

A Review of Fall Detection Research Based on Deep Learning

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Abstract: In recent years, with the intensification of societal aging, falls have emerged as one of the primary health risks threatening the well-being of the elderly, making the effective detection of fall events an urgent problem to address. Fall detection technology based on deep learning has increasingly become a focal point of research due to its powerful automatic feature extraction capabilities. This paper systematically reviews the recent research in fall detection, categorizing the technologies into two main types according to the devices used for data collection: image-based and non-image-based detection methods. The study highlights recent advances in fall detection using Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Temporal Convolutional Networks (T-CNN) frameworks, examining the application and advantages of these methods in processing various types of data, such as video sequences and sensor data. Through an in-depth analysis of the operational mechanisms of multiple deep learning architectures and their performance on different datasets, this paper elucidates the latest advancements and challenges facing current fall detection technologies. Additionally, commonly used fall detection datasets are introduced, including their data scales and application contexts. Finally, this paper provides a summary of recent progress in fall detection techniques, outlines future directions, and presents recommendations for advancement across several dimensions.

Keywords: Fall Detection, Machine Learning, Deep Learning, Wearable Sensors.

1. Introduction

According to United Nations statistics, as of 2023, the global population has exceeded 8 billion. With this continuous population growth, aging has gradually become a prominent issue. China, specifically, is home to the world's largest elderly population. The 2022 national census revealed that individuals aged 60 and above accounted for 18.73% of the total population, indicating that China has entered a moderate aging phase. Experts predict that by 2050, the proportion of elderly people in China will approach 30%, which poses a substantial caregiving burden for families and society at large [1].

With technological advancements, the average lifespan of elderly individuals continues to increase. However, falls remain a major health risk, contributing to nearly 40% of total deaths among elderly individuals in China annually. As people age, physical functions noticeably decline, making them more susceptible to falls in daily life. Without timely rescue, such incidents can lead to irreversible injuries or even death. Consequently, promptly and accurately detecting falls, along with immediate intervention, could significantly reduce subsequent harm.

Recent years have witnessed considerable advances in fall detection technologies, both in image-based and non-image-based methods. In terms of image-based detection, a study by Lin et al. introduced a CNN-based image processing technique combined with the Open Pose framework to estimate posture for fall detection. This system captures 25 key points on the human body, detecting fall events by monitoring the movement of these key points. Experimental results demonstrated that this approach achieved a 98.2% accuracy rate across five different environments [2]. Similarly, Chhetri et al. proposed a vision-based fall detection system using enhanced dynamic optical flow, which addressed the challenge of accuracy in complex environments, such as under changing lighting conditions. By encoding temporal data from optical flow videos, this method improved processing speed and classification accuracy, reducing processing time by 40–50 milliseconds and boosting classification accuracy by approximately 3% [3].

In non-image-based detection, a study by Li et al. introduced a deep learning model based on radar signal spectra, called the Convolutional Bidirectional Long Short-Term Memory (CB-LSTM) model, which detects falls by leveraging spatial and temporal features. Although this system has some limitations in application scenarios, it performs well in fall detection and can be used for intelligent monitoring of elderly individuals [4]. Similarly, Mohammad et al. developed a fall detection system based on wearable sensors, combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to capture short- and long-term dependency features, thus enhancing detection accuracy. This system can not only detect falls but also predict impending falls, allowing preventive safety measures to be taken in advance [5].

In this field, fall detection methods can be broadly classified into two categories based on the type of data collection devices: image-based and non-image-based detection methods. Image-based fall detection primarily relies on cameras or video surveillance systems. Non-image-based detection depends on sensor data, typically from wearable devices or environmental sensors. Therefore, non-image-based methods can be further subdivided into wearable device-based and environment sensor-based detection methods. This paper consolidates advanced technologies in fall detection from both perspectives, providing a comprehensive review of recent developments in the field. It also offers a comparative analysis of commonly used datasets and evaluation criteria, proposing several recommendations for future advancements.

2. Image-Based Fall Detection Techniques

Image-based fall detection methods identify fall incidents by capturing and analyzing human posture and motion within video or image data. In recent years, with advancements in computer vision and deep learning, these techniques have gained significant attention in research. Typically, these methods use cameras to acquire video data and combine traditional image processing techniques with deep learning algorithms to detect and analyze fall events.

The core process involves detecting key points on the human body—such as the head, torso, and limbs—and tracking their positions over time. By analyzing abrupt changes in these points, image-based methods can detect unusual motions indicative of falls. Additionally, convolutional neural networks (CNN) and other deep learning models are employed to improve accuracy by learning patterns in human movements. This integration of real-time image processing and deep learning provides a powerful approach for fall detection, particularly in environments where video monitoring systems are readily available.

2.1. Traditional Image Processing-Based Methods

Early image-based fall detection methods primarily relied on computer vision techniques, processing video or image frames to extract motion information and posture features of the target object to

determine if a fall occurred. Common techniques included background modeling, object tracking, and motion analysis.

2.1.1. Background subtraction

Background subtraction is a classic object detection technique primarily used to separate foreground objects (such as people) from the background in continuous video frames. By constructing a static or dynamic background model and subtracting the background, it isolates the silhouette of moving human figures.

Gutiérrez et al. first built a background model from video frames, then subtracted the background from each frame, leaving only the human figures in the foreground. Through subsequent motion analysis, they monitored human movement trajectories and posture changes. The study also highlights that background subtraction is particularly effective in mitigating environmental changes (such as lighting variations) and aids in preprocessing data for more advanced classification algorithms[6].

2.1.2. Optical Flow Method

The optical flow method is a technique used to estimate pixel-level motion in video frames. By calculating the displacement of pixels between adjacent frames, it can determine the direction and speed of movement within the video. Chhetri et al. encoded the temporal data of optical flow videos using pooling layers, summarizing the video into a single image. This method improved the accuracy of fall detection by 3% and reduced processing time by 40 to 50 milliseconds, especially in challenging lighting conditions. This approach is beneficial for real-time fall detection in complex environments [3].

The optical flow method captures information about the direction and speed of human movement, making it suitable for dynamic scenes and thus more robust when handling complex environments and variable lighting conditions. In contrast, background subtraction is primarily used for foreground extraction in static environments, effectively isolating the silhouette of human figures. However, it is sensitive to environmental changes and can easily be disrupted by variations in lighting or background motion.

2.1.3. Deep Learning-Based Fall Detection

With the widespread application of deep learning in image and video processing, deep learning-based fall detection methods have made significant advancements in terms of accuracy and robustness. These methods can automatically extract complex features from videos or images, offering greater adaptability.

2.1.4. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN) excel at extracting spatial features from images, making them effective for analyzing changes in human posture within video frames. By progressively extracting features through multiple layers, CNNs can recognize the shapes and poses of people and objects. Santos et al. proposed a deep learning framework that utilizes CNN to extract features from video frames to identify fall events. The researchers trained their model using a large dataset of labeled videos, thereby enhancing its accuracy[7].

While CNN are proficient at extracting spatial features from video frames and are suitable for fall detection in static images or short time sequences, they have limitations in modeling long-term temporal dependencies. In contrast, Temporal Convolutional Networks (T-CNN) can simultaneously capture spatial and temporal information, making them more adept at handling long time sequence

data. As a result, T-CNNs demonstrate superior performance in detecting complex fall actions and multi-stage behaviors.

2.1.5. Temporal Convolutional Network (T-CNN) and Long Short-Term Memory (LSTM)

T-CNN is a model that combines Convolutional Neural Networks with time series analysis, enabling it to simultaneously extract spatial and temporal features from video frames. Long Short-Term Memory (LSTM) networks excel at handling temporal dependencies in video data, allowing them to track the history of human movements and predict future states.

In T-CNN, spatial features are first extracted from each frame, and these features are then fed into the LSTM network to utilize time series information for fall detection. This combination facilitates better handling of continuous human movements and fall behaviors.

2.1.6. Pose Estimation and Skeleton Model

Pose estimation techniques construct a skeleton model by extracting key points of the human body (such as the head, shoulders, arms, legs, etc.) to track changes in human posture. Open-source pose estimation tools, such as Open Pose and HRNet, have been widely applied in fall detection.

Lin et al. utilized Open Pose to extract 25 key body joints and input these coordinates into machine learning models like LSTM and GRU to estimate the 2D posture of the human body. This method achieved high accuracy (approximately 98.2%) in fall detection, representing a significant improvement compared to traditional image-based methods[2].

3. Non-Image-Based Fall Detection Techniques

Non-image-based fall detection methods primarily rely on various sensors, such as accelerometers, gyroscopes, pressure sensors, and sound sensors. These methods detect fall events by sensing human movement, positional changes, and environmental features. Compared to image-based methods, non-image detection techniques offer advantages such as strong privacy protection, lower costs, and high real-time performance, garnering significant attention in practical applications. Currently, non-image-based fall detection methods remain the mainstream approach in terms of detection accuracy and precision.

In recent years, intelligent algorithms like deep learning have gradually been integrated with sensor data, providing new technological pathways for non-image-based fall detection. Non-image detection methods can be further divided into two main categories: wearable sensor-based detection and scene sensor-based detection. Both methods utilize different sensor technologies for data collection and processing.

3.1. Wearable Sensor-Based Detection Methods

Wearable sensor-based detection methods typically rely on devices worn by users, which are equipped with multiple sensors such as accelerometers, gyroscopes, and heart rate sensors. These sensors can monitor the body's movement status, posture changes, and physiological signals in real time. When abnormal acceleration or angular velocity is detected, the system assesses whether a fall has occurred.

3.1.1. Accelerometers and Gyroscopes

Accelerometers are among the most commonly used sensors, capable of capturing acceleration changes in various directions. Gyroscopes, on the other hand, are used to measure angular velocity, detecting the degree of body tilt or rotational movements.

Tang et al. proposed a cost-effective fall detection system that utilizes data from accelerometers and gyroscopes, aiming to minimize false positives. It employs a simple threshold-based algorithm to detect falls by monitoring acceleration and direction, achieving a sensitivity of 90% and a specificity of 85%[8].

3.1.2. Combined Sensors and Fusion Algorithms

In modern wearable devices, multiple sensors are often integrated simultaneously, including accelerometers, gyroscopes, magnetometers, and heart rate sensors, to enhance detection accuracy through data fusion. By combining data from different types of sensors, the system can more accurately identify fall events and reduce false positives. Tsinganos et al. compared data fusion from wearable sensors with single-sensor machine learning techniques. The findings indicated that the fusion of data from multiple sensors (such as accelerometers and gyroscopes) produced more accurate results than using a single sensor alone[9].

Combined sensors and fusion algorithms provide more comprehensive motion information by integrating data from various sensors (like accelerometers and gyroscopes), significantly improving detection accuracy and robustness. In contrast, single-sensor methods are more susceptible to data noise or specific environmental factors, resulting in lower accuracy and reliability in detection outcomes.

3.1.3. Machine Learning and Deep Learning-Based Detection

With the widespread adoption of wearable devices, fall detection models based on machine learning and deep learning have gradually replaced traditional threshold-based methods. By extracting features from sensor data and employing classification algorithms such as Support Vector Machines (SVM), decision trees, and K-Nearest Neighbors (KNN), these models can effectively distinguish between normal activities and fall behaviors. In recent years, deep learning methods (such as Convolutional Neural Networks and Recurrent Neural Networks) have also been increasingly applied to fall detection tasks, further enhancing detection accuracy.

3.2. Scene Sensor-Based Detection Methods

3.2.1. Ultrasonic and Infrared Sensors

Ultrasonic sensors measure the distance changes between an object and the sensor by emitting ultrasonic waves and receiving the reflected signals, while infrared sensors determine position and motion by detecting the thermal signals of objects. Usmani et al. proposed a system where ultrasonic sensors monitor distance and movement patterns, while infrared sensors track thermal characteristics to detect abnormal activities indicative of falls. Additionally, machine learning algorithms (such as Support Vector Machines, SVM) are applied to classify the data collected from the sensors, achieving a detection accuracy of 97%[10].

3.2.2. Millimeter-Wave Radar

Millimeter-wave radar can penetrate obstacles such as clothing and walls, accurately detecting human movements, even in dark environments. This technology offers a non-intrusive and privacy-respecting solution for fall monitoring, making it particularly useful in elderly care settings where wearable devices may not be ideal. Malešević et al. developed a system using the Acconeer A111 radar, which employs a Support Vector Machine (SVM) classifier to identify falls by analyzing movement patterns and the distance between the subject and nearby objects. The combination of radar sensing and machine learning enables reliable fall detection and reduces the rate of false positives[11].

In the realm of fall detection, ultrasonic and infrared sensors can detect the position and movement of objects at closer ranges; however, their accuracy is limited by distance and environmental interference, making it challenging to capture subtle human movements accurately. In contrast, millimeter-wave radar offers higher resolution and penetration capabilities, unaffected by lighting conditions or obstructions, providing more stable and precise fall detection results over greater distances and in more complex scenarios.

4. Commonly Used Datasets and Evaluation Criteria

4.1. Commonly Used Datasets

4.1.1. Multicam Fall Dataset (MFD)

This dataset is a publicly available resource for fall detection research in multi-camera environments. It is particularly suitable for fall detection tasks that involve multi-view or scene perception. The dataset includes data for both real falls and simulated falls, making it useful for evaluating image-based and pose estimation algorithms.

4.1.2. UR Fall Detection Dataset

The research team at the University of Rochester created this dataset for fall detection studies. It contains videos of falls and non-fall events, making it suitable for research on fall detection through image processing and pose estimation. Additionally, it includes accelerometer data to complement the video data, allowing for the exploration of multi-sensor fusion techniques. This dataset is one of the commonly used resources in the field.

4.1.3. Le2i Fall Detection Dataset

The Le2i laboratory in France created this dataset, which provides video data of falls and daily activities in various indoor scenarios. It aids researchers in developing computer vision systems capable of automatically detecting falls. With annotated fall events and diverse scenes and subjects, this dataset helps train more accurate fall detection models, especially suited for real-time fall detection in single-camera surveillance environments.

4.1.4. DLR Dataset

This dataset was created by a research team from the German Aerospace Center (DLR). It is designed for human activity recognition and includes data on fall events and other daily activities, primarily collected through sensors such as accelerometers and gyroscopes. This dataset is particularly suitable for fall detection algorithms based on wearable sensors.

4.1.5. SisFall Dataset

It simulates various fall scenarios, particularly targeting the elderly. This dataset is primarily based on accelerometer and gyroscope data collected from wearable devices. It helps improve the accuracy of fall detection in older adults, allowing for timely responses and interventions to reduce the harm caused by falls.

This article compares the common datasets mentioned above and summarizes relevant information about each dataset, including data scale, application scenarios, and data types. Detailed information is provided in Table 1.

Table 1: Summary of Common Datasets

Data Types	Dataset name	Creator	Data size	Application Scenarios	Dataset URLs
Video Data	Multicam Fall Dataset	University of Montreal	Videos recorded with multiple cameras. 221 videos	Health monitoring, elderly care.	https://universe.roboflow.com/fall-detection-yuo1h/multicam-fall-dataset
Video Data	Le2i Fall Detection Dataset	Le2i laboratory	with a resolution of 320x240.	Real-time monitoring, elderly care	https://www.kaggle.com/datasets/tuyenldvn/falldataset-imvia
Sensor Data	SisFall Dataset	research team	Includes 34 videos and 4,510 files.	Fall detection, wearable device research.	https://www.kaggle.com/datasets/nvnikhi10001/sis-fall-original-dataset
Sensor Data (Accelerometer, Gyroscope)	DLR Dataset	German Aerospace Center	Includes sensor data for various activities.	Health monitoring, activity tracking.	
Video and Sensor Data	UR Fall Detection Dataset	Pan-American University of Mexico	Contains videos of various falls and daily activities.	Medical monitoring, rehabilitation, smart home.	https://sites.google.com/up.edu.mx/har-up/

4.2. Evaluation Criteria

In the field of human fall detection, evaluation metrics are essential tools for measuring the performance and reliability of algorithms. Common metrics for assessing the performance of traditional algorithms include accuracy, precision, recall, F1 score, and average detection delay. When evaluating deep learning algorithms, additional specific evaluation criteria are considered, focusing on the training process, computational efficiency, and generalization ability of the models, such as model convergence and the trade-off between model complexity and inference time.

Accuracy reflects the proportion of correctly classified samples among the total number of samples, while precision and recall measure the model's correct identification rate and the false negative rate for fall events, respectively. The F1 score, as the harmonic mean of precision and recall, provides a comprehensive metric that balances both, making it particularly suitable for situations with class imbalance.

In practical applications, average detection delay is crucial, as it assesses the time interval from when a fall occurs to when it is successfully detected, which is vital for timely responses in real-time monitoring systems.

Model convergence is one of the key indicators for evaluating the performance of deep learning algorithms. Convergence typically refers to the property where the model's loss function or performance metrics stabilize as the number of iterations increases during training. For instance,

Wang et al. mentioned that many machine learning-based fall detection algorithms need to focus on model convergence during training to ensure the algorithms effectively learn the features of fall behavior. These algorithms generally achieve convergence by continuously iterating to optimize the loss function, thereby improving both detection accuracy and real-time performance[12].

5. Research Outlook and Challenges

As an important technology for ensuring the safety of the elderly in an aging society, fall detection has made significant progress in recent years. However, with the rapid development of technology and the continuously changing application scenarios, fall detection systems still face many challenges and unresolved issues.

5.1. Research Outlook

5.1.1. Further Development of Multimodal Fusion

In the future, multimodal fusion technology is expected to enhance the accuracy and robustness of fall detection by combining multiple data sources, such as video, sensor signals, and millimeter-wave radar. Current single-modal detection systems may perform sub optimally in certain situations, and multimodal fusion can address this shortcoming. By integrating visual and sensor data, the system can effectively distinguish between falls and normal daily activities, thereby reducing the false positive rate. Through multimodal fusion, the system will be better equipped to adapt to complex real-world environments.

5.1.2. Adaptive Detection and Personalized Models

The future fall detection systems will place greater emphasis on personalized needs. Different users have varying behavioral habits, physical conditions, and usage scenarios. Adaptive models can automatically adjust detection parameters based on users' daily behavior data, dynamically optimizing detection performance to enhance the personalization and adaptability of the detection system.

5.1.3. Edge Computing and Real-Time Processing

With the rise of the Internet of Things (IoT) and edge computing, future fall detection systems will increasingly rely on edge computing to reduce latency and enhance real-time performance by processing data locally on devices. Edge computing will enable fall detection systems to achieve rapid responses on resource-constrained hardware, making it suitable for home environments or wearable devices.

5.1.4. Privacy Protection and Data Security

As privacy concerns continue to grow, future fall detection systems will focus on developing technologies that protect user privacy. Non-contact sensors without imaging, such as millimeter-wave radar, along with differential privacy techniques, will become mainstream, ensuring that data privacy is not compromised while achieving high-precision detection.

5.1.5. Human-Computer Interaction and Smart Home Integration

The future fall detection systems will be deeply integrated with smart home devices to enhance user experience. Through connections with voice assistants, mobile applications, and smart home devices, users can receive real-time fall detection information and effectively interact with the system, providing personalized feedback mechanisms.

5.2. Challenges

5.2.1. Balancing Detection Accuracy and False Positive Rate

The challenge of effectively reducing the false positive rate while improving the accuracy of fall detection systems remains a critical issue. Given that falls occur infrequently, detection systems are often affected by imbalanced datasets, leading to frequent false positives. This not only impacts the practical application of the system but can also diminish user trust in it. Optimizing data balance to reduce false positives will be a key focus for future research.

5.2.2. The issue of system real-time performance and power consumption

Real-time performance is one of the key factors in the application of fall detection systems. However, deep learning algorithms often have high computational complexity, especially in image-based detection, which can lead to significant delays. Additionally, for wearable devices, power consumption directly affects system usability. How to reduce power consumption and latency while ensuring efficient detection is a major challenge at present. There is a need to develop lighter deep learning models and more energy-efficient hardware systems to meet the demands of practical applications.

5.2.3. Insufficient Diversity and Coverage of Datasets

Currently, many publicly available datasets for fall detection have limitations in terms of scene variety, action types, and user demographics. This results in insufficient diversity in the training data, failing to adequately reflect the complexities of real-world situations. For example, commonly used datasets may primarily focus on a specific demographic or environment, leading to reduced generalization ability of the model in different contexts. Since most datasets are sourced from specific experimental settings, they lack the diversity and complexity found in real-life situations, which restricts the system's performance in practical applications.

5.2.4. Lack of Unified Evaluation Standards

Currently, there is a lack of unified evaluation standards in the research of fall detection systems, making it difficult to directly compare results across different studies. Different studies adopt various evaluation metrics (such as accuracy, sensitivity, specificity, etc.), which reduces the comparability of the evaluation results and hinders progress and communication within the field. Newaz et al. noted that each algorithm typically uses its own criteria to define falls and assess detection accuracy, leading to inconsistencies when comparing research results. They advocate for the establishment of common benchmarks for evaluating fall detection systems to enhance the comparability and reliability of research outcomes[13].

6. Conclusion

In recent years, falls have increasingly become a significant health threat to the elderly. With the rapid development of fall detection technologies in smart monitoring and health care, there is hope to reduce the number of elderly individuals who lose their lives due to falls. This paper provides a review of fall detection techniques based on image and non-image data. The contributions of this paper are as follows: (1) The existing fall detection technologies are categorized into two types, summarizing the principles, advantages, and latest research outcomes of different fall detection algorithms in recent years. It focuses on deep learning-based fall detection algorithms, highlighting the application of deep learning technologies, such as Convolutional Neural Networks (CNN), which have significantly

improved the accuracy and real-time performance of fall detection. (2) Common datasets and evaluation criteria are introduced and summarized, analyzing different datasets and outlining their applicable areas. This paper also presents the commonly used evaluation criteria for fall detection. (3) Finally, reasonable research prospects and challenges are proposed regarding the existing issues in the field of fall detection. This paper holds certain significance in the realm of fall detection algorithms and aims to assist future research.

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