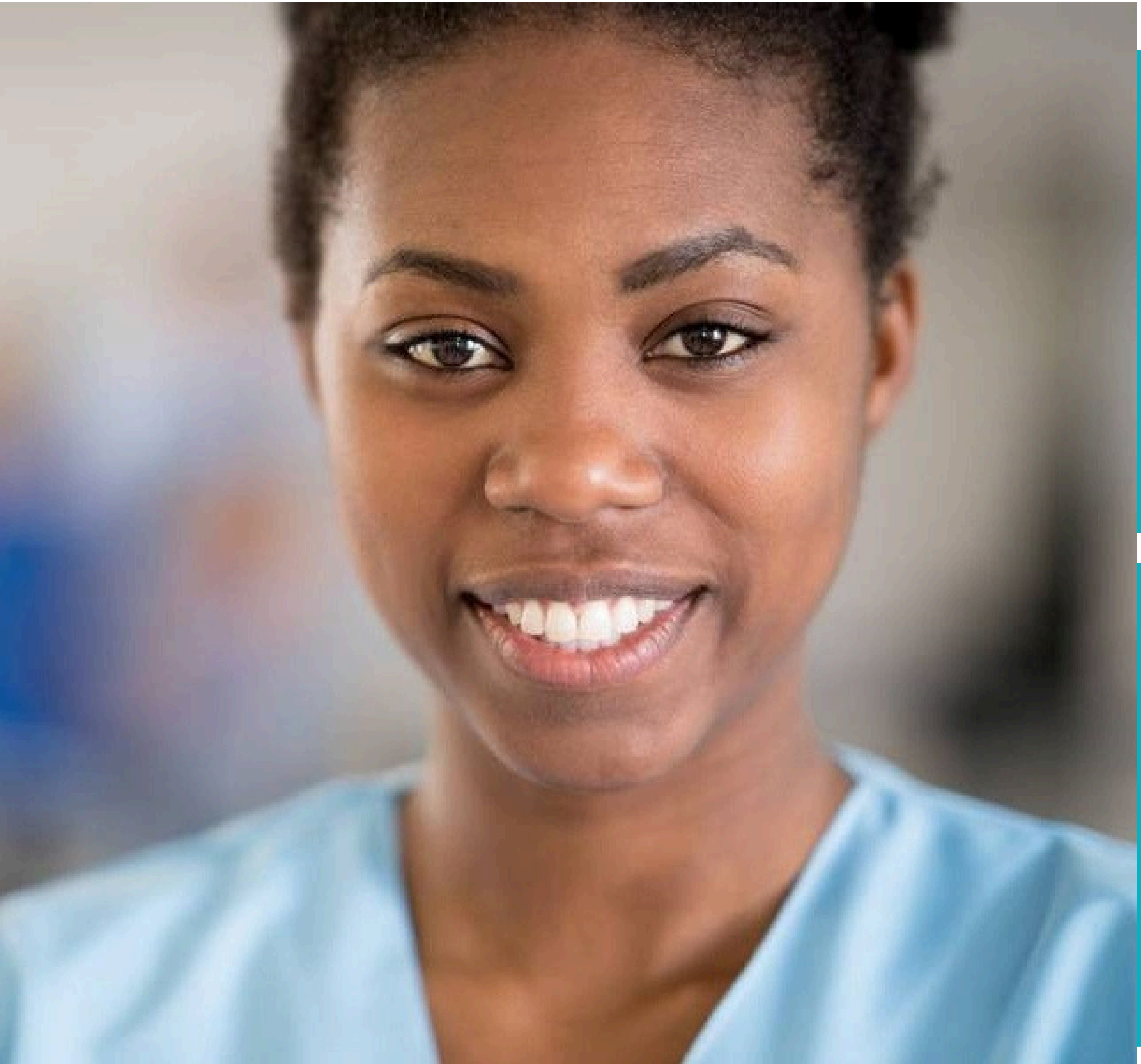
PHN-313
SIGNALS AND SYSTEMS

WEIGHTED DIRECTED GRAPH-BASED AUTOMATIC SEIZURE DETECTION USING EFFECTIVE BRAIN CONNECTIVITY FOR EEG SIGNALS

~BY-GARVIT



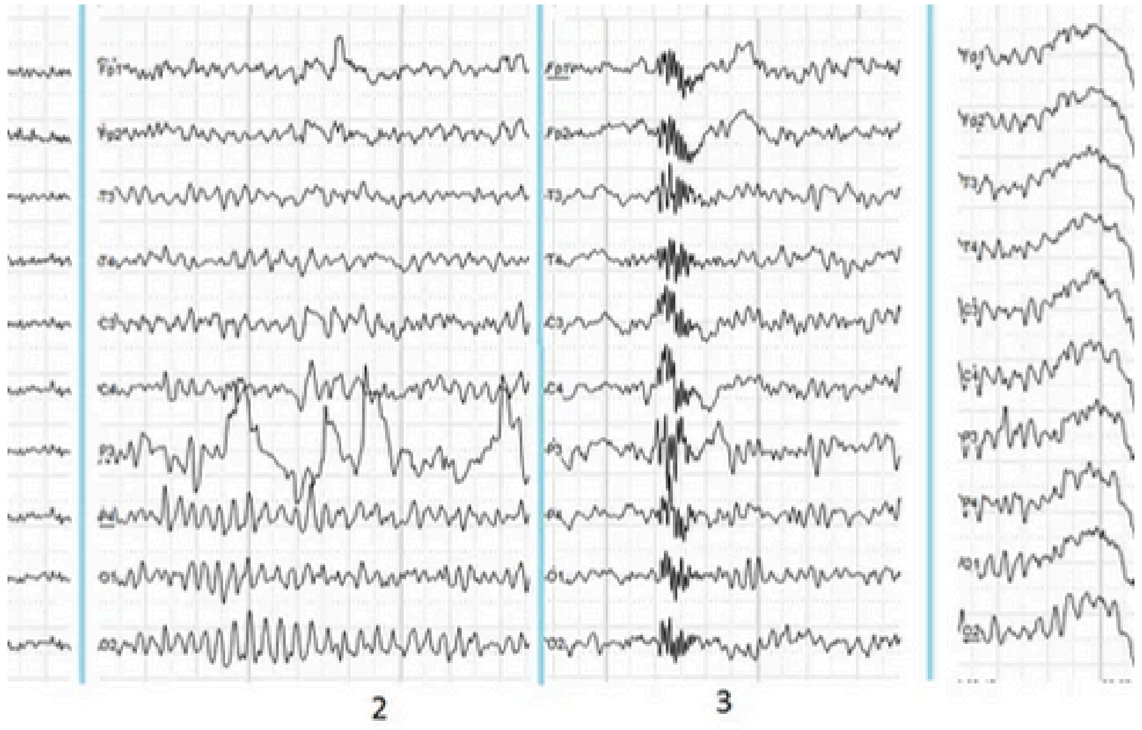
Introduction to Epilepsy

Epilepsy is a neurological disorder affecting 50 million people globally, marked by seizures due to abnormal brain activity. EEG is a critical tool for diagnosing epilepsy by detecting brain wave patterns. However, the manual analysis of long-term EEG recordings is time-consuming, highlighting the need for automated solutions to assist medical professionals.

Traditional EEG analysis methods, including time-domain, frequency-domain, time-frequency, and nonlinear approaches, have limitations. They either lack frequency information or struggle with non-stationary signals and noise sensitivity. Due to these issues, graph theory-based analysis is a more effective alternative for capturing the complex features of EEG signals.

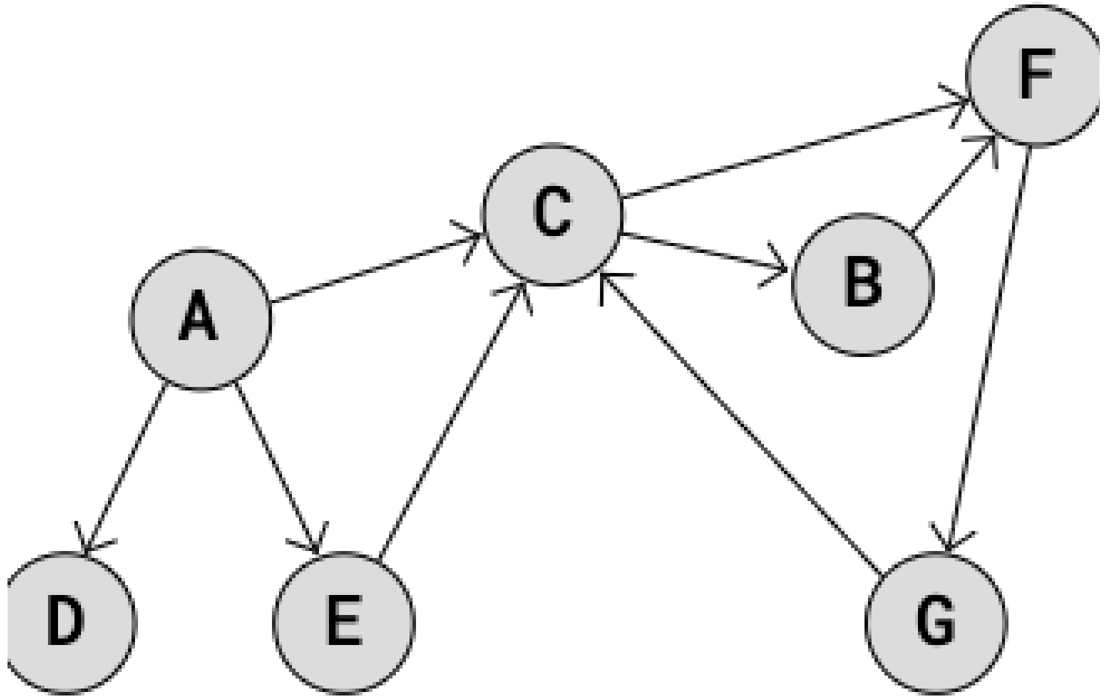
Motivation

Manual EEG analysis is limited, requiring substantial time and effort. Automated seizure detection systems can reduce workload and improve accuracy by using machine learning and signal processing techniques to detect seizures in real time.



Key Concepts

Brain connectivity is classified into structural, functional, and effective connectivity. Effective Brain Connectivity (EBC) captures the directed flow of information between brain regions, making it essential for seizure detection in EEG data.



Research Objective

The goal of this research is to develop an automated seizure detection framework based on a weighted directed graph model using EBC. The system is designed to identify seizure and non-seizure events by analyzing the connectivity between brain regions and leveraging machine learning classifiers.

Methodology Overview

The proposed methodology for automatic seizure detection follows a well-defined process, integrating multiple stages of signal processing, graph theory, and machine learning techniques. Each stage of this framework is crucial to the accurate identification of seizure events, ensuring the model is both robust and efficient.

EEG Signal Preprocessing

EEG signals are filtered using a Butterworth band-pass filter (0.01–32 Hz) to remove noise. The data is then segmented into 1-second windows for localized analysis, ensuring more precise seizure detection.

Graph Construction from EEG Channels

Each EEG channel is treated as a node in a graph, with edges representing the directed flow of information between brain regions

Graph Theory Feature Extraction

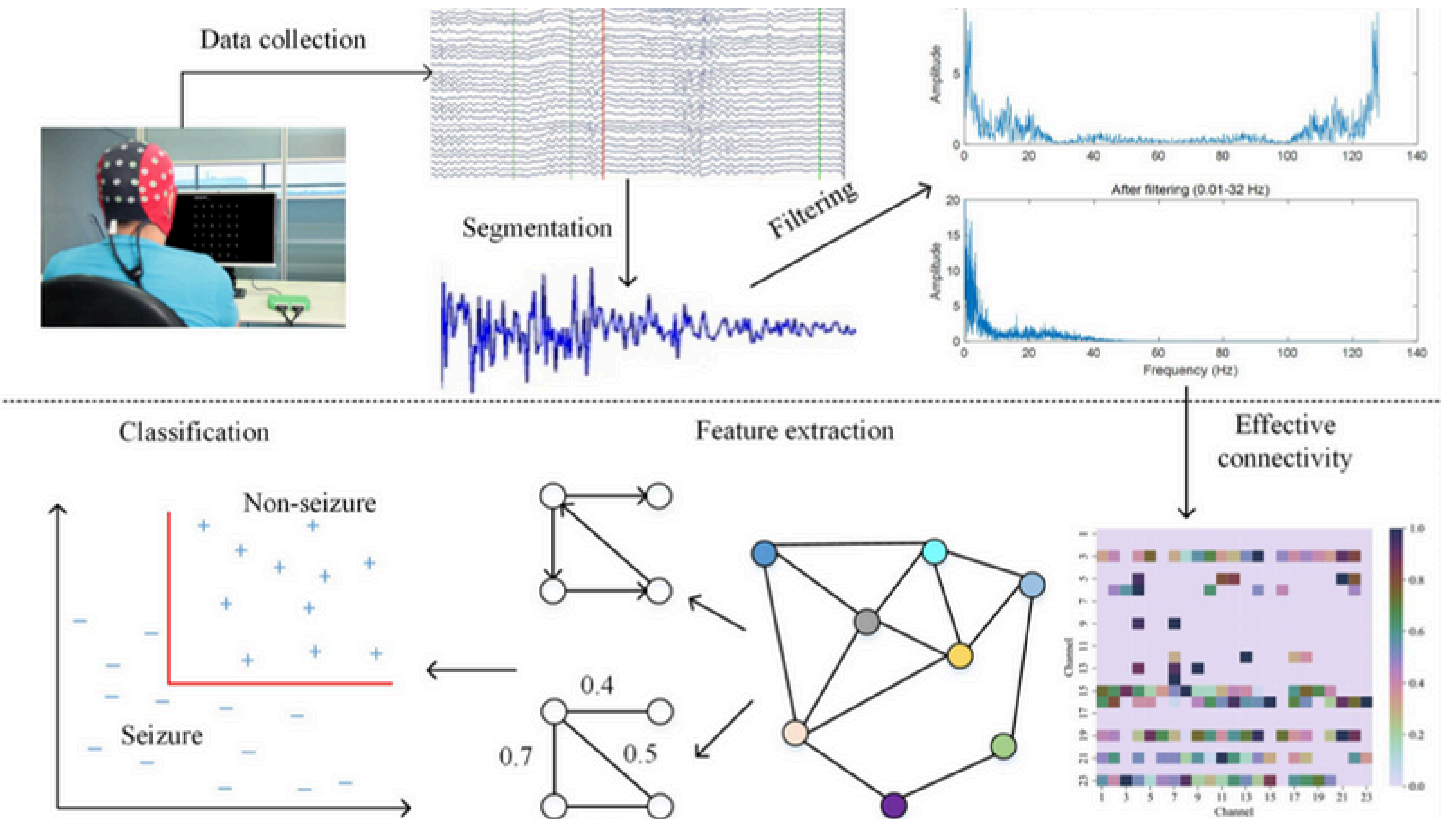
Key graph theory metrics are extracted, including:

- **Characteristic Path Length (CPL):** Measures information transfer efficiency.
- **Global Efficiency (GE):** Represents overall network communication.
- **Modularity (MD):** Captures the brain's network clustering during seizures.

Classification Using Machine Learning

Three classifiers are used to identify seizure events:

- SVM: Separates seizure vs. non-seizure in high-dimensional space.
- Random Forest (RF): Aggregates decision trees for better accuracy.
- KNN: Classifies events based on the nearest neighbors in feature space.


Data collection
Segmentation
Filtering
After filtering (0.01-32 Hz)
Amplitude
Frequency (Hz)
Effective connectivity
Feature extraction
Classification
Non-seizure
Seizure
0.4
0.7
0.5
Channel

Preprocessing of EEG Signals

The preprocessing of EEG signals is a critical step in ensuring that the data used in seizure detection is clean and reliable. In this study, a fourth-order Butterworth band-pass filter was applied to retain only frequencies between 0.01 and 32 Hz—the range most relevant for identifying seizure activity.

EEG signals can be lengthy and noisy, so they must be segmented into smaller windows for efficient analysis. A window size of 1 second is chosen for this study with a non-overlapping approach, ensuring that localized changes in brain activity are captured in a precise manner.

Segmenting the EEG signals helps avoid the inclusion of unnecessary data, which could hinder the performance of the seizure detection algorithms. The non-overlapping windows allow the model to focus on key periods where seizures might occur.

To achieve a balanced representation of ictal (seizure) and interictal (non-seizure) events, the study used all available samples from ictal periods and randomly subsampled interictal samples. This method ensures that the data distribution is not biased toward one category.

Effective connectivity in epilepsy

Multivariate Autoregressive Model (MVAR)

The multivariate autoregressive (MVAR) model is used to describe the dynamics between multiple EEG channels by considering the interactions of signals over time. The signal X(t), which represents the brain activity recorded at m different channels at time t, can be modeled as:

$$X(t) = \sum_{r=1}^{p} A(r)X(t-r) + E(t)$$

Where:

- $X(t)=[X1(t),X2(t),\ldots,Xm(t)]T$ represents the EEG signals at time t across m channels.
- A(r) is a p×p matrix of coefficients that describe the linear influence of the past values X(t−r) on the present values.
- E(t) is the noise vector, assumed to have zero mean and covariance matrix Σ.

Directed Transfer Function (DTF)

The DTF is the ratio of the causal effect of channel j on channel i to the net effect of all other channels on channel i, which has the desirable property of taking a value between 0 (with no causal effect) and 1 (with a strong causal effect).
In DTF, the causal effect of channel j on channel i is represented as follows:

$$\mathrm{DTF}^2_{j\to i} = \frac{|H_{ij}(f)|^2}{\sum_{l=1}^{m} |H_{il}(f)|^2}$$

Where:

- Hij(f) is the element of the transfer matrix representing the causal effect from channel j to channel i.
- The denominator normalizes the influence of all channels on channel i.

Partial Directed Coherence (PDC)

PDC is another measure of directed connectivity, focusing on the direct influence between channels in the frequency domain. It is defined as:

$$\mathrm{PDC}_{i\to j}(f) = \frac{|A_{ij}(f)|}{\sqrt{\sum_{k=1}^{m} |A_{ik}(f)|^2}}$$

Where:

- Aij(f) represents the Fourier transform of the coefficients in the autoregressive model that describe the influence of channel j on channel i.

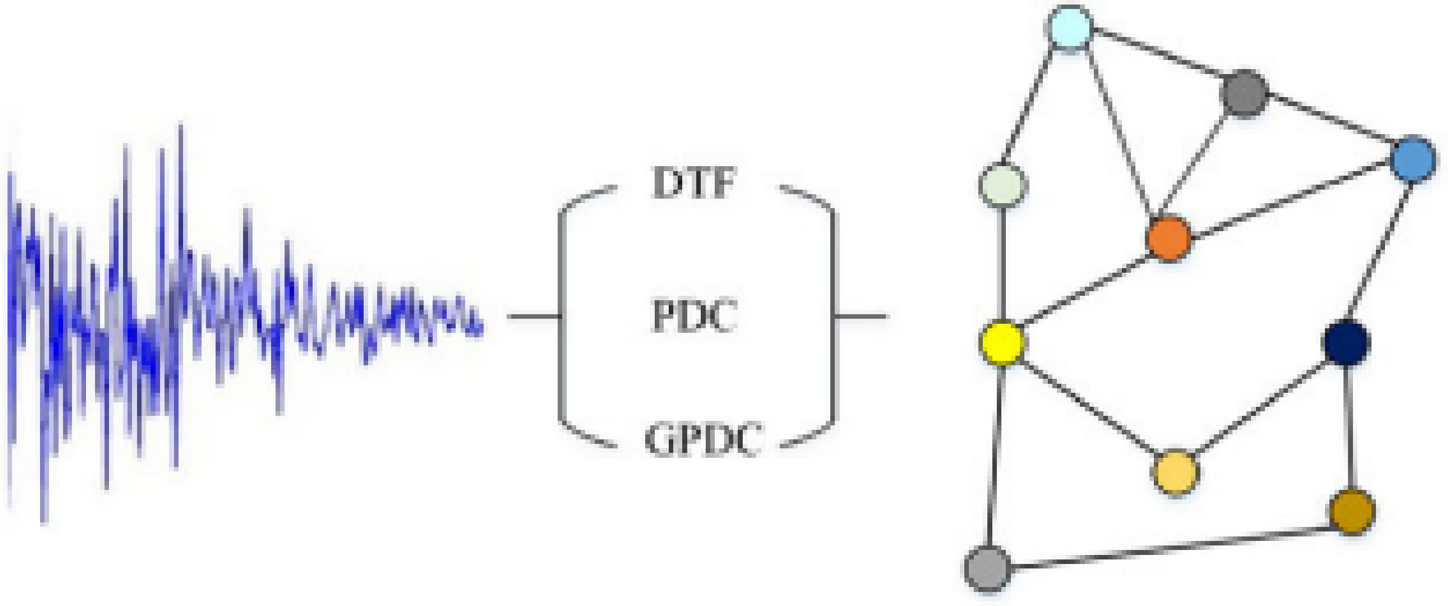
Generalized PDC (GPDC)

GPDC is an extension of PDC that helps to understand the direct influence between channels more clearly. The formula for GPDC is:

$$\mathrm{GPDC}_{i\to j}(f) = \frac{|A_{ij}(f)|}{\sqrt{\sum_{k=1}^{m}|A_{ik}(f)|^2}}$$

Graph Representation and Connectivity Matrix

The MATLAB toolbox of eMVAR was used to calculate DTF, PDC, and GPDC.When calculating PDC, DTF and GPDC, the frequency values are set to [1, 32] with a step size of 0.5. This results in a total of 63 points for f . Averaging over these frequency points yields a matrix W of 23 × 23, where wi j denotes the causal effect of channel j on channel i. Such an EBC network is represented in the form of a graph, where W is used as the weight matrix of the graph.



Graph Measures for Seizure Detection

In the context of EEG-based seizure detection, the brain's connectivity is represented as a weighted directed graph where the vertices correspond to EEG channels and the edges indicate the directed influence between these channels. Graph-theory-based measures are used to extract features that help in classifying seizure and non-seizure events.

Characteristic Path Length (CPL):

Measures the average shortest path between any two vertices in the graph

$$CPL = \frac{1}{M} \sum_{i \in V} \frac{\sum_{j \in V, j \neq i} d_{ij}}{M - 1}$$

where dij is the shortest path length between nodes iii and jjj, and MMM is the total number of vertices in the graph.

Global Efficiency (GE):

Reflects how efficiently information is transmitted across the entire network, calculated as the harmonic mean of the shortest paths between any two nodes

$$GE = \frac{1}{M} \sum_{i \in V} \frac{\sum_{j \in V, j \neq i} d_{ij}^{-1}}{M - 1}$$

Transitivity (T):

It is a measure of the degree to which nodes in the network tend to cluster together.

$$T = \frac{\sum_{i \in V} t_i}{\sum_{i \in V} [(k_i^{\text{out}} + k_i^{\text{in}})[(k_i^{\text{out}} + k_i^{\text{in}} - 1) - 2 \sum_{i \in V} e_{ij} e_{ji}]]}$$

where ti is the number of triangles formed by vertex i, and kout,i and kin,i represent the out-degree and in-degree of node i, respectively.

Modularity (MD):

Quantifies the extent to which a network can be subdivided into smaller, interconnected modules

$$MD = \frac{1}{l} \sum_{i,j \in V} \left[e_{ij} - \frac{k_{out,i} k_{in,j}}{l} \right] \delta(C_i, C_j)$$

where l is the total number of links, and δ(Ci,Cj) is 1 if nodes i and j belong to the same community and 0 else.

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Assortativity Coefficient (AC):

Assortativity coefficient (AC) examines whether nodes with a similar degree tend to be connected to each other. If the AC is positive, this means that nodes in the network tend to be connected to other nodes with similar degrees.

$$AC = \frac{\sum_{(i,j)\in E} k_{out,i}k_{in,j} - \left[\sum_{(i,j)\in E} \frac{k_{out,i}+k_{in,j}}{2}\right]^2}{\sum_{(i,j)\in E} \frac{(k_{out,i})^2+(k_{in,j})^2}{2} - \left[\sum_{(i,j)\in E} \frac{k_{out,i}+k_{in,j}}{2}\right]^2}$$

Average Clustering Coefficient (AvgC):

Measures how likely it is that the neighbors of a node are also connected to each other.The clustering coefficient is a statistical feature of a graph that measures the degree to which a node is to be grouped. The average clustering coefficient AvgC is defined as

$$AvgC = \frac{1}{M}\sum_{i\in V}\frac{t_i}{(k_i^{\text{out}}+k_i^{\text{in}})(k_i^{\text{out}}+k_i^{\text{in}}-1)-2\sum_{j\in V} e_{ij}e_{ji}}$$

Node Strength (NS):

The sum of all link weights connected to a node is the node strength. The average node strength N Si of i is defined as

$$NS_i = \sum_{j\in V} w_{ij}$$

where wij represents the weight of the directed edge from node i to node j.

Graph Entropy (e(G)):

Graph entropy can measure the similarity of two graphs, which is the sum of the vertices in G. Given that a vertex i belongs to V, the entropy ei of i is calculated by

$$e_i = -\sum_{j=0,j\neq i}^{M} w_{ij}\log w_{ij}$$

, the graph entropy of G with M vertices is formulated as

$$e_G = \sum_{i\in V} e_i$$

METRICS

The evaluation metrics used in this work are accuracy (Acc), specificity (Spe), sensitivity (Sen), and area under curve (AUC).
Moreover, statistical analysis is also provided. The receiver operating characteristic (ROC) curve does not specify a fixed threshold, but tries all possible thresholds (cutoff points) and computes multiple pairs of sensitivity and (1-specificity) at each possible threshold.

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FN} + \mathrm{TN} + \mathrm{FP}} * 100\%$$

$$\mathrm{Spe} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} * 100\%$$

$$\mathrm{Sen} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} * 100\%$$

$$\mathrm{AUC} = \int_0^1 \mathrm{ROC}(t)\, dt$$

Experimental Results

How we'll scale in the futureThe authors conducted experiments to evaluate the proposed seizure detection framework using EEG signals. They employed three classifiers: Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbors (KNN) on features extracted using graph theory. The Directed Transfer Function (DTF), Partial Directed Coherence (PDC), and Generalized Partial Directed Coherence (GPDC) methods were used for the estimation of effective brain connectivity.

Patient-Specific Model Results

The performance of the seizure detection method for the patient-specific model is presented in Table 1, where each classifier is evaluated with the three EBC methods.

Cross-Patient Model Results

In the cross-patient model, the leave-one-patient-out (LOO) method was used for evaluation. The results for each patient, sorted by decreasing accuracy.

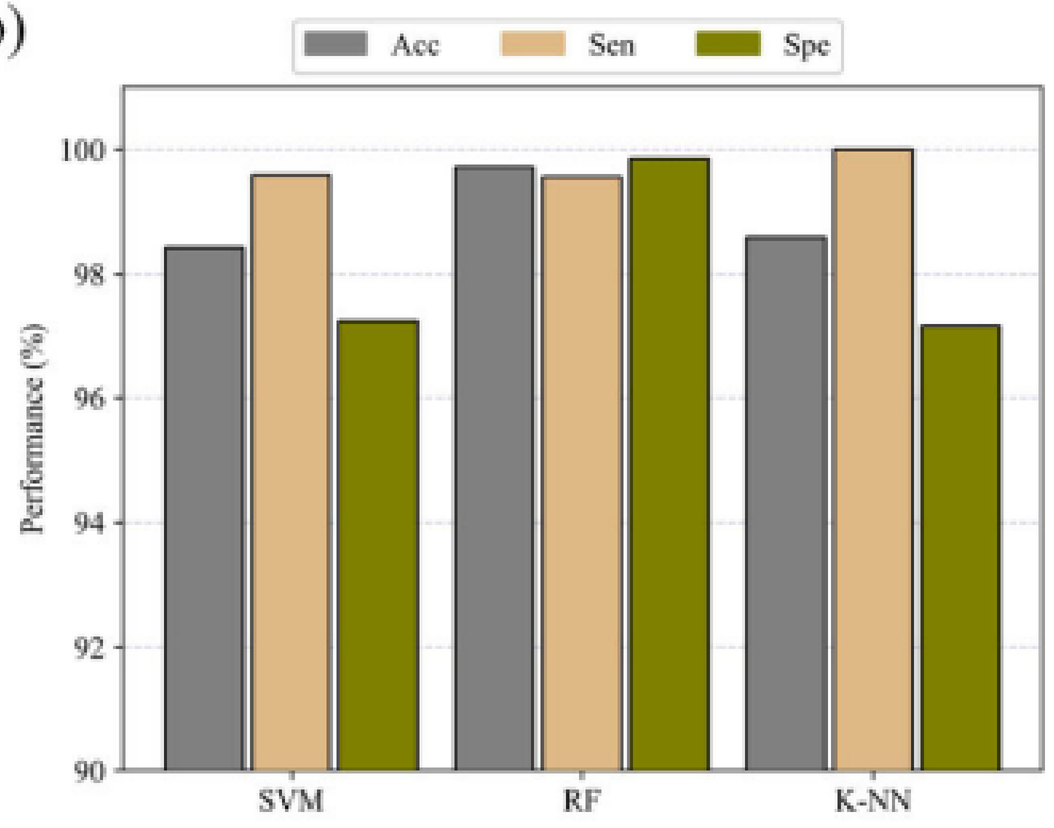
Results: (For Patient Specific Model)

Table 1 The classification results of the proposed method

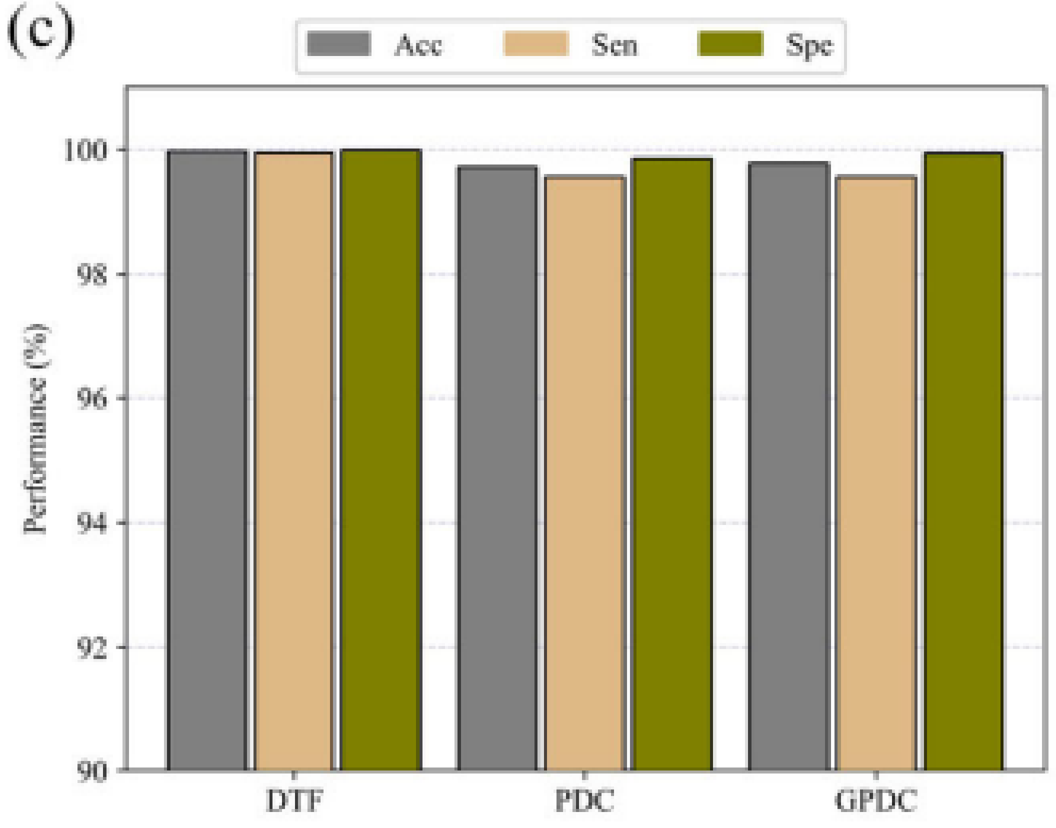
Method	SVM			RF			KNN		
	Acc	Spe	Sen	Acc	Spe	Sen	Acc	Spe	Sen
DTF	99.86	99.99	99.67	99.97	99.99	99.95	99.38	100	98.22
PDC	98.43	97.25	99.59	99.72	99.86	99.56	98.59	97.17	100
GPDC	98.52	97.45	99.63	99.78	99.94	99.56	98.05	96.12	99.97

(b) The classification performance of the three classifiers.
(c)Classification performances for the DTF, PDC, and GPDC methods.

(b)



(c)

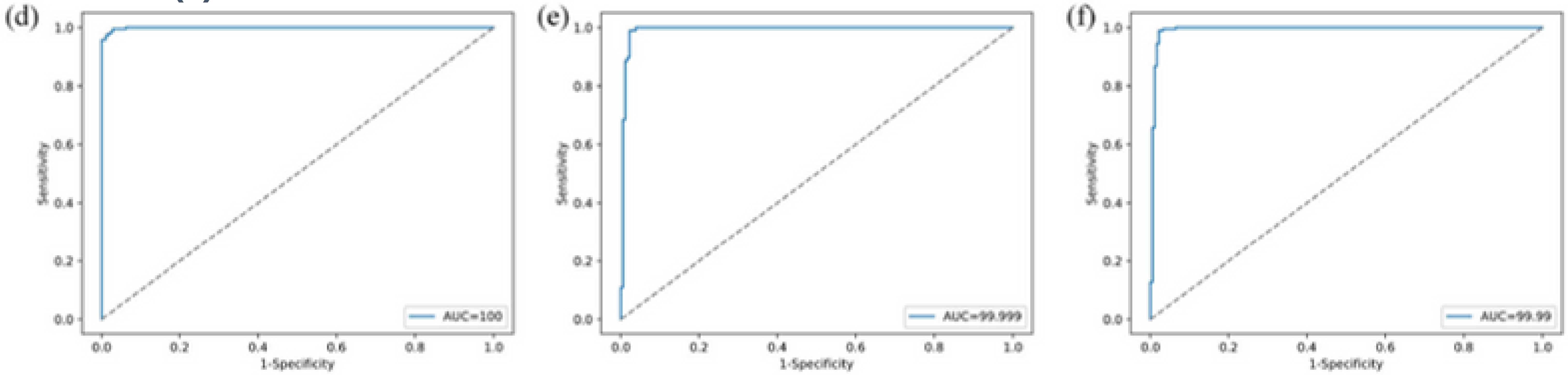


Best Performance:

- DTF + RF achieved the best accuracy at 99.97% and showed excellent performance in both specificity (99.99%) and sensitivity (99.95%).
- KNN also showed high sensitivity (100%) but lower accuracy compared to RF.

Results: (For Patient Specific Model) Contd...

(d) The ROC curve for the classification result of the DTF.
(e)The ROC curve for the classification result of the PDC.
(f) The ROC curve for the classification result of the GPDC.



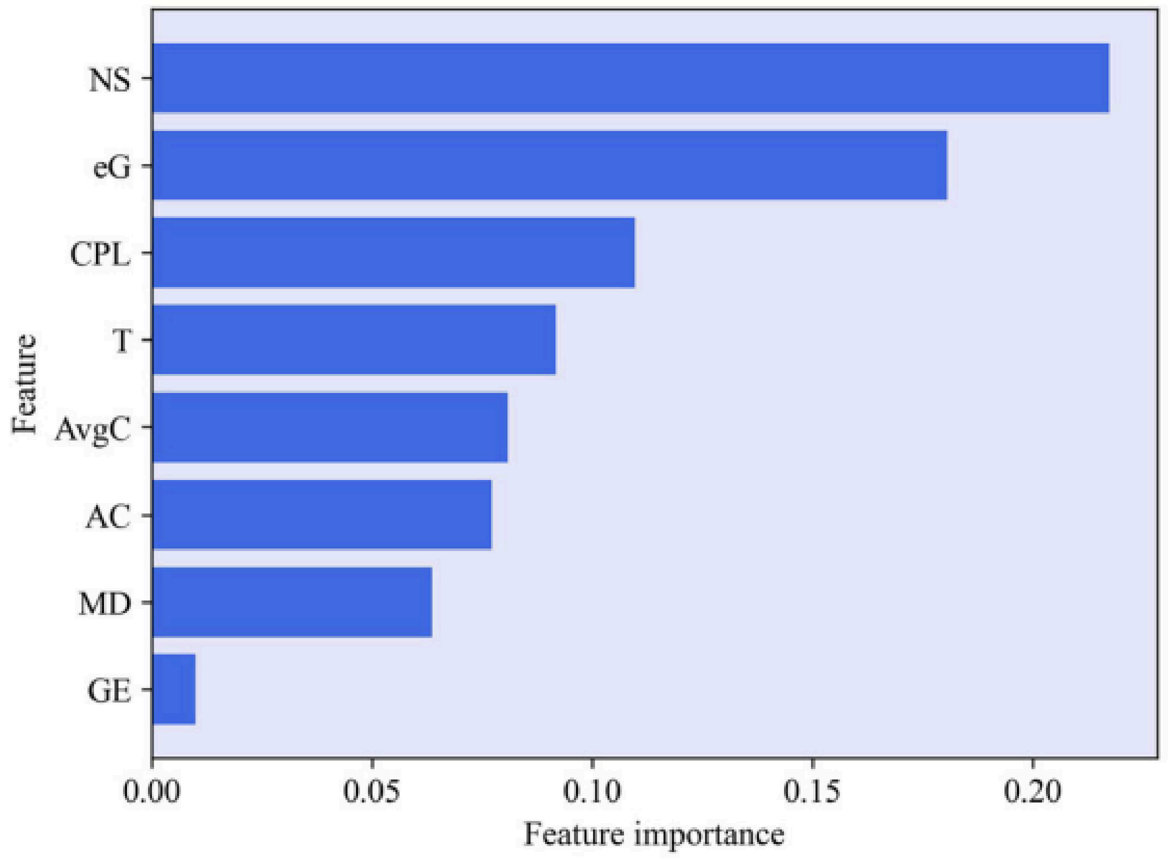


Fig. 3 The importance of the selected features with the RF classifier

Feature Importance

- **Node Strength (NS):**
  - This feature has the highest importance score. It represents the sum of all link weights connected to a node, indicating how strongly each EEG channel is connected to others.
- **Graph Entropy (GE):**
  - Measures the uncertainty or disorder in the graph. High graph entropy indicates complex brain dynamics, which are often associated with seizures.
- **Characteristic Path Length (CPL):**
  - Indicates the average shortest path between nodes in the graph. Shorter paths are often observed during seizures, reflecting the brain's rapid neural connections.
- **Clustering Coefficient (T, AvgC):**
  - Represents the degree to which nodes in the graph tend to cluster together. High clustering is seen in small-world networks, typical of neural networks.
- **Modularity (MD) and Assortativity (AC):**
  - Modularity measures the extent to which the graph can be divided into smaller, highly interconnected modules. Assortativity shows how similar nodes (in terms of degree) are connected.

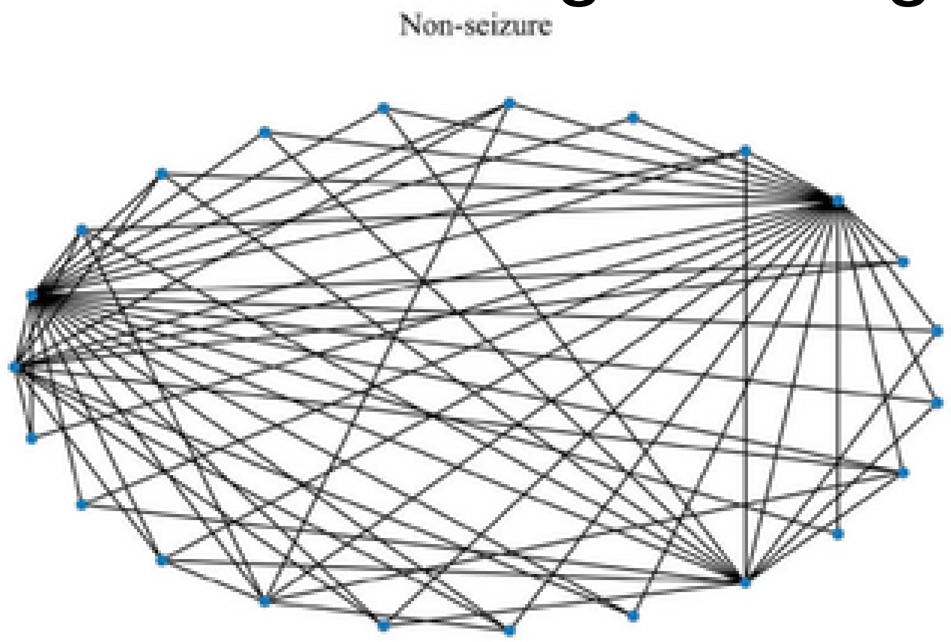
Graph Structure of Seizure and Non-Seizure Events

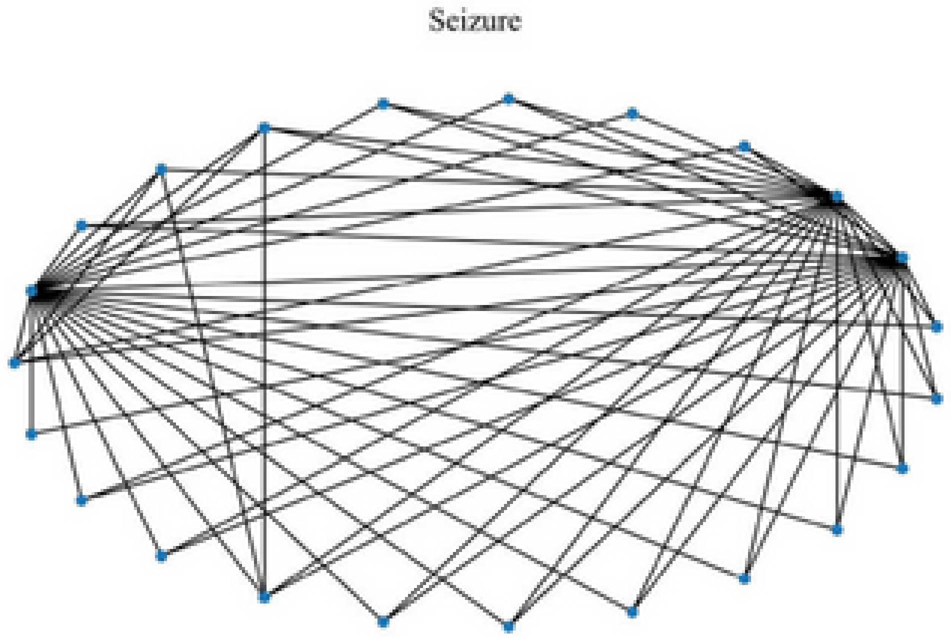
Non-Seizure Graph (Left):

- The graph structure for non-seizure events shows more evenly distributed node connections, with fewer high-degree (hub) nodes.
- The corresponding degree distribution (bottom-left histogram) shows that most nodes have a low degree, indicating sparse connectivity

Seizure Graph (Right):

- During seizures, the graph has more high-degree nodes (hub nodes), which create short paths between many nodes. These hubs represent highly active regions of the brain during a seizure.
- The degree distribution (bottom-right histogram) reflects this, showing a few nodes with much higher degrees than in the non-seizure state.

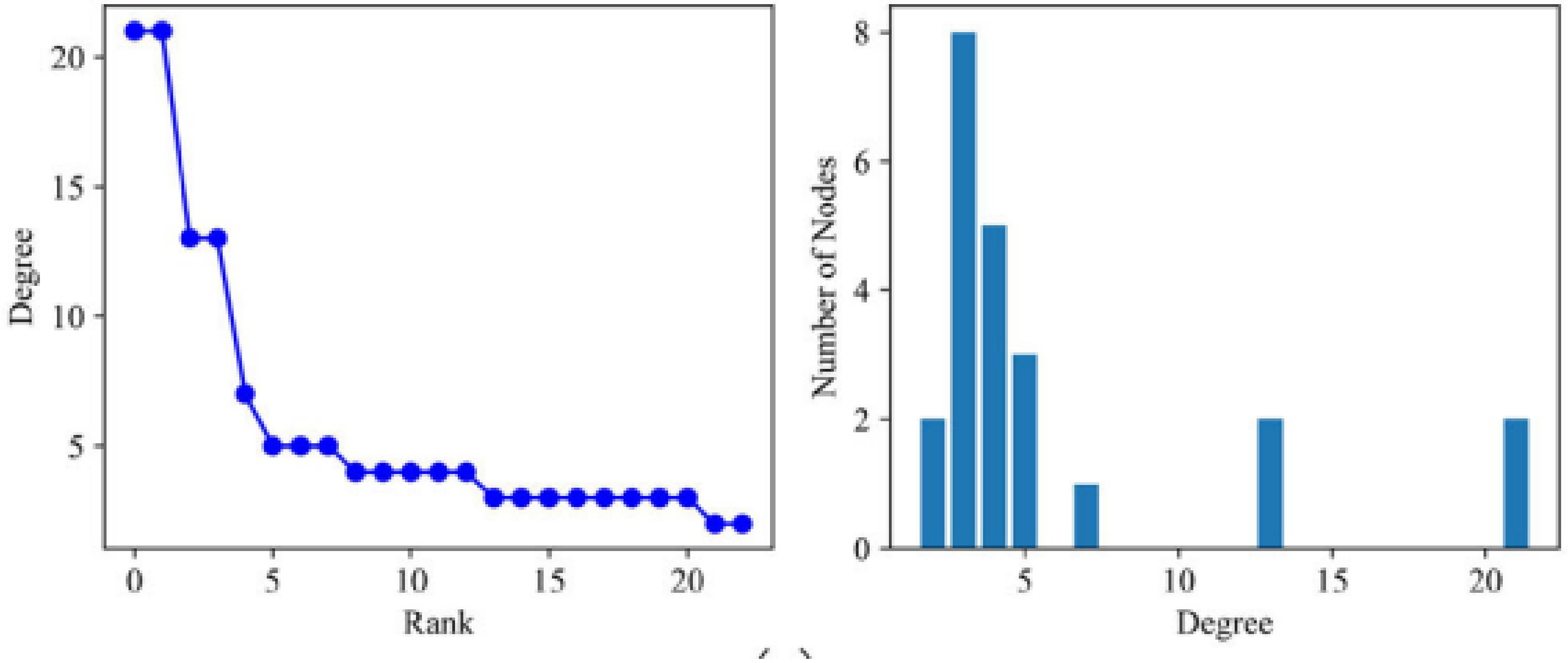




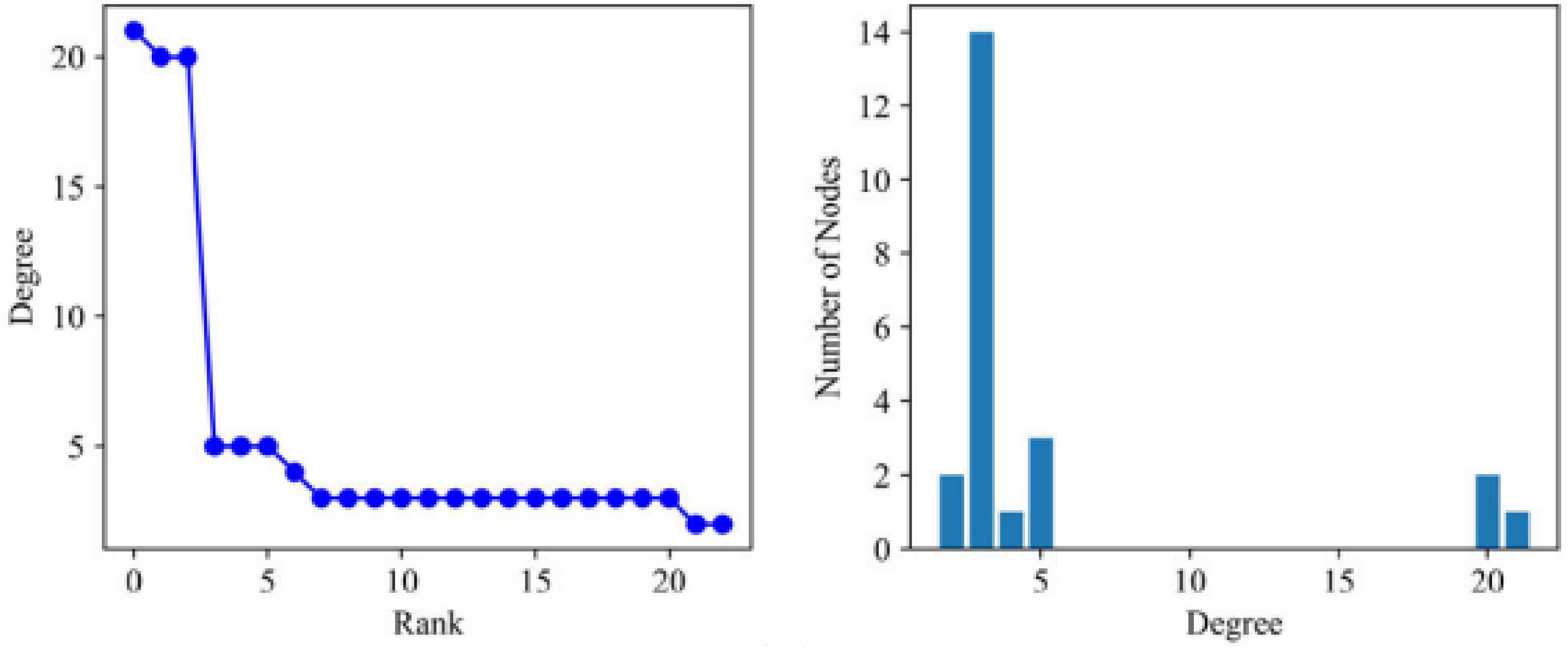
Degree Rank and Histogram:

- The degree rank and histogram plots for both states clearly show that during a seizure, the graph becomes more connected, with more nodes having higher degrees. This reflects a small-world network structure, which is typical in neural networks during high activity states like seizures.

Non-Seizure Condition:



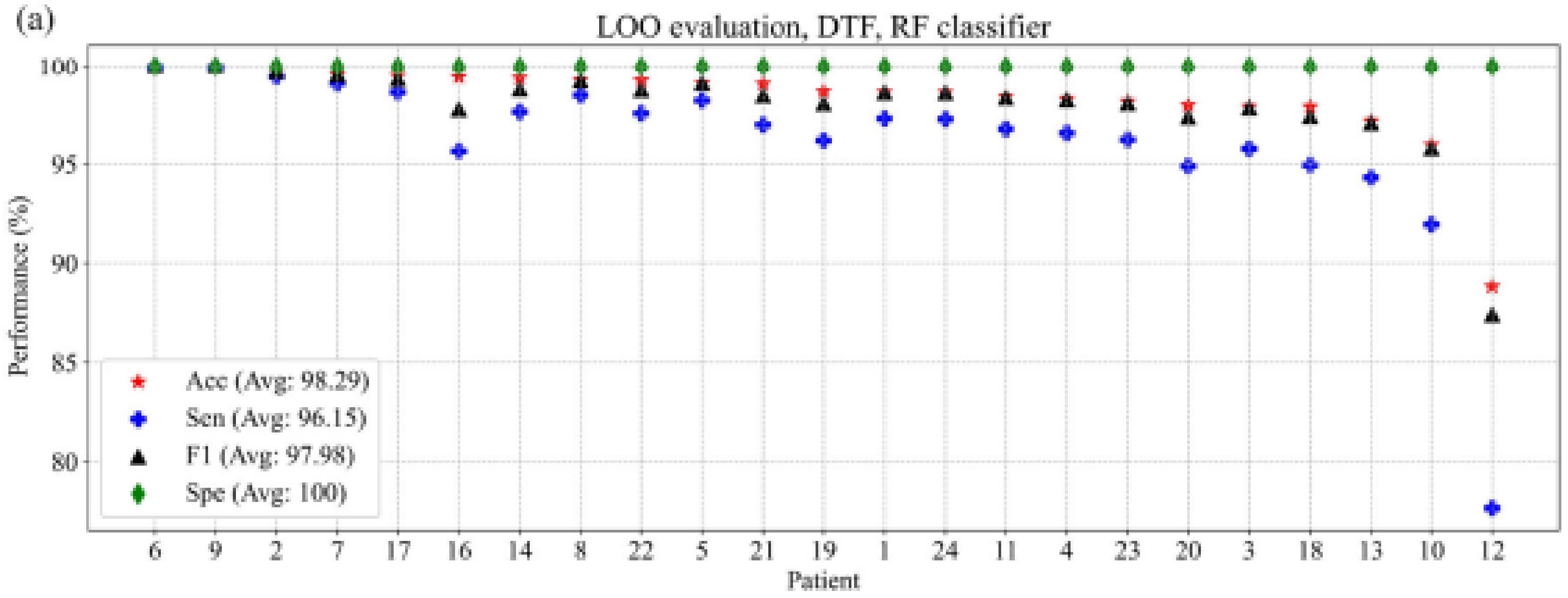
Seizure Condition:

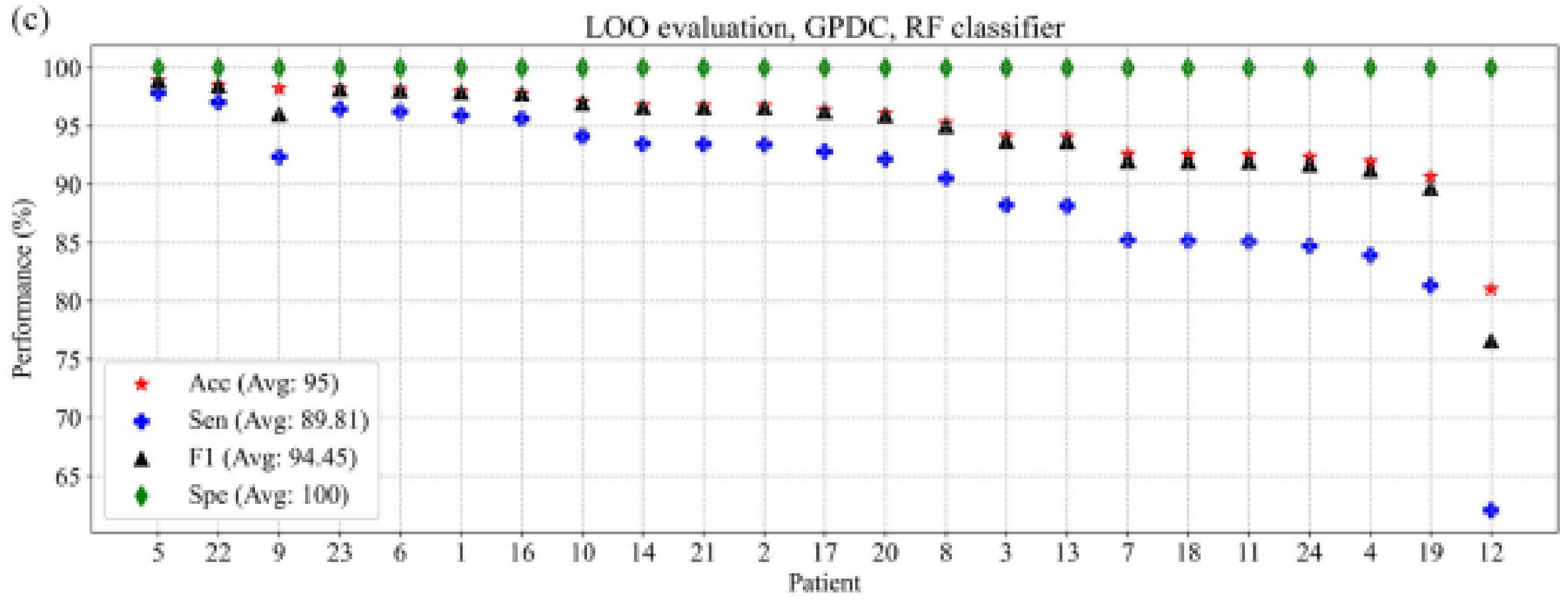


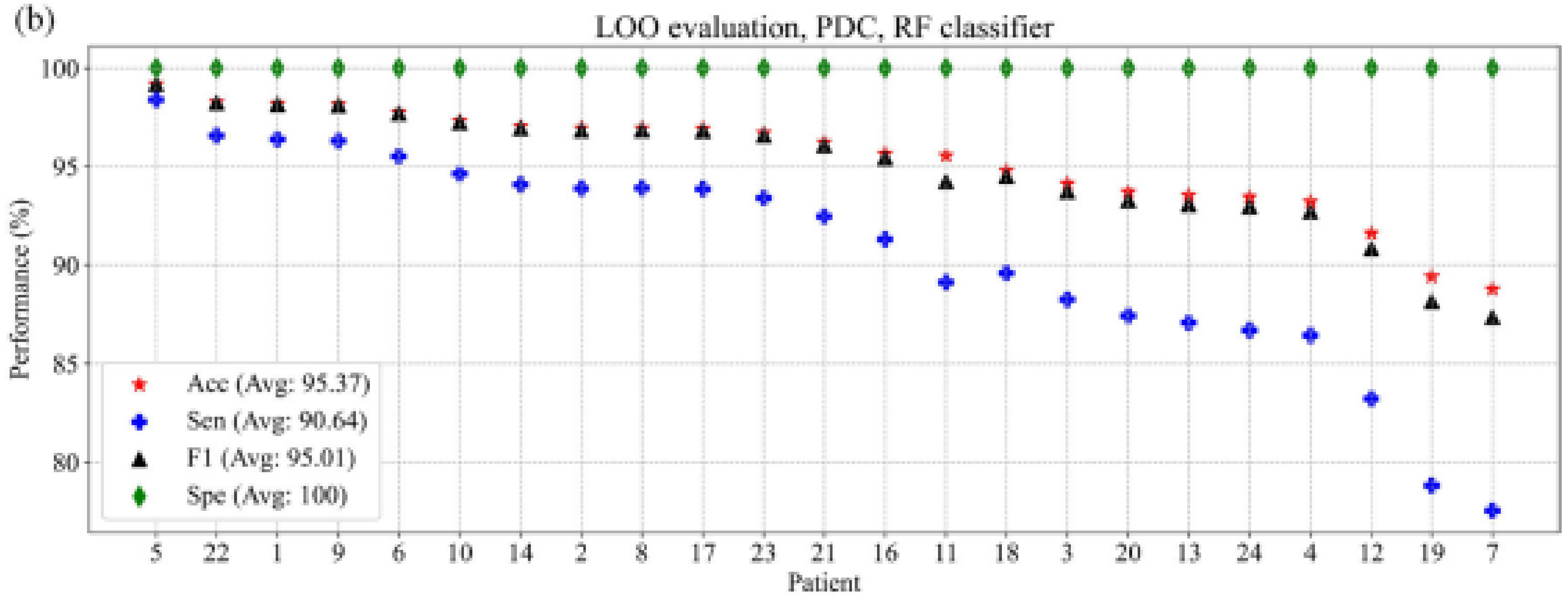
(b)

Results: (For Cross-Patient Model)

The Leave-One-Patient-Out (LOO) method was used to evaluate the cross-patient model, where data from one patient were used for testing while the rest were used for training.







Best Performance:

- DTF + RF again achieved the best average accuracy at 98.29%, with excellent specificity (100%) and sensitivity (96.15%) .
- The DTF method consistently outperformed PDC and GPDC across the experiments, indicating that it captures the directed influences in the brain more effectively.

Limitations

Although the proposed method effectively realizes seizure detection, the limitations and future work of this work are as follows:-

(a)The proposed model can detect seizures from EEG signals, but it also has a weakness in predicting seizures without delay. The next step is to accurately identify the characteristics of a preictal signal to give early warning before a seizure occurs.

(b)The experiments were performed with a small amount of data.To verify the clinical importance of the automatic seizure detection algorithm, a larger dataset and various epilepsy syndromes are required.

Thank you