Proceedings of CONF-SEML 2026 Symposium: Importance of Machine Learning Methods and Analysis in Engineering
DOI: 10.54254/2755-2721/2026.AS32450

Artificial Intelligence and Home Fall Detection: Challenges and Prospects

Jinyang Mu

Minhang Crosspoint Academy at Shanghai Wengi Private Middle School, Shanghai, China
jack20090109@126.com

Abstract. As the world population is aging, fall detection has emerged a major technology in ensuring the safety of the elderly and the provision of rehabilitative services to them at home. Nevertheless, the current studies continue to encounter difficulties regarding the implementation of algorithms, data privacy, and the lack of data. To address this gap, this paper uses an exploratory review method to describe in a systematic manner the status quo in the research concerning artificial intelligence as applied in the area of home fall detection. The process of analyzing 11 chosen core articles demonstrates that the use of AI technology in the area of fall detection is typically represented in: posture estimation-driven visual recognition, wearable sensor-driven time-series analysis, and multimodal monitoring systems in the Internet of Things. It has been found that the objective of AI application in research is to enhance the accuracy and openness of clinical judgment using interpretable AI and advanced filtering procedures. The paper discusses the need to create low cost, high precision, and privacy-sensitive AI systems in the home care setting as well as present a broad view of the system design in the intelligent elder care services in the future.

Keywords: Artificial intelligence, fall detection, pose estimation, wearable devices

1. Introduction

The trend of population aging around the world has become an irreversible social reality. According to the United Nations' prediction, by 2050, the global population aged 65 and above will reach 1.5 billion, and the continuous increase in the proportion of the elderly population poses unprecedented challenges to the medical system and social care models. Against this backdrop, aging in place, which can maintain the independence, familiarity and dignity of life of the elderly, has become the preferred way of elderly care for most elderly people [1]. However, compared with institutionalized care, the home environment has significant deficiencies in safety monitoring and risk intervention, among which the risk of falls is particularly prominent.

Falls are one of the leading causes of traumatic hospitalization among the elderly. Figure 1 illustrates several types of falls that are prone to occur. It also often accompanied by severe physical injuries, such as hip fractures and head injuries, as well as long-term psychological consequences such as fear of falling and avoidance of activities. Even more seriously, fall-related injuries remain one of the significant causes of accidental death and disability among the elderly. Therefore, the development of reliable, continuous, and minimally invasive home fall monitoring and early

DOI: 10.54254/2755-2721/2026.AS32450

warning systems has become a core research topic in the fields of smart health and home-based elderly care [2].

Figure 1. Common types of falls

Current fall detection methods mainly rely on two technical approaches: one is based on the analysis of acceleration, gyroscope or pressure signals from wearable sensors; the other is based on posture recognition and action classification models using computer vision. However, the application of these methods in real home scenarios still faces significant challenges. Firstly, due to multiple constraints such as ethics, privacy and security, real-world fall events are difficult to be systematically collected, resulting in an extremely scarce number of fall samples in the training data, which in turn leads to a serious class imbalance problem. This data bias not only limits the generalization ability of discriminative models but also weakens their robustness in complex home environments. Secondly, the datasets constructed in laboratories often fail to cover the diverse factors in real homes, such as complex lighting conditions, furniture occlusions, various fall patterns and individual differences. Finally, these methods suffer from high false alarm rates and low reliability. In particular home setting, the intricacy of activities used in daily life (sitting and falling) makes it hard to differentiate the normal activities of daily living (ADL) and emergency events to traditional systems [3].

With the fast advancement of artificial intelligence (AI) in recent years, the predicament now has new solutions. AI-based solution applied to various areas has been high [4-6]. Convolutional neural network models may not only make binary decision in case of the occurrence of a fall, but also learn the distribution of human movement underlying to analyzing time dynamics and posture change. This is because the capability allows AI to differentiate between fall sequences that are exceptionally realistic, and can approximate conditions in the home environment that are challenging to replicate in experimental data (e.g., low illumination, occlusion, non-standard fall paths) and hence, has demonstrated to have special benefits in data augmentation and estimating rare events.

Moreover, one of the preconditions of the practical implementation of home monitoring system is a privacy protection. Although traditional RGB video surveillance has increased security, it has led to highly raised concerns about the issue of privacy and ethics of individuals. The new technical variation of privacy-protected fall detection via AI: when applying the raw video to de-identified modalities (skeletal sequences, contours, or heatmaps), the main biomechanical variables are retained, whereas individual identifiability is reduced by a significant margin. With this data generation and modeling technique that involves privacy but is embedded into the commodity, what seems to be a viable solution is the balance between security monitoring and protection of privacy.

Though AI models seem to have a huge potential in the realm of home fall detection, the research currently exists has the following features which include dispersed approaches, various objectives and inconsistent criteria of evaluation. The studies concentrate on different things including the targets of generation, the stages of application, and the reality of application and there is no systematic review and in-depth analysis.

On this basis, the current research intends to carry out a systematic review of how artificial intelligence can be applied in home fall detection, and, based on this, it also attempts to support the answer to the following research questions:

RQ1: How is AI technology specifically applied to the generation and enhancement of home fall detection data?

RQ2: What are the primary objectives and challenges of implementing generative models in real-world home safety scenarios?

2. Methods

2.1. Review design

The proposed research is based on a review-built methodology to look at the use of AI in home fall detection and monitoring cases systematically and exploratory in nature. The given review is not a single research devoted to detection accuracy, but highlights the importance of the ability of generative model to overcome critical shortcomings in the home security systems of the real world, e.g., data scarcity, imbalances in the classes, environmental changes, and preservation of privacy. Due to the emerging and fast emerging nature of AI technologies, the review uses a comprehensive approach, which can be characterized as both exploratory and technologically motivated to determine key research methodological, goals of application, and unresolved issues.

2.2. Literature search strategy

The Web of Science Core Collection has been systematically searched based on the literature to identify literature that offers coverage of high-impact journals in the areas of computer vision, artificial intelligence, healthcare technology, and smart environments.

The search strategy was drafted to identify the studies which were associated with the fall detection, home monitoring, and generative modeling methods. The search terms had been formulated to represent three conceptual dimensions:

(1) fall detection and elderly monitoring,

(2) discriminative or synthetic data modeling, and

(3) vision-based or human motion representations.

We used different combinations of the following keywords to quickly filter Google Scholar: "fall detection", "home monitoring" OR "Aging in Place", "generative adversarial network" OR "GAN", "variational autoencoder" OR "VAE", "diffusion model","synthetic data" OR "data augmentation","pose-based" OR "skeleton-based" OR "vision-based",Only peer-reviewed. The specific search terms are as follows:

TS = (("fall detection") AND ("home monitoring" OR "aging in place") AND ("generative adversarial network*" OR GAN OR "variational autoencoder*" OR VAE OR "diffusion model*") AND ("synthetic data" OR "data augmentation") AND ("pose-based" OR "skeleton-based" OR "vision-based"))

Google Scholar is one of the most comprehensive databases of literature. However, some low-quality research still needs to be excluded. Only peer-reviewed journal articles published in English were considered. Furthermore, only peer-reviewed journal articles were included in this study. Conference papers, posters, and other non-peer-reviewed publications were excluded to ensure

DOI: 10.54254/2755-2721/2026.AS32450

methodological rigor, reliability, and transparency. Conference publications often provide limited details regarding experimental design, dataset characteristics, and reproducibility, and may only represent preliminary results, making them less suitable for review studies focusing on home testing, especially when involving some clinical data. The inclusion and exclusion criteria are summarized in Table 1.

Table 1. Inclusion criteria

Inclusion Criteria	Exclusion Criteria
Studies applying AI or deep learning models to fall detection	Traditional threshold-based non-AI methods
Focus on home-based or rehabilitation-related visual/sensor data	Industrial safety or sports performance analysis
Peer-reviewed journal articles	Non-academic publications or posters
Full-text articles in English (2020-2025)	Non-English publications

2.3. Study selection process

The process of selecting the studies has been done in two stages. The initial phase involved an independent screening of titles and abstracts of all the records retrieved by two reviewers of the records based on the predefined inclusion criteria. Both the reviewers studied each record separately. Whenever there was disagreement, a third reviewer was involved in order to make a final decision. Inter-rater reliability was evaluated with the help of Cohen kappa coefficient that provides the high degree of agreement ($\kappa = 0.84$). The references were handled with the EndNote 21 software, which helped to screen the references and assure the reviewing was blinded.

During the second step, full texts of potentially eligible studies were retrieved, and both of the reviewers, who completed the first screening step, were independently reviewed. A pilot-test of the standardized screening form was done before official screening to refine it on a collection of ten articles. Motives in the exclusion at the full-text stage were recorded. The differences were then settled by means of discussion and the final agreement rate was 96. The list of references is presented in Table.

The titles and abstracts of all retrieved literature were screened separately by two reviewers according to set inclusion criteria during the screening process. References were managed and recorded using EndNote 21 softwares. The two reviewers were responsible to assess each article separately. Should a disagreement arise a third reviewer was called in to come up with the final decision. The inter-reviewer reliability was determined with the help of Cohens kappa and the obtained results indicated high consistency (lk = 0.81). Full-texts that may have suited the inclusion criteria were accessed and analyzed by the two reviewers that had conducted the preliminary screening. A pilot study on five articles was conducted to refreeze the standardized screening table prior to formal screening. The causes of omitting literature in the stage of full-text screening were documented. Conflicts were solved by arguing. Figure 2 displays the search process.

DOI: 10.54254/2755-2721/2026.AS32450

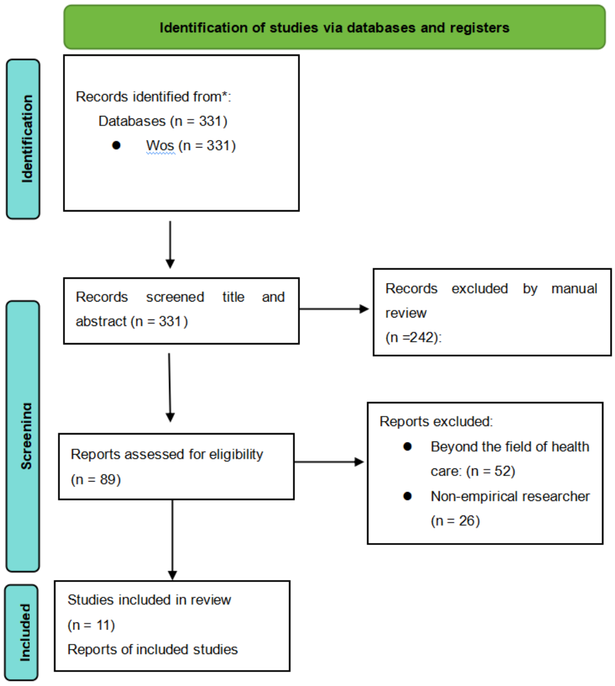

Figure 2. Literature search process

3. Result

The final search results for the literature are shown in Table 2.

Table 2. Summary of literature review results table

No.	Authors	Core Research Objective	Key Technologies	Primary Application Scenarios
1	Chang et al. [7]	Privacy-preserving edge detection	PEFDM, Edge Computing	Home privacy monitoring
2	Chang & Lin	Real-time reporting system	AlphaPose + ST-GCN	Hospital & Homecare
3	Villegas-Ch et al. [8]	Simple & reliable assistant model	Kinect 2.0, Skeletonization	Telemedicine care
4	Yoo & Oh [9]	Wrist-based high-accuracy detection	ANN, Wrist Accelerometer	Convenient wearable care
5	Shalini & Kumar [10]	Transparent & noise-robust system	RNN-LSTM + Explainable AI	Clinical decision support
6	Ko et al. [11]	Integrated health management	Gyro sensor + Heart rate AI	Mobile app monitoring
7	Vaiyapuri et al.	Optimal deep learning for IoT	SqueezeNet + VAE	Smart homecare
8	Tu et al. [12]	Solving data scarcity in wearables	Conditional Diffusion Model	Wrist-based systems
9	Ribeiro et al. [13]	Three-layered computation (Edge/Fog)	Morlet Wavelet + ANN	Non-intrusive homecare
10	Arias-Poblete et al. [14]	Precision risk identification	SVM + EMG signals	Fall risk diagnostic

DOI: 10.54254/2755-2721/2026.AS32450

Table 2. (continued)

11	Juraev et al. [15]	Surveillance action recognition	Transformers + Synthetic Data	Real-world surveillance

Figure 3 illustrates the distribution of primary application scenarios in fall detection research. The results show that wearable-based care and home-related monitoring scenarios (e.g., home privacy monitoring, smart homecare, and non-intrusive homecare) dominate the literature, indicating a strong research focus on continuous, in-situ monitoring for aging populations.

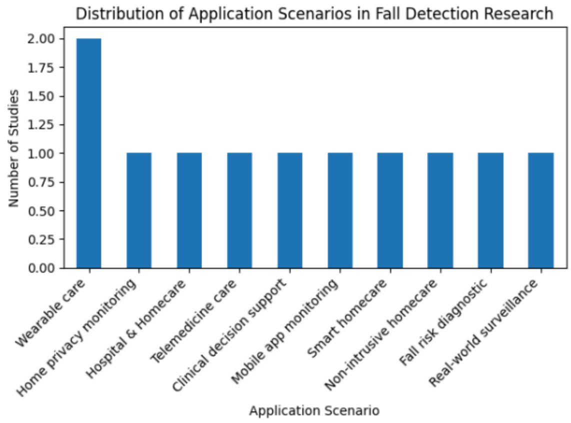

Figure 3. Distribution of primary application scenarios in fall detection research

As shown in Figure 4, the majority of fall detection studies rely on non-generative models (approximately 73%), while only a limited proportion of research adopts generative models (approximately 27%). This imbalance highlights that the application of generative modeling for addressing data scarcity and imbalance in fall detection remains underexplored.

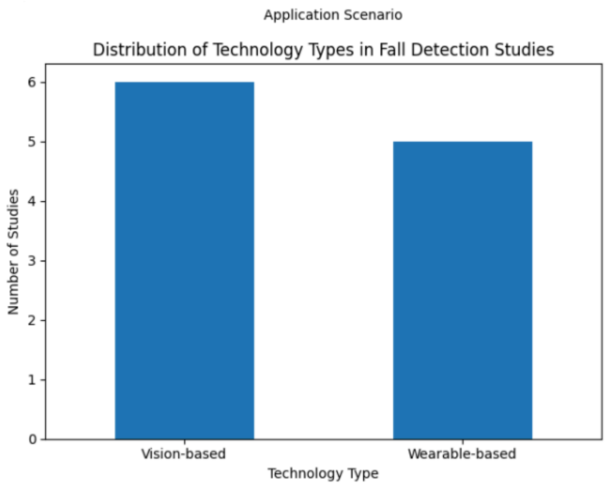

Figure 4. Distribution of technology types adopted in fall detection studies

4. Analysis and discussion

Although the application of artificial intelligence (AI) in fall detection and elderly safety monitoring has aroused widespread research interest, existing studies remain relatively scattered in terms of

DOI: 10.54254/2755-2721/2026.AS32450

perception methods, modeling strategies, and application goals. Current research has not formed a unified methodology or evaluation framework, but rather presents a variety of exploratory practices, which are driven by different technical limitations and deployment environments. This study comprehensively analyzes the current application status of AI-based methods in fall detection and clarifies the main purposes behind these applications.

4.1. Research question 1: how is AI technology specifically applied to the generation and enhancement of home fall detection data

According to published literature, AI-based fall detection can be classified into various overlapping models of application, which are based on the type of data, sensing approach, and the application environment. Computer vision-based vision- and pose-based detectors identify human posture/skeletal characteristics in RGB/depth videos, and deep learning systems including CNNs, ST-GCNs, and Transformers can predict when an individual falls or does not fall; pose-based detectors are typically less sensitive to change in the background, and provide greater protection to personal privacy. Under sensor-based methods, wearable or environmental sensors, like accelerators, gyroscopes, EMG and pressure sensors, submit time-series data that would undergo artificial intelligence algorithms like neural networks, support vegetable machine, or recurrent models to differentiate falls and typical daily activities. More frequently, AI models can additionally be incorporated into edge computing or IoT implementations, where inference is executed on edge devices to minimize latency, bandwidth usage, and privacy threats, instead of focusing directly on algorithm design, but on deployment on smart home systems. Besides, AI is used in data enhancement and augmentation of datasets, where class imbalance and lack of data are addressed in the form of synthetic data sample generation, which also points out the fact that one of the biggest limitations to the study of fall detection is the scarcity of available data.

4.2. Research question 2: what are the primary objectives and challenges of implementing generative models in real-world home safety scenarios

In addition to constructing AI-based fall detection, the literature pinpoints various common factors fueling the idea to use AI in fall detection. Among the essential objectives there is one that is aimed at enhancing safety and promptness in response by automatically tracing falls and informing the caregivers or medical professionals, particularly in a domestic environment where a round-the-clock care cannot be provided. A second important goal is to ease the use of invasive or labor intensive surveillance solutions; AI-based visual/environmental systems are typically not perceived to be obtrusive, but can serve as a background solution, which increases the acceptance of older end users. AI also enables sustained, long-term follow-ups, by processing historical data causing occurrences, which can identify aberrant patterns and risk of falls over time, as opposed to directly concentrating on individual events. Moreover, however, a vast number of works are geared towards solving practical deployment issues, e.g., privacy protection, computational efficiency, and scalability, usually using edge computing or data abstraction methods. Lastly, the research that uses AI in an exploratory tool, building data sets, benchmarking sensing methods and comparing AI models with rule-based systems can also enhance methodological basis of research on fall detection.

DOI: 10.54254/2755-2721/2026.AS32450

5. Conclusion

This paper reviewed and discussed the use of artificial intelligence technologies to detect falls at home, especially in the way of analyzing the information, defining risks, and monitoring safety status among older adults. Analysis indicates that AI-based tools in firewall detectors have various uses in fall detection systems which includes motion features, behavior, long-term tracking, and decision aid. Nevertheless, preserving the promising advances, existing research is incomplete and has constantly had the problem of insufficient data, protection of privacy, and applicability in real-life situations. The presence of most of the current systems remain tested though with limited conditions and are only useful in event-level detection and thus does not have much influence in our daily homesteads. Such a synthesis and the process of identifying common goals and problems in the current state of the investigation allows this study to be seen as contributing to a structure in understanding the current state of the AI-based home fall detection research. The results highlight the necessity of more holistic, privacy-concentrated, and context-sensitive solutions that are more indicative of the real-life situation in aging and home care. The results of this review have some significant suggestions about the future researches concerning the AI-based home fall detector systems. The development of the topic in the future should no longer be based on a simple binary view of falls and non-falls but has to be process-oriented modeling further. The current systems are mostly concerned with the detection of falls as solitary events, without paying attention to pre-fall instability, recovery behavior and post-fall status. Models of AIs with the ability to model dynamics over time and risk building with maturity into risk can be better indicators of the real world of fall incidences and promote preventative measures as opposed to reactive notifications.

References

[1] Gu, D., K. Andreev, and M.E. Dupre, Major trends in population growth around the world. China CDC weekly, 2021. 3(28): p. 604.

[2] Brown, C.V., et al., Risk factors for falls among hospitalized trauma patients. The American Surgeon, 2013. 79(5): p. 465-469.

[3] Gupta, A., et al., Robot learning in homes: Improving generalization and reducing dataset bias. Advances in neural information processing systems, 2018. 31.

[4] Luo, Y., Z. Ye, and R. Lyu. Detecting student depression on Weibo based on various multimodal fusion methods. in Fourth International Conference on Signal Processing and Machine Learning (CONF-SPML 2024). 2024. SPIE.

[5] Niu, T., et al., Decoding student cognitive abilities: a comparative study of explainable AI algorithms in educational data mining. Scientific Reports, 2025. 15(1): p. 26862.

[6] Luo, Y.T., et al., Exploring Information Interaction Preferences in an LLM-Assisted Learning Environment with a Topic Modeling Framework. Applied Sciences, 2025. 15(13): p. 7515.

[7] Chang, W.-J., C.-H. Hsu, and L.-B. Chen, A pose estimation-based fall detection methodology using artificial intelligence edge computing. IEEe Access, 2021. 9: p. 129965-129976.

[8] Villegas-Ch, W., et al., Model for the detection of falls with the use of artificial intelligence as an assistant for the care of the elderly. Computation, 2022. 10(11): p. 195.

[9] Yoo, S. and D. Oh, An artificial neural network–based fall detection. International Journal of Engineering Business Management, 2018. 10: p. 1847979018787905.

[10] Shalini, J. and A. Kumar, An explainable artificial intelligence driven fall system for sensor data analysis enhanced by butterworth filtering. Engineering Applications of Artificial Intelligence, 2025. 158: p. 111364.

[11] Ko, T.-S., B.-J. Kim, and J.-W. Jwa, Development of wearable devices and mobile apps for fall detection and health management. International Journal of Advanced Culture Technology (IJACT), 2023. 11(1): p. 370-375.

[12] Tu, Y.-C., et al., Performance Analysis of Data Augmentation Approaches for Improving Wrist-Based Fall Detection System. Sensors, 2025. 25(7): p. 2168.

[13] Ribeiro, O., L. Gomes, and Z. Vale, IoT-based human fall detection system. Electronics, 2022. 11(4): p. 592.

DOI: 10.54254/2755-2721/2026.AS32450

[14] Arias-Poblete, L., et al., Fall risk detection mechanism in the elderly, based on electromyographic signals, through the use of artificial intelligence. SPORT TK-Revista EuroAmericana de Ciencias del Deporte, 2023: p. 5-5.
[15] Juraev, S., et al., Exploring human pose estimation and the usage of synthetic data for elderly fall detection in real-world surveillance. IEEe Access, 2022. 10: p. 94249-94261.