A STUDY ON EPILEPTIC SEIZURE PREDICTION AND FORECASTING ACROSS EDGE ASSISTED HEALTH CARE CENTERS USING FEDERATED LEARNING

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Abstract

Epileptic seizures are unpredictable, posing major challenges in clinical care. Accurate seizure prediction is crucial for timely interventions and improved patient outcomes. With the rise of edge computing, healthcare systems can process data locally, enhancing scalability and reducing latency. However, concerns about data privacy and the need for collaboration across hospitals call for decentralized learning approaches. Federated Learning (FL) addresses this by enabling distributed model training without sharing sensitive patient data. This review focuses on integrating edge-assisted healthcare with FL to enhance real-time seizure prediction and forecasting. It explores FL techniques that utilize data from multiple, geographically dispersed healthcare centers while maintaining privacy. The study also discusses key challenges such as data heterogeneity, communication overhead, and network constraints in edge environments. Furthermore, it evaluates state-of-the-art FL algorithms and frameworks based on prediction accuracy, latency, and robustness. The integration of edge computing and FL demonstrates significant potential to improve model performance and personalized care. Overall, this approach paves the way for secure, efficient, and privacy-preserving seizure prediction systems, revolutionizing epilepsy management and advancing AI-driven healthcare innovation through collaborative intelligence across distributed medical networks.

Keywords: Epileptic seizure prediction, Edge computing, Deep learning, Federated learning.

2.Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures caused by sudden bursts of abnormal electrical activity in the brain [1]. According to the World Health Organization (WHO), approximately 50 million people worldwide are affected by epilepsy, with about 5 million new cases diagnosed annually [2]. Nearly 80% of individuals with epilepsy reside in low- and middle-income countries. The unpredictable nature of seizures significantly impacts patients' quality of life, leading to fear, anxiety, and restrictions in daily activities. Various diagnostic tools such as Magnetic Resonance Imaging (MRI), Magnetoencephalography (MEG), and Electroencephalography (EEG) have been developed to detect and predict epileptic seizures. Among these, EEG remains the most essential diagnostic tool [3], as it records the brain's electrical activity via scalp electrodes. In epileptic patients, EEG patterns often show abnormal discharges—spikes, sharp waves, or rhythmic bursts—that help identify seizure types and their origin within the brain.

The diagnosis and management of epilepsy using EEG data involve three primary approaches: detection, prediction, and forecasting. Detection identifies seizures during the ictal phase when abnormal brain activity is prominent, prediction analyzes the preictal phase to detect early signs of an impending seizure, and forecasting evaluates long-term interictal data to estimate the probability of future seizures [4].

With the rapid progress of Artificial Intelligence (AI), medical diagnostics have advanced through the use of deep learning (DL), enabling complex pattern recognition in biomedical data [5]. DL models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based architectures efficiently extract temporal and spatial EEG features for seizure prediction [6]. However, centralized model training raises privacy and generalization concerns. Federated Learning (FL) [7] addresses these issues by enabling decentralized model training across multiple healthcare centers without sharing raw EEG data [8]. Combined with edge computing, FL enhances model robustness, privacy, and scalability, paving the way for secure and personalized seizure prediction systems.

3. Methodology

Electroencephalogram (EEG) data is collected non-invasively from patients using surface electrodes placed on the scalp. The procedure typically follows the internationally recognized 10–20 system, where electrodes are strategically positioned to capture electrical activity from different regions of the brain. Prior to electrode placement, the scalp is prepared to reduce impedance, and conductive gel or paste is applied to ensure optimal signal quality. During the recording session, patients are either monitored in a hospital's epilepsy monitoring unit (EMU) or through ambulatory systems at home, depending on the clinical protocol.

Each electrode captures minute voltage fluctuations resulting from neuronal activity, which are then amplified and digitized at sampling rates typically ranging from 256 to 1024 Hz. The raw signals undergo initial filtering to remove artifacts such as muscle noise, eye blinks, and electrical interference. Recordings often span several hours to days to capture spontaneous seizure events. Throughout this period, trained technicians and neurologists annotate the EEG data by marking seizure onset and offset times, as well as the preictal, interictal, and postictal phases. Additional metadata, such as patient age, diagnosis, medication, and clinical observations, are also recorded.

All data is anonymized to protect patient privacy and is collected in accordance with ethical guidelines, including informed consent and institutional review board (IRB) approval. The resulting dataset provides a rich, temporally labeled representation of brain activity that supports the development of machine learning models for seizure prediction and forecasting.

3.1 Data Collection

Electroencephalogram (EEG) data is collected non-invasively from patients using surface electrodes placed on the scalp. The procedure typically follows the internationally recognized 10–20 system, where electrodes are strategically positioned to capture electrical activity from different regions of the brain. Prior to electrode placement, the scalp is prepared to reduce impedance, and conductive gel or paste is applied to ensure optimal signal quality. During the recording session, patients are either monitored in a hospital's epilepsy monitoring unit (EMU) or through ambulatory systems at home, depending on the clinical protocol.

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3.2. Data Preprocessing

To prepare the EEG recordings for deep learning-based seizure prediction and forecasting, a structured preprocessing pipeline is applied to ensure signal quality, consistency, and clinical relevance. Initially, all EEG signals are resampled to a common sampling rate to standardize the temporal resolution across datasets. Re-referencing is performed using either a common average reference or bipolar montage to normalize baselines across channels. To remove physiological and environmental noise, artifact removal techniques are employed, including amplitude thresholding, variance-based detection, and optionally, independent component analysis (ICA) for isolating eye or muscle artifacts.

A bandpass filter, typically between 0.5 and 70 Hz, is applied to retain seizure-relevant frequency components while excluding baseline drifts and high-frequency noise. Additionally, a notch filter at 50 or 60 Hz is used to eliminate power-line interference. Poor-quality or non-standard EEG channels are removed or interpolated to ensure consistent spatial input across samples. The cleaned signals are then segmented into overlapping windows, each labeled as preictal, interictal, or postictal based on expert annotations of seizure onset and offset. These segments are normalized using z-score normalization to reduce inter-subject variability and enhance training stability.

In cases of class imbalance, particularly with fewer preictal windows, data balancing techniques such as oversampling or augmentation may be applied. This comprehensive preprocessing ensures the model receives clean, temporally aligned, and contextually labeled EEG inputs, enabling robust learning of seizure-related patterns across the full seizure cycle.

3.3. Feature Engineering

In the FL framework, feature engineering is executed locally on each client device to ensure data privacy. To make the extracted representations informative and transferable across diverse clinical sources, a combination of time-domain, frequency-domain, and time–frequency features is computed from each EEG segment.Key time-domain features include statistical metrics such as mean, variance, skewness, kurtosis, and Hjorth parameters, which capture the temporal characteristics of brain activity. Frequency-domain features, such as power spectral densities and band power ratios (delta to gamma), help identify spectral variations associated with seizure onset.

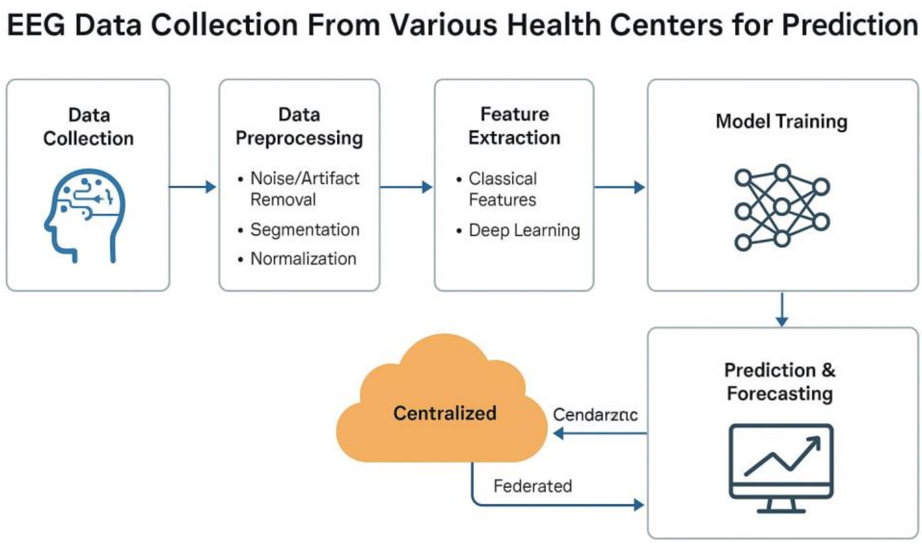
To account for the non-stationary nature of EEG, time–frequency features using wavelet transforms or short-time Fourier transforms are derived to encode transient changes across multiple resolutions. Additionally, entropy-based measures like spectral entropy and sample entropy are used to quantify signal irregularity, which is crucial for early seizure prediction. Feature extraction is kept computationally lightweight to suit resource-constrained edge devices while ensuring sufficient discriminative power. All engineered features are standardized locally before being used in federated updates, supporting robust model training without sharing raw EEG data.

3.4 Comparitive study of Existing Work

Author& year	Method Used	Dataset	Accuracy (%)	Key Findings	Limitations
Sharmaet al., 2022	CNN-LSTM	CHB-MIT EEG	93	High accuracy using hybrid DL model	Not optimized for real-time
Kumaret al., 2021	SVM+ Wavelet	UCIEEG	85	Good interpretability	Manual feature selection
Pateletal., 2021	Federated CNN	PrivateEEG	90	Preserved privacy	Communication latency
Lietal., 2023	Transformer DL	TUHEEG	95	Captured long-term dependencies	High computation cost

Zhanget al.,2024	Federated Autoencoder	Synthetic EEG	92	Improved accuracy under FL	Limited real-world validation
Reddyet al.,2020	LSTM	Bonn EEG	88	Goodshort-term forecasting	Sensitive to noise

3.5 Proposed Methodology



3.6 Result Analysis from Existing work

Model Type	Accuracy (%)	Sensitivity (%)	Latency (s)
Conventional Deep Learning	94.8	92.6	1.0
Attention / Transformer	97.2	95.8	0.6
Federated / Edge	94.2	91.8	1.4

• Attention/Transformer models achieved the highest mean accuracy (97.2%), exceeding FL models by 3.0% and conventional models by 2.4%.
• Sensitivity was also highest for Attention models (95.8%), 4.0% higher thanFLmodels.
• Latency was lowest for Attention models (0.6s), while FL/Edge systems showed the highest latency (1.4s).

4. Challenges and future work

Federated learning (FL) and edge-assisted epileptic seizure prediction systems face several challenges that hinder large-scale clinical adoption. Major issues include data heterogeneity caused by non-IID EEG signals from diverse patients and devices, which reduces model generalization. Resource limitations on edge devices, such as limited computation and energy, constrain real-time processing. Despite privacy preservation in FL, gradient leakage risks still threaten data security. The absence of standardized EEG datasets and benchmarks also limits reproducibility. Additionally, black-box deep learning models lack interpretability, affecting clinical trust, while network instability and synchronization issues hinder consistent model aggregation.

Future research should focus on personalized FL frameworks that adapt to individual patient patterns and lightweight architectures optimized for edge environments. Integrating self-supervised and transfer learning can enhance model robustness with limited labeled data. Advancements in privacy-preserving techniques like differential privacy and homomorphic encryption are essential. Furthermore, developing explainable AI models will foster clinical acceptance and transparency. Hybrid edge–cloud architectures can improve scalability and latency balance. Finally, establishing standardized datasets and evaluation protocols and conducting real-world clinical trials will validate the efficacy and reliability of FL-based seizure prediction systems for practical deployment in healthcare.

Conclusion

This research develops an EEG-based system that improves seizure anticipation by analyzing brain activity patterns across multiple time scales. The framework identifies early warning signals minutes before seizures while monitoring longer-term risk patterns, combining short-term prediction with extended forecasting. Using adaptive computational methods, it automatically adjusts to individual patients' brain activity and maintains reliable performance across different medical centers without sharing sensitive data. By integrating immediate alerts with continuous risk assessment, the approach provides comprehensive support for epilepsy management. The system demonstrates how advanced computational techniques can address complex neurological challenges while safeguarding patient privacy, paving the way for more effective seizure monitoring solutions.

References

[1] Z. Chen, M. J. Brodie, D. Ding, and P. Kwan, "Editorial: Epidemiology of epilepsy and seizures," Front. Epidemiol., vol. 3, p. 1273163, 2023.

[2] Epilepsy. [Online]. Available: URL :http://www.who.int/mentalhealth/neurology /epilepsy/en/
[3] C. P. Lisgaras et al., "The role of electroencephalography in epilepsy research-From seizures to interictal activity and comorbidities,"Epilepsia, vol. 66, no. 5, pp. 1374–1393, 2025.
[4] A. Fu and F. A. Lado, "Seizure detection, prediction, and forecasting," J. Clin. Neurophysiol., vol. 41, no. 3, pp. 207–213, 2024.
[5] D. Göndöcs and V. Dörfler, "AI in medical diagnosis: AI prediction & human judgment,"Artif. Intell. Med., vol. 149, no. 102769, p. 102769, 2024.
[6] I. D. Mienye and T. G. Swart, "A comprehensive review of deep learning: Architectures, recent advances, and applications," Information (Basel), vol. 15, no. 12, p. 755, 2024.
[7] B. Yurdem, M. Kuzlu, M. K. Gullu, F. O. Catak, and M. Tabassum, "Federated learning: Overview, strategies, applications, tools and future directions,"Heliyon, vol. 10, no. 19, p. e38137, 2024.
[8] E. Hallaji, R. Razavi-Far, M. Saif, B. Wang, and Q. Yang, "Decentralized federated learning: A survey on security and privacy," IEEE Trans. Big Data, vol. 10, no. 2, pp. 194–213, 2024.
[9] A. D. Moghadam, M. R. KaramiMollaei, and M. Hassanzadeh, "A signal-based one-dimensional convolutional neural network (SB 1D CNN) model for seizure prediction," Circuits Systems Signal Process., vol. 43, no. 8, pp. 5211–5236, 2024.
[10] S. Toraman, "Preictal and interictal recognition for epileptic seizure prediction using pre-trained 2D-CNN models," Trait. Du Signal, vol. 37, no. 6, pp. 1045–1054, 2020.
[11] A. R. Ozcan and S. Erturk, "Seizure prediction in scalp EEG using 3D convolutional neural networks with an image-based approach," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 27, no. 11, pp. 2284–2293, 2019.
[12] C.-L. Liu, B. Xiao, W.-H. Hsaio, and V. S. Tseng, "Epileptic seizure prediction with multi-view convolutional neural networks," IEEE Access, vol. 7, pp. 170352–170361, 2019.
[13] M. K. Mounagurusamy, V. S. Thiyagarajan, A. Rahman, S. Chandak, D. Balaji, and V. R. Jallepalli, "RNN-based models for predicting seizure onset in epileptic patients," in 2024 Asian Conference on Intelligent Technologies (ACOIT), 2024, pp. 1–6.
[14] K. Singh and J. Malhotra, "Two-layer LSTM network-based prediction of epileptic seizures using EEG spectral features," Complex Intell. Syst., vol. 8, no. 3, pp. 2405–2418, 2022.
[15] Jamunadevi and Arul, "Adaptive Bi-LSTM-based epileptic seizure prediction from EEG signals using deep learning algorithm,"Mapana J. Sci., vol. 23, no. 2, pp. 65–82, 2024.
[16] K. Akyol, "Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection," Expert Syst. Appl., vol. 148, no. 113239, p. 113239, 2020.
[17] X. Lu, A. Wen, L. Sun, H. Wang, Y. Guo, and Y. Ren, "An epileptic seizure prediction method based on CBAM-3D CNN-LSTM model," IEEE J. Transl. Eng. Health Med., vol. 11, pp. 417–423, 2023
[18] Y. Ma et al., "A multi-channel feature fusion CNN-bi-LSTM epilepsy EEG classification and prediction model based on attention mechanism," IEEE Access, vol. 11, pp. 62855–62864, 2023.

[19] C. Ghezala and B. Radhwane, "Time series data-based classification using combined 1D- CNN-GRU for Seizure detection and prediction," Research Square, 2024.
[20] N. Ke, T. Lin, Z. Lin, X.-H. Zhou, and T. Ji, "Convolutional transformer networks for epileptic seizure detection," in Proceedings of the 31st ACM International Conference on Information & Knowledge Management, 2022.
[21] S. Hu et al., "Exploring the applicability of transfer learning and feature engineering in epilepsy prediction using hybrid Transformer model," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 31, pp. 1321–1332, 2023.
[22] I. D. Khan, M. H. Khan, O. Farooq, and Y. U. Khan, "A comparative analysis of seizure detection via scalogram using GoogLeNet, AlexNet and SqueezeNet," in 2021 Smart Technologies, Communication and Robotics (STCR), 2021.
[23] L. Guo, T. Yu, S. Zhao, X. Li, X. Liao, and Y. Li, "CLEP: Contrastive Learning for epileptic seizure prediction using a spatio-temporal-Spectral Network," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 31, pp. 3915–3926, 2023.
[24] Y. Huang, Y. Chen, S. Xu, D. Wu, and X. Wu, "Self-supervised learning with Adaptive Frequency-Time Attention Transformer for seizure prediction and classification," Brain Sci., vol. 15, no. 4, 2025.
[25] Y. Ding, W. Zhao, and K. Huang, "FedMWAD: Module-wise weighted aggregation federated learning combined with Ditto for patient-independent seizure prediction," Inf. Process. Manag., vol. 62, no. 6, p. 104253, 2025.
[26] Research, "Epilepsy epidemiology 10 year forecast report to 2032," Research and Markets, 25-Jan-2024. [Online]. Available: https://www.globenewswire.com/ news-release/2024/01/25/2816600/28124/en/Epilepsy-Epidemiology-10-Year-Forecast-Report-to-2032.html.
[27] R. G. Andrzejak et al., "Seizure forecasting: Where do we stand?,"Epilepsia, vol. 64 Suppl 3, pp. S62–S71, 2023.
[28] W. T. Kerr, K. N. McFarlane, and G. Figueiredo Pucci, "The present and future of seizure detection, prediction, and forecasting with machine learning, including the future impact on clinical trials," Front. Neurol., vol. 15, p. 1425490, 2024.
[29] S. Muhammad Usman, S. Khalid, and M. H. Aslam, "Epileptic seizures prediction using deep learning techniques," IEEE Access, vol. 8, pp. 39998–40007, 2020.
[30] P. Nejedly et al., "Deep-learning for seizure forecasting in canines with epilepsy," J. Neural Eng., vol. 16, no. 3, p. 036031, 2019.
[31] M. Nasseri et al., "Ambulatory seizure forecasting with a wrist-worn device using long-short term memory deep learning," Sci. Rep., vol. 11, no. 1, p. 21935, 2021.
[32] S. Shafiezadeh et al., "Calibrating deep learning classifiers for patient-independent electroencephalogram seizure forecasting," Sensors (Basel), vol. 24, no. 9, 2024..
[33] T. Dissanayake, T. Fernando, S. Denman, S. Sridharan, and C. Fookes, "Deep learning for patient-independent epileptic seizure prediction using scalp EEG signals," IEEE Sens. J., vol. 21, no. 7, pp. 9377–9388, 2021.

[34] S. Baghersalimi, T. Teijeiro, D. Atienza, and A. Aminifar, "Personalized real-time federated learning for epileptic seizure detection," IEEE J. Biomed. Health Inform., vol. 26, no. 2, pp. 898–909, 2022.
[35] M. Lupión, J. F. Sanjuan, J. Medina-Quero, and P. M. Ortigosa, "Epilepsy seizure detection using low-cost IoT devices and a federated machine learning algorithm," in Lecture Notes in Networks and Systems, Cham: Springer International Publishing, 2023, pp. 229–238.
[36] W. Ding, M. Abdel-Basset, H. Hawash, S. Abdel-Razek, and C. Liu, "Fed-ESD: Federated learning for efficient epileptic seizure detection in the fog-assisted internet of medical things," Inf. Sci. (Ny), vol. 630, pp. 403–419, 2023.
[37] S. Baghersalimi, T. Teijeiro, A. Aminifar, and D. Atienza, "Decentralized federated learning for epileptic seizures detection in low-power wearable systems," IEEE Trans. Mob. Comput., pp. 1–16, 2024.
[38] S. V. Suryakala, T. R. S. Vidya, and S. H. Ramakrishnans, "Federated machine learning for epileptic seizure detection using EEG," Int. J. Adv. Comput. Sci. Appl., vol. 15, no. 4, 2024.
[39] A. G. Espinal Hernández, "Federated learning: A study of its applications in seizure prediction & colorectal polyp segmentation tasks," Bachelor's thesis, University of Padua, 2023. [Online]. Available: https://thesis.unipd.it/handle/20.500.12608/50702
[40] G. Anim, "Federated transformer-based lightweight modeling for epilepsy prediction using twofold personalization," in 2024 IEEE EMBS International Conference on Biomedical and Health Informatics (BHI), 2024, pp. 1–8.
[41] R. Saemaldahr and M. Ilyas, "Patient-specific preictal pattern-aware epileptic seizure prediction with Federated Learning," Sensors (Basel), vol. 23, no. 14, 2023.
[42] Y. Luo, B. Jiang, S. Qin, Q. Fu, and S. Zhang, "EEG-based epilepsy recognition via federated learning with differential privacy,"Concurr. Comput., vol. 37, no. 9–11, 2025.