Shinde Sakshi Jaysing, 2026, 14:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

Ai-Based Elderly Care And Fall Detection: A Review Of Wearable, Ambient And Vision Sensing With Machine Learning And Iot Alerting

Shinde Sakshi Jaysing[1] Prof. S. R. Borhade[2] Prof. M. C. Kolse[3] Prof. S. K. Said[4]
Department of Artificial Intelligence and Data Science
Jaihind College of Engineering
Pune, Maharashtra, India

Abstract—Falls are a leading cause of injury among older adults, and a person who falls while living alone may remain on the floor for a long time before help arrives. AI-based elderly care and fall detection systems monitor movement and alert caregivers when a fall is likely. This paper reviews such systems. It examines wearable approaches using accelerometers and gyroscopes with threshold and machine learning classifiers; ambient approaches using floor, radar and Wi-Fi channel sensing that require nothing to be worn; and vision approaches using cameras and human pose estimation. Public datasets of simulated falls and activities of daily living, deep learning models such as CNNs and LSTMs on motion sequences, and IoT alerting through mobile applications are discussed, along with activity monitoring and basic health tracking within ambient-assisted living. A five-layer architecture comprising sensing, edge inference, connectivity, care platform and caregiver application layers is proposed, together with research gaps, objectives, a comparison of sensing approaches and challenges such as false alarms, missed falls, battery life, connectivity, privacy and the gap between simulated and real-world falls. The review emphasizes that such systems support but do not replace medical professionals and emergency services, and concludes that combining sensing modalities with on-device AI can provide timely, reliable and acceptable support for independent living.

Index Terms—Fall detection, elderly care, wearable sensors, accelerometer, ambient assisted living, machine learning, LSTM, IoT alerts

I. INTRODUCTION

For an older person living alone, a fall can mean hours on the floor, leading to dehydration, pressure injuries and fear of falling again. The World Health Organization identifies falls as a major cause of injury and death among older adults worldwide [1]. In India, as families become smaller and children migrate for work, more elderly people live alone.

Automatic fall detection aims to shorten the time between a fall and help. Mubashir *et al.* [2] surveyed fall detection principles, and Igual *et al.* [3] reviewed challenges, including the difficulty of evaluating systems on real falls. Rashidi and Mihailidis [4] placed fall detection within the broader field of ambient-assisted living.

This paper reviews sensing approaches and AI methods for fall detection and proposes an IoT-based elderly care architecture.

II. BACKGROUND AND RELATED WORK

1. Sensing Approaches

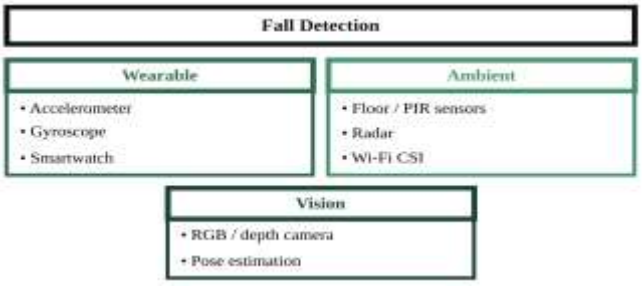


Fig. 1 classifies fall detection systems into wearable, ambient and vision-based approaches.

Fig. 1. Classification of fall detection approaches.

2. Phases Of A Fall

A fall typically consists of a pre-fall phase, a rapid descent with a short period of near free-fall, an impact

© 2026 Shinde Sakshi Jaysing, This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly credited.

with a sharp acceleration peak and a post-fall period of lying still. Detection algorithms look for this pattern.

3. Review Of Related Studies

Wearable. Bourke *et al.* [5] evaluated threshold-based fall detection with a tri-axial accelerometer and showed that upper and lower thresholds on acceleration magnitude can separate many falls from daily activities. Sucerquia *et al.* [6] released SisFall, a dataset of simulated falls and activities recorded with wearable sensors from young and elderly participants, enabling machine learning evaluation. Recurrent networks such as LSTM [7] model temporal patterns in sensor sequences.

Ambient. Wang *et al.* [8] proposed WiFall, which detects falls from changes in Wi-Fi channel state information without any worn device.

Vision. OpenPose [9] estimates body keypoints in real time; the speed and orientation of the torso can indicate a fall.

Systems and challenges. Igual *et al.* [3] noted that most systems are tested on simulated falls by young volunteers, and that false alarms and user acceptance limit real-world use. Rashidi and Mihailidis [4] emphasized privacy and usability for older adults. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Method	Key Findings	Limitations
[5]	Threshold accelerometer detection	Simple, effective thresholds	Simulated falls
[2]	Fall detection survey	Principles and approaches	Review only
[3]	Challenges and trends	Real-world evaluation gap	Review only
[4]	AAL tools survey	Broader elderly care context	Review only
[6]	SisFall dataset	Elderly participants included	Simulated falls
[8]	WiFall Wi-Fi sensing	Device-free detection	Environment-specific
[9]	OpenPose	Real-time keypoints	Camera privacy

III. RESEARCH GAP AND OBJECTIVES

1. Identified Research Gaps

- Few datasets contain real falls of elderly people.
- False alarms lead users to stop wearing or using devices.
- Wearables require charging and remembering to wear them.
- Cameras raise privacy concerns in private rooms.
- Systems rarely combine fall detection with longer-term health trends.

2. Objectives Of The Review

- To review wearable, ambient and vision-based fall detection.
- To examine machine learning models and datasets.
- To study IoT alerting and ambient-assisted living features.
- To propose a five-layer AI-based elderly care architecture.
- To discuss challenges, privacy and responsible deployment.

IV. DESIGN OF THE PROPOSED SYSTEM

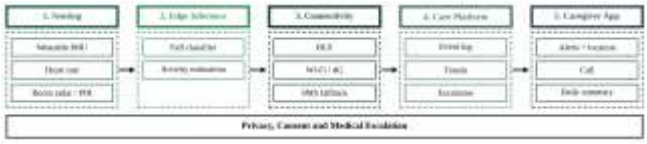


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer AI-based elderly care and fall detection architecture.

1. Sensing Layer

A wrist or waist wearable with accelerometer, gyroscope and optional heart-rate sensor, plus optional room sensors such as radar or PIR, collect data.

2. Edge Inference Layer

A lightweight model on the wearable or a home hub detects falls in real time and estimates activity levels.

3. Connectivity Layer

BLE connects the wearable to a phone or hub; Wi-Fi or mobile data sends alerts, with SMS fallback.

4. Care Platform Layer

A cloud service records events, tracks activity trends and escalates unacknowledged alerts.

5. Caregiver Application Layer

Family members and caregivers receive alerts with location, can call the person and see daily activity summaries.

6. Methodology

Fig. 3 describes the detection workflow. The acceleration magnitude is computed as

$$A = \sqrt{(a_x^2 + a_y^2 + a_z^2)} \quad (1)$$

A candidate fall is flagged when A drops below a free-fall threshold and then exceeds an impact threshold, and a classifier on the surrounding window confirms it. Performance is measured by sensitivity (falls detected) and specificity (non-falls correctly ignored).

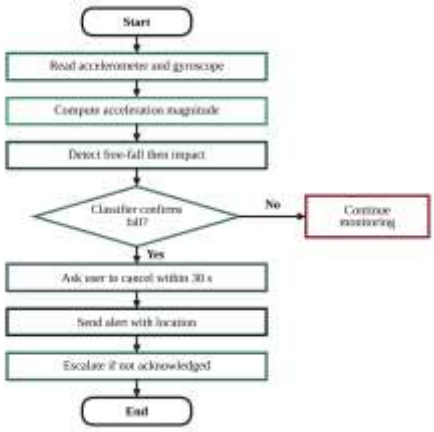


Fig. 3. Fall detection and alerting workflow.

V. DISCUSSION AND COMPARISON

Table II compares sensing approaches. Wearables are accurate and work anywhere but must be worn, ambient sensors are unobtrusive but limited to the home, and vision is informative but raises privacy concerns.

Approach	Accuracy	Coverage	Privacy / Comfort
Wearable threshold	Medium	Anywhere	Must be worn
Wearable + ML	High	Anywhere	Must be worn
Wi-Fi / radar	Medium–High	Home only	Unobtrusive
Camera + pose	High	Room only	Privacy concern

TABLE II Comparison of Fall Detection Sensing Approaches

VI. CHALLENGES AND FUTURE DIRECTIONS

Table III summarizes challenges. Future directions include fall risk prediction from gait, multimodal fusion, voice-based check-ins in local languages and integration with telemedicine.

Challenge	Mitigation
False alarms	ML confirmation; cancel option
Missed falls	Multimodal sensing
Battery life	Low-power edge models
Connectivity	SMS fallback; local alarm
Privacy	On-device processing; no video

TABLE III Challenges and Mitigation

VII. CONCLUSIONS

AI-based fall detection can shorten the time to help and support independent living for older adults. The reviewed literature shows effective wearable, ambient and vision approaches but also persistent problems of false alarms, real-world validation and privacy. A layered IoT system with on-device AI, reliable alerting and caregiver applications can provide continuous support while complementing, not replacing, medical and emergency care.

1. Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the

facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

REFERENCES

1. World Health Organization, "Falls," Fact sheet, Geneva, Switzerland, Apr. 2021.
2. M. Mubashir, L. Shao, and L. Seed, "A survey on fall detection: Principles and approaches," Neurocomputing, vol. 100, pp. 144–152, 2013.
3. R. Igual, C. Medrano, and I. Plaza, "Challenges, issues and trends in fall detection systems," Biomed. Eng. Online, vol. 12, Art. no. 66, 2013.
4. P. Rashidi and A. Mihailidis, "A survey on ambient-assisted living tools for older adults," IEEE J. Biomed. Health Inform., vol. 17, no. 3, pp. 579–590, 2013.
5. A. K. Bourke, J. V. O'Brien, and G. M. Lyons, "Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm," Gait Posture, vol. 26, no. 2, pp. 194–199, 2007.
6. A. Sucerquia, J. D. López, and J. F. Vargas-Bonilla, "SisFall: A fall and movement dataset," Sensors, vol. 17, no. 1, Art. no. 198, 2017.
7. S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Comput., vol. 9, no. 8, pp. 1735–1780, 1997.
8. Y. Wang, K. Wu, and L. M. Ni, "WiFall: Device-free fall detection by wireless networks," IEEE Trans. Mobile Comput., vol. 16, no. 2, pp. 581–594, 2017.
9. Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, and Y. Sheikh, "OpenPose: Realtime multi-person 2D pose estimation using part affinity fields," IEEE Trans. Pattern Anal. Mach. Intell., vol. 43, no. 1, pp. 172–186, 2021.