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# A Novel Decentralized Federated Incremental Learning Framework for ECG and EEG Signal Analysis

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**ABSTRACT** The increasing use of artificial intelligence (AI) in healthcare has revolutionized medical diagnostics, particularly in cardiology and neurology, where electrocardiograms (ECG) and electroencephalograms (EEG) play a crucial role in diagnosing conditions like heart attacks and epilepsy. However, the sensitive nature of medical data poses significant privacy concerns, limiting data sharing between institutions for AI model training. Federated learning (FL) offers a solution by enabling collaborative learning without sharing raw data. Traditional FL approaches rely on centralized servers, which introduce risks such as single points of failure and communication bottlenecks. To address these limitations, we propose a decentralized federated learning (DFL) system combined with incremental learning (IL), allowing continuous adaptation to new data streams while preserving patient privacy. Our architecture utilizes a CNN-BiLSTM model for physiological signal analysis, trained locally at each institution. Model weights are exchanged in a ring topology using an incremental federated averaging algorithm (IncFedAvg), ensuring efficient weight aggregation without a central server. The proposed system demonstrates high accuracy in both ECG arrhythmia classification and EEG seizure detection. Moreover, the incremental learning capability allows the model to adapt to real-time data while maintaining performance. This approach effectively addresses the challenges of privacy preservation and dynamic healthcare data processing, offering a scalable solution for medical institutions.

**KEYWORDS** Deep learning; Decentralized federated learning; Incremental learning; Physiological signals; healthcare data privacy;

## I. INTRODUCTION

The integration of Artificial Intelligence (AI) in healthcare has revolutionized the way medical professionals diagnose and treat diseases [1], particularly in fields like cardiology and neurology [2]. AI-driven models have demonstrated remarkable potential in analyzing complex physiological signals such as Electrocardiograms (ECG) and Electroencephalograms (EEG), which are critical for diagnosing life-threatening conditions like heart attacks and epilepsy [3].

These technologies enable faster, more accurate diagnoses, reducing the burden on healthcare professionals and improving patient outcomes. However, the widespread adoption of AI in healthcare is hindered by several challenges, primarily related to data privacy and the availability of large, diverse datasets [4].

Medical data is highly sensitive, and sharing it across institutions for AI model training raises significant privacy concerns. Regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in Europe impose strict guidelines on handling patient data, making it difficult for institutions to collaborate openly [5]. Traditional approaches to AI model training often require centralized datasets, which are impractical in healthcare due to privacy risks and legal constraints. Federated learning (FL) [6] has emerged as a promising solution to this problem by allowing institutions to collaboratively train models without sharing raw data. Instead, only model updates are exchanged, preserving the privacy of individual patient records.

Despite its advantages, Federated Learning still faces limitations. Most FL systems rely on a central server to aggregate model updates from participating institutions. This introduces vulnerabilities such as a single point of failure and communication bottlenecks [7]. Furthermore, legal restrictions on cross-border data sharing complicate the use of centralized servers in global healthcare collaborations [8]. To address these issues, researchers have proposed Decentralized Federated Learning (DFL), which eliminates the need for a central server by enabling direct communication between institutions in a peer-to-peer manner [9]. While DFL mitigates some of the risks associated with traditional FL, it introduces new challenges, such as complex coordination between institutions and difficulties in aggregating model weights efficiently [10].

Another critical limitation of current FL and DFL approaches is their assumption that all participating institutions have pre-collected datasets ready for training. In reality, healthcare data is generated continuously, requiring models that can adapt to new data streams in real-time [11]. This dynamic nature of healthcare data necessitates an incremental learning approach that allows models to update continuously without retraining from scratch [12].

In this paper, we propose a novel decentralized federated learning architecture that integrates incremental learning to address these challenges. Our system enables medical institutions to train a Convolutional Neural Network-Bidirectional Long Short-Term Memory (CNN-BiLSTM) model locally using their private data while exchanging only model weights with other institutions in a decentralized manner. By leveraging Incremental Federated Averaging (IncFedAvg), our approach ensures efficient weight aggregation across institutions without relying on a central server. Additionally, the incremental learning capability allows the model to adapt to continuous data streams while maintaining high accuracy. This architecture preserves patient privacy and offers a scalable solution for real-time physiological signal analysis in healthcare.

The remainder of this paper is structured as follows: Section 2 reviews related works from the literature, highlighting previous approaches and their limitations. Section 3 presents the proposed approach in detail, including both the model architecture and system architecture, with a focus on its two main aspects: federated learning and incremental learning. Section 4 discusses the experimental results, demonstrating the effectiveness of the proposed method. Finally, Section 5 summarizes the findings of this study and suggests potential directions for future research.

## II. RELATED WORK

Recent advancements in Centralized Federated Learning (CFL), Decentralized Federated Learning (DFL), and Incremental Learning (IL) have significantly contributed to the field of physiological signal analysis, particularly in healthcare applications [13]. Several studies have explored the use of CFL and DFL frameworks for tasks such as ECG and EEG classification. However, many of these approaches face limitations related to centralized coordination or fail to address the continuous arrival of new data, which is crucial in dynamic healthcare environments. In the context of Continual federated learning, the study in [14] proposed a CFL framework for arrhythmia classification using transfer learning, CNNs, and explainable AI (XAI), achieving superior performance on the MIT-BIH dataset. In [15] Ying et al. introduced Fed-ECG, a semi-supervised FL framework for heart abnormality classification using ResNet9 and pseudo-labeling techniques, which showed promising results despite using a centralized server. Goto et al. developed in [16] machine learning models for hypertrophic cardiomyopathy classification using ECGs and echocardiograms, demonstrating that multi-institution models trained in a federated environment showed better generalizability than single-institution models. [17] addressed the issue of non-IID data distribution in FL with FedCluster, which clusters client parameters based on ECG data similarity and outperformed FedAvg on the MIT-BIH dataset. The authors of [18] proposed a personalized FL approach for ECG classification, which uses feature alignment to ensure consistency between global and local data, achieving good accuracy on private datasets. In [19] Jimenez Gutierrez et al. used FL with FedAvg to train deep learning models on heterogeneous ECG data from multiple sources, showing comparable results to traditional training methods. The study in [20] proposes a weighted Federated Learning (FL) approach for arrhythmia classification, where the weight of each client is dynamically adjusted based on its contribution to the global model improvement. This method aims to enhance the accuracy of the global model by prioritizing clients that contribute more significantly to the model's performance. Chen et al. in [21], introduce a new Federated Learning (FL) framework called Group-FL for large-scale driver drowsiness detection. The framework organizes clients into hierarchical groups and gradually aggregates model parameters. A global personalized deep learning model is used to handle variations in EEG signals among clients by extracting shared and fine-grained features for classification.

In the context of DFL, the authors of [22] introduced a DFL framework for epilepsy classification using adaptive ensemble learning during local training, validated through knowledge distillation and public dataset evaluation. [23] combined FL with blockchain in their MetaCL framework to classify multiple physiological signals while preventing catastrophic forgetting through continual learning mechanisms, however, high computational demands limited its scalability. [24] explored improving communication efficiency in DFL over graph-based topologies, showing that DFL can outperform traditional methods in large-scale datasets by reducing communication overhead. In [25] Agrawal et al. introduced a DFL framework for emotion classification using CNN architecture, evaluated on the DEAP dataset. Kim et al. introduce in [10] a decentralized federated learning (DFL) framework for arrhythmia classification. The framework employs a method selection process across four different datasets to simulate a multicenter distributed environment. Additionally, fake data generated by a GAN was used to evaluate the framework's performance, which demonstrated stable results across all datasets, comparable to traditional FL approaches.

Although several works have employed decentralized federated learning (DFL) to address the issue of a single point of failure (SPoF), typically associated with centralized servers, they often overlook the continuous arrival of data, which is crucial in dynamic healthcare environments.

Regarding Incremental Learning, the study in [26] introduced AFLEMP, a multi-modal emotion classification framework using attention mechanisms and incremental learning, evaluated on AMIGOS and DREAMER datasets. Kim et al. in [27] proposed an adaptive authentication system using ECGs with incremental learning to address signal variations due to emotional or physical changes. Fan et al. developed in [28] ABLS, an active and incremental learning system for arrhythmia classification on the MIT-BIH dataset that fine-tunes connection weights over time while reducing time consumption compared to traditional methods. Lastly, in [29], Shi et al. introduced an incremental learning method for arterial fibrillation detection using transfer learning and active learning strategies to continuously update models as new data arrives.

In conclusion, Federated Learning (FL) approaches have successfully addressed the privacy concerns in healthcare by enabling collaborative model training without sharing raw data. However, Centralized Federated Learning (CFL) methods are limited by their reliance on a central server, which introduces vulnerabilities such as network bottlenecks and security risks. To overcome these issues, Decentralized Federated Learning (DFL) has been proposed, eliminating the need for a central server and enhancing system resilience. Despite these improvements, DFL approaches still face challenges in adapting to the dynamic nature of healthcare data, particularly the continuous arrival of new data. This highlights the need for integrating Incremental Learning (IL) into DFL frameworks to ensure real-time adaptability while maintaining privacy and scalability in healthcare settings.

## III. PROPOSED APPROACH

### A. DATASET DESCRIPTION AND PREPROCESSING

In this study, we utilized two well-known datasets for training and evaluating our decentralized federated learning with incremental learning architecture: the MIT-BIH Arrhythmia dataset [30] for ECG analysis and the Bonn University Seizure dataset [31] for EEG analysis. These datasets were selected due to their widespread use in physiological signal processing tasks, such as arrhythmia detection and seizure classification.

The MIT-BIH Arrhythmia Dataset consists of 48 half-hour long two-channel ambulatory ECG recordings obtained from 47 subjects, digitized at 360 samples per second per channel. It is widely used for arrhythmia detection and classification tasks. The Bonn University Seizure Dataset contains EEG recordings from five different sets, each with 100 single-channel EEG segments, sampled at 173.61 Hz, and is commonly used for seizure detection tasks.

The ECG dataset used in this study was highly imbalanced, requiring class balancing techniques. To address this, oversampling was applied to increase the number of samples in underrepresented classes by duplicating them, ensuring a more balanced dataset for training. For the EEG dataset, data augmentation was necessary to increase its size. The chosen method was Gaussian Noise Injection, where noise following a normal distribution was added to the signals, making the model more robust to variations. These preprocessing steps were essential for improving model performance and ensuring that the data was suitable for training in a federated learning environment.

### B. PROPOSED MODEL ARCHITECTURE

To process both ECG and EEG signals effectively, we designed a hybrid deep learning architecture that combines Convolutional Neural Networks (CNNs) with Bidirectional Long Short-Term Memory (BiLSTM) networks. This combination leverages the strengths of both architectures to handle the spatial and temporal characteristics inherent in physiological signals.

CNNs are particularly effective at capturing spatial features from input data by applying convolutional filters across the signal. In our case, CNN layers were used to automatically extract meaningful features from raw ECG/EEG signals without requiring manual feature engineering.

BiLSTMs are an extension of standard LSTM networks designed to capture long-term dependencies in sequential data by processing information in both forward and backward directions. This bidirectional capability allows BiLSTMs to capture contextual information from both past and future time steps, making them ideal for handling physiological signals like ECGs or EEGs that exhibit temporal dependencies.

The architecture consists of multiple convolutional layers followed by BiLSTM layers, which process the extracted features sequentially. The final output layer uses softmax activation for multi-class classification (e.g., arrhythmia types or seizure detection). A visual representation of this architecture is provided in Fig. 1.

### C. PROPOSED SYSTEM ARCHITECTURE

In this section, we present the architecture of the proposed system, which integrates Decentralized Federated Learning (DFL) with Incremental Learning (IL) to address the limitations of existing federated learning models in dynamic healthcare environments. Our proposed architecture overcomes those challenges by decentralizing communication

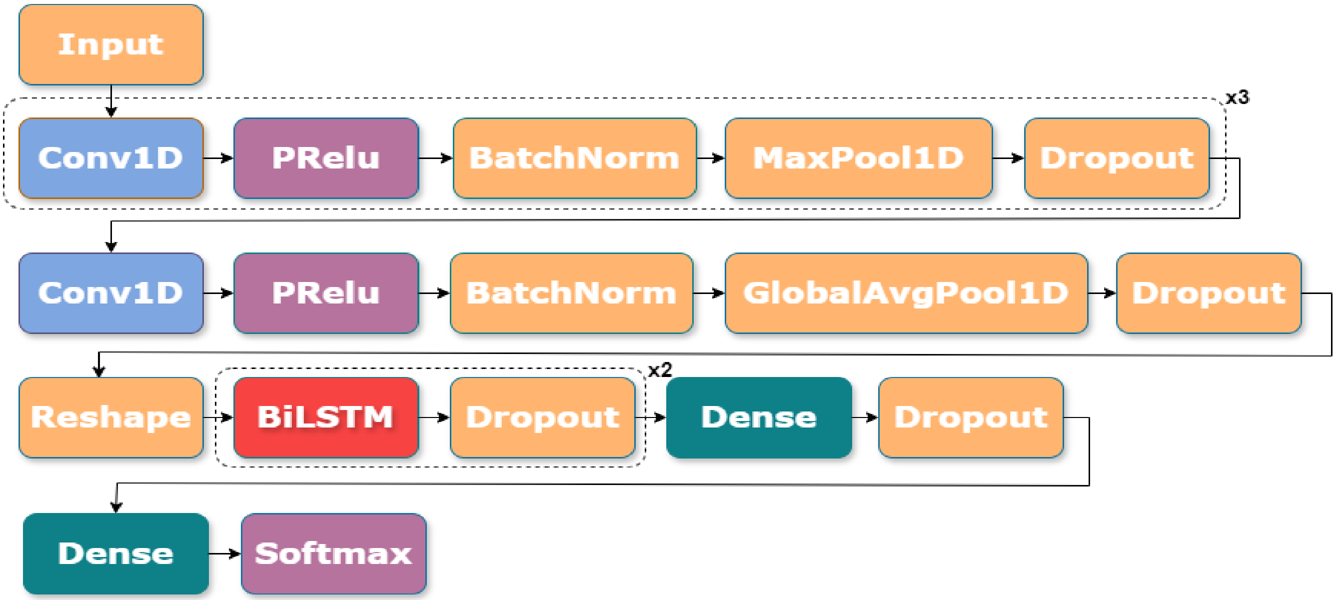


Figure 1. Proposed CNN-BiLSTM model architecture

between medical institutions and incorporating incremental learning to handle real-time data streams.

### 1) Overview of the hybrid architecture

The proposed system architecture is designed to decentralize communication between medical institutions entirely, enabling continuous model updates without relying on a central server. To achieve this, a ring topology is implemented, allowing institutions to exchange model updates directly with their neighbors, as illustrated in Fig. 2 The system consists of two primary components: Decentralized Federated Learning (DFL) and Incremental Learning (IL).

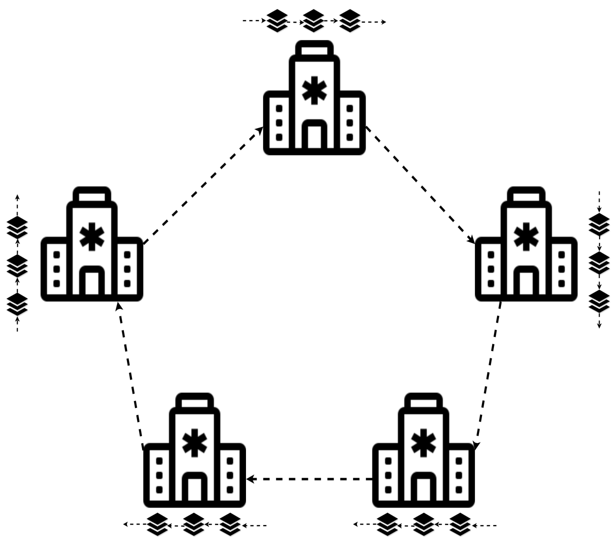

Figure 2. Global representation of the ring topology with data streams coming in real time

The DFL component facilitates privacy-preserving collaboration by ensuring that institutions share only model weights rather than raw data, maintaining data confidentiality. Meanwhile, the IL component allows models to adapt incrementally to newly arriving data without requiring complete retraining, making the system highly dynamic and efficient. Together, these components ensure scalability, adaptability, and robustness in handling the dynamic nature of healthcare environments.

The system's operation is driven by two independent and atomic processes:

- Receive (datat), which handles incoming data batches for incremental learning, and
- Receive (GWk-1), which handles global weights received from the previous institution in the ring topology.

These functions are triggered by reception events, operate in parallel, and function independently, enabling the system to manage decentralized communication and incremental learning simultaneously.

### 2) Decentralized federated learning component

In the DFL component, each medical institution retains its own private model and data, ensuring privacy while enabling collaborative learning across institutions. The key innovation in our approach is the introduction of the Incremental Federated Averaging (IncFedAvg) algorithm, inspired by traditional Federated Averaging [6]. In contrast to centralized FL, where a central server aggregates model weights from all clients, our ring-topology setup allows weight aggregation to occur incrementally and sequentially across multiple rounds until all models converge. In the weight aggregation process, two types of weights are used:

- Local Weights (LW): These are parameters extracted from each model after local training.
- Global Weights (GW): These are the shared weights exchanged between institutions.
- Cycle Index: This index tracks the position of each institution (N) in the ring topology based on the round number (r) and total number of institutions (n). It is calculated using Eq. (1).

$$CycleIndex = N_k + (r + 1) * n \tag{1}$$

The aggregation process begins with each institution calculating its Local Weights (LW) after training on its private data. These weights are then combined with Global Weights (GW) received from the previous institution using the IncFedAvg algorithm (see Eq.2). This process ensures that knowledge is shared across all institutions while maintaining data privacy. The updated Global Weights are then transmitted to the next institution in the ring for further aggregation. This cycle continues over multiple rounds until all local models converge. A visual representation of this process is provided in Fig.3.

$$GW_k = GW_{k-1} + \frac{LW_k - GW_{k-1}}{CycleIndex_{N_k}} \tag{2}$$

### 3) Incremental learning component

To address the limitation of the dynamic nature of healthcare environments in traditional DFL approaches, we incorporate Incremental Learning (IL) within each institution's local model. In this approach, models are updated incrementally as new data batches arrive, allowing them to adapt to real-time data streams without requiring retraining from scratch. The IL component ensures that models continuously improve over time by learning from small batches of new data while retaining previously acquired knowledge. The IncFedAvg algorithm plays a crucial role in this process by aggregating both Local Weights and Global Weights before and after each new batch of data is processed. This allows institutions to update their models incrementally without storing large amounts of historical data. The aggregation process is outlined by Eq. 3.

$$GW_k^{(t)} = GW_{k-1}^{(t-1)} + \frac{LW_k^{(t)} - GW_k^{(t-1)}}{DataIndex_{N_k}} \tag{3}$$

With DataIndex is an index that tracks the number of mini-batches processed during incremental learning. As with DFL, the updated Global Weights are shared with neighboring institutions in the ring topology to ensure that all models benefit from new knowledge acquired at each institution. A visual representation of this incremental learning process is provided in Fig. 4.

### 4) Fault tolerance and dynamic ring reconfiguration

The proposed decentralized federated learning framework incorporates a robust fault tolerance mechanism to ensure system resilience against node failures in healthcare environments. The system employs a monitoring and reconfiguration approach that maintains operational continuity when institutions experience connectivity issues or hardware failures.

Each participating node implements a threshold-based monitoring system that continuously tracks communication with neighboring institutions. When response times exceed

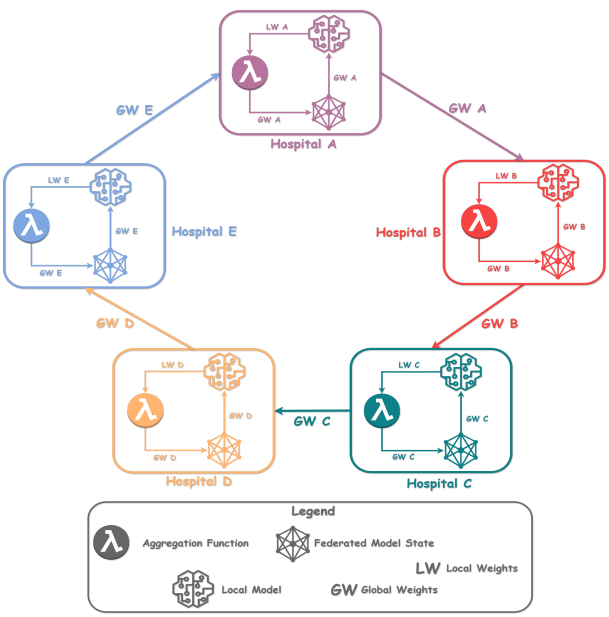


Figure 3. Decentralized federated learning component architecture and process

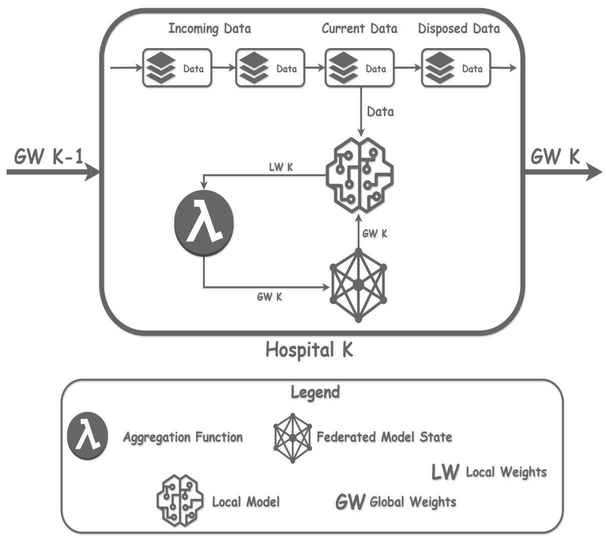


Figure 4. Incremental learning component process at one hospital k

predefined thresholds, the system identifies potentially unresponsive peers through communication timeouts.

Upon detecting an unresponsive node, the system automatically initiates a dynamic topology reconfiguration protocol. Adjacent nodes establish direct connections that bypass the failed institution, effectively maintaining the logical ring structure while physically excluding the unavailable participant. This reconfiguration is reflected in the cycle index calculation (Eq. 1), where both the total number of institutions (n) and the position of the node following the failed one are dynamically adjusted.

When a previously unresponsive node returns online, it undergoes a comprehensive knowledge synchronization phase before full reintegration into the ring. This process involves receiving the latest model state from its predecessor node to rapidly align with the current learning trajectory.

#### 5) Malicious client detection and poisoning attack mitigation

Building upon our fault tolerance mechanisms, the proposed system can also be fortified against malicious clients and poisoning attacks through several established defensive approaches. Our framework can incorporate techniques similar to those presented in recent research on federated learning security. For instance, a forensic analysis approach can be implemented to trace back malicious clients after detecting poisoned model updates, allowing the system to identify and exclude attackers from future training rounds [32].

Additionally, the system can employ specialized detection mechanisms that analyze the statistical properties of client updates to identify potentially malicious contributions before they affect the global model. This proactive detection helps maintain model integrity even when faced with sophisticated poisoning attempts [33].

For comprehensive protection, our architecture supports the integration of blockchain-based consensus mechanisms where a committee of trusted nodes validates updates before integration into the global model. This approach creates an immutable audit trail of all model contributions while establishing a verification layer that prevents compromised clients from corrupting the collaborative learning process [34].

These defensive measures complement our fault tolerance framework by addressing both accidental failures and deliberate attacks, ensuring the robustness and trustworthiness of the decentralized federated learning system in healthcare environments where data integrity directly impacts clinical outcomes.

## IV. EXPIRIMENTAL RESULTS

This section evaluates the proposed hybrid approach, focusing on its robustness against underfitting and overfitting, as well as its generalization capabilities. The experimental evaluation of the proposed system is conducted in three distinct configurations to assess its performance and adaptability. First, the CNN-BiLSTM model is evaluated in a local configuration, where it is trained on 100% of the available data without any distributed or incremental components. This serves as a baseline to understand the model's standalone performance. Next, the system is tested in a distributed configuration using Decentralized Federated Learning (DFL) without incorporating the Incremental Learning (IL) component, allowing us to evaluate the effectiveness of the decentralized approach in preserving privacy and achieving collaborative learning. Finally, the incremental learning component is integrated into the distributed configuration to assess its ability to handle real-time data streams and adapt dynamically to continuously arriving data. The evaluation metrics applied in this study are detailed below. Furthermore, we examine the experimental outcomes of the suggested model of architecture.

### A. EVALUATION METRICS

To evaluate the performance of our proposed model, several key metrics were used. These metrics help in understanding the effectiveness and reliability of the models:

- Accuracy: This is a fundamental metric that measures the proportion of correctly classified instances out of the total instances. It is calculated as in Eq. 4.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made} \tag{4}$$

- Precision: It measures the proportion of true positive predictions among all positive predictions made by the model. It is particularly useful in scenarios where false positives are costly. Precision is calculated as in Eq. 5.

$$Precision = \frac{True\ positive}{True\ positive + False\ positive} \tag{5}$$

- Recall: Recall, or sensitivity, measures the proportion of actual positive instances that were correctly identified by the model. It is crucial in applications where missing a positive instance (false negative) is costly. Recall is calculated as in Eq. 6.

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \tag{6}$$

- AUC: This metric evaluates the model's ability to distinguish between classes by plotting the true positive rate against the false positive rate at various threshold settings. It is calculated as in Eq 7.

$$AUC = \int_0^1 TPR(t)\, dt \tag{7}$$

### B. EVALUATION OF THE TRADITIONAL DEEP LEARNING MODEL

To evaluate the standalone performance of the CNN-BiLSTM model, we first conducted experiments in a local configuration using 100% of the available data. This setup serves as a baseline to assess the model's capabilities without any distributed or incremental components. The evaluation focused on key performance metrics such as accuracy, precision, and recall to provide insights into the model's effectiveness in handling physiological signal classification tasks.

After developing the model, we employed several advanced techniques to maximize its accuracy for both ECG and EEG datasets. A key step was hyperparameter optimization, conducted using the KerasTuner framework in conjunction with the innovative HyperBand algorithm. This process enabled us to identify the optimal set of hyperparameters for our model, ensuring improved performance. Subsequently, the model was trained on ECG and EEG data over various epochs to determine the ideal training duration.

During the training phase, we integrated multiple callback mechanisms, including ReduceLROnPlateau and EarlyStopping, to enhance the efficiency of the learning process and prevent unnecessary computation. The evaluation on unseen test data yielded outstanding results, achieving accuracies of 98.12% for ECG classification and 86.52% for EEG classification—comparable to or exceeding current state-of-the-art benchmarks. These results, along with additional performance metrics, are summarized in Fig. 5, Fig. 6 and Tab.1.

Furthermore, an analysis of the learning curves confirmed the absence of overfitting, underscoring the robustness and generalizability of our model across both ECG and EEG datasets. This highlights its potential as a reliable tool for physiological signal analysis in real-world scenarios.

Table 1. Traditional deep CNN-BiLSTM model results for ECG and EEG data

| | *ECG* | *EEG* |
|---|---|---|
| *Accuracy* | 98.12 | 86.52 |
| *Precision* | 98.25 | 86.31 |
| *Recall* | 97.94 | 84.49 |
| *AUC* | 99.91 | 98.47 |

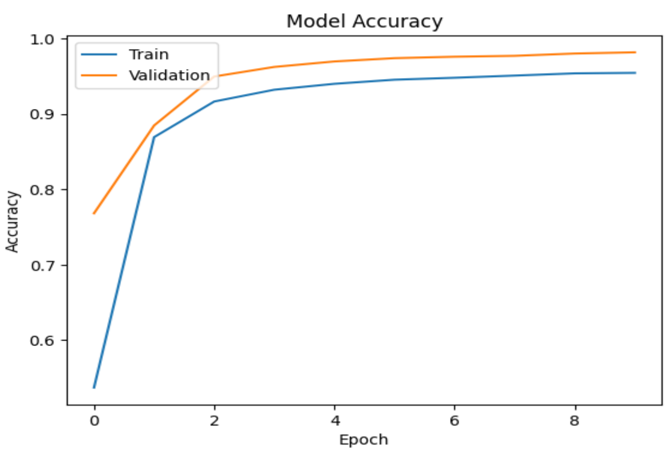


Figure 5. Accuracy of traditional deep CNN-BiLSTM model on 100% of available ECG data in a centralized configuration

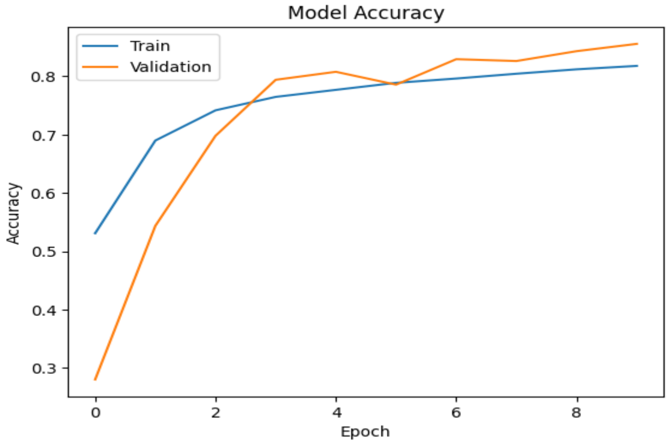


Figure 6. Accuracy of traditional deep CNN-BiLSTM model on 100% of available EEG data in a centralized configuration

### C. DECENTRALIZED FEDERATED APPROACH

To assess the performance of the proposed system in a distributed configuration, we conducted a series of experiments under varying conditions to simulate real-world scenarios. These experiments were designed to evaluate the impact of decentralization and data distribution on model performance. To provide a more precise understanding, we conducted three experiments. Below is a detailed list and description of the experiments performed:

- 1st Experiment: Single institution in Standalone Configuration with 50% of the available data.
- 2nd Experiment: Two institutions in Distributed Configuration.
- 3rd Experiment: Five institutions in Ring Topology.

#### 1) 1st experiment

In the first experiment, the dataset was split into two parts, with only one client trained on 50% of the data. The model achieved an accuracy of 87.43% on ECG data and 80.5% on EEG data, which is significantly lower compared to the accuracy obtained when the client was trained on 100% of the dataset. This reduction in performance highlights the sensitivity of the CNN-BiLSTM model to the size of the training data. Tab. 2 presents the final metric values, and Fig. 7 and Fig. 8 illustrate the accuracy progression over 10 epochs.

Table 2. Results of CNN-BiLSTM model trained on 50% of available data in a centralized configuration

| | *ECG* | *EEG* |
|---|---|---|
| *Accuracy* | 87.43 | 83.5 |
| *Precision* | 87.32 | 83.39 |
| *Recall* | 86.87 | 82.12 |

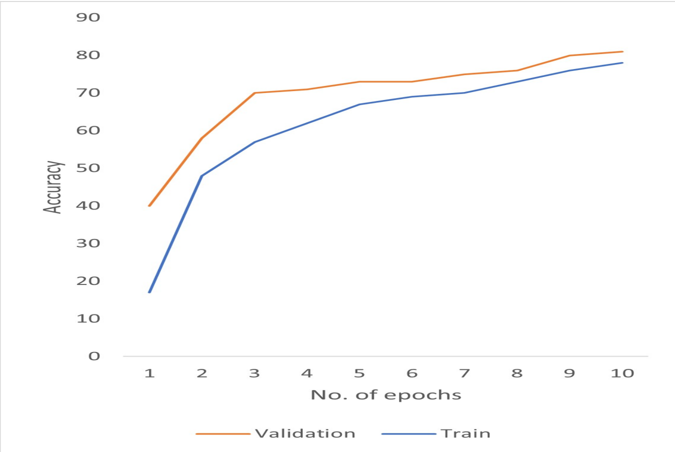


Figure 7. Accuracy of traditional deep CNN-BiLSTM model on 50% of available ECG data in a centralized configuration

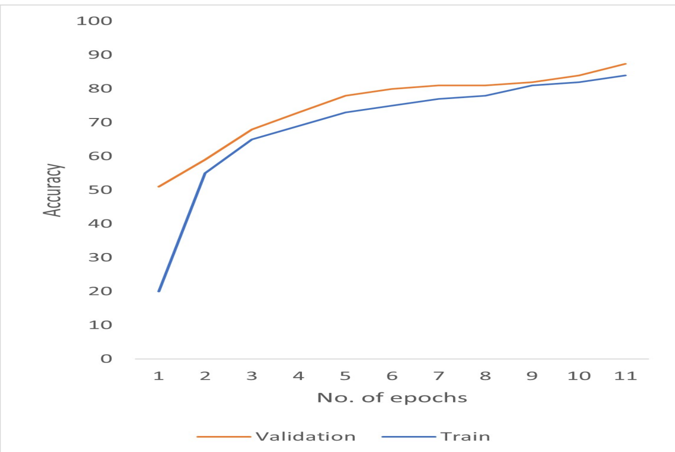


Figure 8. Accuracy of traditional deep CNN-BiLSTM model on 50% of available EEG data in a centralized configuration

### 2) 2nd experiment

In the second experiment, the dataset was distributed between two clients, with each client receiving 50% of the training data. Both clients participated in the training process using the proposed decentralized federated learning approach. As illustrated in the accuracy graphs in Fig. 9 and Fig. 10, the model achieved an accuracy of 97.8% on ECG data and 85.93% on EEG data, with additional performance metrics provided in Tab. 3. The training was conducted over 20 communication rounds, with each round consisting of 10 epochs. These results suggest that the collaboration between the two clients significantly contributed to the improvement in overall accuracy compared to standalone configurations in the first experiment.

### 3) 3rd experiment

In this experiment, we simulated an architecture with five clients, where the training dataset was distributed unevenly to reflect real-world scenarios. Two clients received 15% of the data each, two others were assigned 20% each, and the remaining client was allocated 30% of the data. Each client trained independently, allowing for a comparison of outcomes. This setup mimics practical situations where larger institutions, such as major hospitals, have access to more data, while smaller health centers possess significantly less. The federated model achieved an accuracy of 97.63%, comparable to traditional deep learning approaches, as shown in Fig. 11, Fig. 12 and Tab. 4. The collaborative nature of the federated learning framework enabled the model to benefit from the diverse data contributions across all five clients, the accuracy of the model improved progressively over the communication rounds. As shown

Table 3. Results of decentralized federated model experiment of two clients

| | *ECG* | *EEG* |
|---|---|---|
| *Accuracy* | 97.8 | 85.93 |
| *Precision* | 97.68 | 85.79 |
| *Recall* | 96.73 | 84.75 |

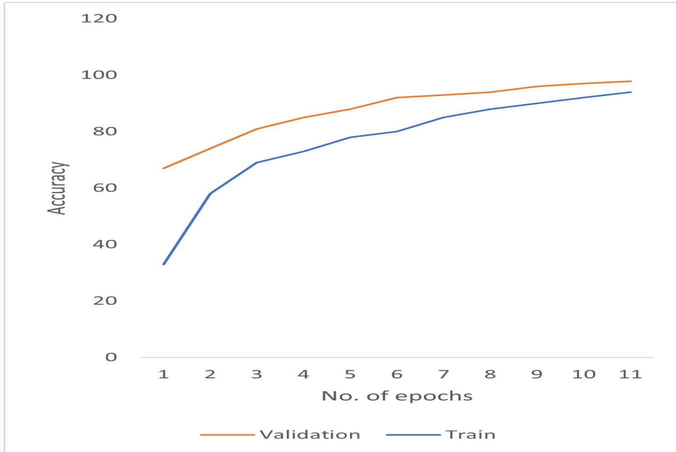


Figure 9. Accuracy of federated model experiment of the two clients on ECG data

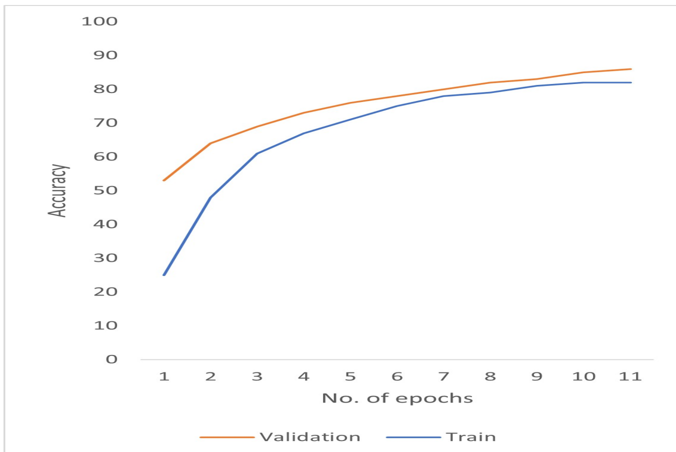


Figure 10. Accuracy of federated model experiment of the two clients on EEG data

Table 4. Results of decentralized federated model experiment with five clients

| | *ECG* | *EEG* |
|---|---|---|
| *Accuracy* | 97.63 | 86.26 |
| *Precision* | 97.51 | 86.71 |
| *Recall* | 96.2 | 85.77 |

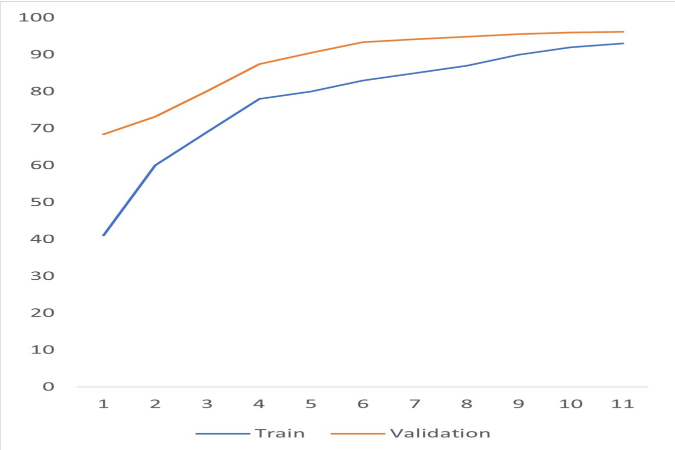


Figure 11. Accuracy of decentralized federated model experiment of five clients on ECG data

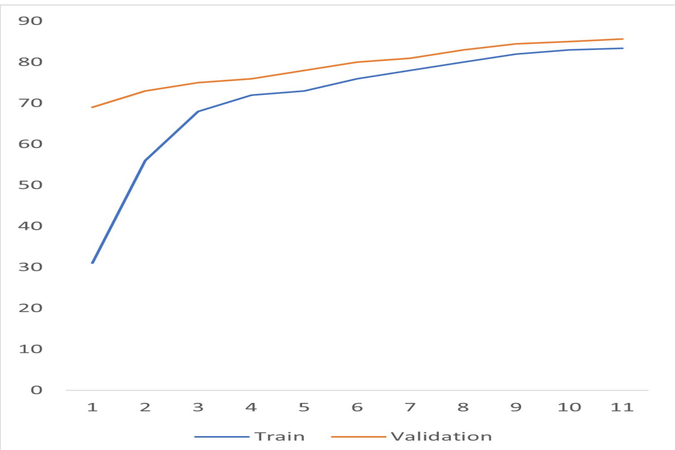


Figure 12. Accuracy of decentralized federated model experiment of five clients on EEG data

in the Fig. 13, the accuracy consistently increased with each round, demonstrating the system's ability to converge effectively and leverage diverse data contributions from all clients. The metrics further highlight the effectiveness of the federated learning approach in enhancing both accuracy and reliability for tasks such as seizure classification and arrhythmia detection. These results underscore the potential of federated learning to leverage distributed data sources for developing robust diagnostic tools in healthcare.

### D. INCREMENTAL DECENTRALIZED FEDERATED DEEP LEARNING

The proposed system, integrating both Decentralized Federated Learning (DFL) and Incremental Learning (IL), was evaluated in a configuration resembling the third experiment. This setup involved five clients organized in a ring topology, with each client receiving data incrementally to simulate real-world scenarios. The evaluation aimed to assess the system's ability to handle distributed and dynamic data while maintaining high performance and adaptability. The hybrid approach achieved an accuracy of 97.42%, which is comparable to the results obtained using the DFL framework without incremental learning. However, the inclusion of IL enabled the model to adapt dynamically to newly arriving data, ensuring continuous learning and improving robustness. The ability to achieve similar accuracy highlights the effectiveness of the incremental component in maintaining performance while processing real-time data streams. As shown in the Fig. 14, the accuracy of the model improved progressively with the reception of new mini-batches by clients. This demonstrates the system's capability to leverage incremental updates effectively, allowing models to converge as more data becomes available.

### E. NETWORK BANDWIDTH ANALYSIS

The decentralized ring topology employed in the proposed architecture offers significant bandwidth efficiency compared to traditional centralized federated learning approaches. In our framework, each institution communicates only with its immediate neighbors rather than a central server, which distributes the communication load more evenly across the network. This approach aligns with findings from recent studies on ring-based federated architectures that demonstrate substantial reductions in communication overhead [35]. Specifically, in our ring topology, each institution transmits model weights of size M bytes to exactly one neighbor per round, resulting in a total network traffic of n×M bytes per round (where n is the number of institutions). As illustrated in Fig. 15, this is more efficient than centralized approaches where each institution must both send to and receive from a central server, resulting in 2n×M bytes of traffic. Furthermore, the ring topology eliminates the bandwidth bottleneck that typically occurs at central servers, which would otherwise need to handle n concurrent connections. This advantage becomes particularly pronounced as the number of participating institutions increases, making our approach highly scalable for large-scale healthcare collaborations.

## V. CONCLUSION

This paper addresses critical challenges in applying machine learning to healthcare, particularly the issues of data availability and privacy. Traditional machine learning approaches often require centralized access to large amounts of data, which is impractical in healthcare due to strict privacy regulations and the distributed nature of medical data across

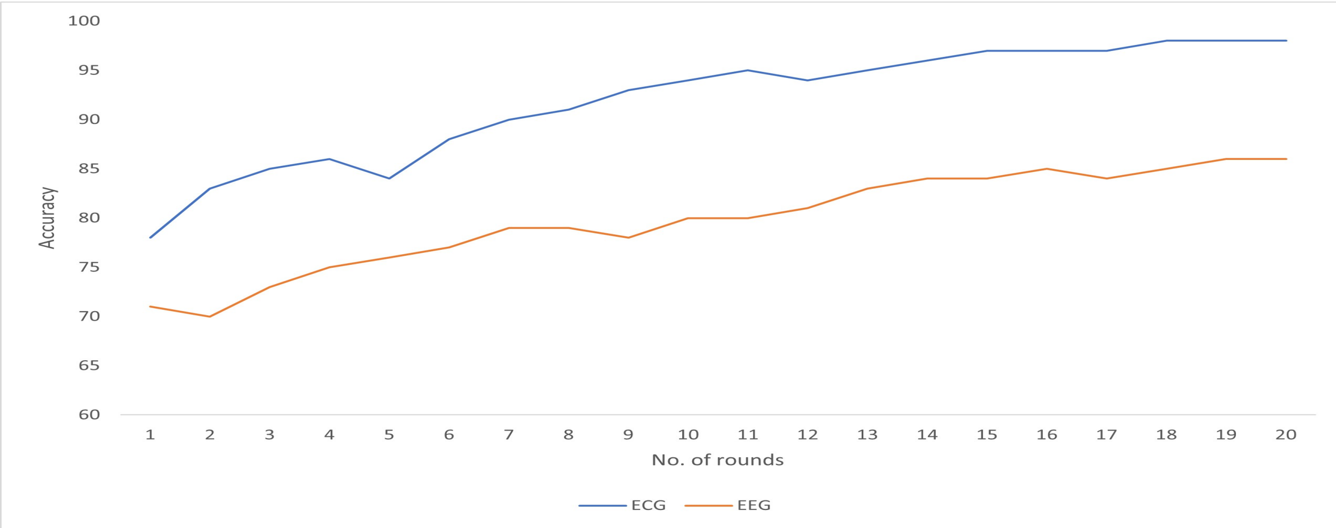


Figure 13. Evolution of accuracy of decentralized federated models experiment with five clients over rounds

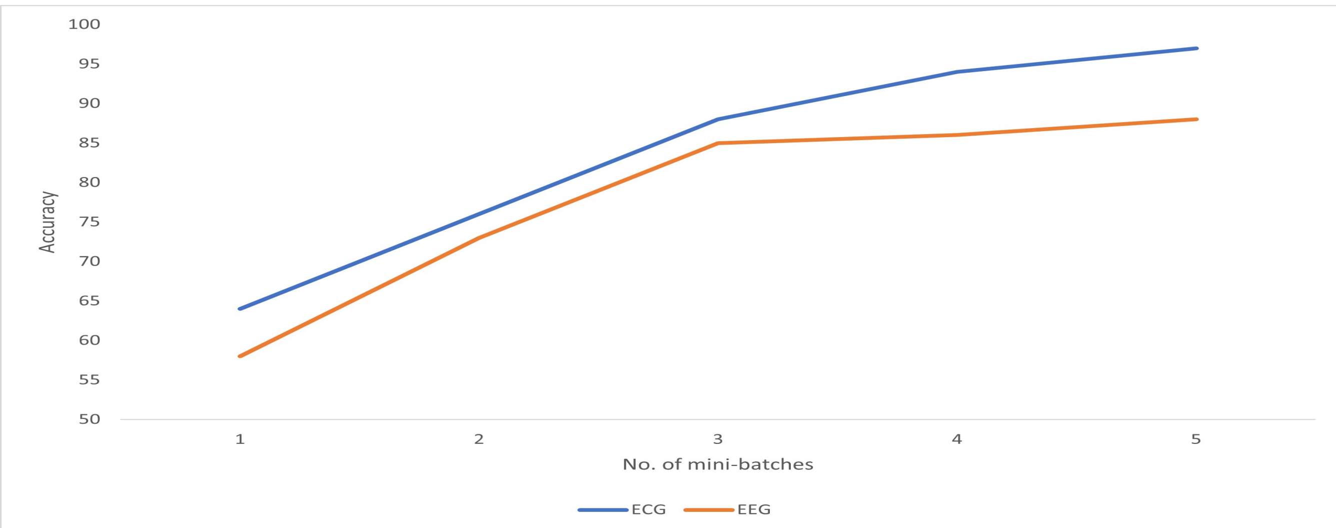


Figure 14. Accuracy of incremental decentralized federated model as data streams arrive

institutions. While Federated Learning (FL) has emerged as a solution by enabling collaborative model training without sharing raw data, traditional FL frameworks rely on a central server, introducing vulnerabilities such as single points of failure and network bottlenecks. Moreover, these frameworks fail to account for the dynamic nature of healthcare data, where new information continuously arrives in real-time.

To overcome these limitations, this paper introduced a hybrid approach combining Decentralized Federated Learning (DFL) and Incremental Learning (IL) to address key challenges in privacy-preserving, scalable, and adaptive healthcare applications. As a foundational step, we developed and validated a CNN-BiLSTM model for physiological signal analysis in a standalone configuration, demonstrating its effectiveness in handling ECG and EEG classification tasks. Building on this validated model, we extended the system to incorporate federated and incremental components, enabling decentralized collaboration among institutions while adapting dynamically to real-time data streams. The proposed system leverages a ring topology for communication, ensuring robust collaboration without reliance on a central server. Experimental results showed that the hybrid approach achieves high accuracy and consistent performance across various configurations, validating its applicability in real-world healthcare scenarios.

For future work, we plan to explore the integration of wavelet-based layers, such as Wavelet Neural Networks (WNN) or WaveletConv blocks, to replace the initial convolutional layers in our CNN-BiLSTM architecture. This modification could potentially yield several significant benefits: (1) enhanced capture of time-frequency features for short-

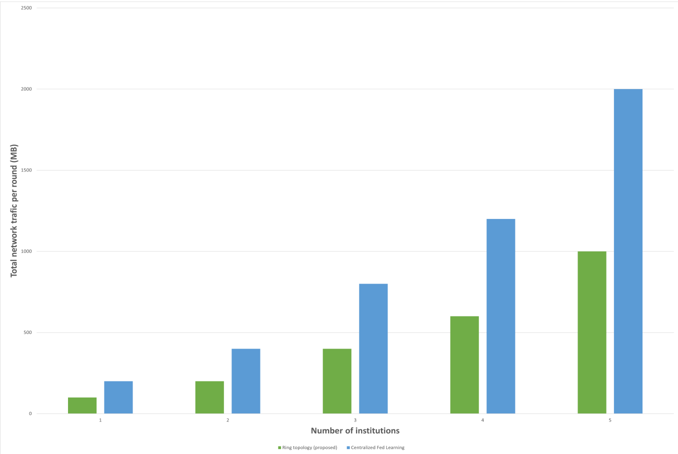


Figure 15. Comparative network bandwidth usage between the proposed ring topology and traditional centralized federated learning architecture.

lived ECG artifacts and brief EEG spikes through localized representations; (2) reduced model size by 20-30% with comparable expressive power, resulting in smaller communication payloads and faster convergence during incremental fine-tuning; (3) improved noise robustness through built-in multiresolution analysis, particularly for handling baseline wander and artifacts without additional preprocessing; and (4) opportunities for personalized local models where institutions could tailor mother-wavelets (e.g., Morlet for ECG, Daubechies for EEG) to their specific sensor characteristics while maintaining global consistency through layer-wise or FedPer aggregation.

We also plan to conduct a comprehensive energy consumption analysis of our decentralized federated incremental learning framework to assess its sustainability in resource-constrained healthcare environments. This analysis will quantify the computational energy requirements across participating institutions, examining how our incremental learning approach reduces power consumption compared to full retraining methods.

Furthermore, we intend to enhance the privacy-preserving aspects of our framework by incorporating homomorphic encryption techniques for secure model weight exchange between institutions. Building upon recent advances in homomorphic encryption-based federated learning, we will implement fully homomorphic encryption (FHE) to enable computations on encrypted model parameters without requiring decryption during the aggregation process. This approach would provide an additional layer of security beyond the inherent privacy benefits of federated learning, protecting against potential inference attacks that might attempt to reconstruct private patient data from model updates.

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