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EDGE AI FOR FALL DETECTION: EVALUATING AI MODELS ON MOBIFALL FOR REAL-WORLD USE

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Abstract

This paper presents a comparative analysis of deep learning models for fall detection, focusing on their accuracy, resource efficiency, and deployment feasibility for edge devices. Leveraging the MobiFall dataset, we evaluate state-of-the-art models, including ConvLSTM with Exponential Smoothing Forecasting (ESF), CABMNet (a hybrid CNN-BiLSTM architecture with attention mechanisms), a denoising LSTM-based Convolutional Variational Autoencoder (CVAE), and FedVAE (a federated learning framework). Each model is assessed based on its ability to balance computational efficiency with detection performance. Our findings highlight trade-offs between model complexity and resource constraints, with the denoising CVAE emerging as the most deployment-ready for wearable devices due to its lightweight architecture and minimal reliance on labeled data. In contrast, models like CABMNet achieve higher accuracy but at the cost of increased computational overhead. The study concludes with recommendations for future research, emphasizing the need for lightweight models, explainable AI (XAI), and real-world validation to improve the practicality and scalability of fall detection systems.

***Index Terms—** Fall Detection, Deep Learning, Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Attention Mechanisms, Variational Autoencoders (VAE), Unsupervised Learning, Resource-Constrained Devices, Wearable Technology, Federated Learning, Explainable AI (XAI), Remote Patient Monitoring (RPM)*

I. INTRODUCTION

Falls represent a significant global health challenge, ranking as the second leading cause of unintentional injury deaths worldwide. Each year, approximately 37.3 million falls require medical intervention [1]. According to the Global Burden of Diseases Study, falls rank as the 18th leading cause of disability-adjusted life years [2]. While the burden of falls is most pronounced among older adults—where they are the leading cause of injury-related deaths for individuals aged 70 and above—children also represent a high-risk group, with falls accounting for the majority of recorded injuries in several studies. This underscores the urgent need for targeted interventions across all age groups to address fall-related injuries more effectively [3].

Over the past decade, extensive research has focused on fall detection systems, ranging from traditional machine learning models to advanced deep learning networks. In previous work, we proposed a real-time patient monitoring framework for fall detection, which demonstrated the potential for early and accurate detection using wearable devices [5]. Building on this foundation, this paper delves deeper into edge AI models, which offer faster decision-making and significantly reduced reliance on cloud-based resources. Edge AI is increasingly recognized as a transformative paradigm for personalized healthcare, enabling real-time and efficient monitoring solutions [5][6]. Training these edge AI models requires large and diverse datasets. However, falls are unpredictable events, making it challenging to create balanced datasets with sufficient information for effective training. Researchers often rely on publicly available datasets to address this limitation. Among these, the MobiFall dataset stands out as a widely used and recognized benchmark for fall detection models due to its extensive and varied motion data collected using wearable sensors.[4] It includes recordings of both daily activities and fall incidents as shown in Table 1, providing a realistic and challenging setting for evaluating the accuracy and robustness of fall detection models. Its comprehensive nature and accessibility make it a valuable resource for researchers to compare and validate different algorithms under consistent experimental conditions. In this study, the MobiFall dataset was utilized to ensure fair and reliable comparisons among the edge AI models analyzed.

Existing studies in literature often compare models trained on different datasets, making it difficult to determine the factors contributing to a model's superior performance. This highlights the need for a comparative analysis of models using standardized metrics and a common dataset, such as MobiFall. These models should be evaluated using a comprehensive framework that considers deployment-relevant factors such as resource efficiency, robustness, and interpretability. This research aims to compare various deep learning fall detection models using the MobiFall dataset. The evaluation will span multiple deployment-relevant metrics, including performance, robustness, interpretability, and resource efficiency. The findings will provide actionable insights for selecting or designing models for edge AI applications in fall detection and will contribute to advancing real-time healthcare monitoring solutions.

II. METHODOLOGY

To ensure a fair and consistent comparison of techniques, this study utilized the widely recognized and highly cited MobiFall dataset, developed by Vavoulas et al. [4]. This dataset includes four distinct types of falls and nine Activities of Daily Living (ADLs), recorded from 57 participants in over 2,500 trials using a smartphone. The MobiFall dataset provides a comprehensive benchmark, enabling the evaluation of fall detection models in realistic and diverse scenarios.

The dataset encompasses the following fall scenarios and ADLs (see Table 1 for details) –

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Table-1. Falls and activities of daily living (adls) recorded in the mobifall dataset (vavoulas et al. [4])

Activity	Description	Trails	Duration
Forward-Lying	Forward fall with hands cushioning the impact	3	10s
Forward-Knees-Lying	Forward fall with knees hitting the ground first	3	10s
Sideward-lying	Sideways fall with bent legs	3	10s
Back-sitting-chair	Backward fall while attempting to sit in a chair	3	10s
Standing	Stationary standing with subtle movements	1	5m
Walking	Continuous normal walking	1	5m
Jogging	Regular jogging activity	3	30s
Jumping	Repeated jumping movements	3	30s

A. Model Selection

The models analyzed in this study were selected based on their application to the MobiFall dataset or datasets with comparable characteristics. Specifically, the inclusion criteria were as follows:

1) **Relevance to Fall Detection:** Deep learning architectures with demonstrated performance on the MobiFall dataset.
2) **Recency:** Studies published after 2020, ensuring alignment with the latest advancements in fall detection technologies.
3) **Deployment Insights:** Studies providing insights into resource efficiency and deployment feasibility on edge devices, critical for real-time patient monitoring in resource-constrained environments.

Models that did not meet these criteria—such as those relying on older datasets, simpler approaches, or lacking performance evaluations on MobiFall —were excluded from consideration. This methodology ensures a focused and equitable comparison across deep learning models, leveraging a common dataset to maintain consistency. By adhering to this structured approach, we were able to evaluate the features and design choices that contribute most significantly to fall detection, particularly in scenarios requiring real-time monitoring and resource efficiency.

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B. Metric Selection

To comprehensively compare the performance and deployability of deep learning fall detection models, we selected the following metrics, which provide detailed insights into their effectiveness, robustness, and feasibility for edge device deployment:

1) **Performance Metric:** Commonly used metrics such as accuracy, sensitivity, specificity, F1 score, and latency allow for a standardized comparative analysis. These metrics quantify the model's effectiveness in identifying fall events while minimizing false positives and negatives.

2) **Resource Efficiency:** This includes memory usage, energy consumption, and model size, which are vital for deployment on resource-constrained edge devices. As Bellavista et al. [7] highlights, a technique that cannot be implemented due to excessive resource demands is less practical for real-world applications.

3) **Robustness**: Metrics such as noise tolerance and error rates by class assess the model's resilience to variations in sensor data and its ability to maintain accuracy across different fall scenarios. Zhang et al. [11] emphasize the importance of prioritizing safety-critical events while avoiding biases toward non-critical classes.

4) **Deployment Readiness:** Model compression and compatibility with edge frameworks are essential for deployment on wearable and battery-powered devices. Smaller, optimized models reduce memory and energy requirements, as proposed by Lin et al. [9].

5) **Data-Related Metrics:** Preprocessing requirements and data augmentation influence both deployment speed and model generalization. Li et al. [10] note that minimal preprocessing simplifies deployment, while effective data augmentation improves performance, especially for small or imbalanced datasets.

6) **Stability:** Metrics like inference consistency and sensitivity to sampling frequency ensure reliable predictions across diverse devices and conditions. Javed et al. [8] argue that models should maintain consistent performance even with varying sampling frequencies, a common constraint in edge devices.

7) **Deployment Constraints:** Hardware requirements and battery life impact, as outlined by Bellavista et al. [7], are critical for ensuring the feasibility of models on wearable devices and other edge platforms.

By employing these metrics, this study aims to provide a comprehensive evaluation of fall detection models, highlighting trade-offs between performance, robustness, and resource efficiency. These insights will help guide the development of more effective and deployable fall detection systems for edge AI applications.

III. DISCUSSION

Fall detection techniques encompass a broad spectrum of methods, including threshold-based techniques, traditional machine learning, and deep learning approaches. Among these, deep learning—particularly hybrid architectures—consistently outperforms others due to its ability to process and analyze complex temporal and spatial patterns [13].

A. Summary of models

1) **ConvLSTM with ESF:** Sarwar et al. [12] developed a model combining convolutional layers for spatial feature extraction and Long Short-Term Memory (LSTM) cells for temporal dynamics. Preprocessing steps included outlier removal, data segmentation via sliding windows, and feature extraction (e.g., acceleration, angular velocity). The Synthetic Minority Over-sampling Technique (SMOTE) was used to address class imbalance, and the model effectively captured movement dynamics. It achieved an accuracy of 97.8%. Additionally, Exponential Smoothing Forecasting (ESF) was incorporated to provide proactive fall prediction, leveraging historical sensor data trends such as vertical acceleration to forecast falls with a lead time of 1100–1250 ms. This approach ensured accurate and timely predictions by using Mean Absolute Error (MAE) as the loss function during preprocessing.

2) **CABMNet:** Soni et al [13] developed a two-stage deep learning model for fall detection that optimizes both spatial and temporal feature analysis. In Stage 1, CNNs with Convolutional Block Attention Modules (CBAM) enhance spatial feature extraction by focusing on the most informative data. In Stage 2, Bidirectional LSTM networks (Bi-LSTMs) with Multi-Head Attention (MHA) capture temporal dependencies and emphasize critical time steps. Preprocessing includes noise reduction via a Kalman filter, data segmentation, and feature refinement. The model achieves superior accuracy of 98.52% while maintaining low latency. Attention mechanisms (CBAM and MHA) improve interpretability and robustness, making CABMNet highly effective for real-world, multi-modal sensor setups.

3) **Denoising CVAE:** Soni et al [14] introduces an unsupervised fall detection method using a denoising LSTM-based Convolutional Variational Autoencoder (CVAE) optimized for wearable devices. The model addresses challenges of limited fall data and computational constraints by training on data representing normal activities of daily living (ADLs), employing hierarchical data balancing and data debugging to enhance performance. Key features include convolutional and LSTM layers for spatial-temporal analysis, denoising training to handle noisy inputs, and an attention mechanism to prioritize significant features. The model achieves high F1 scores across multiple datasets (e.g., 1.0 on MobiFall) with minimal memory usage (157.65 kB), making it suitable for real-world deployment.

4) **FedVAE:** Yang et al [15] uses two specialized variational autoencoders (VAEs): VAEfe compresses high-dimensional data into a latent space for efficient feature extraction, while VAEgen generates synthetic minority samples to balance the dataset. After time-series sensor data is transformed into images via the Gramian angular field method, VAEfe reduces dimensionality and VAEgen addresses class imbalance. A global anomaly detection model (M) is then trained on these processed features, achieving an accuracy of around 99% and an F1-

score of about 0.99 for anomaly detection. Model updates (gradients) are aggregated at a central server using the FedAvg algorithm, minimizing communication overhead and preserving data privacy. The overall approach provides a scalable, privacy-preserving framework for remote patient monitoring

B. Performance Metrics: Characteristics of High- and Low-Performing Models

1) Traits of High-Performing Models

High-performing models, such as CABMNet, MKLS-Net, and Denoising CVAE, exhibit exceptional accuracy and F1 scores, often exceeding 98%. These models share the following characteristics:

a) Hybrid Architectures

The above fall detection studies highlight the effectiveness of hybrid models that integrate CNNs with LSTM networks or their variants. CNNs excel at extracting spatial features, isolating patterns indicative of a fall, while LSTMs capture the temporal evolution of sensor signals. Like specified in ConvLSTM, CABMNet and Denoising CVAE these highbrid models offer insight into how readings change over time during fall events [12][13][14].

b) Attention Mechanisms

Attention mechanisms enable models to emphasize the most critical input features, particularly during transitional movements like stumbling or near-falls. This capability is evident in CABMNet and Denoising CVAE, where incorporating attention improves robustness and minimizes classification errors.[13][14] Notably, adding an attention layer to the CVAE architecture significantly boosts its F1 score by directing the learning process toward essential data points, thereby enhancing model performance.

c) Data Quality

Ensuring robust fall detection requires more than just a large dataset; the data must be balanced and mirror real-world conditions. The Denoising CVAE study [14] incorporates hierarchical data balancing and data debugging, where overlapping ADL and fall data are removed to sharpen the distinction between normal and abnormal activities. Meanwhile, CABMNet [13] applies a Kalman filter for noise reduction, and the ConvLSTM approach [12] uses SMOTE to generate synthetic samples for underrepresented fall classes. Combining data balancing, thorough debugging, and noise-reduction techniques can significantly elevate model performance across diverse deep learning architectures for fall detection.

d) **Unsupervised learning approaches**

It provides a practical way to identify falls without relying on large sets of fall-specific data, instead utilizing more readily available ADL data. By treating falls as anomalies and measuring reconstruction errors, these methods can be effectively applied in real-world settings. Certain models, such as the denoising LSTM-based CVAE, demonstrate both efficiency and suitability for wearable devices with limited memory. [14] Further, integrating data balancing and debugging practices can significantly boost detection accuracy within these unsupervised frameworks.

2) **Insights from Low-Performing Models**
Lower-performing models often lack advanced architectural features or preprocessing steps, which limits their performance:

a) **Simplistic Architectures**

Models relying on basic CNNs or shallow neural networks often fail to capture the sequential nature of fall events. They lack the capacity to learn richer representations, making them less effective for real-world deployment [12].

b) **Insufficient Regularization**
Models without proper regularization, such as dropout or early stopping, are prone to overfitting, leading to poor generalization in varied conditions [12][13].

c) **Minimal Preprocessing**
Models that fail to implement noise reduction or address class imbalance are often unable to distinguish between falls and ADLs, resulting in higher rates of false alarms or missed detections [12][14].

3) **Resource Efficiency and Deployment Readiness**

The reviewed fall detection models demonstrate varying degrees of balance between accuracy, resource usage, and deployment feasibility. A summary of key findings is as follows:

a) **Most Deployment-Ready**
The denoising LSTM-based CVAE excels in resource-constrained environments due to its minimal memory footprint (around 157.65 kB) and significantly fewer parameters (25.6x fewer than some unsupervised counterparts).[14] Its ability to deliver high accuracy (e.g., F1 score of 1.0 in some tests) while remaining lightweight makes it particularly well-suited for edge devices such as wearables or home monitoring systems.

b) **Accuracy vs. Complexity**
Models like CABMNet achieve high accuracy (consistently above 98%) through attention mechanisms (e.g., CBAM, Multi-Head Attention) and deep architectures

(multi-stage CNN-LSTM modules). However, these enhancements often increase computational overhead, making real-time deployment on low-power or battery-operated devices more challenging without further optimization or hardware acceleration.[12]

c) **Interpretability**
Approaches featuring attention layers (e.g., CBAM, Multi-Head Attention) offer enhanced interpretability, as the model can visually highlight critical features in sensor data. [13] By contrast, the denoising CVAE relies on a reconstruction error metric to identify anomalies (falls), providing a straightforward indicator of data irregularities.[14] While this anomaly-based perspective may be simpler to understand, it does not explicitly reveal which specific features triggered the anomaly.

d) **Optimization Needs**
Both ConvLSTM with ESF and FedVAE show promise for specialized scenarios. ConvLSTM + ESF can handle real-time fall detection and early prediction, but detailed resource usage metrics (e.g., model size, computational load) remain unclear [12]. FedVAE optimizes communication efficiency (~95% reduction) in federated learning environments, ensuring data privacy. [14] Yet, the on-device resource requirements are not fully specified, making it less certain for immediate wearable deployment.

Each model's suitability varies based on context—high-accuracy methods might be ideal for clinical settings with reliable infrastructure, while lighter architectures are more viable for home-based or wearable deployments. Further hardware-friendly optimizations (e.g., quantization, pruning) and clarity in resource metrics could enable advanced architectures (like CABMNet or FedVAE) to become more practical for real-time, battery-operated systems.

IV. LIMITATIONS

Despite advancements in Edge AI for fall detection, several challenges remain that must be addressed for effective real-world deployment.

A. Limited Labeled Fall Data

A major challenge in training robust AI models is the scarcity of labeled fall data. Since real-world falls are rare and difficult to capture, models often rely on simulated datasets, which may not fully generalize to real-life scenarios. This limitation impacts model accuracy and requires alternative learning approaches.

B. Computational Constraints on Edge Devices

Deploying deep learning models on resource-constrained edge devices presents significant challenges. Many state-of-the-art models require high computational power, making real-time inference difficult on wearable and IoT-based systems.

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C. **Variability in Sensor Data**

Fall detection models rely on wearable sensors, which may introduce inconsistencies due to sensor placement, user movement patterns, and hardware differences. These variations affect model robustness and generalizability.

D. **Lack of Interpretability and Trust**

The black-box nature of deep learning models makes it challenging to interpret their predictions, especially in critical applications like healthcare. Explainable AI (XAI) techniques are necessary to improve model transparency.

E. **Energy and Battery Constraints**

Wearable devices have limited battery life, and running deep learning models continuously can drain power quickly.

V. FUTURE RESEARCH

To address these limitations, future research should focus on the following key areas:

A. Unsupervised Learning

Future research should focus on exploring unsupervised learning techniques such as Autoencoders (AE), Variational Autoencoders (VAE), and Generative Adversarial Networks (GAN) to minimize the dependency on labeled fall data [14]. These methods can leverage readily available ADL data to identify anomalies, making them more practical for real-world applications where fall data is scarce.

B. Lightweight Models

The development of resource-efficient deep learning models with fewer parameters remains critical for wearable device deployment [17]. Techniques such as model pruning, quantization, and hierarchical data balancing should be employed to reduce computational demands while maintaining high performance. These optimizations will enhance real-time applicability on edge devices with limited memory and power.

C. Explainable AI (XAI)

Enhancing the interpretability of deep learning models using Explainable AI (XAI) techniques is crucial [16]. Transparent models can improve trust and adoption in healthcare, providing insights into decision-making processes and ensuring the reliability of predictions, especially in safety-critical scenarios like fall detection.

VI. CONCLUSION

This paper presented a comparative analysis of various deep learning models for fall detection, highlighting the trade-offs between accuracy, resource efficiency, and deployment readiness. High-accuracy approaches like CABMNet and ConvLSTM with ESF leverage sophisticated attention mechanisms and multi-layer architectures, but their computational demands pose challenges for real-time, low-power deployment. In contrast, the denoising LSTM-based CVAE demonstrates a substantially reduced parameter count and memory footprint, making it a strong candidate for wearable deployment. Furthermore, FedVAE underscores the potential of federated learning in maintaining data privacy and reducing communication overhead, although further exploration of device-level resource usage is needed.

Despite these advancements, real-world deployment remains challenging due to the limited generalizability of models, computational constraints, and difficulty in distinguishing falls from Activities of Daily Living (ADLs). Models prone to overfitting may struggle in diverse environments, necessitating robust regularization and domain adaptation strategies. Additionally, fall detection models must mitigate class imbalance and sensor noise to reduce false alarms and missed detections.

To address these challenges, future research should focus on balancing performance with deployment constraints, integrating explainable AI (XAI) techniques to enhance trust and adoption in healthcare. The development of adaptive learning frameworks can further improve personalization and generalizability across different users and environments. Moreover, unsupervised learning approaches, such as Autoencoders and GANs, offer promising alternatives to minimize dependency on labelled fall data.

By addressing these challenges, Edge AI-based fall detection systems can evolve into practical, scalable solutions that not only enhance real-time patient monitoring but also contribute to personalized and efficient healthcare applications. The advancements in model interpretability, computational efficiency, and privacy-preserving AI will play a crucial role in shaping the next generation of wearable fall detection systems, ultimately improving patient safety and quality of life.

REFERENCES

1. Falls, Organization WH Available: http://www.who.int/news-room/fact-sheets/detail/falls [Accessed 29 Nov 2024].
2. GBD 2016 traumatic brain injury and spinal cord injury collaborators Global, regional, and national burden of traumatic brain injury and spinal cord injury, 1990-2016: A systematic analysis for the global burden of disease study 2016. Lancet Neurol 2019;18:56–87. 10.1016/S1474-4422(18)30415-0
3. James SL, Lucchesi LR, Bisignano C, Castle CD, Dingels ZV, Fox JT, Hamilton EB, Henry NJ, Krohn KJ, Liu Z, McCracken D, Nixon MR, Roberts NLS, Sylte DO, Adsuar JC, Arora A, Briggs AM, Collado-Mateo D, Cooper C, Dandona L, Dandona R, Ellingsen CL, Fereshtehnejad SM, Gill TK, Haagsma JA, Hendrie D, Jürisson M, Kumar GA, Lopez AD, Miazgowski T, Miller TR, Mini GK, Mirrakhimov EM, Mohamadi E, Olivares PR, Rahim F, Riera LS, Villafaina S, Yano Y, Hay SI, Lim SS, Mokdad AH, Naghavi M, Murray CJL. The global burden of falls: global, regional and national estimates of morbidity and mortality from the Global Burden of Disease Study 2017. Inj Prev. 2020 Oct;26(Supp 1):i3-i11. doi: 10.1136/injuryprev-2019-043286. Epub 2020 Jan 15. PMID: 31941758; PMCID: PMC7571347.

4. Vavoulas, C. Chatzaki, T. Malliotakis, M. Pediaditis, and M. Tsiknakis, "*e mobiact dataset: recognition of activities of daily living using smartphones," in Proceedings of the International Conference on Information and Communication Technologies for Ageing Well and e-Health, pp. 143–151, Rome, Italy, April 2016.
5. Ajerla, Dharmitha & Mahfuz, Sazia & Zulkernine, Farhana. (2019). A Real-Time Patient Monitoring Framework for Fall Detection. Wireless Communications and Mobile Computing. 2019. 1-13. 10.1155/2019/9507938.
6. T. Meuser et al., "Revisiting Edge AI: Opportunities and Challenges," in IEEE Internet Computing, vol. 28, no. 4, pp. 49-59, July-Aug. 2024, doi: 10.1109/MIC.2024.3383758.
7. Bellavista, Paolo & Zanni, Alessandro. (2017). Feasibility of Fog Computing Deployment based on Docker Containerization over RaspberryPi. 1-10. 10.1145/3007748.3007777.
8. Javed, H., El-Sappagh, S. & Abuhmed, T. Robustness in deep learning models for medical diagnostics: security and adversarial challenges towards robust AI applications. Artif Intell Rev 58, 12 (2025). https://doi.org/10.1007/s10462-024-11005-9
9. Lin, Bor-Shing & Yu, Tiku & Peng, Chih-Wei & Lin, Chueh-Ho & Hsu, Hung-Kai & Lee, I-Jung & Zhang, Zhao. (2022). Fall Detection System With Artificial Intelligence-Based Edge Computing. IEEE Access. PP. 1-1. 10.1109/ACCESS.2021.3140164.
10. Li, Ruisheng. (2024). A Review of Fall Detection Research Based on Deep Learning. Applied and Computational Engineering. 115. 93-102. 10.54254/2755-2721/2025.18481.
11. Zhang J, Li Z, Liu Y, Li J, Qiu H, Li M, Hou G, Zhou Z. An Effective Deep Learning Framework for Fall Detection: Model Development and Study Design. J Med Internet Res. 2024 Aug 5;26:e56750. doi: 10.2196/56750. PMID: 39102676; PMCID: PMC11333863.
12. M. A. Sarwar, B. Chea, M. Widjaja and W. Saadeh, "An AI-based Approach for Accurate Fall Detection and Prediction using Wearable Sensors," in IEEE, vol., no., pp. 1-10, 2024
13. Soni, H. Yadav, S. Bijrothiya, and V. B. Semwal, "CABMNet: An adaptive two-stage deep learning network for optimized spatial and temporal analysis in fall detection," Biomedical Signal Processing and Control, vol. 96, p. 106506, 2024.
14. Soni, G. Yadav and V. B. Semwal, "Elderly Fall Detection Using Attention Based dilated CNN and dilated BiLSTM," 2024 International Conference on Automation and Computation (AUTOCOM), Dehradun, India, 2024, pp. 575-579, doi: 10.1109/AUTOCOM60220.2024.10486121.
15. Yang, M. Ge, K. Xiang, X. Bai and H. Li, "FedVAE: Communication-Efficient Federated Learning With Non-IID Private Data," in IEEE Systems Journal, vol. 17, no. 3, pp. 4798-4808, Sept. 2023, doi: 10.1109/JSYST.2023.3274197
16. Saraswat et al., "Explainable AI for Healthcare 5.0: Opportunities and Challenges," in IEEE Access, vol. 10, pp. 84486-84517, 2022, doi: 10.1109/ACCESS.2022.3197671
17. Xiaoqun Yu, Seonghyeok Park, Doil Kim, Eungjin Kim, Jaewon Kim, Woosub Kim, Yechan An, Shuping Xiong, A practical wearable fall detection system based on tiny convolutional neural networks, Biomedical Signal Processing and Control, Volume 86, Part C, 2023