Fall Detection and Prevention

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A fall can be described as an unpredicted event leading the participants to rest on the lower level (ground or floor). As a result, it causes injuries that can often be fatal. Psychological grievances are also considered as the consequence of falls. People may suffer from anxiety, depression, activity restriction, and fear of falling. The primary physiological issue in older adults is fear of falling, restricting their Activities of Daily Life (ADL). This fear leads to activity restriction, which may lead to inadequate gait balance and weakened muscle that affects the mobility and independence of older adults. Therefore, remote/wearable technologies are required to track, detect, and prevent falls for improving the overall quality of life (QoL). For this purpose, understanding of falls can be classified as fall prevention and fall detection. Fall detection refers to the detection of a fall using sensors/cameras to summon help. In contrast, fall prevention aims to avert falls by observing human locomotion. Numerous systems have been developed using different sensors and algorithms to detect and prevent the fall.

fall detection fall prevention machine learning

1. Overview

Falls are unusual actions that cause a significant health risk among older people. The growing percentage of people of old age requires urgent development of fall detection and prevention systems. The emerging technology focuses on developing such systems to improve quality of life, especially for the elderly. A fall prevention system tries to predict and reduce the risk of falls. In contrast, a fall detection system observes the fall and generates a help notification to minimize the consequences of falls. A plethora of technical and review papers exist in the literature with a primary focus on fall detection. Similarly, several studies are relatively old, with a focus on wearables only, and use statistical and threshold-based approaches with a high false alarm rate. Therefore, this paper presents the latest research trends in fall detection and prevention systems using Machine Learning (ML) algorithms. It uses recent studies and analyzes datasets, age groups, ML algorithms, sensors, and location. Additionally, it provides a detailed discussion of the current trends of fall detection and prevention systems with possible future directions. This overview can help researchers understand the current systems and propose new methodologies by improving the highlighted issues.

2. Fall Detection

Aging is a worldwide problem related to life expectancy [1]. The World Health Organization (WHO) states that the elderly population is 20% of the world's population [2]. Another report states that older people (above 65 years) will increase to 1.5 billion by the end of 2050 [3]. In general, old age reduces the overall physical, cognitive, and sensory functionalities [4][5]. Therefore, an older adult faces difficulty performing routine tasks such as walking, jogging, eating, and dressing up [6][7][8]. Falling is a significant challenge in the elderly group that can reduce life expectancy. Approximately 35% of people (above 65 years) have one or more falls per year [9]. In addition to old age, several other factors such as environment, physical activity, and cardiovascular disorders cause falls. It is a major source of physical injuries, and often, these injuries require hospitalization [10][11][12]. Annually, 37.3 million falls need medical attention, and 0.65 million falls resulting in deaths [13].

A fall can be described as an unpredicted event leading the participants to rest on the lower level (ground or floor) [14]. As a result, it causes injuries that can often be fatal [15][16]. Psychological grievances are also considered as the consequence of falls. People may suffer from anxiety, depression, activity restriction, and fear of falling [17][18]. The primary physiological issue in older adults is fear of falling, restricting their Activities of Daily Life (ADL) [19]. This fear leads to activity restriction, which may lead to inadequate gait balance and weakened muscle that affects the mobility and independence of older adults. Therefore, remote/wearable technologies are required to track, detect, and prevent falls for improving the overall quality of life (QoL) [20][21]. For this purpose, understanding of falls can be classified as fall prevention and fall detection. Fall detection refers to the detection of a fall using sensors/cameras to summon help. In contrast, fall prevention aims to avert falls by observing human locomotion. Numerous systems have been developed using different sensors and algorithms to detect and prevent the fall.

The authors of [14][22] presented an overview of the fall detection techniques. However, both the studies include relatively old literature published in 2007 and 2008, respectively. Mubashir et al. [23] classified the fall detection approaches into wearable, ambient, and camera-based approaches. Similarly, Igual et al. [24] talks about the issues and trends in fall detection schemes. The study [25] is specific to fall detection using wearable sensors. All the above-mentioned reviews only discuss fall detection schemes with no interest in fall prevention. In 2014, Delahoz et al. [26] presented a review on fall detection and prevention techniques. Recently, Saboor et al. [27] published a review on gait analysis using machine learning. However, only 14% of their studies are specific to fall detection and prevention. Ren et al. [28] present a comprehensive overview of fall detection and prevention techniques. However, most presented schemes use statistical approaches that often generate many false alarms during detection and classification. Furthermore, statistical approaches are less efficient in the presence of complex and nonlinear problems [29]. In general, gait analysis for fall detection and prevention often generates noisy data during the acquisition. Statistical methods are generally sensitive to noisy data that leads to performance degradation [30]. Therefore, the latest research incorporates Machine Learning (ML) because of high classification accuracy for fall detection and prevention. Recently, Islam et al. [31] presents a review on fall detection using deep learning techniques. However, the scope of the review is limited to deep learning techniques for fall detection only. This paper aims to provide an overview of studies using ML for fall detection and prevention. The overall contributions of this paper are as follows:

- It provides an overview of the fall detection and prevention systems using wearables and non-wearables.
- It elaborates on the frequently used ML algorithms in fall detection and prevention.

- It provides a detailed analysis of the recent state-of-the-art studies. The analysis covers the dataset, participants, ML algorithms, acquisition sensors, and their placements.
- It evaluates performance parameters such as accuracy, sensitivity, and specificity for different combinations of ML algorithms, sensors, and placements.
- It provides a detailed discussion on the latest trends in fall detection and prevention systems along with the future directions.

3. Fall Detection and Prevention Systems

The development of fall detection and prevention systems has become a hot research topic during the last few years. Various approaches are used for developing such systems. These systems are classified into two broader categories: wearable systems and non-wearable systems.

3.1. Non-Wearable Systems

Non-wearable systems are composed of sensors placed around the human proximity for data/gait monitoring. These systems are further subdivided into vision-based sensors, and floor-based sensors [32]. Vision sensors such as cameras, infrared sensors, and Laser Range Scanners (LRS) [33] take optical measurements and use image processing for analysis. Video surveillance is a common type of such system, which captures images and uses different algorithms to determine fall occurrence. In contrast, floor-based sensors such as Ground Reaction Force (GRF) sensors and pressure sensors observe the force extracted by human feet to observe the fall [34]. The number of sensors varies from experiment to experiment. The primary drawback of non-wearable systems is their limited coverage. Such systems can be implemented at offices, homes, and experiment labs, making them less scalable and expensive. Non-wearable systems also compromise users' privacy [35][36]. Therefore, it is not optimal to use such systems for most real-life applications.

3.2. Wearable Systems

Wearable systems consist of devices/sensors that can be attached to the human body for data collection. Wearable systems consist of accelerometers, gyroscopes, magnetometers, IMUs, etc. [37]. An overview of wearable sensors is given in **Table 1**. The primary advantage of wearable systems is their ability to collect data outside the laboratory environment [38]. Therefore, such systems are feasible for analyzing fall detection or for preventing falls while performing ADLs. These sensors are often embedded in smartphones that can collect data without investing in any new equipment [39]. Additionally, they provide better privacy than non-wearable systems. However, wearable devices have limited lifetime processing power [40][41]. Furthermore, the wearable's data need further processing using statistical or ML algorithms for decision making, as shown in **Figure 1**.

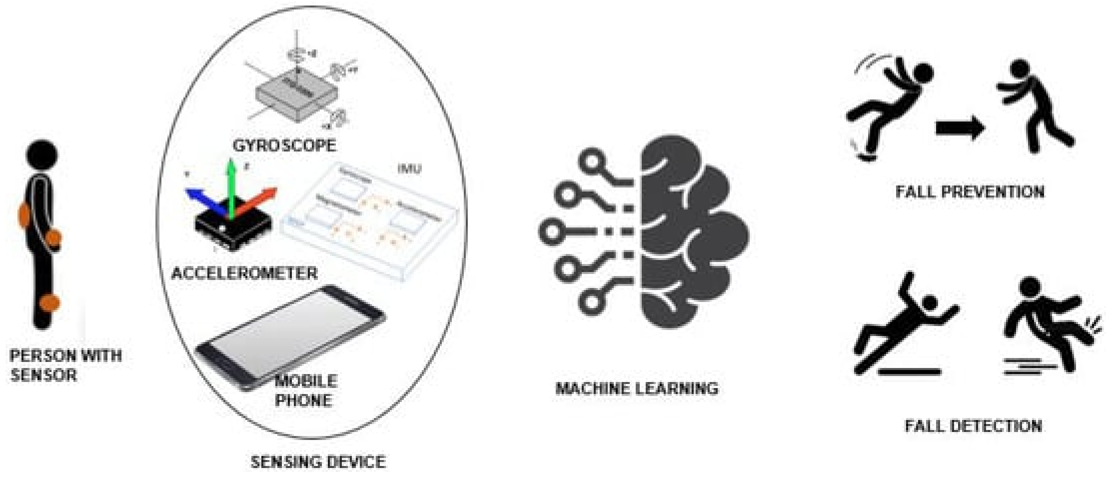

Figure 1. An Overview of Fall Detection and Prevention System.

Table 1. Overview of Wearable Sensor.

The statistical approaches often lead to low classification accuracy and prove to be less efficient with noisy data. Therefore, ML techniques are widely used for fall identification and prevention [42]. Basic fall activities that are identified are falling forward, falling backward, falling sideways, spinning clockwise, and spinning anticlockwise [43]. The ML algorithms classify fall activities from non-fall activities based on the classifier being trained [43][44][45]. Similarly, these ML classifiers identify the abnormalities in gait and try to prevent falls using techniques such as muscle stimulation [46]. An overview of a general system is presented in the next subsection.

3.3. System Overview

The overall system for fall detection and prevention consists of the five steps as shown in **Figure 2**. The first step is data collection depending on the application requirements. There are various data collection methods, i.e., public datasets, controlled environments, and realistic environments. Publicly available datasets include gait features that can be used to develop such systems [47][48]. In contrast, a lab or realistic environment uses wearable [49][50][51][52] or non-wearable devices [53] for data acquisition.

Figure 2. Procedure for fall detection and prevention.

In general, the acquired data are noisy. Therefore, preprocessing helps to remove the noisy and unwanted signals from the data. For that, the system uses preprocessing filters such as Kalman Filter [54] and Median Filter [55] etc. The third step is feature extraction to obtain the desired features from the preprocessed data. The features can vary from experiment to experiment performed by different researchers. For example, in speech recognition, the desired features are sound length, noise ratio, matching filters, and relative power. Similarly, edges and objects are used as desired features in computer vision applications. In contrast, fall detection or prevention applications require a change in acceleration, rotation, or angular velocity as the desired feature set. The slight change in any of these parameters helps visualize the gait changes, resulting in fall detection or fall prevention. Therefore, the mean, standard deviation, and variance of these features are considered valuable data for such application. Overall, feature selection is a crucial step, as classification accuracy heavily relies on the selected features. Feature selection also reduces the dataset volume and cost of the pattern recognition process. Features can be selected using filter methods or wrapper methods [56][57].

A large number of features can cause overfitting, while fewer features may cause underfitting. Therefore, this step requires additional attention to enhance the overall performance of the system. The fourth step uses ML algorithms to classify irregular gait, falls, or ADL. Generally, it divides the data into training and testing data. The ratio of each data type depends on the experiment of system design. This step applies the ML algorithms on training data to identify fall activities or irregular gait for fall prevention. After training the classifier, it uses test data for the performance evaluation. This step includes various matrices such as the accuracy, sensitivity, and specificity of the results obtained to analyze the system’s overall performance. As we can see, the ML algorithms help in identifying fall detection or prevention. Therefore, the next section discusses the functionality of major machine learning algorithms used for fall detection and prevention.

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