Information Fusion 114 (2025) 102696

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Survey on data fusion approaches for fall-detection

Ehsan Rassekh, Lauro Snidaro *

Department of Mathematics, Computer Science and Physics, University of Udine, Italy

ARTICLE INFO

Keywords:
Fall detection
Machine learning
Deep learning
Computer vision

ABSTRACT

Human fall detection is a critical research area focused on developing methods and systems that can automatically detect and recognize falls, particularly among the elderly and individuals with disabilities. Falls are a major cause of injuries and deaths among these populations, and timely intervention can reduce the severity of consequences. This article presents a comprehensive review of fall detection systems, emphasizing the use of cutting-edge technologies such as deep learning, sensor fusion, and machine learning. The research explores a variety of methodologies and strategies employed in fall detection systems, including the integration of wearable sensors, smartphones, and cameras. By examining various fall detection techniques and their experimental results, the article highlights the effectiveness of these systems in identifying and classifying falls. The study also addresses the challenges and limitations associated with fall detection systems, emphasizing the need for ongoing research and advancements. In summary, this research contributes to the development of advanced fall detection systems, demonstrating their potential to improve the quality of life for the elderly, alleviate healthcare burdens, and provide reliable solutions for fall detection and classification.

1. Introduction

Falls among the elderly pose a critical public health concern as they can lead to incapacitating fractures and trigger severe psychological challenges, ultimately diminishing an individual's level of independence. Falls are the primary cause of injury-related fatalities among individuals over 79 and rank as the second most common cause of unintentional injury-related deaths across all adult age groups [1]. Among individuals over 80 years old living in community settings, half of them, as noted in [2], encounter at least one fall annually, while 40% of this group experience repeated falls, as highlighted in [3]. Concerning the economic implications for the sustainability of national healthcare systems, the worldwide medical expenses linked to falls amounted to approximately $50.0 billion in 2015 [4]. There exists a connection between falling and the fear of falling: the fear instilled by a past fall might increase the chances of falling again [5]. Abundant research endeavors have been conducted to devise approaches and techniques aimed at enhancing the functional capabilities of older and unwell individuals. Certain methodologies incorporate cameras, sensors, and computer technologies. These systems catered to the elderly not only enhance their autonomy by fostering a sense of security within a supportive setting but also diminish the physical workload involved in their care, thereby decreasing the necessity for nurses or other support staff [6]. This research aims to outline existing fall detection systems and their results, intending to serve as a foundation for future advancements.

Fig. 2 depicts the percentage distribution of particular algorithms used for fall detection in an extensive dataset compiled by us through scraping Google Scholar for articles related to "fall detection". This dataset encompasses more than 1000 papers focused on various algorithms used in fall detection systems. The figure visually depicts the breakdown of algorithm adoption, emphasizing the prevalence of specific algorithms within the research domain. Fig. 3 presents the breakdown of scholarly articles on fall detection identified in Google Scholar spanning from 1990 to 2024. This figure outlines a chronological overview of the publication trends in fall detection, showcasing the progression and development of research throughout the years. By examining these publication trends, valuable insights can be gleaned regarding the advancement of fall detection research, the introduction of novel technologies, and the primary areas of focus within the academic community across different time periods.

Sensors and the integration of deep learning (DL) play crucial roles in the detection and recognition of falls. Various sensor-based methodologies are employed for fall detection, encompassing a wide array of sensor types. To discern the conclusive outcomes of fall occurrences based on sensor data, machine learning (ML), DL, and artificial intelligence (AI) techniques are utilized. Researchers globally have demonstrated considerable enthusiasm in recognizing human activities. In recent years, there has been an introduction of various methodologies concentrating on recognizing a wide range of activities, including walking, running, jumping, jogging, falling, and beyond. According

* Corresponding author.
E-mail addresses: rassekh.ehsan@spes.uniud.it (E. Rassekh), lauro.snidaro@uniud.it (L. Snidaro).

https://doi.org/10.1016/j.inffus.2024.102696
Received 14 June 2024; Received in revised form 3 September 2024; Accepted 12 September 2024
Available online 16 September 2024

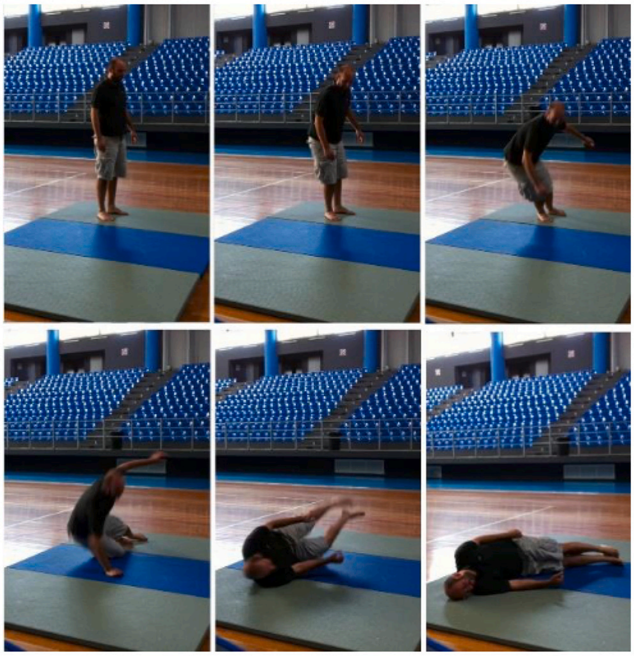

Fig. 1. An example of The MobiFall Dataset: A series of frames depicting a sideways fall with bent legs [7].

to [8], the researchers provided a valuable asset in the domain of real-time Human Activity Recognition (HAR) by presenting an extensive guide for real-time fall detection. Among these activities, fall detection stands out significantly due to its common occurrence and the substantial risk it poses to individuals of all age groups, especially impacting the elderly. Generally, these applications use sensors adept at detecting abrupt shifts in movement. They can be integrated into wearable gadgets like smartphones, necklaces, or smart wristbands, ensuring convenient and effortless wearability. Within fall detection strategies, the initial phase involves identifying human activities, a step that facilitates the detection of fall incidents. Accurate recognition of human activity holds a pivotal role in effectively and accurately detecting falls. Fig. 1 displays an example from The MobiFall Dataset, showcasing a sideways fall with bent legs. There are some excellent public datasets available for fall detection using wearable technologies which are discussed in Table 6. Each dataset is described in terms of the year the data was collected, the approach for fall detection, the sensors utilized and the types of metrics used to validate the detection system. These datasets can be highly beneficial to researchers and developers working in this area as they provide a common set of metrics and graded and validated data sets to test and compare the algorithms. Through the use of these public datasets, wearable fall detection devices are expected to be reliable and accurate enough to prevent and identify falls when they occur.

In this review, we systematically selected literature focusing on fall detection systems published between 2010 and 2024. Our selection process involved a comprehensive search of over 100 papers from various academic journals and conference proceedings that specifically address advancements in fall detection methodologies. We employed specific criteria for inclusion, which included the relevance of the study to fall detection, the application of ML and DL techniques, and the utilization of various sensor technologies such as wearable devices, cameras, and radar systems. The review encompasses a wide range of perspectives and innovations in the field, providing a key to understanding current trends and challenges. To this end, we have grouped the reviewed literature by the research methods and sensor types used in each work. This organization will give the reader a structured way to analyze the advancements of fall detection systems through the years, showing what technological and methodological advancements have been made in the field.

2. Evaluation metrics

Various performance metrics are employed to assess the effectiveness of systems. Accuracy, specificity, and sensitivity are examples of such metrics used to assess and distinguish between different systems. In the realm of fall detection, True Positives (TP) represent accurately identified "fall" instances. False Positives (FP) denote cases incorrectly labeled as "non-fall". True Negatives (TN) correspond to correctly identified "non-fall" instances. False Negatives (FN) are examples erroneously classified as "fall". A dependable system should aim to minimize both False Positive and False Negative rates [9,10].

2.1. Accuracy

Accuracy is defined as the ratio of correct instances to the total number of cases. Accuracy serves as a metric that condenses the entire confusion matrix into a single value. One primary drawback of accuracy is its incapacity to address imbalanced datasets, such as those found in real-world fall data where non-fall events outnumber falls. Like Negative Predictive Value (NPV), accuracy is influenced by the larger group, with the impact scaling in proportion to the imbalance magnitude. Consequently, in real-world fall detection research, accuracy tends to prioritize the accurate identification of non-fall events over that of falls [9]. Accuracy can be determined using the following formula.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2.2. Negative Predictive Value

Negative Predictive Value (NPV) represents the ratio of non-fall events correctly classified as such to the total true non-fall happenings. Therefore, NPV offers insights into the system's accuracy in identifying non-fall events. A high NPV indicates that the system correctly disregards a significant number of non-fall instances compared to the falls it misses. Thus, for false negatives (FN) to have a substantial impact, the occurrences of falls and non-falls must be roughly equal. However, in real-world fall datasets, falls are typically much rarer than non-fall events, leading to NPV scores often exceeding 0.99 out of 1 [9]. Nine studies included NPV in their findings [11–19]. NPV can be determined using the following formula.

$$NegativePredictiveValue = \frac{TN}{TN + FN} \tag{2}$$

2.3. Sensitivity

Sensitivity (referred to as recall and true positive rate) is the fraction of falls accurately identified. The miss rate (false negative rate), which is the reciprocal of sensitivity, measures the percentage of undetected falls. Sensitivity is widely regarded as the most frequently cited metric [9]. Sensitivity can be determined using the following formula.

$$Sensitivity = \frac{TP}{TP + FN} = \frac{TP}{P} \tag{3}$$

Miss Rate can be determined using the following formula.

$$MissRate = \frac{FN}{FN + TP} = \frac{FN}{P} = 1 - Sensitivity \tag{4}$$

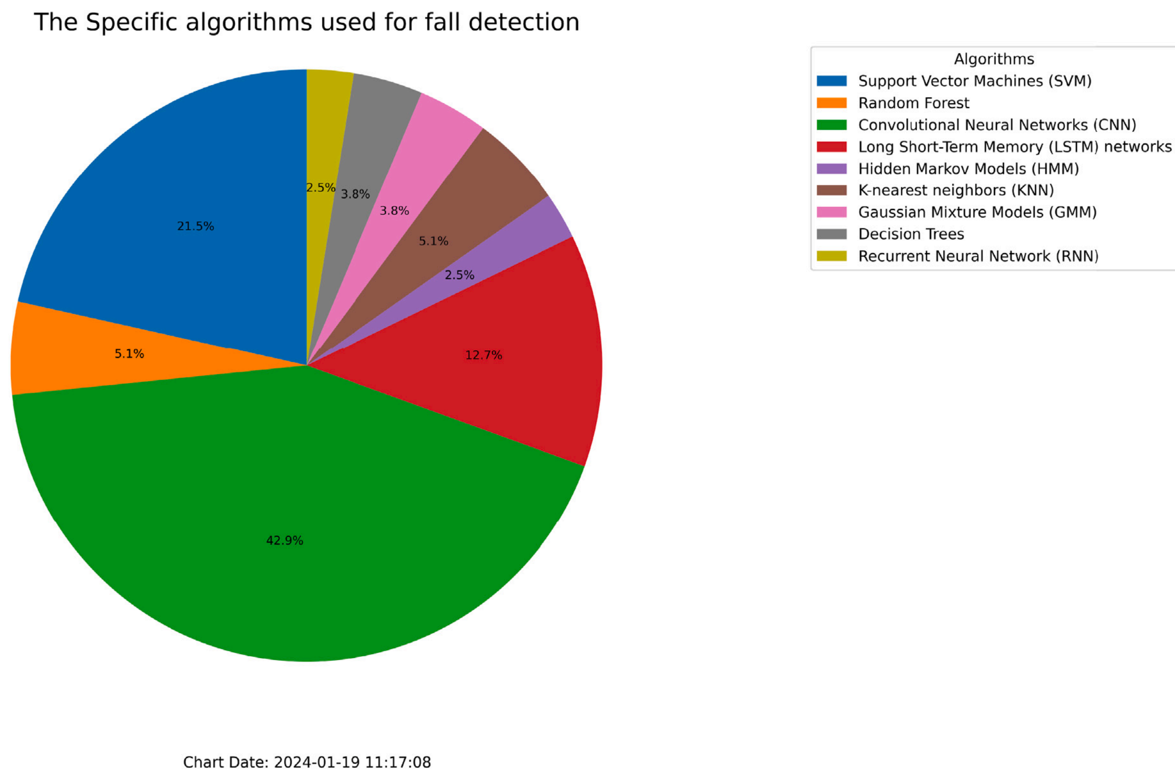

Fig. 2. Percentage of the specific algorithms for fall detection among all the research works found from 1990 to 2024.

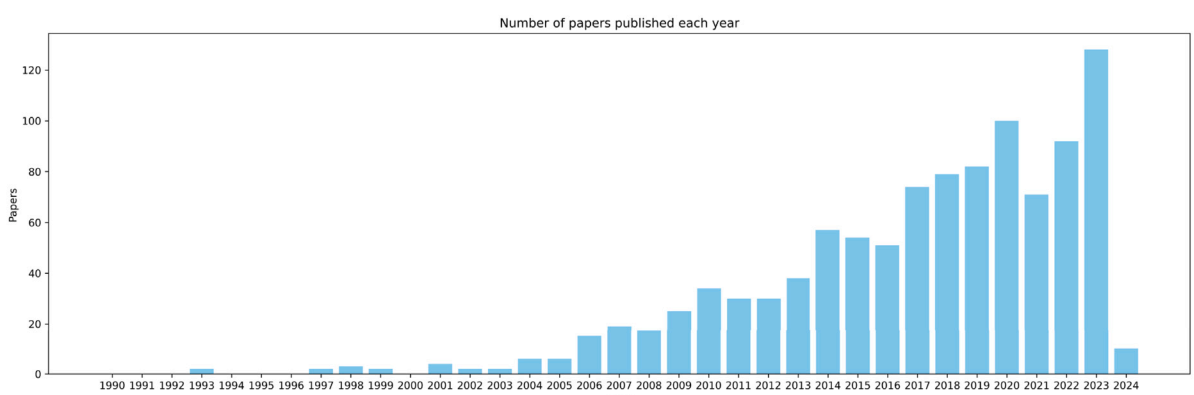

Fig. 3. Fall detection research papers found in Google Scholar from 1990 to 2024.

2.4. Specificity

Specificity, also known as the true negative rate, indicates the proportion of non-fall events correctly detected. It measures the ability to avoid false positives (false alarms). The false positive rate, the opposite of specificity, indicates the percentage of non-fall events that are incorrectly identified as falls [9,10]. Specificity can be determined using the following formula.

$$Specificity = \frac{TN}{TN + FP} = \frac{TN}{N} \tag{5}$$

$$FalsePositiveRate = \frac{FP}{FP + TN} = \frac{FP}{N} = 1 - Specificity \tag{6}$$

2.5. Precision

Precision (also referred to as positive predictive value) represents the fraction of alarms that correspond to true falls. It indicates the likelihood that an alarm will indeed signal a fall rather than a false alarm. For instance, a precision value of 0.5 implies that half of the alarms will be genuine falls, while the other half will be false alarms (1 false positive for each detected fall) [9]. Precision can be determined using the following formula.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

2.6. F-measure

The F-measure (also referred to as F-score) is the harmonic mean of sensitivity and precision. The F-measure takes into account all outcomes except true negatives (non-falls). In the context of fall detection, the key priorities are detected falls (TP), missed falls (FN), and false alarms (FP). By considering all these outcomes, the F-measure offers a comprehensive assessment of performance [9]. F-Measure can be determined using the following formula.

$$F - Measure = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \tag{8}$$

3. Data fusion approaches

Presently, our world is reshaped by the fascinating and powerful power of DL, sensors, and ML. All these cutting-edge technologies are leading to a new horizon in finding new innovative ways, low-cost, reliable, and more accurate systems to combat the huge public health problem related to falls among elderly and disabled people. This section describes the fusion of multiple sensors and ML methods that have been used to automatically detect and diagnose falls, in order to reduce their consequences and severity through timely intervention. The prominent role of wearable devices, smartphone-based applications, and cameras is reviewed by focusing activities for fall detection, with a common reliance on accelerometers. In the later subsection, the modern fall detection methods including their experimental validation in the literature are discussed signifying the advancement of technology and the efficiency of fall detection systems. The fusion of these cutting-edge technologies has significantly advanced the state of the art in fall detection systems, enhancing the security and well-being of individuals at risk of falls. This Fig. 5 depicts a high-level overview of fall detection systems. In the diagram, this fall detection system workflow is shown from data collection and analysis. The framework contains an Long Short-term Memory (LSTM) model for fall detection, and this data is then sent through a data processing autoencoder. Once a fall is detected by the system, a sound alert is produced. Additionally, in instances of a fall event, the fall detection system will send an alert to family members or the hospital emergency services to ensure that help is reached in a timely manner. The diagram serves as a way to understand the parts and functions of a fall detection system, specifically from data processing to development of an alert for optimal fall detection and response.

3.1. Machine learning approaches

Andò et al. [20] present a novel multisensor data-fusion approach for the classification of activities of daily living (ADL) and fall events, particularly focusing on monitoring elders and individuals with neurological pathologies. The system utilizes a smartphone equipped with inertial sensors to gather data on user dynamics and employs advanced algorithms for event classification and notification to caregivers. The approach demonstrates high specificity and sensitivity in classifying falls and ADL, with potential applications in patient monitoring, well-being, and active aging. The system's ability to automatically detect events and notify caregivers, as well as track the evolution of user pathology during rehabilitation tasks, makes it a valuable tool for ensuring user safety and providing real-time awareness of critical events. The results obtained from tests with users confirm the effectiveness of the proposed approach in falls and ADL classification tasks, highlighting its potential for practical implementation in assistive technologies.

Gjoreski et al. [21] present a method for fall detection and activity recognition using wearable sensors, which won the Challenge Up: Multimodal Fall Detection competition. The method is based on a multi-sensor data-fusion machine-learning approach that utilizes accelerometers and gyroscopes. It was evaluated on a dataset collected from 12 subjects, with 3 cases used for testing. The method involves several key steps, including data preprocessing, sensor orientation correction, feature extraction, feature selection, and classification. Notably, the authors performed an unsupervised similarity search to optimize the method for the 3 test subjects by finding the three most similar users to the test users. This helped in tuning the method and its parameters to achieve the highest recognition performance. The evaluation results showed that the method achieved 98% accuracy and the highest recognition performance in the competition, with an F1-score of 82.5%. The researchers also discuss related work, algorithm comparison, and the final evaluation results, including confusion matrices and detailed analysis of the recognition performance for different activities and users. In conclusion, the method demonstrated robust performance in fall detection and activity recognition, achieving high accuracy and identification scores, and winning the competition. The authors also discussed potential future improvements, such as reducing the number of sensors for practical implementation.

Li et al. [22] focus on the application of multisensor data fusion for human activities classification and fall detection. It highlights the need for automatic systems and sensors capable of classifying human activities and promptly detecting critical events such as falls, especially in the context of an aging population and increasing incidence of multi-morbidity conditions. The paper compares the performance of individual sensors, such as accelerometers, video-camera detectors, and radar technology, and explores the advantages and disadvantages of each type of sensor in terms of performance, end-users' acceptance, cost, power consumption, and ease of use. The investigation aims to leverage the strengths of each sensor through information fusion to improve the overall system performance. The experimental data is collected using a radar sensor, a RGB-D Kinect, and a tri-axial accelerometer within a smartphone. The research involves 10 different activities, including walking, sitting, standing, and falling, with 16 participants ranging in age from 23 to 58 years. The measurements are collected in an office environment at Glasgow University. Features are extracted from the data of each sensor, and different classifiers based on supervised ML are used to analyze the data. The results show that combining information from heterogeneous sensors, such as radar and accelerometer, significantly improves the overall classification accuracy. The authors also investigate the addition of features extracted from a RGB-D Kinect sensor, which further increases the overall classification accuracy. The authors conclude by outlining future research directions, including the collection of additional data involving more participants, more indoor scenarios, and more deployment geometries for the sensors. It also mentions the integration of additional sensors, such as inertial measurement units, and the consideration of different approaches to feature selection and information fusion techniques.

Ezatzadeh et al. [23] present a detailed study on the development of a multi-camera fall detection (MC-FD) framework using video surveillance technology. The main motivation for this systems is to address the concern of sudden fall accidents, particularly for elderly and disabled individuals, by automatically detecting falls from video sequences. The framework is designed to be an assistive technology for surveillance systems and aims to overcome challenges such as occlusion and visibility. The framework is structured into three main stages: preprocessing, feature extraction, and decision-making model. In the first stage, the silhouette of a person in the video is segmented and smoothed using morphological operations to create precise background images. Feature extraction involves extracting important information from moving objects, such as shape and motion characteristics, to distinguish falls from other activities. This includes using techniques like blob analysis, motion history image (MHI) technique, and approximated ellipse parameters to derive the features. The decision-making model stage involves training a supervised model using feature vectors from the previous steps for each camera. Methods such as Support Vector Machine (SVM) and Hidden Markov Model (HMM) are used for fall detection in video sequences. The research also discusses the integration of classification results from different cameras and various decision-making models. The paper includes experiments and results, where a multi-camera dataset is used for evaluation. Various examination measures, such as accuracy, sensitivity, and specificity, are employed to analyze the effectiveness of the proposed method. The authors compares the suggested MC-FD framework with related works and highlights the advantages of the proposed approach, particularly in terms of accuracy and computational complexity.

Li et al. [24] present a study on distributed radar information fusion for gait recognition and fall detection. The research focuses on a fusion framework that uses data from multiple, distributed radar sensors to classify gait styles and detect critical accidents such as falls. The data used in the work was collected from a network of radar sensors placed

Table 1
Performance comparison of the methods of Section 3.1.

Papers	Dataset	Methods	Performance
Ando et al. [20]	Inertial sensors embedded in the user module (a smartphone)	Focuses on smart algorithms developed for the ADL classification	Average value of the specificity index is 0.98
Gjoreski et al. [21]	Dataset recorded using multiple types of sensors: wearable sensors, ambient sensors, and vision devices	Feature extraction, feature selection, and classification	82.5% F1-score, and 98% Accuracy
Li et al. [22]	Data collected by different sensors: tri-axial accelerometer, micro-Doppler radar, and depth camera	Classification algorithms	Overall classification accuracy is 91.3%
Ezatzadeh et al. [23]	Multiple cameras (Auvinet et al. [25])	SVM and HMM - Feature extraction (SOP)	Accuracy is 99.55%
Li et al. [24]	Dataset collected in the Computational Intelligence for Radar (CI4R) Lab at the University of Alabama	Naïve Bayes combiner (NBC), linear SVM, Random-Forest Bagging Trees, VGG-16	Accuracy is 84%
Z. Chen et al. [26]	Data collected from Grid-EYE or HC-SR04 sensors	SVM	Accuracy increased to 96.7% when sensor fusion is used

in different locations, including one Ancortek frequency-modulated continuous wave radar and three ultra-wide-band Xethru radars. The work looks into various ways of combining information, like merging features, using a soft approach with classifier confidence levels, and a hard approach with a Naïve Bayes combiner. They tested different classifiers, including linear SVM, Random-Forest Bagging Trees, and five pre-trained neural networks. The VGG-16 network outperformed the other models, achieving an accuracy of approximately 84%, especially when paired with the Naïve Bayes combiner. In their experiments, they gathered data from 14 volunteers who showcased 12 distinct walking styles. This included variations like walking at different speeds, dragging one foot, using walking aids, and simulating falling events. To capture this data, they strategically positioned radar sensors in three different locations relative to the subjects. The study delves into the intricacies of processing and analyzing the data. They explore the utilization of traditional classifiers and venture into the domain of transfer learning(TL) with pre-trained networks. Additionally, they compare the performance of various fusion techniques using both conventional classifiers and the transfer learning approach. The results indicate that TL can outperform conventional classifiers, and fusing information from distributed radar sensors is beneficial for gait recognition and fall detection. This research concludes by outlining possible future directions for the work, including evaluating the information fusion method on a wider platform and considering sequential classification tasks and meta-learning of pre-trained networks.

Chen and Wang [26] explore a sensor fusion strategy designed for fall detection, with a specific focus on healthcare for the elderly. It introduces a system that combines infrared and ultrasonic sensors to estimate the user's location, size, and temperature profile. For fall detection, the system employs a SVM algorithm, a widely adopted ML technique for activity recognition and classification. The research evaluates different feature sets and conducts experiments to simulate the daily activities of the elderly, including standing, sitting, stooping, forward falling, and sideway falling. The results of the experiments show that sensor fusion significantly improves fall detection accuracy. The study also discusses the challenges, such as the difficulty in obtaining real fall data from elderly participants, and highlights potential areas for future improvemente. This research evaluates different feature sets and conducts experiments to simulate the daily activities of the elderly, including standing, sitting, stooping, forward falling, and sideway falling. The results of the experiments show that sensor fusion significantly improves fall detection accuracy. The paper also discusses the challenges in fall detection, such as the difficulty in obtaining real falling activities of the elderly for testing, and the potential for further enhancements in the future.

Table 1 presents a performance comparison of various methods discussed in this section for fall detection systems. Each row corresponds to a specific study, detailing the dataset used, the methods employed, and the performance metrics achieved. Also, Table 2 outlines the advantages and limitations of various fall detection methods discussed in this section. Each row corresponds to a specific study, summarizing the strengths and weaknesses of the approaches used for detecting falls.

3.2. Deep learning approaches

Xu et al. [27] propose a fusion fall detection algorithm that combines a threshold-based method (TBM) and a convolutional neural network (CNN) to detect falls using a wearable device named SHFFD. The TBM captures the entire fall process based on triaxial acceleration samples, while the CNN classifies suspected fall events. The algorithm aims to achieve high sensitivity and specificity, and it optimizes the feature set at the TBM stage to minimize power consumption. Experimental results show high performance with a sensitivity of 98.04%, specificity of 96.91%, and accuracy of 97.46%. The algorithm addresses the critical need for effective fall detection systems among the elderly, aiming to mitigate the adverse effects of falls and improve health monitoring.

Li et al. [28] present a framework for multimodal sensor fusion using a bi-directional LSTM network to sense and classify daily activities and high-risk events such as falls. The data used in the study includes continuous activity streams from FMCW radar and three wearable inertial sensors. The work discusses the experimental setup, data collection, data-processing, feature extraction, and classification approaches. It also introduces a novel hybrid approach of soft-hard combination fusion for information fusion. The proposed framework and fusion schemes were validated on data from 16 participants, demonstrating an average classification accuracy of approximately 96%. The paper concludes by discussing future work and potential improvements.

Nahiduzzaman et al. [29] discuss the development of a recurrent neural network (RNN)-based framework for detecting falls and daily activities of elderly patients with neurological disorders using the Internet of Things (IoT). The system also facilitates patient management by referring them to a doctor when necessary. The proposed model fuses knowledge from both smartphone/wearable and camera data and is trained and tested using open-labeled and UR datasets. The performance evaluation shows that the proposed method is effective and outperforms its counterparts. The paper also provides a literature review of existing fall/activity detection and patient management systems, as well as a detailed explanation of the system model, methodology, and numerical results.

Table 2
Advantages and limitations of the methods of Section 3.1.

Papers	Advantages	Limitations
Ando et al. [20]	Multisensor data-fusion approach, High sensitivity and specificity, Automatic event detection and notification, Non-invasive monitoring, Robustness against user variability, Real-time awareness, Potential for rehabilitation monitoring	Testing population, Dependence on sensor placement, Potential for misclassifications, Limited contextual awareness, Long-term data collection needs, Sensitivity to fall dynamics
Gjoreski et al. [21]	High accuracy, Multi-sensor approach, Data preprocessing and orientation correction, Extensive feature extraction, Feature selection, Unsupervised similarity search	Number of sensors, Data labeling issues, Short duration activities, Complexity of implementation, Limited generalizability
Li et al. [22]	Improved classification accuracy, Comprehensive activity recognition, High overall accuracy, Adaptability to different scenarios	Misclassification issues, Dependence on sensor placement, Complexity of information fusion, Need for extensive data collection
Ezatzadeh et al. [23]	High accuracy, No calibration required, Efficient use of multiple cameras, Local decision-making, Lower computational complexity	Single activity and individual tracking, Data transfer vulnerability, False positives
Li et al. [24]	Contactless sensing technology, Multiple radar sensors, Data fusion techniques, Transfer learning, Improved fall detection, Diverse gait classification	Dependency on radar placement, Complexity of gait patterns, Limited dataset, Computational load, False alarms, Need for further validation
Z. Chen et al. [26]	High detection accuracy, Non-wearable solution, Privacy-friendly, Cost-effective, Real-time monitoring, User localization, Adaptability	Performance evaluation challenges, Lower accuracy at longer distances, False positives and negatives problem, Limited feature set, Angular scanning limitations, Continuous activity identification difficulty, Dependence on environmental conditions

Cai et al. [30] present a fall detection method based on dense block with a multi-channel convolutional fusion (MCCF) strategy, as shown in Fig. 4. The proposed method aims to address the problem of information loss in DL networks and reduce data redundancy. It utilizes a densely connected network structure called MCCF-DenseBlock to fully extract information and avoid network overloading. An improved transition layer is also introduced to reduce data redundancy. The method is evaluated using the UR Fall Dataset and compared with five state-of-the-art fall detection methods. The experimental results demonstrate that the proposed method outperforms existing methods in terms of accuracy, precision, sensitivity, specificity, and F-score.

Divya et al. [31] introduce the evolution of computing paradigms, focusing on cloud computing, fog computing, and mist computing. It highlights the limitations of cloud computing for real-time applications and introduces fog and mist computing as solutions to reduce latency and bandwidth consumption. The proposed architecture involves edge devices, mist layer, fog-layer, and cloud for efficient fall detection with low latency and high accuracy. It also covers the compression of deep neural networks for deployment on edge devices and the decision-making process for raising alarms. The proposed architecture aims to enhance performance in real-time applications and reduce latency in decision-making.

A fall detection and classification system using two cameras is described in [32]. It begins by describing the traditional workflow for fall detection systems, which includes data collection, windowing, feature extraction, and learning and inference. The data set used contains information about various activities such as falling, walking, standing, sitting, and picking up objects. The proposal involves segmenting the data into 1-second windows with 0.5 s of overlapping, extracting features from the images, and using a CNN for classification. The experiments compare the performance of the CNN model with classical ML methods such as SVM, Random Forest (RF), Multi-Layer Perceptron (MLP), and K-Nearest Neighbors (KNN). The evaluation metrics used include accuracy, sensitivity, specificity, precision, and F1-score. The results show that the proposed CNN model outperforms classical ML methods in terms of accuracy, sensitivity, specificity, precision, and F1-score. The work also discusses the performance of the proposed system for fall detection and classification compared to other approaches, highlighting its competitive performance and simplicity in architecture. Furthermore, the proposal is evaluated for fall detection using both monocular and multi-camera vision-based approaches. The results indicate that the multi-camera approach offers robust solutions for recognizing falls, even in the presence of occlusions in a viewpoint.

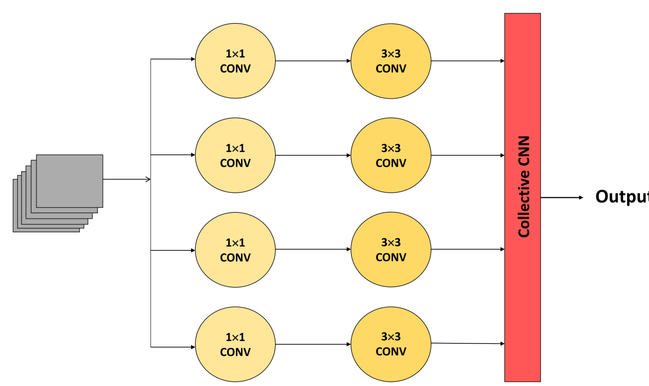

Fig. 4. The structure of a MCCF layer (re-imaged from [30].

The proposal also demonstrates competitive performance in classifying daily activities and falls using the multi-camera vision-based approach. Overall, the proposed fall detection and classification system using CNN and multi-camera vision-based systems shows promising results, offering robust solutions for fall detection and classification.

Alanazi et al. [33] provide an in-depth review of a human fall detection system proposed using multi-stream 3D Convolutional Neural Networks CNNs with fusion. It starts by introducing the computer vision (CV) field and its importance in developing knowledge of information derived from videos and digital images. Deep learning models such as hierarchical probabilistic models, neural networks, and even supervised and unsupervised feature learning algorithms that are used for developing CV systems including image processing processes are highlighted here. They introduce the concept of image fusion, which involves combining crucial details from multiple images to create a single, more accurate and informative image. The fusion process aims to make images more suitable for machine and human perception and easier to comprehend. Additionally, the study outlines the proposed human fall detection system, which utilizes multi-stream 3D CNNs with fusion. The system is designed to classify different phases of a human fall, such as standing or walking, falling, fallen, and at rest, using video sequences. The proposed method includes preprocessing video sequences and outlines the model architecture and specifications. It describes the use of a 4-branch architecture with 67 layers, including 3D convolutional blocks, batch normalization, rectified linear unit

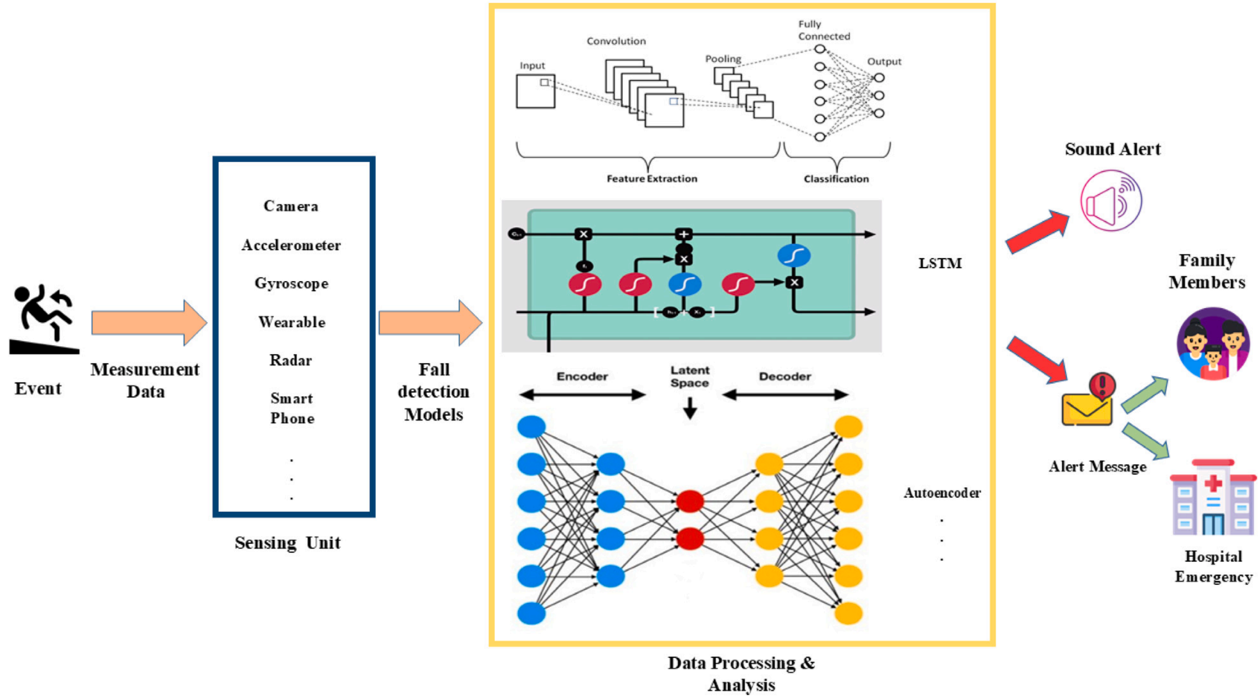

Fig. 5. High-level schematic for fall detection systems.

(ReLU) layers, max-pooling layers, and fully connected (FC) layers. The architecture is designed to capture spatial and temporal information from video frame sequences. The research details the database used in the experiments, which includes fall detection videos and normal videos obtained from different locations. It also discusses the experimental setup, including the hardware and software used in training and testing the models. The experiments involved a three-fold cross-validation approach to ensure the generalization and reliability of the results. The findings from the experiments are displayed, indicating the performance ratings of the suggested multi-stream 3D CNN model versus different other recent models such as GoogleNet, SqueezeNet, ResNet18, and DarkNet19. The proposed model delivered the best results regarding accuracy, sensitivity, specificity, and precision showing its potential to advance human fall detection. Moreover, the research contains a section addressing the effectiveness of the suggested approach in relation to other fine-tuned state-of-the-art models. It also compares it with similar works, revealing the better performance of the proposed multi-stream 3D CNN model.

A combination of wearable devices and depth data from a camera is proposed in [34] to address the problem related to fall injuries that afflict the elderly population. It focuses on the role of technology in enhancing security and self-sufficiency among senior citizens. Three different fall detection algorithms are presented in the study, and they pay special attention to the proper synchronicity of data from wearables and the information received by a camera for fully accurate and reliable detection of falls. There is a thorough description of the synchronization process between the wearable inertial device and the vision-based device (Microsoft Kinect sensor). The paper describes the use of an ad-hoc acquisition software for acquiring data from Kinect and accelerometers, with such synchronization achieved by using timestamps and correcting according to transmission times and delays. The proposed fall detection algorithms are then elaborated with reference to the system setup, acceleration data processing, and parameters specific to each algorithm. The research assesses the effectiveness of algorithms using an ADLs and fall dataset, with the results being discussed in terms of accuracy, sensitivity, and specificity. The experimental results also demonstrate the effectiveness of the proposed algorithms in detecting falls with Algorithm 3 being the most accurate one. The research also describes the limitations that can be developed and some future enhancements, such as increasing the dataset size or including more people in tests to have a wider range of testing algorithms.

It is possible to state that [35] provides a significant contribution to the development of fall detection systems based on leading-edge technologies like DL and image fusion. The issue of human-based segmentation CNN models as well as the course of evaluating falling action classification is featured there. Two experiments were carried out using the Le2i fall dataset, whereby results reveal that this approach is suitable for enabling accurate detection of actions representative or indicative of fall actives to be captured on videos. The paper starts by talking about various ways to detect falls. It looks into using DL methods and low-resolution thermal sensors along with recurrent neural networks. The discussion also dives into the difficulties associated with using supervised classification algorithms and explores using anomaly detection as a strategy based on semi-supervised learning. After that, the research delves into the technical details of the experiments, breaking down the technical aspects. This includes a rundown of the equipment, details about the dataset, and an explanation of how they fine-tuned the human segmentation model. The research also sheds light on the metrics employed to evaluate performance, covering accuracy, sensitivity, specificity, and precision. The findings from their experiments are laid out in detail, revealing impressive accuracy, sensitivity, specificity, and precision when it comes to spotting fall actions in videos. Their proposed approach demonstrates superior performance compared to other comparable methods, highlighting its potential for practical, real-world applications. The work also describes the three-fold cross-validation technique they employed to guarantee the strength and applicability of their results.

Table 3 provides a performance comparison of different methods for fall detection systems discussed in this section. Each row represents a specific study, including details on the dataset used, the methods applied, and the performance metrics achieved. Further, Table 4 highlights the advantages and disadvantages of various fall detection methods covered in this section. Each row summarizes a particular study, outlining the strengths and weaknesses of the approaches used for detecting falls.

Table 3
Performance comparison of the methods of Section 3.2.

Papers	Dataset	Methods	Performance
Xu et al. [27]	Sisfall dataset and the FARSEEING dataset	TBM and CNN	Accuracy is 97.46%
Li et al. [28]	Recording data at the University of Glasgow	Bi-directional LSTM network	Accuracy is 96%
Nahiduzzaman et al. [29]	UR Fall Dataset	RNN, SVM, Random Forest	Accuracy is 95%
Cai et al. [30]	UR Fall Dataset	Proposed MCCF-DenseBlock	Accuracy is 96.6%
Divya et al. [31]	Smart cameras, and wearable sensors such as the gyroscope, accelerometer, Kinect, etc. collect the data to detect falls.	Deep Convolutional Neural Network (D-CNN)	Accuracy is 98.13%
R. Espinosa et al. [32]	UP-Fall Detection dataset	SVM, RF, MLP, KNN, and Proposed (CNN)	Accuracy is 95.64%
Alanazi et al. [33]	Le2i fall detection dataset [36]	Multi-stream 3D Convolutional Neural Networks	Accuracy is 99.03%
S. Gasparrini et al. [34]	Includes two IMUs mounted on the wrist and waist of the subject, and a Microsoft Kinect v2 sensor	Threshold-based (Custom 3 different algorithms)	Average accuracy: Algorithm-1 79% Algorithm-2 90% Algorithm-3 99%

Table 4
Advantages and limitations of the methods of Section 3.2.

Papers	Advantages	Limitations
Xu et al. [27]	High sensitivity and specificity, Fusion of methods, Optimized feature set, Wearable device design, Data transmission efficiency, Real-time processing	Dependence on thresholds, Potential for false alarms, Computational complexity of CNN, Limited dataset diversity, Calibration requirements, Energy consumption during transmission
Li et al. [28]	High classification accuracy, Multimodal sensor fusion, Continuous activity recognition, Hybrid fusion approach, Robustness across participants, Realistic validation method	Potential misclassification, Dependency on sensor placement, Complexity of implementation, Limited participant diversity, Sensitivity to noise, Overfitting risk
Nahiduzzaman et al. [29]	Early fall detection, Multimodal data fusion, Real-time monitoring, ML integration, Performance comparison	Dependence on sensor data, Computational cost, Limited dataset scope, Sensitivity vs. Specificity trade-off, Future integration needs
Cai et al. [30]	Automatic feature extraction, Dense connections, Reduced information loss, Improved transition layer, High performance	Complexity of network, Computational cost, Dependence on quality of input data, Generalization to diverse environments
Divya et al. [31]	Low latency decision making, Multimodal data utilization, Edge processing, Ensemble learning, Efficient data filtering, Personalized alarm settings, Improved accuracy	Dependency on data quality, Challenges in real-time data collection, Potential for false alarms, Limited scalability, Energy consumption, Complexity of implementation, Reliance on connectivity
R. Espinosa et al. [32]	High accuracy, Robustness to occlusion, Simple CNN architecture, Privacy considerations, Competitive performance	Dependence on image quality, Privacy issues, Computational complexity, Limited dataset diversity, Environmental variability
Alanazi et al. [33]	High accuracy, High sensitivity and specificity, Use of image fusion, Lightweight model, Robustness	Single person detection, Dataset dependency, No segmentation or localization, Hardware limitations, Standard deviation variability
S. Gasparrini et al. [34]	Data fusion approach, Synchronization, Multiple algorithms, Low complexity, High specificity, Comprehensive dataset	Sensitivity issues, Orientation dependence, Limited fall types, Skeleton estimation limitations, Need for additional sensors, Testing population

4. Sensor technologies for fall detection systems

In recent years, the development of sensor technologies has played a pivotal role in advancing the field of fall detection systems, addressing a critical aspect of healthcare and eldercare. Falls among the elderly population pose significant risks, often leading to severe injuries and a decline in overall well-being. Recognizing the urgency to enhance preventative measures, researchers and engineers have focused their efforts on harnessing the capabilities of various sensor technologies. This section delves into the cutting-edge advancements and methodologies employed in sensor-based fall detection systems, exploring the diverse range of sensors utilized, their integration into comprehensive systems, and the impact these technologies have on improving the safety and quality of life for individuals at risk. From wearable devices to ambient sensors, the landscape of sensor technologies offers a multifaceted approach to detecting falls, providing a foundation for the design and implementation of robust and effective fall detection systems.

Until now, scholars have explored various classifications for fall detection systems. For instance, in their study, Nooruddin et al. [10] categorized fall detection systems into two groups: single sensor-based and multiple sensor-based systems. The classification is determined by the number of sensors employed in capturing real-world scenarios. Single sensor-based systems use data from a single sensor for feature extraction and classification, while multiple sensor-based systems utilize data from several sensors for these purposes. Sensors like Wi-Fi or Bluetooth modules, used solely for communication, are not factored into the categorization if they are not employed for feature extraction or classification. Fig. 8 shows the taxonomy of fall detection systems by Noradin et al. According to this paper [10], systems that are based on a single sensor rely on one sensor or module for gathering data. These systems utilize sensors such as accelerometers, gyroscopes, or depth cameras for data collection. After data collection, it undergoes processing and is then transmitted to a detection method, such as threshold-based algorithms (Chen et al. [37], Mehmood et al. [38]), ML models, or statistical models (Sanchez and Muñoz [39]; Yhdego et al. [40]; Yacchirema et al. [41]). Systems utilizing a threshold-based algorithm compare gathered data with predetermined thresholds for detection. Conversely, systems employing ML or statistical models forward the collected data to a pre-existing model trained on comparable datasets. Fall detection sensors were divided into categories based on different functionalities, and Table 5 presents some of these categories and examples. These categories were Motion Sensors (e.g., accelerometers and gyroscopes), Pressure Sensors (e.g., floor pressure sensors

Table 5
Fall detection sensor categories.

Sensor category	Examples of sensors	Description
Motion sensors	Accelerometers, Gyroscopes, IMUs Magnetometers, INS	Measure movement and changes in velocity. Measure magnetic field strength, enable precise motion tracking.
Pressure sensors	Floor pressure sensors, Bed sensors Seat cushion sensors, Weight sensors	Detect changes in pressure, indicating a fall. Monitor pressure distribution for fall detection in specific areas.
Wearable sensors	Smartwatches, Fitness trackers Health patches, Smart clothing	Portable devices with accelerometers and gyroscopes. Wearable solutions for continuous health monitoring.
Vision-based sensors	Depth cameras, CV systems RGB cameras, Infrared cameras Time-of-flight cameras	Use visual data to identify patterns and anomalies. Capture color and infrared images for enhanced analysis. Measure the time taken for light to travel to objects.
Proximity sensors	Infrared sensors, Ultrasound sensors Capacitive proximity sensors, LiDAR	Measure proximity and detect body heat. Use electric fields or laser beams for distance measurement.
Impact/Vibration sensors	Vibration sensors Impact sensors, Tilt sensors	Detect vibrations caused by a fall or impact. Measure impact force and tilt angles for fall assessment.
Health monitoring sensors	Heart rate monitors Pulse oximeters, Blood pressure monitors ECG sensors	Measure heart rate variations during and after a fall. Monitor blood oxygen levels and pressure for health insights. Record electrical activity of the heart.
Environmental sensors	Smart home sensors, GPS trackers Temperature sensors, Humidity sensors Gas sensors	Monitor activities and location for context. Measure ambient conditions for additional context. Detect the presence of specific gases in the environment.
Audio/Sound sensors	Voice and Sound sensors Microphones, Acoustic sensors Ambient noise sensors	Detect unusual sounds or calls for help. Capture audio data for analysis and context. Monitor background noise levels in the environment.

and weight sensors), Wearable Sensors (e.g., smartwatches and health patches), Vision-based Sensors (e.g., depth cameras and RGB cameras), Proximity Sensors (e.g., infrared sensors and LiDAR), Impact/Vibration Sensors (e.g., vibration sensors and tilt sensors), Health Monitoring Sensors (e.g., heart rate monitors and ECG sensors), and Environmental Sensors (e.g., smart home sensors and GPS trackers).

4.1. Fall detection using accelerometers

According to [44,45], an accelerometer is a device instrumental in quantifying the acceleration or deceleration of an object relative to its local frame of reference. Available in both single-axis and multi-axis configurations, these devices facilitate the determination of both the magnitude and direction of acceleration, treated as a vector quantity. Accelerometers find diverse applications across various domains, including orientation determination, vibration analysis, shock detection, and assessment of falls. The study described in [46] aims to enhance current smartphone fall detection systems by analyzing the triaxial acceleration data obtained from the smartphone's built-in accelerometers. By determining key thresholds for falls and non-falls, a new threshold-based fall detection method is proposed. This approach not only differentiates fall incidents from common daily activities like walking, running, and sitting, but also recognizes falls in four directions (forward, backward, left lateral, and right lateral). The majority of contemporary portable gadgets come equipped with Microelectromechanical systems (MEMS) accelerometers, which serve the purpose of detecting screen orientation, position, and other functionalities [10, 47–49]. By integrating ensemble stacked autoencoders (ESAEs) with one-class classification utilizing the convex hull (OCCCH), [37] introduces a new intelligent fall detection technique named ESAEs-OCCCH, which leverages accelerometer data from a wrist-worn smartwatch. The method first employs ESAEs for unsupervised feature extraction to address the limitations of manual feature extraction in terms of expertise and time requirements. Subsequently, OCCCH is utilized for pattern recognition. To enhance fall detection performance and stability, a combination of majority voting strategy and weight adaptive adjustment strategy is implemented. Two experiments are conducted to simulate thirteen fall activities (FAs) and sixteen ADLs, including rigorous hand and wrist movements, based on the behavioral patterns of elderly individuals, the uncertainties in ADLs and FAs, and the impact of intense hand activities on accelerometer signals. These experiments involve young volunteers of diverse genders, ages, heights, and weights. The results of the experiments showcase the effectiveness and reliability of the proposed approach. Mehmood et al. [38] introduce an innovative fall detection method using SHIMMER™ wearable sensors, that employs the Mahalanobis distance on real-time data to detect fall incidents. This approach demonstrates greater resilience compared to traditional distance measurement techniques commonly used in existing fall detection systems. The study initially crafted a practical dataset comprising three common daily activities – walking, sitting (on and off a chair), and standing still – which are frequent precursors to falls in the elderly population. The effectiveness of the proposed algorithm was assessed through testing and validation to detect fall events. The results were encouraging, demonstrating performance levels on par with leading-edge fall detection methodologies.

Yhdego et al. [40] introduce initial research on a fall detection technique utilizing transfer learning, as part of a broader initiative to merge efficient ML with personalized musculoskeletal modeling for mitigating fall injuries in elderly individuals. Drawing from the significant advancements in image-based object recognition achieved with D-CNN, the authors choose a pre-trained kinematics-based ML approach using extensive annotated accelerometry datasets. These accelerometer datasets are transformed into images using time-frequency analysis, specifically through scalograms generated by the continuous wavelet transform filter bank. Subsequent data augmentation on these scalogram images enhances accuracy, addressing the constraints of limited labeled fall sensor data and enabling transfer learning from the pre-existing model. Experimental findings on publicly accessible URFD datasets illustrate that transfer learning outperforms conventional methods when dealing with sparse labeled training data.

Yacchirema et al. [41] introduce the IoTE-Fall system, an intelligent solution designed to detect falls among elderly individuals in indoor settings by leveraging the Internet of Things and an ensemble ML algorithm. The IoTE-Fall system integrates a 3D-axis accelerometer within a 6LowPAN wearable device to capture real-time movement data from elderly volunteers. To enhance fall detection accuracy, the study evaluates four ML algorithms (decision trees, ensemble, logistic regression, and Deepnets) based on metrics such as AUC ROC, training time, and testing time. Acceleration data is processed and examined at the network edge using an ensemble-based predictive model identified as the most effective for fall detection. Results from data collection,

Table 6
List of public datasets for wearable fall detection systems.

Dataset	Characteristics of the sensor	Year	Approach	Evaluation metrics
DLR [42]	Inertial Measurement Unit (IMU) worn on the belt	2010	Bayesian Network(BN) - HMM	Recall rate between 93% and 100%
LDPA [43]	4 external IMUs (tags) - sensors use ultra-wideband (UWB) technology	2010	Multi-agent system methods - machine-learning (Random Forest classifier - SVM)	Accuracy(ML agents: 72% - Expert-knowledge agents: 88% - Meta-prediction agents: 91.33%)
MobiFall MobiAct [7–105]	Data were collected from the accelerometer, gyroscope and orientation sensors of a Samsung Galaxy S3 smartphone with the LSM330DLC inertial module (3D accelerometer and gyroscope)	2013–2016	IBk classifier algorithm	Accuracy of 99.88%
EvAAL [106]	Three 3-axis accelerometers were placed on the chest, thigh, and ankle	2013	TriLAR	Classification accuracy: 98.03 ±0.62%
TST Fall detection [107]	2 external IMUs, Waist - Wrist	2014	Ad-Hoc segmentation algorithm - inter-frame processing algorithm	Accuracy: 98.33%
tFall [108]	One smartphone (Using the accelerometers integrated into smartphones)	2014	Nearest neighbor-based technique(NN) - SVM	SVM(sensitivity(SE): 0.929% - specificity(SP): 0.917%) NN(sensitivity(SE): 0.9% - specificity(SP): 0.84%)
UR Fall Detection [109]	The detection of the fall is done on the basis of accelerometric data and depth maps	2014	Threshold-based fall detection - SVM	Accuracy: 98.33%
Erciyes University [110]	Each unit comprises three tri–axial devices (accelerometer, gyroscope, and magnetometer/compass)	2014	(k-NN) classifier-least squares method(LSM)-(SVM)-Bayesian decision making(BDM)-dynamic time warping(DTW)-artificial neural networks(ANNs)	The best results with the k-NN classifier and LSM, with sensitivity, specificity, and accuracy all above 99%
Cogent Labs [111]	Two SHIMMER (Sensing Health with Intelligence Modularity Mobility and Experimental Reusability) sensor nodes were affixed to the chest and thigh of each subject. These nodes were utilized to capture and relay data from the subjects to a remote PC	2015	J48 Decision Trees	F-measure of 94%
Gravity Project [112]	Thigh (smartphone in a pocket) - Wrist (smartwatch)	2015	Threshold based and pattern recognition techniques	Accuracy: 68%
Graz UT OL [113]	They utilized five state-of-the-art Android smartphone models, each carried in a small bag attached to the hip	2015	N/A	N/A
UMAFall [114]	1 Smartphone - 4 external IMUs (Ankle, Chest, Thigh, Waist Wrist)	2016	Threshold-based detection mechanisms	Sensitivity: 80% - Specificity: 95%
FARSEEING [115]	Inertial sensors (IMU) - Waist or Thigh	2016	N/A	N/A
SisFall [116]	It comprises acceleration data captured by two accelerometers and rotation data detected by a gyroscope	2017	Threshold-based classification	Accuracy: 96%
UniMiB SHAR [117]	Smartphone (the first one with the smartphone in the right pocket and the second in the left)	2017	ML algorithm classification	N/A
SMotion [118]	Shimmer sensor (Shimmer's primary offering is its wireless sensor platform, enabling real-time capture and transmission of diverse data sensed from various sources)	2017	KNN	Accuracy: 96%
IMUFD [119]	7 external IMUs (Chest, Head, Left ankle, Left thigh, Right ankle, Right thigh, Waist)	2017	SVM - Threshold-based algorithms	SVM(sensitivity:96% and specificity: 96%) Threshold-based(Kangas3phase) (sensitivity: 94% and specificity: 94%)
DU-MD [120]	IMU sensor (Wrist)	2018	N/A	N/A
SmartFall and Notch datasets [121]	Smartwatch (MS Band) - IMU sensor	2018	Deep recurrent neural network	Accuracy: 86%
UP-Fall [62]	Five IMU sensors (Ankle, Neck, Thigh (pocket) Waist, Wrist)	2019	ML-models - CNN	Accuracy: 95.1%
DOFDA [122]	IMU sensor (Waist)	2019	N/A	N/A
KFall [123]	An inertial sensor attached on low back - Camera	2021	DL model(ConvLSTM) - Threshold-based - SVM	ConvLSTM(specificity: 99.01%) - SVM(specificity: 94.87%) - Threshold-based(specificity: 83.43%)
EGOFALLS [124]	Data was collected using two types of wearable cameras: the OnReal G1 and CAMMHD Bodycams	2023	Decision fusion technique - RF - SVM - ResNet50 [125]	Internal cross-validation(binary classification with an accuracy of 97.8% - 12-class classification with an accuracy of 85%) - External cross-validation(The late decision fusion model(binary classification with an accuracy of 87.5% - 12-class classification with an accuracy of 52%))

interoperability services, data processing, analysis, emergency alerts, and cloud services demonstrate that their system achieves accuracy, precision, sensitivity, and specificity levels exceeding 94%.

A novel approach for identifying instances of falls by utilizing acceleration data and a HMM is proposed in [50]. A portable device equipped with a tri-axial accelerometer was employed to gather acceleration data from the chest of individuals. From this data, feature sequences (FSs) were derived and utilized as observations to train an HMM for fall detection. The likelihood of the input FS produced by the model was determined as the criterion for detection. Through experimental findings, it was revealed that the proposed technique achieved an accuracy of 97.2%, a sensitivity of 91.7%, and a specificity of 100%, showcasing the effectiveness of their method in identifying fall events.

A discreet solution based on smartphones that combines information from ML classification within a state machine algorithm is reported in [51]. The smartphone's accelerometer data is continuously monitored when the device is carried in the user's pocket or belt. When a fall is detected, the user's location is tracked, and notifications are sent via SMS and email to designated contacts. The accuracy of the fall detection algorithm proposed here reaches approximately 97.5% for both pocket and belt placements. In summary, this solution can effectively identify fall events without causing unnecessary disruptions to users through false alarms, and it offers the benefit of not altering the user's daily routines as no additional external sensors are needed.

A fall-detection algorithm is proposed in [52] by combining a basic threshold method with a HMM using 3-axis acceleration. A wearable fall-detection device has been developed to implement this algorithm and detect falls. Various parameters related to falls using 3-axis acceleration are introduced and applied to a straightforward threshold method. Falls identified by the threshold are then processed by two types of HMM to differentiate between a fall and an ADL. The outcomes from the threshold method, HMM, and a fusion of both were compared and assessed. The amalgamation of the threshold method and HMM reduced hardware complexity, and the proposed algorithm demonstrated higher accuracy compared to the basic threshold approach. Optimal outcomes were achieved by configuring the threshold parameters at ASVM = 2.5 g and $\theta = 55°$, leading to the system attaining accuracy levels of 99.5%, specificity of 99.69%, and sensitivity of 99.17%.

4.2. Fall detection using depth cameras

Depth cameras are employed to create a 2D image that illustrates the distance from a designated point to various points within a scene. The pixel values in the resulting image reflect the depth or distance of these points [10]. In contrast, images captured by RGB cameras lack depth information, as the pixels in such images represent the intensities of the corresponding points [53]. Utilizing depth cameras and the resulting depth images enables accurate determination of the location of objects or individuals in a given environment. These depth images are particularly useful for detecting fall incidents. Systems based on depth cameras predominantly utilize ML models for the identification and categorization of fall events and ADL [54].

In [55] a robot designed for eldercare is introduced to address two specific challenges encountered by the elderly population. The first involves continuously tracking elderly individual indoors, while the second pertains to fall detection. A detailed examination of the hardware and software components, along with the control architecture of the robot, is provided in this work. This study introduces the creation and advancement of a robot designed for eldercare. The robot is customized to address two specific challenges encountered by the elderly population. The first challenge involves continuously tracking the elderly individual indoors, while the second pertains to fall detection. A detailed examination of the hardware and software components, along with the control architecture of the robot, is provided in this paper. The robot's hardware design includes various features like a perception system that integrates a 2D Lidar, IMU, and camera for tasks such as environment mapping, localization, and fall detection. The software architecture of the robot is described as having layers dedicated to perception, mapping, and localization. Experimental testing is conducted to verify the robot's ability to plan paths using Hector SLAM (simultaneous localization and mapping) [56] and the RRT [57] technique, showing an average positioning accuracy of 93.8%. Detection of falls among the elderly is accomplished using the YOLOv7 [58] algorithm with a success rate of 96%. The experimental findings are analyzed and discussed.

A system based on depth images and wavelet moment is proposed in [59]. In the beginning, they standardize the picture as reported to each pixel in the picture relative to the distance from the midpoint, then polar coordinates the standardized picture. Second, the Fast Fourier Transform (FFT) of the picture is performed. Thirdly, the characteristic vectors of the picture are extracted by utilizing wavelet change. Ultimately, utilizing the minimum distance and SVM classification strategies recognizes human behaviors. Countless tests are led on a huge number of human conduct tests and the normal achievement rate of this calculation is more than 90%. The exploratory outcomes demonstrate that the proposed calculation is strong and has great identifying capacity and application prospects.

An algorithm is proposed in [60] to identify hazardous situations in the living space to ensure the safety of senior citizens. The researchers utilized a depth camera to generate a binary image and applied a Canny filter to outline it. Subsequently, falls were detected based on the outlined image output. By analyzing the white pixels in the outline image and categorizing them into 15° segments based on their tangent vector angles, falls were identified when the majority of angles were below 45°. The dataset comprises more than 700 images, and the experimental results confirm the effectiveness of the proposed algorithm in fall detection. The system evaluated the precision, sensitivity, and specificity at 97.1%, 94.9%, and 100%, respectively. Utilizing an RGB-D camera enables the system to operate flawlessly even under low-light conditions. Moreover, the system functions effectively in scenarios with multiple individuals.

Tran et al. [61] have introduced a new fall detection system utilizing the Kinect sensor. The system's innovations are twofold. Initially, recognizing that using all joints to represent human posture lacks relevance and robustness due to the Kinect's inability to accurately track all joints in various human postures, the authors define and calculate three features (distance, angle, velocity) based on only key joints. Secondly, to differentiate falls from activities like lying down, the Support Vector Machine technique is proposed. To evaluate the reliability of the suggested features and joints for fall detection, extensive experiments were conducted on 108 videos encompassing 9 activities (4 falls, 2 fall-like scenarios, and 3 daily activities). The results of the experiments demonstrate the system's accurate and robust fall detection capabilities.

4.3. Fall detection using infrared sensors

An infrared sensor is an electronic device designed to detect infrared light emitted by objects within its range. While IR sensors can identify motion, they do not offer specific details about the moving object [10]. Given that humans emit infrared radiation, IR sensors are commonly employed for monitoring human movements [62]. Infrared systems are typically primarily designed for surveillance applications [63]. Data generated by IR sensors is often used to generate 3D representations or blocks depicting environmental infrared radiation. Following feature extraction, different ML or statistical models are applied to identify falls and ADLs [64].

Yan Jiang et al. [66] introduced a novel lightweight human fall detection method based on a DL network. Initially, they devised an image acquisition tool using an infrared array sensor to compile an infrared human fall dataset comprising 10 240 images. This dataset encompasses 5216 fall images, 4024 non-fall walking cases, and 1000

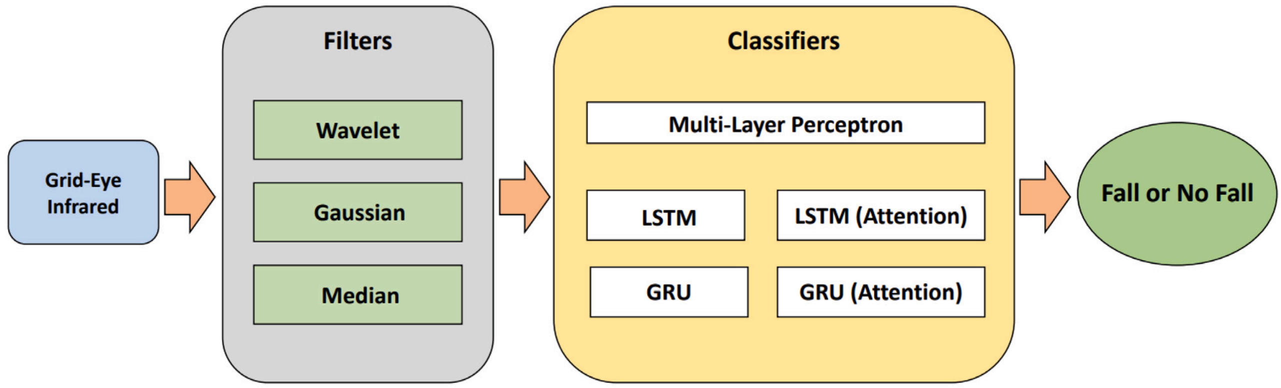

Fig. 6. Proposed fall detection classification workflow in (re-imaged from [65]).

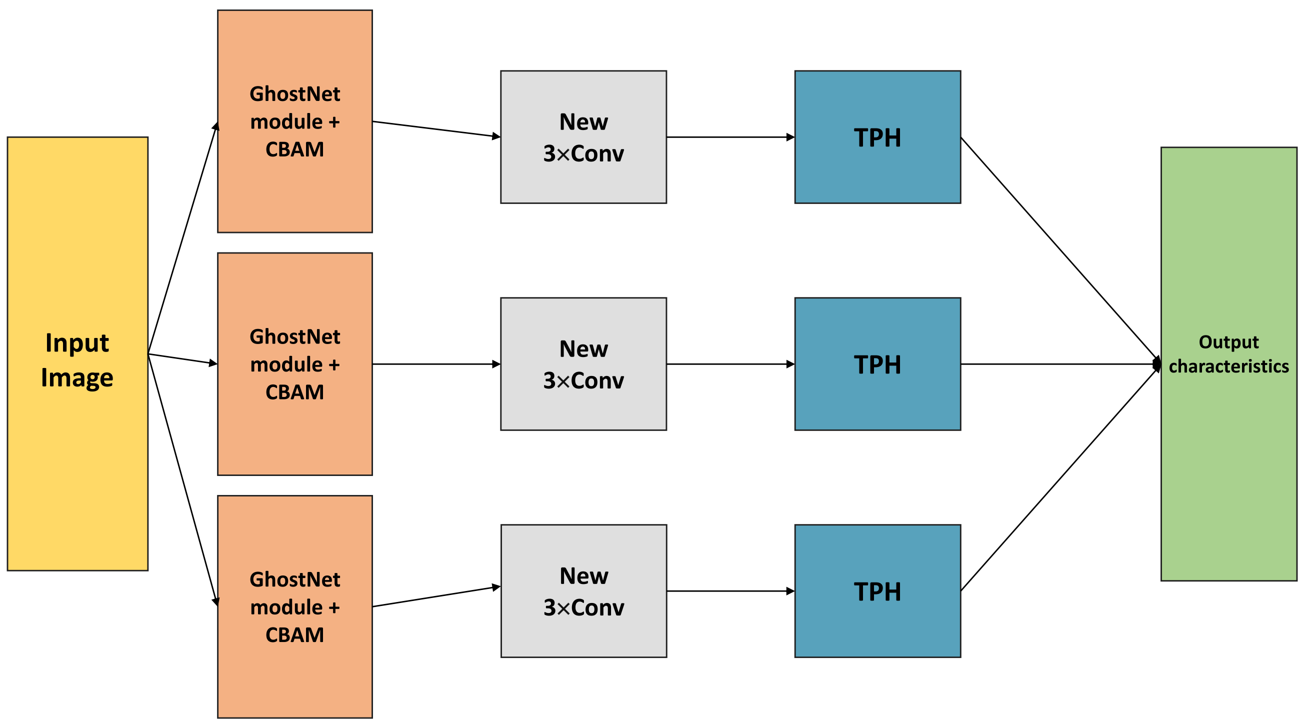

Fig. 7. Single-stage YOLOv5 network based on GhostNet and attention mechanism improvement (re-imaged from [66]) (GhostNet [67], Convolutional Block Attention Module (CBAM) [68], and Transformer Prediction Head (TPH) [69]).

instances of other poses. Additionally, they include a supplementary set of 10 videos for testing purposes, captured in diverse living environments with varying ambient temperatures. To tackle challenges linked with infrared images like noise and low definition, they employ the RetinexNet algorithm for image preprocessing, significantly enhancing image quality for more precise analysis and detection. Next, they enhance a modified YOLOv5 network by integrating the Convolutional Block Attention Module and Transformer Prediction Head modules to capture and extract relevant features for fall detection, as shown in Fig. 7. Utilizing the GhostNet architecture further optimizes the network's performance, and deploying the model on the Huawei Altas embedded platform yields a real-time detection frame rate of 38.61 FPS, surpassing the original YOLOv5-based fall detector's performance at 34.78 FPS. Their method exhibits exceptional fall detection accuracy, with an average accuracy of 96.52%, outperforming the original YOLOv5 fall detector at 88.46%. These results highlight the effectiveness of their approach, showcasing enhanced fall detection accuracy and real-time performance compared to the original YOLOv5 algorithm.

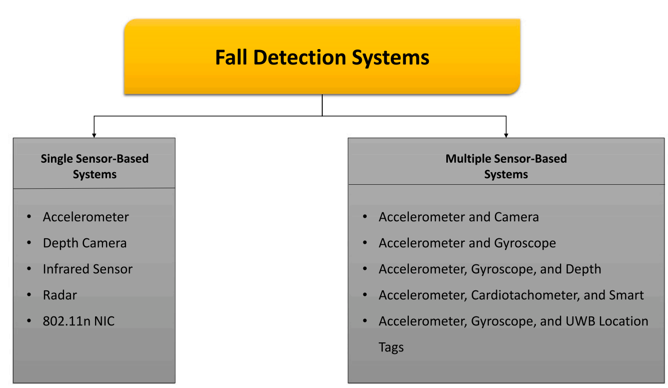

Fig. 8. Taxonomy of the reviewed fall detection systems (re-imaged from [10]).

Existing approaches to fall detection rely on camera-based systems and accelerometers to monitor body movements and positions.

Nevertheless, these techniques are plagued by elevated false-positive occurrences and privacy concerns. Liu et al. [70] in their study, address these shortcomings by fusing infrared sensors and accelerometers with sophisticated machine-learning algorithms for fall detection. Their investigation demonstrates that by amalgamating data from multiple sensors, a convolutional neural network (CNN) can effectively identify falls with heightened precision and recall rates. The aggregated findings showcased a model that integrated data from both sensors. Initially, the image data underwent simplification into black and white. Subsequently, the accelerometer data was incorporated into the model and trained alongside the modified infrared data using convolutional neural networks. This approach yielded promising results, achieving an accuracy rate of approximately 92%. Integrating the accelerometer data with the infrared data proved instrumental in sustaining overall accuracy by capturing the person's motion data throughout the fall during training. Rather than solely relying on static images of fallen individuals, the model now included information on the person's acceleration during the fall. The infrared sensor data complemented the accelerometer in accurately detecting falls, evident from the impressive 93% recall rate. Moreover, post-fall thermal readings of individuals on the ground significantly contributed to the model's ability to identify actual falls. In summary, the fusion of these two datasets significantly enhanced the model's recall rate while preserving its original accuracy, thereby reducing instances of missed falls—a critical aspect in real-world scenarios. This study aims to steer forthcoming progress in the domain, aiding researchers, engineers, and healthcare practitioners in crafting innovative solutions to enhance the well-being of the elderly and alleviate healthcare burdens.

To get a highly precise and low-cost fall detection system for elders, a fall detection system based on an infrared array sensor and multidimensional feature fusion is proposed in [71]. First, they propose a new data collection method using an infrared array sensor, that effectively enlarges the detection area. Then personnel positioning is done before fall detection, which can ensure real-time detection while reducing computational complexity. Additionally, a sliding window algorithm is developed and four key features of a fall are extracted from the collected data, which is suitable for the online detection. Among them, the four characteristics include the change in the center of mass of the falling process, the change in the speed, the change in the area of the person, and the change in variance. Finally, based on the refined features, the SVM classifier is introduced to identify falls and improve classification accuracy. The experimental results validate that the proposed fall detection system shows good fall detection accuracy and great practicality.

In this study [65], the researchers present a fall detection system using infrared array sensors along with several DL techniques, including LSTM [72] and gated recurrent unit models. For data processing, they have adopted a two-step approach: (1) pre-processing data filtering and (2) ML classification using neural networks. For filtering, they have tested Wavelet, Gaussian, and Median filters. For classification, they have tested several deep learning models, including MLPs, LSTM, and gated recurrent unit GRU [73], as shown in Fig. 6. To assess their approaches, they have created a dataset containing over 300 falls in multiple configurations. Assessed using fall data collected in two different sets of configurations, they demonstrate that their approach provides notable improvement over prior works utilizing the same infrared array sensor.

Chen et al. [74] present a low-resolution privacy-preserving infrared array sensor applied for elderly tracking and fall detection. The sensor comprises a 16×4 thermopile array with a corresponding $60° \times 16.4°$ field of view. Each pixel or thermopile element within the infrared sensor contains a temperature value. Two infrared sensors were affixed to the wall in separate locations as part of their system to capture three-dimensional image information. The human form foreground was discerned by subtracting the image from the background model using temperature difference characteristics. Using the foreground temperature, the angle of arrival (AOA) from each sensor was derived. Location was estimated through an AOA-based positioning algorithm. The estimated position underwent regression modeling to reduce positioning error. Consequently, the mean error of their tracking algorithm registered 13.39 cm. In contrast, the fall detection algorithm was actualized by extracting features from falling actions. Two sensors simultaneously recorded the action. The sensor with the larger foreground region served feature extraction. The extracted features applied to a KNN classification model for fall detection. In the experiment, 80 fall actions and 80 normal actions were gathered. Ultimately, 95.25% sensitivity, 90.75% specificity, and 93% accuracy were achieved.

The study [75] presents the methodology for data acquisition, preprocessing, and feature extraction, with a focus on statistical properties as generalizations. Three classification scenarios were examined — neural network, nn enhanced by feature selection, and DL system. The discriminative statistical classifiers' (multilayer perceptron) effectiveness within the DL system was improved by adding a feature selection block using Gram–Schmidt orthogonalization, which determines the feature rankings, and an NPCA block, which transforms the raw data onto a non-linear manifold and reduces the data dimensionality. The system achieved 94% sensitivity and 96% precision, indicating its potential for real-world applications.

4.4. Fall detection using radars

Radar systems function by tracking objects using radio waves to ascertain their position, dimensions, and velocity. A typical radar comprises a transmitter capable of generating electromagnetic radiation within the radio and microwave spectra, a receiving antenna, a receiver, a transmitting antenna, and a processor to discern the attributes of detected entities [10]. The transmitter emits radio waves [76] which reflect off objects. An object's location and speed can be derived from analyzing the reflected waves. Doppler radar has seen widespread application in fall detection setups. Doppler radar represents a specialized form that exploits the Doppler effect [77,78]. It emits microwave signals and evaluates how targets alter the frequency of returning signals [79,80]. A variety of signal processing methods are generally employed to identify falls based on radar data [81,82].

Modern monostatic radar-based HAR systems excel when human activities are directed towards or away from the radar. However, these systems face limitations in detecting motion perpendicular to the radar's boresight axis, hindering their ability to classify multidirectional human activities. As described in [83], the authors address this critical physical layer challenge in contemporary HAR systems by proposing a distributed MIMO radar configuration. This setup involves multiple antennas of a millimeter wave (mm-wave) MIMO radar system (Ancortek SDR-KIT 2400T2R4) deployed in an indoor environment. The proposed HAR system includes two independent and identical monostatic radar subsystems that capture multidirectional human movement from two perspectives, enabling the computation of two distinct time-variant (TV) radial velocity distributions. A feature extraction network processes these distributions to extract relevant features, which are then used by a multiclass classifier to identify five types of human activities. The multiperspective MIMO-radar-based HAR system achieves an impressive classification accuracy of 98.52%, outperforming the SISO (single-input–single-output) radar-based HAR system by over 9%. This innovative approach overcomes the physical layer limitations of modern HAR systems based on monostatic SISO or MIMO radar configurations.

Current low-cost fall detection systems based on Doppler radar face difficulties due to false alarms and the absence of post-fall health monitoring, which significantly affects their accuracy and overall suitability for fall detection. Tewari et al. [84] present a cost-effective and robust solution for a fall detection system with post-fall health monitoring capability using a 3.18 GHz continuous-wave Doppler radar sensor. Data collection for the experiment was conducted in-house under the supervision of a healthcare professional and included various activities such as standing, sitting, sleeping, running, walking, falling, sit-to-stand transitions, and stand-to-sit transitions. The authors propose an algorithm with four hierarchical stages, each with specific goals. Given the complexity, the model is trained differently for each stage to maximize classification accuracy. The system architecture is designed to minimize computational costs and power consumption through modular implementation in stages, utilizing low-power equipment and incorporating traditional ML algorithms. Experimental results demonstrate a fall detection accuracy of 93.24% and a breath rate measurement error of 2.26%, which is comparable to recent state-of-the-art approaches. The findings demonstrate the effectiveness of the proposed system in addressing the challenges of false alarms and post-fall health monitoring while maintaining cost-effectiveness and accuracy in fall detection.effectiveness and accuracy in fall detection.

Kittiyanpunya et al. [85] present a novel fall detection system that uses radar data and DL. The system is designed with the goal of accurately identifying when elderly individuals have fallen in real-time. To develop and test the approach, researchers conducted a study involving 10 participants performing various activities like standing, walking, sitting, sleeping and simulated falls in 5 different indoor environments. A millimeter-wave FMCW radar was used to continuously monitor the participants and collect radar scattering signals. These signals were processed into 1D point cloud representations describing the spatial dimensions of subjects over time. Doppler velocity data reflecting subjects' motion was also derived. The point clouds focused specifically on the up–down or z-axis were selected, along with the Doppler velocities. This served as the input data fed into a LSTM neural network, a type of DL model well-suited for sequence classification. Preprocessing like filtering and sliding windows was applied to clean the radar data before training and validating the LSTM. Various window sizes were evaluated to determine the best for fall detection performance. The results demonstrated the proposed approach using z-axis point clouds and velocities as LSTM inputs could detect falls in real-time with over 99.5% accuracy. No false alarms were reported. By leveraging radar sensing and DL, the system shows promise for accurately and automatically identifying falls without cameras for non-invasive senior monitoring.

Radar technology shows great promise for monitoring the health and safety of elderly individuals living at home independently. When humans move their bodies, the radar signals returned from their motions are non-stationary in nature, meaning they vary over time and frequency. Because of this, time-frequency (TF) analysis is crucial for identifying the constant and changing velocity components of different body parts as they move. This information about how different body parts are moving is important for distinguishing between different types of motions. In this research [86], the authors propose using radar for fall detection through a time-frequency based DL approach. Deep learning allows complex patterns in large datasets to be identified without needing human programmers to manually select which features to analyze. The proposed method learns the intricate patterns present in the time-frequency signatures of radar signals without any human intervention. It then feeds the underlying learned features into a classifier to determine if a fall has occurred. To test the effectiveness of the proposed DL fall detection method, the researchers used experimental radar data. They compared the performance of their approach against other techniques, such as principal component analysis methods which reduce high-dimensional data and methods requiring humans to manually select a few dominant features of the signals to analyze. When evaluating the ability to correctly detect fall events in the data, the proposed DL system achieved an 87% success rate. This demonstrates the potential of this radar and DL combination for accurate in-home fall detection monitoring of elderly individuals.

The research proposed in [78] utilizes Wavelet Transform (WT) assisted by a ceiling mounted Doppler radar system for detecting human falls. The radar is capable of sensing all movements, including those caused by falls or regular non-fall activities, through the Doppler effect. Reliable fall detection methodology has been developed by the researchers employing radar measurements aided by WT. WT facilitates analyzing the time-frequency characteristics of motions, which are unique for falls in comparison to other activities. The detection approach consists of two stages. The initial stage acts as a pre-filter utilizing WT coefficients at a designated scale to pinpoint possible falls. The secondary stage forms feature vectors by leveraging WT coefficients across multiple consecutive frames and various time scales for the classification of falls versus normal activities. Specific wavelet functions like "rbio3.3", "db3", "sym3", "rbio1.3", and "bior2.2" delivered higher accuracy for pre-screening, while "rbio3.3", "coif4", "db10", "bior2.6", and "db11" performed better for classification. Assessments relying on data collected in laboratories, bathrooms, and senior living facilities validated the promising and robust performance of the proposed WT-driven fall detection methodology. With the WT pre-filter and classifier, the system achieved 93% accuracy, 97.1% sensitivity, and 92.2% specificity in identifying falls.

4.5. Fall detection using 802.11n NIC

The wireless environment comprises electromagnetic signals within the radio or microwave frequency ranges, carrying binary data [87]. Changes in the wireless channel caused by human interactions can be leveraged by ML or statistical models to detect falls [10,88].

Keenan et al. [89] describe the development and deployment of an affordable, precise, and non-intrusive wireless fall detection system using readily available 802.11n WLAN network interface cards (NICs). The system leverages the channel state information (CSI) of the wireless link between a sender and a receiver. Notably, the system goes beyond utilizing just the CSI amplitude by also analyzing the phase difference across two receiving antennas to identify distinct patterns associated with a person falling. Through extensive experiments, they demonstrate that the CSI phase difference offers a more detailed measure at 5 GHz compared to the amplitude. The proposed fall detection method comprises two stages. Initially, they swiftly differentiate between fall-like actions and actual falls to reduce computational demands. Subsequently, they devise a classification algorithm with novel features to identify three types of falls: walking-falls, standing-falls, and sitting-falls. The concept of a sitting-fall, where a person falls while transitioning from sitting to standing or vice versa, is introduced as a more subtle scenario compared to walking-falls or standing-falls. New features for signal classification, such as the rate of change of the standard deviation of the CSI phase difference, are introduced. Rigorous experiments are conducted to assess the performance of the proposed fall detection system, revealing a balanced accuracy of 96% compared to 91% for the leading state-of-the-art solution [90].

Both wearable and non-wearable fall detection systems have been developed in the past. However, fall detection systems utilizing WiFi CSI have gained significant attention from researchers due to their non-intrusive and cost-effective nature. While there are ML based fall detection systems using WiFi CSI already in existence, those trained on extensive datasets tend to achieve lower accuracy compared to systems trained on more limited datasets. To address these challenges, a new DL-based fall detection approach is proposed [91]. Initially, various WiFi CSI collection tools are implemented and assessed for their potential in fall detection. A comprehensive dataset comprising over 700 CSI samples, encompassing various types of falls and daily activities conducted in four different indoor settings both on and off the primary paths, is curated to create a highly accurate fall detection method. Using this dataset, a deep learning-based classifier is developed employing an image classification algorithm. Unlike other fall detection systems, the proposed technique requires only down sampling and reshaping during pre-processing. The performance of the proposed fall detection system is evaluated using the constructed dataset, surpassing the accuracy of two other existing systems. It achieves a precision of over 96% for CSI collected in all four environments and 99% for CSI collected in specific combinations of the environments.

Human activity recognition is a broad field of research. While some existing solutions rely on sensors and CV, they have significant limitations. To address these limitations, device-free solutions using radio signals like home WiFi, specifically 802.11, are being explored. Recently, CSI available in 802.11n WiFi networks has been proposed for detailed analysis [92]. CSI can detect basic human activities such as walking, sitting, standing, and running in both line-of-sight and non-line-of-sight indoor environments. Two algorithms were developed — one using SVM for classification and another using LSTM recurrent neural networks. The SVM approach applies sophisticated preprocessing and feature extraction with wavelet analysis, while the LSTM directly processes the raw data after cleaning noise. Both algorithms were tested to determine if they could accurately identify human activities and presence using CSI data collected indoors in both line-of-sight and non-line-of-sight scenarios. They demonstrate the ability to accurately identify activities and human presence and compare the two methods in terms of precision and efficiency. Additionally, they expand the experimental setup to include the detection of human falls, a significant application in ambient assisted living (AAL). The results indicate that the developed algorithms can effectively detect falls. Moreover, they illustrate that the algorithms can also estimate the headcount in a room using CSI data, marking an initial step toward recognizing intricate social behaviors and activities [92].

Wang et al. [88] examine how human activities influence the propagation model of wireless signals. They introduce a new, non-intrusive detection technique named WiFall, which relies on advanced wireless technologies. WiFall utilizes the temporal variability and spatial diversity of CSI as indicators of human activities. Since CSI is readily available in commonly used wireless infrastructures, WiFall eliminates the need for hardware modifications, specific environmental setups, or wearable devices. The researchers implement WiFall on laptops equipped with standard 802.11n network interface cards. They test WiFall in different indoor scenarios and layout configurations. Experimental results show that WiFall achieved 87% detection precision with an average false alarm rate of 18%.

4.6. Multiple sensor-based fall detection systems

Researchers in the fields of wearable sensors and CV are actively exploring ways to monitor and identify falls and everyday activities through automated recognition of human actions. In the realm of human–machine interaction, various combinations of sensors and communication tech are commonly employed to capture human behavior. Numerous scholars have explored AI methods to spot actions, comprehend scenarios, and create more efficient systems for recognizing human actions. However, detecting outdoor activities using a mix of human actions requires effective strategies, though extracting features can be quite a complex task in developing systems for recognizing human activity. Hafeez et al. [93] suggest a solution for detecting human activities using hybrid descriptors based on robust features to yield accurate results. Their work addresses challenges such as identifying complex backgrounds with multiple humans in video frames. Initially, inertial signals and video frames are preprocessed using noise reduction techniques. Next, the frames are used to eliminate the background by identifying human movements and extracting silhouettes. These silhouettes are then used to extract key points of the human body, creating a skeleton. Subsequently, features in both time and frequency domains are extracted from inertial signals, while geometric features are extracted from skeleton body points. Finally, multiple sets of features are combined and input into a zero-order optimization model, followed by logistic regression to recognize each action. The proposed system's effectiveness was evaluated on three benchmark datasets: the UP Fall dataset, the University of Rzeszow Fall dataset, and the SisFall dataset. The results demonstrated its significance, achieving accuracies of 91.51%, 92.98%, and 90.23%, respectively, on these datasets.

Wu et al. [94] seek to develop an automated system for detecting falls using multiple wearable sensors and determining the best locations for sensor placement. Six sensors are positioned on various body parts to collect real-time movement data. The autoregressive integrated moving average model is used to eliminate autocorrelation from the initial data. Subsequently, the multidimensional data undergo principal component analysis for processing. A new threshold technique based on a multivariate control chart is introduced for fall detection. This method offers high accuracy and can be tailored to individuals by establishing the detection threshold using their personal historical data. Volunteers engaged in various activities and staged falls for testing. Compared to most single-sensor systems, the proposed multi-sensor setup demonstrated superior sensitivity (94.8%) and specificity (95.2%), particularly at a low sampling rate of 20 Hz. Evaluation of different sensor placement locations revealed that three sensors placed on the waist, arm, and thigh effectively distinguished falls from other movements.

Boutellaa et al. [95] introduced a novel fall detection system utilizing various signals captured by multiple wearable sensors. The system leverages the covariance of the raw signals and a nearest neighbor classifier. In addition to feature extraction, the covariance matrix is employed as a simple method to combine signals from multiple sensors, improving classification performance. Testing on two publicly accessible fall datasets, CogentLabs and DLR, shows that the proposed method is effective both with a single sensor and when integrating data from multiple sensors. Geodesic metrics are shown to offer superior fall detection accuracy compared to the Euclidean metric. The highest classification accuracies achieved are 92.51% and 98.31% for the CogentLabs and DLR datasets, respectively.

As reported in [96], a novel fall detection system is presented that utilizes wearable devices like smartphones and tablets equipped with cameras and accelerometers. By having the portable device worn by the individual, monitoring is not confined to specific areas but can track the person's movements wherever they go, unlike fixed sensors placed in certain rooms. The inclusion of a camera provides a wealth of data, and the findings demonstrate that combining camera and accelerometer data not only improves the detection rate but also reduces false alarms compared to systems relying solely on accelerometers or cameras. The camera-based aspect of fall detection involves the use of histograms of edge orientations in conjunction with gradient local binary patterns. The performance of this method is compared with using original histograms of oriented gradients (HOG) [97] and a modified version of HOG. Experimental results show that the proposed method outperforms the use of original HOG and modified HOG, resulting in lower false positive rates for camera-based detection. Furthermore, an accelerometer-based fall detection method is employed, and the fusion of these two sensor modalities creates a robust fall detection system. Experiments and trials conducted with actual Samsung Galaxy R phones demonstrate that the combined approach utilizing both sensor modalities offers significantly higher sensitivity and a notable decrease in false positives during daily activities compared to using only accelerometers or cameras. The system demonstrated a sensitivity of 96.36% and a specificity of 92.45% in detecting falls from a standing position, and a sensitivity of 90.91% and a specificity of 66.04% in detecting falls from a sitting position.

To mitigate the risk of elderly individuals falling in areas where video surveillance is not feasible due to privacy concerns, a monitoring system that respects their privacy is essential. The work described in [98] introduces a system for detecting elderly falls using ultrasonic sensors. These sensors, which utilize ultrasonic technology, consist of paired receivers and transmitters connected to an Arduino microcontroller. They transmit signals related to falls by elderly individuals via WiFi to a central processing unit. The sensors are strategically positioned in an array on the room's roof and walls. The system analyzes these signals to identify the presence of a person based on distance sensing and to distinguish between actions such as standing, sitting, and falling by comparing patterns with predefined templates of top and side signals. In experimental trials, the proposed system achieved an approximate 93% accuracy rate in detecting falls.

Su et al. [99] present a system that uses multiple sensors to combine data from the waist and thigh regions. The gathered data is transmitted wirelessly to a computer or mobile device using Bluetooth technology. They have developed a pre-impact fall detection model based on discrimination analysis. Human activities are categorized into three groups (non-fall, backward fall, and forward fall) using a hierarchical classifier. To enhance the accuracy of classification, optimal discriminant features are chosen for each layer of the classifier. The outcomes of feature selection demonstrate that angular velocity and angle data from the waist and thigh play a crucial role in activity classification. Their approach effectively distinguishes falls from non-falls (with a sensitivity of 98.1% and specificity of 98.8%) by integrating information from the waist and thigh regions.

Majumder et al. [100] introduce a system for predicting falls by combining sensor data from smartphones with a smartshoe. In a prior study, the researchers developed a pair of smart shoes equipped with four pressure sensors and a Wi-Fi module in each shoe to discreetly gather data in various settings. By merging the sensor data from the smartshoe and smartphone, they conducted a series of comprehensive experiments in a laboratory setting to assess both typical and irregular walking patterns. The system on the smartphone is capable of issuing an alert to notify the user of potentially risky walking patterns, thereby helping prevent potential falls. Through validation using a decision tree with 10-fold cross-validation, they achieved a 97.2% accuracy rate in detecting abnormal gait patterns.

Despite recent advances in fall detection, there are hurdles that remain for maximizing the efficiency and adoption of fall detection systems. One major limitation is associated with single-camera and multi-camera approaches. Single-camera systems might struggle with occlusion and a limited field of view while multi-camera systems might suffer from complexities such as synchronization errors and increased computational demands. Relatively new research has even proposed the use of 360-degree cameras [101–103], which allow for a more comprehensive view of the environment and might be able to handle some occlusion restrictions, although they will still face challenges in terms of processing power and real-time analysis. In addition, complete implementation of a fall detection system is another hurdle, with additional obstacles like low-latency requirements for timely alerts, combinations of sensors and other factors that might help enable full implementation of a fall detection system in real-time. Finally, one of the more important hurdles for video-based systems, is the concern of privacy implications of continuous monitoring [104], as this might create aversion among users given the surveillance context. Addressing these challenges is crucial for fall detection technology to be accepted in real-world situations.

5. Future work

As the field of fall detection systems continues to advance, several areas warrant further investigation and research. The following section outlines potential future research directions and open problems that could be addressed in order to significantly improve the effectiveness and applicability of fall detection technology.

5.1. Advancements in sensor technology

While traditional technologies like accelerometers and cameras are effective, they can have limitations in terms of accuracy and reliability. Future research should focus on developing advanced sensor technologies that can improve detection capabilities, reduce false positives, and enhance the overall robustness of fall detection systems. This includes exploring novel sensor modalities, such as radar and infrared technologies, which may offer advantages in specific environments.

5.2. Improvement of machine learning algorithms

Although ML has made significant strides in fall detection, there is still a need for more sophisticated algorithms that can accurately classify falls and distinguish them from other activities. Future work should consider incorporating DL techniques, ensemble methods, and transfer learning to improve classification performance. Additionally, semi-or unsupervised learning could be beneficial in overcoming the problem of a limited number of labeled training data.

5.3. Real-world testing and validation

The effectiveness of fall detection systems must be validated through extensive real-world testing. Future research should focus on deploying these systems in diverse environments and among various populations, including different age groups and individuals with varying health conditions. This will provide valuable insights into the systems' performance and adaptability in real-life scenarios.

5.4. User acceptance and privacy concerns

User acceptance of fall detection technologies, especially among the elderly, is crucial for their practical success. Future work shuould investigate the social and ethical implications of continuous monitoring, taking into account privacy concerns and user acceptance. The goal of research in this field is is to develop technologies that protect user privacy while providing effective monitoring and intervention.

5.5. Interdisciplinary approaches

Interdisciplinary approaches are essential when considering the limitations of fall detection systems. Researchers from healthcare, computer science, engineering, and social domains should collaborate to develop solutions that address the evolving nature of fall detection systems and user preferences.

5.6. Long-term monitoring and health outcomes

Investigating the long-term health outcomes of fall detection technologies for the elderly and disabled populations is a key factor. Future research could focus on how these systems can improve quality of life, promotion of independence, and decreasing healthcare costs. Longitudinal studies may provide valuable insights into the effectiveness of fall detection technologies in preventing falls and associated injuries over time.

6. Conclusions

In this survey, we present a comprehensive overview of the current state of fall detection systems, focusing on the integration of multiple sensors and advanced machine learning techniques. We discuss a wide range of techniques for fall detection, including sensor fusion, deep learning, and machine learning. We examine the use of wearable devices, smartphones, and cameras, emphasizing the importance of accurate human activity recognition for effective fall detection. In addition, we provide a detailed analysis of different fall detection methods and their performance, as measured by metrics such as accuracy, sensitivity, specificity, and F1 score. This study considers the use of bidirectional LSTM networks, recurrent neural networks, the MCCF strategy, cloud computing, fog computing, and wearable sensors for fall detection. We also evaluate the performance of different fall detection systems using these metrics. Furthermore, we point out the obstacles and limitations associated with fall detection systems, including the challenges of acquiring authentic falling data for testing purposes and the need for further advancements in future studies. In summary, the research reviewed in this work contributes significantly to the advancement of sophisticated fall detection systems using deep learning, sensor fusion, and machine learning. The results highlight the potential of these systems to improve the well-being of the elderly, reduce healthcare burdens, and offer reliable solutions for fall detection. Continued exploration and innovation are crucial in this field to enhance the precision and efficiency of fall detection systems.

CRediT authorship contribution statement

Ehsan Rassekh: Writing – review & editing, Writing – original draft, Conceptualization. **Lauro Snidaro:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] N. Noury, A. Fleury, P. Rumeau, A.K. Bourke, G. Laighin, V. Rialle, J.-E. Lundy, Fall detection-principles and methods, in: 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2007, pp. 1663–1666.

[2] S.K. Inouye, C.J. Brown, M.E. Tinetti, et al., Medicare nonpayment, hospital falls, and unintended consequences, N. Engl. J. Med. 360 (23) (2009) 2390.

[3] C.H. Orces, H. Alamgir, Trends in fall-related injuries among older adults treated in emergency departments in the USA, Inj. Prev. (2014).

[4] C.S. Florence, G. Bergen, A. Atherly, E. Burns, J. Stevens, C. Drake, Medical costs of fatal and nonfatal falls in older adults, J. Am. Geriatr. Soc. 66 (4) (2018) 693–698.

[5] M. Mubashir, L. Shao, L. Seed, A survey on fall detection: Principles and approaches, Neurocomputing 100 (2013) 144–152.

[6] R. Igual, C. Medrano, I. Plaza, Challenges, issues and trends in fall detection systems, Biomed. Eng. Online 12 (1) (2013) 66.

[7] G. Vavoulas, M. Pediaditis, E.G. Spanakis, M. Tsiknakis, The MobiFall dataset: An initial evaluation of fall detection algorithms using smartphones, in: 13th IEEE International Conference on BioInformatics and BioEngineering, IEEE, 2013, pp. 1–4.

[8] H. Liu, T. Xue, T. Schultz, On a real real-time wearable human activity recognition system, in: Proceedings of the 16th International Joint Conference on Biomedical Engineering Systems and Technologies, Lisbon, Portugal, 2023, pp. 16–18.

[9] R.W. Broadley, J. Klenk, S.B. Thies, L.P. Kenney, M.H. Granat, Methods for the real-world evaluation of fall detection technology: A scoping review, Sensors 18 (7) (2018) 2060.

[10] S. Nooruddin, M.M. Islam, F.A. Sharna, H. Alhetari, M.N. Kabir, Sensor-based fall detection systems: a review, J. Ambient Intell. Humaniz. Comput. 13 (5) (2022) 2735–2751.

[11] T. Kaburagi, K. Shiba, S. Kumagai, T. Matsumoto, Y. Kurihara, Real-time fall detection using microwave Doppler sensor—Computational cost reduction method based on genetic algorithm, IEEE Sens. Lett. 3 (3) (2019) 1–4.

[12] F. Bagala, C. Becker, A. Cappello, L. Chiari, K. Aminian, J.M. Hausdorff, W. Zijlstra, J. Klenk, Evaluation of accelerometer-based fall detection algorithms on real-world falls, PLoS One 7 (5) (2012) e37062.

[13] F. Bloch, V. Gautier, N. Noury, J.-E. Lundy, J. Poujaud, Y.-E. Claessens, A.-S. Rigaud, Evaluation under real-life conditions of a stand-alone fall detector for the elderly subjects, Ann. Phys. Rehabil. Med. 54 (6) (2011) 391–398.

[14] S. Chaudhuri, D. Oudejans, H.J. Thompson, G. Demiris, Real world accuracy and use of a wearable fall detection device by older adults, J. Am. Geriatr. Soc. 63 (11) (2015) 2415.

[15] J. Howcroft, J. Kofman, E.D. Lemaire, Prospective fall-risk prediction models for older adults based on wearable sensors, IEEE Trans. Neural Syst. Rehabil. Eng. 25 (10) (2017) 1812–1820.

[16] J.Y. Lee, Y. Jin, J. Piao, S.-M. Lee, Development and evaluation of an automated fall risk assessment system, Int. J. Qual. Health Care 28 (2) (2016) 175–182.

[17] K. Shiba, T. Kaburagi, Y. Kurihara, Fall detection utilizing frequency distribution trajectory by microwave Doppler sensor, IEEE Sens. J. 17 (22) (2017) 7561–7568.

[18] F. Alfayez, S.B. Khan, IoT-blockchain empowered Trinet: optimized fall detection system for elderly safety, Front. Bioeng. Biotechnol. 11 (2023).

[19] C.-Y. Hsieh, K.-C. Liu, C.-N. Huang, W.-C. Chu, C.-T. Chan, Novel hierarchical fall detection algorithm using a multiphase fall model, Sensors 17 (2) (2017) 307.

[20] B. Andò, S. Baglio, C.O. Lombardo, V. Marletta, A multisensor data-fusion approach for ADL and fall classification, IEEE Trans. Instrum. Meas. 65 (9) (2016) 1960–1967.

[21] H. Gjoreski, S. Stankoski, I. Kiprijanovska, A. Nikolovska, N. Mladenovska, M. Trajanoska, B. Velichkovska, M. Gjoreski, M. Luštrek, M. Gams, Wearable sensors data-fusion and machine-learning method for fall detection and activity recognition, in: Challenges and Trends in Multimodal Fall Detection for Healthcare, Springer, 2020, pp. 81–96.

[22] H. Li, A. Shrestha, F. Fioranelli, J. Le Kernec, H. Heidari, M. Pepa, E. Cippitelli, E. Gambi, S. Spinsante, Multisensor data fusion for human activities classification and fall detection, in: 2017 IEEE Sensors, IEEE, 2017, pp. 1–3.

[23] S. Ezatzadeh, M.R. Keyvanpour, S.V. Shojaedini, A human fall detection framework based on multi-camera fusion, J. Exp. Theor. Artif. Intell. 34 (6) (2022) 905–924.

[24] H. Li, J. Le Kernec, A. Mehul, S.Z. Gurbuz, F. Fioranelli, Distributed radar information fusion for gait recognition and fall detection, in: 2020 IEEE Radar Conference, RadarConf20, IEEE, 2020, pp. 1–6.

[25] E. Auvinet, F. Multon, A. Saint-Arnaud, J. Rousseau, J. Meunier, Fall detection with multiple cameras: An occlusion-resistant method based on 3-d silhouette vertical distribution, IEEE Trans. Inf. Technol. Biomed. 15 (2) (2010) 290–300.

[26] Z. Chen, Y. Wang, Infrared–ultrasonic sensor fusion for support vector machine–based fall detection, J. Intell. Mater. Syst. Struct. 29 (9) (2018) 2027–2039.

[27] T. Xu, H. Se, J. Liu, A fusion fall detection algorithm combining threshold-based method and convolutional neural network, Microprocess. Microsyst. 82 (2021) 103828.

[28] H. Li, A. Shrestha, H. Heidari, J. Le Kernec, F. Fioranelli, Bi-LSTM network for multimodal continuous human activity recognition and fall detection, IEEE Sens. J. 20 (3) (2019) 1191–1201.

[29] M. Nahiduzzaman, M. Tasnim, N.T. Newaz, M.S. Kaiser, M. Mahmud, Machine learning based early fall detection for elderly people with neurological disorder using multimodal data fusion, in: International Conference on Brain Informatics, Springer, 2020, pp. 204–214.

[30] X. Cai, X. Liu, M. An, G. Han, Vision-based fall detection using dense block with multi-channel convolutional fusion strategy, IEEE Access 9 (2021) 18318–18325.

[31] V. Divya, R. Leena Sri, Intelligent real-time multimodal fall detection in fog infrastructure using ensemble learning, in: Challenges and Trends in Multimodal Fall Detection for Healthcare, Springer, 2020, pp. 53–79.

[32] R. Espinosa, H. Ponce, S. Gutiérrez, L. Martínez-Villaseñor, J. Brieva, E. Moya-Albor, Application of convolutional neural networks for fall detection using multiple cameras, in: Challenges and Trends in Multimodal Fall Detection for Healthcare, Springer, 2020, pp. 97–120.

[33] T. Alanazi, G. Muhammad, Human fall detection using 3D multi-stream convolutional neural networks with fusion, Diagnostics 12 (12) (2022) 3060.

[34] S. Gasparrini, E. Cippitelli, E. Gambi, S. Spinsante, J. Wåhslén, I. Orhan, T. Lindh, Proposal and experimental evaluation of fall detection solution based on wearable and depth data fusion, in: ICT Innovations 2015: Emerging Technologies for Better Living 7, Springer, 2016, pp. 99–108.

[35] T. Alanazi, K. Babutain, G. Muhammad, A robust and automated vision-based human fall detection system using 3D multi-stream CNNs with an image fusion technique, Appl. Sci. 13 (12) (2023) 6916.

[36] I. Charfi, J. Miteran, J. Dubois, M. Atri, R. Tourki, Optimised spatio-temporal descriptors for real-time fall detection: comparison of SVM and Adaboost based classification, J. Electron. Imaging (JEI) 22 (4) (2013) 17.

[37] L. Chen, R. Li, H. Zhang, L. Tian, N. Chen, Intelligent fall detection method based on accelerometer data from a wrist-worn smart watch, Measurement 140 (2019) 215–226.

[38] A. Mehmood, A. Nadeem, M. Ashraf, T. Alghamdi, M.S. Siddiqui, A novel fall detection algorithm for elderly using SHIMMER wearable sensors, Health Technol. 9 (2019) 631–646.

[39] J.A. Urresty Sanchez, D.M. Muñoz, Fall detection using accelerometer on the user's wrist and artificial neural networks, in: XXVI Brazilian Congress on Biomedical Engineering: CBEB 2018, Armação de Buzios, RJ, Brazil, 21-25 October 2018 (Vol. 1), Springer, 2019, pp. 641–647.

[40] H. Yhdego, J. Li, S. Morrison, M. Audette, C. Paolini, M. Sarkar, H. Okhravi, Towards musculoskeletal simulation-aware fall injury mitigation: transfer learning with deep CNN for fall detection, in: 2019 Spring Simulation Conference, SpringSim, IEEE, 2019, pp. 1–12.

[41] D. Yacchirema, J.S. de Puga, C. Palau, M. Esteve, Fall detection system for elderly people using IoT and ensemble machine learning algorithm, Pers. Ubiquitous Comput. 23 (5) (2019) 801–817.

[42] K. Frank, M.J. Vera Nadales, P. Robertson, T. Pfeifer, Bayesian recognition of motion related activities with inertial sensors, in: Proceedings of the 12th ACM International Conference Adjunct Papers on Ubiquitous Computing-Adjunct, 2010, pp. 445–446.

[43] B. Kaluža, V. Mirchevska, E. Dovgan, M. Luštrek, M. Gams, An agent-based approach to care in independent living, in: Ambient Intelligence: First International Joint Conference, AmI 2010, Malaga, Spain, November 10-12, 2010. Proceedings 1, Springer, 2010, pp. 177–186.
[44] D.S. Ward, K.R. Evenson, A. Vaughn, A.B. Rodgers, R.P. Troiano, Accelerometer use in physical activity: best practices and research recommendations, Med. Sci. Sports Exerc. 37 (11 Suppl) (2005) S582–8.
[45] D. Rand, J.J. Eng, P.-F. Tang, J.-S. Jeng, C. Hung, How active are people with stroke? Use Accelerometers Assess Phys. Act. (2008).
[46] J.-S. Lee, H.-H. Tseng, Development of an enhanced threshold-based fall detection system using smartphones with built-in accelerometers, IEEE Sens. J. 19 (18) (2019) 8293–8302.
[47] G.L. Santos, P.T. Endo, K.H.d.C. Monteiro, E.d.S. Rocha, I. Silva, T. Lynn, Accelerometer-based human fall detection using convolutional neural networks, Sensors 19 (7) (2019) 1644.
[48] P. Van Thanh, D.-T. Tran, D.-C. Nguyen, N. Duc Anh, D. Nhu Dinh, S. El-Rabaie, K. Sandrasegaran, Development of a real-time, simple and high-accuracy fall detection system for elderly using 3-DOF accelerometers, Arab. J. Sci. Eng. 44 (2019) 3329–3342.
[49] S. Ranakoti, S. Arora, S. Chaudhary, S. Beetan, A.S. Sandhu, P. Khandnor, P. Saini, Human fall detection system over IMU sensors using triaxial accelerometer, in: Computational Intelligence: Theories, Applications and Future Directions-Volume I: ICCI-2017, Springer, 2019, pp. 495–507.
[50] H. Cao, S. Wu, Z. Zhou, C.-C. Lin, C.-Y. Yang, S.-T. Lee, C.-T. Wu, A fall detection method based on acceleration data and hidden Markov model, in: 2016 IEEE International Conference on Signal and Image Processing, ICSIP, IEEE, 2016, pp. 684–689.
[51] B. Aguiar, T. Rocha, J. Silva, I. Sousa, Accelerometer-based fall detection for smartphones, in: 2014 IEEE International Symposium on Medical Measurements and Applications, MeMeA, IEEE, 2014, pp. 1–6.
[52] D. Lim, C. Park, N.H. Kim, S.-H. Kim, Y.S. Yu, et al., Fall-detection algorithm using 3-axis acceleration: combination with simple threshold and hidden Markov model, J. Appl. Math. 2014 (2014).
[53] Y. Xu, J. Chen, Q. Yang, Q. Guo, Human posture recognition and fall detection using Kinect V2 camera, in: 2019 Chinese Control Conference, CCC, IEEE, 2019, pp. 8488–8493.
[54] X. Kong, Z. Meng, L. Meng, H. Tomiyama, Three-states-transition method for fall detection algorithm using depth image, J. Robot. Mechatron. 31 (1) (2019) 88–94.
[55] A. Elwaly, A. Abdellatif, Y. El-Shaer, New eldercare robot with path-planning and fall-detection capabilities, Appl. Sci. 14 (6) (2024) 2374.
[56] H. Liu, J. Luo, YES-SLAM: YOLOv7-enhanced-semantic visual SLAM for mobile robots in dynamic scenes, Meas. Sci. Technol. 35 (3) (2023) 035117.
[57] M.M. Massoud, A. Abdellatif, M.R. Atia, Different path planning techniques for an indoor omni-wheeled mobile robot: Experimental implementation, comparison and optimization, Appl. Sci. 12 (24) (2022) 12951.
[58] C.-Y. Wang, A. Bochkovskiy, H.-Y.M. Liao, YOLOv7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2023, pp. 7464–7475.
[59] Y. Ding, H. Li, C. Li, K. Xu, P. Guo, Fall detection based on depth images via wavelet moment, in: 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI, IEEE, 2017, pp. 1–5.
[60] X. Kong, L. Meng, H. Tomiyama, Fall detection for elderly persons using a depth camera, in: 2017 International Conference on Advanced Mechatronic Systems, ICAMechS, IEEE, 2017, pp. 269–273.
[61] T.-L. Le, J. Morel, et al., An analysis on human fall detection using skeleton from Microsoft Kinect, in: 2014 IEEE Fifth International Conference on Communications and Electronics, ICCE, IEEE, 2014, pp. 484–489.
[62] L. Martínez-Villaseñor, H. Ponce, J. Brieva, E. Moya-Albor, J. Núñez-Martínez, C. Peñafort-Asturiano, UP-fall detection dataset: A multimodal approach, Sensors 19 (9) (2019) 1988.
[63] S. Moulik, S. Majumdar, FallSense: An automatic fall detection and alarm generation system in IoT-enabled environment, IEEE Sens. J. 19 (19) (2018) 8452–8459.
[64] G. Mastorakis, D. Makris, Fall detection system using Kinect's infrared sensor, J. Real-Time Image Process. 9 (2014) 635–646.
[65] X. Fan, H. Zhang, C. Leung, Z. Shen, Robust unobtrusive fall detection using infrared array sensors, in: 2017 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems, MFI, IEEE, 2017, pp. 194–199.
[66] Y. Jiang, T. Gong, L. He, S. Yan, X. Wu, J. Liu, Fall detection on embedded platform using infrared array sensor for healthcare applications, Neural Comput. Appl. 36 (9) (2024) 5093–5108.
[67] K. Han, Y. Wang, Q. Tian, J. Guo, C. Xu, C. Xu, Ghostnet: More features from cheap operations, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 1580–1589.
[68] S. Woo, J. Park, J.-Y. Lee, I.S. Kweon, Cbam: Convolutional block attention module, in: Proceedings of the European Conference on Computer Vision, ECCV, 2018, pp. 3–19.
[69] Y. Liu, Y.-H. Wu, G. Sun, L. Zhang, A. Chhatkuli, L. Van Gool, Vision transformers with hierarchical attention, Mach. Intell. Res. (2024) 1–14.
[70] Z. Liu, Detecting falls through convolutional neural networks using infrared sensor and accelerometer, in: 2023 IEEE 20th International Conference on Smart Communities: Improving Quality of Life using AI, Robotics and IoT, HONET, IEEE, 2023, pp. 152–155.
[71] Y. Yang, H. Yang, Z. Liu, Y. Yuan, X. Guan, Fall detection system based on infrared array sensor and multi-dimensional feature fusion, Measurement 192 (2022) 110870.
[72] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (8) (1997) 1735–1780.
[73] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, Y. Bengio, Learning phrase representations using RNN encoder-decoder for statistical machine translation, 2014, arXiv preprint arXiv:1406.1078.
[74] W.-H. Chen, H.-P. Ma, A fall detection system based on infrared array sensors with tracking capability for the elderly at home, in: 2015 17th International Conference on E-Health Networking, Application & Services (HealthCom), IEEE, 2015, pp. 428–434.
[75] S. Jankowski, Z. Szymański, U. Dziomin, P. Mazurek, J. Wagner, Deep learning classifier for fall detection based on IR distance sensor data, in: Computer Systems for Healthcare and Medicine, River Publishers, 2022, pp. 169–192.
[76] S.P. Rana, M. Dey, M. Ghavami, S. Dudley, Signature inspired home environments monitoring system using IR-UWB technology, Sensors 19 (2) (2019) 385.
[77] H. Yoshino, V.G. Moshnyaga, K. Hashimoto, Fall detection on a single doppler radar sensor by using convolutional neural networks, in: 2019 IEEE International Conference on Systems, Man and Cybernetics, SMC, IEEE, 2019, pp. 2889–2892.
[78] B.Y. Su, K. Ho, M.J. Rantz, M. Skubic, Doppler radar fall activity detection using the wavelet transform, IEEE Trans. Biomed. Eng. 62 (3) (2014) 865–875.
[79] C. Ding, Y. Zou, L. Sun, H. Hong, X. Zhu, C. Li, Fall detection with multi-domain features by a portable FMCW radar, in: 2019 IEEE MTT-S International Wireless Symposium, IWS, IEEE, 2019, pp. 1–3.
[80] B. Erol, M.G. Amin, Radar data cube processing for human activity recognition using multisubspace learning, IEEE Trans. Aerosp. Electron. Syst. 55 (6) (2019) 3617–3628.
[81] H. Sadreazami, M. Bolic, S. Rajan, CapsFall: Fall detection using ultra-wideband radar and capsule network, IEEE Access 7 (2019) 55336–55343.
[82] H. Sadreazami, M. Bolic, S. Rajan, Fall detection using standoff radar-based sensing and deep convolutional neural network, IEEE Trans. Circuits Syst. II 67 (1) (2019) 197–201.
[83] S. Waqar, M. Muaaz, M. Pätzold, Direction-independent human activity recognition using a distributed MIMO radar system and deep learning, IEEE Sens. J. (2023).
[84] R.C. Tewari, S. Sharma, A. Routray, J. Maiti, Effective fall detection and post-fall breath rate tracking using a low-cost CW Doppler radar sensor, Comput. Biol. Med. 164 (2023) 107315.
[85] C. Kittiyanpunya, P. Chomdee, A. Boonpoonga, D. Torrungrueng, Millimeter-wave radar-based elderly fall detection fed by one-dimensional point cloud and Doppler, IEEE Access (2023).
[86] B. Jokanovic, M. Amin, F. Ahmad, Radar fall motion detection using deep learning, in: 2016 IEEE Radar Conference, RadarConf, IEEE, 2016, pp. 1–6.
[87] N.M. Fung, J.W.S. Ann, Y.H. Tung, C.S. Kheau, A. Chekima, Elderly fall detection and location tracking system using heterogeneous wireless networks, in: 2019 IEEE 9th Symposium on Computer Applications & Industrial Electronics, ISCAIE, IEEE, 2019, pp. 44–49.
[88] Y. Wang, K. Wu, L.M. Ni, Wifall: Device-free fall detection by wireless networks, IEEE Trans. Mob. Comput. 16 (2) (2016) 581–594.
[89] R.M. Keenan, L.-N. Tran, Fall detection using Wi-Fi signals and threshold-based activity segmentation, in: 2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications, IEEE, 2020, pp. 1–6.
[90] H. Wang, D. Zhang, Y. Wang, J. Ma, Y. Wang, S. Li, RT-Fall: A real-time and contactless fall detection system with commodity WiFi devices, IEEE Trans. Mob. Comput. 16 (2) (2016) 511–526.
[91] Y. Chu, K. Cumanan, S. Smith, O. Dobre, et al., Deep learning based fall detection using WiFi channel state information, IEEE Access (2023).
[92] N. Damodaran, E. Haruni, M. Kokhkharova, J. Schäfer, Device free human activity and fall recognition using WiFi channel state information (CSI), CCF Trans. Pervasive Comput. Interact. 2 (2020) 1–17.
[93] S. Hafeez, S.S. Alotaibi, A. Alazeb, N. Al Mudawi, W. Kim, Multi-sensor-based action monitoring and recognition via hybrid descriptors and logistic regression, IEEE Access (2023).
[94] Y. Wu, Y. Su, Y. Hu, N. Yu, R. Feng, A multi-sensor fall detection system based on multivariate statistical process analysis, J. Med. Biol. Eng. 39 (2019) 336–351.
[95] E. Boutellaa, O. Kerdjidj, K. Ghanem, Covariance matrix based fall detection from multiple wearable sensors, J. Biomed. Inform. 94 (2019) 103189.
[96] K. Ozcan, S. Velipasalar, Wearable camera-and accelerometer-based fall detection on portable devices, IEEE Embed. Syst. Lett. 8 (1) (2015) 6–9.

[97] K. Ozcan, A.K. Mahabalagiri, M. Casares, S. Velipasalar, Automatic fall detection and activity classification by a wearable embedded smart camera, IEEE J. Emerg. Sel. Top. Circuits Syst. 3 (2) (2013) 125–136.

[98] C. Nadee, K. Chamnongthai, Multi sensor system for automatic fall detection, in: 2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference, APSIPA, IEEE, 2015, pp. 930–933.

[99] Y. Su, D. Liu, Y. Wu, A multi-sensor based pre-impact fall detection system with a hierarchical classifier, in: 2016 9th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI, IEEE, 2016, pp. 1727–1731.

[100] A.J.A. Majumder, I. Zerin, S.I. Ahamed, R.O. Smith, A multi-sensor approach for fall risk prediction and prevention in elderly, ACM SIGAPP Appl. Comput. Rev. 14 (1) (2014) 41–52.

[101] S. Saurav, R. Saini, S. Singh, A dual-stream fused neural network for fall detection in multi-camera and 360-degree videos, Neural Comput. Appl. 34 (2) (2022) 1455–1482.

[102] S. Saurav, R. Saini, S. Singh, Vision-based techniques for fall detection in 360-degree videos using deep learning: Dataset and baseline results, Multimedia Tools Appl. 81 (10) (2022) 14173–14216.

[103] Dhiraj, R. Manekar, S. Saurav, S. Maiti, S. Singh, S. Chaudhury, Neeraj, R. Kumar, K. Chaudhary, Activity recognition for indoor fall detection in 360-degree videos using deep learning techniques, in: Proceedings of 3rd International Conference on Computer Vision and Image Processing: CVIP 2018, Volume 2, Springer, 2020, pp. 417–429.

[104] R. Yang, Privacy and surveillance concerns in machine learning fall prediction models: implications for geriatric care and the internet of medical things, AI Soc. 39 (4) (2024) 1969–1973.

[105] G. Vavoulas, C. Chatzaki, T. Malliotakis, M. Pediaditis, M. Tsiknakis, The mobiact dataset: Recognition of activities of daily living using smartphones, in: International Conference on Information and Communication Technologies for Ageing Well and E-Health, Vol. 2, SciTePress, 2016, pp. 143–151.

[106] S. Kozina, H. Gjoreski, M. Gams, M. Luštrek, Three-layer activity recognition combining domain knowledge and meta-classification, J. Med. Biol. Eng. 33 (4) (2013) 406–414.

[107] S. Gasparrini, E. Cippitelli, S. Spinsante, E. Gambi, A depth-based fall detection system using a Kinect® sensor, Sensors 14 (2) (2014) 2756–2775.

[108] C. Medrano, R. Igual, I. Plaza, M. Castro, Detecting falls as novelties in acceleration patterns acquired with smartphones, PLoS One 9 (4) (2014) e94811.

[109] B. Kwolek, M. Kepski, Human fall detection on embedded platform using depth maps and wireless accelerometer, Comput. Methods Programs Biomed. 117 (3) (2014) 489–501.

[110] A.T. Özdemir, B. Barshan, Detecting falls with wearable sensors using machine learning techniques, Sensors 14 (6) (2014) 10691–10708.

[111] O. Ojetola, E. Gaura, J. Brusey, Data set for fall events and daily activities from inertial sensors, in: Proceedings of the 6th ACM Multimedia Systems Conference, 2015, pp. 243–248.

[112] T. Vilarinho, B. Farshchian, D.G. Bajer, O.H. Dahl, I. Egge, S.S. Hegdal, A. Lønes, J.N. Slettevold, S.M. Weggersen, A combined smartphone and smartwatch fall detection system, in: 2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing, IEEE, 2015, pp. 1443–1448.

[113] A. Wertner, P. Czech, V. Pammer-Schindler, An open labelled dataset for mobile phone sensing based fall detection, in: Proceedings of the 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services on 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services, 2015, pp. 277–278.

[114] E. Casilari, J.A. Santoyo-Ramón, J.M. Cano-García, Analysis of a smartphone-based architecture with multiple mobility sensors for fall detection, PLoS One 11 (12) (2016) e0168069.

[115] J. Klenk, L. Schwickert, L. Palmerini, S. Mellone, A. Bourke, E.A. Ihlen, N. Kerse, K. Hauer, M. Pijnappels, M. Synofzik, et al., The FARSEEING real-world fall repository: a large-scale collaborative database to collect and share sensor signals from real-world falls, Eur. Rev. Aging Phys. Act. 13 (2016) 1–7.

[116] A. Sucerquia, J.D. López, J.F. Vargas-Bonilla, SisFall: A fall and movement dataset, Sensors 17 (1) (2017) 198.

[117] D. Micucci, M. Mobilio, P. Napoletano, Unimib shar: A dataset for human activity recognition using acceleration data from smartphones, Appl. Sci. 7 (10) (2017) 1101.

[118] M. Ahmed, N. Mehmood, A. Nadeem, A. Mehmood, K. Rizwan, Fall detection system for the elderly based on the classification of shimmer sensor prototype data, Healthc. Inform. Res. 23 (3) (2017) 147–158.

[119] O. Aziz, M. Musngi, E.J. Park, G. Mori, S.N. Robinovitch, A comparison of accuracy of fall detection algorithms (threshold-based vs. machine learning) using waist-mounted tri-axial accelerometer signals from a comprehensive set of falls and non-fall trials, Med. Biol. Eng. Comput. 55 (2017) 45–55.

[120] S.S. Saha, S. Rahman, M.J. Rasna, A.M. Islam, M.A.R. Ahad, DU-MD: An open-source human action dataset for ubiquitous wearable sensors, in: 2018 Joint 7th International Conference on Informatics, Electronics & Vision (ICIEV) and 2018 2nd International Conference on Imaging, Vision & Pattern Recognition, icIVPR, IEEE, 2018, pp. 567–572.

[121] T.R. Mauldin, M.E. Canby, V. Metsis, A.H. Ngu, C.C. Rivera, SmartFall: A smartwatch-based fall detection system using deep learning, Sensors 18 (10) (2018) 3363.

[122] V. Cotechini, A. Belli, L. Palma, M. Morettini, L. Burattini, P. Pierleoni, A dataset for the development and optimization of fall detection algorithms based on wearable sensors, Data Brief 23 (2019).

[123] X. Yu, J. Jang, S. Xiong, A large-scale open motion dataset (KFall) and benchmark algorithms for detecting pre-impact fall of the elderly using wearable inertial sensors, Front. Aging Neurosci. 13 (2021) 692865.

[124] X. Wang, EGOFALLS: A visual-audio dataset and benchmark for fall detection using egocentric cameras, 2023, arXiv preprint arXiv:2309.04579.

[125] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 770–778.