Federated Machine Learning for Epileptic Seizure Detection using EEG

S. Vasanthadev Suryakala[1]*, T. R. Sree Vidya[2], S. Hari Ramakrishnans[3]
Department of Electronics and Communication Engineering, College of Engineering and Technology,
SRM Institute of Science and Technology, Kattankulathur, Chennai, India[1]
Department of Electronics and Communication Engineering, Tagore Engineering College, Chennai, India[2]
Department of Electronics and Communication Engineering, Tagore Engineering College, Chennai, India[3]

***Abstract*—Early seizure detection is difficult with epilepsy. This use of Electroencephalography (EEG) data has proven transformational, however standard centralized machine learning algorithms have privacy and generalization issues. A decentralized approach to epileptic seizure detection using Federated Machine Learning (FML) is presented in this research. The concentration of critical EEG data in conventional models may compromise patient confidentiality. The proposed FML technique trains models using local datasets without sharing raw EEG recordings. Hence the data set used for the model is devoid of noise thus rendering preprocessing unnecessary. Training using decentralized data sources broadens the model's seizure pattern repertoire, improving its adaptability to case heterogeneity. The Federated Machine Learning (FML) model shows that the suggested method for EEG-based epileptic seizure identification is promising for healthcare implementation and deployment. The proposed approach obtains sensitivity, specificity, and accuracy of 98.24%, 99.23%, 99% respectively. The proposed study is validated with the existing literature and the developed model outperforms the existing study.**

***Keywords*—Federal Machine Learning (FML); electroencephalography; epileptic seizure; cross-decentralization; health care; sensitivity**

I. Introduction

A neurological condition that affects a large number of people, epilepsy, is inextricably intertwined with the complications of seizure detection that are both timely and exact. There is little doubt that the paradigm shifts that have occurred toward the utilization of electroencephalography (EEG) data have been transformational. However, typical centralized machine learning models, which are the mainstays of analysis, struggle with severe hurdles. These issues generally revolve around the delicate balancing act of privacy concerns and restricted generalization. The purpose of this study is to examine the undiscovered territories of Federated Machine Learning (FML) as a potential source of hope in the context of epileptic seizure detection. This paper will begin on an adventure into new terrain. The most important thing is to choose a decentralized strategy, which is a way to gracefully avoid the obstacles that are encountered by standard techniques.

To solve these obstacles and enhance the identification and monitoring of epilepsy, research has been carried out. A study that was conducted by Fisher and colleagues and titled "A practical clinical definition of epilepsy" (Epilepsia, 2014) highlights the need to have a definition of epilepsy that is both patient-oriented and practical to improve diagnosis and make it easier to do research in this area. The research covers the difficulties associated with identifying epilepsy as well as the significance of considering the impact that it has on the lives of sufferers. In addition, a review paper titled "Epilepsy: Comorbidities and Quality of Life" (Epilepsy Research, 2016) was written by Jette and her colleagues. This study investigates the many comorbidities that are linked with epilepsy and the influence that these comorbidities have on the quality of life of those who have the disorder. An emphasis is placed throughout the essay on the significance of comprehensive treatment that extends beyond the control of seizures.

As a tool that has shed light on the complex interplay of electrical activity in the human brain, electroencephalography (EEG) has become an indispensable tool in the field of neuroscience. A non-invasive and crucial instrument, it records neural signals in real time, allowing for the identification and characterization of different brain processes, such as seizures in epileptics.

Central to electroencephalogram (EEG) technology is the measurement of electrical potentials caused by the coordinated firing of brain cells. Electrodes placed on the scalp measure and record voltage changes that are the outcome of postsynaptic potential summation, allowing this to be accomplished. The unique waveforms captured by these recordings represent various brain states.

Because it can record and describe patterns associated with seizures, EEG is very helpful in the setting of epilepsy. Electroencephalogram (EEG) characteristics are unique to seizures because of the abrupt and aberrant synchronization of neuronal firing that occurs during these episodes. Neurologists rely on these signatures—which include spikes, sharp waves, and rhythmic discharges—to make precise diagnoses and formulate effective treatment plans.

An electroencephalogram (EEG) is a crucial diagnostic and monitoring tool for epilepsy. It is a fundamental tool in neurology because it can record the ever-changing electrical landscape of the brain in real-time, detect patterns associated with seizures, and give important information for treatment choices. With the integration of EEG and new methods like Federated Machine Learning, epileptic seizure detection might become much more efficient and accurate, all while protecting the privacy of patient's personal information, thanks to the rapid advancements in technology.

Management of sensitive medical data is difficult, especially when using machine learning for diagnosis and prediction. Traditional methods gather and store data in a single repository. These techniques have considerable drawbacks, especially in patient privacy and data security. Centralized Approach Limitations: 1) Privacy Issues: Centralized models aggregate massive volumes of sensitive medical data from several sources. 2) Data Security Risks: Malicious attackers target centralized repositories. A security breach in such a store might jeopardize a massive amount of sensitive patient data. 3) Regulatory Compliance Challenges: HIPAA and GDPR are strict data protection laws in the healthcare business. Centralized methods must traverse complicated regulatory frameworks, increasing administrative costs and legal penalties for noncompliance.

Distributed and federated machine learning models address centralized method concerns. Distributed machine learning models provide advantages over the difficult centralized technique. 1) Protecting Patient Privacy: Federated Learning (FL) allows model training on dispersed devices without exchanging raw data [1]. This keeps critical patient data on local servers, lowering the danger of privacy breaches from centralized techniques.2) Improving Data Security: FL localizes data to reduce large-scale data breaches [2]. Devices exchange just model updates, frequently encrypted parameters, decreasing the attack surface and improving data security. 3) Compliance with Regulations: Decentralized models meet legal requirements by keeping data safe and making it easier to follow data security rules [3]. FL is designed so that groups can work together on machine-learning projects while still following the complicated rules that govern healthcare.

Using compression methods for model changes before sending them can cut down on communication costs by a large amount. Some methods, like quantization (which represents model parameters with fewer bits) and scarification (which sends only important parameter changes), can help with bandwidth problems. New compression methods and improvement strategies designed for FML situations are still being studied [4]. Techniques that change compression levels based on the network and the device's powers help communication go more smoothly1.

Problems caused by different datasets can be fixed by making the aggregation process better by adding weighted means based on device performance or data quality [5]. Using safe multi-party computation and homomorphic encryption, along with other advanced aggregation methods, can make privacy-preserving aggregation even stronger. Researchers are still working on creating pooled optimization methods that can handle non-IID (non-identically distributed) data and make models more accurate and faster to converge [6]. Federated learning works better when customized grouping methods are used that take into account the fact that healthcare data is often inconsistent. When you combine edge computing features, you can train and predict models locally, so you don't have to talk to a central computer all the time [7]. Edge devices can train the model at first and only send updated versions to the central computer after they have been improved. This reduces the effect of connection overhead. New developments in edge computing technologies, like edge-centric collaborative learning frameworks, let more complicated model training tasks be done nearby [7]. This method not only cuts down on contact needs, but it also makes it easier for edge devices to make decisions in real-time.

Participation mechanisms that change over time let devices join or leave the federated learning process based on their availability or how well they fit the present learning job [8]. The shared learning process is more flexible when the learning rate is changed automatically based on the features of each device. Researchers are looking into ways to change involvement and learning rates based on reinforcement learning [9]. The goal of these improvements is to make shared learning work better by responding automatically to changing network conditions and device capabilities.

A small number of studies have used both standard machine learning and deep learning to find esp seizures. By taking out important features from EEG data, SVMs have been used to find seizures. But these methods often depend on traits that were made by hand, which makes it harder for them to find complex trends in the data [10].

To sort EEG data into groups, ensemble methods such as Random Forests have been used. They are easy to understand, but the fact that they depend on specific feature engineering could make it harder for them to capture complex time patterns [11].

CNNs have been used to learn features straight from raw EEG data. They are very good at showing how things depend on each other in space, but sometimes they may not be able to show how things change over time [12].

A type of neural network called LSTMs has been used to describe sequences in time-series data, such as EEG data. They are good at showing time dependencies, but they might have trouble with disappearing gradients and long-term dependencies [13].

The current models have some problems with how accurate they are and how well they can be used in other situations.

A lot of statistics about epilepsy are not balanced, with only a few cases showing real seizures. When datasets aren't fair, models can be skewed toward the majority class, which makes them less sensitive and more likely to give false positives [14].

It is possible for EEG readings to be very different between people. Models learned on data from one person might not work well on other people because their brains are built differently, their electrodes may not be placed correctly, or their seizures may be different [15].

Some machine learning models might have trouble figuring out the long-term time frame that is important for epileptic seizures. It might be possible to deal with short-term dependence, but it's still hard to fully capture the pre- and post-ictal phases [16].

Artifacts can show up in EEG records like eye blinks, muscle movements, or electrical interference. Models might mistake these effects for seizure patterns, which would make them less specific and raise the risk of false positives [17].

Federated Machine Learning was the subject of a thorough review piece that focused on its ideas and uses [9]. The paper doesn't talk about EEG data in particular, but the ideas it does talk about are a good starting point for understanding how FML deals with privacy issues when dealing with private data. The paper talks about different ways to protect privacy, such as differential privacy, and stresses how important it is to train models without a central server.

A standard federated learning framework for epileptic seizure detection utilizing deep learning on a cluster of computers is proposed [18]. The technique was tested on the NVIDIA Jetson Nano Developer Kit using the EPILEPSIAE database, one of the largest public epilepsy datasets for seizure detection. The framework has 81.25% sensitivity, 82.00% specificity, and 81.62% geometric mean. A customized variation of federated learning was also examined, where each computer trained a deep neural network (DNN) to learn the discriminative electrocardiography (ECG) properties of the observed person's epileptic seizures based on its local data. The results show that tailored federated learning improves all performance metrics with a sensitivity of 90.24%, specificity of 91.58%, and geometric mean of 90.90%.

Research proposed based on a three-tier approach for epileptic seizure prediction using the Federated Learning (FL) model [19] to use a large number of seizure patterns from globally distributed patients while protecting data. A bi-timescale local model is developed using the Spiking Encoder (SE) and Graph Convolutional Neural Network (Spiking-GCNN). Each local model uses FL-aggregated seizure knowledge from medical centres to calculate the coarse-grained personalized preictal likelihood. Bi-timescale modelling and Spiking-GCNN-based epileptic pattern learning yielded 96.33% sensitivity and 96.14% specificity on the CHB-MIT EEG dataset. The federated learning improves the suggested system by 96.28% for accuracy.

The challenges of centralized machine learning in epileptic seizure detection is addressed and Federated Machine Learning (FML) model has been proposed as a decentralized solution to address privacy, security, and data handling issues while improving accuracy and patient privacy. It underscores the importance of EEG data and the potential of FML to revolutionize healthcare data analysis.

In conclusion, the inability of centralized methods to handle private medical data, along with the need to protect patient privacy and improve data security, makes the use of autonomous models like Federated Learning in healthcare settings very appealing. FL is a big step toward a more ethical and safe way to handle healthcare data because it reduces privacy issues and makes sure that rules are followed.

II. Material and Method: Federated Machine Learning

The healthcare business is facing several pressing problems, and federated machine learning (FML) could solve many of them. The capacity to enable cross-decentralized healthcare system collaborative learning without jeopardizing the protection of sensitive patient data is one of its notable benefits.

The goal of the machine learning paradigm known as Federated Machine Learning (FML) is to protect the confidentiality of local datasets while training models on distributed servers or devices. With FML, the learning process is decentralized, so each device may train its model locally, as opposed to the standard centralized machine learning strategy, which aggregates and stores data in a central server. Sharing just the model updates—as aggregated parameters or gradients—reduces the need to transmit raw data. When data security and privacy are of the utmost importance, FML's decentralized nature shines.

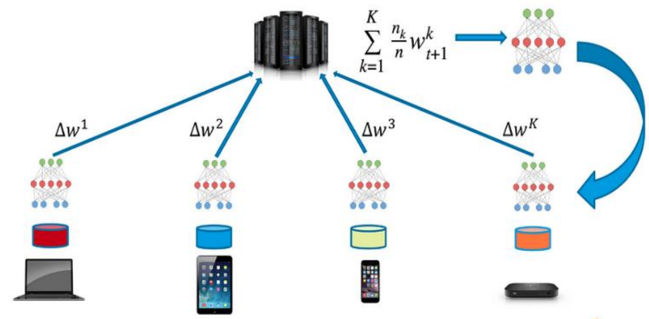

Fig. 1. Federated machine learning model.

The federated ML model is seen in Fig. 1. A global model is the result of combining model modifications made during local training. The model parameters might be averaged or gradients combined to achieve this aggregate. An all-encompassing and broadly applicable comprehension of the data is provided by the aggregated model, which is a representation of the collective knowledge acquired from all participating devices. To keep data transfers between devices to a minimum, FML places an emphasis on efficient communication. No raw data is sent; only model changes are communicated by devices. Because less data needs to be transferred, the communication overhead is reduced, making FML a good fit for situations where network capacity is restricted or when data privacy is a top priority.

Model training over distributed devices is based on the following principles.

1) Training for local models: Model training on each device's local dataset is done individually. Because decentralized data sources are diverse, this first training takes into account information unique to the local setting.

2) Revised model: Model updates, such as parameter updates or gradients, are generally generated by each device after local training. This update incorporates the insights, patterns, and characteristics related to that device, as well as the information obtained from the local dataset.

3) The world model as a whole: A global model is generated by aggregating the model updates from all devices. This worldwide model is an example of a collaborative learning product that draws on information from all around the world. By distributing the contributions from different types of data evenly, the aggregation process hopes to keep the model accurate.

For the most part, iterative processes are used for local training, model updates, and global model aggregation. In order to promote continuous learning throughout the decentralized network, devices keep improving their models using new global information.

Here is the method for the federated machine learning model, broken down into its parts.

III. Experimental Results

The Dataset collect from UCI Machine Learning Repository is used for the research study. The original dataset from the reference consists of five different folders, each with 100 files, with each file representing a single subject/person. Each file is a recording of brain activity for 23.6 seconds. The corresponding time-series is sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time. So, we have total 500 individuals with each has 4097 data points for 23.5 seconds.

The proposed federated machine learning uses five client nodes for implementing the system. Three machine learning algorithms are deployed to test the performance of the proposed system, namely decision tree classifier, multilayer perceptron classifier, and logistic regression.

Algorithm of FL
1. intialize :The Central Server: A global model is initialized and a group of clients (C) is chosen and given global model Every client i has their own local dataset (Di) and model (wi). 2. Training of Local Models: Client i: Gets the glbal model wt from the main server. Updates the local model wi with its most recent state by training it with its most recent dataset, Di. Determines the loss function's gradients using its local data: Calculates the change in weight w i as a function of time L(wt; Di) 3. Aggregation of Models: • Client i: Transfers data pertaining to local model modifications Δwi to the main server. • Central Server: Combines all the model changes that have been received: The weight allocated to client i (e.g., depending on data size) is denoted by α i, and cahnge in Δ w = Σ(i ∈ C) α i * Δ wi Update the global model: w(t+1)= wt + Δw. 4.repaeat step 2 to 3 number of rounds have passed.. Combining Models: • Update of the global model by avearge of all local model

The experimental setup parameters used for the experimental study are presented in Table I.

The research work uses a flower framework for deploying federated machine learning with 5 no of participating nodes, 3 Machine learning models like random forest, Multilayer perceptron, and logistic regression are trained with the simulation setup given in Table I.

TABLE I. EXPERIMENTAL SETUP

Model	***Parameter value***
Federated machine learning frame work	Flower framework
Number of nodes	5
Multilayer Perceptron Classifier	solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(5, 2),
Logistic Regression	Tolerance for stopping criteria= 1e-4, max_iterint=100, solver='lbfgs'
Decision tree	
Model aggregation method	Average
Batch size sd	64
No of batches	50
No of epochs	100

As a first step of analysing the proposed method, exploratory data analysis is carried out and shown in Fig. 2. The Fig. 2 shows the raw data of ECG signal of seizure-affected people data and non-epics seizure data.

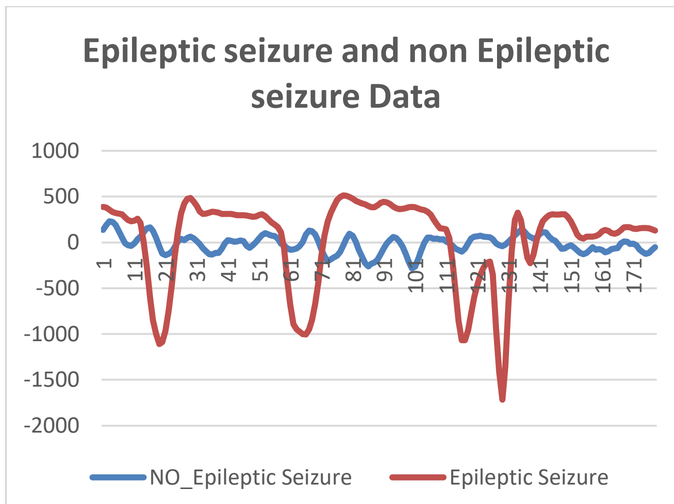

Fig. 2. EEG signal of epileptic seizure and non-epileptic seizure case.

From Fig. 2, it is evident that Epileptic Seizure data and non-Epileptic Seizure data are sitting in different amplitude domains so it is possible to classify them effectively.

Fig. 3 shows the box plot of EEG signal of epileptic seizure and non-epileptic seizure data. From the diagram it is evident the epileptic seizure data and non-epileptic data both has average values of zero but the median value of both is different and also the range of values taken by the both data are different which again prove that both data distributions are in different amplitude domain which can be effectively classified by a classifier.

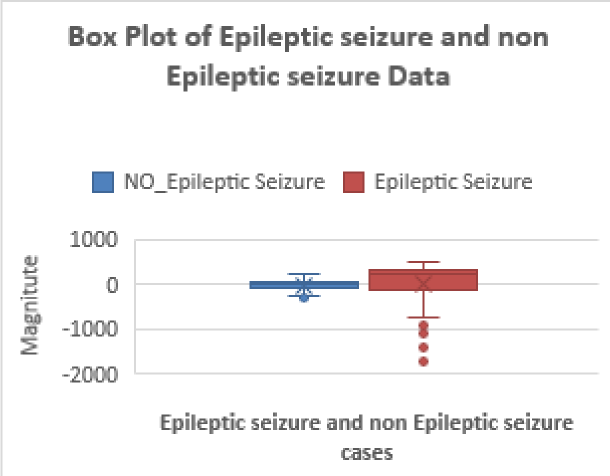

Fig. 3. Box plot of EEG signal of epileptic seizure and non-epileptic seizure case.

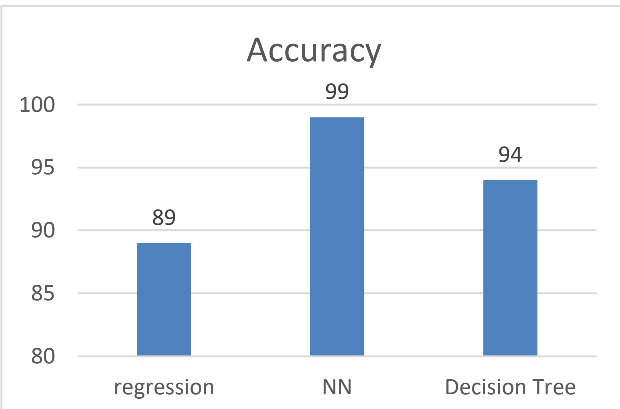

Fig. 4. Accuracy of various machine learning models in federated machine learning.

Federated machine learning of three algorithms is evaluated and plotted in Fig. 4. Figure shows that among the three algorithms, the neural network model achieves the highest accuracy with 99% and decision tree is the second highest accuracy with 94% and the regression model achieves 89%. Those performances are evaluated with the aggregated model after Federated machine learning.

The time complexity of federated machine learning (FL) depends on several factors in the specific FL setup and algorithm used.

1) Number of communication rounds: This refers to the number of times local models are uploaded from devices to the central server, aggregated, and redistributed. Each round involves communication overhead and potential computation on the server. In general, the complexity is linear in the number of rounds (O(R)).

2) Local data size: The amount of data each device uses to train its local model impacts the local computation cost. Typically, the complexity is linear in the local data size (O(n)).

3) Model size: The complexity of aggregating and updating the global model scales with its size. This can be linear (O(m)) or quadratic (O(m^2)) depending on the aggregation method and model architecture.

The time complexity of the federated machine learning for training the three machine learning models is also evaluated which is given in Fig. 4.

From Fig. 4, it is evident that the decision tree model takes a long training time and neural letter model takes the second highest training time and regression takes the least time. The training time complexity shows that the proposed model can be deployed easily in a practical system.

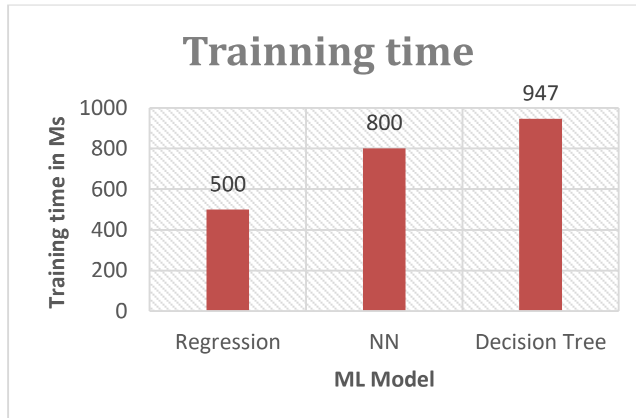

Fig. 5. Training time of Federated machine learning algorithms.

From Fig. 5, it is evident that the decision tree model takes a long training time and neural letter model takes the second highest training time and regression takes the least time. The training time complexity shows that the proposed model can be deployed easily in a practical system.

TABLE II. PERFORMANCE COMPARISON

Method	*Technique employed*	*Accuracy achieved*
Baghersalimi[18]	Federated Deep neural network	Sensitivity of 90.24%, Specificity of 91.58%
Saemaldahr, R.[19]	Federated Spiking Encoder (SE) and Graph Convolutional Neural Network (Spiking-GCNN).	96.33% Sensitivity, 96.14% Specificity. 96.28% accuracy
Proposed	Federated Neural network	sensitivity of 98.24%, specificity of 99.23% 99% accuracy

Table II shows the performance analysis comparison with the literature work. From Table II, it is evident that the proposed work outperformed compared to the literature work. Literature work can achieve 96.33% of sensitivity but the proposed work can achieve 98.24%. similarly, the proposed work achieves 99.23% specificity whereas the literature maximum of 96.14% was only achieved. The proposed work achieves 99 % accuracy whereas literature could even touch only 96%.

IV. Conclusion

EEG signal-based epileptic seizure detection framework is presented with a Federated machine learning mechanism. The proposed mechanism ensures the security and privacy of the data while applying data analytics of data to predict the presence and absence of seizure. Maximum accuracy of 99% is achieved by using a neural network model under federation machine learning. The time complexity of the proposed framework was analysed and it shows for the neural network model it takes 800 milliseconds to train the model to predict or classify the seizure. This time complexity proves that the proposed model or framework can be deployed practically to train using federated machine learning. The future work of the proposed framework will be analysing the communication overhead and providing some security measures while sharing the locally trained model with the aggregating server.

References

[1] Beaulieu-Jones, B. K., Wu, Z. S., Williams, C., Lee, R., Bhavnani, S. P., Byrd, J. B., & Greene, C. S., “Privacy-preserving generative deep neural networks support clinical data sharing” Circulation: Cardiovascular Quality and Outcomes, 12(7), e005122, 2019.

[2] Yang, Q., Liu, Y., Chen, T., & Tong, Y., “Federated machine learning: Concept and applications”, ACM Transactions on Intelligent Systems and Technology (TIST), 10(2), 1-19, 2019.

[3] Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., ... & Zhao, S., “Advances and open problems in federated learning”, Foundations and trends® in machine learning, 14(1–2), 1-210, 2021.

[4] McMahan, B., Moore, E., Ramage, D., Hampson, S., & y Arcas, B. A., “Communication-efficient learning of deep networks from decentralized data”, In Artificial intelligence and statistics (pp. 1273-1282). PMLR, 2017.

[5] Bonawitz, K., Ivanov, V., Kreuter, B., Marcedone, A., McMahan, H. B., Patel, S., ... & Seth, K., “Practical secure aggregation for privacy-preserving machine learning”, In proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security (pp. 1175-1191), October 2017.

[6] Konecný, J., McMahan, H. B., Yu, F. X., Richtárik, P., Suresh, A. T., & Bacon, D., “Federated learning: Strategies for improving communication efficiency”, arXiv preprint arXiv:1610.05492, 8, 2016.

[7] Li, D., & Wang, J.,”Fedmd: Heterogenous federated learning via model distillation”, arXiv preprint arXiv:1910.03581, 2020.

[8] Wang, S., Tuor, T., Salonidis, T., Leung, K. K., Makaya, C., He, T., & Chan, K., “Adaptive federated learning in resource constrained edge computing systems”, IEEE journal on selected areas in communications, 37(6), 1205-1221, 2019.

[9] Yang, Q., Liu, Y., Chen, T., & Tong, Y., “Federated machine learning: Concept and applications”, ACM Transactions on Intelligent Systems and Technology (TIST), 10(2), 1-19, 2019.

[10] Shoeb, A., “Application of machine learning to epileptic seizure onset detection and treatment”, MIT, 2009.

[11] Sharma, M., & Pachori, R. B., “A survey on EEG signal classification techniques”, IET Signal Processing, 12(2), 125-133, 2018.

[12] Acharya, U. R., & Sree, S. V., “Application of higher order spectra for automated classification of epileptic EEG signals”, Expert Systems with Applications, 39(10), 9072-9078, 2012.

[13] Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., & Falk, T. H., “Deep learning-based electroencephalography analysis: a systematic review”, Journal of Neural Engineering, 16(5), 051001, 2019.

[14] Shoeb, A., & Guttag, J., “Application of machine learning to epileptic seizure detection”, In Proceedings of the 27th international conference on machine learning (ICML-10) (pp. 975-982), 2010.

[15] Gotman, J., “Automatic recognition of epileptic seizures in the EEG”, Electroencephalography and Clinical Neurophysiology, 54(5), 530-540, 1982.

[16] Faust, O., Acharya, U. R., Adeli, H., & Adeli, A., “Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis”, Seizure, 26, 56-64, 2015.

[17] Osorio, I., Frei, M. G., & Wilkinson, S. B., “Real-time automated detection and quantitative analysis of seizures and short-term prediction of clinical onset”, Epilepsia, 39(6), 615-627, 1998.

[18] S. Baghersalimi, T. Teijeiro, D. Atienza and A. Aminifar, "Personalized Real-Time Federated Learning for Epileptic Seizure Detection," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 2, pp. 898-909, 2022.

[19] Saemaldahr, R. and Ilyas, M., “Patient-Specific Preictal Pattern-Aware Epileptic Seizure Prediction with Federated Learning”, Sensors, 23(14), p.6578, 2023.