



AI-Based Elderly Care and Fall Detection: A Review of Wearable Sensors, Machine Learning, IoT, and Edge AI Approaches

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Abstract. The growing number of older adults has increased the need for monitoring tools that can support safety and help caregivers respond quickly. Age-related changes in balance, strength, and movement may make falls more likely, while a person who lives alone may not be able to call for help immediately. This review looks at three studies that use different ways to identify falls. Care Fall analyses smartwatch accelerometer and gyroscope signals with threshold rules and machine-learning methods. A second system combines motion and basic health sensors with a microcontroller and GSM/Wi-Fi alerts. The third approach uses a camera, the YOLOv5s model, and an edge-computing device for visual detection. Together, the studies show that wearable sensors, embedded systems, and camera-based AI can all support fall monitoring, but they differ in cost, privacy, response time, and practical use. Common concerns include false alarms, changes in fall patterns, environmental limitations, battery life, and data protection. The review compares the systems and outlines areas that need further testing before these approaches can be relied on in everyday care.

Keywords: Elderly care, fall detection, artificial intelligence, machine learning, Internet of Things, wearable sensors, edge AI, smart healthcare, emergency alerts.

I. Introduction

Keeping older adults safe is an important concern for families and healthcare providers. With age, a person may experience reduced muscle strength, slower reactions, or changes in balance. These changes can make everyday movement more difficult and can increase the chance of a fall. The concern is greater when someone lives alone or cannot quickly reach a phone after an accident.

Traditional monitoring often depends on family members, nurses, or caregivers being nearby. This support is valuable, but it is difficult for another person to supervise someone continuously. An automatic system could recognise a possible fall and send an alert without requiring the older adult to make a call.



Artificial intelligence (AI) can examine movement signals or images to identify patterns associated with a fall. Internet of Things (IoT) technologies allow sensors and devices to share information with phones, online services, or caregivers. In wearable designs, motion sensors are attached to the person. Embedded systems combine sensors with microcontrollers and communication modules. Camera-based systems examine visual information, while edge computing processes data close to the device instead of sending every item to a remote server.

Each option has benefits and limitations. Wearables collect movement close to the body but must be worn correctly. Camera systems do not require a wearable but need a suitable view of the person and careful privacy protection. Embedded devices can combine sensing with local alarms and remote alerts. Reviewing these options side by side helps identify which issues remain before such systems are used in real homes.

II. Review Methodology and Literature Selection Criteria

This review considers three research papers supplied for the study of AI-based elderly care and fall detection. They were chosen because they describe different technical designs and provide information about sensing, processing, system implementation, or measured performance.

The papers were examined using the following criteria:

- Topic relevance: focus on fall detection, older-adult safety, or health monitoring.
- Technology: use of sensors, AI methods, embedded hardware, or IoT communication.
- Method: explanation of how data are gathered, processed, and classified.
- Evaluation: availability of performance measures or practical observations.
- Application: support for alerts, wearable devices, privacy, or deployment.
- Limitations: challenges reported by the authors and possible improvements.

For each study, the abstract, introduction, technical method, results, discussion, conclusion, and references were considered. The key information was then grouped to compare design choices, strengths, and limitations. Since the studies use different datasets, devices, and metrics, their reported numbers should be read in the context of each original experiment rather than treated as a direct head-to-head test.

III. Literature Review

1. Care Fall: Automatic Fall Detection through Wearable Devices and AI Methods

Ruiz-Garcia and colleagues (2023) describe Care Fall, a fall-monitoring approach built around a smartwatch. The watch uses a three-axis accelerometer and a three-axis gyroscope to record changes in movement and rotation. The paper compares a rulebased method, which checks signals against chosen thresholds, with machine-learning methods that use features taken from the sensor data.

The evaluation uses the Erciyes University and UMA Fall datasets. The authors report better classification when accelerometer and gyroscope information is combined with machine learning than with the threshold-based approach alone. On the Erciyes



dataset, the reported results are 98.4% accuracy, 98.9% sensitivity, and 96.7% specificity. On UMA Fall, the reported values are 95.5% accuracy, 98.6% sensitivity, and 93.7% specificity.

These results suggest that combining movement signals can help separate falls from ordinary activities. However, the experiments rely on existing recordings and simulated falls. More testing with different users, daily routines, and real care settings is needed before assuming that the same performance will be achieved in practice.

2. AI-Powered Elderly Fall Detection

The paper by Niraimathi, Akshatha, and Harini (2026) presents a wearable IoT device intended to detect falls and monitor basic health information. An ESP8266 or ESP32 microcontroller connects to an MPU6050 motion sensor, a DS18B20 temperature sensor, and a pulse sensor. The design also includes a buzzer, a 16×2 LCD, a SIM800L GSM module, and the Blynk IoT application.

The described detection method checks acceleration magnitude against set thresholds and uses gyroscope readings as additional movement information. When a possible fall is identified, the device can sound a buzzer, display an emergency message, send an SMS through GSM, and share readings through Blynk over Wi-Fi.

For simulated forward falls, the paper reports 93.3% detection, while backward falls are detected at 86.7%, giving an average sensitivity of about 90%. The reported false-positive rate during normal activity is 6.7%. SMS alerts take around 5–8 seconds, and Blynk updates have a latency below two seconds when Wi-Fi is stable. A key advantage is that motion sensing, basic health monitoring, and alerts are brought together in one design. However, false alarms, differences between users and fall types, missing GPS location, and battery life remain concerns.

One point needs careful interpretation: the abstract refers to machine learning, while the detailed method and conclusion describe threshold-based decisions. This makes the implemented algorithm less clear. Larger tests and a more precise description of the method would make the results easier to assess.

3. Edge AI-Based Fall Detection for an Elderly Care Robot

Ben Halima, Ben Abdallah, and Haggege present a camera-based system intended for use with an elderly-care robot. An RGB camera captures images, and an NVIDIA Jetson Nano processes them locally. The YOLOv5s object-detection model identifies visual patterns, while additional processing over time helps distinguish a fall from postures such as sitting or standing.

The paper describes a dataset of 4,116 images assembled from public fall-detection image collections and divided into training, validation, and test sets. The system runs inference on the edge device and sends a short alert to a caregiver after a fall is confirmed.

The reported test results include 93.6% precision, 92.8% recall, 95.8% mean Average Precision at an IoU threshold of 0.5, and 66.5% mAP at an IoU threshold from 0.5 to 0.95. Processing speed is reported at about seven frames per second without TensorRT and up to twelve frames per second with optimisation. Local processing can reduce the need to send continuous video to a cloud service. Still, lighting, camera position, blocked views, and complex backgrounds can affect detection. The authors also point to the need for more realistic home testing and stronger attention to privacy and response time.



IV. Comparative Analysis of Existing Studies

The three studies approach the same problem using different sensing and processing designs. Care Fall uses movement data from a wearable; the embedded IoT design connects several sensors to a microcontroller and sends alerts; the edge-AI design analyses camera images locally. Their hardware, communication methods, and reported performance measures are therefore not identical.

1. Comparison of System Architecture

Care Fall analyses smartwatch accelerometer and gyroscope readings with threshold rules or machine-learning models. It can focus on the wearer's movement without requiring a camera in the room. The embedded sensor system gathers motion and physiological readings, processes them on a microcontroller, and can activate a buzzer or LCD while sending alerts through GSM or Wi-Fi. The camera-based design uses an RGB camera and YOLOv5s on an NVIDIA Jetson Nano, with TensorRT optimisation to improve processing speed.

2. Comparison of Reported Performance

Care Fall reports accuracy, sensitivity, and specificity for two datasets. The embedded 2026 system reports detection sensitivity for forward and backward simulated falls, a false-positive rate, and notification timing. The edge-AI study reports precision, recall, mAP, and frames per second. These measures describe different aspects of performance and should not be compared as if all systems were tested under one common experiment.

3. Comparison Table

Feature	Care Fall (2023)	AI-Powered Fall Detection (2026)	Edge AI Fall Detection (2025)
Main approach	Wearable AI	Embedded sensor system	Camera-based edge AI
Data source	Accelerometer and gyroscope	Motion and physiological sensors	RGB camera frames
Processing	Thresholds and machine learning	Threshold-based decisions with sensor inputs	YOLOv5s object detection
Hardware	Smartwatch / wearable sensors	ESP8266/ESP32 and sensor modules	NVIDIA Jetson Nano and camera
Communication	Depends on implementation	GSM SMS and Wi-Fi/Blynk	Local edge processing; alert method depends on implementation
Reported metrics	Accuracy, sensitivity, specificity	Sensitivity, false-positive rate, alert latency	Precision, recall, mAP, FPS
Main benefit	Detailed movement information	Integrated sensing and remote alerts	No dedicated wearable is required
Main challenge	Generalisation and consistent use	False alarms and communication reliability	Lighting, occlusion, camera position, privacy



IV. Interpretation of the Comparison

No single design removes every difficulty. Wearables can measure movement directly but depend on the person wearing the device. Embedded systems can provide local warnings and remote messages, but their decision rules must avoid confusing ordinary activity with a fall. Camera-based systems remove the need for a wearable but require a useful camera view and introduce additional privacy considerations.

A future design could combine selected features—for example, using wearable measurements and another sensor to verify uncertain events. Such a combination would need careful testing and clear privacy safeguards. Additional sensors may improve confidence, but they can also raise cost, energy use, maintenance effort, and system complexity.

V. Research Challenges and Identified Gaps

1. False Alarms and Missed Falls

A system must tell a genuine fall apart from normal actions such as sitting quickly, bending, or lying down. Too many incorrect alerts may cause caregivers to stop responding carefully, while a missed fall may delay help. The reviewed studies use different solutions, but their evaluations are not standardised. Shared test scenarios would make their strengths and weaknesses easier to compare.

2. Differences in Fall Patterns

Falls may happen forward, backward, or sideways, and movement is affected by a person's ability, walking aids, furniture, and surroundings. The embedded study reports different detection rates for forward and backward falls. Future evaluations should include a wider range of movements and users instead of relying mainly on a small set of recorded examples.

3. Environmental and Sensor Limitations

Wearable readings may change with sensor position, orientation, noise, or inconsistent use. Embedded devices can be affected by calibration, loose connections, or power interruptions. Camera systems may struggle with poor lighting, awkward angles, blocked views, or a person moving outside the frame. Reliable hardware installation and fault handling are as important as the detection algorithm.

4. Real-Time Processing and Communication

A useful system needs to detect an event and notify a caregiver quickly. Processing speed, network availability, and message delivery can all affect response time. The reviewed papers report different measures, including SMS delivery, Blynk latency, and video frame rate. Future work should measure the complete delay from a fall event to successful receipt of an alert.

5. Privacy and Data Protection

Monitoring may involve movement records, health readings, or images from a private home. Such information can reveal personal routines, and video may identify a person or their surroundings. Systems should collect only necessary data, restrict access, and protect information in storage and during transmission. Where possible, local processing and limited retention of raw data can reduce exposure. Users should be told clearly what is collected and why.



6. Energy Use and Maintenance

Devices intended for continuous monitoring must operate for long periods. Sensing, wireless communication, and computation all use power, and frequent charging may be inconvenient. Designs should consider efficient algorithms, suitable batteries, and low-battery alerts. Caregivers also need simple ways to notice disconnected sensors and communication failures.

7. Limited Comparability of Published Results

The studies use different datasets, hardware, and evaluation measures. High sensitivity from a wearable experiment cannot be directly compared with high precision from a camera-based experiment, and frame rate alone does not show how accurately falls are detected. A common evaluation protocol should report relevant measures such as sensitivity, specificity, precision, recall, false alarms, missed falls, energy use, and end-to-end alert delay.

8. Methodological Transparency

Research papers should explain their hardware, data collection, algorithms, decision rules, training process, and evaluation clearly. In the 2026 sensor-based paper, the abstract mentions machine learning while the detailed method describes threshold-based decisions. Future studies should state whether a system uses fixed thresholds, a trained classifier, or a combination, and explain how its model or thresholds were selected so others can repeat the evaluation.

VI. Conclusion and Future Scope

This review considered three ways of supporting elderly fall detection through AI, wearable devices, embedded sensors, IoT communication, and edge computing. Care Fall uses smartwatch accelerometer and gyroscope signals with machine-learning methods. The AI-Powered Elderly Fall Detection design combines motion and basic health sensors with a microcontroller and emergency alerts. The edge-AI study applies YOLOv5s to camera images on an embedded computing device.

The reported findings show that each approach has potential, but each also has practical limits. Wearables depend on regular use and reliable sensor readings. Embedded systems must distinguish falls from normal movement and maintain dependable communication. Camera-based systems need suitable visual coverage and must address lighting, obstruction, processing speed, and privacy.

The reported scores cannot be treated as a direct ranking because the studies were not evaluated under the same conditions or with the same metrics. Future work should test systems in realistic settings, reduce false alarms, improve notification reliability, manage energy use, and protect personal information. Researchers should also describe their algorithms clearly so that results can be reproduced. Lightweight AI, context-aware decisions, carefully chosen sensor combinations, and local processing may be useful directions, but these ideas need further evaluation. The overall aim is to develop affordable, dependable, comfortable, and privacy-aware systems that help caregivers and support older adults' safety and independence.

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