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Fall Detection and Prevention Systems: Sensor Type Perspective

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ABSTRACT

Falls among older adults pose significant health risks, making their prevention and detection critical areas of research. This review examines fall detection and prevention systems, categorizing them based on sensor types and utilization methods: wearable sensors, environmental sensors, radio-frequency-based sensors, and hybrid systems. Additionally, it explores the methods employed within these systems. Given the limitations of traditional linear approaches in accurately detecting falls, recent research emphasizes artificial intelligence (AI) techniques, particularly machine learning (ML) and deep learning (DL), to enhance detection accuracy and system functionality. The review provides an overview of the sensors and algorithms used in fall detection and prevention systems, alongside their outcomes. Key findings and challenges related to specific sensors and systems are discussed in detail. This analysis offers researchers a comprehensive understanding of current technologies, highlights the contributions of AI methods, and outlines potential future directions in the field. By evaluating sensors, methodologies, and system sensitivities, the aim is to contribute to the development of effective solutions tailored to specific sensitivities.

Sensör Tipleri Perspektifinden: Düşme Algılama ve Önleme Sistemleri

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ÖZ

Yaşlı bireylerde düşmeler, önemli sağlık riskleri oluşturmakta ve bu durum, önleme ve tespit çalışmalarını kritik bir araştırma alanı haline getirmektedir.
Bu derleme, düşme tespit ve önleme sistemlerini kullanılan sensör türleri ve yöntemlerine göre sınıflandırarak incelemektedir: giyilebilir sensörler, çevresel sensörler, radyo frekansı tabanlı sensörler ve hibrit sistemler. Ayrıca, bu sistemlerde kullanılan yöntemler ele alınmaktadır. Geleneksel doğrusal yaklaşımların düşme olaylarını doğru bir şekilde tespit etmedeki sınırlamaları göz önüne alındığında, son yıllarda makine öğrenmesi (ML) ve derin öğrenme (DL) gibi yapay zeka (YZ) teknikleri üzerine yapılan araştırmalar ön plana çıkmaktadır. Bu derleme, düşme tespit ve önleme sistemlerinde kullanılan sensörler ve algoritmalar ile bunların sonuçlarına dair kapsamlı bir bilgi sunmaktadır. Belirli sensörler ve sistemlerle ilgili temel bulgular ve zorluklar detaylı bir şekilde tartışılmaktadır. Çalışma, mevcut teknolojiler hakkında araştırmacılara geniş bir bakış açısı kazandırmayı, YZ yöntemlerinin katkılarını vurgulamayı ve alanın gelecekteki yönelimlerini ortaya koymayı hedeflemektedir. Sensörler, metodolojiler ve sistem duyarlılıkları değerlendirilerek, etkili ve hassasiyetlere uygun çözümlerin geliştirilmesine katkı sağlanması amaçlanmaktadır.

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1. Introduction

Advancements in medicine and global population growth contribute to an increase in the proportion of the elderly population. The World Health Organization (WHO) predicts that by 2050, the number of elderly individuals will exceed 1.5 billion. According to a report from 2015 by WHO, the elderly population (aged 60 and above), which was 900 million at the time, accounted for 22% of the world's population. Furthermore, it is indicated that the annual fall rate among adults aged 70 and above is expected to increase from 32% to 42%. Falls have both physical and psychological effects that restrict the quality of life for the elderly (Qiu et al. 2019). Serious injuries resulting from falls, such as fractures, bruises, and head traumas, or even mild injuries that limit daily activities, can diminish a person's quality of life (Faes et al. 2010). The fear of falling leads to a decrease in engaging in physical activities, resulting in a decline in mobility and muscle strength, and an increased risk of falling. The development of a fear of falling can reduce one's joy of life and diminish their commitment to life (Kuzuya et al. 2006), (Zhu et al.2021). Consequently, it is an essential need for the elderly to detect falls in order to provide timely assistance if falls cannot be prevented or to issue warnings by predicting falls in order to improve overall quality of life (Yu et al. 2008).

Falls can be divided into two main categories: fall detection and prevention. Fall detection involves using data obtained from sensors or cameras to detect a fall event and make a distress call. Fall prevention aims to predict and prevent falls by observing human movements. Various strategies, such as combinations of different sensors, artificial intelligence methods, and threshold-based approaches, are being explored in fall detection and prevention studies.

Over the past twenty years, fall detection and prevention strategies have become a significant focus in addressing the issue of falls among the elderly. Particularly, fall detection methods have been extensively investigated by researchers. These systems aim to obtain more data by utilizing different types of sensors and process the data using statistical and artificial intelligent methods. Efforts have been made to achieve more successful results through the use of artificial intelligence algorithms and analysis techniques. Sensor types used in fall detection and prevention systems are classified and shown in Figure 1.

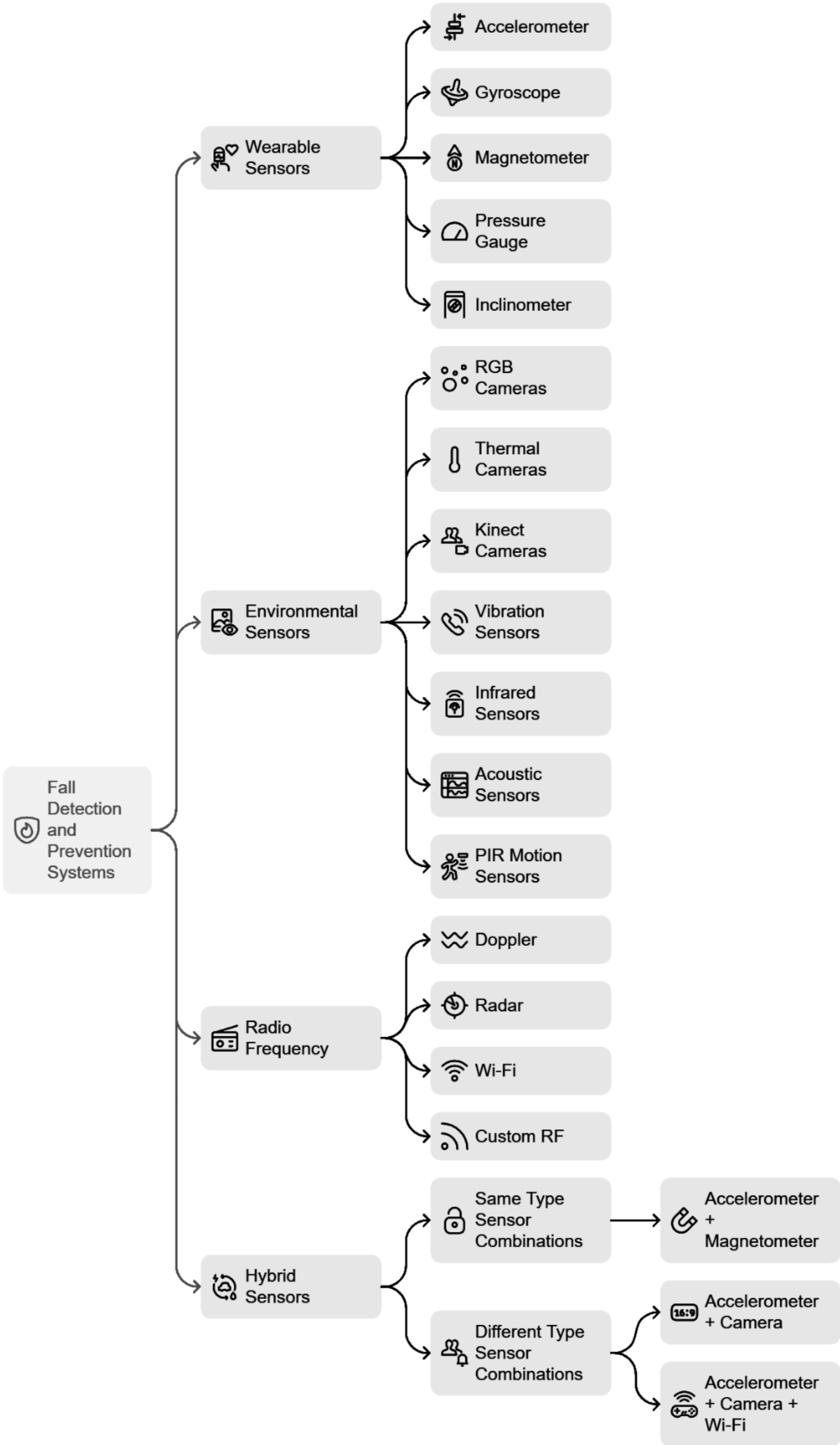

Figure 1. Fall detection and prevention systems classified with sensor type.

Fall detection and prevention systems work by measuring sensor data in three basic time periods: before the fall, during the fall and after the fall. While fall prevention systems generally focus on pre-fall sensor data from these time intervals, fall detection systems focus on sensor data during and after the fall. One of the fall detection studies only considers the large acceleration effect (Hwang et al. 2004). In some systems, more successful results have been achieved with different combinations of sensor number and type. Among these, studies were found in which a three-axis accelerometer and gyroscope were preferred for fall detection (Li et al. 2009). In another study, to improve the performance, the authors proposed a multi-modal fall detection, which is a three-step fall detection strategy consisting of multiple signal sources, including an accelerometer, audio and video techniques (Zhang et al. 2013). Fall detection studies have been carried out using different sensors such as accelerometer and microphone sensors in the smartphone (Shakeri 2017). In articles (Shahzad et al. 2018) and (Quadros et al. 2018), the authors effectively detected falls using machine learning, one of the artificial intelligence methods. Finally, in recent years, attention has been drawn to studies using Radio Frequency (RF)-based Wi-Fi and Bluetooth technologies, which are carried out on the principle of measuring the strength of the signal weakened after the absorption of wireless network signals (Wang et al. 2016; Yusuf et al. 2021).

The categorization of sensor types and combinations applied to enhance the efficacy of fall detection systems is examined in this review under the following subcategories:

- Studies utilizing wearable (inertial) sensors,
- Studies employing environmental sensors, which include both image-based approaches (RGB, depth sensors, Kinect cameras) and non-image-based methods (such as passive infrared (PIR) sensors and vibration sensors),
- Measurements and studies based on Radio Frequency (RF) signals, including Wi-Fi and custom RF configurations,
- Studies employing combined sensor systems, involving various sensor types and combinations, such as cameras, accelerometers, PIR sensors, and pressure sensors.

In the second section, sensors are described in terms of their material properties, while the methodology section outlines the literature review approach. The third section classifies fall detection and sensing systems based on the types of sensors employed. The reviewed studies are analyzed to identify the strengths and limitations of each sensor type and system approach. In the fourth section, a comprehensive discussion is provided on the advantages and disadvantages of these studies. Finally, the fifth section presents recommendations derived from the review findings and proposes future research directions in this field.

2. Materials and Methods

This section explains the types of sensors encountered in the literature review and their fundamental operating principles. The methodology section provides an overview of the study's position within the literature along with some explanation.

2.1 Materials

The fundamental definitions, sensor types, primary categorization, and working principles of fall detection and prevention systems are detailed in this section.

2.1.1 Sensor Types

In studies on fall detection and prevention systems, various approaches have been proposed using different sensor types and artificial intelligence (AI) techniques. The sensor types frequently encountered in literature can be divided into four main categories: wearable sensors, environmental sensors, radio frequency (RF)-based sensors, and hybrid systems (Figure 2).

Wearable sensors directly measure body movements using sensors such as accelerometers, gyroscopes, and magnetometers. These sensors are placed on different parts of the body to detect joint movements and body dynamics.

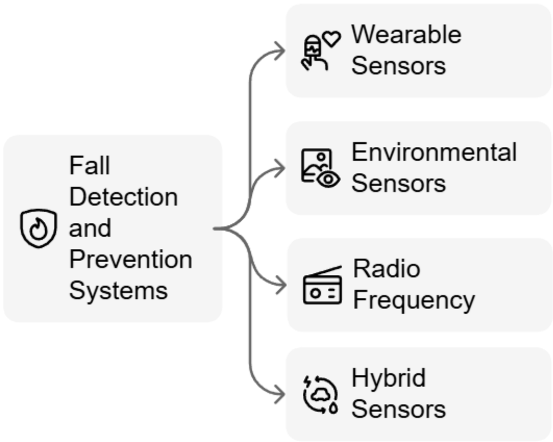

Figure 2. Fall detection and prevention systems classified with sensor type.

Wearable sensors, which are commonly used in fall detection systems, are attached to the body to continuously monitor and analyze movements (Fig. 3).

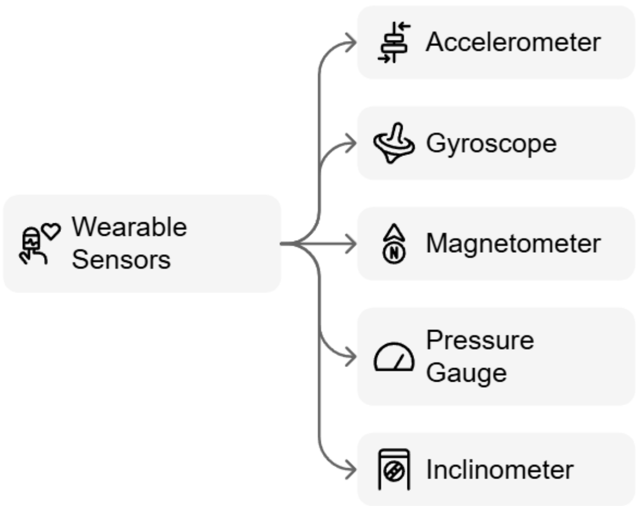

Figure 3. Wearable sensors in fall detection and prevention systems

Accelerometers are sensors that measure body movement acceleration along three axes (x, y, z). In fall detection systems, they are used to continuously monitor an individual's movement dynamics and identify fall events. Accelerometers can analyze parameters such as step count, duration of physical activity, energy expenditure, and posture changes (Kangas et al., 2012). Due to their lightweight, low cost, low power consumption, and small size, they are widely used in wearable devices.

Gyroscopes measure the angular velocity of the body and are typically used in conjunction with accelerometers to enable a more detailed analysis of movements. They play a crucial role in detecting sudden rotational movements during falls, helping to determine the direction and intensity of the motion. Studies indicate that integrating gyroscopes with accelerometers enhances the accuracy of fall detection systems (Liu et al., 2020). However, gyroscopes have high power consumption and, when used alone, may result in a high rate of false positives (Najafi et al., 2003).

Magnetometers measure magnetic fields to provide orientation information. In fall detection systems, they are used to determine the body's spatial orientation and detect sudden position changes during a fall (Ojetola et al., 2015). Magnetometers are commonly found in smartphones and wearable devices. However, they can be influenced by environmental magnetic fields, which limits their accuracy when used alone. For more reliable results, they are typically combined with accelerometers and gyroscopes (Yang and Hsu, 2010).

Pressure sensors measure the force applied to the body and are used to detect pressure changes that occur during a fall. They are particularly placed in shoe soles or other body regions to detect impact forces and assess fall severity (Tong et al., 2018). In fall detection systems, pressure sensors are often integrated with other sensors to analyze physical contact and pressure distribution. However, their accuracy may vary depending on their placement on the body.

Barometers are sensors that measure atmospheric pressure to detect changes in altitude. In fall detection systems, they are used to identify sudden drops in elevation. Rapid altitude changes occurring during a fall can be detected by barometric sensors, contributing to fall event identification. They play a significant role in detecting falls in environments with elevation differences, such as multi-story buildings and staircases (Ejupi et al., 2016). However, their sensitivity can be affected by atmospheric conditions, limiting their reliability when used alone. Therefore, they are often integrated with accelerometers and gyroscopes to develop more accurate fall detection systems (Lin et al., 2017).

Inclinometers are sensors that measure the tilt angle and deviation from the vertical axis. In fall detection systems, they are used to detect sudden angular changes in body posture. By utilizing gravity-based measurements, they analyze postural changes and detect angular differences during a fall. Additionally, they can be employed to monitor postural abnormalities and balance disorders (Sun et al., 2018).

Due to their low power consumption and small size, these sensors can be easily integrated into portable devices. However, their sensitivity to movement can lead to a high rate of false positive alarms, and their accuracy in fall detection is limited when used alone. Therefore, they are typically combined with other sensors, such as accelerometers and gyroscopes, to achieve more reliable results.

Environmental sensors that are not positioned on the body, include camera-based (RGB, depth, thermal) systems and passive infrared (PIR) sensors. Camera-based systems detect falls using image processing techniques, while PIR sensors operate by detecting thermal changes caused by the movement of living beings. They are strategically placed in living spaces (e.g., residences, care facilities) to detect falls and identify factors that increase the risk of falls. The performance and features of different camera types used in fall detection systems play an important role in increasing the effectiveness of these systems. In this context, RGB cameras, Kinect cameras (depth cameras), and thermal cameras, which are evaluated within the scope of environmental sensors, are among the basic imaging systems used in the detection of falls (Figure 4).

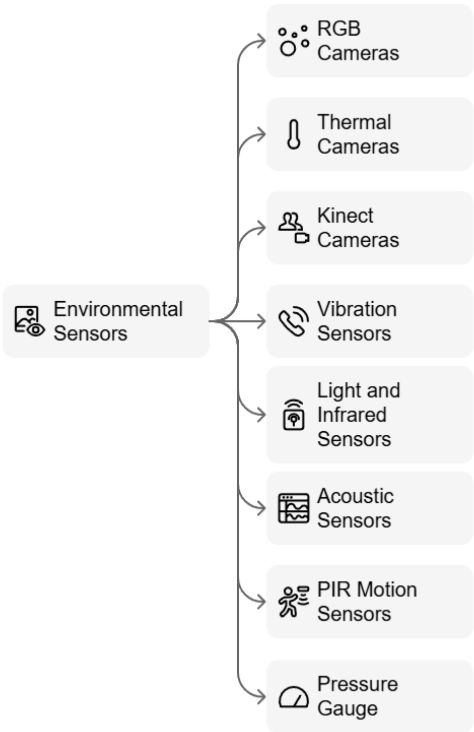

Figure 4. Fall detection and prevention systems classified with environmental sensors.

RGB cameras are widely used in fall detection systems due to their low cost and widespread availability (Mastorakis and Makris, 2014). These cameras provide three-channel (red, green, blue) imaging, allowing for a detailed visual analysis of the environment. In studies utilizing a single camera, fall detection is achieved by analyzing changes in the human silhouette over time (Rougier et al., 2011). Image processing techniques are used to detect fall instances, analyze movement patterns, and identify abnormal situations. However, RGB cameras are sensitive to ambient lighting conditions, and their detection accuracy decreases under low or variable light levels (Kwolek and Kepski, 2014). To address these limitations, they have been integrated with deep learning-based object detection algorithms such as YOLOv5, resulting in more reliable fall detection systems (Redmon et al., 2016). Additionally, to mitigate privacy concerns, techniques such as 2D skeleton estimation are employed instead of raw RGB images (Shotton et al., 2011). To improve reliability, multi-camera systems capable of capturing images from different angles have been proposed (Stone and Skubic, 2011).

Thermal cameras operate solely based on temperature distribution data and offer high accuracy rates regardless of ambient lighting conditions (Feng et al., 2014). These systems detect falls by recognizing body temperature variations and allow the use of simpler deep learning models due to their low-resolution thermal images (Feng et al., 2014). Thermal imaging systems provide significant advantages in privacy-sensitive environments since they do not contain personal identifying information such as facial recognition and rely solely on heat distribution data (Feng et al., 2014). However, due to their low resolution, detailed body movement analysis becomes challenging. Therefore, integrating thermal cameras with additional sensors or other imaging systems is recommended for fall detection.

Kinect Cameras (Depth Cameras) provide RGB-D data, enabling distance measurements between a person and the ground, as well as motion analysis (Zhang, 2012). Depth sensors generate three-dimensional maps of the environment using active infrared light projection to obtain distance information. This enhances accuracy by analyzing body posture and key joint movements during a fall (Stone and Skubic, 2011). Microsoft Kinect is one of the most widely used depth cameras and serves as a valuable tool for detailed analysis of fall events by performing 3D skeleton joint estimation (Shotton et al., 2011). Kinect systems address some privacy concerns associated with RGB cameras by utilizing depth information. However, these systems require high computational power, while their low-cost versions allow for in-home gait assessments (Clark et al., 2012). Nevertheless, the primary drawbacks of Kinect systems include higher costs compared to RGB cameras and their superior performance at shorter distances (Khoshelham and Elberink, 2012).

Vibration sensors detect vibrations caused by falls or sudden movements. They are used to identify vibrations occurring on the ground during a fall and to analyze an individual's gait pattern. Vibration data can provide information on step length, walking speed, and balance (Jenkins et al., 2016). These sensors offer comfortable, contact-free monitoring but may generate false alarms depending on the surface characteristics. Additionally, installation costs can be high.

Light sensors measure ambient light levels and help assess fall risk. They can analyze fall risks under low-light conditions since inadequate lighting can cause elderly individuals to lose their balance (Santos et al., 2013). These sensors can also track daily activities by analyzing light variations to estimate wake-up and sleep times or movements between rooms. Although light sensors are easy to install and cost-effective, they may be affected by external factors such as sunlight and artificial lighting. Their accuracy in fall detection is limited when used alone.

Pressure sensors analyze fall events by measuring pressure applied to the surface. They can detect sudden pressure changes on the ground during a fall and work in conjunction with vibration sensors. Additionally, they are used for monitoring in-bed movements, analyzing sleep duration, sleep patterns, and mobility levels (Al-Nashash et al., 2015). Pressure sensors can also assess gait balance by analyzing step pressure changes and provide reliable data since they directly measure pressure variations. However, they have a limited detection area, and the presence of pets or other individuals may lead to false alarms.

Motion sensors are used to detect an individual's movements, with passive infrared (PIR) sensors being the most used type. They are employed for:

- Detecting falls by identifying sudden movement changes,
- Evaluating an individual's mobility level,
- Identifying prolonged inactivity, which may indicate a potential fall (Pannurat et al., 2014).

These sensors can cover large areas, are easy to install, and are cost-effective. However, they may generate false alarms due to pet movements or other individuals and can be affected by environmental factors such as temperature changes.

In contrast, non-body-worn environmentally positioned sensors include camera-based (RGB, depth, thermal) systems and passive infrared (PIR) sensors. Camera-based systems detect falls using image processing techniques, while PIR sensors work by detecting thermal changes resulting from the movements of living beings.

RF-based systems, which use wireless communication technologies, track the movements of individuals and detect falls using Wi-Fi signals. Hybrid systems integrate different sensor types to provide more comprehensive monitoring and detection capabilities. RF sensors utilize radio frequency waves to analyze transmitted and received waveforms during communication. Additionally, they leverage channel state information (CSI) obtained from Wi-Fi wireless networks to detect movements. These detection systems can be categorized into three primary groups (Figure 5).

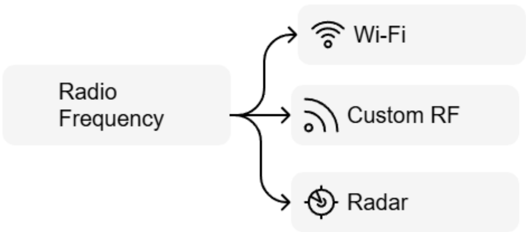

Figure 5. RF sensors for Fall detection and prevention systems

Wi-Fi is an RF-based technology that operates within the framework of IEEE 802.11 standards, enabling wireless data transmission (IEEE, 2020). This widely used technology functions in the 2.4 GHz and 5 GHz frequency bands to facilitate local network and internet access. However, wireless data exchange in such networks is continuously subjected to signal attenuation, reflections, and occasional data packet loss (Figure 6).

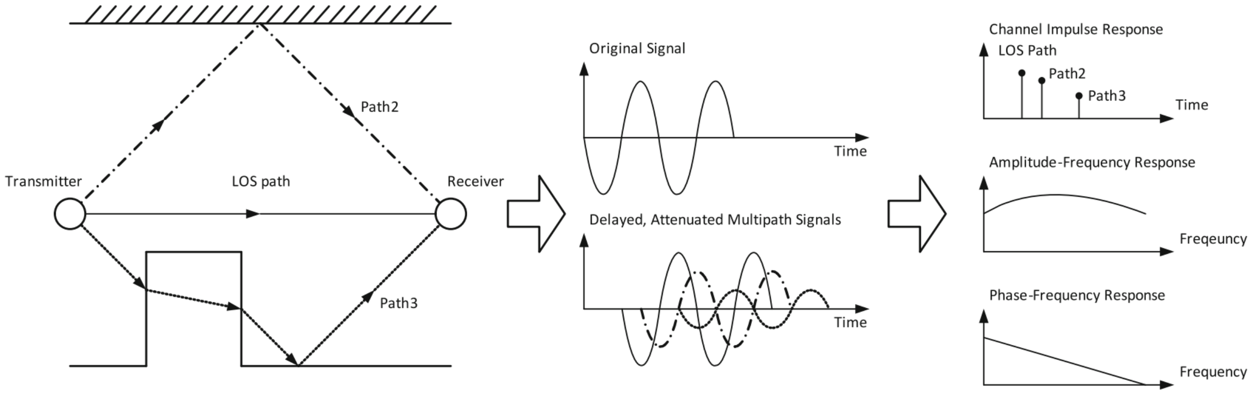

Fig.6 Multipath propagations, received signals, and channel responses (Yang et al., 2013)

Channel State Information (CSI) is used to determine wireless channel characteristics. CSI represents a set of parameters that define the amplitude and phase properties of a wireless channel. On the receiver side, it measures the impact of the signal on different subcarriers, thereby reflecting the physical state of the channel (Xie et al., 2019). CSI data is applied in various domains, including environmental sensing, indoor localization, motion recognition, and wireless communication optimization (Wang et al., 2017).

2.2. Method

In this section, existing literature on sensor-based fall detection and prevention systems has been evaluated based on review articles published by leading academic publishers (Mohan et al., 2024; Costa Junior et al., 2021; Purwar and Chawla, 2024; Usmani et al., 2021; Anonymous, 2022). Each cited paper in these reviews was assessed for accessibility and content, and similar or unavailable studies were excluded from the scope. Additionally, the literature was expanded and updated by searching for articles published after the review papers through Google Scholar. When selecting articles, preference was given to those published in reputable journals by publishers such as IEEE, Elsevier, Wiley, and Springer. To ensure comprehensive coverage and avoid overlooking unique contributions in the literature, a limited number of conference papers and articles published in SCI-indexed journals were also included.

3. Sensors in Fall Detection and Prevention Systems

Many different studies in the field of fall detection and prevention have been carried out using various sensor types and combinations. The data obtained was processed with different methods and fall detection and prevention systems were developed. Among these methods, solutions have been produced by using threshold value, artificial intelligence methods without threshold value and artificial intelligence approaches with integrated threshold value. Studies on sensors and their combinations continue to be carried out to increase the effectiveness of fall detection and prevention systems and to obtain more reliable results.

3.1. Wearable Sensors

It is well established that the majority of fall detection studies utilize accelerometers, gyroscopes, or other sensor types capable of detecting sudden impacts, changes in body orientation, or tilts. To monitor these variations in the human body, one or more sensors are strategically placed on different body parts of older adults, enabling the identification and differentiation of falls from Activities of Daily Living (ADL).

Wearable inertial sensors, including accelerometers, gyroscopes, and magnetometers, are commonly employed to detect and measure physical movements. These sensors are widely used to capture motion data from various body regions due to their compact size, affordability, and real-time data processing capabilities. They can be integrated into specially designed devices, general-purpose development boards, smartphones, and smartwatches. When attached to the body, these devices can detect abrupt changes, analyze gait patterns, monitor body posture, and capture muscle control signals. Consequently, falls and other physiological changes can be effectively detected (Figure 7).

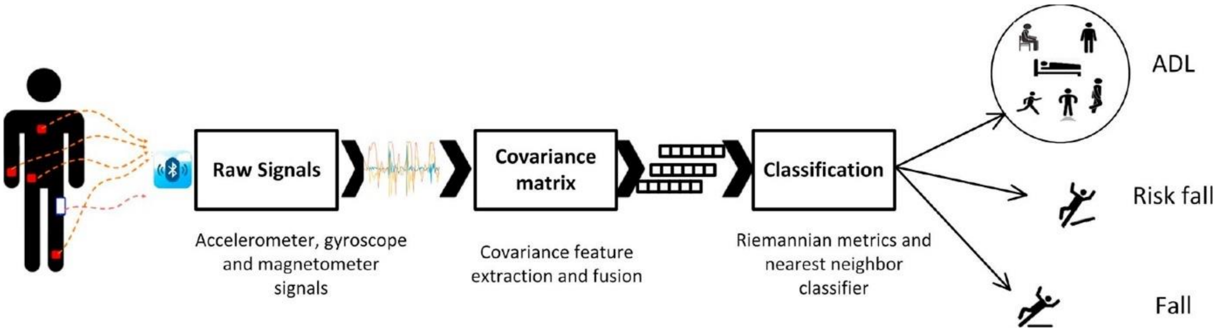

Figure 7. ADL and fall detection with multiple wearable sensor (Boutellaa et al. 2019)

A significant portion of research on fall detection and prevention leverages inertial sensors to monitor body movements and identify fall events. These sensors are recognized as effective tools for early detection and prevention by accurately tracking individual movements. Currently, two- or three-axis accelerometers and gyroscopes are widely utilized, and some studies suggest that integrating these sensors with additional inertial sensors can enhance accuracy (Table 1).

Wang et al. proposed an approach that combines the threshold-based screening method with machine learning models such as Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Decision Tree, Random Forest (RF), and XGBoost for fall detection (Wang et al. 2024). The study by Otanasap et al. also contributes to the research in this field (Otanasap et al. 2023). Salah et al. developed a fall prevention system that uses only accelerometers and has a high accuracy rate (Salah et al. 2022). Casilari et al. proposed a gyroscope-based fall detection method (Casilari et al. 2020). Kostopoulos et al. developed a fall detection method based on inertial sensors for elderly individuals (Kostopoulos et al. 2016). Su et al. performed fall detection using gyroscopes in their studies (Su et al. 2016) (Table 1).

Table 1. Fall detection and prevention system studies using inertial sensors.

Sensor Class	Sensor	Sensor Location	Activity	Classification Algorithm	Performance	Reference
WSHAR	3A	Wrist-Waist-Neck	FD	Treshold with KNN, SVM, DT, RF, XGBoost	ACC (avarage):99,65%	Wang et al. 2024
WSHAR	3A	Chest	FP	LR	ACC: 99,48% S: 95,31%	Otanasap et al. 2023
WSHAR	3A	NA	FD	CNN	ACC:95,55%	Salah et al. 2022
WSHAR	2G	Arm	FD	CNN	S:99%	Casilari et al. 2020
WSHAR	3A	Arm	FD	DT	ACC: 93,75%	Yacchirema et al. 2018
WSHAR	3A	Hip, back of calf and foot	FD	k-NN SVM	ACC: 81,2% ACC: 88,77%	Suriani et al. 2018
WSHAR	SW 3A	Wrist	FD	SVM and NB	ACC: 86%	Mauldin et al. 2018
WSHAR	3A	Chest, Arm	FD	k-NN	F-Score: Chest 98% F-Score: Arm 92%	Putra et al. 2018
WSHAR	3A	Between l3 and l5 vertebrae	FP	BBS	RMSE=1,66	Shahzad et al. 2017
WSHAR	G	Right Calf and Arm	FP	Hierarchical classifier	ACC: 97,5% S: 98,1%	Sue et al. 2016
WSHAR	3A	Body, Left and Right Body	FP	Visual classification	S: 76,1-89.4%	Fino et al. 2015
WSHAR	3A	Lever	FP	LR	ACC: 90-100%	Liu et al. 2014
WSHAR	3A	All Body Part Segmented	FP	ICA and NN	ACC: 95,4%	Martelli et al. 2014
WSHAR	3A	Rear Tread	FP	BBS-task based method	ACC: 87,2% S: 89,5%	Simila et al. 2014

Wearable Sensor-based Human Activity Recognition (WSHAR), 3 axis accelerometer (3A), Not Available (NA), convolutional neural network (CNN), Fall Detection (FD), Fall Prevention (FP), k-Nearest Neighbors (k-NN), Naïve Bayes (NB), Support Vector Machine (SVM), Accuracy (ACC), 2-axis gyroscope (2G), 2-axis gyroscope (2G), 3-axis gyroscope (3G), microgyroscope (uG), Sensitivity (S), Root Mean Square Error (RMSE), Scoreberg balance scale (BBS), Logistic Regression (LR), Smart Watch (SW), Neural Network (NN), Independent Component Analysis (ICA), Decision Tree (DT)

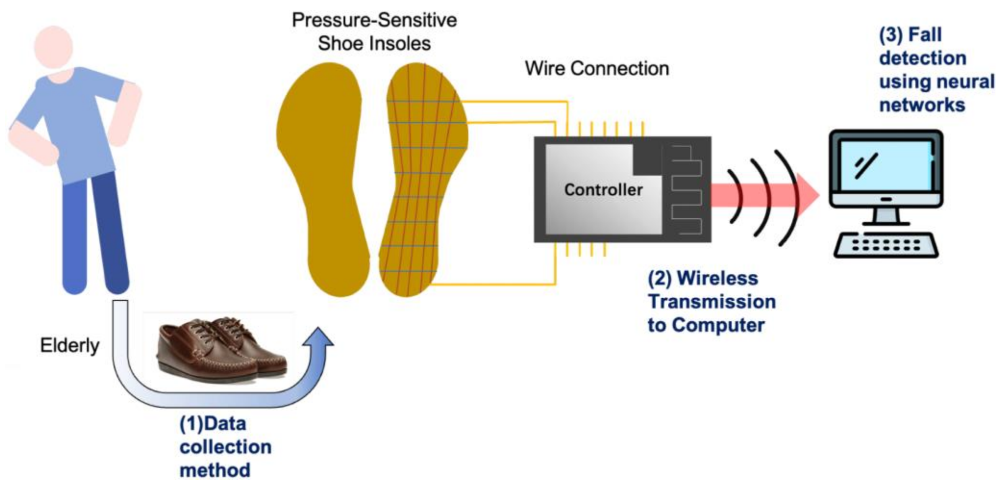

Figure 8. Pressure sensor-based fall detection system (Guo et al. 2024)

Fall detection and fall prevention systems with pressure sensors presented on table 2. In the study of (Guo et al. 2024) a pressure-based fall detection system for the elderly placed a pressure sensor on each insole equipped with 5 × 9 resistive films and uses the ResNet3D algorithm. The 2023 paper by Wang et al. aims to recognize human movements using a shoe-based triboelectric nanogenerator (TENG) for fall detection application. The researchers use a TENG system integrated into the sole of the shoe to generate electrical signals from the friction between the human body and the shoe. These signals are used to distinguish different human movements such as walking, running, jumping, and falling (Wang et al. 2023). In another Lu et al., it was stated that only pressure sensors were used to detect prevent falls (Lu et al. 2019). Similarly, in the study of Chaccour et al., it was stated that only pressure sensors were used to detect or prevent falls in Figure 8 (Chaccour et al. 2016) (Table 2).

Table 2. Pressure sensors for fall detection and fall prevention systems

Sensor Class	Sensor	Sensor Location	Activity	Classification Algorithm	Performance	Reference
WSHAR	Resistive Pressure Sensor	Insole (Shoe)	FD	ResNet(2+1)D	ACC (fall detection): 91% ACC (activity recognition): 94%	Guo et al. 2024
WSHAR	Triboelectric Nanogenerator (TENG)	Shoe-Surface Interface	Fall Detection	AI-Based Anomaly Detection	Not Specified	Wang et al. 2023
WSHAR	Barometer	Neck	FD	DMAF and KF	S: 95,2%	Lu et al. 2019
WSHAR	Resistance-Based Pressure	Shoe Sole	FP	Threshold	Risk level from 0,256 to 0,27	Chaccour et al. 2016
WSHAR	Foot Pressure Sequence	Under Foot	FD	SLR	P: 0,658-0,889	Light et al. 2015
WSHAR	Pressure		FP	Quantitative Gait Markers	Slow walking speed risk ratio: 69,95%	Verghese et al. 2009

Wearable Sensor-based Human Activity Recognition (WSHAR), 3 axis accelerometer (3A), Fall Detection (FD), Fall Prevention (FP), Stepwise Logistic Regression (SLR), Differential Moving Average Filter (DMAF), Kalman Filter (KF), Sensitivity (S), Precision (P)

Siwadamrongpong et al. developed a low-cost fall prevention system utilizing EEG and EMG sensors, integrating machine learning algorithms such as the K-nearest neighbors (KNN) classifier to detect postural stability and identify instances of unbalanced walking (Siwadamrongpong et al. 2022). The EEG sensor detected movement intentions by recognizing Movement-Related Cortical Potential (MRCP) patterns with an accuracy of 83,3%, while the EMG sensor analyzed muscle conditions and classified movement safety with an accuracy of 80%. The KNN model further distinguished between stationary, walking, and unbalanced walking states with an accuracy of 89%. Similarly, ZiYing et al. employed IMU sensors and EMG signals for fall prediction and detection, utilizing the Random Forest algorithm to classify abnormal gait, normal gait, and fall events, with results indicating superior accuracy for IMU-based detection compared to EMG signals (ZiYing et al. 2021). Additionally, previous research has explored fall detection using only electromyography (EMG) (Han et al., 2017), (Xi et al., 2017), as illustrated in Figure 9.a. Other studies, though limited, have employed inclinometers exclusively for fall detection (Sun et al., 2016), as shown in Figure 9.b. The range of sensor technologies used in fall detection is not confined to these examples, as further studies integrating EMG and inclinometers are summarized in Table 3.

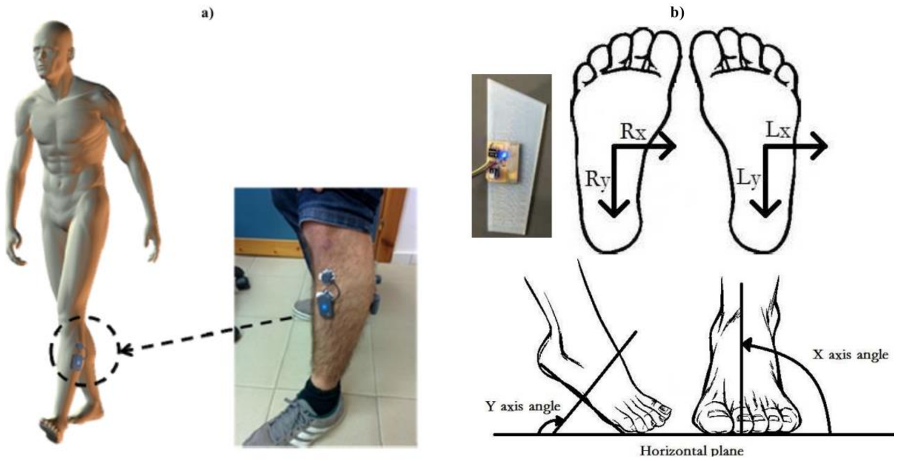

Figure 9. a) EMG sensor-based fall detection system (Leone et al. 2015) **b)** Inclinometer based fall detection system (Sun et al. 2016)

Table 3. EMG and inclinometer sensors for fall detection and prevention systems

Sensor Class	Sensor	Sensor Location	Activity	Classification Algorithm	Performance	Reference
WSHAR	IMU + EMG Sensors	Lower Limb (Leg Muscles)	FD	Random Forest (RF)	IMU: 94,72% (3-class), 87,70% (4-class); EMG: 71,91% (3-class), 67,76% (4-class)	Siwadamrongpong et al. 2022
WSHAR	EEG (Cz position) + EMG Sensors	Scalp (EEG), Muscles (EMG)	FP	K-Nearest Neighbors (KNN) for posture, Match Filter for EMG, MRCP detection	83,3% (EEG), 80% (EMG), 89% (KNN for posture)	ZiYing et al. 2021
WSHAR	sEMG	Gastrocnemius and Tibilias Muscles	FD	LDA	S:91,3%	Leone et al. 2018
WSHAR	sEMG Electrodes	Left Lower Extremity	FD	FMMNN	S: 98,7%	Xi et al. 2017
WSHAR	sEMG Electrodes	Two-Way	FD	BEMG	S: 69,2%	Han et al. 2017
WSHAR	Ag/AgCl electrodes	Lower Extremity	FP	Markov Random Field based Fisher-Markov selector	S: 89,1%	Leone et al. 2017
WSHAR	Inclinometer	Shoe Sole	FD	Threshold	Risk level 0,27	Sun et al. 2016
WSHAR	Inclinometer	-	FD	Quantitative gait markers	Slow walking speed risk ratio: 69,95%	Sun et al. 2015

Wearable Sensor-based Human Activity Recognition (WSHAR), 3 axis accelerometer (3A), Fall Detection (FD), Fall Prevention (FP), Bidirectional EMG (electromyographic sensor network model), Fuzzy Min-Max Neural Network (FMMNN), Linear Discriminant Analysis (LDA), Sensitivity (S)

However, the accelerometer remains the most widely utilized sensor in fall detection and prevention systems, either independently or in combination with other sensor types. Its widespread preference is attributed to its ability to offer feasible, rapid, real-time, and effective solutions for fall detection while capturing various critical parameters. Furthermore, as demonstrated in Tables 1, 2, and 3, accelerometer-based fall detection and prevention systems exhibit superior performance compared to those employing pressure sensors, electromyography, or inclinometers.

3.2. Environmental Sensor Based Systems

Having established a classification framework based on sensor types (single or mixed) in preceding sections, this section delves into environment-based fall detection and prevention systems. These systems, encompassing both wearable and environmental sensors, share the core functionalities of tracking body movements, capturing environmental data, and ultimately aiming to detect or sense falls. The research examined in this category employs a diverse range of sensors, including microphones, ground pressure sensors, infrared sensors, cameras, and thermal sensors. Notably, these environmental sensors are strategically placed within living spaces such as bedrooms, living rooms, kitchens, and bathrooms. To facilitate a more granular analysis, the studies pertaining to this section will be further explored under two distinct subheadings: environmental and visual perception.

3.2.1. Non-Visual Environmental Sensing

In environment-based systems, environmental sensors collect acoustic, vibration and pressure signals of the body. Data is used try to detect situations before, during and after a fall by using computer non-visual data-based approaches (Figure 10).

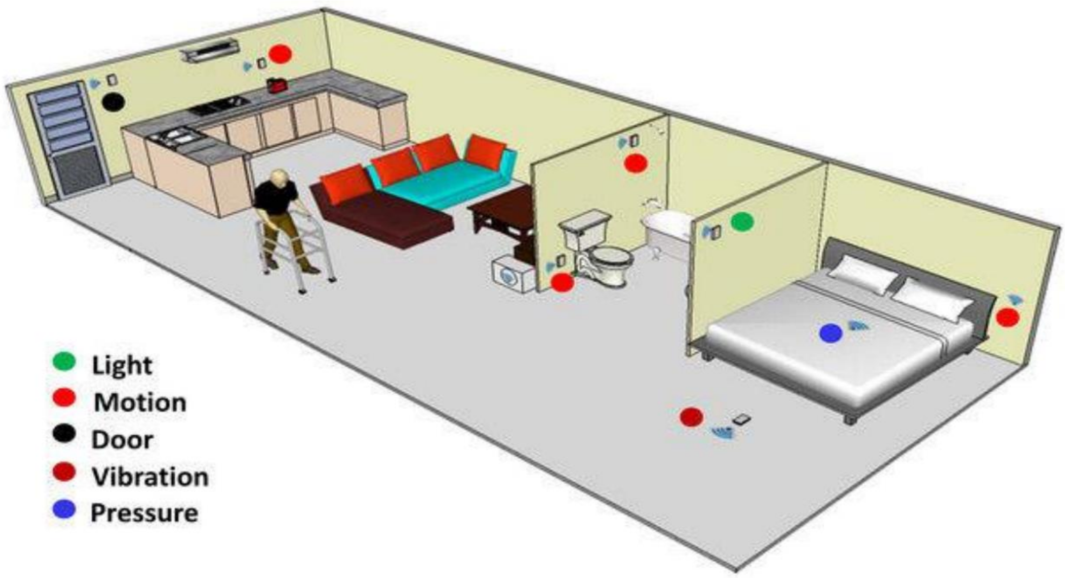

Figure 10. Environmental sensors for fall detection (Birku et al. 2018)

Chen et al. (2024) proposed a fall detection system called FA-Fall based on acoustic signals. In this system, a pair of audio transceivers capable of passive and active acoustic detection were used (Chen et al. 2024). The algorithm used is based on a multimodal classification framework that includes an attention mechanism and an anomaly detection mechanism.

Table 4. Nonvisual environment-based sensors for fall detection and fall prevention

Sensor Class	Sensor Type	Sensor Location	Activity	Classification Algorithm	Performance	Reference
ASHAR	Acoustic Sensors (Passive and Active)	Indoor (Various)	FD	Multimodal Classification (Attention + Anomaly Detection)	Accuracy: 98,97% in typical conditions, >90% in challenging environments with background noise	Chen et al 2024
ASHAR	MEMS PIR and Thermopile IR Array Sensors	Bathroom (Indoor)	FD (Bathroom Falls)	BP Neural Network (3-layer)	Precision: 94,45%, Recall: 90,94%, Accuracy: 92,81%, F1-Score: 92,66%	He at al 2023
ASHAR	Pressure Sensors	Bed, Mattress	FD (On/Off-Bed)	Random Forest (RF)	ACC: 100%	Youngkong et al 2021
ASHAR	Sensor Pad	Ground	FD	NB, SVM, DTJ48	ACC: 96,2% S: 95%	Muheidat et al. 2018
ASHAR	Acoustic sensor	Floor	FD	Mel-Frequency Cepstral Coefficients and SVM	F1-Score: 98,66%-100%	Droghini et al. 2017
ASHAR	Audio Signals	Microphone	FD	Acoustic-LTP	ACC: 97,41%	Irtaza et al.- 2017
ASHAR	Infrared Sensor Array	Wall	FD	SVM	ACC:97,1-0,99%	Fan et al. 2017
ASHAR	Piezoresistive Pressure Sensor	Floor	FD	Custom Method	S: 88,8%	Chaccour et al. 2015
ASHAR	Infrared laser	Not Available	FP	Logistic Regression	Effective elderly at high risk	Nishiguchi et al. 2013
ASHAR	Resistive Pressure Sensor Array	Ground	FP	Multi Resolution	Fall Easily predicted.	Morgado et al. 2012
ASHAR	3A	Rear tread	FP	CHAT and MOP are reliable in distinguishing fall	Not Available	McGrath et al. 2012

Ambient Sensor-based Human Activity Recognition (ASHAR), 3 axis accelerometer (3A), Fall Detection (FD), Fall Prevention (FP), Naïve Bayes (NB), Support Vector Machine (SVM), Centroid of Heel and Toe points (CHAT), Centre of Pressure (COP), Accuracy(ACC), Sensitivity(S), Specificity(SP)

Similarly, He et al. developed a fall detection system using Micro-electromechanical Systems Pyroelectric Infrared (MEMS PIR) sensor and a thermopile IR array sensor (He et al. 2023). As an algorithm, a three-layer BP (Backpropagation) neural network was used along with image processing techniques, including a low-pass filter and double boundary scans.

Youngkong et al. utilized pressure sensors in their study (Youngkong et al. 2021). In their previous research, the authors monitored and classified bed movements with a single pressure sensor. Since fall events are more dynamic, they proposed a new system incorporating a dual pressure sensor in this study.

Additionally, machine learning algorithms were applied, with the Random Forest algorithm achieving 100% accuracy as the most effective fall detection model.

Droghini and Irtaza designed a fall detection mechanism using acoustic signals by extracting Mel-Frequency Cepstral Coefficient (MFCC) features (Droghini et al., 2018; Irtaza et al., 2017). Since falls and daily activities exhibit different vibration patterns, this system can be used for both fall detection and daily activity classification.

In ground-based measurements, vibration signals are typically obtained through piezoresistive pressure sensors (Chaccour et al., 2015; Muheidat et al., 2018) or sensor pads/mats (Morgado et al., 2012; McGrath et al., 2012). Infrared sensors have also been used in fall detection (Fan et al., 2017) and prevention systems (Nishiguchi et al., 2013) (Table 4).

The most employed strategies for fall detection involve the use of both acoustic and pressure signals. However, research indicates that sound-based approaches demonstrate superior performance compared to pressure-based methods. Additionally, the integration of pressure and infrared sensors-whose use has increased in recent years has also been widely adopted in fall detection and prevention systems.

Although environment-based fall detection systems offer several advantages, they also present certain limitations. A primary challenge stems from the inherent constraints of these systems. Since sensors are installed within a specific indoor environment, they are limited by their detection range and the presence of passive areas where falls may go undetected. Moreover, these systems often assume that the monitored individual is alone, which may not always be the case. Environmental sensors are also highly susceptible to external noise and erroneous data. Factors such as falling objects, variations in flooring materials, and background noise can negatively affect system performance, potentially triggering false alarms. Consequently, these limitations can undermine the overall reliability and effectiveness of the system.

3.2.2. Visual Sensing Based Systems

Cameras, which have become an integral part of daily life for security and communication purposes, can be integrated into environment-based fall detection and prevention systems as visual data sources. Camera-based solutions may incorporate various imaging technologies, including RGB cameras, depth cameras (e.g., Kinect), thermal sensors, and multi-camera configurations. The primary information extracted from these camera systems in fall detection studies includes tracking head trajectories, analyzing body shape changes, and assessing posture (Figure 11).

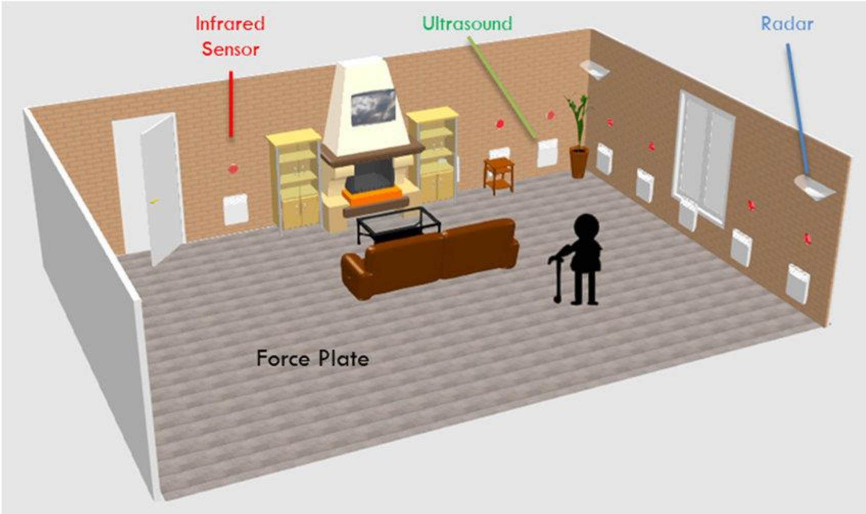

Figure 11. Different vision sensor-based fall detection model (Rastogi et al. 2022)

In the study conducted by Denkovski et al., various video sensors, including RGB, infrared, and thermal cameras, were employed for fall detection (Denkovski et al. 2024). Autoencoder-based algorithms and their variants were utilized for anomaly detection, and a novel multi-objective loss function, termed "Temporal Shift," was introduced. This function was designed to enhance network structures that process visual information flow. The analyses demonstrated that the proposed method significantly improved the performance of different models, including 3D convolutional autoencoders, attention-based U-Net CAE, and multi-modal neural networks. This approach has potential applications not only in fall detection but also in broader anomaly detection tasks.

Similarly, in the study by Ke et al., the YOLOv5 model was implemented for fall detection (Ke et al. 2023). Given its ability to process video data via a webcam, the model can be integrated into smart home systems using IoT devices. Various YOLOv5 variants were tested on the CAU CAFall dataset, specifically designed for home environments, and the results indicated that the YOLOv5s model was the most suitable for fall detection applications.

A more straightforward application of image-based methods was proposed by Tian et al. (2022), who analyzed silhouette changes over time using the k-Nearest Neighbor (kNN) algorithm based on a single-camera image. This approach was considered a low-cost solution; however, a major limitation of image-based techniques is their sensitivity to viewing angles, which can significantly impact performance. To mitigate this issue, multi-camera systems have been utilized to expand the detection area and capture images from multiple perspectives. For instance, Fan et al. (2013) achieved high fall detection accuracy by deploying eight cameras within a room.

In addition to conventional camera-based approaches, depth cameras have demonstrated potential for enhancing system accuracy. Devices such as Kinect improve fall detection performance by measuring the distance between individuals and the ground. Studies by Zhao et al. (2019) and Li et al. (2018) have shown that detecting fundamental joint movements using depth cameras contributes to the overall effectiveness of fall detection and prevention systems. Furthermore, thermal sensors, which can achieve accuracy rates of up to 99,7%, represent another widely adopted imaging technology. Compared to other methods, depth camera-based approaches have garnered increased attention in recent research. An overview of various imaging systems is provided in Table 5.

Table 5. Visual sensors for fall detection and prevention system

Sensor Class	Sensor Type	Sensor Location	Activity	Classification Algorithm	Performance	Reference
ASHAR	RGB, Infrared, Thermal Cameras	Home (Multi-Modal)	FD	Autoencoder Variants (3D Conv, U-Net, Multi-Modal NN)	AUC ROC +0,20 (U-Net CAE with Temporal Shift)	Denkovski et al 2024
ASHAR	RGB Camera	Home (IoT)	FD	YOLOv5 (YOLOv5s and YOLOv5x)	P: 82,2% (YOLOv5x) / P:79,6% (YOLOv5s)	Ke et al 2023
ASHAR	RGB Camera	Camera	FD	Machine Vision with Fall Logic	ACC: 94,5%	Tian et al. 2022
ASHAR	Depth Camera	Kinect V2 / Orbbec Astra depth camera	FD	Up Body Extraction	ACC: 92,3%	Zhao et al. 2019
ASHAR	Kinect Sensor	Kinect Sensor	FP	Two feet movement tracking Risk level from 0,256 to 0,27		Li et al. 2018
ASHAR	Multiple Kinect sensors	Active area	FP	Slow walking speed risk ratio: 106,995% for every 10 cm/s reduction Confidence Interval 1,001-1,142		Li et al. 2018
ASHAR	RGB Camera	8 cameras built into the room	FD	LR	ACC: 95,2%	Fan et al. 2017
ASHAR	Thermal imaging camera	Active area	FP	SVM	ACC: 99,7%	Song et al. 2017
ASHAR	Depth Camera	Depth camera	FD	Fall Vector Algorithm	ACC: 97,1%	Kong et al. 2017
ASHAR	Depth Camera	Depth videos	FD	SOV	ACC: 89,63-100%	Akagündüz et al. 2017
ASHAR	RGB camera and line laser	in shoes	FP	Reducing the risk of falling by detecting objects on the ground		Li et al. 2017
ASHAR	Thermal sensor	ceiling-wall corner	FD	STIP and Fisher vector framework	ACC: 99,61%	Vadivelu et al. 2016
ASHAR	Smart camera with embedded system	wall	FP	Custom smart camera and framework		Kutchka et al. 2016
ASHAR	Thermal visual imager	ceiling	FD	FDP	ACC: 68%	Rafferty at el. 2016
ASHAR	Microsoft Kinect Camera	Active area	FP	Successful enough to be used in fall prediction		Dubois et al. 2014

Ambient Sensor-based Human Activity Recognition (ASHAR), 3 axis accelerometer (3A), Fall Detection (FD), Fall Prevention (FP), Naïve Bayes (NB), Support Vector Machine (SVM), Accuracy(ACC),Precision (P), Logistic Regression(LR), Silhouette Orientation Volume (SOV), Fall Detection Process (FDP), Spatio-Temporal Interest Points (STIP)

With the widespread adoption of cameras, particularly in security systems and mobile devices, their costs have declined, facilitating the expansion of camera-based fall detection systems. However, despite their advantages, such systems also present several challenges. First, camera-based solutions require substantial computational and storage resources to execute real-time algorithms effectively. The interpretation of images necessitates sophisticated computer vision techniques that demand high processing power, leading to additional hardware costs. Second, privacy concerns arise due to the need to capture and store actual images of individuals. Lastly, system calibration and performance may be compromised by the limited field of view and fixed camera angles, potentially reducing detection accuracy over time.

3.3. Radio Frequency Based Sensing

In fall detection, Radio Frequency (RF) based systems could be classified by including environment-based systems. However, in this section, it was deemed appropriate to evaluate RF-based systems in a separate category due to signal type, data size, special antenna and positioning methods. Considering the latest developments and trends in this category, it was found more appropriate to evaluate it in a different category. RF signals are reflected or absorbed following an abnormal distribution path according to body movement speed. Studies in the literature have shown that fall detection and prevention can be achieved when RF signal attenuation or fluctuations in wireless channel status information are applied as input to a fall detection system (Figure 12).

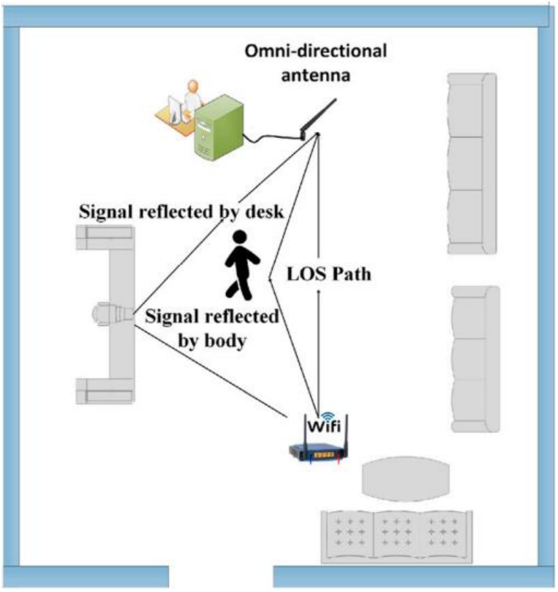

Figure 12. Radio frequency-based fall detection system working principle (Lubna et al. 2022)

Wireless frequency (RF) based systems can be classified as single-type sensor systems and mixed-sensor systems as shown in Table 6. Chi et al. developed a Wi-Fi-based fall detection system called XFall, which minimizes the impact of environmental variables by utilizing an environment-independent feature known as the velocity distribution profile (Chi et al. 2024). To enhance classification accuracy, an attention-based encoder was designed to distinguish different fall types, while a cross-modal learning framework was implemented to facilitate large-scale model training with limited Wi-Fi data. When tested in a real-world environment, XFall demonstrated high accuracy and a low false alarm rate.

Table 6. Fall detection and prevention systems with RF signals

Sensor Class	Sensor Type	Sensor Location	Activity	Classification Algorithm	Performance	Reference
ASHAR	Uniform Sensors	Wi-Fi signals	FD	Attention-Based Encoder + Cross-Modal Learning (Pre-Trained Visual Model)	ACC: 96,8%, Miss Alarm Rate: 3,1%, False Alarm Rate: 3,3%	Chi et al 2024
ASHAR	Uniform Sensors	Wi-Fi (CSI-Based)	FD	Deep Learning-Based Image Classification	Accuracy: 96% (All Environments), 99% (Specific Combinations)	Chu et al 2023
ASHAR	Uniform Sensors	Wi-Fi (CSI-Based)	FD	Deep Learning-Based (DNN Generative Model + User Identification Network)	False Alarm Rate: 5,7%, Missed Alarm Rate: 3,4%	Yang et al 2023
ASHAR	Uniform Sensors	Wi-Fi signals	FD	DTW barycenter averaging (DBA) algorithm	Accuracy: 95%	Hu et al. 2021
ASHAR	Uniform Sensors	Multi-antenna FMCW radio	FD	CNN	Accuracy: 92%	Tian et al. 2018
ASHAR	Hybrid Sensors	802,11n NIC	FD	Singular Value Decomposition	Precision: 94%	Wang et al. 2018
ASHAR	Uniform Sensors	Radar	FD	Deep Learning	Accuracy: 92%	Jokanovic et al. 2017
ASHAR	Uniform Sensors	Microwave doppler sensor	FD	Deep Learning	Accuracy: 95%	Shiba et al. 2017
ASHAR	Uniform Sensors	FMCW radar	FP	FMCW	Not available	Tang et al. 2017
ASHAR	Hybrid Sensors	Wi-Fi device	FD	SVM	Sensitivity: 92	Wang et al. 2016
ASHAR	Uniform Sensors	FMCW radar	FP	GaN HEMT Doherty amplifier with FMCW	Not available	Tang et al. 2016
ASHAR	Uniform Sensors	RF Detection Device	FP	WISP sensor	Not available	Visvanathan et al. 2012

Fall Detection (FD), Fall Prevention (FP), Fall prevention with wearable radar (FMCW)

Yang et al. introduced FallDar, a Wi-Fi-based deep learning-supported fall detection system (Yang et al. 2023). FallDar aims to mitigate performance degradation caused by environmental variability by incorporating features resistant to environmental factors, such as fall speed. By simulating diverse fall scenarios with a deep neural network (DNN)-based generative model, motion diversity was enhanced. Additionally, a user identification network was employed to extract person-independent features without requiring new user data. FallDar was implemented on commercial Wi-Fi devices and tested over a six-month period. Chu et al. proposed a novel deep learning-based method for fall detection using Wi-Fi channel state information (CSI) (Chu et al. 2023). Their study evaluated various Wi-Fi CSI collection tools and assessed their effectiveness in fall detection. The researchers compiled a comprehensive dataset containing over 700 CSI samples encompassing different fall types and daily activities across four distinct indoor environments. This dataset was utilized to train a deep learning classifier based on an image classification algorithm. Unlike other approaches, the proposed method requires only sampling and reshaping in the preprocessing stage, simplifying data preparation.

Hu et al. developed a system that investigates the impact of body speed variations on Wi-Fi signals during a fall (Hu et al. 2021). Their study analyzed changes in wireless signals by considering the physiological effects of falling on movement patterns. Wang et al. demonstrated that commercial Wi-Fi devices could be effectively used for fall detection by leveraging wireless CSI to differentiate falls from fall-like activities (Wang et al. 2016).

Tian et al. employed multi-antenna Frequency Modulated Continuous Wave (FMCW) radio signals for fall detection (Tian et al. 2018). Their approach involved extracting complex spatial and temporal features from these signals and training a convolutional neural network (CNN) to perform fall detection with high accuracy. Tang et al. developed an FMCW radar-based fall prevention system that continuously measured the distance between the radar and the surrounding environment (Tang et al. 2016). By analyzing the relationship between body movements and radar frequency, the system aimed to predict fall risks proactively.

Overall, radio frequency (RF) signals, which are prevalent in daily life, offer a non-intrusive and privacy-preserving approach to fall detection and prevention. However, RF-based systems face several challenges, including signal interference from external sources, coexistence with multiple devices operating on different communication standards (e.g., Wi-Fi, Bluetooth), and the limited coverage of wireless networks.

3.4. Systems with Hybrid Sensing

Research indicates that fall detection systems based on a single sensor or homogeneous sensors can lead to low accuracy and high false alarm rates. To improve the performance of fall detection systems, the integration of various sensors with different functions is necessary. In this context, sensor fusion-based systems, consisting of either homogeneous or heterogeneous sensors, have been developed and examined in various studies (Table 7).

In a study by Kavuncuoğlu et al., 10 different machine learning algorithms and 26 features were tested using the Sisfall dataset for fall detection (Kavuncuoğlu et al. 2024). The Random Forest Classifier (RFC) achieved 97.94% accuracy with the autocorrelation feature, while the Support Vector Machine (SVM) showed 98.60% accuracy with time series features. By combining features with the Quintuple approach and using Extremely Randomized Trees (ETC), the system achieved 98.69% accuracy, 98,28% precision, and 99.08% specificity. These methods demonstrated high performance in fall detection and data transfer across age groups.

Another study by Lin et al. proposed a wearable device system for fall detection and verification in elderly individuals. This system uses a nine-axis inertial sensor, including a three-axis accelerometer and gyroscope, to determine the user's postures (standing, sitting, lying) (Lin et al. 2023). The resulting force is calculated using three-axis acceleration, while the gradient descent algorithm is used to determine the tilt angle. Barometer data is used to convert the height value, and postures (sitting, standing, walking, lying, and falling) are identified. The fall direction and acceleration changes can determine the fall severity. Additionally, through IoT and smart speakers, falls can be verified by asking the user questions via the smart speaker. The system aims to reduce maintenance times by real-time posture identification and fall reporting.

Sensor combinations can consist of inertial sensor types, environmental sensors, or a heterogeneous mix of ambient and inertial sensors. For example, a novel fall detection system utilizing an accelerometer, microphone, and camera has been proposed (Silhouette Orientation Volumes for Efficient Fall Detection in Depth Videos - PubMed). Additionally, Quadros et al. suggested the use of inertial sensors such as a three-axis accelerometer, gyroscope, and magnetometer for fall detection (Quadros et al. 2018).

Table 7. Uniform sensors for fall detection and prevention systems

Sensor Type	Sensor Type	Sensor Location	Activity Type	Classification Algorithm	Performance	Reference
WSHAR	Uniform Sensors	3A, 3G, 3M + Belly	FD	RF,SVM,ET	ET ACC:98,69% ET S:98,28%	Kavuncuoğlu et al 2024
ASHAR	Uniform Sensors	3A,3G and 3M	FD	SVC	ACC: 98,3%	Fawaz et al. 2023
WSHAR	Uniform Sensors	3A, 3G, 3M and Barometer + Chest-Worn	FD	State Machine (Direct Posture Operation)	Real-time fall recognition and report	Lin et al 2023
ASHAR	Uniform Sensors	A + P and Sensitive Insoles	FP	Fuzzy Mamdan	ACC: 90%	Amiroh et al. 2021
ASHAR	Uniform Sensors	3A,3G and 3M	FD	Machine Learning Methods	ACC: 99% S: 100%	Quadros et al. 2018
ASHAR	Uniform Sensors	3A and 3AA	FD	PCA with Threshold	S: 94,8%	Wu et al. 2018
ASHAR	Uniform Sensors	4-probe Electromicrophone + 3A on T-Shirt	FP	Vertical velocity measurement	Over 75%	Leone et al. 2018
ASHAR	Uniform Sensors	3A and Barometric	FD	Wavelet-based ML	ACC: 82-96%	Ejupi et al. 2017
ASHAR	Uniform Sensors	3A and G3	FP	MLP	ACC: 83-90%	Hemmatpour et al. 2017
ASHAR	Uniform Sensors	3A and 3G	FD	BN	ACC: 95,67% S:99%	He et al. 2017
ASHAR	Uniform Sensors	3A + 3G Right Side and Side Waist Area	FP	Neural Network	ACC:75% F1: 77,8%	Howcroft et al. 2017
ASHAR	Uniform Sensors	IR + Pressure	FD	FSM	S: 88,2%	Lu et al. 2016
ASHAR	Uniform Sensors	iPhone– 4 pressure Sensors	FP	DT	ACC: 97,2%	Majumder et al. 2014
ASHAR	Uniform Sensors	3A and 3G	FP			Thella et al. 2014

Wearable Sensor-based Human Activity Recognition (WSHAR), 3 axis accelerometer (3A), 3 axis angular accelerometer (3AA), Not Available (NA), convolutional neural network (CNN), Fall Detection (FD), Fall Prevention (FP), k-Nearest Neighbors (k-NN), Naïve Bayes (NB), Support Vector Machine (SVM), Accuracy (ACC), Sensitivity (S),2-axis gyroscope (2G), 2-axis gyroscope (2G), 3-axis gyroscope (3G), 3-axis magnetometer (3M), Infrared (IR) and Pressure (P) Sensor , Decision Tree (DT), Multilayer Perceptron (MLP), Bayesian Network Classifier (BN), Support Vector Classification (SVC), Finite State Machine (FSM)

In fall detection and prevention research, sensor fusion approaches have been employed to enhance the accuracy and efficiency of detection systems.

Table 8. Hybrid sensors for fall detection and prevention systems with.

Sensor Type	Sensor Type	Sensor Location	Activity Type	Classification Algorithm	Performance	Reference
ASHAR	Hybrid Sensors	Thermal Array Sensors + mmWave Radar Sensor + Indoor (Room, Ceiling, Wall, Corner)	FD	Random Forest (RF)	Accuracy: 97,9%, F1-Score: 0,945; RF: ACC: 92,2%, R: 0,881, P: 0,805, F1-Score: 0,841	Rezaei et al 2023
ASHAR	Hybrid Sensors	Vision-Based, RF Signals, Acoustic Sensors + Indoor (Smart Homes)	FD	Machine Learning, Pattern Recognition	Fall Detection: High accuracy in detecting falls;	Raeis et al 2021
ASHAR	Hybrid Sensors	3A + KDC	FD	LSVM	ACC: 98,9% S: 99%	Kepski et al. 2018
ASHAR	Hybrid Sensors	Wi-Fi + 3A	FD	SVM and Adaboost	ACC: 95%	Ramezan et al. 2018
ASHAR	Hybrid Sensors	3A + KDC + micro-doppler radar	FD	SVM	ACC: 91,3%	Li et al. 2017
ASHAR	Hybrid Sensors	Line laser (shoe size), RGBC (upper side of shoes)	FP	SAD	Successful indoors.	Li et al. 2017
ASHAR	Hybrid Sensors	KDC, WSHAR	FP	NN	Sensor-based self-assessment can be applied for fall risk.	Ejupi et al., 2015
ASHAR	Hybrid Sensors	Pulse-Doppler radar, one Microsoft KDC, 2 pieces RGBC	FP	Correlation with Kinect (p<,01)	Radar speed correlation (p<,05)	Rantz et al. 2015
ASHAR	Hybrid Sensors	3A + RGBC + microphone	FD	Not Available	ACC: 94%	Zhang et al. 2013

Kinect Depth Camera (KDC), RGB camera (RGBC), Summing Absolute Difference (SAD), Neural Network (NN), Linear Support Vector Machine (SVM), Fall Detection (FD), Fall Prevention (FP), Accuracy (ACC), Sensitivity (S)

Rezaei (2023) conducted a study utilizing millimeter-wave (mmWave) radar technology for fall detection in elderly individuals, eliminating the need for wearable devices. Radar sensors were strategically positioned in two different locations within a room (sidewall and ceiling), and data collected from these sensors were used to manually extract features. Various machine learning algorithms, including multilayer perceptron (MLP), random forest, k-nearest neighbor (kNN), and support vector machines (SVM), were applied to classify falls. Additionally, a convolutional neural network (CNN)-based deep learning model was developed using an "occupancy grid" input derived from 3D point cloud data. Experimental results demonstrated that the random forest algorithm achieved the highest accuracy (92.2%) when the sensor was ceiling-mounted, while the CNN model provided a slight improvement with an accuracy of 92.3%. These findings indicate that mmWave radar technology is an effective and viable approach for fall detection.

Raeis et al. (2021) explored device-free sensors and their applications in human activity recognition (HAR) for well-being assessment in smart home environments. Unlike wearable or object-attached sensors, device-free sensors operate without direct physical contact, allowing for passive monitoring of individuals' movements. This study examined the applications of device-free sensors in fall detection, cognitive assessment, respiratory monitoring, and dementia diagnosis (Table 7).

Leone et al. (2018) integrated electromyography and accelerometer sensor data to detect pre-fall trauma, achieving a pre-detection time of over 750 milliseconds before a fall event. Similarly, Rantz et al. (2018) developed a comprehensive fall prevention system by combining pulse-Doppler radar, Microsoft Kinect 2, and webcam data. Their system provided detailed insights into human activities and gait balance characteristics, demonstrating that sensor fusion-based approaches yield high-accuracy detection and prediction outcomes (Table 8).

With continuous technological advancements, the diversity of sensors has increased, prompting researchers to explore various sensor combinations to enhance fall detection performance and minimize false alarm rates. However, despite the progress in fall detection and prevention research, these systems have not yet been widely adopted in daily life. This limited adoption is attributed to practical challenges associated with high-accuracy fall detection methods. Many of these systems require the continuous use of environmental and inertial sensors, which is often impractical. Additionally, the vast amount of data generated complicates the design of information processing systems, presenting challenges in terms of portability and usability in everyday settings.

4. Discussion

In this study, the classification of sensor types was carried out according to sensor types, and their strengths and weaknesses are summarized below according to sensor type classes.

4.1 Challenges and Solutions in Wearable Sensors

High False Positive Rate: Wearable sensors, particularly accelerometers, often exhibit high false positive rates due to their sensitivity to motion. This issue arises when routine activities generate movement patterns similar to falls, leading to erroneous fall detection.

Solution, To address this challenge, integrating accelerometers with additional sensors such as gyroscopes and magnetometers can enhance motion analysis accuracy. The fusion of data from multiple sensors enables more precise movement characterization, thereby reducing false alarms.

Power Consumption: Certain wearable sensors, such as gyroscopes, exhibit high power consumption, which reduces battery life and necessitates frequent recharging.

Solution: Optimizing power consumption by selecting low-power sensors or implementing duty-cycling techniques can extend battery life. Instead of continuous data collection, sensors can be activated at predefined intervals or in response to specific events.

Susceptibility to Environmental Magnetic Fields: Magnetometers are vulnerable to external magnetic field interference, which can compromise sensor accuracy and lead to erroneous readings.

Solution: To enhance reliability, magnetometers should be used in conjunction with accelerometers and gyroscopes. This multi-sensor approach compensates for environmental influences, improving the robustness of motion detection.

Placement Sensitivity: The accuracy of pressure sensors is influenced by their placement on the body, which can lead to variability in measurement accuracy.

Solution: To improve measurement precision, pressure sensors should be integrated with complementary sensors that analyze physical contact and pressure distribution. Strategic placement in areas such as shoe insoles can facilitate more accurate fall impact detection.

Limited Accuracy in Standalone Use: Some sensors, such as inclinometers, exhibit high motion sensitivity, limiting their effectiveness in fall detection when used independently.

Solution: While inclinometers can detect abrupt angular changes, their reliability improves when combined with accelerometers and gyroscopes. This multi-sensor fusion enhances the accuracy of fall detection algorithms.

User Convenience and Portability: Continuous use of wearable sensors may not be practical for all users, and employing multiple sensors simultaneously increases system complexity, reducing user-friendliness.

Solution: Designing sensors to be compact, lightweight, and seamlessly integrated into commonly used devices such as smartwatches or smartphones can enhance usability and user acceptance.

Challenges in Data Collection: The infrequency and unpredictability of real-world falls make data collection challenging. Most available datasets are derived from controlled environments or simulated falls by younger individuals, limiting their generalizability.

Solution: Collecting real-world fall data from elderly individuals using wearable devices in daily life is crucial for improving system accuracy and reliability. Incorporating diverse datasets can enhance the robustness of fall detection models.

In summary, challenges associated with wearable sensors can be addressed through sensor fusion, power optimization, environmental interference mitigation, improved usability, and real-world data collection, ultimately leading to more reliable fall detection systems.

4.2 Challenges and Solutions in Environmental Sensors

Environmental sensor-based systems encounter several challenges, including limited detection range, false alarms, privacy concerns, high costs, and dependence on lighting conditions. The following solutions can mitigate these issues:

Limited Detection Range and Passive Zones: Environmental sensors are restricted to a specific area, leading to coverage gaps where falls may go undetected.

Solution: Deploying multiple sensors, including acoustic, pressure, and infrared sensors, expands coverage and minimizes blind spots. Studies show that integrating accelerometers, microphones, and cameras enhances fall detection performance.

High False Alarm Rate: Environmental sensors are susceptible to background noise and erroneous readings from falling objects, floor types, and environmental sounds. Additionally, these systems often assume the monitored individual is alone, which may not always be accurate.

Solution: Implementing advanced noise filtering and signal processing techniques improves data quality. Adaptive systems that adjust to environmental changes further enhance reliability.

Privacy Concerns: Camera-based systems raise privacy concerns due to continuous surveillance in personal spaces.

Solution: Using privacy-preserving techniques such as 2D skeleton modeling instead of direct video recording allows effective motion analysis while safeguarding user privacy.

High Cost: Certain environmental sensors, such as depth cameras, are expensive to acquire, install, and maintain.

Solution: Cost-efficient alternatives, such as strategically placing standard cameras with optimized algorithms, can achieve similar results while minimizing expenses.

Dependency on Lighting Conditions: RGB cameras struggle in low-light environments, affecting detection accuracy.

Solution: Integrating thermal or depth cameras ensures consistent performance regardless of lighting conditions. Additionally, deep learning algorithms improve recognition in varying environments.

By applying these solutions, environmental sensor-based fall detection systems can achieve higher reliability, accuracy, and user-friendliness.

4.3. Challenges and Solutions in Vision-Based Systems

Viewpoint Dependency: The performance of vision-based fall detection is influenced by camera angles, occlusions, and spatial constraints.

Solution: Deploying multi-camera setups enhances coverage, reduces blind spots, and improves accuracy by capturing movements from multiple perspectives.

High Computational Demands: Real-time image processing requires significant computational resources, increasing hardware costs and power consumption.

Solution: Optimizing algorithms and employing edge computing can reduce processing overhead and enable efficient real-time analysis.

Privacy Concerns: Direct video recording raises privacy concerns, limiting user acceptance.

Solution: Techniques such as 2D skeleton tracking provide motion analysis while ensuring privacy protection by avoiding direct visual representation of individuals.

Limited Field of View: Single-camera setups have restricted coverage, potentially missing falls occurring outside their field of view.

Solution: Integrating depth cameras (e.g., Kinect) improves spatial accuracy and complements traditional RGB cameras, increasing detection reliability.

Performance in Low-Light Conditions: Standard RGB cameras perform poorly in dim lighting, leading to decreased detection accuracy.

Solution: Combining deep learning-based detection algorithms with thermal cameras enhances recognition performance under varying lighting conditions.

By incorporating these advancements, vision-based fall detection systems can achieve improved reliability, scalability, and privacy protection.

4.4. Challenges and Solutions in RF-Based Systems

Limitations of Single-Sensor Systems: Exclusive reliance on RF sensors may result in high false alarms and lower detection accuracy.

Solution: Combining RF signals with inertial and environmental sensors enhances overall detection reliability by leveraging multiple data sources.

RF Signal Processing Challenges: Environmental factors such as signal attenuation and interference affect detection performance.

Solution: Advanced signal processing techniques can compensate for fluctuations and improve fall detection accuracy.

Hybrid Sensor Integration: Standalone RF-based systems may not provide sufficient contextual data for accurate detection.

Solution: Integrating RF technologies with sensors like Kinect and Doppler radar enhances overall system performance and robustness.

Advantages of RF-Based Systems: RF-based solutions offer privacy-preserving, unobtrusive fall detection without requiring wearable devices, making them suitable for multi-occupant environments with minimal maintenance requirements.

Disadvantages of RF-Based Systems: Challenges such as signal interference from Wi-Fi, Bluetooth, and limited coverage range impact reliability.

Solution: Future research should focus on refining RF-based technologies, minimizing external interferences, and expanding detection capabilities.

In conclusion, RF-based fall detection systems present a promising approach for privacy-preserving and unobtrusive monitoring. By integrating hybrid sensor solutions and refining RF signal processing techniques, these systems can become more effective and widely applicable.

5. Conclusions

Enabling a happy and secure life for the elderly necessitates addressing the critical aspects of fall detection and prevention. This study has systematically classified fall detection sensors based on their types and analyzed their respective strengths and weaknesses. The challenges encountered in wearable, environmental, vision-based, and RF-based sensor systems have been examined, along with potential solutions to enhance their efficacy.

Wearable sensors, particularly accelerometers, gyroscopes, and magnetometers, exhibit limitations such as high false positive rates, power consumption concerns, and environmental susceptibility. Addressing these challenges through sensor fusion, power optimization techniques, and improved placement strategies enhances their accuracy and practicality. Furthermore, the integration of wearable sensors into commonly used devices such as smartphones and smartwatches can significantly improve user convenience and adoption.

Environmental sensor-based systems face issues related to limited detection range, false alarms, privacy concerns, and high costs. Multi-sensor deployment, advanced noise filtering, and privacy-preserving techniques such as 2D skeleton modeling offer viable solutions to these challenges. Additionally, the strategic use of cost-efficient alternatives and the integration of thermal or depth cameras can enhance their effectiveness across various environmental conditions. However, it is essential to ensure that these solutions respect individuals' privacy and maintain their standard of living consistently throughout their daily routines.

Vision-based fall detection systems are affected by viewpoint dependency, computational demands, privacy concerns, and performance limitations in low-light conditions. The deployment of multi-camera setups, algorithmic optimizations, and privacy-conscious approaches such as skeleton tracking can improve detection accuracy and user acceptance. Furthermore, integrating deep learning techniques with thermal imaging can ensure robust performance under diverse lighting conditions.

RF-based fall detection solutions provide a non-intrusive and privacy-preserving alternative to traditional approaches. Unlike other sensor-based systems, RF-based solutions can monitor multiple individuals simultaneously without requiring wearable devices, minimizing disruption to daily life. These systems effectively address privacy concerns while eliminating the need for frequent maintenance or transportation of additional equipment. Furthermore, RF-based methods, when combined with advanced signal processing techniques, can significantly improve detection accuracy and reliability.

Given the increasing emphasis on artificial intelligence (AI) in healthcare applications, future research should focus on integrating AI-driven methodologies with RF-based systems to enhance real-time processing capabilities while ensuring computational efficiency. While threshold-based analytical methods provide speed, they are often susceptible to false alarms. AI-based systems, on the other hand, offer superior accuracy but require significant computational resources. A promising future direction lies in hybrid approaches that leverage both AI and analytical models to balance efficiency, accuracy, and cost-effectiveness.

Future Perspectives

As fall detection technology continues to evolve, RF-based systems stand out as a promising approach due to their ability to provide unobtrusive, privacy-conscious monitoring. The integration of AI-based algorithms with RF technology is expected to enhance predictive analytics, allowing for more accurate and timely fall detection. Future studies should focus on refining hybrid AI-RF solutions that optimize computational efficiency while ensuring robust real-world applicability. By leveraging these advancements, fall detection and prevention systems can become more adaptive, user-friendly, and effective in safeguarding the well-being of elderly individuals.

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