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A Privacy-Preserving Federated Spatiotemporal Dynamic Graph Neural Network Framework for Epileptic Seizure Prediction

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abstract

Epilepsy ranks among the most prevalent and debilitating neurological disorders, globally affecting an estimated 50 million individuals across all age groups and socioeconomic backgrounds [WHO, 2019]. In recent years, research on its prediction methods has made significant progress, driven by advancements in artificial intelligence technology. Epilepsy prediction models based on electroencephalogram (EEG) signals and deep learning have become an important research direction in the field of neuroscience, and related research results have shown an exponential growth trend. However, there are still several key problems that need to be solved in existing research: First, the mainstream model architecture are focused on traditional neural network framework, exclusively trained in centralized settings that are incompatible with the privacy regulations and data-sharing constraints governing real-world clinical environments; second, the deep learning approaches, including recent Graph Neural Network (GNN) models, using static graph modeling methods, which ignore the dynamic network topological evolution characteristics of EEG signals in the time-varying process, fails to effectively explore the high-order nonlinear correlation characteristics contained in the topological structure of brain functional networks; To address this limitation, this paper proposes a patient-dependent privacy-preserving Federated Learning framework that integrates an epilepsy prediction model DygonNet based on spatiotemporal dynamic graph neural network, a local learning model at each federated client, deployed within a cloud-based simulation environment. In the proposed architecture, the CHB-MIT, SWEC-ETHZ and the TJU-HH iEEG datasets are treated as three independent federated clients representing distinct clinical sites, each performing federated training on their private EEG data, while a central

cloud server simulated on Google Colab Pro aggregates the model updates using the Federated Averaging (FedAvg) and FedProx algorithms without ever accessing raw patient recordings. The model defines the dynamic graph structure of EEG signals, innovatively introduces the Transformer model and dynamic graph neural network into the field of epilepsy prediction to fully learn the temporal and spatial characteristics of EEG signals, and proposes a hierarchical graph pooling mechanism based on the attention mechanism in a Federated environment. Experiments show that the model shows excellent epilepsy prediction performance on both public and private datasets.

Key Words： Epilepsy Prediction, Deep Learning, Dynamic Graph Neural Networks, electroencephalographic, Federated Learning, FedAvg, FedProx

1. Introduction

As one of the most common brain diseases in the world, epilepsy not only causes physiological damage, but also has a profound impact on patients' cognition, psychology and socio-economics. Although the ILAE 2014 diagnostic criteria[1] have improved the efficiency of disease identification, about 30% of patients with drug-resistant epilepsy are exposed to the risk of uncontrollable seizures for a long time due to the ineffectiveness of drugs[2][3]. Cognitive impairment is a typical sequelae, manifested as core functional defects such as memory and attention[4], while social discrimination causes more than 40% of patients to experience anxiety or depression[5]. The economic burden is also heavy. A Danish study showed that the average annual treatment cost for patients was as high as 30,683 euros[6], highlighting the consumption of social resources by the disease. The limitations of current ASM treatment (such as side effects[7] and unclear mechanisms of drug resistance[8][9]) have forced the academic community to explore non-drug intervention paths. Epilepsy prediction technology has become a core strategy to reduce SUDEP mortality (risk reduction of 61%[10]) and improve patients' quality of life because it can warn of seizures 5-30 minutes in advance[11]. The automated identification of a preictal brain state preceding the clinical onset of a seizure by a clinically useful interval of several minutes has therefore emerged as one of the most actively researched problems at the intersection of neuroscience, biomedical signal processing, and machine learning. A reliable prediction system would enable timely prophylactic interventions such as the delivery of focal electrical stimulation, the automated administration of fast-acting medication, or simply the issuance of a warning to the patient and caregivers, substantially improving patient safety and quality of life.

Team[17] highlight the advantages of tree structure algorithms in processing nonlinear features. The innovative application of MLP is reflected in the optimization of model architecture. Yang et al.[18] focus on time series characteristics, and Li team[19] develops end-to-end models, which expand the application boundaries of traditional neural networks. Graph Neural Networks (GNNs) have emerged as a powerful paradigm specifically designed to operate on non-Euclidean, graph-structured data. In the EEG context, each electrode naturally corresponds to a graph node, while edges encode the functional or structural connectivity between pairs of brain regions. By propagating information along these edges through differentiable message-passing mechanisms,

GNNs can simultaneously learn node-level temporal features and graph-level connectivity patterns, providing a richer and more biologically interpretable representation of EEG dynamics. Recent works—including GCN-based[12], attention-based[13], and hybrid GCN-LSTM architectures[14] have demonstrated that GNNs consistently outperform conventional DL models on seizure prediction benchmarks, confirming the relevance of graph-based modeling for this application. Existing GNN-based seizure prediction models rely on a centralized training approach that aggregates EEG recordings from multiple patients onto a single server. This reliance on centralization poses challenges in practical clinical settings for various reasons. Firstly, EEG data is highly sensitive and regulated by laws such as HIPAA and GDPR, which restrict cross-institutional sharing. Secondly, the extensive volume of high-resolution EEG data generated makes centralized aggregation impractical and costly. Lastly, centralizing heterogeneous data introduces biases due to variations in recording equipment, protocols, demographics, and seizure characteristics. Federated Learning (FL), introduced by McMahan et al. [15], provides an elegant solution to this trilemma. In the FL paradigm, a global model is maintained on a central cloud server, while training proceeds in a fully decentralized manner, each participating institution trains a local copy of the model on its private data and transmits only the resulting model weight updates never the raw data to the server for aggregation. The Federated Averaging (FedAvg) algorithm and its variants (e.g., FedProx[16]) have been shown to achieve performance levels comparable to centralized training across a wide range of medical applications, while providing strong operational privacy guarantees and enabling collaboration among institutions that would otherwise be unable to share their data. Despite significant progress, existing research still faces dual challenges: on the one hand, the dependence of traditional models on artificial feature design (such as Savadkoohi[12] multi-domain features) restricts the generalization ability of models; on the other hand, as revealed by Purnima et al.[20], although traditional algorithms perform well in data-scarce scenarios, the problem of limited feature learning ability has not been fundamentally solved. It is worth noting that the successful practice of Teijeiro team[21] showing that through the combination of algorithm optimization and hardware adaptation, traditional models still have irreplaceable advantages in specific scenarios such as wearable devices, which provides important direction inspiration for subsequent research.

In the research of epilepsy prediction models, traditional neural network models represented by CNN, RNN, Transformer and their variants occupy an important position. These models have unique advantages in complex feature learning and time series modeling, and are therefore widely used in epilepsy prediction tasks. In the field of CNN, feature extraction methods have undergone a paradigm shift from manual design to autonomous learning. Early researchers such as Khan[22] and Truong et al.[23] relied on traditional methods such as wavelet transform and Fourier transform to generate feature inputs. Although this method can retain features with clear physical meanings, it has the risk of information loss. In 2020, the end-to-end model of Xu's team[24] broke through this limitation and directly processed the original EEG signal through 6 layers of deep convolutional layers, while automatically learning spatiotemporal features and reducing the preprocessing time by 60%. RNN models continue to make breakthroughs in the field of time series analysis. After multiple optimizations of the LSTM infrastructure, Tang Yunqi

et al.[25] integrated the electronic search algorithm into the BPTT training process, which increased the parameter convergence speed by 35% and achieved a 5-minute short-term warning of epileptic seizures. The innovation of Bi-LSTM is more clinically valuable. The wavelet-BiLSTM model constructed by Cheng's team[26] captures the characteristics of pre-seizure signs through bidirectional information flow, achieving an accuracy of 99.47% in 4 patients with intractable epilepsy; the ResNet-BiLSTM hybrid model developed by Chen Lianghui[27] extracts time-frequency detail features through the residual module, which advances the seizure warning time to 25 minutes. It is worth noting that Singh et al.[28] combined spectral features with LSTM, and increased the sensitivity to 96.8% while keeping the model lightweight, reflecting the synergistic optimization effect of feature engineering and model architecture.

The existing bottlenecks are mainly reflected in: 1) Although the Shahbazi model[29] achieved a sensitivity of 98.21%, its computing power consumption (3.2W) exceeded the load limit of wearable devices; 2) The performance fluctuations caused by individual differences are significant, such as the standard deviation of cross-patient tests in the Ali experiment[30] reached ±12%; 3) The lack of model interpretability restricts clinical adoption, especially in FDA certification. Faced with verification difficulties, solving these challenges requires algorithm-hardware collaborative innovation, such as the integration of neuromorphic computing chips, which may become a breakthrough direction.

The MC-ViT model developed by Hussein et al.[31] realizes multi-domain feature interaction through a 12-layer Transformer block, and achieves an F1-score of 87.6% in interictal detection, establishing a benchmark for subsequent research. Innovation in feature preprocessing methods is also critical. Yan et al.[32] used short-time Fourier transform with improved Hanning window to increase the time-frequency resolution by 19%, and the model specificity reached 92.8% after combining with Transformer. Architecture optimization shows a diversified trend. Zhang Xiaoling's[33] ViT model uses a hierarchical attention mechanism to implement differentiated feature weighting for the δ, θ, α, β, and γ frequency bands, which improves the ability to capture low-frequency rhythm features by 25%. The Qi team[34] proposed a channel-adaptive ViT, which achieves key channel screening through learnable masks and maintains an average accuracy of 93.65% while reducing the amount of computation by 30%. In response to real-time requirements, the lightweight ViT designed by Dong et al.[35] introduced a deep separable attention mechanism, with an inference speed of 127 frames per second, meeting the requirements of clinical real-time monitoring.

Cross-model collaboration has become an important development direction. The CNN-Transformer two-stream network constructed by Deng et al.[36] reduces the long-term dependency modeling error by 18% through the feature fusion of the spatial convolution branch and the temporal attention branch. The Transformer-LSTM hybrid model proposed by Xia et al.[37] uses a gated attention mechanism to dynamically integrate the outputs of two types of networks, and still maintains a stable accuracy of 89.4% in a noisy environment. It is worth noting that the 3D Transformer-CNN architecture developed by Dong et al.[38] extends the seizure prediction window to 40 minutes by simultaneously processing time-space-frequency features through three-dimensional attention blocks.

The dynamic reconstruction characteristics of epileptic brain networks place higher demands on prediction models. The defects of traditional static GNNs that rely on prior

graph structures were clearly exposed in the study of Ashokkumar[39]: the fixed functional connection graph constructed by them had a false negative rate of 27% in preictal detection, while the dynamic graph model could reduce it to 9%. This prompted researchers to turn to dynamic graph neural networks (DGNNs), whose core breakthrough lies in the joint modeling of "graph structure-time evolution". Lian et al.[40] pioneered a global-local DGNN framework, which updated the brain network connection weights every 5 seconds through a learnable adjacency matrix generation module, and increased the detection rate to 91% in iEEG data 30 minutes before the onset.

Dynamic graph construction methods have shown diversified development. Time-varying functional connectivity (TVFC) has become a mainstream technical path, While FL has been broadly validated in the context of medical imaging and electronic health records, its application to EEG-based neurological analysis remains an emerging area of investigation. The unique challenges of EEG data including high temporal resolution, strong inter-subject variability, and the non-stationary nature of brain activity introduce specific difficulties for federated optimization that differ substantially from those encountered in image-based tasks. Saemaldahr and Ilyas[41] proposed a patient-specific preictal pattern-aware seizure prediction framework based on FL, demonstrating that federated training can preserve individual patient patterns while enabling knowledge transfer across distributed sites. Their work, published in Sensors, represents one of the first direct applications of FL to seizure prediction. However, their model relies on a conventional CNN architecture and does not exploit the graph structure of multi-electrode EEG recordings. Abbaszadeh et al.[42] addressed the problem of federated seizure prediction across heterogeneous EEG datasets using lightweight deep learning models, with an explicit focus on the non-IID data distribution problem. By treating each dataset (including CHB-MIT and the Helsinki dataset) as a separate federated client, they demonstrated that global FL models can achieve competitive accuracy compared to locally trained baselines. While this work is closely related to the present study in terms of experimental design, it does not employ GNN architectures and therefore cannot leverage the dynamic graph-structured connectivity information intrinsic to multi-electrode EEG. Lim et al. [43] introduced FCEEG, a federated learning framework specifically designed for EEG-based seizure diagnosis, comparing FedAvg and FedProx aggregation strategies on a proprietary clinical dataset. Their results confirmed that FedProx yields more stable convergence than FedAvg under heterogeneous data conditions, a finding that motivates the comparative evaluation of both algorithms in the present work. Suryakala et al. [44] further explored federated machine learning for epileptic seizure detection, applying standard classifiers (SVM, Random Forest) within a FL pipeline and evaluating the communication overhead introduced by federated aggregation. Notably, a recent investigated privacy-preserving edge FL for seizure detection on CHB-MIT, deploying lightweight models at simulated edge nodes and evaluating inference latency alongside standard classification metrics. This work reinforces the feasibility of using cloud-simulated FL environments as a credible experimental platform, as adopted in the present study. More recently, an FL-based epilepsy prediction system integrating feature selection with federated training was proposed in Scientific Reports, demonstrating that federated models can achieve performance levels comparable to centralized baselines even when trained on highly heterogeneous multi-site data.

2. Methods

2.1 Datasets

This study employs three distinct datasets for experimental validation: the publicly available CHB-MIT and SWEC-ETHZ datasets, as well as a Tianjin University proprietary TJU-HH dataset. Detailed characteristics of these datasets are outlined below:

CHB-MIT Dataset

The CHB-MIT scalp EEG dataset, curated by Boston Children's Hospital and archived in the MIT EEG database, comprises 24 patients (23 pediatric subjects with drug-resistant epilepsy) containing 198 annotated seizure episodes[45] . For methodological consistency, seizures occurring within 30-minute intervals were considered single events. Inclusion criteria required:

1) Preictal manifestations preceding seizures
2) ⩾2 seizure events per subject
3) Exclusion of recordings with insufficient preictal durations or mismatched temporal segmentation criteria

SWEC-ETHZ Dataset

This intracranial EEG (iEEG) dataset, jointly collected by the University of Bern Department of Neurology and ETH Zurich's Institute for Integrative Systems Biology, contains 2656 hours of monitoring from 18 drug-resistant epilepsy patients implanted with 24–128 electrodes[46]. The dataset includes 116 consecutive seizure events sampled at 512/1024 Hz, with expert-validated annotations. Seventeen patients' recordings were selected for analysis.

TJU-HH Dataset

The proprietary TJU-HH iEEG dataset comprises intracranial recordings from Tianjin Huanhu Hospital (2019–2020), involving 17 surgical candidates with drug-resistant epilepsy. Each subject received 40–120 stereotactic electrodes sampled at 2048 Hz. Five patients were excluded due to incompatibility with study protocols. Inclusion required ⩾ 2 documented seizure events during monitoring, yielding final data from 8 patients.

2.2 Preprocessing

The preparation of time-segment samples constitutes a critical phase in the experimental workflow of this study, encompassing two sequential stages: data preprocessing and temporal segmentation, which serve as prerequisite steps for model training. The proposed epileptic seizure prediction model operates as a binary classifier designed to distinguish between preictal (pre-seizure) and interictal (inter-seizure) EEG signals. Consequently, raw EEG data undergo systematic preprocessing and segmentation into uniformly sized temporal samples during this preparatory stage, with

the comprehensive workflow illustrated in *figure 1*.

To standardize input parameters across heterogeneous datasets, all EEG recordings were downsampled to a unified sampling frequency of 256 Hz. This necessitated resampling procedures for the SWEC-ETHZ and TJU-HH datasets, which originally operated at 512/1024 Hz and 2048 Hz, respectively. EEG signals are inherently susceptible to contamination by various biological and environmental artifacts, including electromyographic interference, ocular movements, power line noise, and instrumentation artifacts, which degrade signal quality. To mitigate these effects, a 5th-order Butterworth bandpass filter (0.1–64 Hz) was applied to suppress high-frequency noise while preserving physiologically relevant components. The Butterworth filter, characterized by its maximally flat passband response and progressive stopband attenuation, has been extensively validated in epilepsy prediction tasks.

Temporal segmentation was implemented using a non-overlapping sliding window technique, a standard approach in EEG signal processing. The preprocessed EEG data were partitioned into consecutive 1-second epochs (256 samples per window), generating discrete time-segment samples for subsequent model training and evaluation. This fixed-duration segmentation ensures temporal consistency while preserving critical neurodynamic features associated with seizure transitions.

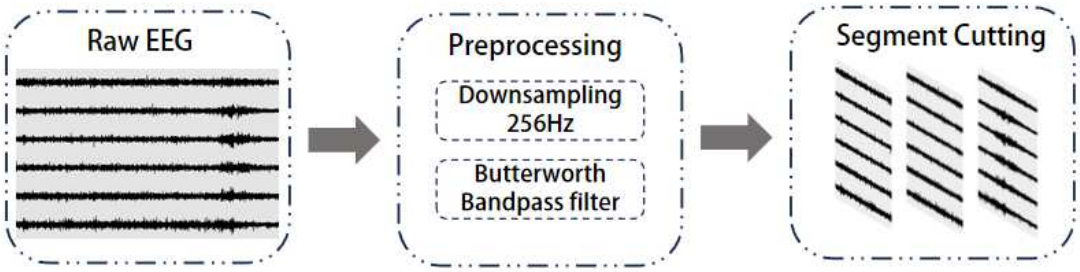


Figure 1: The preparation of time-segment samples

2.3 Model

We proposed an epilepsy prediction model based on spatiotemporal dynamic graph neural network named DygonNet. The model structure is shown in *Figure 2*. DygonNet consists of data acquisition module, data preprocessing module, Conformer module, dynamic graph module, dynamic graph neural network and feature embedding module, graph pooling module, etc. The overall experimental process is shown in *Figure 2* & *Figure 3*. The EEG data after preprocessing is input into the model, and the corresponding graph structure is generated through the dynamic graph module. At the same time, the local and global features are extracted through the Conformer module. The graph structure and related features are organically combined with the dynamic graph neural network through feature embedding. In the iteration process of the graph, the implicit association relationship between the time series graphs is extracted, and then the attention graph pooling mechanism is used for efficient graph pooling, and the classification of pre-epileptic EEG data and inter-epileptic EEG data is completed.

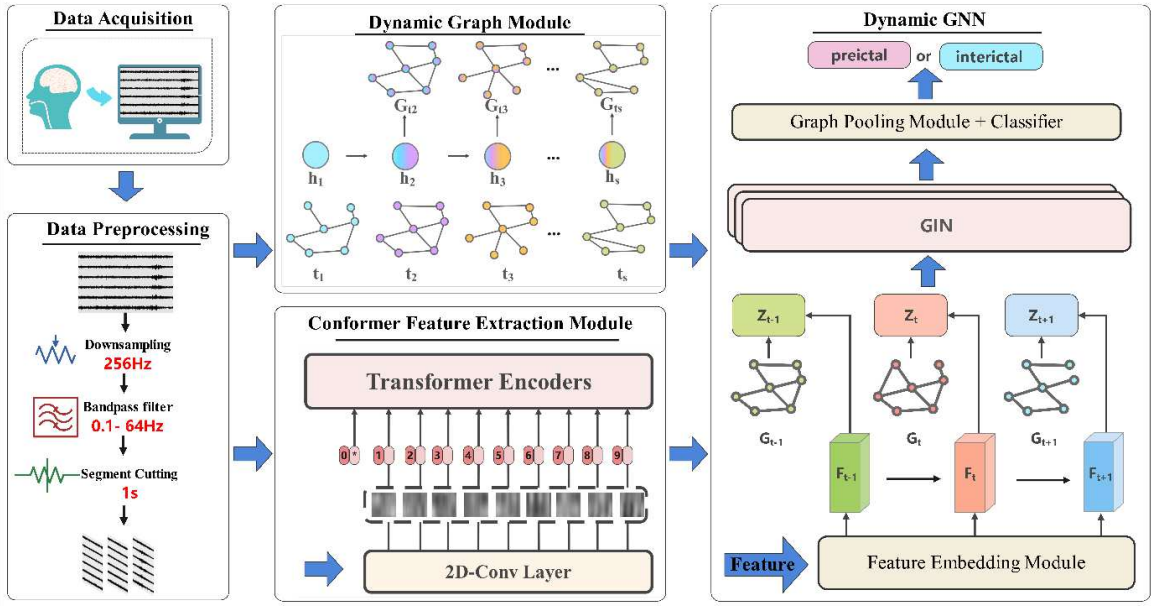


Figure 2: Schematic diagram of the DygonNet model

Conformer module

Conformer is a hybrid network that combines CNN and Transformer. It makes full use of CNN's local feature extraction capabilities and Transformer's global dependency modeling capabilities, and can effectively extract multi-dimensional features of EEG signals. Inspired by Vision Transformer(VIT), the Conformer structure uses an encoder structure and introduces a two-dimensional convolutional layer as a module for local feature extraction. The overall structure is shown in *Figure 3*.

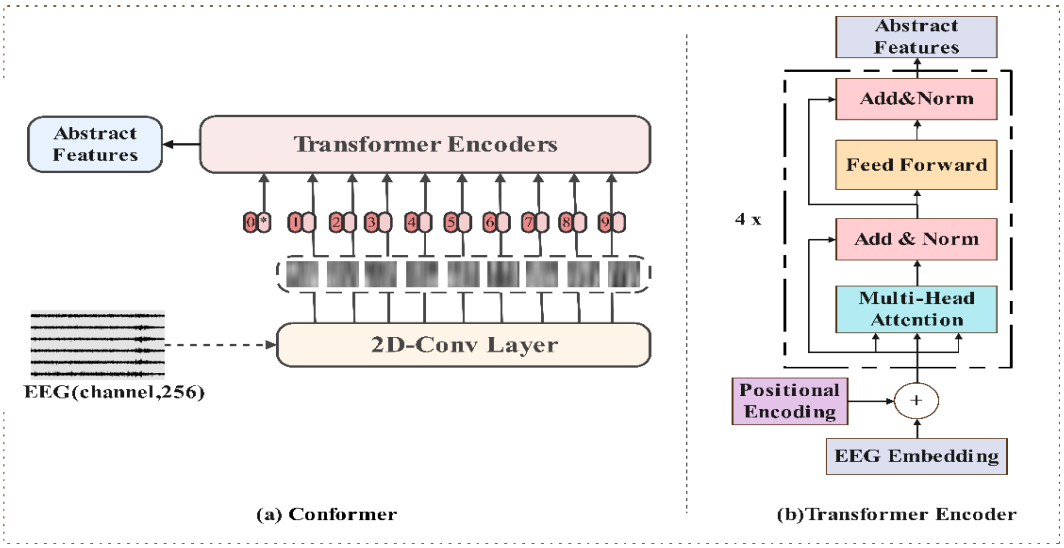


Figure 3: Schematic diagram of the Conformer feature extraction module structure

As a feature extraction module in DygonNet, the Conformer structure can be used to extract multi-channel features and time series features of EEG signals. After the data preprocessing steps shown in *Figure 1*, the sampling frequency of the EEG signal is unified to 256Hz, and the time window used when dividing the time segments is 1s. Therefore, the shape of each time segment sample is (channel, 256), where channel is the number of channels of the EEG signal, which is also the number of acquisition electrodes included in this study. For different patients, the number of channels of the EEG signal is different. After data preprocessing, the time segment samples can be used as input data for the feature extraction module Conformer.

CNN can process EEG signals more effectively through local connections and weight sharing, and abstract multi-channel EEG signals into high-dimensional features of multi-channel embedding. Inspired by the field of natural language processing, this paper regards the channels of different EEG signals as different words in a sentence, and the data after the convolution operation of the multi-channel EEG signal is called multi-channel EEG embedding. Multi-channel EEG embedding replaces word embedding in natural language processing as the input of the Transformer encoder. Here, the convolutional network selected in this paper is a single-layer two-dimensional convolutional layer, and the two-dimensional convolution kernel shape selected is (1, 9). The convolution kernel performs convolution operations separately on the time dimension of different channels, and rearranges the dimensions of the processed data, replacing the word embedding processing method to provide an adaptive serialization representation for the Transformer Encoder.

Afterwards, the Transformer Encoder module will abstract the input multi-channel EEG embedding into higher-dimensional global and local feature values through the channel attention mechanism. In 2021, Dosovitskiy et al. [47] first applied the Transformer to computer vision tasks and proposed VIT, which can achieve efficient image classification tasks using only the decoder. This paper draws on the model structure of VIT and only uses the Transformer Encoder module to extract high-dimensional features of EEG signals. The structure is shown in *Figure 3* (b). The key to Transformer Encoder's ability to extract high-dimensional features from multi-channel EEG signals lies in the channel attention mechanism.

dynamic graph

The dynamic graph structure used in this paper is initialized by the static graph structure and evolved from it. The definition of the EEG static graph structure G is shown as follows.

$$G = \{V, E, A\}$$

Wherein, V represents the set of nodes in the graph structure. In this paper, each graph node represents a channel of the EEG signal. E represents the set of edges in the graph structure. In this paper, it means the correlation between channel signals. A represents the adjacency matrix of the graph structure. The adjacency matrix can represent the structural information of the graph.

In order to capture the correlation relationship of the dynamic brain network, this paper measures the weight of the edge by the cross-correlation method between channels, and selects the edge according to the edge weight value. The cross-correlation calculation method is shown as follows.

$$W_{ij} = \left| X_{:,i,:} * X_{:,j,:} \right|$$

Wherein, $X_{:,i,:}$ and $X_{:,j,:}$ are the original single-channel EEG signals v_i and the signals v_j after data preprocessing, W_{ij} is the absolute value of and after the normalized cross-correlation calculation, and the symbol $*$ represents the cross-correlation calculation. For each graph, the τ edges with the highest weight are selected globally and retained. In this paper, the value of τ is the number of channels corresponding to the EEG signal

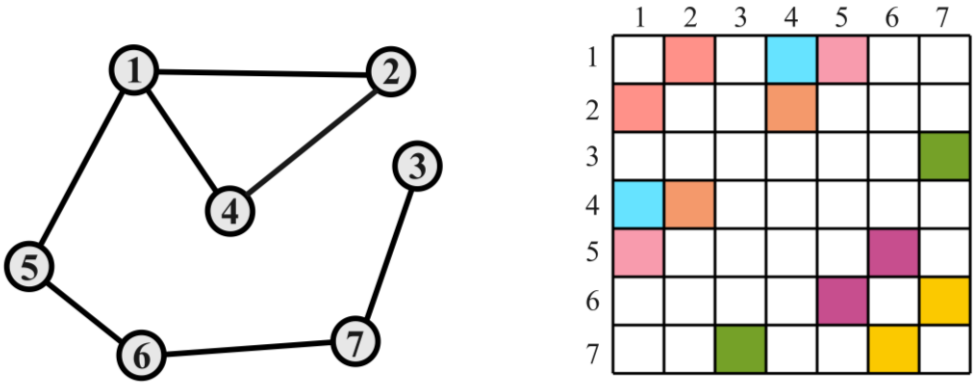


Figure 3: Schematic diagram of graph structure and adjacency matrix. Taking 7-channel EEG signal as an example, τ is set to 7. The color blocks in the adjacency matrix represent weights and the numerical value of the normalized cross-calculation correlation between channels

The characteristic of the dynamic graph is that its construction process occurs at runtime, and the graph structure can be adjusted in real time according to the input data and the predetermined iteration mechanism, so as to better adapt to diverse tasks and application scenarios, and include the time series relationship and other implicit relationships into the dynamic graph structure. Considering that the EEG graph structure at different times is dynamically changing, there will be implicit associations and time series relationships between these graphs, so this paper adopts the dynamic graph structure as the research object. This paper defines the EEG dynamic graph structure. The EEG signal X of time period T is evenly divided into EEG signals $X_T = (X_{T_1}, X_{T_2}, \ldots, X_{T_s})$ of equal time interval $T = \{T_1, T_2, \ldots, T_s\}$. The corresponding graph structure forms a time graph sequence: $G_T = (G_{T_1}, G_{T_2}, \ldots, G_{T_s})$. The graph structure has the same nodes but different structures at different times, and has temporal dynamics. Among them, the graph structure G_{T_1} at the initial moment of each graph sequence is initialized according

to the static graph structure, and the graph sequence at subsequent moments $(G_{T_2}, G_{T_3}, \ldots, G_{T_s})$ will be affected by the graph structure of the previous moment.

Taking into account the temporal dependencies between dynamic sequential graph structures, this paper improves the iterative process of dynamic graph structures. By drawing on the idea of RNN, this paper introduces the structure of hidden states of graph structures, so that the graph structure can obtain the state characteristics of the graph structure at previous moments through hidden states during the iteration process, and can learn the relationship between different time steps, which is convenient for improving information propagation. The iterative process of dynamic graph structures is shown in *Figure 5*.

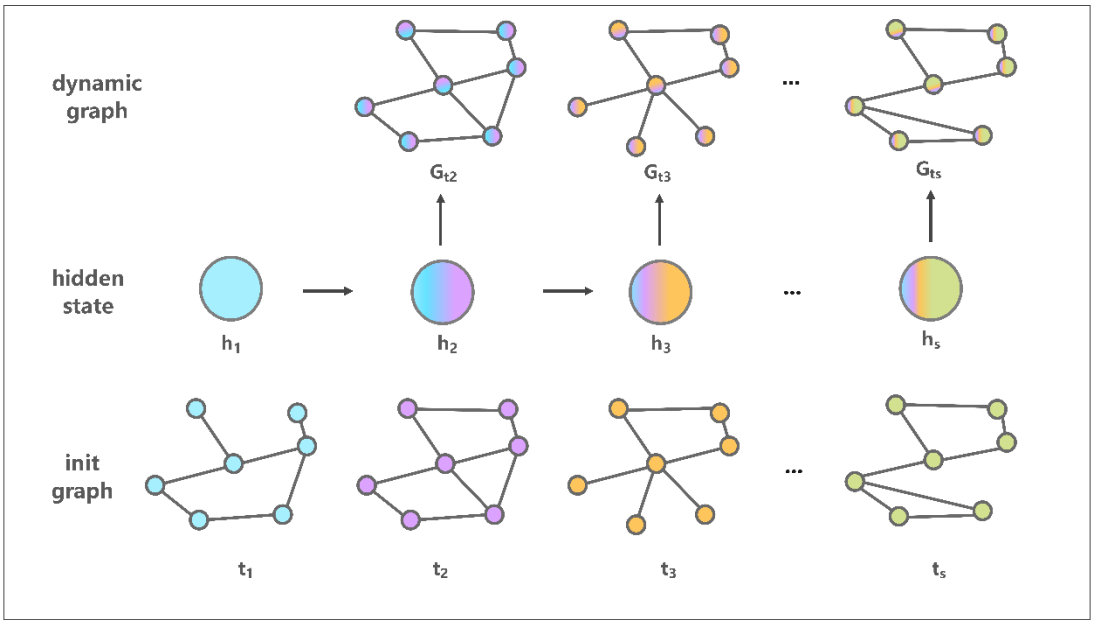


Figure 4: Dynamic graph iteration diagram

dynamic graph neural network and feature embedding module

This paper constructs a dynamic graph neural network based on the time snapshot method, treating the dynamic graph as a set of static graphs, each of which represents a time snapshot. The Graph Isomorphism Network(DGIN) is applied independently on each time snapshot for learning. The structure of the dynamic graph neural network model (Dynamic Graph Isomorphism Network, DGIN) in this study is shown in *Figure 6*.

This module uses the graph isomorphism network GIN to capture the node spatial features of each time slice and constructs it as the main body of the dynamic graph neural network (Dynamic Graph Isomorphism Network, DGIN); it uses the temporal convolutional neural network (Temporal Convolutional Network, TCN) to extract

temporal information and other abstract features as the feature embedding layer of the model

The proposed seizure prediction framework employs a Temporal Convolutional

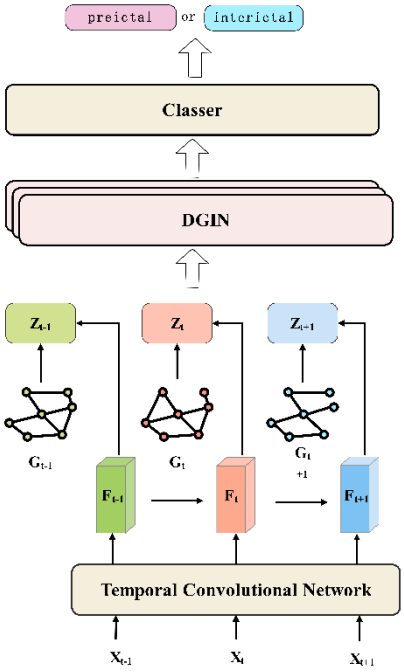


Figure 5: Schematic diagram of the dynamic graph neural network model structure

Network (TCN) as the feature embedding layer and adopts a Graph Isomorphism Network (GIN)-based dynamic graph neural network as its structural backbone. Key parameters of the TCN component are configured as *Table 1*.

Table 1: TCN model parameters

TCN Layers	Layer Shape	Dilation
TCN-1-layer	(1, 64)	1
TCN-2-layer	(64, 128)	2
TCN-3-layer	(128, 256)	3

Graph pooling

The epilepsy prediction model proposed in this study is essentially a binary classification problem of graphs. The main factor that currently limits the

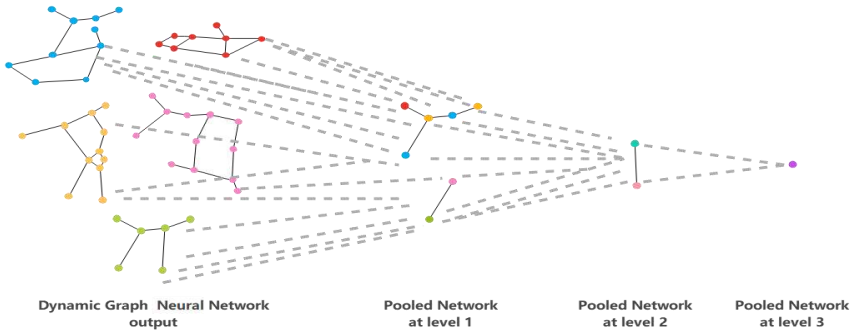


Figure 6: Schematic diagram of graph pooling mechanism, which realizes hierarchical expression of graph through layered pooling

effectiveness of graph neural network models is the flatness of the network architecture. It only relies on the edge propagation information of the graph and cannot aggregate information hierarchically, resulting in its own flatness. Ying et al.[48] proposed a hierarchical pooling mechanism DiffPooling, which can better learn the hierarchical representation of the graph compared to global pooling, which is conducive to improving the classification effect of the graph classification model. For the dynamic graph of each time slot, DiffPooling designs a two-dimensional convolutional neural network layer, clusters the nodes into clusters according to the given parameter pooling ratio, and the nodes serve as channels for feature extraction in CNN. This paper adopts a hierarchical graph pooling mechanism for graph pooling, as shown in *Figure 7*.

2.4 Federated Learning Protocol

The FL protocol orchestrates the following collaborative training of the DygonNet model across the three federated clients (CHB-MIT, SWEC-ETHZ and TJU-HH) without requiring the transfert of raw EEG recordings. The protocol follow the standard FL communication round structure and is implemented using the Flower (flwr) framework, which provides a flexible and framework-agnostic FL implementation compatible with PyTorch-based DygonNet model.

System model

The federated system comprises one central server S and $K = 3$ clients $\{C_1, C_2, C_3\}$, where C_i for $i = 1,2,3$ corresponds to CHB-MIT, SWEC-ETHZ, and TJU-HH datasets, where each client C_i hold a local private dataset D_i size $n_i = |D_i|$, with $n = \sum_i n_i$ denoting the total number of training samples across all the clients. The following assumptions are made:

- Raw EEG data never leaves the client. Only the modl weight updates (gradients or parameter deltas) are transmitted to the server.
- The local data distribution D_i are heterogeneous and non-identically distributed, reflecting the realistic across-site variability of clinical EEG.
- All clients participate in every communication round (full participation). Asynchronous or partial participation is left for future work.
- The server is assumed to faithfully execute the aggregation protocol but may attempt to infer client data from the received updates.

Global Objective Fusion

The global FL optimization objective is defined as the weight sum of local empirical lossed:

$$\min_{w} F(W) = \sum_{k} {}^{n_k}/_{n} \cdot F_k(W)$$

Where W denotes the global model parameters, and $F_k(W) = \frac{1}{n_k}\sum_{i\epsilon D_k}(x_i, y_i; w)$ is the local empirical loss of client C_k evaluated over its private dataset D_k with $I(\cdot)$ denoting the binary cross-entropy loss function.

FedAvg Aggregation Algorithm

The primary aggregation strategy employed in this work is Federated Averaging **(FedAvg)**, introduced by McMahan et al. [15]. At each communication round t, the server broadcasts the current global model weights w^t to all clients. Each client C_k initializes its local model with w^t and performs E local epochs of mini-batch stochastic gradient descent (SGD) on its private dataset D_k, yielding updated local weights ${w^{t+1}}_k$. The server then aggregates the local updates via weight averaging:

$$w^{t+1} = \sum_{k} {}^{n_k}/_{n} \cdot {w^{t+1}}_k$$

The round iterates until a convergence criterion is met—defined here as the change in global loss falling below a threshold ε.

FedProx Aggregation Algorithm

To address the convergence instability introduced by the non-IID data distribution between the datasets, we also evaluate **FedProx** as an alternative aggregation strategy. **FedProx** augments the local objective of each client with a proximal regularization term that penalizes local model parameters for deviating excessively from the current global model.

$$\min_{w_k} h_k(w_k; w^t) = F_k(w_k) + \left(\mu/2\right) \cdot \|w_k - w^t\|^2$$

Where $\mu \geq 0$ is the proximal regularization coefficient that controls the trade-off between local optimization fidelity and global model consistency. When $\mu = 0$, **FedProx** reduces to standard **FedAvg**. For $\mu > 0$, the proximal term constrains local updates from straying too far from the global model, mitigating client drift under heterogeneous data distributions. The aggregation step remains identical to **FedAvg**.

Cloud Similation environment

In the absence of a real distributed cloud infrastructure, the proposed model framework is deployed and evaluated in a simulated cloud environment using **Google Colab Pro**, a widely accessible cloud computing platform that provides on-demand access to GPU-accelerated virtual machines. This choice is motivated by three considerations: (i) **Google Colab Pro** constitutes a genuine cloud computing environment (Google Cloud infrastructure, NVIDIA GPU instances), making it appropriate to claim cloud-based experimentation; (ii) its accessibility lowers the barrier to reproducibility for the community; and (iii) the simulation faithfully reproduces the computational dynamics of clients FL system, as the communication overhead and synchronization overhead are explicitly measured and reported.

The federated simulation is implemented using the Flower (flwr) framework, which provides native support for in-process simulation of multi-client FL systems. In the simulation, the server and both clients execute within the same Python process on a single **Google Colab Pro** instance, with client-to-server and server-to-client communication serialized to measure network overhead. Each client's dataset partition is loaded independently into memory, and local training is performed sequentially to emulate parallel client execution.

3. Experiments

In order to more objectively compare the epilepsy prediction effect of the DygonNet model proposed in this chapter, this chapter selected two excellent models in recent epilepsy prediction research for comparative experiments under the same experimental conditions. Truong et al.[49] proposed a CNN-based epilepsy prediction model, proposed

using short-time Fourier transform to extract EEG frequency domain and time domain information, and selected 2D-CNN as the classifier to construct an epilepsy prediction model. This article uses the name EEG-CNN to refer to this model for comparative experiments. The model architecture is shown in *Figure 8*.

Song et al.[50] proposed an epilepsy prediction model based on spatiotemporal Transformer. The model extracts the temporal and spatial features of EEG through a one-dimensional convolution module, and then directly connects them through the Transformer self-attention module to further extract spatiotemporal features to construct a prediction model. This paper uses the name EEG-Transformer to refer to this model, and conducts comparative experiments under the same experimental conditions. The model architecture is shown in *Figure 9*.

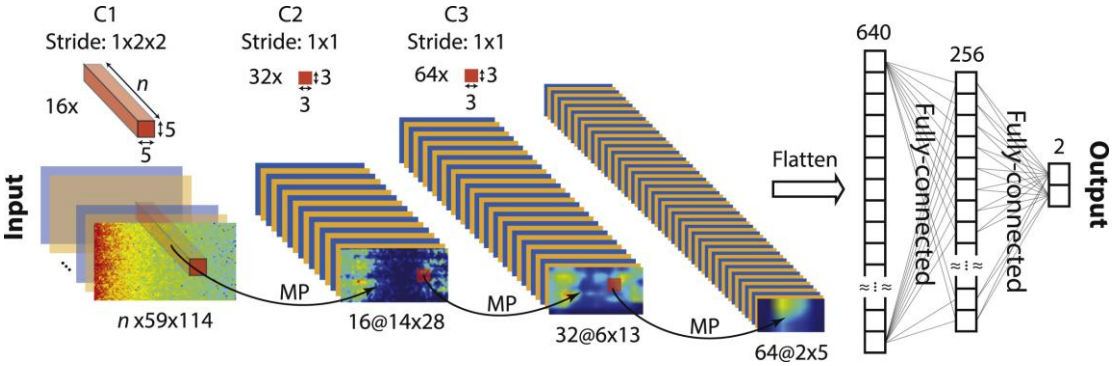


Figure 7: Schematic diagram of EEG-CNN architecture

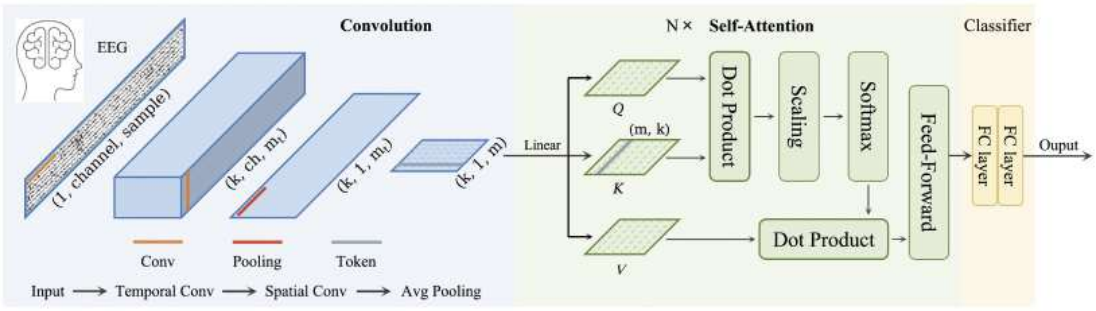


Figure 8: Schematic diagram of EEG-Transformer architecture

3.1 Model performance

As shown in *Figure 10*, the performance of the DygonNet model on the CHB-MIT dataset is that on average, the model achieved an accuracy of 0.9001, a specificity of 0.9032, a sensitivity of 0.8935, an F1 score of 0.8971, and an AUC index of 0.9510, which generally reached a high level of epilepsy prediction. In particular, the prediction level of patients chb01, chb02, and chb13 reached a near-perfect state. *Figure 3* to Figure 11

shows the performance comparison of the EEG-CNN, EEG-Transformer, and DygonNet models on different datasets. It can be seen from the figures that the prediction performance of the DygonNet model has a significant advantage on the CHB-MIT dataset.

As shown in Figure 11, the DygonNet model achieved an accuracy of 0.8889, a specificity of 0.8667, a sensitivity of 0.9116, an F1 score of 0.8945, and an AUC index of 0.9444, which generally reached a high level of epilepsy prediction. In particular, the epilepsy prediction model level of patients ID03, ID12, ID14, and ID18 reached a nearly perfect state. As shown in Figure 11, DygonNet's epilepsy prediction ability on the SWEC-ETHZ dataset is superior to the advanced models in recent studies, and there is a significant difference.

As shown in Figure 11, the DygonNet model achieved an accuracy of 0.9347, a specificity of 0.9381, a sensitivity of 0.9319, an F1 score of 0.9338, and an AUC index of 0.9685, which generally reached a high level of epilepsy prediction. In particular, the epilepsy prediction model level of patients TJU01, TJU03, TJU04, and TJU05 reached a nearly perfect state. However, the model performance of patient TJU07 was poor, with an AUC below 0.9. As shown in Figure 11, DygonNet's epilepsy prediction ability on the TJU-HH dataset is better than the EEG-CNN model in recent studies, and is comparable to the performance of the EEG-Transformer model.

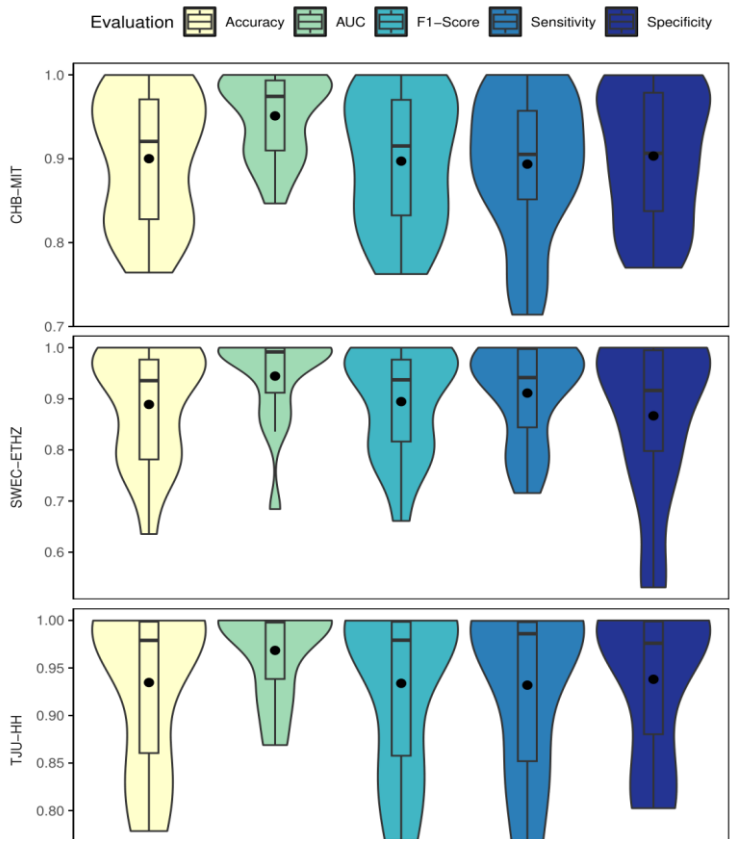


Figure 9: Distribution of prediction effects of the DygonNet model on different datasets

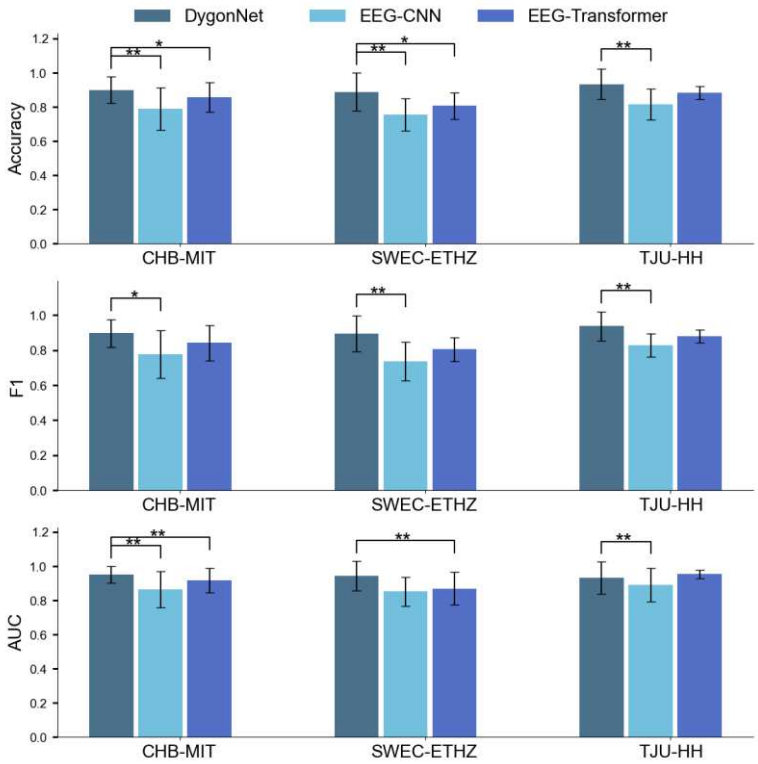


Figure 11: Comparison of prediction performance of EEG-CNN, EEG-Transformer and DygonNet models on three datasets. *P<0.05, **P<0.01, ***P<0.001, Wilcoxon signed-rank test, histograms are mean ± standard error.

3.2 Ablation experiment

In order to verify the effectiveness of the influence of different modules in the DygonNet model proposed in this paper on the model's epilepsy prediction ability, this section conducts ablation experiments on three data sets for verification. The ablation experiments conducted in this section will verify the effectiveness of the three modules: Conformer module, dynamic graph structure and graph network, and layered graph pooling. The ablation experiment results are shown in *Table 2*, *Table 3* and T*able 4*. The experiment shows that the Conformer module, dynamic graph structure and graph network, and layered graph pooling modules in the DygonNet model have a positive impact on the model's epilepsy prediction ability, and the dynamic graph structure and graph network contribute the most, followed by the Conformer module. The contribution of layered graph pooling is the lowest.

Table 2: Ablation experiments of different models on the CHB-MIT dataset

Conformer	Dynamic Graph Architecture	hierarchical graph pooling	Accuracy	AUC
×	√	√	0.8712	0.9386
√	×	√	0.8197	0.9011
√	√	×	0.8769	0.9436
√	√	√	0.9001	0.9510

Table 3: Ablation experiments of different models on the SWEC-ETHZ dataset

Conformer	Dynamic Graph Architecture	hierarchical graph pooling	Accuracy	AUC
×	√	√	0.8567	0.9416
√	×	√	0.7965	0.8798
√	√	×	0.8214	0.9142
√	√	√	0.8889	0.9444

Table 4: Ablation experiments of different models on TJU-HH dataset

Conformer	Dynamic Graph Architecture	hierarchical graph pooling	Accuracy	AUC
×	√	√	0.8236	0.9144
√	×	√	0.8196	0.9089
√	√	×	0.8631	0.9352
√	√	√	0.9347	0.9685

3.3 Clinical Performance Results

Comparison Baselines:

To rigorously evaluate the proposed FL DygonNet framework, the following five baselines are defined:

- **Centralized- DygonNet**: The proposed DygonNet model trained in a fully centralized manner by pooling all data on a single server. This constitutes the performance upper bound, as it benefits from full data visibility but violates patient privacy.
- **FL-DygonNet (FedAvg)**: The proposed framework using the Federated Averaging aggregation algorithm [McMahan et al.,[15]
- **FL-DygonNet (FedProx)**: The proposed framework using the FedProx aggregation algorithm Li et al.,[16] with proximal coefficient mu selected via grid search on the validation set.

*T*able 5: Ablation experiments of different models on the CHB-MIT dataset

Model	**Accuracy**	**AUC**
Centralized DygonNet	0.9301 (0.2)	0.9581 (0.3)
FL- DygonNet (FedAvg)	0.8686 (0.4)	0.9189 (0.4)
FL- DygonNet (FedProx)	0.8932 (0.3)	0.9452 (0.3)

*T*able 6: Ablation experiments of different models on the SWEC-ETHZ dataset

Model	**Accuracy**	**AUC**
Centralized DygonNet	0.9185 (0.2)	0.9074 (0.2)
FL- DygonNet (FedAvg)	0.8496 (0.3)	0.9081 (0.2)
FL- DygonNet (FedProx)	0.8681 (0.3)	0.9312 (0.3)

*T*able 7: Ablation experiments of different models on the TJU-HH datas*et*

Model	**Accuracy**	**AUC**
Centralized DygonNet	0.8734 (0.2)	0.9241 (0.2)
FL- DygonNet (FedAvg)	0.8492 (0.2)	0.9089 (0.3)
FL- DygonNet (FedProx)	0.8972 (0.3)	0.9455 (0.4)

T*able 5* to t*able 7* reports the clinical seizure prediction performance of all three models evaluated on client datasets under the leave-one-seizure-out cross-validation protocol. Results are averaged across all patients and folds; standard deviations are reported in parentheses to reflect inter-patient variability

3.4 Discussion

The experimental performance of the DygonNet model on the CHB-MIT scalp EEG dataset, SWEC-ETHZ intracranial EEG dataset, and TJU-HH intracranial EEG dataset shows that the DygonNet model proposed shows excellent epilepsy prediction performance on more than 90% of the patient data on centralized and performs worse on hospital's own locally trained model on its native test data. This indicates that each hospital still achieves its highest performance by training solely on its own EEG recordings. The epilepsy prediction performance of a small number of patients still needs to be further improved.

The DygonNet model has shown excellent epilepsy prediction performance on both the scalp EEG dataset (CHB-MIT) and the intracranial EEG dataset (SWEC-ETHZ, TJU-HH), proving that the model has good generalization performance in different types of EEG data. The results in T*able 5* to T*able 7* reveal several key findings. First, the proposed FL - DygonNet framework achieves performance levels that are close to the centralized upper bound, with an accuracy as shown in tables, demonstrating that the privacy constraint imposed by the federated protocol incurs only a marginal clinical performance cost. second, FedProx consistently outperforms FedAvg across all datasets, a result attributable to the proximal regularization term that mitigates the client drift introduced by the non-IID distribution between CHB-MIT, SWEC-ETHZ and TJU-HH. As shown in Figure 11, the patient-dependent epilepsy prediction model DygonNet proposed in this paper performs better than or equivalent to the epilepsy prediction models EEG-CNN and EEG-Transformer proposed in recent related literature on the three datasets, reaching the advanced level in the field of epilepsy prediction.

4. Conclusion

Through the review and analysis of relevant papers in the field of cloud computing

and epilepsy prediction research, this research points out a critical and largely unexplored challenge at the intersection of clinical neuroscience and cloud-based distributed machine learning: the development of a privacy-preserving, multi-institutional framework for epileptic seizure prediction from electroencephalographic (EEG) signals. While Graph Neural Networks (GNNs) have recently established themselves as the leading paradigm for EEG-based seizure prediction owing to their inherent ability to model the graph-structured functional connectivity between electrode sites, there is insufficient research on epilepsy prediction models based on graph structures, the dynamic nature of EEG graph structures is ignored, and there are few solutions to the problem of insufficient EEG data, and epilepsy prediction models based on small sample learning. All existing GNN-based approaches rely on centralized training protocols that are fundamentally incompatible with the legal, logistical, and ethical constraints governing real-world clinical data sharing. Simultaneously, Federated Learning (FL) has emerged as the established solution for privacy-preserving collaborative training in distributed healthcare environments, yet has never been combined with GNN architectures in the context of seizure prediction

To bridge this gap, we proposed FL-DygonNet, a federated dynamic graph neural network framework based on spatiotemporal dynamic graph neural network. It combines convolutional neural network and Transformer to effectively extract local and global features of EEG, and the dynamic graph neural network extract implicit correlations between EEG data transformations at each time step, proposing an efficient graph pooling based on attention mechanism. The CHB-MIT, SWEC-ETHZ and TJU-HH datasets are instantiated as independent federated clients, where each trains a local GNN model on their private EEG data within a cloud environment simulated on Google Colab Pro. A central cloud server coordinates the global learning process through iterative model aggregation using both the FedAvg and FedProx algorithms, without ever accessing raw patient recordings. The GNN model constructs a dynamic functional connectivity graph from multichannel EEG segments, capturing preictal spatiotemporal patterns through differentiable message-passing over the electrode graph. This design embeds the privacy-preserving guarantee directly into the training architecture, making the framework suitable for deployment across institutions subject to HIPAA and GDPR regulatory constraints.

However, the research in this paper still has the following shortcomings: From the perspective of cloud environment, the federated training protocol was evaluated in a simulated cloud environment (Google Colab Pro) rather than a real-world distributed infrastructure, involving physically separated institutional nodes. While this simulation accurately reproduces the computational and communication dynamics of FL, it does not account for real-world network variability, asynchronous client availability, hardware heterogeneity, or the latency introduced by wide-area network communication between geographically distributed hospitals. From the perspective of data, the epilepsy prediction model constructed, only relies on EEG data, where EEG is not the only physiological indicator of epileptic seizures. Studies have shown that electrocardiogram, electromyogram, respiratory data, blood oxygen index, etc. may be correlated with

epileptic seizures. From the perspective of the model, the proposed framework are all patient-dependent epilepsy prediction models, and there are few studies on patient-independent epilepsy prediction models in current research. Patient-independent or cross-patient seizure prediction remains an open and particularly challenging problem in the field, as EEG signatures of the pre-ictal state vary substantially across individuals in terms of morphology, frequency content, and spatial distribution. The federated aggregation mechanism introduced in this work provides a first step toward cross-site generalization, but does not fully resolve the cross-patient generalization challenge.

In summary, this paper demonstrated that the combination of Graph Neural Networks and Federated Learning constitutes a principled, practically feasible, and clinically relevant approach to privacy-preserving epileptic seizure prediction from distributed multi-institutional EEG data. By treating two heterogeneous public datasets as independent federated clients within a cloud-simulated environment, the proposed FL-GNN framework achieves competitive clinical performance while satisfying the privacy, scalability, and regulatory requirements of real-world clinical deployment.

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