Advancements in Personalized Federated Learning for Epileptic Seizure Detection

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Abstract: Personalized federated learning for Epileptic seizure detection represents a promising avenue for improving the accuracy and efficiency of seizure detection systems while safeguarding individual privacy. Epilepsy is a neurological disorder characterized by recurrent seizures, and timely detection of these events is critical for effective management and intervention. Traditional centralized approaches to seizure detection face challenges related to data privacy, scalability, and diversity of data sources. Federated learning (FL) offers a decentralized paradigm where models are trained cooperatively across various clients or data silos without centralizing sensitive data. This study discusses the state-of-the-art in personalized federated learning for epileptic seizure detection. The study focuses on the fundamentals of federated learning and its applicability to healthcare settings, especially with regard to epilepsy management. Recent advancements in personalized seizure detection algorithms tailored to federated learning settings, machine / deep learning models, client /data distribution and performance are reviewed. Furthermore, challenges and opportunities in deploying federated learning systems for epileptic seizure detection are examined. Finally, insights into the current landscape of personalized federated learning for epileptic seizure detection are discussed with experimental analysis inspiring further research.

1 INTRODUCTION

Epilepsy remains an eminent medical problem with widespread implications, affecting over 65 million individuals worldwide (World Health Organization, 2019). Despite advancements in medical and surgical interventions, a substantial proportion of epilepsy patients continue to experience uncontrolled seizures, leading to significant morbidity and impaired quality of life (Kwan & Brodie, 2000). The capacity to anticipate epileptic seizures earlier in their beginning holds extraordinary potential for upgrading patient outcomes by enabling timely therapeutic interventions and seizure prevention strategies (Schulze-Bonhage, 2008).

Epileptic seizure detection has been a topic of intense research, driven by the pressing need to improve the management and well-being of individuals with epilepsy. Over recent times, researchers have investigated various approaches to predict epileptic seizures, with increasing emphasis on leveraging advanced computational techniques, particularly deep learning, for analyzing electroencephalography (EEG) signals (Zhang et al., 2020). Plenty of methodologies, ranging from conventional AI strategies, advanced deep learning approaches to Federated Learning (FL) concepts, have been explored in pursuit of accurate and reliable seizure prediction models.

Federated learning performs collaborative model training across distributed data sources, such as multiple healthcare institutions or individual patient devices (Kairouz et al., 2019) as portrayed in Figure 1. Privacy-preserving approaches are pivotal in developing a personalized Federated Learning framework for epileptic seizure detection (Qin et al., 2021). Traditional centralized approaches to seizure detection encounter obstacles related to information protection, versatility, and the heterogeneity of information sources. In response, federated learning

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emerges as a promising solution, offering a decentralized paradigm for cooperative model preparation across distributed data sources while preserving individual privacy.

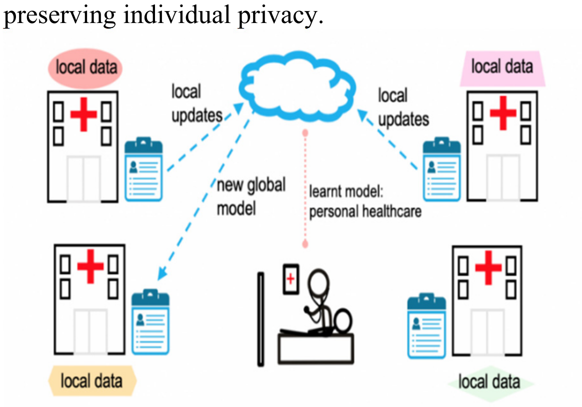

Figure 1: Federated Learning framework in healthcare setting (Tian, 2019).

Federated learning leverages the diversity of data sources in seizure detection by utilizing local data processing, aggregating model updates, integrating heterogeneous data, enhancing generalization, scaling efficiently, and allowing for personalization. This approach results in more accurate, generalizable, and robust seizure detection models that respect patient privacy and encourage collaboration among several medical institutions. EEG signals provide valuable perception into the dynamic electrical activity of the brain and serve as key biomarkers for detecting epileptic seizure events. Recent advancements in Federated learning methodologies have spurred a fundamental change in seizure prediction research, offering new avenues for extracting complex patterns and temporal dynamics from EEG data.

In this study, we synthesize recent research findings in Federated learning methodologies applied to epileptic seizure forecast utilizing EEG signals. By consolidating recent advancements, this research provides insights into the current developments, identifies emerging trends, and proposes future directions for advancing seizure detection in epilepsy management. By synthesizing recent research findings and identifying emerging trends, this study seeks to add to the ongoing dialogue in the field of epilepsy research and neuroinformatics. Our objective is to elucidate the promise of Federated learning techniques in revolutionizing seizure prediction and their relevance for clinical application, patient management, and healthcare resource allocation. Ultimately, our objective is to stimulate further research endeavors and foster collaborative efforts aimed at translating innovative seizure prediction algorithms into impactful clinical tools for the benefit of epilepsy patients worldwide.

2 DATASETS FOR EPILEPTIC SEIZURE DETECTION USING FL

The prosperity of personalized federated learning in epileptic seizure detection relies heavily on the openness of diverse and well-annotated EEG datasets. In this section, we introduce key datasets that serve as foundational resources for training and evaluating personalized seizure detection models. These datasets encompass an extent of seizure types, patient demographics, and recording modalities, giving priceless bits of knowledge to the headway of strong and versatile seizure identification.

TUH EEG Seizure Corpus (TUH EEG Seizure Corpus, 2024): The 26,846 clinical EEG recordings that were gathered at Temple University Hospital make up this extensive archive. The TUSZ subset specifically focuses on seizure events, providing valuable data for studying epilepsy, seizure detection algorithms, and related research in neuroscience and clinical applications. Over 150 hours of EEG data, 615 EDF files, and 247 sessions are included.

CHB-MIT Scalp EEG Database (CHB-MIT Scalp EEG Database, 2024): This collection consists of EEG recordings of individuals with epilepsy, comprising both seizure and non-seizure recordings. This database, gathered by Boston Children's Hospital, includes EEG recordings from kids with unmanageable epilepsy. Several days were spent monitoring the subjects after they discontinued anticonvulsant medications. This was done to observe their seizures and determine their suitability for surgical intervention. The recordings were obtained from 22 people and organized into 23 cases, 17 females, aged 1.5–19 years and 5 males, aged 3–22 years.

Epilepsy EEG Database (EEG-ID, 2024): EEG recordings from epileptic patients are included along with seizure event annotations. It provides a wide variety of seizure kinds and patient profiles to create customized models. The EEG database includes recordings of 21 patients with medically intractable focal epilepsy. At the University Hospital Freiburg in Germany's Epilepsy Center, data were collected during invasive preoperative epilepsy monitoring. The epileptic focus was found in the neocortical brain structures in eleven patients, the hippocampal region in eight patients, and both in two patients. A Neurofile

NT digital video EEG system with 128 channels, a 256 Hz sampling rate, and a 16-bit log-to-digital converter was used to record the EEG data.

EPILEPSIAE Dataset (EPILEPSIAE Dataset, 2024): The dataset includes EEG reports from epileptic patients that are accompanied by seizure start and finish timings. Annotated EEG information from around 200 epileptic patients is available in the EU database. 50 of these individuals have internal brain recordings with up to 122 channels. Every dataset offers EEG data at a maximum sampling rate of 2500 Hz for at least 96 hours of nonstop recording. The EEG data is supplemented with patient data and magnetic resonance imaging data.

3 EXPLORATION OF RESEARCH IN EPILEPTIC SEIZURE DETECTION

Epilepsy is a neurological disorder characterized by recurrent seizures that presents a significant challenge in healthcare due to the critical need for timely detection and intervention. In this section, we explore different machine learning approaches used by researchers for the effective detection of epileptic seizures.

3.1 Traditional Methods

Early research on seizure prediction primarily used traditional machine learning algorithms and handcrafted features extracted from EEG signals (Mirowski et al., 2009; Mormann et al., 2007; Tzallas et al., 2009). These features included non-linear, frequency and time domain characteristics, such as statistical moments, entropy measures, wavelet coefficients and spectral densities. Though these methods were effective, they required domain-specific knowledge. Also, these methods pose difficulties in capturing complex, nonlinear patterns in EEG data (Wu et al., 2024).

3.2 Evolution of Deep Learning

The progress in deep learning, particularly the application of long short-term memory (LSTM), recurrent neural networks (RNN), and convolutional neural networks (CNN) has transformed seizure prediction. These models utilize automated feature extraction and can effectively model both spatial and temporal relationships, leading to improved predictions (Hosseini et al., 2020; Acharya et al., 2018; Shoeibi et al., 2021). Further, these models can learn both local and global patterns in EEG data effectively, improving predictive accuracy (Kunekar et al., 2024; Xu et al., 2020). Another important milestone in the evolution of deep learning models is Transfer learning, where models pre-trained on larger datasets are optimized for seizure detection datasets (Liu et al., 2019; Chen et al., 2022; Yu et al., 2023). The incorporation of multi-modal data is another approach used to enhance seizure prediction. When EEG signals were combined with contextual information related to EEG data, the accuracy of the predictions improved reducing false alarms (Moridani & Farhadi, 2017).

3.3 Personalized Federated Learning

Federated Learning allows multiple machines to collaboratively train models by combining updates from decentralized data sources, all while preserving data privacy and security (Konecny et al., 2016). This method enhances prediction models by utilizing diverse datasets without incorporating sensitive patient information. Model personalization involves adapting the global models to reflect individual patient characteristics and seizure patterns. Fine-tuning of the models locally, personalized updates, ensembling of model outputs and client-side adaptation enhance the global model's detection accuracy while safeguarding the privacy of datasets on the client side. Personalized federated learning might offer the desired benefits because the patterns of seizure vary from one person to another. There is a difference in how individuals experience seizures due to their onset, duration, and character. Triggers for these seizures are not the same in patients.

Personalized federated learning customizes models according to individual patterns as well as responses. It facilitates the adjustment of models over time, especially in situations such as epilepsy where seizure patterns can change or respond differently to treatment. By adapting models to individual patients and updating them with data from wearables or other sources, it is expected that the models would be able to better tune to new situations for each patient. Traditional learning requires that data from different users or devices be independently and identically distributed which is not always true for real-world cases. Such heterogeneity of data can be addressed through Personalized Federated Learning by adapting models to individual client's data distributions considering variations thereby resulting in better performance on diverse data.

In FL, the training task is divided among various devices or institutions for labeling the data. This approach overcomes the energy inefficiency during model training where traditional approaches may consume substantial energy limiting their suitability for long-term, continuous monitoring. The Personalized federated learning method will turn out to be highly beneficial in epileptic cases where accurate identification of seizure events is required while preserving patient privacy. The information about each patient is kept at the client end itself without being stored in the central server and only the gradients or model weights are shared to the central server. By incorporating this measure, the confidentiality of the patient data is maintained.

FL models can be used in wearable or implantable devices to monitor patients in real time in order to detect any anomalous patterns. This allows for immediate intervention, like alerting caregivers or administering treatments when a seizure is detected. Federated learning enables scalable and efficient personalized seizure detection models across numerous patients and healthcare institutions. This approach enables access to advanced seizure detection technologies regardless of the patient's geographical location or resources available in the healthcare system. By distributing computational tasks, using local devices for training, reducing data transmission needs, and aggregating updates only centrally, federated learning enhances the scalability and computational efficiency of seizure detection systems. This decentralized method aids in handling large volumes of data and scales dynamically. Model will be improved continuously in a centralized manner but resource consumption will be low.

In federated learning, challenges such as communication overhead and model convergence are tackled in many ways. Compression of model updates at the central server and aggregation is done periodically to handle communication overhead. Model convergence can be tackled using learning rates in model tuning adaptively and using advanced optimization algorithms (Kairouz et al., 2021; McMahan et al., 2017). These methods reduce communication costs and handle diverse data across devices, ensuring efficient seizure detection model training. By addressing these issues, federated learning can enhance computational efficiency, and maintain reliable and accurate seizure detection capabilities.

In summary, personalized federated learning holds an incredible commitment to improving epileptic seizure detection by tailoring models to individual patients, preserving privacy, adapting to changes over time, reducing annotation burdens, enabling real-time monitoring, and enhancing scalability and accessibility across healthcare systems. Recent research has explored the utilization of federated learning techniques for epileptic seizure detection. In the area of expertise in Personalized Federated Learning for Epileptic Seizure Detection, the research landscape may be characterized by a scarcity of academic papers available for review. Personalized federated learning for epileptic seizure detection is a relatively new and emerging field within both the medical and machine learning communities. Consequently, there are very few published works addressing this intersection.

Saleh Baghersalimi et al. (Baghersalimi et al., 2021) introduced a FL approach for epileptic seizure detection on mobile platforms, using NVIDIA Jetson Nano units. They train neural networks on preprocessed ECG segments, showcasing FL's performance over centralized training, with personalized FL offering further improvements. The trade-off between model detection accuracy and training efficiency is discussed, highlighting the benefits of FL in preserving data privacy while achieving comparable performance to centralized training. The authors also address challenges related to energy consumption on mobile platforms by carefully designing the synchronization process. They optimize synchronization frequency to balance accuracy and energy consumption, achieving promising results for practical deployment. Overall, their work demonstrates the viability of deploying FL-based seizure detection systems on resource-constrained devices to attain better capabilities.

Raghdah Saemaldahr et al. (Saemaldahr and Ilyas, 2023) suggested a multi-tier architecture for epileptic seizure detection. By leveraging a large number of seizure patterns from patients spread throughout the globe, this design protects patient privacy while sharing data. The two-level edge layer model affects the preictal state determination process on both a local and global level through model-assisted decision-making. As a learned local model, the Spiking Encoder is connected to the Graph CNN using a time-series analysis with dual granularity method. Every local model calculates the preictal likelihood in the coarse-grained personalization by utilizing the combined seizure understandings gathered from the various medical institutions via FL. In fine-grained personalization, the Adaptive Neuro Fuzzy Inference System is used to identify individuals with epileptic seizures by analyzing the aftereffects of the FL model, heart rate variability data, and patient-specific clinical features.

S. Baghersalimi et al. (Baghersalimi et al., 2023) suggest an FL approach that ensures patient privacy and complies with healthcare standards by having different hospitals work together on model training without directly exchanging patient data. In the experimental setting, patient data is partitioned by age range and kind of seizure among hospitals. Geometric Mean, Specificity, and Sensitivity are examples of evaluation metrics. Four hospitals make up the scenario for the decentralized training setup. Each hospital trains locally, shares model updates, and assesses ensemble models for seizure detection. The learning parameters entail training DNNs by using the Adam optimizer with TensorFlow on pre-processed 3-second ECG and EEG segments. Utilizing the Raspberry Pi and Kendryte K210 platforms, energy consumption analysis is carried out. The suggested ensemble learning approach significantly improves seizure detection correctness, especially in large-scale FL.

W. Ding et al. (Ding et al., 2023) present a Federated Edge Server-based Epileptic Seizure Detection (Fed-ESD) system tailored for the Internet of Medical Things (IoMT) environment. Through comprehensive experimentation and analysis, the authors showcase the system's robust performance in detecting epileptic seizures. They compare Fed-ESD with advanced approaches, demonstrating its superiority in correctness and efficiency. Additionally, scalability experiments highlight Fed-ESD's ability to maintain detection performance with a rising number of edge nodes. Privacy, communication latency, and energy consumption analyses underscore the system's practical viability, especially in battery-operated IoMT devices. They conclude by proposing future directions, such as improving interpretability and addressing data heterogeneity, to further enhance Fed-ESD's applicability in real-world IoMT scenarios. Overall, the study presents Fed-ESD as a promising tool for distributed epileptic seizure prediction in medical IoMT applications.

Marcos Lupion, et al. (Lupion et al., 2023) offer a novel method for identifying epileptic seizures that utilizes federated machine learning algorithms and inexpensive IoT devices. It starts by outlining the shortcomings of the available detection techniques and then suggests a system that gets around those drawbacks, like high cost and short battery life. Wearable technology is used in the system architecture to send data to a central device, where a federated machine learning algorithm is used to detect seizures while protecting user privacy. According to preliminary results, compared to conventional methods, detection rates and efficiency gains are promising. The research provides a thorough approach to continuous seizure monitoring that may prove advantageous in terms of cost, effectiveness, and privacy protection. This makes it ready for future study and practical implementation.

S. Vasanthadev S et al. (Suryakala et al., 2024) presents an innovative strategy to overcome the difficulties in distinguishing epileptic seizures. It begins by outlining the privacy and generalization concerns that limit centralized machine learning's ability to handle EEG data. Privacy concerns are addressed by the decentralized strategy, which permits model training utilizing local datasets without sharing raw EEG recordings. Background information on epilepsy, EEG technology, and the significance of precise seizure detection in healthcare are discussed. Time complexity analysis has been performed to assess how FL can be applicable in real-world scenarios. Comparisons with previous research have been carried out which demonstrates improved sensitivity, specificity, and accuracy. Overall, the paper presents a well-structured study with valuable insights into epileptic seizure detection using FL, offering significant implications for healthcare data analysis and patient care.

Amin Aminifar et al. (Aminifar et al., 2024) present a framework for privacy-preserving federated learning designed for wearable technology over IoT infrastructure and mobile health under resource constraints. It addresses the challenges of decentralized healthcare data, emphasizing real-time epileptic seizure detection. The framework integrates high-quality hospital data with distributed deep learning to reduce computing and communication overheads while maintaining prediction accuracy. It employs federated learning and Secure Multiparty Computation (SMC) to ensure data privacy, evaluated through implementation on Amazon's AWS cloud platform. It does, however, recognize certain drawbacks, such as the assumption of homogeneous device resources, and suggests further research into how to support heterogeneous devices and computational power in FL scenarios.

These researches collectively contribute to advancing the field of personalized federated learning for epileptic seizure detection, addressing challenges related to privacy preservation, model personalization and model robustness. An overview of recent research in FL for epileptic seizure detection is provided in Table 1.

4 CHALLENGES AND FUTURE DIRECTIONS

Challenges in personalized federated learning for epileptic seizure detection include the scarcity of annotated EEG datasets, limiting the availability of labeled data necessary for training accurate seizure detection models. Moreover, existing models struggle to generalize over diverse patient populations due to variations in seizure patterns. Data heterogeneity is a significant challenge as seizure patterns and nature diverge significantly among patients, as well as within the same individual over time. This heterogeneous nature of seizure patterns complicates model development, requiring adaptable and robust architectures to incorporate these variations. Ensuring data privacy and security is vital in FL but yet challenging. FL must safeguard sensitive medical data during transmission and aggregation. It may be vulnerable to attacks such as model and data poisoning. The communication overhead is another challenge as there is a requirement for frequent model updates which can strain network resources. Another issue is the interpretability of deep learning models. The complexity of models and their uninterpretable decisions hinder their application in clinical practice as understanding, interpretation and trust of the decisions are very important in clinical practices.

Table 1: Overview of recent research in Federated Learning for epileptic seizure detection.

Authors (Year)	Dataset	Machine / Deep Learning Models	Data / Client Distribution	Performance Metrics
S. Baghersalimi et al., 2021	EPILEPSIAE dataset - one-lead ECG and 19-channel EEG data of 30 patients	MLP, 1 Dimensional Convolutional Neural Network, Residual 1-DCNN	29 patient data across 4 clients	Sensitivity: 90.24%, Specificity: 91.58%
Raghdah Saemaldahr et al., 2023	CHB-MIT EEG dataset, Bonn EEG dataset, NSC New Delhi EEG dataset	Spiking Encoder, Graph Convolutional Neural Network, Adaptive Neuro-Fuzzy Inference System (ANFIS)	Not specified	Sensitivity: 96.33%, Specificity: 96.14% for CHB-MIT dataset
S. Baghersalimi et al., 2023	EPILEPSIAE dataset, TUSZ dataset	Ensemble learning (ECG+EEG) using Deep neural networks	4 hospital clients and non-IID client data distributions	EPILEPSIAE Dataset Avg Sensitivity: 89%, Avg Specificity: 88.4% TUSZ Dataset Avg Sensitivity: 87.9%, Avg Specificity: 83.8%
W. Ding et al., 2023	EPILEPSIAE dataset	Lightweight spatiotemporal transformer network	29 edge nodes	Sensitivity: 76.8%, Specificity: 81.74%, Accuracy: 79.2%
Marcos Lupi´on, et al., 2023	Simulated dataset	CNN with LSTM layers	Wearable IoT devices data of 4 users	Train time: 278s, Recall: 0.88, Precision: 0.88, F-Score: 0.88
S. Vasanthadev et al., 2024	UCI Machine Learning Repository	Neural Network, Decision Tree, Logistic Regression	5 client nodes	Accuracy: Neural Network: 99%, Decision Tree: 94%, Logistic Regression: 89%
Amin Aminifar et al., 2024	CHB-MIT dataset	Deep Neural Network (DNN)	Data Distributed among multiple hospitals or patients' mobile devices /sensors	Accuracy DNN: 88.4%

Looking ahead, addressing these challenges requires collaborative initiatives to overcome data scarcity issues. Partnerships between research institutions, healthcare providers, and patient advocacy groups can facilitate data sharing and resource pooling for model advancement and approval. Future research directions must aim at addressing current limitations and advancing the field of epileptic seizure prediction. Novel methodologies of federated learning approaches must be proposed to enhance model scalability, privacy, and collaboration across multiple healthcare institutions. Opportunities in FL must be identified for integrating multimodal data sources, such as EEG, clinical metadata, and genetic information, to enhance the correctness and reliability of seizure prediction models. Future research endeavors should prioritize the development of interpretable and explainable deep machine learning models tailored for seizure detection. Improving clinicians' understanding and trust in model predictions will be crucial for their adoption in clinical practice. Additionally, advancements in wearable EEG technology offer promise for translating seizure prediction algorithms into practical clinical tools. Real-time monitoring systems can enable prompt action and customized care, eventually leading to better patient outcomes in epilepsy management.

5 EXPERIMENTAL ANALYSIS AND RESULTS

This section discusses the efficacy of Federated learning in epileptic seizure detection through experimental analysis. In this research, the dataset was gathered from the UCI Machine Learning Repository (Data.world, last accessed 2023/05/21). Five distinct folders, each holding 100 files make up the original dataset. Each file in the folder represents a single individual. Every file contains a 23.6-second recording of brain activity. It includes 500 people's EEG recordings, with 4097 data points collected across 23.6 seconds from each of them. These data points are divided into 23 chunks per individual, each chunk containing 178 data points for 1 second. This results in 11,500 rows of data, with 178 columns of EEG data points and the 179th column representing the label. The explanatory variables X1 to X178 form the 178-dimensional input vector. Table 2 depicts the experimental setup used for analysis.

Table 2: Experimental Setup.

Aspect	Details
Model	CNN-LSTM
Input	1D sequential EEG data
Architecture	Conv1D: 32 filters, kernel size 3, ReLU activation MaxPooling: kernel size 2 LSTM: 64 hidden units FC: 32 units, ReLU activation FC Output: sigmoid activation
Personalization	Personalized Federated Learning with 10 users
Local Training	Random sampling of 10% data for each user Adam optimizer, learning rate = 0.001, 30 epochs
Loss Function	Binary Cross-Entropy Loss (BCELoss)
Validation	Global model evaluated on validation set after aggregation

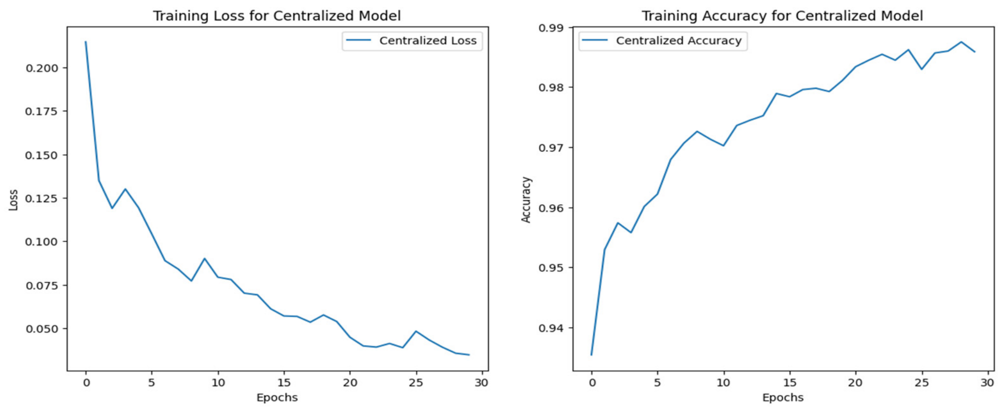

Figure 2: Centralized Model for Personalized Epileptic Seizure Detection.

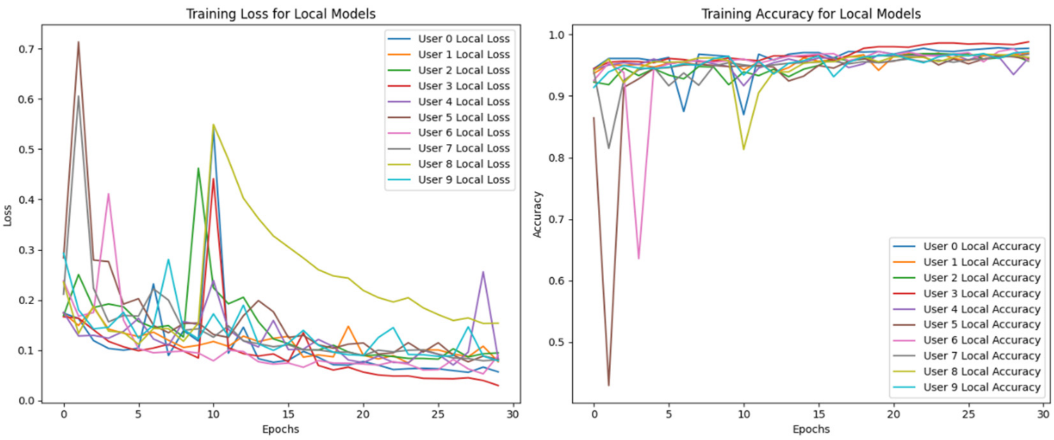

Figure 3: Federated Learning Model for Personalized Epileptic Seizure Detection.

The Convolutional neural networks (CNNs) and long short-term memory (LSTM) networks are combined in the CNN-LSTM architecture. It employs a 1D convolutional layer for feature extraction followed by max-pooling to reduce spatial dimensions. The LSTM layer captures temporal dependencies, while fully connected layers process the extracted features for prediction. This architecture is well-suited for tasks involving 1D sequential data, such as EEG recordings, as it effectively captures both spatial and temporal patterns.

Figure 2 shows the training loss and training accuracy of centralized model learning whereas Figure 3 shows the training loss and training accuracy of the FL model. The x-axis represents the number of epochs, which are iterations over the training data. The y-axis in the training loss graph depicts the loss, and the y-axis in the training accuracy graph depicts the accuracy.

Table 3: Comparison of Federated Learning and Centralized Learning Models.

Model	Accuracy Achieved
Federated Learning Model for Personalized Epileptic Seizure Detection	Global Model: 93.09%
Centralized Model for Personalized Epileptic Seizure Detection	98.09%

Table 3 portrays the accuracy scores of the Federated learning model and the Centralized machine learning model for seizure detection. As evident from Table 3, the decentralized approaches in federated learning may entail a reduction in accuracy compared to centralized methods due to the heterogeneous nature of data samples. However, they offer valuable privacy and scalability benefits that are paramount in privacy-sensitive applications. Striking a balance between accuracy and privacy remains a key challenge in the design and implementation of federated learning systems.

6 CONCLUSION

In conclusion, this study provides a complete outline of recent advancements in epileptic seizure forecast utilizing federated learning techniques applied to EEG signals. Through a thorough examination of relevant literature and methodologies, key insights have been gleaned regarding the efficacy, challenges, and future prospects of seizure prediction in a federated learning setup. Developments in personalized federated learning for the detection of epileptic seizures present a viable way to address patient variability and the requirement to protect patient privacy in medical records. Models can be trained on decentralized patient data by utilizing federated learning techniques, which leads to improved performance customized to individual seizure patterns. This strategy encourages scalability and generalizability across a range of patient populations while protecting patient privacy by permitting training without disclosing raw data. Additionally, customized seizure detection models facilitate the creation of individualized treatment. Research collaborations in this field promote information exchange and group advancement toward better seizure detection technologies and patient treatment.

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