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Automated Fall Detection for Disabled Individuals Using Mobile Phone Sensors and Machine Learning: A Survey

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ABSTRACT

Fall risks to health and safety are especially dangerous for those with impairments. An automated fall detection system is necessary, especially in medical and senior care. The elderly and individuals with impairments are particularly susceptible to falls, which frequently result in severe injuries and complications, thereby presenting a considerable threat to their overall health. The early discovery and response to a fall incidence can reduce immobilization and consequent health complications, saving lives. Automatic fall detection systems quickly and reliably indicate falls and dispatch medical or emergency assistance. Researchers have introduced various automatic fall detection methods using machines or deep learning. Most fall detection systems depend on wearable or stationary sensors, which restricts the user's mobility and accessibility. Conversely, mobile sensor-based fall detection leverages the widespread presence of smartphones by obtaining motion information via their integrated accelerometers and gyroscopes. Our primary objective is to develop a reliable fall detection method using a mobile phone sensor and machine learning. This paper examines several methods employed in the identification of falls and emphasizes the significance of utilizing mobile phone sensors in the process of fall detection. It also discusses recent research in this domain and highlights research challenges. This could potentially foster further innovation in the field.

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1. INTRODUCTION

People of all ages are susceptible to falls, which are a common occurrence and can have serious consequences. Unfortunately, falls happen frequently to people with disabilities who struggle with balance, strength, and mobility. Serious and long-lasting effects could result from these falls. Injuries sustained as a result of falls, such as fractures, sprains, or head traumas, may be more likely to occur in people who have disabilities [1]. The potential consequences of these injuries include an extended hospital stay and recovery period, which could impede their ability to perform activities independently. Furthermore, the expenses associated with medical care and rehabilitation after a fall can be substantial, increasing the financial strain already experienced by individuals with disabilities and their families [2]. Ensuring prompt fall detection while positioned in a chair among individuals with disabilities is not merely practical; it constitutes a critical component of healthcare and overall welfare. According to data from the National Centre for Statistics and Information, out of the 42,304 individuals with disabilities in Oman, 10,880 are children [3]. It may present obstacles to achieving independence, self-harm, and maintaining a positive mental health status. Therefore, it is vital to address fall-related issues before attempting to improve the overall well-being of people with disabilities. The combination of machine learning and smartphone sensors can create a reliable fall detection system, giving the disabled more freedom and security in their daily lives [4]. Utilizing sensors such as accelerometers and gyroscopes, mobile devices capture comprehensive data on orientation, movement, and surrounding conditions, subsequently analyzed in real-time by ML models. Trained on labelled datasets, these models swiftly identify unique patterns indicative of falls, allowing for precise classification and immediate alerts or notifications upon detection. Moreover, ML-based systems exhibit adaptability to individual behaviors and environmental nuances, effectively minimizing false alarms and enhancing responsiveness. Support vector machines (SVM), decision trees (DT), and deep neural networks train models on labelled datasets to recognize fall signatures. With the widespread availability and accessibility of mobile devices, these innovative solutions become readily deployable, promising heightened safety and reassurance for both disabled individuals and their caregivers, ultimately fostering greater independence and well-being.

2. BACKGROUND

Fall detection systems have advanced significantly in the last few years as a result of the application of machine learning (ML) and deep learning (DL) techniques.

Video-Based Systems [5][6]: The motion of an individual is captured and analyzed by video-based fall detection systems. These systems may use cameras or video sensors. These systems track and analyze body postures, patterns of motion, and sudden changes in the position of a person using computer vision techniques and DL algorithms. An alert is sent immediately when there is a possibility of a fall, allowing for prompt assistance. These systems are particularly useful in settings where visual data can provide helpful context for fall events, such as those found in healthcare facilities or assisted living communities, where they have proven to be very effective. Video surveillance, on the other hand, raises privacy concerns because it involves continuously recording people, which could mean invading their private lives, and the effectiveness of video-based systems can be affected by things like lighting, camera placement, and obstructions. Additionally, the implementation and upkeep of a video-based fall detection system may require significant resources, including financial investment.

Audio-Based Systems [7][8]: Audio-based fall detection systems use microphones to record and analyze sounds that happen when someone falls, like when they hit the ground hard or when they are crying out in pain. ML and DL algorithms are applied to audio data to identify fall-related audio signals. Support vector machines (SVM) and random forests, as well as deep learning (DL) models such as convolutional neural networks (CNN) and recurrent neural networks (RNN), can be trained to recognize patterns in audio data associated with falls. They can recognize distinct sound patterns made during a fall event. They improve safety for the elderly and those with mobility issues by providing an extra layer of fall detection capabilities. However, elements such as ambient noise, the magnitude of the fall, and the kind of surface the fall occurs on can determine how successful audio-based solutions are. It can be difficult to distinguish between falls and other noises.

Wearable Devices [9][10]: Activity trackers and smartwatches are examples of wearable devices that utilize a variety of sensors to monitor a person's movements, including gyroscopes and accelerometers. The sensor data is processed by ML algorithms to detect falls based on predefined motion patterns and impact characteristics. Wearable fall detection systems provide portability in addition to continuous monitoring, making them an excellent choice for people who want to keep an active lifestyle while ensuring their safety. These devices improve users' autonomy and sense of security by sending them real-time alerts and fitting easily into their daily routines. Individuals, on the other hand, may not always wear or charge their devices regularly, which can lead to lapses in monitoring and, as a result, reduce the effectiveness of the fall detection system. Some users may be concerned about their privacy as a result of constant monitoring via wearable devices. The initial investment required to acquire wearable devices, as well as any subsequent subscription charges, may pose a significant obstacle to their widespread adoption.

Ambient Sensor-based System [11] [12]: The movements and activities of a person are continuously monitored by ambient sensor-based fall detection systems, which make use of a network of sensors that are installed throughout the home. These sensors, which collect and send behavioral data about people, include infrared sensors, pressure mats, and motion detectors. The information is subsequently analyzed using ML algorithms, which allow for the real-time detection of unusual or fall-indicative patterns. These systems are especially useful in home-based or assisted living situations since they are respectful of an individual's right to privacy while providing a thorough and discrete solution for fall detection. This makes them highly beneficial. Ambient sensor-based systems are essential for improving the safety and well-being of the elderly and those with mobility issues in their familiar living environments because they can detect possible fall occurrences and notify caretakers or emergency services in advance. Environmental factors such as the existence of pets or additional objects, changes in lighting conditions, disturbance from electrical devices, and variations in lighting can affect sensors even when they have enhanced detection. It can be expensive to set up the computing infrastructure needed for ambient sensor-based systems and to buy and install the necessary sensors.

Smartphone-Based Systems [13]: Fall detection systems based on smartphones utilize the sensors that are built into phones, such as GPS, gyroscopes, and accelerometers. Machine learning algorithms analyze sensor data to determine motion patterns and geographic locations to determine the occurrence of falls. These setups are convenient for people who always have their smartphones on them due to their portability, affordability, and ease of use. The use of a smartphone for fall detection provides a solution that is covert and can be applied in a variety of contexts. This ensures that users are protected both at home and while they are travelling. However, it has issues with battery life, user compliance, and device position. The incorporation of modern sensor technology, data processing, and user adoption are critical factors that determine the effectiveness of mobile sensor-based systems.

Table 1 summarizes the issues in each type of fall detection system. Table 2 lists the different sensors in the mobile phone [14].

Table 1. Summary of the Fall Detection Systems

System	Issues
Video-Based Systems	• Video monitoring increases privacy concerns, especially in homes and hospitals. • Low lighting can degrade fall detection systems. • Fall detection accuracy may be compromised, or blind areas may be introduced by suboptimal camera placement. • Accurate fall detection may be hindered by obstructions in the field of view or cluttered environments. • High equipment costs may limit video-based fall detection system usage.
Audio-Based Systems	• Accurate fall detection may be impeded by ambient noise present in diverse environments. • Falls can take many various forms, ranging from small missteps to larger-scale mishaps. • Recognizing falls on different surfaces is difficult since the sound produced depends on the surface.
Wearable Devices	• Individuals may not wear or charge devices regularly. • Wearables constantly capture personal data, posing privacy concerns. • The expenditure is linked to the procurement of wearable devices.
Smartphone-Based Systems	• The sensors found in smartphones, although robust, might possess certain constraints. • The optimization of sensor data processing in real-time on mobile devices is crucial to mitigate the risk of excessive battery depletion and system resource utilization. • The continuous monitoring of individuals that is required for fall detection via sensors raises privacy concerns.

Table 2. Mobile phone sensors

Sensors	Uses
Accelerometer	Detects changes in orientation and modifies the viewing angle appropriately.
Gyroscope	Finds angular momentum (roll, pitch, and yaw).
Magnetometer	Detects the magnetic field of the Earth and functions as a digital compass.
Barometer	Measures the air pressure and makes weather widgets easier.
Image Sensor	Offers the ability to capture both still images and videos.
Microphone	Record Audio.
Wi-Fi Sensor	Allows Wi-Fi communication.
Bluetooth Sensor	Allows for Bluetooth-based wireless communication.
Location Sensors (GPS)	Uses GPS satellites to locate target areas on a map or image.
Temperature Sensor	Conducts temperature measurements and enables weather widgets.
Humidity Sensor	Conducts humidity measurements and enables weather widgets.
Ambient Light Sensor	Controls the level of brightness of the display.
Proximity Sensor	Determines the distance of the screen to our body.
Touch Sensor	Facilitates the operation through touch.
NFC Sensor	Touches or approaches comparable gadgets to communicate.
Infrared Sensor	Able to detect temperature.
Back-Illuminated Sensor	Customize the light that is caught when taking a picture.

3. RELATED WORKS

Andrew [15] presented intelligent algorithms to detect falls utilizing digital sensing technologies like the accelerometer and watch clock readings in real-time. The proposed algorithm, which is built into the watch, figures out falling measures and matches them with patterns of falling. Each movement accelerates differently and generates a pattern. If the fall pattern matches, the watch will send a Bluetooth order to the phone to call for medical assistance.

Smartphone accelerometers and gyroscopes were used by Kadhum et al. [16] to create a fall recognition system. The system distinguishes falls from other activities of daily living (ADLs). Artificial neural network (ANN) and support vector machine (SVM) classifiers have been utilized to find an accurate falling classifier utilizing smartphone inertial sensors. The accuracy of the SVM-based classifier is demonstrated to be 99.27%, surpassing the current state-of-the-art results that utilize smartphone data.

A smartphone-based fall detection system that can distinguish between falls and routine activities was created by Panagiotis et al. [17]. For such systems, Android devices with sensors and connection services are ideal. To increase accuracy, this study employs a kNN classifier in conjunction with a threshold-based methodology. This study also presents the details of a power regulation and personalization system. The system achieved an excellent fall detection sensitivity of 97.53% and a specificity of 94.89%, which is comparable to the associated works.

Harari et al. [18] proposed a smartphone-based fall detection system that uses accelerometer and gyroscope sensors to monitor motion and detect falls. The system is built on the idea that smartphones are becoming increasingly prevalent in people's daily lives. The system successfully detected falls with a high degree of accuracy (95%), and it comes with a web portal for exploring data and receiving real-time alert notifications. The proposed fall detection system makes use of logistic regression as its machine learning technique. The study emphasizes how smartphones could be used in practical situations to detect falls.

Nooyimsai et al. [19] use two openly accessible datasets, UniMiB SHAR and UMAFall, to investigate different combinations of CNN models and ML algorithms. To choose the best hybrid model, the accuracy ratings are compared. On the UniMiB SHAR dataset, the hybrid model that combines the AlexNet and additional trees approach receives the highest accuracy score of 95.27%. When used on the UMAFall dataset, the hybrid model, which combines the Xception model with the support vector machine/k-nearest neighbours/extra trees algorithms, gets the best accuracy score of 82.24%.

Fang et al. [20] provide a detailed implementation of a fall detection system for smartphones running Android. The system employs accelerometer data to detect occurrences of falls and subsequently transmit alerts to designated contacts. After testing several algorithms for detecting falls, researchers found that those with the highest sensitivity (72.22%) and specificity (73.78%) performed the best. The impacts of phone attachment locations were also investigated in this study. In addition, analysis of the fall detection software's impact on energy consumption showed a small increase compared to normal operation. No expensive hardware modifications or extra sensors are needed to run the system.

Isabel et. al [21] investigates smartphone sensors' ability to distinguish falls from daily activities using accelerometer, magnetometer, and gyroscope data. Various sensor combinations are tested on experimental data (MobiFall) to propose an efficient, low-power fall detection algorithm achieving 100% sensitivity and 93% specificity. To make the system more flexible and adaptable to different user scenarios, more research is necessary. Table 3 summarizes the related works in the domain.

Table 3. Summary of the existing works

Author (s)	Dataset	ML/DL Methods	Performance
Kadhum et al. [16]	Smartphone Dataset	SVM Classifier	Accuracy = 99.27%
Panagiotis et al. [17]	MobiAct	kNN Classifier	Sensitivity = 97.53% Specificity = 94.89%
Harari et al. [18]	Smartphone Dataset	Logistic Regression Classifier	Accuracy=95%
Nooyimsai et.al. [19]	UniMiB SHAR, and UMAFall	AlexNet + Trees approach Xception + support vector machine/k-nearest neighbours/extra trees algorithms	Accuracy=95.27%. Accuracy=82.24%.
Fang et al. [20]	Smartphone Dataset (Human Activities)	Threshold-based methods	Sensitivity=72.22% Specificity=73.78%

Isabel et al. [21]	MobiFall	Threshold-based methods	Sensitivity=100% Specificity=93%

4. PERFORMANCE METRICS

Performance metrics are essential for evaluating the effectiveness of mobile phone sensor-based fall detection systems. Table 4 lists various evaluation metrics for assessing fall detection.

Table 4. Evaluation Metrics [22]

Metrics	Description
Accuracy	The accuracy metric evaluates the overall accuracy of fall detection. Accuracy = (TP + TN) / (TP + TN + FP + FN)
Sensitivity	Sensitivity measures the ability of the system to detect actual falls. Sensitivity= TP / (TP + FN)
Specificity	Specificity measures the ability of the system to identify non-fall occurrences. Specificity= TN / (TN + FP)
Precision	Precision measures the percentage of detected falls that were accurately identified. Precision= TP / (TP + FP)
F1-Score	The F1-Score balances precision and recall. F1-Score = 2 * (Precision * Recall) / (Precision + Recall)
False Positive Rate	It measures the rate at which non-fall events are misclassified as falls. False Positive Rate= FP / (FP + TN)
False Negative Rate	Actual falls are misclassified as non-falls. False Negative Rate= FN / (TP + FN)
Area Under the Receiver Operating Characteristic Curve	AUC-ROC assesses the model's fall detection performance. In discrimination, larger values indicate better performance.
Confusion Matrix	The confusion matrix shows in more detail the number of true positives, true negatives, false positives, and false negatives.
Matthews Correlation Coefficient	Matthews Correlation Coefficient balances classification performance by including true and false positives and negatives. Matthews Correlation Coefficient = (TP * TN - FP * FN) / sqrt ((TP + FP)(TP + FN)(TN + FP)(TN + FN))

- TP – True Positive: True Positives are instances that were correctly classified as positive by the model.
- TN – True Negative: True Negatives are instances that were correctly classified as negative by the model.
- FP – False Positive: False Positives are instances that were incorrectly classified as positive by the model.
- FN – False Negative: False Negatives are instances that were incorrectly classified as negative by the model.

5. RESEARCH ISSUES

Fall detection using mobile phone sensors is a promising field of study with several challenges.

- A large, diverse dataset with real fall events is difficult to collect and annotate.
- Fall detection may capture cell phone data, causing privacy concerns.
- Standardizing and assuring device performance is difficult with various sensor data.
- Sensor data may have drift, artifacts, and noise. Accurate fall detection requires data preparation to clean and filter.

- Personalized fall detection systems that match a person's movement and behaviors are desirable but challenging tasks.
- Optimizing algorithms is critical to reducing energy consumption.
- Fall detection sensitivity and false alarm reduction are difficult trade-offs.
- Environmental factors and electromagnetic interference can impact mobile phone sensors.

6. CONCLUSION

Mobile phone sensor-based fall detection is a potential field for increasing age-related safety and well-being. The introduction section of this paper emphasizes the importance of fall detection. The background section outlines the primary types of fall detection approaches. The literature review discusses various approaches and methodologies utilized in fall detection systems based on mobile phone sensors. Existing research works have employed various machine learning algorithms, including k-nearest neighbors, support vector machines, and tree-based models. In particular, deep learning algorithms like AlexNet Xception were employed in some research. Additionally, it addresses critical evaluation metrics and provides insights into the challenges encountered in the research.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest in this work.

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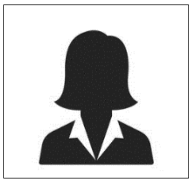

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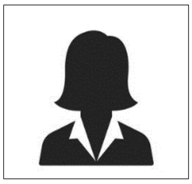

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