Fall Detection Methods for Elderly People- A Comprehensive Survey

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***Abstract*— This survey research gives a thorough analysis of sensor technology and picture preprocessing methods for fall detection systems for elderly people. Caretakers face serious health hazards and difficulties when an older person falls. Numerous sensor-based and vision-based solutions have been put forth to deal with this problem. This survey talks about the difficulties with effective implementation of these techniques, such as sensor location, data fusion, and power management. It also examines several pictures' preprocessing methods, including background removal, object detection, tracking, and feature extraction, which are crucial for improving the precision and responsiveness of vision-based systems. This study also examines the benefits and drawbacks of the various sensor technologies used, such as accelerometers, gyroscopes, depth cameras, infrared sensors, pressure mats, and wearables. Important data on elderly falls is also provided to further emphasize how urgent it is to have effective fall detection systems. With the help of improved fall detection systems, this study will serve as a significant resource for researchers and practitioners, leading future developments to increase the safety and well-being of senior people**

Keywords*— Computer Vision, Machine Learning, Deep Learning, Sensors, Image Preprocessing, CNN, LSTM, Fall, Detection.

I. Introduction

The phenomenon of falls among elderly individuals has become a matter of utmost importance and concern in today's aging societies. As the world's population continues to age, the impact of falls on the health and well-being of older adults has garnered significant attention. Understanding the intricacies of how and why these falls occur is essential for developing effective fall prevention and monitoring strategies. Elderly individuals often experience falls due to various factors, including age-related changes in balance and mobility, chronic health conditions, medication side effects, and environmental hazards. Their postures during falls can vary, with common patterns including trips, slips, and missteps, often leading to sudden loss of balance. The consequences of such falls are far-reaching, encompassing physical injuries like fractures and head trauma, as well as psychological effects like fear of falling again and a decline in overall mobility. As the average age of the falling elderly population varies by region, it is crucial to examine the specific risks faced by different countries and cultures.

With an increasing trend of global mobility, many children of aging parents now reside abroad, making it challenging for them to be physically present to offer immediate assistance in times of need. This geographical separation can be particularly distressing during serious fall incidents, as elderly individuals may find themselves without immediate access to family members who can provide help or coordinate emergency responses. The inability to receive prompt aid from loved ones can exacerbate the physical and emotional consequences of a fall, leaving the elderly person feeling isolated and vulnerable. In such circumstances, technology-driven solutions that enable remote monitoring, automatic fall detection, and communication with family members or healthcare providers become vital lifelines, offering a sense of security and support despite the physical distance. The information obtained from the World health organization WHO shows that the approximate rate of falling 65 age people is 28 to 35%, and the 32 to 42% of age 70 is increasing day by day.

In recent years, modern technology has revolutionized the way we care for elderly individuals, with one particularly impactful application being the detection of falls and timely alerts to their caregivers. Falls among the elderly are a significant concern, often resulting in serious injuries and reduced quality of life. Leveraging the power of advanced technologies, such as motion sensors, wearable devices, and smart home automation, allows for the development of unobtrusive and effective fall detection systems. By harnessing the potential of modern technology, we can enhance the well-being of our elderly population and ensure that they receive the prompt care and support they need to lead fulfilling lives.

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A significant increase in studies examining various sensor and image preprocessing based techniques for precisely identifying falls among the elderly has been observed recently in the field of fall detection research. This survey paper aims to comprehensively review and compare these sensor and image-based methodologies, shedding light on their individual strengths, limitations, and applicability in real-world scenarios. Furthermore, we will delve into the challenges faced by these approaches when deployed in today's dynamic and diverse environments, seeking to identify potential areas of improvement and avenues for further research to foster the development of robust and effective fall detection systems. By presenting an in-depth analysis of the state-of-the-art techniques, this survey aims to contribute to the advancement of fall detection technology and facilitate its integration into the lives of the elderly, promoting their safety and well-being in an increasingly aging society.

The major contributions of this survey are discussed as follows:

- This survey efficiently points down all the major contributions of authors who have made their contributions for the fall detection systems in the past five years.

- In this survey, we have noted down the two main approaches and their detailed explanations, used by all researchers world-wide, i.e., sensor based and image-based approaches.

- Sensor based and image-based systems possess many challenges in their way to deployment and after deployment too. This survey mentions down all the challenges of the well-known research in this domain.
- This survey is designed in such a way that all scholars and students would get the idea of fall detection systems and their applicability.

- Detailed methodology of the fall detection systems including feature extraction methods and signal preprocessing for the sensors are also mentioned down.

II. Related Works

The authors of this research have provided a summary of the fall detection research and have also covered the key issues surrounding fall detection. For this, they have gathered and analyzed relevant documents, and facts. Out of all the documents, they have only selected a few articles based on three criteria: sensor, performance, and algorithms [1]. The authors in this research have discussed a number of automatic techniques as well as methods that will track elderly people's daily activities to detect falls by watching their movements. They have analyzed a number of methodologies and classified them according to their strengths and weaknesses. The methods they have discussed fall primarily into three categories [2]. This research displays the performance, difficulties, and restrictions of the fall detection system's multisensory data fusion as well as the most recent approaches and trends are discussed in this paper. In comparison to single sensor approaches, this paper emphasizes the benefits of developing multimodal fall detection systems and discusses issues that will be helpful going forward [3]. Similarly, the authors here have prepared the survey for different fall detection systems and their underlying algorithms and the methods of fall detection are categorized into three groups: wearable device-based, vision device-based, and ambience device-based. These methods are contrasted with one another and may be used in future research [4]. The authors of this paper have presented the three stages of a fall, including prediction, prevention, and detection. They have created a fall diagnosis system that includes edge, fog, and cloud layer illustrations. For upcoming work, they have also discussed the difficulties of fall diagnosis [5]. The authors of this survey claim to be researching the specifications needed for fall detection systems, as well as showcasing recent works on the subject using a machine learning approach. They have also analyzed the difficulties encountered in fall detection systems using literature survey [6]. The survey here conveys three different categories of fall detection algorithms: wearable technology, which is affordable, inconvenient, but accurate; audio-based technology, which is affordable but convenient compared to wearable technology; and video-based technology, which is accurate and simple to install, and these three technologies will perform best. [7]. In this survey paper, the authors discuss various fall detection systems based on Field Programmable Gate Arrays [FPGAs] and provides an explanation of key theoretical concepts, practical applications, and algorithms for accelerometer-based fall detection systems. The authors also provide the main design steps for fall detection systems [8]. The authors of this paper have used the Neyman-Pearson framework to design the detection method. In order to gather information about the movement of elderly people, they have also attached a TelosW mote with an accelerometer to their waists. They have spent a lot of time working on this to increase the effectiveness and accuracy of the detection system [9].

III. Methodology

Sensor-based and machine learning (ML) based approaches have gained popularity in the last five years of research regarding fall detection for elderly people due to their combined effectiveness and practicality. Sensor-based methods leverage a diverse range of devices, such as accelerometers, gyroscopes, and pressure sensors, to capture motion and environmental data, enabling accurate and unobtrusive fall detection in real-time. These sensors are readily available, affordable, and non-intrusive, making them suitable for continuous monitoring of the elderly without disrupting their daily activities. On the other hand, ML-based techniques offer the ability to process and analyze large volumes of sensor data, enabling the creation of sophisticated fall detection algorithms. Machine learning models can learn patterns indicative of falls from labeled datasets, allowing for continuous improvement and adaptability to different scenarios and individuals. The combination of sensor-based and ML-based approaches harnesses the strengths of both technologies, resulting in robust and reliable fall detection systems. As research progresses, the integration of these methods holds great promise in enhancing the safety and care of elderly individuals, reducing the risk of fall-related injuries, and providing timely assistance when needed.

In Figure number 1, a detailed flowchart of how this whole process carries out, and how sensor based and image-based approaches work are displayed.

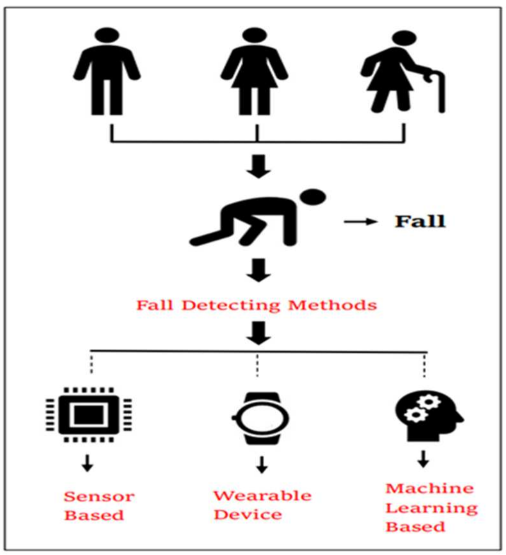

Figure 1. Flow Diagram for the Fall Detection systems

A. Sensor Based Approach

The methodology for fall detection using sensor-based systems involves the integration of various sensors to capture the movements and behaviors of individuals. These sensors, such as accelerometers, gyroscopes, and sometimes magnetometers, are strategically placed on the body or within the environment to collect motion-related data. This data is then processed and analyzed to detect sudden and abnormal changes that might indicate a fall event. The fall detection process typically encompasses signal preprocessing, feature extraction, and classification stages. Preprocessing involves filtering and noise reduction to enhance the quality of the sensor data. Feature extraction involves identifying relevant characteristics from the sensor signals that can help distinguish between normal activities and fall events. Finally, classification techniques, often machine learning algorithms, are applied to differentiate between fall and non-fall patterns based on the extracted features. These algorithms are provided with rule-based threshold values that conclude instances of both fall and non-fall movements. Once trained, the system can accurately recognize fall events in real-time based on new incoming sensor data. This approach leverages the advantages of sensor technology to provide prompt and reliable fall detection, offering increased safety and timely assistance for individuals at risk of falls.

Let us now discuss the three important steps of the sensor-based systems.

1. ***Signal Preprocessing***: Signal preprocessing is the initial step in the fall detection process, aimed at enhancing the quality of the raw sensor data. This involves techniques such as noise filtering, data resampling, and signal conditioning. The sensor data collected from accelerometers, gyroscopes, and other sensors can contain noise and artifacts due to various factors, including sensor inaccuracies, movement irregularities, and environmental interference. Preprocessing techniques are applied to remove or reduce these unwanted components, ensuring that the data is accurate and reliable for further analysis.

2. ***Feature Extraction***: Feature extraction involves identifying specific characteristics or patterns in the pre-processed sensor data that are indicative of fall events. These features act as discriminative markers that distinguish between normal activities and fall-related movements. Features can include statistical parameters (mean, variance, skewness), frequency domain components (spectral energy), and time-domain characteristics (jerk, orientation changes). The choice of features depends on the sensor modality, the type of movements being detected, and the complexity of the analysis. Effective feature extraction is essential for providing relevant information to the classification stage.

3. ***Classification Stage***: In the classification stage, the extracted features are used to differentiate between fall and non-fall events. Rule-based threshold systems involve setting predefined thresholds for specific features based on empirical observations or expert knowledge. When the extracted feature values exceed these thresholds, the system classifies the event as a fall. For instance, if the magnitude of acceleration surpasses a certain threshold within a short time frame, it could indicate a rapid fall movement. Rule-based approaches are straightforward to implement and require no extensive training; however, they may be limited in their adaptability to different scenarios and individuals.

In a rule-based threshold system, the decision-making process is determined by a set of predetermined rules that dictate when a fall is detected based on specific feature values and their relationships. While these systems can provide quick and simple fall detection, they might lack the adaptability and customization that machine learning-based approaches offer.

Sensors are the heart of this approach. The kind of sensors that are generally used by the researchers to support their methodology are shown in the table number 1.

TABLE I. POPULAR SENSORS AND THEIR FUNCTIONALITIES

Sensors	Functionality
Accelerometer	Measures acceleration forces in various directions. Detects changes in motion and orientation, crucial for identifying sudden falls.
Gyroscope	Measures angular velocity and rate of rotation. Provides information about rotational movements and helps determine body orientation.
Magnetometer	Measures magnetic field strength and direction. Used in combination with other sensors to determine orientation relative to the Earth's magnetic field.
Pressure Sensor	Measures changes in atmospheric pressure. Can be used to detect posture changes, such as sitting or lying down.
Inertial Measurement Unit (IMU)	Combines accelerometer, gyroscope, and sometimes magnetometer data to provide comprehensive information about motion, orientation, and angular velocity.

Also, the capabilities and efficacy of sensor-based fall detection systems are improved by the Internet of Things (IoT) technology integration. Real-time data gathering, analysis, and response are made possible by IoT, which enables seamless connectivity and communication across various sensors, wearable technology, and centralized platforms. Systems for detecting falls that are IoT-enabled can send sensor data, such as acceleration and orientation data, to a processing server or cloud platform. As a result, fall incidents can be continuously monitored for and quickly detected, allowing automated alarms to be sent to family members, carers, or emergency services. IoT also enables remote monitoring, allowing carers to check a person's history of falls and daily activity patterns via mobile applications or web interfaces.

B. *Image Based Approach*

Computer vision techniques are used by mages-based fall detection systems to analyse photos or video streams and find instances of falls. These systems frequently include cameras, depth sensors, or other visual input devices to record people's postures and motions. Several phases, including image acquisition, preprocessing, feature extraction, and classification, go into the creation of image-based fall detection systems. In order to improve their quality and eliminate noise, images or frames from video streams are recorded and pre-processed. Then, using feature extraction techniques, pertinent traits are found, including body posture, movement direction, and spatial correlations. To identify fall and non-fall activities based on the extracted features, machine learning techniques, such as deep neural networks, support vector machines, or decision trees, are trained on labelled datasets. In order to identify abrupt changes in posture or unusual motions suggestive of a fall, the trained model can then analyse real-time visual data. Since wearable devices are not necessary for unobtrusive fall detection, image-based solutions are suited for a variety of settings and user preferences.

The development of precise and dependable systems for image-based fall detection has previously investigated a variety of computer vision techniques. These investigations looked into how to capture human postures and motions using RGB cameras, depth sensors, and combinations of the two. To extract pertinent information from image data, techniques including human posture estimation, motion analysis, and spatial-temporal modelling have been used. Convolutional and recurrent neural networks, among other deep learning architectures, have been successfully used to distinguish between fall and non-fall activities. To improve system robustness, researchers have tackled issues like occlusion, changing lighting, and various surroundings. Numerous studies have also looked at real-time performance, taking into account how quickly and effectively fall detection systems may be put into operation. The goal of image-based fall detection research is to develop precise, non-intrusive technologies that can improve people's safety and well-being, especially the elderly, by facilitating quick help in the event of fall accidents.

IV. CHALLENGES IN SENSOR AND IMAGE BASED APPROACHES

There are a number of difficulties involved in creating sensor-based fall detection systems that must be carefully taken into account. To enable correct analysis, integrating data from heterogeneous sensors—each with unique properties—requires meticulous synchronisation and harmonisation. It is essential to choose the best sensor placements to provide both effective fall detection and user comfort. Noise and artefacts can degrade the quality of sensor data, which makes the development of advanced noise reduction algorithms necessary. The system must be able to adapt to a variety of settings, which is made difficult by the real-world unpredictability in human movements and behaviours. To achieve high detection accuracy while reducing false positives, specialised algorithms are required for unbalanced datasets when falls are uncommon relative to everyday activity. It is crucial to choose the right threshold values for fall detection because improper settings can result in missed falls or pointless alarms. Effective algorithm design is necessary since wearable devices have limited computational and battery capacity. It can be difficult to guarantee real-time performance for timely warnings, especially on devices with limited capabilities.

In the Table number 2, a detailed work description of all the research work of this expertise and their challenges are noted down.

TABLE II. RELATED WORKS WITH THEIR CHALLENGES

Researchers	Approach	Methodology	Challenges	Accuracy	Year
VMR Anakala, etc. [10]	Sensor Based.	Threshold based system, with a CNN classifier model.	1. Lack of AI Generalization 2. Accuracy and False Positives	N/A	2023
Sakshi Shukralia, etc. [11]	Sensor Based.	ISBFD (Inertial Sensor Based Fall Detection) concept, utilizing real-time accelerometer data from smartphones.	1. Data Variability 2. Ethical and Privacy Concerns	93%	2023
Nader Maray, etc. [12]	Combined.	A fall detection technique utilizing a combination of 1-D point cloud and doppler velocity data as inputs to a Long Short-Term Memory (LSTM) network.	1. Practicality and User Acceptance 2. Model Drift across devices	N/A	2023
Chainarong Kittiyanpunya, etc. [13]	Machine Learning.	Machine Learning with multimodal dataset	1. Data Collection and Variation 2. Feature Selection and Input Dimensionality	99.50%	2023
Chainarong Kittiyanpunya, etc.[14]	Millimeter -Wave Radar -Based.	Created LSTM network employed as intelligent classifier and millimeter wave frequency modulated continuous wave for collection of radar signals	N/A	99.50%	2023
Sakorn Mekruksavanich etc. [15]	Wearable Based	Using Hybrid deep residual neural network.	1. Always attached to body 2. Model optimization	95.1%	2022
Ekram Alam a, etc. [16]	Vision Based.	Discussing about different metrics that helps in assess performance of fall detection system.	N/A	N/A	2022
Xiaodan Wu a, etc. [17]	Mobile Sensors.	Using deep learning technology for automatic fall detection.	1. Sensor Modalities Integration 2. Difficult to determine complex fall.	99.56% and 60.69%	2022

V. CONCLUSION

The necessity to improve the safety and wellbeing of elderly people has resulted in notable breakthroughs in the field of fall detection systems. Utilizing accelerometers, gyroscopes, and other sensors on wearable technology, sensor-based techniques record motion data. These techniques address issues such data heterogeneity, the best location for sensors, and real-time performance. Image-based systems, on the other hand, use computer vision techniques to overcome obstacles including appearance variability, occlusions, and privacy issues related to camera use. Machine learning algorithms that span from conventional approaches like rule-based threshold systems to complex deep learning models support both approaches. We face challenges like dataset variability, resource limitations, and ethical concerns as we go through sensor-based and image-based fall detection. The convergence of technology, user-centric design, and ethical responsibility holds the key to solving these problems. Fall detection systems will effectively protect the independence and dignity of our older population in the future thanks to the convergence of IoT connection, machine learning process, and a dedication to user acceptance.

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