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Wireless Body Area Networks: A Promising Technology for Fall Detection – A Review

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Abstract—Falling is a major risk factor for the senior population, who may suffer significant injuries, loss of independence, or even death. Various fall detection devices, including wearable and environment-based sensors that employ IoT and AI to detect falls and monitor everyday activities, have been created to solve this issue. However, the utilization of cutting-edge AI methods like machine and deep learning models and the availability of high- quality data are both necessary for these systems to function effectively. Recent research has demonstrated that CNN-based models are the most accurate in detecting falls, but it is still necessary to construct lightweight deep models for older people. Overall, there is potential for intelligent IoT-enabled fall detection and monitoring systems to improve the safety and well-being of the elderly population.

Index Terms—Internet of Things (IoT), Artificial Intelligence (AI), Activities of daily living (ADL), Realtime assistance, Ma- chine learnings

I. INTRODUCTION

By gathering data [19], [24] from IoT sensors like accelerometers, gyroscopes, and barometers and using machine learning algorithms to analyses the data, fall detection systems can distinguish between falls and non-falls. For real-time fall detection and alerting, this entails developing a model utilizing a dataset of fall-related and non-fall actions and putting the model on a device, such a wristwatch.

To give a comprehensive evaluation of the state of fall detection technologies as shown in Fig 1, this review article looks at recent studies on sensor-based systems, machine learning-based systems, and smartphone-based systems. Along with recommendations for more research to increase the effectiveness and uptake of these technologies, the difficulties associated with creating and putting fall detection systems into use will also be covered. The remaining part of the paper is structured as follows. The related work is described in Section II. Comparative analysis is included in Section III. At last, Part IV concludes the work.

II. RELATED WORK

The goal of the [7] paper was to create accelerometer- based predictive models of older women's fall risk. Using accelerometers for a week to gather data from 44 older women, followed by a year of fall monitoring, was the methodology used in this work. Using machine learning techniques, the gathered data was used to create models for predicting the likelihood of falling. In this paper, accelerometer data was found to be helpful in forecasting the likelihood that older women may fall, and machine learning models demonstrated strong predictive accuracy. The work does, however, have a number of limitations, including a small sample size, a brief follow-up time, and a lack of diversity in the sample group, which may have an impact on how broadly applicable the results are. The work also didn't look into whether the suggested models could be used in actual-world situations.

The work [8] showed how combined sensors and energy devices could be used to create a wearable fall detector. To detect and analyze fall incidents, the process included creating a wearable device including accelerometers, gyroscopes, and a battery. On healthy young test subjects, the device's performance was assessed considering its specificity and sensitivity for detecting falls. The research revealed that the created device has a high sensitivity and specificity for effectively detecting falls. The work does have some drawbacks, though, such as the use of a small sample number of healthy young volunteers, who might not accurately represent the fall patterns and traits of older adults. The work also didn't look at the device's viability in real-world situations, and it didn't deal with the issue of false alarms or privacy issues related to the usage of wearable fall detectors.

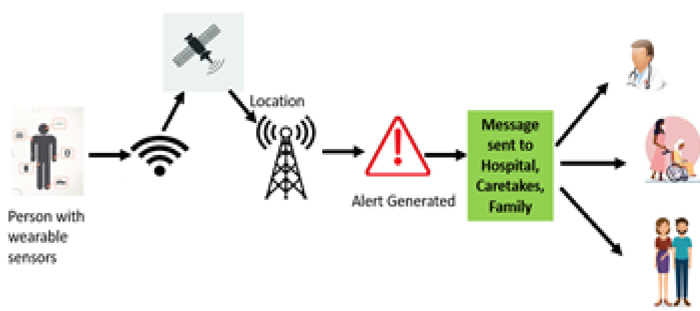

Fig. 1. Block diagram for ML-based fall detection

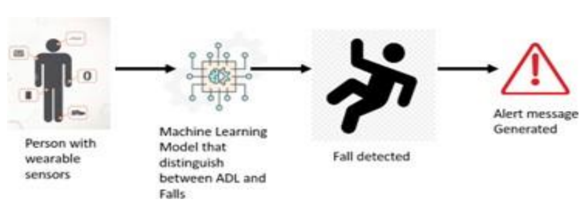

Fig. 2. Block Diagram of Fall detection usingIoT

The purpose of paper [10] was to create a fall detection system that made use of wearable sensors and machine learning methods. Utilizing accelerometers and gyroscopes put on their wrists, waists, and ankles while engaging in various daily activities, including falls, nine healthy volunteers' data were gathered utilizing this technology. The development and evaluation of fall detection models using machine learning methods was then done utilizing the gathered data. The study discovered that the created fall detection models had low false positive rates and a high degree of fall detection accuracy.

The [12] paper described the creation of a sophisticated sensor system for identifying falls in senior citizens. The approach entailed creating a smart sensor that may be worn by senior citizens or put in their houses using a mix of accelerometers, pressure sensors, and infrared sensors. A rule- based algorithm was used to analyze the sensor data in order to find falls. The paper discovered that the created smart sensor system had a low rate of false positives while achieving excellent accuracy in detecting falls.

An improved fall detection system for monitoring older people using consumer home networks is presented in this [13] article. The suggested system detects and reports falls in real-time by combining ZigBee-based wireless sensors, a Raspberry Pi, and a cloud-based server. The system uses a variety of methods to identify falls and differentiate them from other daily activities, such as the wavelet transform, principal component analysis, and k-nearest neighbor. The effectiveness of the system was assessed using information gathered from actual tests, and the results displayed that the suggested technique had a high degree of precision and sensitivity in detecting falls. The work's drawbacks, which could have an impact on how well the system performs in actual situations, include the work's small sample size and lack of population variety.

A one-class classifier outlier removal method and skeletal feature-based fall detection system utilizing Microsoft Kinect v2 were proposed in the [14] work by Seredin et al. (2019). The suggested technique uses a one-class classifier to detect fall occurrences while extracting characteristics from the skele- ton data provided by Kinect. This work's shortcoming is that the suggested method can only be used to find falls that happen in a certain setting. The authors argue that additional research is required to confirm the proposed technique in additional settings and demographics.

The author of [15] looked on wearable fall detection sys- tems' usage of gyroscope measurements. The methodology involves using accelerometers and gyroscopes installed on healthy individuals' wrists, waists, and ankles to collect data as they engaged in various daily activities, including falls. The effectiveness of employing gyroscope measures alone or in combination with accelerometer measurements in detecting falls was then examined using the data that had been gathered. According to the study, adding gyroscope data to wearable fall detection systems increased their accuracy and dependability, particularly when it came to identifying slow falls and head impacts.

The author of [16] suggested system based on body area network (BAN). The approach involved creating a BAN-based system that can detect falls by mounting accelerometers and gyroscopes on various body areas. The system's performance was assessed in terms of sensitivity and specificity for detecting falls on a set of healthy test subjects. The study discovered that the created system had a low rate of false positives while achieving excellent accuracy in detecting falls. The work looked into how the number and placement of sensors affected the efficiency of fall detection.

The work [19] by Boutellaa et al. suggests a fall detection system based on covariance matrix analysis that utilizes many wearable sensors. Tri-axial gyroscopes and accelerometers that are fastened to the waist, chest, and ankle are used in the work to gather data. To extract features like the mean, standard deviation, and covariance matrix, the data is processed and examined. Then, based on these features, a machine learning algorithm is employed to categorize falls and non-falls. With an overall accuracy of 97.40% and a sensitivity of 96.70%, the work asserts to have achieved great accuracy in fall detection. The work's main drawback is that it used a small sample size—just ten people—and hence might not be entirely representative of the population as a whole.

The paper [20] describe the creation of a wearable sensor- based fall detection system. In order to distinguish falls from other activities, the system uses a mix of accelerometer and gyroscope sensors to detect falls. The wearable gadget, which can be worn around the waist, incorporates the sensors. Simulated autumn trials and in-person testing on senior citizens are used to evaluate the system. The outcomes demonstrate the system's high degree of fall detection accuracy and its potential for use in the real world. The paper does, however, have certain drawbacks, such as a small sample size and insufficient testing in outside settings.

A novel hierarchical fall detection technique using a multiphase fall model is proposed in the paper [21] by Hsieh et al. By categorizing falls into distinct phases and using various strategies for each phase, the proposed algorithm leverages a hierarchical framework to increase the accuracy of fall detection. The program can accurately detect falls with a high level of sensitivity and specificity using just one wearable accelerometer sensor. The weakness of this paper is that it is based on simulations rather than actual data, which may limit its usefulness in actual circumstances.

The paper [22] suggested integrating IoT and deep learning technology to create a human fall detection system as shown in Fig 2. The method entailed gathering data from sensors mounted on the human body, such as accelerometers and gyroscopes, and sending it via IoT to a cloud-based server. Convolutional neural networks (CNNs) as well as long short-term memory (LSTM) networks were specifically used in the processing and analysis of the data to identify falls. The system's evaluation was based on a dataset comprising both falling and non-falling actions, measured by accuracy, sensitivity, and specificity metrics. According to the paper, the suggested system detected falls with a high degree of accuracy and few false positives. The use of a tiny dataset and the absence of real-world testing are two of the paper's many drawbacks.

The paper [24] suggested an IoT and big data-based system. The method entailed gathering information from wearable sensors, including accelerometers and gyroscopes, and sending it through the Internet of Things to a cloud server. To find falls, the data was then examined using big data techniques like data mining and machine learning. Using a dataset of fall and non- fall behaviors, the system's performance was assessed in terms of accuracy and sensitivity in identifying falls. According to the paper, the suggested system detected falls with a high degree of accuracy and few false positives. The paper does have some drawbacks, though, such as the necessity for wearing sensors that can be uncomfortable for the user and possible privacy issues with IoT-based fall detection systems. The possible drawbacks of adopting big data approaches for fall detection were not discussed, nor were the costs and practicalities of putting the proposed system into practice in real-world settings examined.

In the research paper [25], a fall detection technique is presented that makes use of CNN (Convolutional Neural Net- work) and IR-UWB (Impulse Radio Ultra-Wideband) sensors. The suggested technique entails employing IR-UWB sensors that are attached to the body to gather data and developing a CNN model to divide the sensor data into groups for fall and non-fall. The trained model is then applied to real-time fall detection. The efficiency of the suggested strategy is assessed by tests carried out on a dataset made up of actual falls and everyday living activities.

The paper [26] suggested a fall detection system that uses kinematic and melcepstrum-related parameters and data from infrared depth sensors. In order to identify falls, the process entailed gathering information from infrared depth sensors, which recorded people's movements and extracting kinematic and melcepstrum-related properties. Machine learning techniques like decision trees, random forests, and support vector machines were applied to categorize the extracted attributes. Using a dataset of fall and non-fall behaviors, the system's performance was assessed in terms of accuracy and sensitivity in identifying falls. According to the paper, the random forest algorithm performed best and the proposed system achieved high accuracy in detecting falls with few false positives. The paper is constrained by a number of factors, including the requirement for specialized tools like infrared depth sensors and potential privacy issues related to their use. Additionally, the possible drawbacks of utilizing machine learning techniques for fall detection were not discussed, nor were the cost and feasibility of putting the proposed system into practice in real- world.[33-38]

A unique fall detection system based on twin pressure sen- sors was suggested by the [28] paper. It can monitor patients and notify carers in real-time. The technology, which consists of two pressure sensors connected to a floor mat, monitors pressure changes brought on by falls and uses Bluetooth to send an alarm to the caregiver's smartphone. Through studies with volunteers simulating falls, including lateral, forward, and backward falls, the paper assessed the system's performance. We calculated and compared the system's sensitivity, specificity, and accuracy to those of other fall detection systems. The findings demonstrated that the suggested system had good sensitivity and specificity, and that it performed on par with previous fall detection systems. The paper's shortcoming is that an alert must be activated by the user falling on the pressure sensors, which may not be appropriate for all falls.

An article by [29] Bourke and Lyons propose a threshold- based technique for fall detection using a bi-axial gyroscope sensor. While participants engaged in various actions, such as walking, sitting, standing, and falling, data was collected from the sensors they were wearing for the paper. The threshold- based method was developed and put to the test using the data gathered. The algorithm's accuracy and specificity for detecting falls were 94% and 98%, respectively. The paper did not take into account the influence of different fall types or the impact of sensor placement on the accuracy of the algorithm because it was only able to analyze a small sample size of 10 healthy young individuals.

The accelerometer and gyroscope, two in-built sensors included in smartphones, are used in this [30] paper. The program initially collects features from sensor data before applying machine learning to categorize them as fall or non- fall. Using data gathered from simulated falls, the system's performance was assessed, and it was discovered to have a high accuracy rate. The necessity of wearing the smartphone on one's person, the potential for false alerts, and the system's constrained range as a result of Bluetooth technology used to connect to a remote server are all drawbacks of the system, according to the authors.

An accelerometer-based fall detection system for cellphones is presented in this [31] paper. The technology analyses accelerometer data from the smartphone to find falls using a machine learning technique. The system is tested on a dataset of actual falls and activities after the algorithm has been trained using a dataset of simulated falls and real-world activities. The findings demonstrate the system's high fall detection accuracy and low false positive rate. However, the system needs the smartphone to be worn in a precise position and may not function effectively if the user is holding the phone or if the smartphone is not worn properly.

In this [32] paper, a straightforward technique for detecting falls using a smartphone's accelerometer is proposed. The technique involves identifying a big and abrupt change in the accelerometer data, which suggests a potential fall occurrence. After that, the system looks for a period of inactivity, which could indicate that the user hasn't recovered from the fall. An alarm is set off to notify carers or emergency services if this requirement is satisfied. The system was put to the test on a smartphone by the authors, who then assessed how well it performed using both simulated falls and actual falls by healthy participants. The findings demonstrated that the algorithm produced few false positives while achieving a high detection rate. The algorithm does, however, have several drawbacks, such as its reliance on the accuracy of the accelerometer data and the requirement that the phone be carried in a particular way for optimum performance.

III. COMPARATIVE ANALYSIS OF THE EXISTING LITERATURE

This comparison analysis's objective is to evaluate and contrast several fall detection system varieties based on specified parameters. These parameters include the number of sensors used, whether they are wearable or not, the kind of sensors used, the methods of detection used, the real-time monitoring and response abilities, the accuracy of identifying falls, sensitivity of identifying falls, and specificity of identifying activities of daily living (ADLs) which are not associated with falls as shown in Table1. This paper will shed light on the benefits and drawbacks of various fall detection systems by analysis and comparison of their performance. It will also assist in determining which fall detection method is most suited to a certain situation.

This table provides an overview of all the devices and techniques employed in the field of preventing and detecting falls in older people. Internet of Things (IoT) devices, Wearable sensors and machine learning methods are all covered in the study. Fall detection systems' primary goal is to promptly identify falls and stop major injuries by sending out emergency help. But creating such systems is difficult since it requires maintaining accurate communication, high precision, and low power consumption. The review also emphasises the significance of developing fall detection solutions that are accessible to older people and easy to use.

IV. CONCLUSION

This research offers a comprehensive overview of the most recent findings in the field of research on elder fall detection and prevention as a whole. The ideas and tactics the authors offer for this industry include using wearable sensors, machine learning, and Internet of Things (IoT) technologies, to name just a few. High accuracy, low power consumption, and reliable communication are only a few of the challenges faced while developing fall detection systems, and the review provides use- ful information on these issues. Professionals and researchers interested in the subject of fall detection and prevention for seniors may find this overview to be informative.

TABLE I
COMPARISON OF EXISTING FALL DETECTION TECHNIQUES

Ref.	Single / Multiple Sensor	Wearable Or Non-Wearable	Sensors	Detection Techniques	Real Time Monitoring and Response	Accuracy of identifying falls (In %)	Sensitivity of identifying falls (In %)	Specificity of identifying activities of daily living (ADLs) (In %)
[7]	1	Wearable	Accelerometer	Machine learning algorithms	No	82.30%	89.50%	88.90%
[8]	3	Wearable	A tri-axial gyroscope, a magnetometer	Threshold-based methods	No	94.10%	96.30%	93.10%

			and tri-axial accelerometer					
[9]	1	Wear-able	Tri-axial accelerometer sensor	Recurrent neural network (RNN)	Yes	97.40%	98.30%	96.40%
[10]	1	Wear-able	Tri-axial accelerometer	Performance of four machine learning algorithms	No	96.10%	97.40%	95.30%
[11]	1	Wear-able	Tri-axial accelerometer	Predefined thresholds and machine learning techniques.	Yes	94.50%	96.80%	93.20%
[12]	1	Wear-able	Accelerometer	Threshold-based approach	Yes	Not reported	98%	80%
[13]	NA	Wear-able	Home Networks	Threshold-based approach	Yes	98.90%	97.50%	95.60%
[14]	1	Wear-able	Kinect v2	One-class classifier outlier removal technique	Yes	98.73%	97.30%	Not reported
[15]	1	Wear-able	Gyroscopes	Threshold-based methods, machine learning algorithms, and hybrid approaches	Yes	98.00%	96.60%	98.20%
[16]	Mul-tiple	Wear-able	Body area network	Machine learning	Yes	98.90%	98.20%	99.30%
[17]	1	Wear-able	Tri-axial accelerometer	Machine learning algorithms	Yes	Not reported	Not reported	Not reported

			sensor					
[18]	1	Wear-able	Accelerometer	Threshold-based methods, machine learning algorithms, and combination methods	Yes	Algorithm A (82.50 %) Algorithm B (75.00 %) Algorithm C (72.50 %) Algorithm D (80.00 %)	Algorithm A (97.50 %) Algorithm B (80.00 %) Algorithm C (95.00 %) Algorithm D (90.00 %)	Algorithm A (69.00 %) Algorithm B (70.00 %) Algorithm C (48.00 %) Algorithm D (70.00 %)
[19]	Mul-tiple	Wear-able	Multiple sensors	Machine learning covariance matrix	Yes	97.40%	96.70%	97.70%
[20]	NA	Wear-able	NA	Threshold-based method and support vector machine	No	Not reported	Not reported	Not reported
[21]	NA	Wear-able	NA	Hierarchical algorithm	Yes	98.30%	96.20%	99.10%
[22]	NA	Non-Wearable	Cameras	Deep learning model	Yes	Not reported	Not reported	Not reported
[23]	NA	Non-Wearable	Cameras	Analyzing changes in pixel patterns and motion trajectories	Yes	93.6%.	95.70%	91.50%
[24]	2	Wear-able	Accelerometer and gyroscope	IoT and big data technologies	Yes	96.50%	97.20%	96.30%
[25]	1	Wear-able	IR-UWB sensor	CNN algorithm	Yes	97.80%	96.80%	98.80%
[26]	1	Non-Wearable	Infrared depth sensors	Machine learning algorithms	Yes	96.70%	100%	95.80%
[27]	1	Non-Weara	Microsoft Kinect v2	Machine learning methods for	Yes	96.43%	97.06%	96.15

		ble	depth sensor	recognizing falls and define fall risk.				
[28]	2	Non-Wearable	Pressure sensors	Measurement of the pressure difference between two sensors	Yes	96%	96%	96%
[29]	1	Non-Wearable	Bi-axial gyroscope	Threshold-based fall-detection	Yes	93.33%	86.67%	100%

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