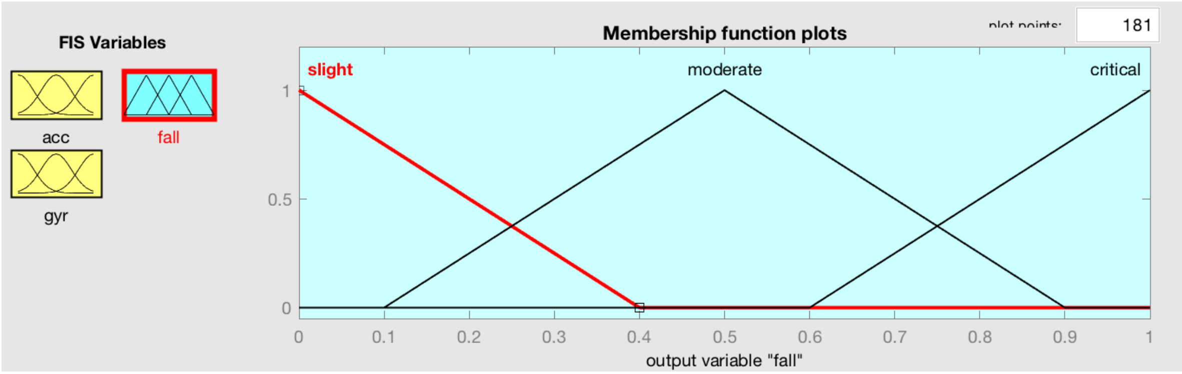


Fig. 6. Output: fall.

The core of the FIS is to define a set of fuzzy rules (IF-THEN) to identify the movements of daily life from those of a fall. The fuzzy rules are defined in Table 1:

Table 1. Fuzzy rules IF-THEN.

Number	Fuzzy rule
1	IF Peaks-Accelerometer IS Minimum AND Peaks-Gyroscope IS Minimum THEN Fall IS Slight
2	IF Peaks-Accelerometer IS Minimum AND Peaks-Gyroscope IS Medium THEN Fall IS Moderate
3	IF Peaks-accelerometer IS Minimum AND Peaks-Gyroscope IS Maximum THEN Fall IS Critical
4	IF Peaks-accelerometer IS Medium AND Peaks-Gyroscope IS Minimum THEN Fall IS Slight
5	IF Peaks-accelerometer IS Medium AND Peaks-Gyroscope IS Medium THEN Fall IS Slight
6	IF Peaks-accelerometer IS Medium AND Peaks-Gyroscope IS Maximum THEN Fall IS Moderate
7	IF Peaks-Accelerometer IS High AND Peaks-Gyroscope IS Minimal THEN Fall IS Slight
8	IF Peaks-Accelerometer IS High AND Peaks-Gyroscope IS Medium THEN Fall IS Slight
9	IF Peaks-Accelerometer IS High AND Peaks-Gyroscope IS Maximum THEN Fall is Slight

Machine Learning Algorithms

In this work, we propose five well-known machine learning algorithms (C4.5, Logistic Regression, Random Forest, C4.5, MLP, and SVM) that are trained, tested, and validated on labeled accelerometer and gyroscope data to distinguish falls from ADL's. The following is a description of the five chosen ML classifiers.

Logistic Regression

Logistic regression is a well-known classification technique that uses a regression technique internally. First, compute a measure that is closely associated with the probability of each target class, and then it must identify the example that belongs to the class with the highest probability (Fenner, 2019).

C4.5

C4.5 is a decision tree classifier widely used in ML algorithms for fall detection (Lee & Tseng, 2019; Ramachandran & Karuppiah, 2020; Badgujar & Pillai, 2020; Rastogi & Singh, 2021, Rashid, et al., 2021; Wang et al., 2024).

Random Forest

Both classification and regression tasks frequently use the Random Forest technique, a type of supervised learning method, for fall detection (Rastogi & Singh, 2021, Alizadeh, et al., 2021; Zermane et al., 2023; Kausar et al., 2023; Wang et al., 2024, Jain et al., 2024). It consists mainly of decision trees classified based on features, which use ensemble learning to solve complex problems and improve model performance.

Multi-Layer Perceptron

A multi-layer perceptron (MLP) is a type of supervised neural network that has input, hidden, and output layers of fully interconnected neurons. The learning process of an MLP is generally completed in two stages, a feed-forward pass and a feed-backward pass (Cartwright, 2021). Several works have used MLP to classify falls (Kerdegari et al., 2013; Kausar et al., 2023; Urresty Sanchez, 2024).

Support Vector Machine

A robust classifier that converts the original data into a new high-dimensional space is the Support Vector Machine (SVM). The Support Vector Machine (SVM). This mapping is typically accomplished by a kernel (Fenner, 2019). It is extensively employed to identify falls (Charfi et al., 2012; Rashid, et al., 2021; Badgujar & Pillai, 2020; Alizadeh, et al., 2021; Jain et al., 2024).

Model preparation using Machine Learning algorithms

First, we load the Sisfall dataset and apply all pre-processing steps to obtain the normalized magnitudes for the accelerometer and gyroscope. After that, it organizes the data according to its features (X) and labels (Y), respectively. X collects the magnitudes from the accelerometer and gyroscope. In Y, there are two classes labeled as falls and ADL. Next, we apply a training test split function to divide the dataset into training (80%) and testing (20%) sets. The system employs five machine learning algorithms, and subsequently assesses the predictions by calculating the model's accuracy score.

5 Results

Normal activities like walking or sitting involve repetitive and predictable movements. The accelerometer magnitude during these activities typically shows peaks at low frequencies due to the rhythmic nature of walking or the constant acceleration during sitting. However, a fall can cause sudden changes in the accelerometer's magnitude. The accelerometer measures a rapid change in acceleration magnitude, leading to significant high-frequency peaks. The most common method to detect falls, or ADL, is to set a threshold for which peaks are considered relevant and indicative of a fall or ADL.

Figures 7 and 8 display the data obtained from the accelerometer and gyroscope. A fall occurs when a person experiences one. The accelerometer records a change in the *x*, *y*, and *z* axes. In contrast, in the gyroscope, the axis that has recorded this fall is the *x* axis.

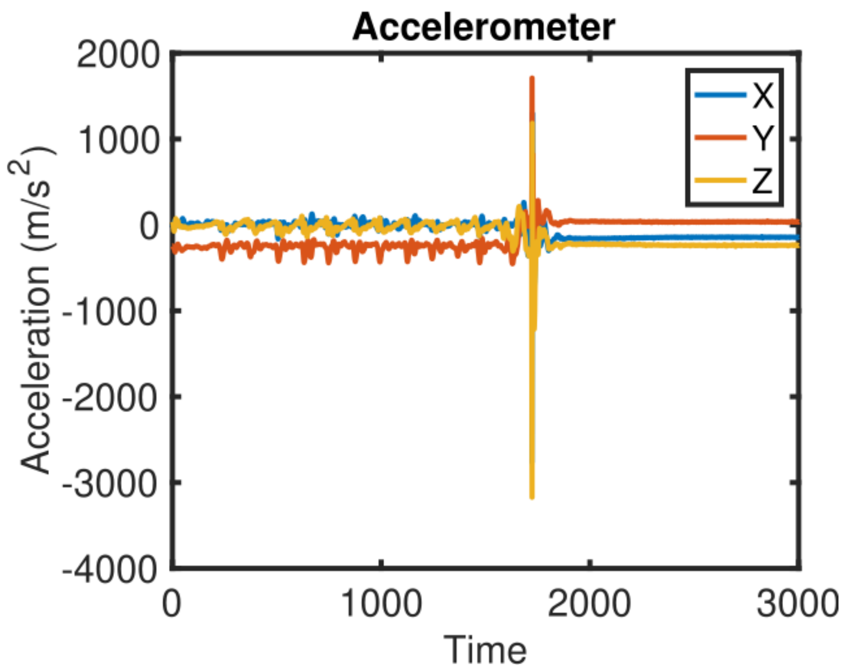


Fig. 7. Linear acceleration velocity in the X, Y, and Z axes of the fall of an adult person using the accelerometer.

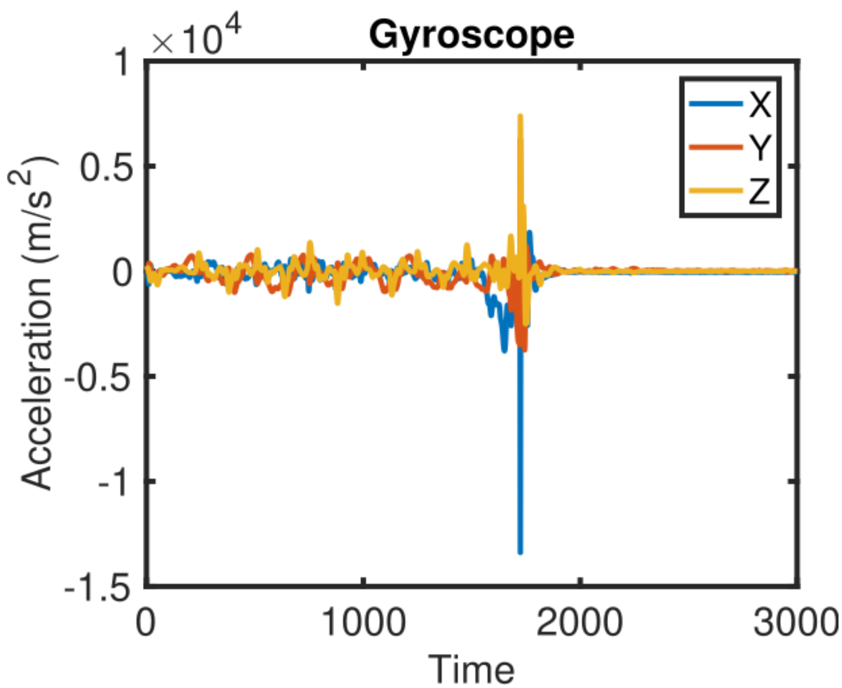


Fig. 8. Linear acceleration velocity in the X, Y, and Z axes of the fall of an adult person using the gyroscope.

We pre-process the acceleration data through the *x*, *y*, and *z* axes to obtain their magnitude; we then remove and normalize their gravity. Figures 9 and 10 illustrate this process for the accelerometer and gyroscope, respectively. Finally, we find the peaks in the magnitudes of the accelerometer and gyroscope to distinguish between a daily activity and a fall.

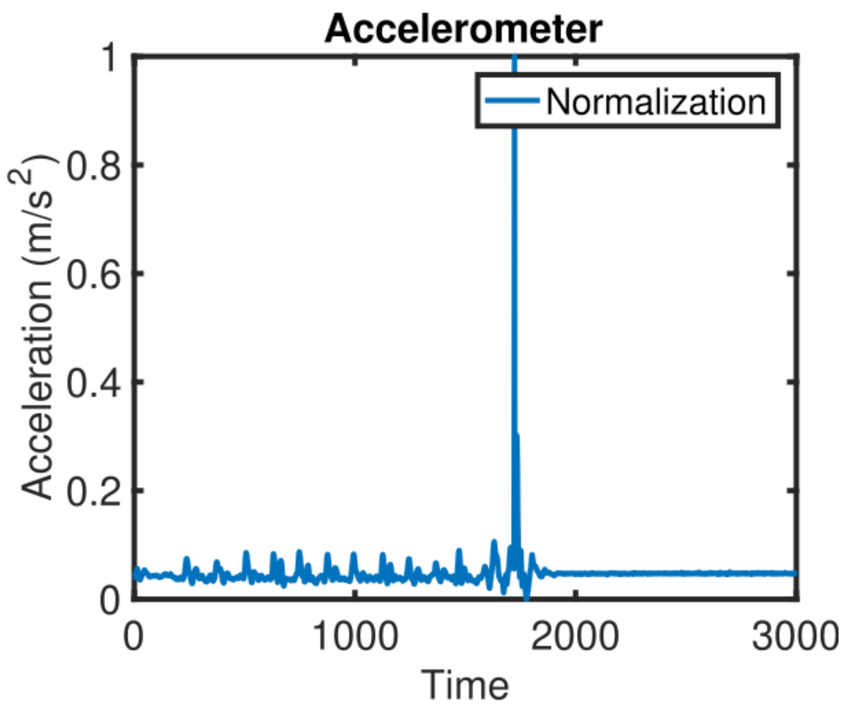


Fig. 9. Normalization min-max of magnitude for accelerometer.

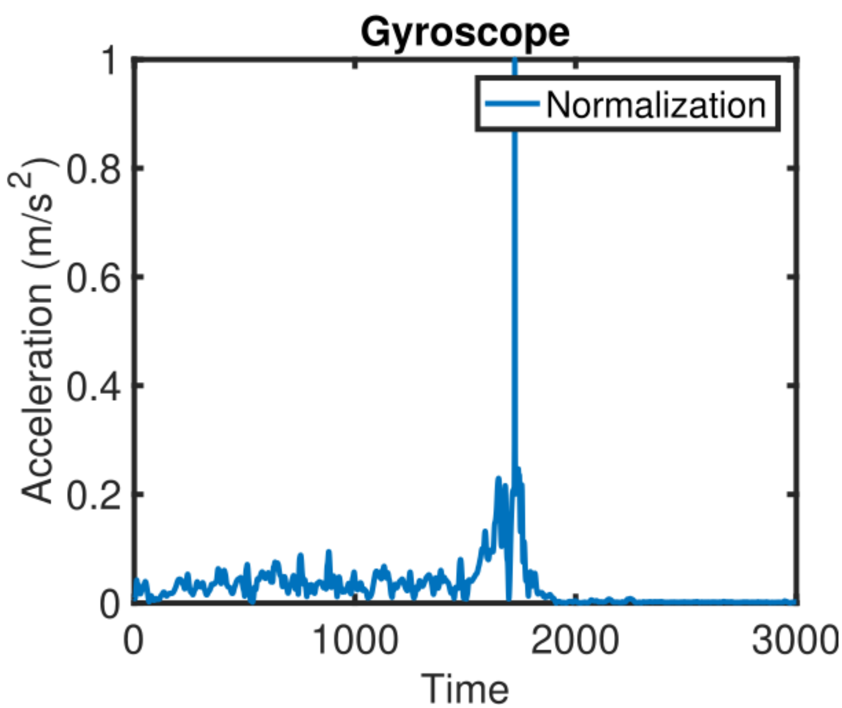


Fig. 10. Normalization min-max of magnitude for gyroscope.

To distinguish between falls and ADLs, we proceeded to analyze the peaks, and we found that a fall typically shows a sharp peak followed by a sudden decrease in acceleration. Figure 11 shows the peak detection when an elderly person falls against the ground.

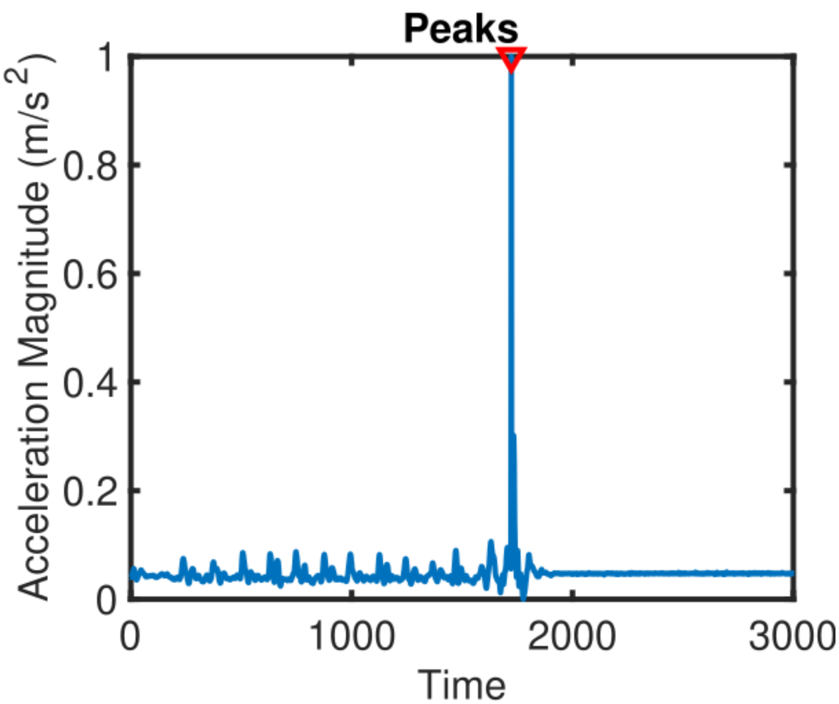


Fig. 11. Peak detection of a fall using the accelerometer.

On the other hand, the gyroscope graph more clearly shows a sharp spike in the normalized magnitude, followed by a rapid decrease in acceleration. The gyroscope registers these slight movements in the low frequencies of the signal, indicating that the person has unfortunately fallen to the ground and is attempting to get up. The gyroscope correctly discriminates a fall from an ADL based on the repetitive body movements at these low frequencies. (see Figure 12).

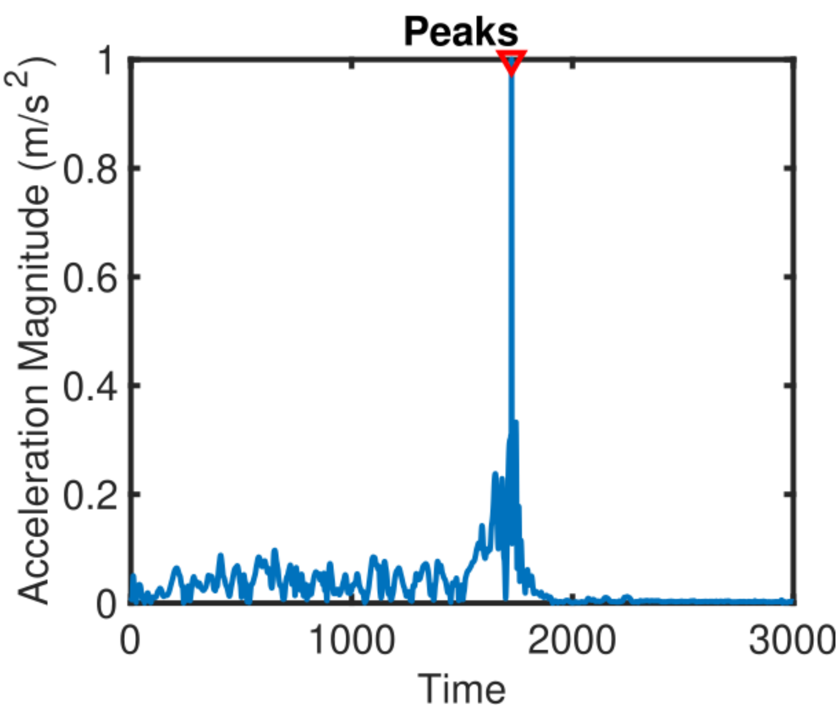


Fig. 12. Peak detection of a fall using the gyroscope.

Once the accelerometer's normalized magnitude detects a peak that exceeds the fall detection threshold, we analyze the gyroscope's normalized magnitude. When a gyroscope peak exceeds the fall detection threshold, it inverts its normalized magnitude. The next step involves analyzing the peaks of this inverted signal. This step is significant because it reveals several peaks near the gyroscope-defined threshold, indicating a possible fall. The above indicates the micromovements that the person makes when impacting the ground or a nearby object. Spikes typically display sudden changes in a short period of time. Figure 13 illustrates this procedure by detecting a fall using an accelerometer. We obtain 5 peaks from the accelerometer device.

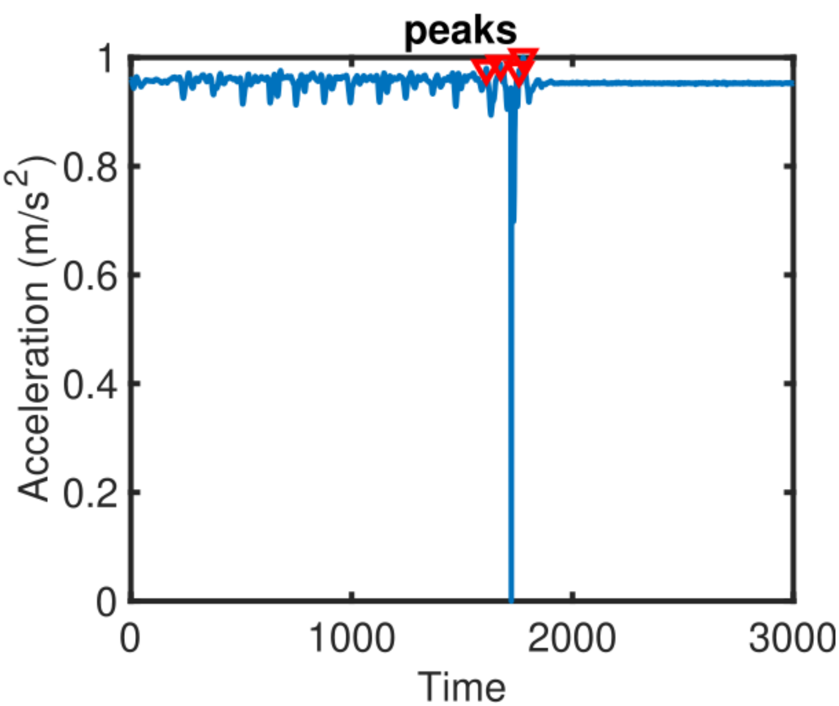


Fig. 13. Peak detection of a fall using the gyroscope.

The peaks of a fall involve a specific sequence of events: the rapid deceleration of the person's fall, followed by impact. Following these sudden changes in inverted magnitude, the gyroscope observes a series of rapid movements, identifying 185 peaks after the fall. Figure 14 shows the detection of peaks detected by the gyroscope.

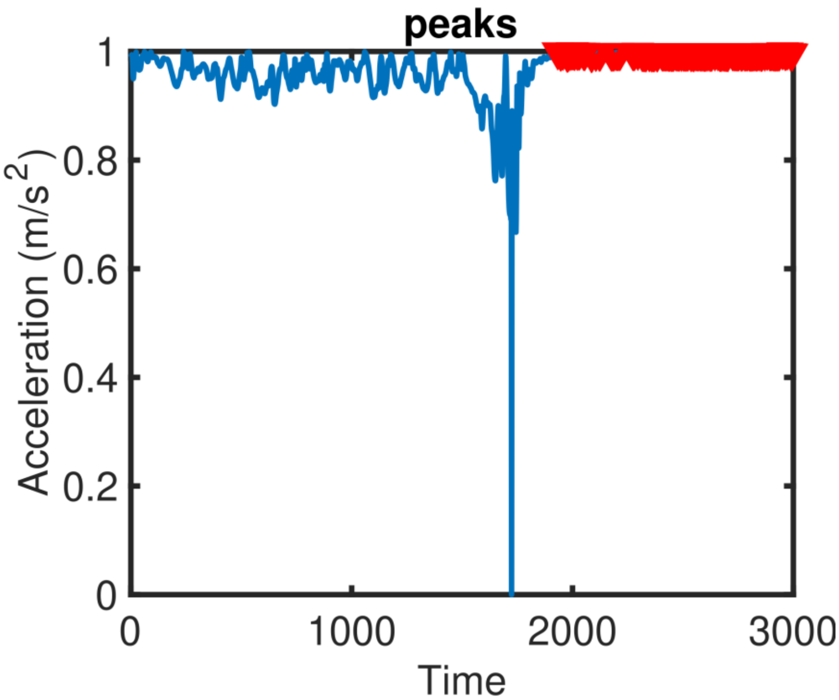


Fig. 14. Fall detection using inverse of the normalized magnitude.

The fuzzy inference system receives both accelerometer and gyroscope peak numbers, activating the following rule: IF Peaks-accelerometer IS Minimum AND Peaks-Gyroscope IS Maximum THEN Fall IS Critical. This fusion enhances the reliability of a fall detection system when using fuzzy logic. We tested and compared our models using four criteria: sensitivity, specificity, precision, and F1 score (Tharwat, 2021). These were Fuzzy Logic type-I and ML algorithms on the Sisfall dataset for falls and ADL.

In Figure 15 is show the metrics of classification using a Random Forest algorithm proposed to classify ADL and falls. The algorithm demonstrates a 96% performance.

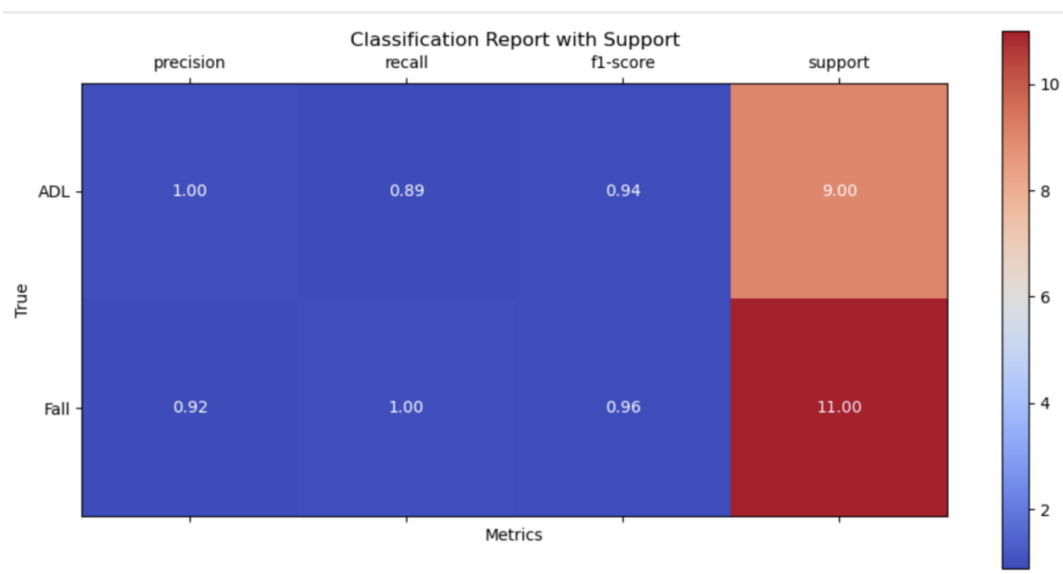


Fig. 15. Metrics of classification of falls using a Random Forest Algorithm.

Figure 16 shows the classification metrics using a proposed MLP algorithm to classify ADL and falls. The algorithm achieves 95% performance. MLP used a 98x100x2 topology, which was defined as 5000 iterations.

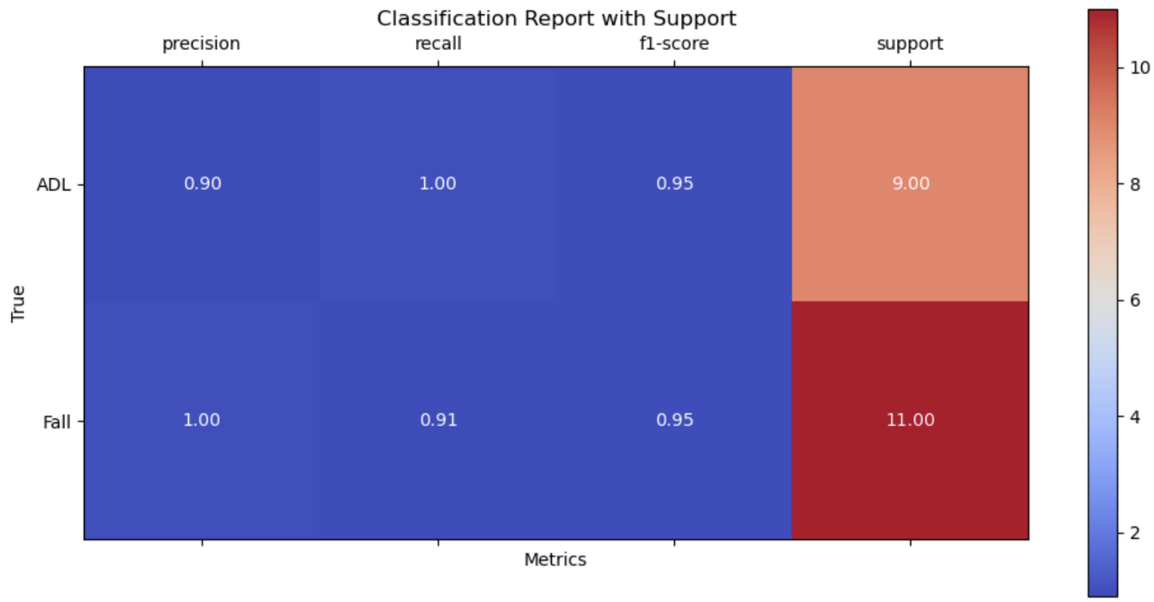


Fig. 16. Metrics of classification of falls using a MLP Algorithm.

Figure 17 shows the metrics of classification using a DT algorithm proposed to classify ADL and falls. The algorithm performs with a 95% accuracy rate.

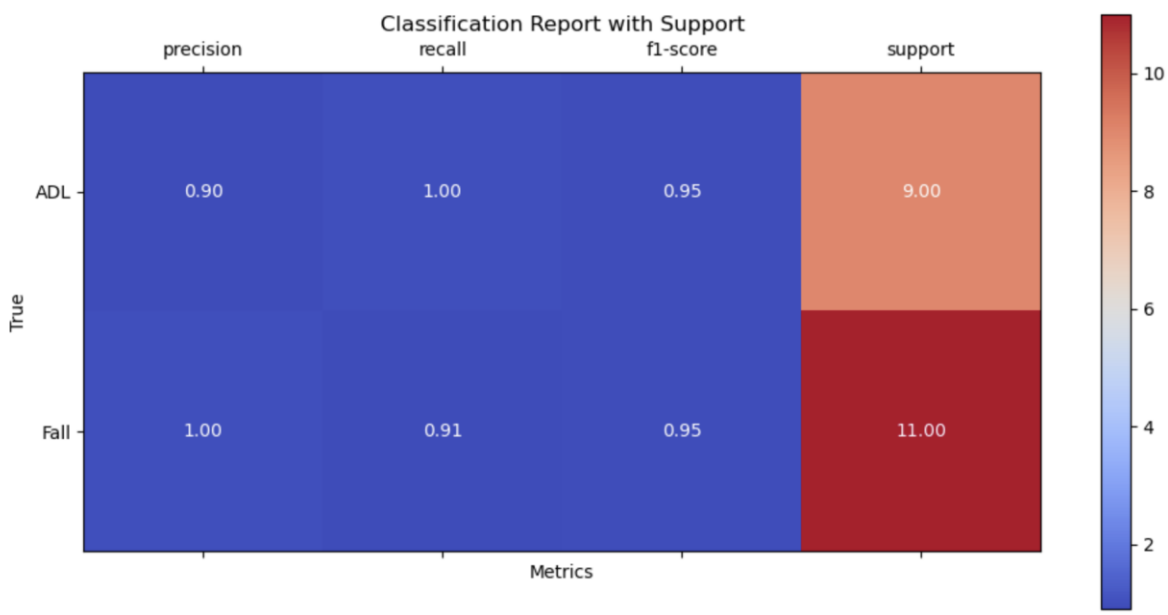


Fig. 17. Metrics of classification of falls using a DT Algorithm.

Figure 18 shows the classification metrics using a proposed LR algorithm to classify ADL and falls. We observe that this algorithm performs at a 96% efficiency.

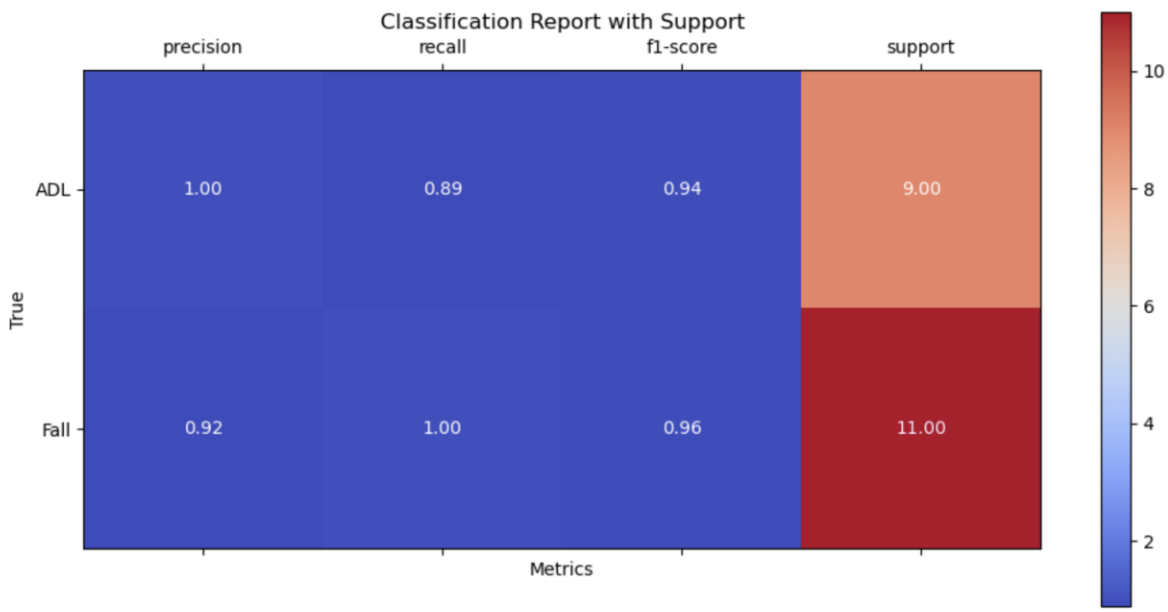


Fig. 18. Metrics of classification of falls using a LR Algorithm.

Figure 19 shows the classification metrics using a proposed SVM algorithm to classify ADL and falls. It is observed that this algorithm performs at 92%. We used a linear kernel for SVM.

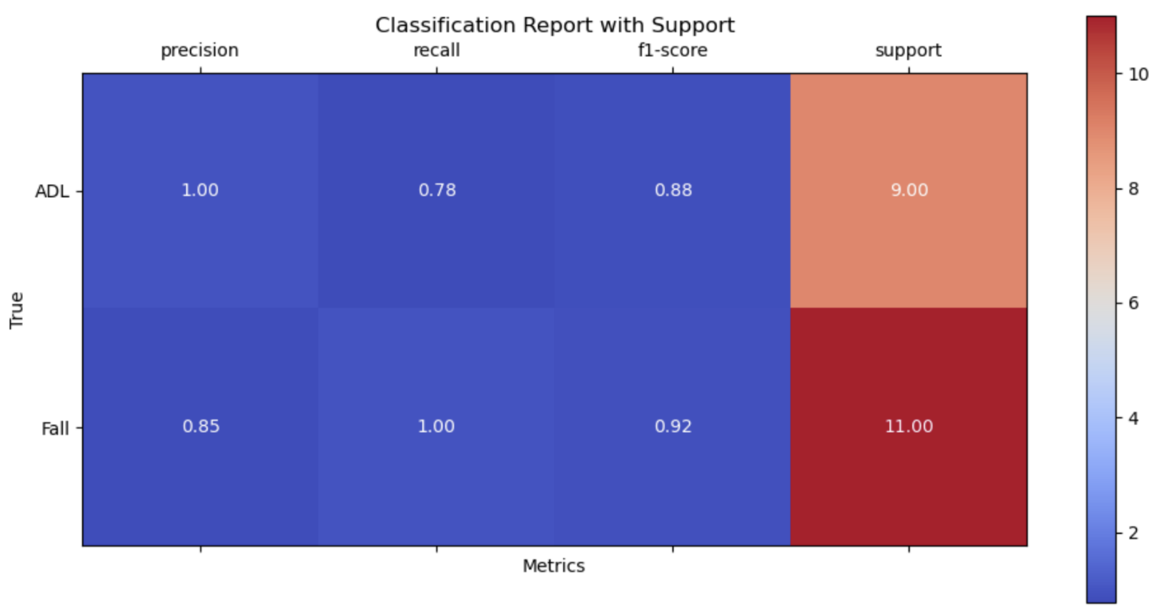


Fig. 19. Metrics of classification of falls using a SVM Algorithm.

The results of the fuzzy logic type-I model, and five machine learning algorithms are shown in Table 2. There is also a comparison with other similar methods found in the literature that use accelerometer and gyroscope readings as a starting point. We conducted the comparison only with methodologies that employ the same evaluation metrics. In certain cases, only a portion of the evaluation metrics receive reporting. For those who have not reported, a double dash appears in the table. The best result for each metric appears in bold

Table 2. Fuzzy rules IF-THEN.

Algorithm	Sensitivity	Specificity	Precision	F1-score
ML (Saaed et al., 2021)	--	--	--	95.91%
Optimization (Huynh et al., 2015)	96.30%	96.20%	--	--
Threshold-based (Rahkman et al., 2014)	--	--	--	93.33%
SVM, ANN (Fula & Moreno, 2024)	90.57	--	--	--
Transformed-based (Yhdego et al, 2023)	--	--	--	96.00%
LSTM-based (Yhdego et al, 2023)	--	--	--	97.00%
Threshold-based (Ushman et al, 2023)	90.00%	85.00%	87.50%	--
Vision (Wang & Deng, 2024)	90.30%	89.66%	89.73%	90.02%
Clustering-EGG (Al Dujaili et al., 2024)	--	--	--	97.10%
SVM (Badgujar & Pillai, 2020)	--	--	84.17%	--
Decision Tree (Badgujar & Pillai, 2024)	--	--	95.87%	--
Threshold-based (Rahkman et al., 2014)	--	--	--	93.33%
Decision Tree (Rashid et al., 2021)	--	--	96.00%	--
Fusion method (Wang et al., 2024)	99.62%	98.81%	99.55%	--
SVM (Alizadeh et al., 2021)	99.00%	87.00%	93.00%	--
MLP (Urresty Sanchez, 2024)	98.10%	98.10%	98.10%	--
Our model with Fuzzy Logic	94.94%	**100%**	96.92%	**97.40%**
Our model with DT	91.00%	**100%**	**100%**	95.00%
Our model with SVM	**100%**	78.00%	85.00%	92.00%
Our model with MLP	91.00%	**100%**	**100%**	95.00%
Our model with Random Forest	**100%**	89.00%	92.00%	96.00%
Our model with RL	**100%**	89.00%	92.00%	96.00%

The fuzzy logic type-I approach performed the best, with an F1-score of 97.40%. These results are very superior to other methods, such as those that include thresholds, machine learning algorithms, neural networks, and clustering techniques, among others. In contrast, our machine-learning algorithms proposed to detect and classify falls and ADLs are very competitive with other similar approaches.

4 Conclusions

In this work, we enhance the detection and classification of ADLs and falls, utilizing integrated data from an accelerometer and a gyroscope.

Machine learning algorithms require special attention, particularly in the validation process. To guarantee an algorithm's performance in future work, validation techniques such as 10-fold cross validation or leave-one-out cross validation are required. While the evaluation of the models may lead to significant changes in the percentages, they mitigate the risk of overfitting and enhance the reliability of the classification rates. The algorithms would require more execution time to yield results, but the estimation would be more robust. Another aspect to consider in the future would be to merge the data obtained from the accelerometer and the gyroscope and train them in deep-learning models with cross-validation methods such as 10-fold cross-validation or the 0.632 bootstrap technique.

To improve the classification of ADL's and falls, we propose to divide the accelerometer and gyroscope's spectral data into smaller segments of time for further analysis. To validate our model for fall detection, we will use diverse datasets that include a variety of falls and ADLs. This will help to ensure that our model performs well across different scenarios and individuals.

Future works will design a self-created base for everyday movements and falls. We are considering two scenarios: indoor and outdoor daily living activities. We plan to recreate the falls with the help of young people practicing gymnastics. We will design a device that fuses the signals of an accelerometer, a gyroscope, and a magnetometer to send signals through a cell phone or a sound sensor, thereby activating alerts.

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