

# A Comprehensive Review on Deep Learning based Fall Detection in Elderly People

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**Abstract**— Elderly people are more vulnerable to falls, which can result in serious injuries, a lower quality of life, and higher medical expenses. Traditional fall detection methods, such as wearable sensors or vision-based systems, face limitations in accuracy, comfort, and practicality. Recent advancements in deep learning have significantly improved fall detection capabilities by leveraging powerful computational models for data analysis and feature extraction. With an emphasis on important methodologies, architectures, and datasets utilized in the area, this paper offers a thorough literature analysis of deep learning-based fall detection strategies. It investigates several deep learning techniques applied to sensor-based and video-based fall detection systems, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models. The review also emphasizes the difficulties encountered in practical application, including data privacy and computing cost, and the need for robust datasets. Finally, future research directions are proposed to address current limitations and improve fall detection systems' dependability and effectiveness for elderly care.

**Keywords**— Fall detection, CNN, RNN, LSTM, GRU

## I. INTRODUCTION

Falls are a serious and growing public health issue, especially for the elderly [1], [2], [3]. The consequences of falls extend beyond the immediate physical trauma, encompassing reduced mobility, diminished standard of living, higher medical costs, and even mortality [1]. According to the World Health Organization, falls are a leading cause of harm and fatalities in older adults, emphasizing the urgent need for effective prevention and intervention strategies [2]. Traditional fall detection methods, while available, often suffer from limitations in accuracy, usability, and cost-effectiveness [4], [5]. These limitations stem from factors such as reliance on manual feature extraction, susceptibility to environmental noise, and the inherent difficulty in consistently capturing fall events in real-world settings [4]. Wearable sensor-based systems, for example, can be intrusive and uncomfortable, leading to non-compliance among users [5]. Vision-based systems, while offering a non-intrusive alternative, struggle with challenges like variations

in lighting, occlusion, and background clutter [6]. deep learning's rise as a branch of artificial intelligence distinguished by its capacity to automatically extract complex patterns from data [7], [8], [9], offers a transformative approach to addressing these limitations. The various stages of a falling detection system is shown in figure.1. The present state of research is methodically examined in this survey of the literature on deep learning-based fall detection systems for elderly individuals, encompassing various data acquisition techniques, deep learning architectures, datasets, performance metrics, and emerging challenges. The review will also analyze the comparative advantages and disadvantages of different approaches, provide a thorough synopsis of the field's progress and potential future directions.

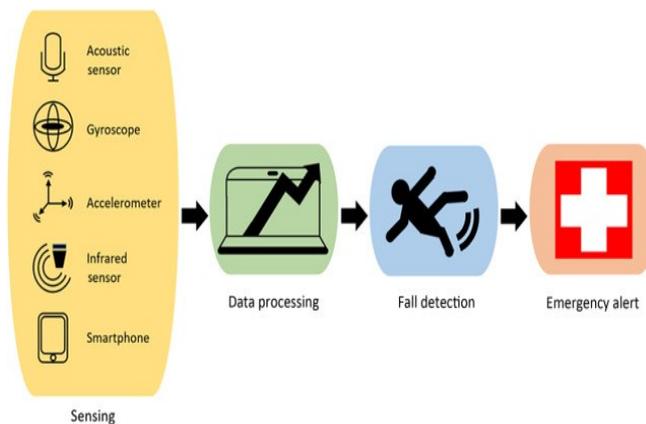


Fig 1. Fall detection system

### 1.1. Data Acquisition and Preprocessing Techniques

The quality and features of the input data determine how effective any deep learning-based fall detection system is. Data acquisition methods and subsequent preprocessing steps significantly influence the system's performance and robustness. This section explores the prevalent data sources and preprocessing techniques employed in the literature.

## 1.2 Sensor-Based Data: Accelerometers, Gyroscopes, and IMUs

A substantial body of research leverages data from wearable sensors, primarily accelerometers, gyroscopes, and inertial measurement units (IMUs) [7], [8], [10], [11]. These sensors measure linear acceleration, angular velocity, and orientation, respectively, providing a rich source of information about the wearer's movements [7]. Accelerometers capture the forces acting on the body, while gyroscopes measure rotational motion. IMUs combine these capabilities, offering a more comprehensive representation of body dynamics [8]. The data collected from these sensors are typically time-series signals, reflecting the continuous changes in acceleration and orientation over time [10]. Preprocessing of sensor-based data is crucial to mitigate the effects of noise and artifacts, thereby improving the accuracy of fall detection. Common preprocessing steps include:

### 1.3 Vision-Based Data: RGB Cameras and Depth Sensors

Vision-based approaches offer a non-intrusive alternative to wearable sensors, utilizing RGB cameras or RGB-D sensors (combining RGB and depth information) to capture video data [1], [2], [16], [17]. These methods rely on extracting visual features from the video frames to detect falls. The preprocessing steps commonly employed include:

### 1.4 Other Data Sources: RFID, WiFi CSI, and Radar

Beyond the prevalent sensor-based and vision-based approaches, research has explored alternative data sources for fall detection:

**RFID (Radio-Frequency Identification):** Contactless fall detection systems have been developed using passive UHF RFID tags strategically placed in the environment [5]. These systems measure fluctuations in the Received Signal Strength Indicator (RSSI) to detect changes in the user's position and movement patterns [5]. Preprocessing involves filtering RSSI signals to remove noise and extract relevant features, such as signal strength variations and temporal patterns [5].

**WiFi CSI (Channel State Information):** WiFi CSI reflects the characteristics of the wireless channel between a WiFi access point and a device. Changes in CSI due to human movement can be used for fall detection without requiring wearable sensors [19]. Preprocessing includes noise reduction, feature extraction from CSI data (e.g., signal strength, phase), and potentially data segmentation [19].

**Radar:** Radar systems offer non-contact monitoring capabilities, using radio waves to detect and track human movement [20], [21], [22]. Preprocessing often involves time-frequency analysis (e.g., wavelet transform) to retrieve pertinent characteristics from the radar signals, such as micro-Doppler signatures reflecting the movement of different body parts [20]. These techniques are particularly useful in environments with poor lighting or occlusion, where vision-based methods might fail [22]. The selection of a data source is influenced by elements like cost, invasiveness, environmental constraints, and the availability of suitable sensors and datasets [21].

## II DEEP LEARNING ARCHITECTURES FOR FALL DETECTION

Numerous deep learning architectures, each with unique advantages and disadvantages, have been investigated for fall detection. This section gives a summary of the most prevalent architectures and their applications in fall detection.

### 2.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a cornerstone of deep learning, especially well-suited for processing image and video data [2], [9], [23], [16]. Their ability to automatically recognize the spatial hierarchies of features makes them useful for extracting relevant information from visual data or from images representing sensor data [12], [13].

In vision-based systems, CNNs can directly classify video frames or image sequences as falls or non-falls [2]. The network learns to recognize patterns in the images that are characteristic of falls (e.g., sudden changes in pose, rapid motion) [9]. CNNs can be used as feature extractors, providing input to other classifiers [24], [25]. The CNN learns a set of discriminative features from the input data (e.g., sensor readings or images), and these features are then fed into a simpler classifier (e.g., SVM, Random Forest) for fall detection [24][43].

For spatiotemporal data (e.g., video sequences or multiple sensor readings over time), 3D CNNs are employed to capture both spatial and temporal relationships [17]. These networks can learn features that are sensitive to both the spatial configuration of the body and the temporal evolution of movement [17]. The choice of CNN architecture (e.g., AlexNet, VGGNet, ResNet, Inception) based on the particular use and the data's complexity.

Variations in architecture, such as the depth of the network, the number of convolutional layers, and the use of pooling layers, can significantly affect performance [23].

### 2.2 Recurrent Neural Networks (RNNs), LSTMs, and GRUs

For processing sequential data, recurrent neural networks (RNNs), in particular Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs), are especially well-suited [8], [26], [10], [11]. RNNs maintain an internal state that enables them to identify temporal dependencies in the data since it is updated at every time step [8]. This capability is crucial for fall detection, as falls typically involve a sequence of movements over time [26]. LSTMs and GRUs address the Problem of the vanishing gradient, which can hinder the training of standard RNNs on long sequences [10].

LSTMs and GRUs can be directly trained to classify sequences of sensor readings or video frames as falls or non-falls [11]. The network gains the ability to recognize data's temporal patterns that point to falls [11]. In order to capitalize on the advantages of both designs, CNNs and RNNs are

frequently combined [16], [27]. The RNN analyzes the time sequence of the spatial information that the CNN has extracted from the data (such as photos or sensor readings) in order to identify falls [16]. This approach often leads to improved accuracy compared to using CNNs or RNNs alone [27]. The choice between LSTMs and GRUs depends on factors such as the length of the input sequences and the computational resources available. GRUs generally have fewer parameters than LSTMs, making them more computationally efficient [10].

### 2.3 Autoencoders and Variational Autoencoders

Autoencoders are unsupervised learning models that learn a compressed representation of the input data [3], [4], [15]. They are made up of a decoder that reconstructs the input data from the latent representation and an encoder that maps the input data to a lower-dimensional latent space [3]. The autoencoder is trained on data representing normal activities. During testing, the reconstruction error is used to identify anomalies, which are interpreted as potential falls [3]. Falls, being unusual events, tend to have higher reconstruction errors compared to normal activities [4]. VAEs are a more advanced type of autoencoder that incorporates probabilistic modeling, enabling them to handle noisy data and generate new samples [15]. VAEs can be particularly useful for fall detection when dealing with datasets that have limited numbers of fall events [25].

### 2.4 Other Architectures: Capsule Networks, Transformers, and Hybrid Models

Capsule networks offer improved robustness to variations in viewpoint and occlusion compared to traditional CNNs [12]. They capture pose information more effectively, making them suitable for vision-based fall detection in challenging scenarios [12].

In sequential data, transformers, which were first created for natural language processing can capture long-range dependencies. [18]. Because of their attention mechanism, they may concentrate on pertinent portions of the input sequence, which makes them potentially useful for processing long sensor readings or video sequences [18].

Many studies combine different architectures to leverage their respective strengths [28], [27]. For instance, a CNN may be used in a hybrid model for feature extraction from images and an RNN for capturing temporal dependencies in the sequence of features [27]. The design of the deep learning architecture is tailored to the specific data modality (sensor data, video, etc.), the available computational resources, and the desired performance characteristics [28].

## III . DATASETS AND EVALUATION METRICS

The evaluation of fall detection systems relies heavily on the availability of appropriate datasets and the selection of relevant performance metrics. This section examines the commonly used datasets and the metrics employed to estimate the performance of deep learning-based fall detection models.

### 3.1 Publicly Available Datasets

Several publicly available datasets have been instrumental in the advancement of fall detection research [9], [4], [24], [11]. These datasets provide standardized benchmarks for comparing different methods and assessing their performance across various conditions. However, these datasets exhibit variations in size, sensor modalities, and the complexity of the activities captured, influencing the generalizability of the results.

**UR Fall Detection Dataset:** This dataset contains recordings from several subjects performing various activities, including falls [24]. It provides accelerometer and gyroscope data and is frequently used to evaluate sensor-based fall detection methods [24].

**SisFall Dataset:** This dataset consists of accelerometer data collected from multiple subjects performing daily living activities and falls [27]. It's often employed to assess the robustness of algorithms to variations in individual movement patterns [27].

**Le2i Fall Detection Dataset:** This dataset combines RGB video and depth sensor data, offering a resource for evaluating vision-based methods [17]. The dataset's challenges include variations in lighting and viewpoints [17].

**UP-FALL Dataset:** This dataset provides multisensor data (accelerometer, gyroscope, pressure) from individuals performing various activities including falls [29]. It's useful for evaluating the performance of multi-sensor fusion techniques [29].

**Other Datasets:** Numerous other publicly available datasets exist, each with its unique characteristics and constraints. The selection of a dataset based on the particular research question and the type of data being used (e.g., sensor data, video, radar).

### 3.2 Evaluation Metrics

Various metrics are employed to assess fall detection systems' performance, each offering a different perspective on the system's capabilities. The choice of metrics based on the application and the relative importance of minimizing false positives versus false negatives [30].

Commonly used metrics include:

- **Accuracy:** The overall correctness of the classification (percentage of correctly classified samples).
- **Precision:** The percentage of accurately recognized falls in all samples that were categorized as falls.
- **Recall (Sensitivity):** The percentage of falls that were accurately detected out of all actual fall incidents.
- **F1-score:** The precision and recall harmonic mean, providing a balanced measure of performance.
- **Specificity:** The percentage of accurately detected non-falls out of all non-fall occurrences.

- AUC (Area Under the ROC Curve): A measure of the classifier's capacity to differentiate between falls and non-falls across different thresholds.

complexity, are also important considerations, particularly in real-world applications [7], [9], [12], [27]. A more thorough evaluation of the system's performance can be obtained by reporting several metrics rather than depending just on one.

Other Metrics: Other metrics, such as response time, power

Approach	Data Type	Architecture	Advantages	Disadvantages
Sensor-based <a href="#">[7]</a> , <a href="#">[8]</a> , <a href="#">[10]</a> , <a href="#">[11]</a> , <a href="#">[16]</a> , <a href="#">[27]</a> , <a href="#">[30]</a>	Accelerometer, Gyroscope, IMU	CNN, LSTM, GRU, Hybrid CNN-RNN	High accuracy (achieving up to 99+% in some studies <a href="#">[7]</a> , <a href="#">[21]</a> ), relatively low cost, wearable, suitable for continuous monitoring	Privacy concerns, user compliance issues, potential for sensor drift or malfunction, susceptible to noise and motion artifacts
Vision-based <a href="#">[1]</a> , <a href="#">[2]</a> , <a href="#">[3]</a> , <a href="#">[4]</a> , <a href="#">[6]</a> , <a href="#">[17]</a> , <a href="#">[18]</a> , <a href="#">[39]</a>	RGB, RGB-D images, video	CNN, 3D-CNN, Autoencoders, Transformer Networks	Non-intrusive, potential for context awareness (detecting falls within a broader activity context), can capture subtle body movements	Sensitive to lighting conditions, occlusion, background clutter, computationally expensive, requires significant processing power, dataset bias can be a major issue
Other modalities (RFID, WiFi CSI, Radar) <a href="#">[5]</a> , <a href="#">[19]</a> , <a href="#">[20]</a> , <a href="#">[21]</a> , <a href="#">[22]</a> , <a href="#">[40]</a> , <a href="#">[41]</a> , <a href="#">[42]</a>	RSSI fluctuations, WiFi Channel State Information, Radar signals	CNN, LSTM, Capsule Networks, other architectures	Contactless, unobtrusive, potential for wider coverage area, suitable for privacy-sensitive scenarios	Limited availability of publicly available datasets, potential for interference from other sources, signal attenuation issues (especially for WiFi and RFID), need for sophisticated signal processing

consumption (for wearable systems), and computational

**Table 1. Comparative Analysis of Different Deep Learning Approaches**

**3.3 Comparative Analysis of Different Deep Learning Approaches:** The selection of deep learning architecture significantly impacts the performance and characteristics of a fall detection system. Table.1 provides a comparative analysis of different approaches based on their strengths, weaknesses, and suitability for various data modalities.

**3.4 Analysis of Performance Metrics Across Studies**

Performance metrics from a number of important studies on deep learning-based fall detection are compared in this section. Note that the specific metrics reported and the methodologies employed vary across studies, making direct

comparison challenging. Table 2. Analyses performance metrics with diversity of approaches.

#### IV. CHALLENGES AND LIMITATIONS

Despite the significant progress in deep learning-based fall detection, several challenges and limitations remain to be addressed. These challenges hinder the widespread deployment and adoption of these systems in real-world settings.

##### 4.1 Data Acquisition Challenges

The collection of qualitative fall datasets is a significant bottleneck in the field [10], [15]. Falls are infrequent events, making it difficult and expensive to collect sufficient data to train robust deep learning models. Furthermore, the ethical considerations associated with collecting data on falls, particularly from vulnerable elderly individuals, require

careful attention [10]. The lack of standardization in data collection protocols across different studies makes it difficult to compare results directly [15].

##### 4.2 Class Imbalance

The inherent imbalance between the number of fall events and non-fall events in fall detection datasets presents a significant challenge [10], [31]. Deep learning models can be biased toward the majority class (non-falls), leading to poor performance in detecting the minority class (falls) [10]. Techniques to address class imbalance, such as oversampling, undersampling, and cost-sensitive learning, are crucial but may not fully solve the problem [31].

##### 4.3 Generalization and Robustness

The performance of deep learning models can be highly dependent on the specific characteristics of the training data. Generalizing to unseen environments, different individuals, and variations in sensor placement or lighting conditions remains a challenge [6], [32]. The real-world applicability of models trained on one dataset may be limited by their poor performance on another [6]. Robustness to noise and artifacts in the data is also critical for reliable fall detection in real-world settings [32].

**Table 2. Analysis of Performance Metrics Across Studies**

Study	Data Type	Architecture	Dataset	Accuracy	Precision	Recall	F1-score
Aslam et al. (2023) [7]	Sensor (Accelerometer, Gyroscope, Infrared)	DL-ANN (Deep Learning-Artificial Neural Network)	Custom Dataset	97%	96%	97%	96%
Li et al. (2017) [2]	Vision (Video)	CNN	Not specified, 10-fold cross-validation	99.98%	-	-	-
Alanazi et al. (2022) [17]	Vision (Video)	4S-3DCNN (four-branch architecture 3D CNN)	Le2i	99.03%	99.00%	99.68%	99.00%
Yi et al. (2024) [15]	Sensor	Denosing LSTM-based Convolutional Variational Autoencoder (CVAE)	Not specified	-	-	-	1.0
Mahmoud et al. (2024) [11]	Sensor (IMU)	KNN, Random Forest, SVM, Gradient Boosting, GRU, LSTM, CNN	UPFALL	93.5% (KNN), - (others)	-	-	-

Al-Rakhami et al. (2021) [26]	Sensor	Deep Gated Recurrent Unit (DGRU)	Public Datasets (not specified)	Higher than state-of-the-art	-	-	-
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#### 4.4 Computational Constraints

The deployment of complex deep learning models on resource-constrained devices, such as smartwatches or embedded systems, is often limited by computational power and memory constraints [15], [33]. Real-time processing is essential for fall detection, and computationally expensive models may not be suitable for these applications [15]. Model compression techniques and the use of lightweight architectures are necessary to address these limitations [33].

### V. FUTURE DIRECTIONS AND CONCLUSION

Deep learning has enormous potential to enhance fall detection systems, notwithstanding the difficulties. Addressing the shortcomings of existing techniques requires the creation of deep learning architectures that are more reliable and effective. This entails investigating cutting-edge architectures created especially for fall detection, adding class imbalance managing algorithms, and improving generalisation abilities. For deployment on devices with limited resources, lightweight architectures that reduce memory footprint and computational complexity are required [34], [33]. Fall detection systems can be made more reliable and accurate by combining data from several sensors, such as accelerometers, gyroscopes, cameras, and radar [10], [35]. By combining data from many sources, multimodal techniques can lessen dependency on any one sensor modality and offer a more thorough picture of the user's activities [35]. As a result, individual sensor readings may perform better and be less susceptible to noise or artefacts [10].

It is crucial to address the lack of autumn data. The number and diversity of training datasets can be greatly increased by using sophisticated data augmentation techniques and creating synthetic data, which will improve the resilience and generalisation of the model [18], [15]. The model's capacity to manage real-world changes can be enhanced by simulating different fall scenarios and climatic variables using synthetic data [18]. Increasing fall detection systems' openness and reliability is essential for boosting user confidence and promoting clinical adoption. By offering insights into the deep learning models' decision-making process, explainable AI (XAI) techniques seek to make it simpler to comprehend why a specific event was categorised as a fall or non-fall [36]. This can enhance the system's overall dependability and assist in identifying possible biases [36].

The ultimate goal is to integrate fall detection systems into broader elderly care platforms that provide comprehensive

monitoring and support. This involves seamless integration with other healthcare technologies, remote monitoring capabilities, and alert systems that can quickly connect individuals to emergency services [37]. These integrated solutions can improve senior citizens' general safety and wellbeing by encouraging their independence and offering prompt support when required [30].

In conclusion, deep learning has shown itself to be an effective tool for developing fall detection technology, with the potential to greatly enhance senior citizens' safety and happiness. While challenges remain in data acquisition, model robustness, and computational constraints, ongoing research focused on developing more efficient architectures, exploring multimodal approaches, and addressing class imbalance is establishing the path for more precise, reliable, and widely deployable fall detection models [38]. The integration of these systems into comprehensive elderly care platforms will be essential to achieving the maximum potential of deep learning in this crucial area of healthcare.

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