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Review

A Survey of IoT-Based Fall Detection for Aiding Elderly Care: Sensors, Methods, Challenges and Future Trends

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Abstract: Remote monitoring of a fall condition or activities and daily life (ADL) of elderly patients has become one of the essential purposes for modern telemedicine. Internet of Things (IoT) and artificial intelligence (AI) techniques, including machine and deep learning models, have been recently applied in the medical field to automate the diagnosis procedures of abnormal and diseased cases. They also have many other applications, including the real-time identification of fall accidents in elderly patients. The goal of this article is to review recent research whose focus is to develop AI algorithms and methods of fall detection systems (FDS) in the IoT environment. In addition, the usability of different sensor types, such as gyroscopes and accelerometers in smartwatches, is described and discussed with the current limitations and challenges for realizing successful FDSs. The availability problem of public fall datasets for evaluating the proposed detection algorithms are also addressed in this study. Finally, this article is concluded by proposing advanced techniques such as lightweight deep models as one of the solutions and prospects of futuristic smart IoT-enabled systems for accurate fall detection in the elderly.

Keywords: artificial intelligence; internet of things; fall detection; wearable sensors; old people

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1. Introduction

Recently, the World Health Organization (WHO) reported that there are approximately 684,000 disastrous falls worldwide each year, with a majority of victims being individuals over the age of 60 [1]. This large percentage places it behind road traffic injuries as the leading cause of unintentional injury fatality. Falls are considered as a main public health concern for the elderly around the world, of which over 80% are in low-income and middle-income countries. Without a doubt, the injuries that elderly people sustain as a result of falls have far-reaching effects on their families, as well as for healthcare institutions and society in general [2]. Emergencies can occur without recognition and even without warning. That is why fall detection technology in medical warning systems is such a critical and life-saving feature. If, for any reason, you were not able to reach the assistance button after a fall (or in a medical emergency), a medical alert system's automated fall detection feature could give you a peace of mind that you would still get the care you need [3].

Fall detection devices employ alert systems technology to identify and provide emergency assistance to a senior who is prone to falls [4]. If the user falls, these systems will quickly activate the sensor. The built-in technology can be placed around the neck, around the wrist, or on the waist, depending on the device. For premium service charges, most medical alert companies incorporate the fall detection capability within their medical alert system [5]. Some firms sell fall detection gadgets that can be worn separately from one's medical alert button. The cost of the second device may be added to the monthly subscription plan. In the last few years, fall detection has garnered significant concern from both industry and academic research, as seen in Figure 1. It can be noticed that the number of research articles has increased dramatically. Furthermore, the topic of fall-likelihood prediction, which is based on modern applications concentrated on fall prevention, such as the Internet of Things and artificial intelligence, is also quite important [6].

Accelerometers, a sort of low-power radio wave technology sensor, are used in fall detection systems to continuously monitor the user's movements [6]. Three-axis accelerometers, such as those in smartwatches and smartphones, are employed in state-of-the-art fall detection devices. Some fall detection systems have a built-in tri-axial accelerometer that uses Biosensor's patented algorithms. By detecting unexpected changes in body motions, fall warning detectors can determine whether a user has fallen [7]. The device can assess a person's body position, physical activity, and the smoothness with which movements are being sped up. If these variables are in the danger zone and a fall has happened, the smart device will automatically activate an emergency fall alarm and contact emergency response agents for assistance.

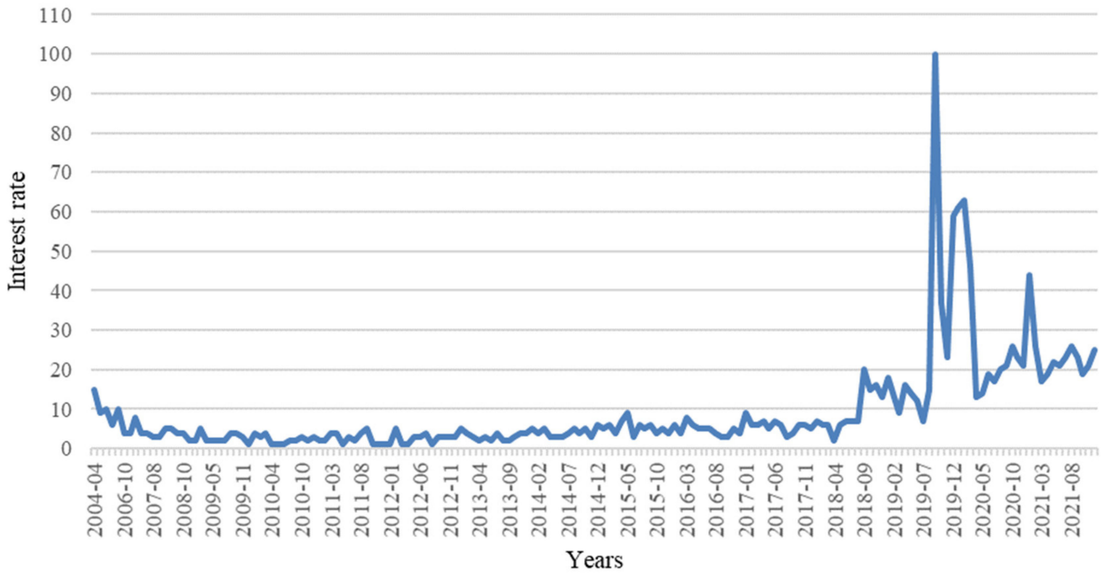

Figure 1. Fall detection interest rate, start April 2004-to-December 2021. The experimental data is taken from "Google Trends" based on "fall detection" as the search object. The results are equalized using the largest rates; therefore, the highest interest rate has a value of 100.

One commercial approach for preventing falls is the use of personal emergency response systems (PERS) [8]. Individuals who fall can use these clinical alarm devices to invoke an emergency department by pressing a button. While the PERS system is useful in many instances, it is rendered worthless if the user is completely unconscious or unable to reach the button. Even when the system is available, recent cohort research indicated that roughly 80% of older persons who were wearing a PERS did not use it to call for aid after falling. Passive monitoring approaches have been proposed to identify falls due effectively and precisely to the problems connected with PERS systems [9]. Several options are currently available, the majority of which are wearable devices, cameras, microphones, and pressure sensors implanted beneath the flooring that are incorporated in the domestic surroundings. Based on the best of our knowledge, this article presents the first survey of IoT-based fall detection systems, including different wearable and non-wearable sensor types, machine learning and deep learning detection algorithms. In addition, the article also describes the challenges and the future trends of fall detection systems, such as the availability of public datasets of falls for senior people and the development of new lightweight deep models for accurate fall detection with minimal hardware resources.

The remainder of this paper is divided into the following sections: Section 2 gives an overview of relevant fall detection methods using current technologies. The taxonomy of current methods for fall detection is described in Section 3. Sections 4 and 5 demonstrate techniques of machine learning and provide a discussion, respectively. Finally, conclusions and future directions of this research are presented in Section 6.

2. Current Technologies for Detecting Falls

In the diagnosis and treatment of disorders, health monitoring is crucial. Fall detection devices, for example, can help detect anomalies and transmit real-time signals to health and social care professionals about the abnormalities [10]. Fall detection systems based on wearable devices have been increasingly popular in recent years due to various advantages, such as being lightweight, low-cost, energy-saving, and non-intrusive. In recent years, the growth of fall detection and prevention approaches has been a prevalent study area. For the development of such systems, a variety of methodologies are used [11]. Artificial intelligence (AI), Internet of Things (IoT), and cloud computing-based systems are the three primary categories in which these technologies fall.

2.1. Artificial Intelligence

Artificial intelligence gives the system the ability to detect falls based on the dataset and data trends. Sensors produce data connected with various fall parameters during the data collection procedure. As a result, machine learning methods are utilized to categorize or identify fall actions based on the requirements of an application [12]. For fall detection as well as other activity detection, deep learning techniques are becoming the preferred method, particularly for visual detectors and sensor fusion [13]. Another area of fall detection examination is deep reinforcement learning, which is based on psychological and neuroscientific theories about how humans adapt to changing environments and improve their behaviors. Deep reinforcement knowledge incorporates both deep and reinforcement learning to expand detection alternatives that respond to changing environments, while preserving accuracy and robustness.

Figure 2 shows the five processes that make up the overall system for fall detection methodology. Depending on the application's needs, data collection from sensing devices is the first step. In the second step, the noisy and undesired signals are removed from the collected fall data. Feature extraction from fall datasets, which takes the preprocessed data and extracts the desired features, is the third step. In the fourth step, machine learning techniques are applied to classify abnormal falls and ADL. It separates the data into two categories: training and testing. Finally, different evaluation matrices, such as accuracy and confusion matrices, are used in the performance assessment step to analyze the system's overall outcome.

Figure 2. Fall detection overall procedure system using machine learning (ML) algorithms.

2.2. Internet of Things

The Internet of Things (IoT) is a relatively new technology that has a great potentiality for developing a fall detection system. To construct fall diagnosis systems, this emerging technology could supply data processing, communication channels, and smart sensors [14]. IoT also offers powerful processing and storage capabilities, as well as providing services to the other layers of edge and cloud computing [15,16]. Edge, as well as fog computing, can be used to detect falls. Edge devices process data and are located near other devices and users. On the other hand, fog nodes are located near local networks and other system infrastructure.

Wireless communication systems such as 5G comprise both physical and software virtual network functions [17]. To begin with, 5G is expected to become a significant and generic communication technology for the Internet of Things. It brings the potential to transmit data at fast speeds and with low latency, which could aid the development of IoT systems for fall detection [18]. Second, passive sensing technologies can be implemented using 5G cellular. Unlike other types of RF-sensing systems, such as Wi-Fi and radar, the 5G wireless network may be used as a pervasive sensing method in both indoor and outdoor environments for fall detection. Intelligent systems or networks powered by IoT and deep learning could be utilized for a variety of ubiquitous sensing and smart monitoring systems, allowing older people to live independently and with a high quality of life [19].

2.3. Cloud Computing Based Systems

The Smart IoT Gateway sends data about the falls to Cloud Services, which stores it in a document-oriented database (MongoDB). After a fall, the model is reconstructed and trained via a cloud-hosted machine learning platform (BigML) with representational state transfer (REST) and an application program interface (API), before being locally instantiated in the gateway [20]. Fog computing, in terms of architecture, allows for the decentralized distribution of different processing levels of data throughout the associated edge devices. Smart solutions that can perform data processing and connect directly with one another are more appealing for real-time applications than cloud computing systems [21,22].

Figure 3 depicts the general system architecture for fall detection, as proposed in [21]. The Internet of Things device, such as a mobile phone or wearables, can sense the environment, gather, process, and transmit data. When the targeted person falls after a certain amount of time, the mobile application can automatically call an emergency service or a caregiver or family member. The data from the sensors are transferred to a cloud-based data center. If the fall detection is done via the medical cloud service, the data are sent to the machine learning web service, which is in control of classifying the situation over time. This web service determines whether or not there has been a fall.

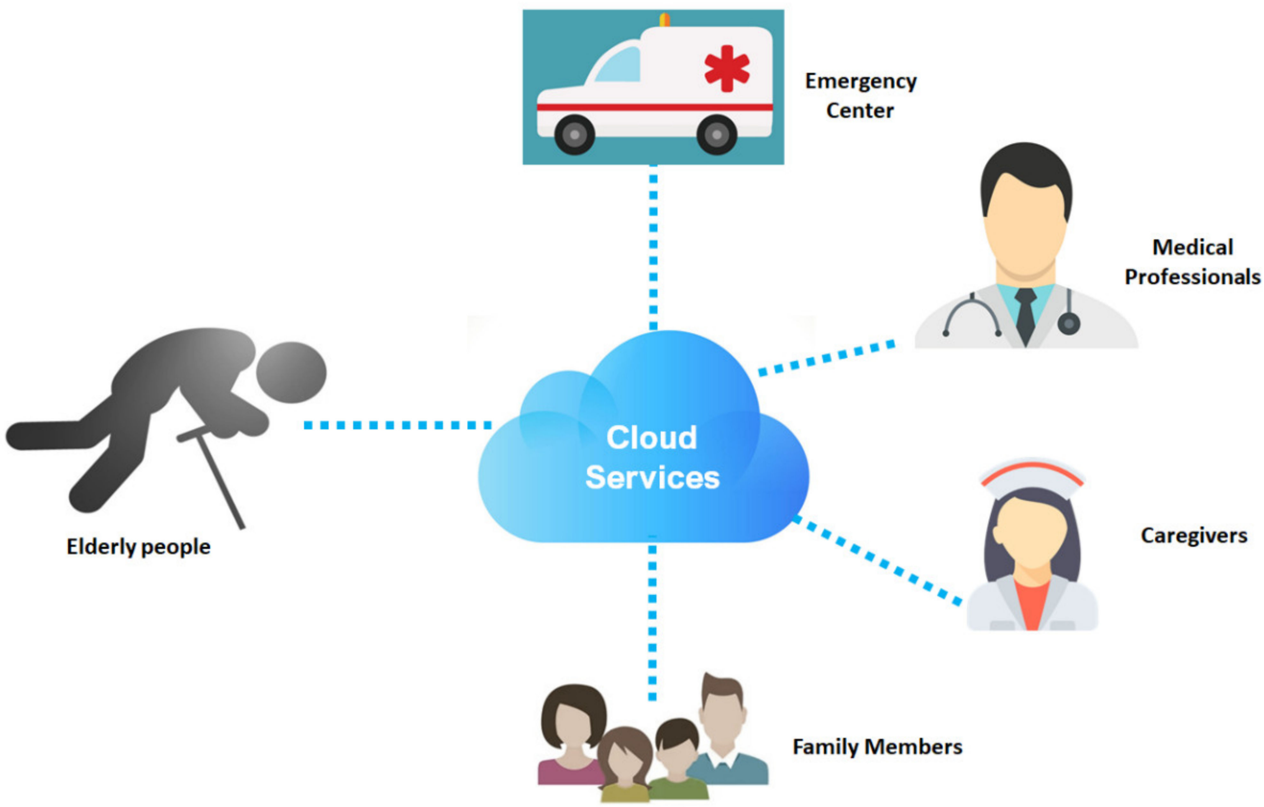

Figure 3. Fall detection system architecture general model.

2.4. Edge Computing Based Systems

Edge computing, also known as mobile edge computing, is a modern and booming computer paradigm that was founded recently [15]. Its ultimate goal is to transfer computation from the cloud to the network's edge. Edge computing, in other terms, will be an efficient architecture for computations and storage close to the data source. Edge, as well as Fog computing, can be used to detect falls [16]. Edge devices process data and are located near other devices and users. On the other hand, fog nodes are located near local networks and other system infrastructure. Edge computing also has positives in terms of energy consumption, response time, scalability, mobility, cost, security, and other factors that are similar to those of personal computing services. As a result, edge computing is well suited to be used in conjunction with AI for the detection of human falls with more accuracy and precision [23].

3. Fall Detection Methods and Technologies

3.1. Taxonomy of Current Methods

This section presents the different methods and technologies of fall detection systems in previous studies as illustrated in Table 1. Noury et al. [24] place a strong emphasis on the mechanics of a fall, as well as the methods for detecting it and the evaluation criteria which rely on statistical analysis. They look at a variety of analytical methods for detecting falls, including thresholds on sensor reading velocity, no movements detection, and the sudden polarity inversion of the acceleration vector. Xinguo [5] focuses on identifying the methods and basics of fall detection for old people. In this survey, fall detection methods are divided into three categories based on the type of fall detector: wearable device, ambient device, or vision based. The classification is further refined based on the type of analysis into motion, posture, proximity, body shape, and 3D head movement. Perry et al. [25] classified real-time approaches into three categories: techniques that solely measure acceleration, techniques that integrate acceleration with other gyroscope data and static orientation to acquire fall events. Hijaz et al. [26] presented the techniques used for detecting falls and irregular movements of the elderly by monitoring their daily activities. In this research, the surveyed techniques are classified into three categories: based on video analysis, based on acoustic and ambient sensors, and based on kinematic sensors. Mubashir et al. [27] emphasized in their review on different fall detection systems and their underlying algorithms, that fall detection methods are divided into three classes: wearable device-based, ambiance device-based, and camera-based. These classes are then refined into smaller ones based on the type of accelerometry, posture analysis, audio/visual ambiance sensing, shape modeling, and others.

Delahoz and Labrador [28] conducted a survey on fall detection and prevention systems and provide a qualitative comparison among them. They categorized the sensors into two types, namely wearable and external sensor devices. The external sensors are further split into vision-based or ambient-based systems. They also list the main aspects of machine learning algorithms, e.g., feature extraction, construction, and selection. In addition, they compared the time complexities of various classification algorithms, which are decision trees, K-Nearest Neighbor, and SVM, and discussed model evaluation strategies. Some major design concerns for fall detection and prevention systems, such as privacy, cost, energy consumption, obstructiveness, and others, are also highlighted. A discussion of the possible physical, psychological, and environmental risk factors that may lead to a fall is presented. Schwickert et al. [29] perform a systematic review of wearable-sensor-based fall detection systems. They look at whether previous research on fall detection used artificially recorded falls in a lab setting or spontaneous falls in real-life scenarios.

Zhang et al. [30] look at research publications that employ vision sensors only. They present some publicly available datasets on fall detection. They classified vision-based approaches that use one or more RGB cameras, as well as 3D depth cameras. Automatic fall detection systems were the main focus of the survey given by Pannurat et al. [31]. In this study, the authors categorized the current platforms into two classes: wearable and ambient devices. Furthermore, they divided the classification techniques into two sub-categories: rule-based and machine learning-based algorithms. Other topics of fall detection systems were also covered, including sensor types and position, subject information, classification algorithms, and performance evaluation. Furthermore, they evaluated different fall detection products in terms of size, weight and type of sensors and battery with their operational functions; and then make predictions about future developments in the field.

Igual et al. [32] examined 327 research publications on fall detection, and divided them into two main systems, namely context-aware systems and wearable devices including smartphones. The context-aware systems are classified based on system components such as cameras, pressure and infrared sensors, and microphones. Ward et al. [33] analyzed relevant techniques based on the usage and implementation technology for detecting fall events, warning end-users such as relatives of patients and healthcare workers for assistance. They divide fall detection technology into three categories: manually controlled devices, body-worn automated alarm systems, and devices that detect changes that might lead to a fall. Luque et al. [34] presented a comparative study and major characteristics of developed Android-based systems of fall detection. They argue that most smartphone fall detection solutions rely on machine learning (pattern matching) or preset thresholds.

Casilari et al. [35] explored fall detection methods for Android-based smartphones. They highlighted and compared various algorithms in previous studies, considering many characteristics, e.g., proposed system design, applied sensors, methods and reaction in the event of a false alarm.

From a data availability standpoint, Khan and Hoey [36] conducted a review of fall detection approaches. They divided these approaches into two high-level classes based on whether the available training data for falls are sufficient or not, not considering the type of sensors employed or feature extraction or selection algorithms. Casilari-Pérez et al. [37] presented a review paper on applying artificial neural networks (ANNs) in fall detection systems that rely on wearable sensors. The authors of this study split fall detection methods into three categories based on the features that are given to the ANN-based classifiers. The first category includes features based on the raw data from the sensor measurement. The second category includes fall detection features derived from the pre-processing measurements. The last category contains fall features based on a combination of raw sensor data and other features calculated from the sensor readings.

The authors of [38] conducted a comprehensive review of all papers, projects, and patents on the topic of fall prediction, detection, and prevention from around the world. The review divided the relevant works into categories depending on the technique they employed, their types, and their accomplishments. The approach proposed by Ribeiro et al. [39] is based on IoT devices deployed in people's homes. The suggested non-wearable solution is non-intrusive and can be used in a variety of settings, including residences, hospitals, rehabilitation centers, and homes for the elderly. Edge, fog, and cloud are all part of the solution's three-layer processing architecture. For human fall classification, an artificial intelligence model based on ANNs and a mathematical model based on the Morlet wavelet are both employed and contrasted. The results demonstrated that combining both models is practical and beneficial to the system, with a 92.5% accuracy and no false negatives.

Table 1. Taxonomy of main fall detection methods with different sensing devices.

Authors	Year	Methods
Noury et al. [24]	2007	Using analytical methods with thresholds of accelerometer sensor readings.
Xinguo [5]	2008	Categorized methods based on wearable, computer vision and ambient devices.
Perry et al. [25]	2009	Using techniques that measure only the acceleration or combined with gyroscope and static orientation data for fall detection.

Table 1. *Cont.*

Authors	Year	Methods
Hijaz et al. [26]	2010	Categorized methods into vision based, ambient-sensor based, and kinematic-sensor based approaches.
Mubashir et al. [27]	2013	Three main classes, namely wearable devices based, ambience device based, and vision based.
Delahoz and Labrador [28]	2014	Categorized methods into wearable devices and external sensors that includes vision based and ambient sensors.
Zhang et al. [30]	2015	Utilizing vision-based methods with RGB and 3D depth cameras.
Igual et al. [32]	2013	Categorized into context-aware systems and wearable devices including smartphones.
Ward et al. [33]	2012	Dividing the applied technologies based on manually operated devices, body worn automatic alarm systems and devices that sense the high risk of falling.
Casilari et al. [35]	2015	Systematic classification and comparison of various proposed detection algorithms with respect to the system architecture, sensors, methods and false alarm cases.
Khan and Hoey [36]	2016	Two high level categories have been defined: sufficient training data for falls or insufficient (or no training) data for falls, without considering sensor types and/or feature extraction/selection methodologies.
Casilari-Pérez et al. [37]	2019	Split methods based on the features that are used to feed the neural network classifiers into three categories: (1) Raw data obtained, (2) Features derived from the sensor readings, and (3) Combination of the raw data and other derived features.
Ribeiro et al. [39]	2022	Using IoT framework, human fall classification was achieved by using ANNs model and a mathematical model of the Morlet wavelet, based on measurements of two accelerometers, a microphone and a doppler sensor.

3.2. Fall Detection Sensor Types

Lapierre et al. [40] enumerate 10 various technologies, including inertial sensors and locating systems, vision sensors, sound and infrared sensors, pressure sensors, etc. These technologies are divided into three main classes based on the hardware resources: wearable technologies, ambient technologies, and a mix between wearable and ambient technologies together. Inertial sensors (e.g., accelerometers) and locating systems (e.g., Global Positioning Systems) are two forms of hardware that are used in wearable technology. Vision sensors and sound sensors like cameras and microphones, respectively, are examples of ambient technology.

Sensors that assist fall prediction and detection are divided into three categories by Mozaffari et al. [41]: motion sensors, physiological sensors, and environmental sensors. The accelerometer is the key sensor in the motion sensors group for detecting falls by detecting the variation in body acceleration [42]. The accelerometer measures the rate at which an object's velocity changes with respect to time in m/s^2 or G unit in three dimensions: x, y and z, i.e., acceleration. In case of the body acceleration exceeding the predefined threshold value for the fall, there is a possibility of a fall. It is a straightforward approach to detecting a fall using threshold values of the measured acceleration. The gyroscope, on the other hand, is a mechanical device, which monitors angular motion around x, y, and z-axes. The gyroscope detects falls forward/backward or left/right by measuring orientation in pitch, roll, and yaw. Magnetometers detect the direction of a fall event by measuring the geomagnetic field. Physiological sensors monitor the body's vital indicators [43].

In the aftermath of a fall, vital signs are usually altered quickly due to shock. The physiological changes can be used to establish the likelihood of a fall. Electrocardiography is a technique for recording electrical signals generated by the heart muscle and displaying the state of the heart in various scenarios [44]. The procedure of measuring blood volume changes is known as photoplethysmography. Spirometers are diagnostic tools that measure lung capacity and airflow. Galvanic skin response is a component of the human sympathetic nervous system that reveals electrical features of the skin. Blood pressure is measured in systolic and diastolic units, with systolic being the highest and diastolic being the lowest. Furthermore, sensors can track the blood's oxygen saturation. Electrooculography is a technique that uses the retina's resting potential to quantify eye movement. Physiological signals can be easily recognized, such as body temperature, or they can be detected more complexly, as indicated above. A system of smart environmental sensors is used in smart environments to detect falls by voice, light intensity changes, and distance between the body and the floor. In [45], this study proposed radio signals of Wi-Fi connections for detecting falls from the physical components in the environment. In addition, environmental sensors are categorized as vision-based sensors. A fall event can be identified by analyzing RGB images and video streams from 2D and 3D cameras [46–49], based on color and/or thermal postures processing.

Sensor positioning is still an important topic, as mentioned in previous research [50]. For body position [51], body area sensors are placed in a predetermined area such as the chest, hands, and pocket of a shirt. Environmental positions for sensor placement include the bed, the floor, the walls, and event items such as a tap or a handhold. Some integrated sensors can be embedded in platforms like smartphones [52–57] or wristwatches [58,59]. Wi-Fi, Bluetooth [60–62], ZigBee [63,64], and other communication channels [65,66] are used to connect with the sensors.

4. Fall Detection Machine Learning Techniques

Machine learning is usually classified into unsupervised learning and supervised learning. Supervised learning is increasingly being utilized for fall detection in two stages: training and validation. The following are some of the most popular machine learning methods to detect a fall:

- Artificial Neural Network (ANN): Its general architecture includes three main layers, namely inputs, a hidden layer, and outputs. The hidden layer links between the inputs and outputs layers. It consists of multi-internal layers. Training of this algorithm is complex due to the nature of hidden layers as a black box. It becomes unobvious to clarify how a fall event occurred [67,68]. The ANNs have a high tolerance for heterogeneous data with precise results, making them suitable for detecting falls, particularly in the fog-computing layer used on smart devices to save the required high computing resources, e.g., graphical processing units (GPUs).
- Support vector machines (SVMs) are algorithms that divide multidimensional data into two categories. SVM is simpler than ANN for small and high dimensionality datasets. It is recommended for the edge-computing layer, specifically on fall postures [67,69,70].
- Decision Trees: This algorithm divides data into two classes of either fall or non-fall, according to the path taken through a tree-like graph according to a set of conditions. Learning is clear and simple in this algorithm, making it suitable for investigating the causes of falls, particularly the physiological data to classify the patterns and possible risk of falls [71,72]. For instance, changes in blood pressure or oxygen levels are correlated to the falling.
- Naive Bayes: It is a relatively straightforward algorithm with high accuracy and performance. It needs less memory and time requirements to train the classifier. As a result, it can be used to detect falls directly on edge devices [73].
- Deep Learning: The Internet of Things (IoT) includes several sensors that can continuously generate big data with velocity, volume, and variety [74]. The ANN with many hidden layers was developed as a deep learning method to process large amounts of data [75]. Unlike traditional machine learning algorithms, deep learning does not require external feature extractors. However, it takes a long time to train a big dataset, while a short time for the process of prediction. Similar to neural networks, processing still appears to be a black box and is difficult to comprehend [76].

5. Discussions

In this section, we highlight the current benefits, obstacles and limitations related to fall detection systems based on machine learning methods and IoT technologies, providing suggested solutions and relevant future trends in this field as follow.

5.1. Public Fall Datasets

The perceptron was fed using extracted features of the obtained data in prior Multi-Layer Perceptron (MLP) investigations. Recent research has suggested that raw data acquired from wearable sensors be fed directly into neural network classifiers [37]. This eliminates the challenge of selecting a suitable feature extractor or the need for additional preprocessing steps before utilizing machine learning models to detect falls. As a result, no computing expense is required to identify data features, and smart detector implementation can be simplified by using inexpensive wearable devices, such as smartwatches.

Raw data, on the other hand, is not necessarily the greatest place to start when building intelligent classification systems. The use of public and open access datasets as benchmarking tools for evaluating algorithms is on the rise. In any event, it is important to emphasize the lack of an internationally agreed benchmarking dataset for evaluating and comparing FDSs. With only four studies employing it, the SisFall repository [77], one of the largest datasets for the evaluation of FDSs, is the most popular dataset.

Only five of the 15 studies use several repositories to validate their findings, with Khojasteh et al. [78] being the only one to use three public datasets to assess their suggested architecture: DaLiaC [79], UMAFall [80], and Epilepsy [81]. However, a proper evaluation of such systems is still questionable with experimental difficulties. The majority of previous studies are systematically tested on falling volunteers because of the inherent difficulty of justifying detection systems with real falls by elderly people (the main target individuals of these studies). A study [82] showed significant differences between the mobility patterns of real-life falls and those of simulated falls.

In [83], the authors demonstrated how person-specific information like gender and age may be used to improve the modelling process of a deep neural network classifier for increasing the overall system's fall prediction effectiveness. In [84], the effect of weight and age on the accuracy of the detection system of falls event is explored, and the results showed that the detecting efficacy improves with age. Falls are merely imitated by the young subjects, like in previous circumstances. As a result, the ANN is trained on falls caused by teenagers only. The results demonstrated that if the network is trained using daily activities acquired from the elderly, young participants' falls may be distinguished more effectively. This is simply explained by the fact that the daily activities carried out by youth people are often faster and/or more effective than those carried out by older persons [37]. As a result, it is more difficult to separate the dynamics of juvenile ADLs from those connected with a fall. This finding demonstrated the difficulties of extending results from healthy and young volunteers to the elderly people. However, it also suggested that fall detection in the younger volunteers may be viewed as a worst-case scenario for evaluating a particular detection method of falls.

5.2. Fall Detection Sensors and Devices

The great majority of the proposals surveyed in this review research rely solely on accelerometer readings for detection. Only in ten of the studies does the system employ the information produced from the gyroscope measurements (as additional inputs) [37]. Given that inertial measurement units (IMUs) have a combination of accelerometers and gyroscopes as standard, the computational times based on hardware resources should be minimal, especially the signals from the gyroscopes in the detection decision. The systematic examination of the benefits brought by integrating the gyroscope and accelerometer readings is still an open question in the research field. Recent research with CNNs has shown that using gyroscope signals can improve discrimination reliability when compared to solely using accelerometer measures [69].

One of the current problems with portable fall detection sensors is the long delay time for getting the appropriate assistance to arrive at the site where the fall happens [85]. The injured person's life may be lost as a result of this delay before getting the necessary assistance or medical treatment. Therefore, there is a trend to develop a reliable video-based fall detection sensor that will eventually exceed existing portable fall detection sensors as follows. The video-based sensor will be cost-effective and more accurate in detecting falls to provide fast response detection of a fall; consequently, the delay time to provide the necessary assistance to the injured person will be reduced. Moreover, it will protect people's privacy by using only the binary image of the person. Furthermore, older people will be more comfortable without wearing portable fall detection devices all the time during their daily activities [85]. However, it is not always the ideal case, especially for elderly people with cardiac and breathing disorders, because there is always a need to monitor all their vital signs via wearable sensors.

5.3. Smart Detection Methodologies

Fall signals are simply measured by body sensors, e.g., accelerometers, and sent to an external device for intelligent decision-making processing, like a PC with a wireless module such as Bluetooth, as presented in [86]. This external device is responsible for analyzing the acquired signals of the accelerometer sensors and, with a developed neural network classifier, the decision of fall detection is taken. In [87], the authors built a framework using a field-programmable gate array (FPGA) kit to apply the ANNs classifier to develop an embedded vision-based detection system of falls. A digital signal processor (DSP) was utilized to accelerate the ANNs functionality in the context-aware system, as described in [88]. A bio-inspired optical sensor has been used in this study. However, embedded wearable detection systems and solutions based on FPGAs and DSPs are still under development and not implemented as realized commercial systems yet. In most previous studies, wearables are just utilized for sensing and collecting data in the experiments. After finalizing the experimental phase, the recorded sample signals are extracted from the datasets for training and testing the proposed algorithm, either in a hardware or a software form using MATLAB and/or other programing languages like C++.

Comparing neural network models with other machine learning and/or thresholding techniques is usually focused on the performance of the discrimination function only, while other technological features are ignored [37]. Therefore, physical characteristics of operation, e.g., memory size, consumption of energy and processor capacity, and running time/speed may affect the outcome performance metrics to evaluate these smart algorithms successfully. The execution time for the training phase of ANN models was estimated to be higher than other methods in a comparative study of six machine learning algorithms [89]. In contrast, the computational time of the testing phase for ANN models can have the same value as, or be even lower than, other methods to obtain the detection decision.

5.4. Challenges and Future Research

In our daily lives, a fall might occur while doing complex tasks like cycling, therefore it is not as straightforward as a fall while walking. The dataset of complicated activities is multi-dimensional, containing dependent and independent information in many dimensions with different formats. The edge, fog, and cloud layers of an IoT architecture provide processing, storage, data management, and decision for fall cases. Three steps have been proposed for a diagnostic system of falls [46]: prediction, prevention, and detection mode, with each stage determining which layer is appropriate. Stages should be implemented on each layer utilizing protocols, energy efficiency, and device-to-device and layer-to-layer transmission techniques, as well as specialized learning algorithms for each layer. A smartphone, for example, can detect falls on the edge and in the fog computing layers.

Because a wearable processor, such as a wristwatch, is currently too weak to execute advanced learning algorithms effectively, data are sent to another device situated in fog. Without the need of additional layers, high-performance processors could be proposed to identify the falls by processing measured data and authenticating fall occurrences at the edge. Smart sensors are more complicated than regular sensors because they contain small microprocessors, noise filters, transducers, and amplifiers. Thousands or millions of them are spread in an IoT environment, and they must be logically connected in order to supply energy, communicate with one another, increase sensor lifetime, and overcome the shortage of processing and storage capacities. Even though many research studies have been carried out on sensor placement, which might be static or dynamic, this aspect still remains one of the most difficult subjects in the field.

Another method for monitoring is the implanted sensor that is static and within the body [89]. Sensors should be protected from unexpected impact, have a network connection, and be pleasant to wear in both static and dynamic environments. Prediction is crucial in determining when a fall event will occur. The importance of abnormal trunk, leg standing duration, and body histograms in predicting fall occurrences has been examined. Future studies might look into dizziness, epilepsy, hypertension, and cramping (muscle contraction). The most significant component of the prediction system is understanding fall risks, based on physiological parameters such as heart rates and blood pressure of elderly population [21,40]. The predictions stage's outputs are utilized to create smarter IoT-based settings.

6. Conclusions and Outlook

In this article, we demonstrated many fall detection algorithms, methods and systems based on IoT technology in previous studies. These proposed fall detection systems (FDSs) mainly used artificial neural networks as automated decision-making algorithms to identify fall situations using the measured readings of sensing devices. The advantage of smartphones and/or smart watches has been widely exploited to build a wearable FDS, because they already have the required built-in hardware resources, such as accelerometers and gyroscopes with wireless mobile communications, e.g., Wi-Fi and 5G networks. Other physiological signals, namely heart rate, electromyogram (EMG) and blood pressure have been also applied for FDSs in some particular research works.

Smart devices like smart phones and watches provide a good opportunity to realize the developed FDSs based on the available hardware resources and wireless sensors in IoT environments. Evaluating fall datasets generated by different sources and accelerometers may contribute to the robustness capabilities of the proposed detection algorithm, because it can deal with variable resolution and sampling rates, verifying its generality. Furthermore, employing artificial intelligence techniques presents the main module of current FDSs. Nevertheless, a pre-processing stage of sensing data, such as thresholding, is needed to reduce error possibilities in identifying fall cases by machine learning algorithms. The computational and power costs of implementing machine learning techniques for fall detection should be kept at minimum levels during the design and implementation stages of practical FDSs.

Moreover, there is a new trend for applying deep learning techniques and convolutional neural network (CNN) architectures [90] as fall detection algorithms, because of their advantages over classical machine learning methods such as automated feature extraction at different levels with external extractors. Additionally, lightweight deep models have been proposed [91] for mobile-based applications. That presents potentially a new version of smart IoT-based classifiers for detecting fall accidents of elderly patients.

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