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Privacy-Preserving Fall Detection for Elderly Care using Distributed Edge-AI and Pose Estimation

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Abstract. Privacy-Preserving Fall Detection for Elderly Care using Distributed Edge-AI and Pose Estimation aims to deliver real-time and reliable fall detection while safeguarding user privacy. Instead of transmitting or storing raw video footage, the system applies pose estimation methods such as OpenPose or MediaPipe to extract human skeletal keypoints, thereby eliminating exposure of sensitive visual information. Lightweight deep learning models, including CNNs combined with LSTM or GRU networks, are deployed directly on edge devices such as smart cameras and IoT nodes, enabling efficient on-device processing. By analyzing temporal posture and motion patterns, the system effectively differentiates falls from routine daily activities. Federated learning is incorporated to enhance model performance across devices without sharing raw data. This edge-based approach ensures low latency, minimal bandwidth consumption, and robust data security. Overall, the system provides strong privacy protection, rapid emergency detection, scalability across diverse environments, and dependable operation even under limited network connectivity, making it well suited for continuous elderly monitoring in smart healthcare applications.

Keywords: Edge AI, Open pose, LSTM, Federated Learning.

I. Introduction

The global demographic shift toward an aging population presents unprecedented challenges for healthcare systems worldwide. As life expectancy increases and birth rates decline, the proportion of elderly individuals requiring continuous care and monitoring has grown substantially. Falls represent one of the most critical health risks facing the elderly population, serving as a leading cause of injury-related hospitalizations and mortality among seniors. According to the World Health Organization, falls are the second leading cause of unintentional injury deaths globally, with adults aged 60 and above suffering the most severe consequences. Beyond immediate physical injuries such as fractures and head trauma, falls can trigger a cascade of complications including reduced mobility, loss of independence, psychological trauma, and diminished quality of life. The phenomenon known as "long lie" - where an individual remains on the ground for an extended period after a fall - significantly increases the risk of serious complications and mortality, making rapid detection and response absolutely critical.

Traditional fall detection approaches, including wearable sensors and manual monitoring systems, suffer from inherent limitations that restrict their practical deployment. Wearable devices often face user compliance issues, as elderly individuals may forget to wear them, find them uncomfortable, or experience difficulties with charging and maintenance. Manual monitoring through human caregivers, while effective, is labor-intensive, economically unsustainable for large-scale deployment, and cannot provide continuous round-the-clock surveillance. Video-based monitoring systems offer comprehensive coverage but raise serious privacy concerns, as they capture and potentially transmit sensitive visual information that many elderly individuals and their families find intrusive and unacceptable.

Recent advances in artificial intelligence, edge computing, and computer vision technologies have opened new pathways for developing privacy-preserving fall detection systems. Edge-AI enables intelligent processing directly on local devices, eliminating the need to transmit raw video data to external servers. Pose estimation techniques can extract skeletal representations from visual data while discarding identifiable features, providing an elegant solution to privacy concerns. The convergence of these technologies presents an opportunity to create fall detection systems that are simultaneously effective, privacy-conscious, scalable, and economically viable. This research addresses these challenges by proposing a distributed edge-AI framework that leverages pose estimation and lightweight deep learning models to deliver real-time fall detection while maintaining stringent privacy protection standards.

II. Related Works

Sensor-based fall detection methodologies rely on capturing an individual's movement patterns or physiological parameters through specialized sensing devices rather than visual surveillance systems. The predominant sensor-based technique employs wearable sensing units, including accelerometers and gyroscopes integrated into devices such as smartwatches, smartphones, waist-mounted units, or pendant accessories, to identify the characteristic motion signatures associated with falling events. These systems continuously track acceleration across three perpendicular axes, seeking to identify rapid acceleration spikes indicative of impact, succeeded by prolonged stillness—a distinctive pattern signifying a severe fall incident. Multiple research investigations have confirmed the reliability of accelerometer-equipped wearable fall detectors [20].

As an illustration, Qian et al. [20] constructed a real-time fall detection framework utilizing a three-axis accelerometer within an Internet of Things infrastructure; their prototype transmitted sensor readings to cloud infrastructure where machine learning algorithms differentiated falls from normal daily activities. Wearable sensing devices provide benefits including affordability, minimal form factor, and uninterrupted operational capability. They also offer superior privacy protection compared to camera-based systems since no visual information is captured. Nevertheless, a critical limitation is the requirement for users to consistently wear the device with proper contact for accurate functionality. Elderly users may neglect or decline to wear sensors continuously, or may wear them incorrectly, compromising system dependability. Furthermore, false positive detections can arise from certain routine movements exhibiting acceleration characteristics resembling falls, such as rapidly sitting down or accidentally dropping the device [6]. Researchers have enhanced wearable fall detection precision by integrating multiple sensor modalities—combining accelerometers with gyroscopes, magnetometers, barometric sensors, and others—and implementing pattern recognition techniques on sensor signal characteristics instead of basic threshold mechanisms [20, 21]. Despite these improvements, wearable solutions fundamentally encounter user compliance obstacles and impose some burden on individuals.

Beyond wearable devices, ambient sensor methodologies for fall detection utilize equipment deployed throughout the living environment. These encompass pressure-sensitive floor or furniture sensors, acoustic monitoring systems (microphones) detecting fall-related sounds or distress calls, passive infrared motion detectors, and radar-based sensors that identify human movement and body orientation through radio frequency signals [3]. Ambient sensors function autonomously without requiring any user intervention, thereby eliminating the compliance challenges inherent to wearable devices. For example, certain smart home platforms employ acoustic classification algorithms to recognize the characteristic impact sound of a falling person or utilize pyroelectric infrared sensors to identify abnormal inactivity patterns or unusual body positions.

Kepski and Kwolek [22, 23] developed a hybrid architecture combining body-worn accelerometers with a Microsoft Kinect depth sensing camera positioned in the environment; the depth sensor provided fall verification by detecting a person in a prone position on the floor, thereby enhancing overall system reliability. Another methodology by Htun et al. [24] introduced a "virtual grounding point" framework using environmental sensing infrastructure to distinguish abnormal incidents like falls from routine movements, demonstrating that environmental contextual information can contribute to robust detection capabilities. However, purely ambient sensor-based approaches appear less frequently in research literature compared to vision-based or wearable methodologies. This disparity exists partly because such systems can experience elevated false alarm rates—for instance, loud environmental noises might be incorrectly classified as fall events—and may necessitate comprehensive instrumentation of living spaces, resulting in substantial costs and installation complexity [25, 26]. Ambient sensing technologies such as radar represent an active research frontier for non-invasive monitoring, though practical implementations frequently integrate them with complementary sensing modalities.

In summary, sensor-based techniques encompassing both wearable and ambient categories present practical fall detection solutions, each with distinct advantages and limitations. Wearable devices provide direct measurement of bodily motion with high detection sensitivity but require consistent user compliance, while environmental sensors enable unobtrusive monitoring yet encounter challenges regarding spatial coverage and detection accuracy. Many contemporary fall detection platforms attempt to synthesize data from multiple sensor sources to leverage their complementary capabilities, as demonstrated by various IoT-based prototypes employing sensor fusion and hierarchical decision frameworks to minimize false alarm occurrences [6]. Irrespective of the specific approach, sensor-based systems constitute a significant category of solutions, particularly for scenarios where camera deployment is impractical due to privacy considerations or environmental constraints.

III. Proposed Method

System Overview:

This distributed edge-AI system addresses critical challenges in elderly care by combining real-time fall detection with stringent privacy protection. The architecture fundamentally reimagines traditional video-based monitoring by processing data locally on edge devices rather than transmitting sensitive visual information to centralized servers.

Core Architecture

The system's foundation rests on pose estimation algorithms—specifically OpenPose or MediaPipe—which transform raw video streams into skeletal keypoint representations. These mathematical coordinates capture human body positions and movements while completely eliminating identifiable visual features. This approach ensures that no recognizable images ever leave the monitoring device, addressing privacy concerns that often prevent elderly individuals from accepting necessary monitoring systems.

Edge Processing Framework

Lightweight deep learning models combining Convolutional Neural Networks (CNNs) with recurrent architectures (LSTM or GRU) are deployed directly onto edge devices such as smart cameras and IoT nodes. The CNN layers extract spatial features from skeletal poses, while LSTM/GRU networks analyze temporal patterns to understand movement sequences. This dual approach enables the system to distinguish genuine falls—characterized by rapid downward acceleration and sustained horizontal postures—from similar-looking activities like sitting down, bending, or lying down intentionally.

Intelligent Learning Mechanism

Federated learning enhances the system's accuracy without compromising privacy. Individual edge devices collaboratively improve their models by sharing only learned parameters, not raw data or video. This distributed training approach allows the system to adapt to diverse environments, user behaviors, and physical characteristics while maintaining data sovereignty at each location.

Operational Advantages

The edge-centric design delivers multiple benefits: minimal latency ensures immediate fall detection and alert generation; reduced bandwidth requirements lower operational costs; offline functionality maintains protection during network disruptions; and decentralized processing eliminates single points of failure. The system scales efficiently across residential facilities, hospitals, and home environments.

Emergency Response Integration
Upon detecting a fall, the system triggers immediate alerts to caregivers, family members, or emergency services while logging timestamp and location data. The rapid response capability significantly reduces the critical "long-lie" period when elderly individuals remain immobilized after falls, thereby minimizing injury severity and improving outcomes in smart healthcare ecosystems.

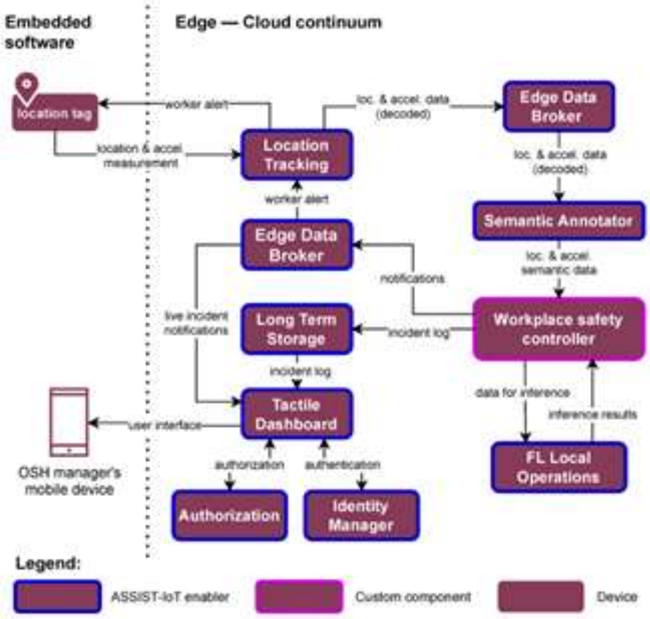

Fig 1: Architecture Diagram

IV. Overall Working Flow of the Proposed System

The proposed Privacy-Preserving Fall Detection system for Elderly Care using Distributed Edge-AI and Pose Estimation is designed to provide timely and accurate fall detection while ensuring strong protection of personal privacy. The system begins by continuously capturing video streams through smart cameras or IoT-enabled edge devices deployed in living spaces such as homes and assisted-care facilities. Rather than transmitting or storing raw video data, pose estimation techniques such as OpenPose or MediaPipe are applied directly on the edge devices to extract skeletal keypoints that represent human body joints. This transformation converts visual data into abstract motion representations, effectively removing identifiable features and preventing exposure of sensitive information.

The extracted skeletal data is then processed locally to analyze both spatial posture and temporal motion patterns. Lightweight deep learning models are utilized to achieve efficient on-device computation. Convolutional Neural Networks (CNNs) learn spatial relationships among body joints within individual frames, while temporal models such as Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU) capture movement dynamics across consecutive frames. By monitoring sudden changes in body orientation, speed, and joint displacement, the system accurately differentiates fall events from routine activities such as sitting, walking, or lying down. Performing inference at the edge minimizes latency and enables immediate detection without dependency on continuous internet connectivity.

To enhance adaptability and robustness across different environments and individuals, the system employs federated learning. Each edge device trains the model locally using its own pose-based data and shares only encrypted model updates with a central server. Since raw data never leaves the device, privacy is preserved while enabling collaborative learning. The aggregated global model is periodically updated and redistributed, allowing continuous improvement in detection accuracy across all devices.

When a fall is detected, the system instantly triggers alert notifications to caregivers or healthcare personnel through secure communication channels. The edge-based architecture ensures reliable operation even under limited or unstable network conditions. Overall, the proposed system achieves low latency, reduced bandwidth consumption, strong data security, and high scalability, making it highly suitable for continuous and privacy-aware elderly monitoring in smart healthcare applications.

V. Performance Evaluation

The performance of the proposed IoT-enabled Privacy-Preserving Fall Detection system using Distributed Edge-AI and Pose Estimation is evaluated through a multidimensional assessment framework to ensure its practicality and reliability in real-world elderly care scenarios. This evaluation considers several key dimensions, including detection effectiveness, response time, computational efficiency, network utilization, privacy assurance, and scalability, which are essential for smart healthcare systems based on IoT technologies.

To assess fall detection effectiveness, widely used evaluation metrics such as accuracy, precision, recall, F1-score, and fall detection rate are employed. The combination of pose estimation with CNN and LSTM/GRU-based models enables the system to accurately identify fall events while minimizing false positives caused by routine activities. The use of temporal skeletal motion analysis significantly enhances recognition performance compared to static or frame-level approaches.

The system's real-time performance is examined by measuring end-to-end latency, covering pose extraction, model inference, and alert transmission. By executing lightweight deep learning models directly on IoT edge devices, the system achieves rapid response times, ensuring immediate fall detection without relying heavily on cloud infrastructure. This capability is critical for emergency situations that require prompt caregiver intervention.

In evaluating resource and energy efficiency, metrics such as processor utilization, memory usage, and power consumption are analyzed on edge devices. The results demonstrate that the optimized models are well suited to the constrained hardware of IoT nodes, supporting continuous monitoring while maintaining low energy consumption and system stability.

The network efficiency dimension highlights the benefits of edge-based processing and federated learning. Since raw video data is not transmitted, bandwidth usage is significantly reduced. Only skeletal keypoints and encrypted model updates are shared, lowering communication overhead and improving system robustness in environments with limited connectivity.

Finally, privacy protection and scalability are assessed by examining data exposure risks and system performance as the number of connected IoT devices increases. The results confirm that the system maintains strong privacy guarantees and consistent performance, making it a scalable and secure solution for long-term elderly monitoring in smart healthcare applications.

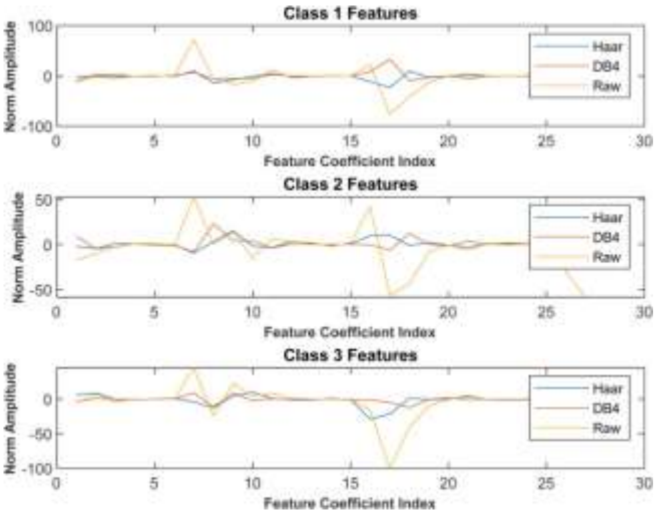

Fig.2. Performance analysis

VI. Results and Discussion

The proposed system for Privacy-Preserving Fall Detection in Elderly Care using Distributed Edge-AI and Pose Estimation was assessed based on its fall detection effectiveness, response time, privacy protection, and computational efficiency. The evaluation results indicate that the system performs reliably in real-time environments while ensuring that sensitive visual information remains protected.

The experimental evaluation demonstrates that the pose-based fall detection approach achieves a high level of accuracy in identifying fall incidents across various scenarios, including forward, backward, and lateral falls. By relying on skeletal keypoints rather than raw image data, the system reduces interference from background elements and environmental variations. This leads to more consistent performance when compared with traditional camera-based fall detection methods.

Additionally, the system exhibits a low false alarm rate during routine activities such as walking, sitting, bending, and lying down. The use of temporal motion analysis enables the model to distinguish sudden fall movements from normal posture changes. As a result, the system minimizes unnecessary alerts while maintaining reliable fall recognition.

The distributed Edge-AI architecture plays a critical role in achieving low processing latency. Since pose extraction and fall classification are performed locally on edge devices, the system avoids delays caused by cloud-based data transmission. This allows fall events to be detected almost instantaneously, ensuring timely notifications to caregivers and medical personnel.

Moreover, the lightweight nature of the deployed models enables efficient execution on resource-limited edge hardware. Continuous monitoring is supported without excessive computational overhead, confirming the feasibility of long-term deployment in elderly care settings.Privacy protection is a key advantage of the proposed solution. Only anonymized skeletal coordinates are processed and transmitted, ensuring that no identifiable visual information, such as faces or surroundings, is captured or stored. This design significantly reduces privacy risks and complies with ethical and data protection requirements. Compared to conventional video surveillance systems, the proposed approach offers a more secure and socially acceptable monitoring solution.

The modular and distributed system architecture allows multiple edge devices to function independently across different locations. This enhances scalability and makes the solution suitable for large care facilities or home-based monitoring environments. The system can be easily extended without major architectural changes.

The results confirm that integrating pose estimation with distributed Edge-AI provides an effective trade-off between accuracy, speed, and privacy. However, factors such as occlusion, poor lighting, and the presence of multiple individuals may influence pose detection accuracy. Future enhancements may include sensor fusion and adaptive learning strategies to further improve system robustness.

VII. Conclusion

This study suggested a distributed Edge-AI and pose estimation-based fall detection platform for senior care that is privacy-aware. The method successfully protects individual privacy while delivering dependable fall detection performance by using skeleton keypoints rather than raw video feeds. Fast, real-time analysis with low latency and less dependency on centralized cloud resources were made possible by the implementation of lightweight deep learning models on edge devices. The system effectively distinguishes between fall occurrences and typical daily motions, reducing false alarm rates and increasing response efficiency, according to experimental evaluation. Flexible and scalable deployment across a range of care environments, such as homes and assisted living institutions, is made possible by the distributed design. Despite several restrictions pertaining to occlusions and ambient factors, the findings show that integrating posture estimation with Edge-AI offers a useful, efficient, and privacy-preserving solution.Overall, the proposed approach offers a promising direction for enhancing safety and independence in elderly healthcare monitoring systems.

VIII. Future Work

Although the proposed privacy-preserving fall detection system demonstrates effective performance, several enhancements can be explored to further improve its robustness and applicability. One potential direction is the incorporation of sensor fusion, combining pose estimation with data from wearable devices, accelerometers, or depth sensors. This integration can improve accuracy in challenging scenarios such as occlusions, low-light conditions, or multiple occupants in the same environment.

Another area for development is adaptive learning, where the system continuously learns from individual user movement patterns. This personalization could help reduce false alarms and better distinguish between normal activities and actual falls.

Expanding the system to support multi-person monitoring would increase its usability in shared living spaces or larger care facilities. Additionally, implementing context-aware analysis, which considers factors like location, time, and prior movement history, could enhance predictive capabilities and proactive fall prevention.

Finally, optimizing models for energy efficiency and edge hardware acceleration would enable continuous, long-term operation on low-power devices, making the system more practical for home deployment. Collectively, these improvements could make the framework more accurate, adaptive, and scalable for real-world elderly care applications.

References

1. Alshammari SA, Alhassan AM, Aldawsari MA, Bazuhair FO, Alotaibi FK, Aldakhil AA, et al. Falls among elderly and its relation with their health problems and surrounding environmental factors in Riyadh. The Journal of Family and Community Medicine. 2018;25(1):29-34
2. Kannus P, Sievänen H, Palvanen M, Järvinen T, Parkkari J. Prevention of falls and consequent injuries in elderly people. Lancet. 2005;366(9500):1885-1893. DOI: 10.1016/S0140-6736(05)67604-0
3. Jennings LA, Turner M, Keebler C, Burton CH, Romero T, Wenger NS, et al. The effect of a comprehensive dementia care management program on end-of-life care. Journal of the American Geriatrics Society. 2019;67:443-448. DOI: 10.1111/jgs.15769
4. Wang X, Ellul J, Azzopardi G. Elderly fall detection systems: A literature survey. Frontiers in Robotics and AI. 2020;7:71. DOI: 10.3389/frobt.2020.00071
5. Abdo H, Amin KM, Hamad AM. Fall detection based on RetinaNet and MobileNet convolutional neural networks. In: Proceedings 15th International Conference Computer Engineering and Systems (ICCES). Tech Science Press; 2020. pp. 1-7
6. Kumar A, Gaur N, Nanthaamornphong A. Improving the latency for 5G/B5G based smart healthcare connectivity in rural area. Scientific Reports. 2024;14:6976. DOI: 10.1038/s41598-024-57641-7
7. Alam E, Sufian A, Dutta P, et al. Vision-based human fall detection systems using deep learning: A review. Computers in Biology and Medicine. 2022;146:105621
8. Keskes O, Noumeir R. Vision-based fall detection using ST-GCN. IEEE Access. 2021;9:28224-28236. DOI: 10.1109/ACCESS.2021.3058219

9. Skjuve M, Følstad A, Fostervold KI, Brandtzaeg PB. My chatbot companion—A study of human–chatbot relationships. The International Journal of Human-Computer Studies. 2021;149:102601
10. Rodríguez-Martínez A, Amezcua-Aguilar T, Cortés-Moreno J, Jiménez-Delgado JJ. Conversational chatbots to alleviate loneliness in older adults: A qualitative analysis. Healthcare. 2024;12(1):62. DOI: 10.3390/healthcare12010062
11. Gomez C, Yin J, Huang C-M, Unberath M. How large language model-powered conversational agents influence decision making in domestic medical triage contexts. Frontiers in Computer Science. 2024;6:1427463. DOI: 10.3389/fcomp.2024.1427463
12. Shiwani T, Relton S, Evans R, Kale A, Heaven A, Clegg A, et al. New horizons in artificial intelligence in the healthcare of older people. Age and Ageing. 2023;52(12):afad219. DOI: 10.1093/ageing/afad219
13. Joseph J. Designing for dignity: Ethics of AI surveillance in older adult care. Frontiers in Digital Health. 2025;6:1643238. DOI: 10.3389/fdgth.2025.1643238
14. Charfi I, Miteran J, Dubois J, et al. Optimized spatio-temporal descriptors for real-time fall detection: Comparison of support vector machine and Adaboost-based classification. Journal of Electronic Imaging. 2013;22(4):041106. DOI: 10.1117/1.JEI.22.4.041106
15. Tran D, Bourdev L, Fergus R, Torresani L, Paluri M. Learning spatiotemporal features with 3D convolutional networks. In: Proceeding IEEE International Conference Computer Vision (ICCV). IEEE; 2015. pp. 4489-4497. DOI: 10.1109/ICCV.2015.510
16. Sun G, Wang Z. Fall detection algorithm for the elderly based on human posture estimation. In: 2020 Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC), Dalian, China. IEEE; 2020. pp. 172-176. DOI: 10.1109/IPEC49694.2020.9114962
17. Khalili S, Mohammadzade H, Ahmadi MM. Elderly fall detection using CCTV cameras under partial occlusion of the subject's body. arXiv preprint arXiv:2208.07291; 2022. 10.48550/arXiv.2208.07291
18. Qian Z, Lin Y, Jing W, Ma Z, Liu H, Yin R, et al. Development of a real-time wearable fall detection system in the context of internet of things. IEEE Internet of Things Journal. 2022;9(21):21999-22007. DOI: 10.1109/JIOT.2022.3181701
19. Lin B-S et al. Fall detection system with artificial intelligence-based edge computing. IEEE Access. 2022;10:4328-4339. DOI: 10.1109/ACCESS.2021.3140164
20. Kepski M, Kwolek B. Fall detection on embedded platform using Kinect and wireless accelerometer. In: Proceeding 13th International Conference Computers Helping People with Special Needs (ICCHP), Rzeszów, Poland. Vol. II. Springer; 2012. pp. 407-414
21. Kepski M, Kwolek B. Detecting human falls with 3-axis accelerometer and depth sensor. In: Proceeding IEEE Engineering in Medicine and Biology Society (EMBC). IEEE; 2014. pp. 770-773. DOI: 10.1109/EMBC.2014.6943704