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Time–Frequency Based EEG Epileptic Seizure Detection Using MiniMax-Normalized Domain Graph-Informed Adaptation Neural Networks with Channa Argus Optimization

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Abstract

The neurological disorder epilepsy causes repeated seizures because it leads to irregular brain activity. The medical field uses Electroencephalography (EEG) signals to monitor patients and diagnose their conditions. But, effective automated seizure detection is challenging because of the complicated EEG traces, artifacts, and inter-patient consistency. Traditional machine learning and deep learning algorithms usually use either time-dependent or spectral EEG features, which restrict the possibility of detecting detailed information related to seizures. In addition, missing values, signal artifacts, and dataset variability affect classification reliability and model stability. To overcome these limitations, a framework, Domain Graph-Informed Adaptation Neural Networks with Channa Argus Optimization (DG-IANN-CAO), is developed for EEG-based seizure detection. Initially the process uses two benchmark datasets which include the Bonn EEG Dataset and the Children's Hospital Boston–Massachusetts Institute of Technology (CHB-MIT) Dataset. EEG signals undergo preprocessing using Missing Values Imputation using Fuzzy K-Top Matching Value (MVI-FKMV) to handle incomplete signal values and improve signal quality. Next, the Discrete Quaternion Quadratic Phase Fourier Transform (DQQPFT) is applied to obtain time–frequency representations of EEG signals. Discriminative features are then extracted using a Multiscale Local-Context Transformer Network (ML-CTN) to capture contextual and multiscale signal characteristics. Seizure classification is performed using Domain Graph-Informed Adaptation Neural Networks (DG-IANN), which integrate Enhanced Domain Adaptation Attention Network (EDAAN) and Graph-Informed Neural Networks (G-INN) to model structural relationships within EEG features. Finally, network parameters are optimized using the Channa Argus Optimizer (CAO) to enhance convergence and classification stability. Experimental evaluation shows that the proposed framework achieves 99.1% accuracy, 98.7% precision, 98.5% recall, and 98.6% F1-score on the Bonn dataset, while achieving 98.9% accuracy and 98.3% F1-score on the CHB-MIT dataset, with a reduced error rate of 0.9%, demonstrating superior performance compared with several existing seizure detection approaches.

Keywords: Epilepsy, electroencephalography,seizure detection, Domain Graph-Informed Adaptation Neural Networks, Children's Hospital Boston–Massachusetts Institute of Technology.

1. Introduction

Epileptic seizures are neurological disturbances that take place as a result of uncontrolled and irregular electrical activity occurring in the brain, which affects millions of individuals across the globe and to a great extent contributes to poor quality of life [1]. Precise seizure detection is important for clinical diagnosis, patient monitoring, and treatment planning [2]. EEG signals are commonly used in the analysis of seizures because they provide comprehensive information about brain activity at various time and frequency scales [3]. The process of manual EEG data verification requires neurologists to spend time which results in subjective findings that can create mistakes during the lengthy assessment process[4]. This means that automatic seizure detection systems have received significant interest in recent years [5]. Conventional machine learning methods are based on manually designed features derived from time-domain or frequency-domain analysis and, in most cases, fail to capture the complex patterns in EEG signals [6]. Deep learning methods have become very useful alternatives, as they do not require the user to design hierarchical representations; instead, they can be learned automatically directly from raw or preprocessed EEG data [7]. Specifically, time-domain and frequency-domain information are useful for making the models sensitive to both temporal and spectral properties of epileptic seizures [8]. This combination of analysis enhances the ability and accuracy of seizure detection systems [9].

Although deep learning models perform well, they remain black boxes, thereby limiting clinical trust and interpretability [10-11]. Explainable Artificial Intelligence (XAI) has been proposed to provide information

about what the model is doing and the signal patterns that matter when making decisions [12]. By combining deep learning and XAI, one can create a system that detects seizures with high accuracy while remaining transparent and clinically meaningful [13-14]. Therefore, this paper will provide a time-frequency seizure detection system using deep learning and explainable AI to improve the accuracy and interpretability of the detection system to be implemented by the clinicians [15].
This study is motivated by the need to come up with an accurate and reliable seizure detection system through the combination of time-domain and frequency-domain data due to EEG signals. The currently developed deep learning models are not easily interpretable thus limiting their use in clinics. Thus, the transparency can be enhanced with the introduction of Explainable Artificial Intelligence (XAI), which can give an insight into how the model makes the decisions, and thus the system will be more reliable in terms of medical use.

Novelty and contributions
The present study introduces a novel deep learning architecture, DG-IANN-CAO, of effective EEG-based seizure classification which integrates time-frequency signal representation, transformer-based feature extraction, and graph-based neural classification in one architecture. Compared with traditional approaches that consider only temporal or spectral characteristics, the proposed framework simultaneously captures the temporal, spectral, and structural correlations of EEG signals. In contrast, the CAO optimization scheme enhances parameter sensitivity and model convergence, leading to improved detection rates and greater stability across a range of datasets. The significant contributions of the proposed are,

- The new time-frequency based EEG seizure detection system (DG-IANN-CAO) is suggested, and this system unites the sophisticated preprocessing, feature extraction, and the best classification as a manner of enhancing the detection of seizures.
- A ML-CTN that utilized to represent discriminative temporal and spectral EEG properties.
- To model structural dependence among the EEG features and to enhance the classification performance, a DG-IANN is designed by optimizing through the CAO.
- Extensive experiments on the both datasets demonstrate the effectiveness of the proposed framework, achieving 99.1% accuracy and 98.6% F1-score, outperforming several existing seizure detection approaches.

The research study is organized as follows: Section 2 offers an overview of earlier studies. Section 3 provides a detailed explanation of the proposed method and Section 4 presents the research findings. Section 5 provides the conclusion.

2. Literature Survey
This section reviews recent research on applying deep learning (DL) and machine learning (ML) approaches to seizure detection. A detailed comparison of these studies is summarized in Table 1.
In 2022, Fatima Hassan et al. [16]presented a seizure-detection framework that combined machine learning classifiers with convolutional neural networks (CNNs) as its core detection technology. The EEG signals underwent initial processing through the Butterworth filter which functioned to remove noise and enhance signal quality. The CNN system generated automatic extraction of EEG signal features after the initial preprocessing stage. The obtained feature set was further trimmed down with the aid of mutual information and estimators that helped to select only the most useful features and perform dimensional reduction. The process of feature selection achieved two objectives because it reduced redundancy while it improved learning efficiency. The optimal subset of the features was then fed as an input to the various machine learning classifiers to detect and classify seizures.
In 2024, Abdulwahhab et al. [17]introduced a deep learning model which uses machine learning algorithms to detect epileptic seizure activity through analysis of EEG signals. The method included two processing streams which used convolutional neural networks (CNNs) and recurrent neural networks (RNNs) with long short-term memory (LSTM) models for their processing. The model used time-frequency representation and EEG raw signals as its input data. The researchers used Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT) methods to produce spectrogram and scalogram images from EEG signals. These representations reflected time and spectral property of brain activity. The images that were generated served as the CNN architecture inputs and the temporal connections were represented by the RNN-LSTM architecture.
In 2023, Zaid et al. [18] introduced a deep learning-based seizure classification model which applied to preprocessed and modified EEG signals instead of raw EEG signals. A number of EEG signal preprocessing variations were investigated to improve feature representation. In the study, various forms of EEG signals were compared such as the original EEG signals, standardized signals, and the combination of original signals with the squared, differentiated, and Fast Fourier Transform (FFT) signals. These processed signals were provided as inputs to multiple deep learning architectures, including a Deep Neural Network (DNN), a simple one-dimensional convolutional neural network (1D-CNN), and a moderately complex 1D-CNN model. The framework focused on improving seizure classification performance by transforming signals and integrating frequency-domain information.
In 2022, Kumar et al. [19] introduced a smart seizure-detection methodology, which combines variational mode decomposition (VMD) and Hilbert transform to extract feature of EEG records. First, the VMD technique was applied to break down EEG signal into intrinsic mode functions in order to separate the signal components of

various frequency bands. The Hilbert transform then followed to determine signal characteristics of significance in the obtained modes, after the decomposition. These extracted features represented temporal and spectral properties of the EEG signals. The feature set was then supplied to a stacked neural network (SNN) architecture that performed seizure detection and classification by learning complex patterns associated with epileptic brain activity.

In 2023, Pandey et al. [20]designed a complete deep learning model which combines Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks to perform EEG signal classification. The model was used to process EEG signals and categorize into three classes including preictal, normal and seizure classes. In the architecture, CNN layers were used to automatically derive spatial and local temporal features on EEG signals without the use of handcrafted feature extraction. The feature representations were subsequently extracted and inputted into the LSTM layers to entail the long-term dependence in the sequence of EEG signals. This CNN-LSTM model allowed the automatic learning of the features, the time patterns and the classification of the results with one deep learning system.

In 2022, Shen et al. [21]created an EEG-based dynamic seizure-detection system based on signal processing and machine learning. The first step, which was performed, was discrete wavelet transform, which was used to break down EEG signals into various sub-frequency bands, allowing the analysis of signal quality on different frequency subsets. These sub-band signals were then extracted to provide the discriminative features using eight eigenvalue-based algorithms. The support vector machine classifier was applied to three health control seizure-free and seizure-active EEG state features after the feature extraction process was completed. The RUSBoosted tree ensemble RUSB-TE was used to perform real-time seizure onset detection by analyzing classified signals from continuous EEG recordings.

In 2026, Ghosh et al. [22]presented a patient-free seizure-detection system that processed short EEG snippets to monitor patients. One-second windows of EEG had been processed by the system and nested cross-validation had been employed to avoid data leakage in training the model and its evaluation. The extraction of features was done in the form of several domains such as temporal, spectral, wavelet as well as spatial representations using Common Spatial Pattern (CSP). The training folds were conducted through feature selection, spatial filtering, and hyperparameter optimization to ensure evaluation integrity. The framework produced a compact set of features representing the meaningful signal features. The K-Nearest Neighbours (KNN) and the Randolph Forest were traditional classifiers that were used to explore the selected features to identify seizures.

In 2023, Poorani S et al. [23]trained patient-specific patient seizure detectors based on EEG signals over the CHB-MIT dataset. Two variants of deep learning were used to process EEG signals and detect the presence of a seizure. The former used one-dimensional convolutional neural network (1D-CNN) to acquire spatial patterns directly using the EEG signals. The second model included a hybrid system that integrated CNN with Long Short-Term Memory (LSTM) network. Spatial features of EEG signals were extracted by CNN layers and temporal dependencies of seizure patterns were learned by LSTM layers in this architecture. The framework aimed at assessing the performance of models on the identities of various patients in order to study the variability in seizure detection.

In 2024, Sun et al. [24] introduced a multi-input deep feature learning network (MDFLN) model was presented in order to analyze EEG signals in both time-domain and time-frequency displays. The framework automatically obtained the information of features with the help of deep learning networks that processed many signal views. Time-domain EEG and time–frequency representation have been used together to obtain complementary signal properties. These representations were used to learn intricate patterns of features using deep layers of learning. The deep features that were extracted were then presented into a bidirectional long short-term memory (BLSTM) network to identify seizure and non-seizure EEG events. Multi-view learning strategy improved the representation of features through a combination of data in the various signal domains.

In 2023, Varlı M et al. [25] developed a unified deep learning system of epileptic seizure activity detection, epileptic region detection, and EEG signal classification. It analyzed raw EEG signals as well as images of the time frequency of the EEG time series. Continuous Wavelet Transform (CWT) and Short time Fourier Transform (STFT) were used to transformed the EEG signals to scalogram and spectrogram images respectively. These image representations obtained the time and frequency patterns involved with seizure activity. Images were generated by CWT and STFT method and used to create separate models. The framework also incorporated combinations of signal representations to enhance feature extraction and improve the analysis of EEG-based seizure patterns.

Table 1: Summary of Literature Survey

Ref. No	Method	Advantages	Disadvantages
[16]	CNN	Efficient feature extraction using CNN; dimensionality reduction improves classifier performance	Multiple stages increase computational complexity; feature selection may lose important information.
[17]	RNN	Combines temporal and spectral information; captures sequential EEG patterns effectively	Image transformation increases preprocessing costs and increases model complexity.

[18]	1D-CNN architectures	Uses different signal transformations to improve representation; reduces dependence on raw EEG	Requires extensive preprocessing combinations; model performance depends on signal transformation choice
[19]	Stacked Neural Network	Effective signal decomposition and feature extraction; captures multi-frequency EEG patterns	The decomposition process increases computational overhead.
[20]	CNN–LSTM	Automatic feature extraction without handcrafted features; captures temporal dependencies	Deep architecture requires large computational resources.
[21]	DWT feature extraction with SVM and RUSB-TE	Effective frequency-band analysis, suitable for real-time seizure onset detection	Traditional ML methods may not capture complex nonlinear EEG patterns.
[22]	KNN	Patient-independent framework; computationally efficient with compact feature set	Traditional classifiers may limit scalability for large datasets.
[23]	LSTM	Deep learning models capture spatial and temporal EEG characteristics	Patient-specific models reduce generalization capability
[24]	MDFLN	Integrates time-domain and time–frequency features; improved feature representation	Multi-input architecture increases training complexity.
[25]	STFT	Uses both raw signals and time–frequency images; enhances seizure pattern detection	The image generation step increases the preprocessing time.

Table 1 below presents a summary of the latest studies on the application of machine-learning methodologies and models of deep learning to EEG-generated seizure detection. The table presents the reference number, the applied method, and the strengths and weaknesses of both methods. The deep learning models that have been used in several studies to learn discriminative features with EEG signals include CNNs, RNNs, 1D-CNNs, CNNLSTM, LSTM and MDFLNs. Temporal and frequency properties of EEGs were also obtained with other signal processing tools that included DWT, STFT and feature decomposition techniques. Although these techniques proved to be effective in feature extraction and the enhancement of seizure detection, a number of limitations were observed which included the high complexity of calculations, high preprocessing needs, poor generalization and limited scalability. Thus, an effective, but no doubt efficient, framework that incorporates strong feature representations, improved interpretability, and computational efficiency is still required to ensure reliable seizure detection.

2.1 Problem Statement and Research Gap

The problem of epileptic seizure detection from EEG signals is difficult, as the human brain's activity is neither stationary nor simple. Traditional diagnosis relies on neurologists manually inspecting EEG recordings, a time-consuming method prone to human error, especially in long-term assessment. Though many machine learning and deep learning methods have been proposed for automated seizure detection, one limitation of many existing methods is that they use either time-domain or frequency-domain features to detect only a subset of the full set of epileptic brain signal features. Additionally, deep learning networks including CNNs, RNNs and hybrid networks usually entail complex computation and heavy preprocessing. Most deep learning frameworks are also black-box models, which is also a strong limitation as they do not provide much clinical knowledge to the clinicians. This incompetence to be transparent erodes trust and restricts their use in practice in medicine. Thus, it is necessary to have an effective seizure detection model that combines time-domain and frequency-domain representations and has explainable AI mechanisms to make the model more transparent, reliable, and clinically supportive.

3. Proposed Methodology

DG-IANN-CAO is a proposed seizure-detection framework that combines preprocessing, feature extraction, deep learning-based detection, and optimization, achieving high accuracy in detecting epileptic seizure activity in EEG signals. The system uses EEG signals as input, first from the Bonn EEG Epilepsy Dataset and, secondly, from the CHB-MIT EEG Dataset. In preprocessing, MVI-FKMV is used to handle missing or corrupted EEG samples by approximating values based on similarity to adjacent signals. The meaningful features extracted with the ML-CTN after preprocessing are represented as both local contextual features and long-range dependencies in the EEG signals, in light of attention-based multiscale processing. The features obtained are then fed to the DG-IANN, which combines EDAAN and G-INN to learn domain-insensitive, structurally correlated

representations of EEG. The last stage involves the CAO adjusting the DG-IANN parameters to detect seizures best and ensure the model functions efficiently. Figure 1 illustratesthe proposed framework.

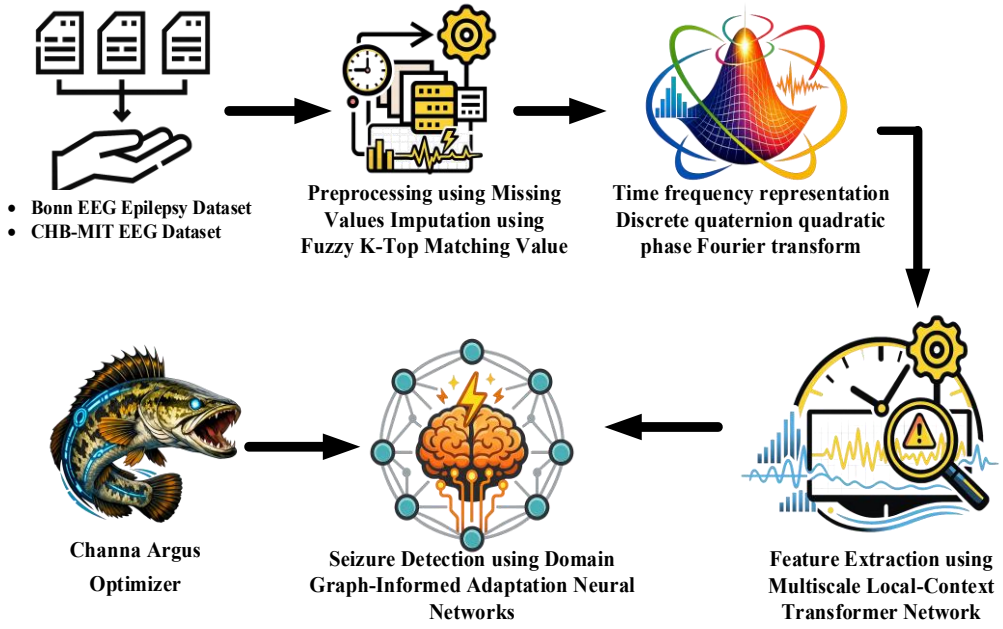


Figure 1: Proposed Methodology

3.1. Data Collection

EEGs are obtained in the current research using two publicly available benchmark datasets: the Bonn Dataset and the CHB-MIT Dataset. These data offer normalised EEG signals for research on seizure detection. The EEG data obtained are directly used as input to the proposed framework and then fed to the preprocessing phase for further processing.

3.2. Preprocessing using Missing Values Imputation Using Fuzzy K-Top Matching Value

The MVI-FKMV [26] is used to deal with missing or incomplete EEG values caused by noise, recording artifacts or transmission errors. The method calculates nonexistent data through its process of finding the closest matching samples which exist in the dataset and using fuzzy weight distribution to strengthen the reliability of the imputation method.

Initially, the similarity between EEG samples is measured as the absolute difference in their utility values. This distance measure determines how closely related two samples are and is given as in equation (1).

$$d = \left|U(D) - U(J)\right| \qquad (1)$$

where d represents the distance between two samples, while $U(D)$ and $U(J)$ denote the utility functions of states D and J. A smaller distance indicates higher similarity, and the top-K matching samples are selected based on this value.

Next, the fuzzy matching relationship used to estimate missing values is defined as in equation (2).

$$\eta_{function} = \{T, (1-\Delta)\} \qquad (2)$$

where $\eta_{function}$ represents the fuzzy matching function, T denotes the selected top-matching samples, and H represents the variation between samples. The factor assigns greater importance to samples with lower variation, enabling more accurate estimation of missing values. Lastly, the EEG signals are reconstructed using imputed values, which are then passed for further processing.

3.3. Time–Frequency Representation using Discrete Quaternion Quadratic Phase Fourier Transform (DQQPFT)

The DQQPFT[27] has been used in this work to develop a time-frequency representation of EEG signals. EEG signals are highly non-stationary, with seizure patterns characterized bytemporal and spectral changes. Thus, the preprocessed EEG signals are converted to a joint time-frequency space using DQQPFT, thereby effectively representing the patterns associated with seizures.

In the first step, the DQQPFT representation of the EEG signal is calculated according to equation (3).

$$\Phi^{G}_{A_1,A_1}(x_1,x_2) = \sum_{\xi_1=0}^{M_1-1}\sum_{\xi_2=0}^{M_2-1} Q_{A_1}(\xi_1,x_1)\phi(\xi_1,\xi_2)Q_{A_2}(\xi_2,x_2) \qquad (3)$$

where $\Phi^{G}_{A_1,A_1}(x_1,x_2)$ denotes the transformed time–frequency representation of the EEG signal, Q_{A_1} and Q_{A_1} represent quaternion kernel matrices, and (ξ_1,x_1) denotes the input EEG signal matrix.

The signal representation matrix is defined asin equation (4).

$$\phi(\xi_1,\xi_2)=\begin{pmatrix}\phi(1,1)\\ \cdots\\ \phi(M_1,M_1)\end{pmatrix} \quad (4)$$

where M_1 and M_2 denote the signal dimensions used for transform computation.

Finally, the quaternion-valued transform result is expressed asin equation (5).

$$R^{G}_{A_1A_2}[e](x_1,x_2)=R^{G}_{A_1A_2}[\tilde{e}](x_1,x_2)+iR^{G}_{A_1A_2}[\hat{e}](x_1,x_2) \quad (5)$$

where the real $R^{G}_{A_1A_2}[e]$ and $iR^{G}_{A_1A_2}[\hat{e}]$ imaginary components jointly represent the complete time–frequency characteristics of the EEG signal.

The EEG signals are transformed into discriminative time-frequency representations that retain temporal variations and spectral information. The received representations are then sent to the ML-CTN to extract features and process them for additional seizure detection.

3.4. Feature Extraction using Multiscale Local-Context Transformer Network (ML-CTN)

The ML-CTN [28] is used in this work to extract both temporal and contextual data of EEG data. The transformer-based architecture is efficient at modeling long-range dependencies, and multiscale processing helps capture differences in seizure patterns across different time resolutions.

The first step is learning the relationships between the features using an attention mechanism that highlights significant signal patterns. Attention operation can be represented as in equation (6).

$$Attention = soft\max\left(\frac{RL^{S}}{\sqrt{e_l}}\right)U \quad (6)$$

where $Attention$ represents the computed attention weights, e_l denotes the input embedding representation, RRR indicates the representation dimension, L^S represents the sequence length of EEG signals, and U denotes the projected feature matrix. This mechanism assigns higher importance to relevant EEG features while suppressing less informative components.

Next, the hidden feature representation is updated using a residual attention block, as shown in equation (7).

$$Y_1^s = lmsa(bn(Y^{s-1})) + Y^{S-1} \quad (7)$$

where Y_1^s represents the updated hidden state, $lmsa$ denotes the linear multi-head self-attention operation, bn represents batch normalization, and Y^{s-1} is the previous layer feature representation. This step enhances contextual information by learning relationships among EEG signal segments.

Further refinement of features using multiscale contextual processing is described in equation (8).

$$Y^s = msc(bn(Y_1^s)) + Y_1^S \quad (8)$$

where msc represents the multiscale contextual operation used to capture EEG patterns at different temporal resolutions, and Y^s denotes the final extracted feature representation. Finally, the extracted multiscale contextual features are forwarded to the seizure detection stage for classification.

3.5. Seizure Detection using Domain Graph-Informed Adaptation Neural Networks (DG-IANN)

The DG-IANN, a combination of the Enhanced Domain Adaptation Attention Network (EDAAN) and Graph-Informed Neural Networks (G-INN), are used for seizure detection. The EDAAN component aims to learn domain-invariant representations of EEG features using attention mechanisms that selectively emphasize important seizure patterns and downplay differences across subjects and recording conditions. Then, using a graph-based method, G-INN model learns relationships among EEG feature nodes which allows the network to detect complex structural dependencies in the signal patterns. DG-IANN framework: DG-IANN enhances the performance and stability of the EEG-based seizure detection through domain adaptation in conjunction with graph-informed learning. The architecture of the DG-IANN is shown in Figure 2.

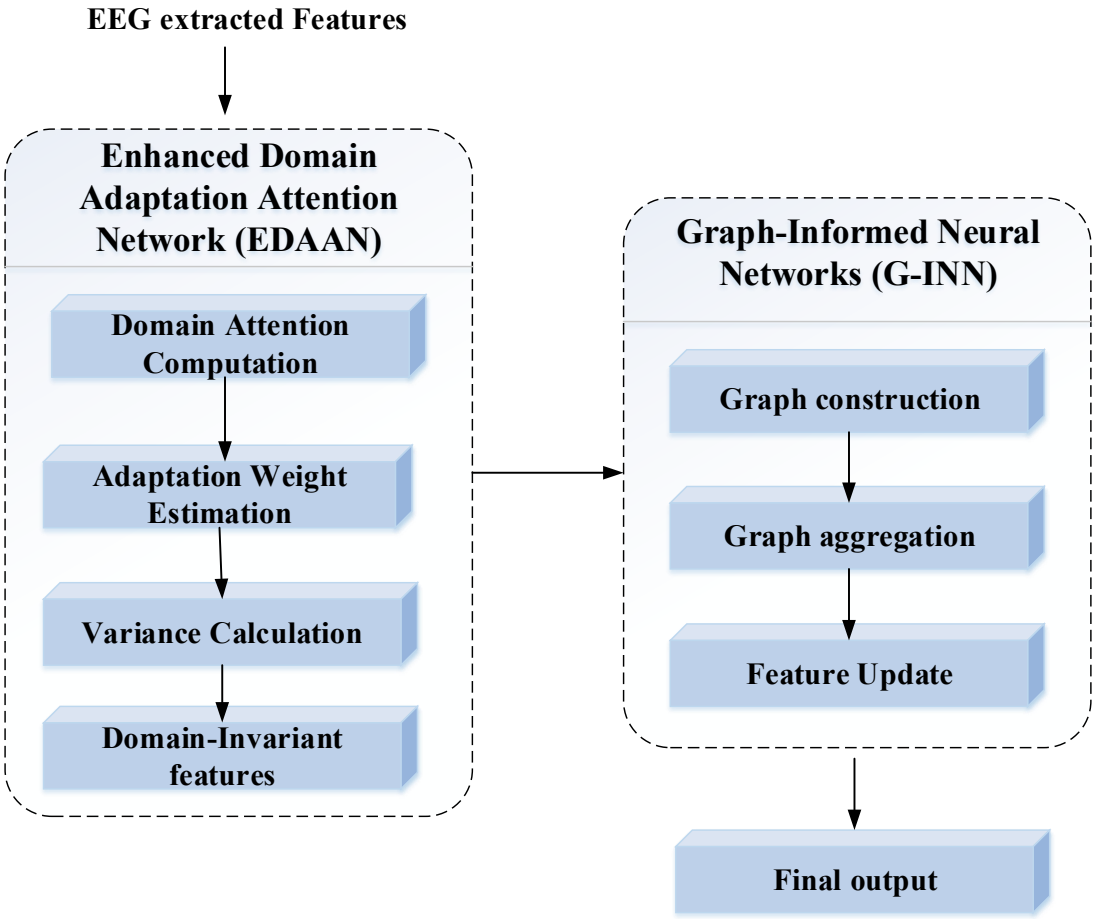


Figure 2: The architecture of the DG-IANN for Seizure detection

3.5.1.Enhanced Domain Adaptation Attention Network (EDAAN)

The EDAAN [29] is the network that is used to learn domain-inspired and discriminative EEG representations to detect seizures. There are domain variations in the EEG data acquired from subjects or across recording conditions that could influence the generalization ability of the detection model. To solve this problem, EDAAN proposes an attention-based domain adaptation mechanism that focuses on seizure features while suppressing the impact of domain-related changes.

First, the mean of the feature response activations is computed to obtain the domain attention coefficient. The coefficient is the total contribution rate of extracted features by the group of features, and it is expressed as follows (equation (9)).

$$\beta_d = \frac{1}{G \times X} \sum_{j=1}^{G} \sum_{i=1}^{X} k_{d,j,i} \qquad (9)$$

where β_d denotes the domain attention coefficient, G represents the number of feature groups, X indicates the number of feature elements in each group, and $k_{d,j,i}$ represents the extracted feature response. This operation provides a normalized attention value representing the average feature importance.

Next, the domain-adaptation weight is estimated to quantify each feature group's contribution to the learning process. This is expressed as in equation (10).

$$m_j^t = -\log(E(G_j^t)) \qquad (10)$$

where m_j^t represents the adaptation weight, G_j^t denotes the feature group representation, and E indicates the expectation function. This formulation enhances important EEG features while suppressing less informative domain-specific variations.

Further, the variability of feature responses across domains is calculated using the variance measure in equation (11).

$$\omega_f^2 = \frac{1}{G \times X - 1} \sum_{j=1}^{G} \sum_{i=1}^{X} (k_{d,j,i} - \beta_d)^2 \quad (11)$$

where ω_f^2 denotes the variance of the feature attention weights. The variance is used to evaluate how the features are spread over the EEG components, which allows the network to detect salient patterns in terms of seizures. Using these processes, the EDAAN module adaptively highlights domain-invariant EEG features, which are then sent to the Graph-Informed Neural Networks (G-INN) for further seizure detection.

3.5.2.Graph-Informed Neural Networks (G-INN)

The G-INN [30] module is used to learn the structural relationship between the EEG feature representations of the EDAAN. Under this method, EEG properties are modeled as nodes in a graph, with the relationships among nodes defining the connections and relationships between various signal components. The graph-informed layer takes node features and compresses neighborhood data to produce a finer representation. This transformation of the graph can be represented as in equation (12).

$$K^{HJ}(y) = g\left(\hat{M}^S y + c\right) \quad (12)$$

where y represents the input feature vector, $\hat{M}^S$ denotes the normalized adjacency or graph structure matrix describing relationships between nodes, c represents the bias term, and g is the nonlinear activation function that introduces learning capability into the network.

The feature update for each node is obtained by aggregating information from its neighboring nodes, as formulated in equation (13).

$$y_j^{'} = \sum_{i \in M_{in}(j) \cup \{j\}} y_i \, \mu_i + c_j \quad (13)$$

where $y_j^{'}$ represents the updated feature of node j, $M_{in}(j)$ indicates the neighboring nodes connected to node j, μ_i represents the weight parameter, and c_j is the bias parameter.

To further enhance feature learning when multiple feature representations are available for each node, the graph-informed layer processes K input features per node as in equation (14).

$$K^{HJ}(y) = g\left(\hat{M}^S vertcat(y) + c\right) \quad (14)$$

where $vertcat(y)$ denotes the vertical concatenation of multiple feature vectors associated with each node. This operation allows this model to combine various feature information with the graph structure.

This graph-based feature-propagation and aggregation mechanism enables the G-INN module to produce clean, structurally accurate EEG representations. The DG-IANN structure then uses these additional features to detect seizures accurately, and the Channa Argus Optimizer (CAO) to fine-tune the DG-IANN model's parameters to improve performance.

3.6. Channa Argus Optimizer

The CAO [31]is a nature-inspired metaheuristic optimization algorithm inspired by the hunting and defensive behavior of the Channa argus fish. The algorithm managed to cover the exploration of the search space quite efficiently, when trading off exploitation at the local level. In this paper, CAO is used to maximize the proposed DG-IANN model to enhance seizure detection performance. The optimizer will adjust significant learning parameters of the DG-IANN model to improve classification accuracy and minimise detection error.

Step 1: Initialization

Initially, a population of candidate solutions representing different DG-IANN parameter sets is randomly generated within the defined search boundaries.

$$Y_{j,k} = KA + (up - lb) \times rand, \qquad j = 1,2,\ldots,M \;\; and \;\; k = 1,2,\ldots,D \quad (15)$$

Here, $Y_{j,k}$ represents the position of the j^{th} candidate, up and lb indicates the upper and lower bounds of the search range. It is a random readjustment, which results in a random value of 0-1 in order to create diversity in the population, total number of candidates and dimensions.

Step 2: Random Generation

The candidate solutions are evenly spread in the search space. The possible combinations of parameters of DG-IANN are reflected in different solutions, and the optimizer can find solutions to a wide range of possible combinations.

Step 3: Fitness Function

All candidate solutions are analyzed by means of fitness function which is based on the classification performance of DG-IANN model.

$$F = optimizing(\mu_i) \quad (16)$$

Here, F refers to the fitness function.

Step 4: Hunting strategies (exploration phase)

CAO is used to imitate the hunting behavior of Channa argus in exploration phase to investigate new areas of the solution space. The position of every candidate solution is updated as in equation (17).

$$X_j(s+1) = T(s) + R(s) \otimes (p \times (H(s) - X_j(s)) + (1-p) \times (\overline{X}(s) - X_j(s))) \quad (17)$$

Where $X_j(s), X_j(s+1)$ represents the current and updated position, $T(s)$ is an elite, $R(s)$ is a vector of Gaussian-distributed random numbers, and the factor p controls the weight between moving toward the best solution $H(s)$ and the population centroid $\overline{X}(s)$. This phase allows the optimizer to discover promising parameter regions for DG-IANN.

Step 5: Escaping strategy (exploitation phase)

In the exploitation stage, the algorithm performs local search around promising solutions, mimicking the defensive and adaptive behavior of Channa argus.

$$X_j(s+1) = L(s) + H(s) + Q(s) \otimes (p \times (H(s) - X_j(s)) + (1-p) \times (\overline{X}(s) - X_j(s))) \quad (18)$$

Here, the local leader guides exploitation in promising regions and serves as a stochastic vector that introduces slight variations for local exploration. This step improves the parameter configuration of the DG-IANN model.

Step 6: Termination

These procedures are to be repeatedly done until the optimality of the fitness value is established to become stagnant. The optimal parameter set of the DG-IANN model is then selected as the best candidate, resulting in higher seizure detection performance. The flowchart of the CAO is shown in Figure 3.

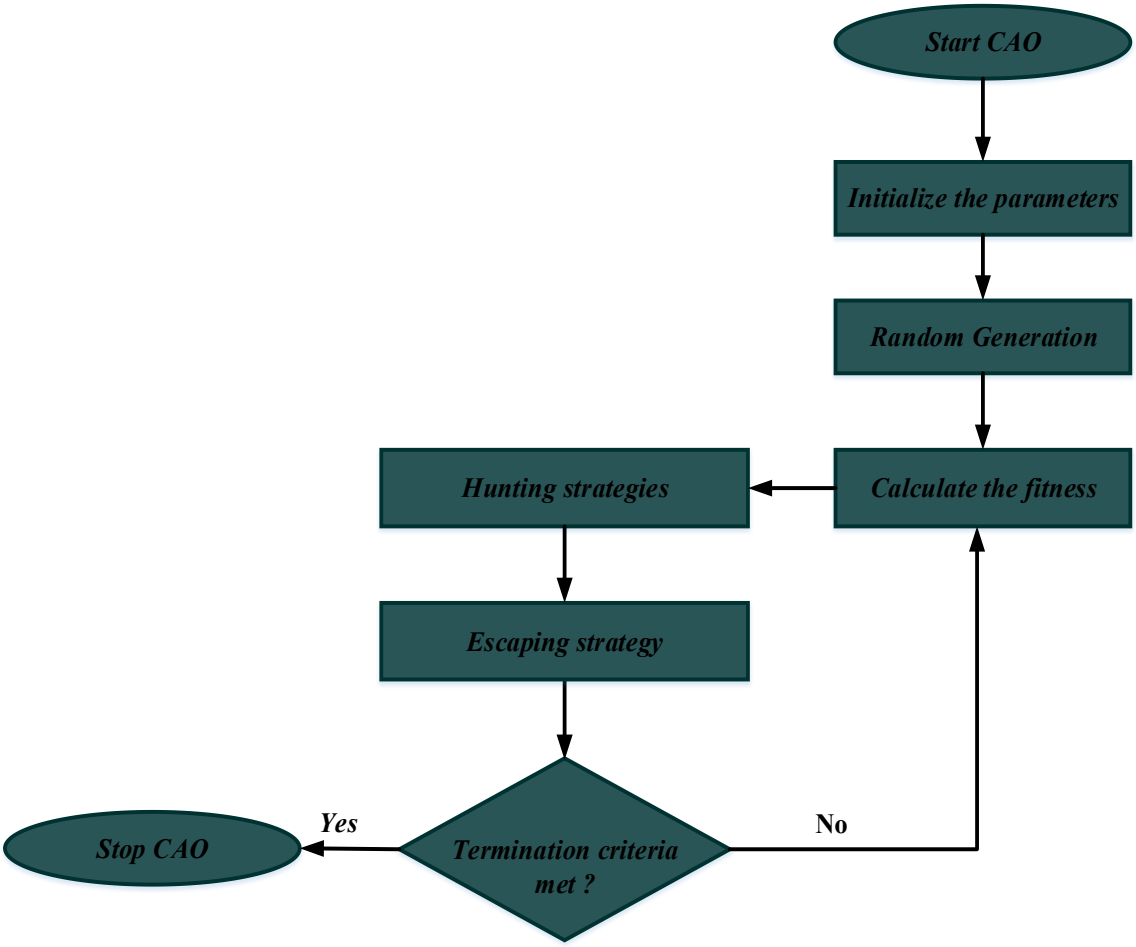


Figure 3: The flowchart of CAO

4. Results and Discussion

This section presents the experimental findings for the proposed EEG-based seizure detection model, DG-IANN-CAO. The simulation is written in Python and can use a GPU to ensure efficient computation. The proposed model is tested on the common performance measures and compared to a number of the already existing machine learning and deep learning models, such as CNN [16], RNN [17], 1D-CNN [18], SNN [19], CNN-LSTM [20], RUSB-TE [21], KNN [22], LSTM [23], MDFLN [24], and STFT [25]. The experiments are conducted on the Bonn EEG Epilepsy Dataset and the CHB-MIT EEG Dataset. Table 2 shows the experimental setup and configuration in the simulation.

Table 2: Experimental Setup

Parameter	Configuration
GPU	NVIDIA GeForce RTX 4090
Operating System	Windows 10 (64-bit)
Programming Language	Python
Deep Learning Framework	PyTorch
CUDA Version	CUDA 12
cuDNN Version	cuDNN 8
Proposed Model	DG-IANN
Optimization Algorithm	CAO
Loss Function	Cross-Entropy Loss
Learning Rate	0.001
Optimizer	Adam
Batch Size	32
Number of Epochs	200
Activation Function	ReLU
Dropout Rate	0.3
Datasets	• Bonn EEG Dataset • CHB-MIT EEG Dataset
Classification Task	• Epileptic, Non-Epileptic • Interictal, Preictal, Ictal, Postictal

Table 2 presents the experimental setup used to test the proposed DG-IANN-CAO framework. The system runs Python simulations which use the PyTorch deep learning framework and operates on a computer that uses Windows 10 64-bit with a NVIDIA GeForce RTX 4090 graphics card. The DG-IANN model trains using Cross-Entropy loss together with the Adam optimizer which operates at a learning rate of 0.001. The training is performed over 200 epochs, with a batch size of 32, the ReLU activation function, and a dropout rate of 0.3. The experiments on seizure classification are conducted using the Bonn EEG and CHB-MIT EEG datasets.

4.1 Dataset Description

This part outlines the Bonn [32] and CHB-MIT [33] datasets used to evaluate the proposed time-frequency-based deep learning architecture for seizure detection. These sets provide normal EEG recordings for assessing the effectiveness of the designed seizure-detection model.

4.1.1 Dataset 1: Bonn Dataset

The Bonn Dataset was gathered at the University of Bonn and subsequently converted to the UCI Epileptic Seizure Recognition dataset. The data consists of 500 original EEG recordings, each with 4097 data points, organized into sequences of 178 samples. The dataset is split into five classes. Class 1 is seizure (epileptic) activity, and Classes 2-5 are EEG signals recorded from normal brain areas and tumor-affected areas that depict non-seizure (non-epileptic) conditions. In binary classification, seizure samples will be labeled 1 (epileptic), and the rest will be labeled 0 (non-epileptic). Table 3 shows the training and test values used in the experiments.

4.1.2 Dataset 2: CHB-MIT Dataset

CHB-MIT EEG data is a product of the cooperation between Children's Hospital Boston and Massachusetts Institute of Technology. This data consists of non-invasive EEGs of 23 children diagnosed with epilepsy whose ages are between 1.5 and 22 years. EEG signals are sampled in the International 1020 electrode position, with a 256 Hz sampling rate, and 16-bit resolution. The EEG segments are 5 seconds long and contain about 1280 data points per channel. The information mainly finds its use in the categorization of the stage of the seizures which includes the interictal, preictal, ictal, and postictal. The details of the training and testing samples used in this study are provided in Table 4.

Table 3: Class-Wise Distribution of Bonn Dataset

Class	Total No. of Records	Training (75%)	Testing (25%)
Epileptic	2300	1725	575
Non-Epileptic	9200	6900	2300
Total	11,500	8625	2875

Table 3 displays the distribution of the EEG records of the Bonn dataset when it comes to epileptic and non-epileptic. The dataset was comprised of 11,500 samples divided into 75 and 25 percent training and testing respectively.

Table 4: Class-Wise Distribution of CHB-MIT Dataset

Class	**Total No. of Records**	**Training (75%)**	**Testing (25%)**
Interictal	400	300	100
Preictal	400	300	100
Ictal	400	300	100
Postictal	400	300	100
Total	1600	1200	400

Table 4 demonstrates the breakdown of EEG records in the CHB- MIT data by their classes. The data will contain 1600 samples in four classes such as Interictal, Preictal, Ictal and Postictal. In an experimental assessment, three quarters of the information is utilized in the training course and the other quarter in testing.

4.2 Performance metrics

The offered DG-IANN-CAO strategy demonstrates success through multiple performance metrics which include accuracy and precision and recall and F1-score and specificity and error rate. The proposed seizure detection framework performance evaluation uses existing method results as benchmarks for comparison. The equations which determine these performance measures are shown in Table 5.

Table 5: Performance metrics

Performance metrics	**Equations (19-24)**
Accuracy	$Accuracy = \frac{AX + AU}{AX + AU + BX + BU}$ (19)
Precision	$\Pr ecision = \frac{AX}{AX + BX}$ (20)
F1-Score	$\text{F1-score} = 2 \times \frac{AX}{2AX + BX + BU}$ (21)
Error rate	$Error\ rate = \frac{BX + BU}{AX + AU + BX + BU}$ (22)
Specificity	$Specificity = \frac{AU}{AU + AX}$ (23)
Recall	$\text{Re}\,call = \frac{AX}{AX + BU}$ (24)

where AX represents True Positive, AU true negative, BX false positive, and BU false negative.

4.3 Performance evaluation of the proposed model

The proposed DG-IANN-CAO model aims to achieve precise seizure detection from EEG records. The first step is to process EEG data with MVI-FKMV to address missing data. DQQPFT then computes time-frequency representations of the signals. Then, ML-CTN elicits discriminative temporal and contextual features. The DG-IANN is used to classify seizures by integrating G-INN with EDAAN to acquire relationships between domain-invariant and structural EEG features. Lastly, CAO is used to optimize the DG-IANN parameters to enhance the detection performance. The efficacy of the offered approach is confirmed by comparing it with the current strategies.

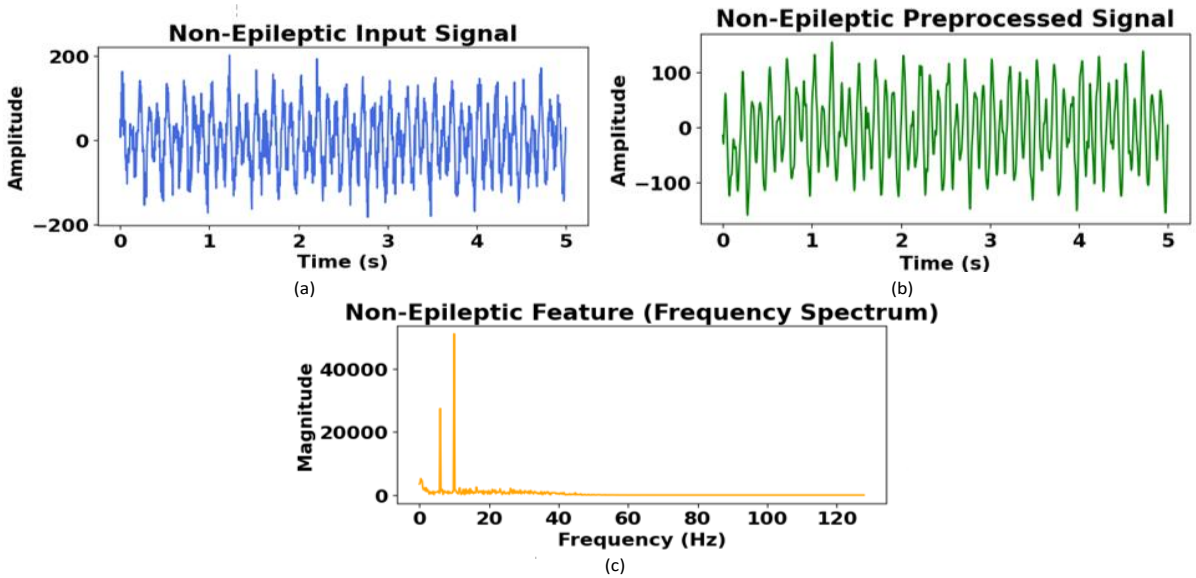


Figure 4: Non-epileptic EEG signal Analysis: a) Raw Input, b) Preprocessed Signal, and c) Frequency Spectrum
Figure 4 represents the Non-epileptic EEG signals analysis with a) Raw Input, b) Preprocessed Signal, and c) Frequency Spectrum. Figure 4(a) shows the non-epileptic raw EEG signal over a 5-s interval, with amplitudes ranging from -200 to 200 µV, which represent normal brain activity patterns. Figure 4(b) shows the signal after noise removal with MVI-FKMV, which is reduced to between -120 and 120 µV, producing a smoother signal. Figure 4(c) shows the frequency spectrum; the main components are found in the range of 8-15 Hz, with an intensity of almost 45,000.

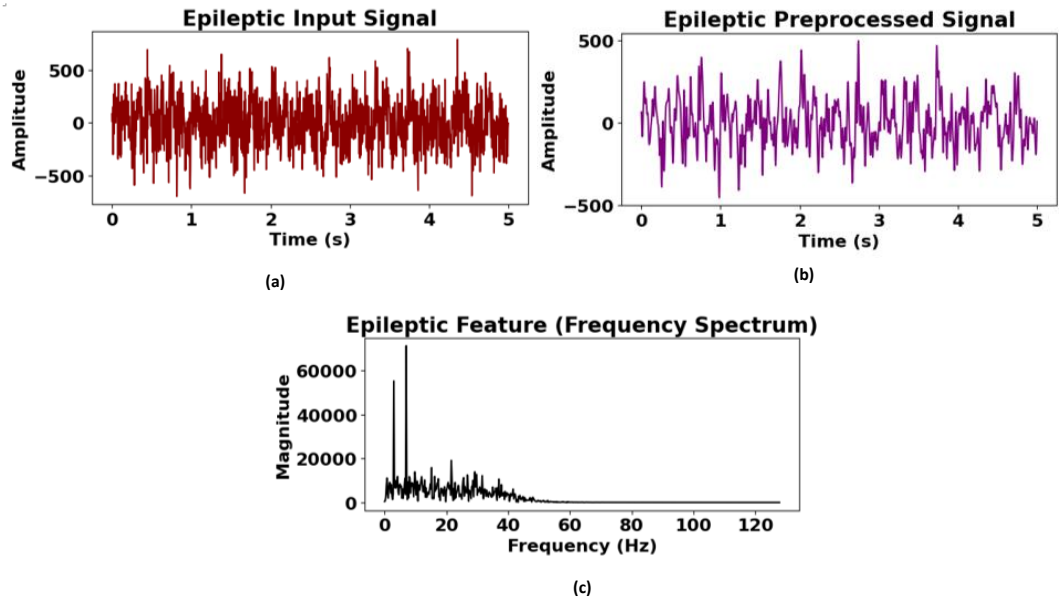


Figure 5: Epileptic EEG Signal Analysis: a) Raw Input, b) Preprocessed Signal, and c) Frequency Spectrum
Figure 5 shows the analysis of the Epileptic EEG signal with a) Raw Input, b) Preprocessed Signal, and c) Frequency Spectrum. Fig. 5(a) depicts the epileptic raw EEG signal over a 5-s period, with an amplitude range of about -600 to 600 µV,indicating abnormal neural activity. Figure 5(b) shows the signal after the MVI-FKMV has been used, with the noise minimized and the signal level stabilized between -500 and 500 ug. Figure 5(c) shows the frequency spectrum, with dominant frequency components around 5-12 Hz and magnitude values near 60,000.

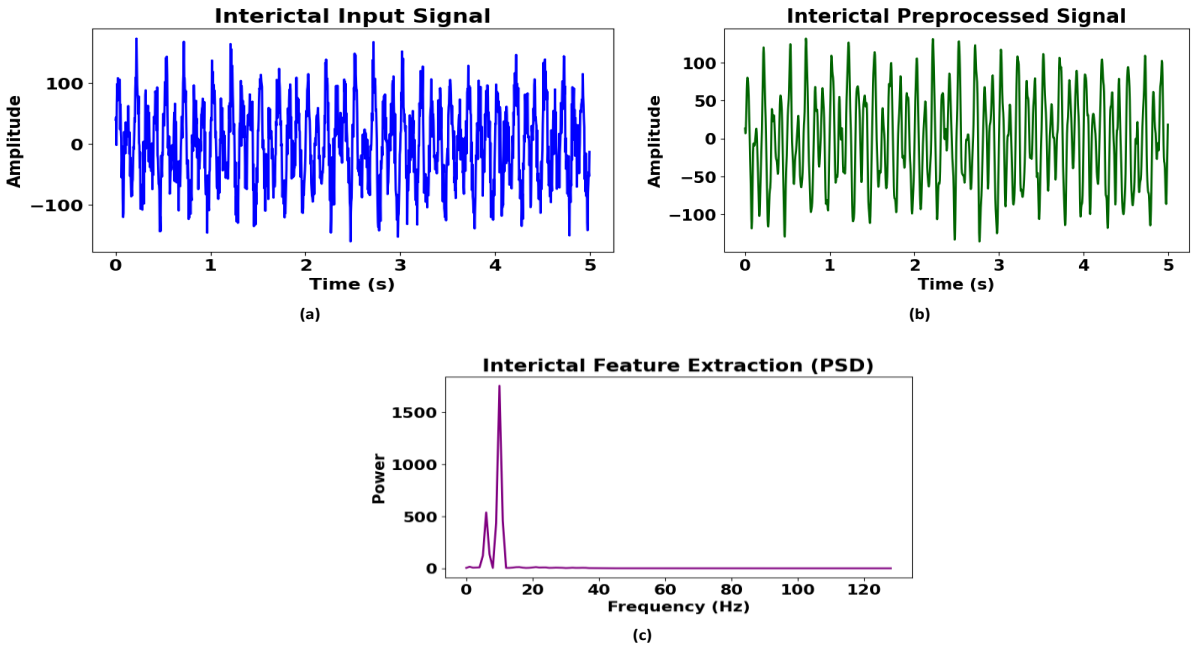


Figure 6: Interictal EEG Signal Analysis: a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD)
The Interictal EEG signal analysis displayed in Figure 6 has a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD). Figure 6(a) shows the interictal raw EEG signal recorded over a 5-s period, with magnitudes varying from -150 to 150 µV, reflecting brain activity between seizure attacks. The preprocessed signal shown in Figure 6(b) is generated after noise removal, and the signal amplitude is kept within 120 -120 mu V. Figure 6(c) shows the feature extraction using PSD, with major frequency components around 1015Hz and a power value around 1700.

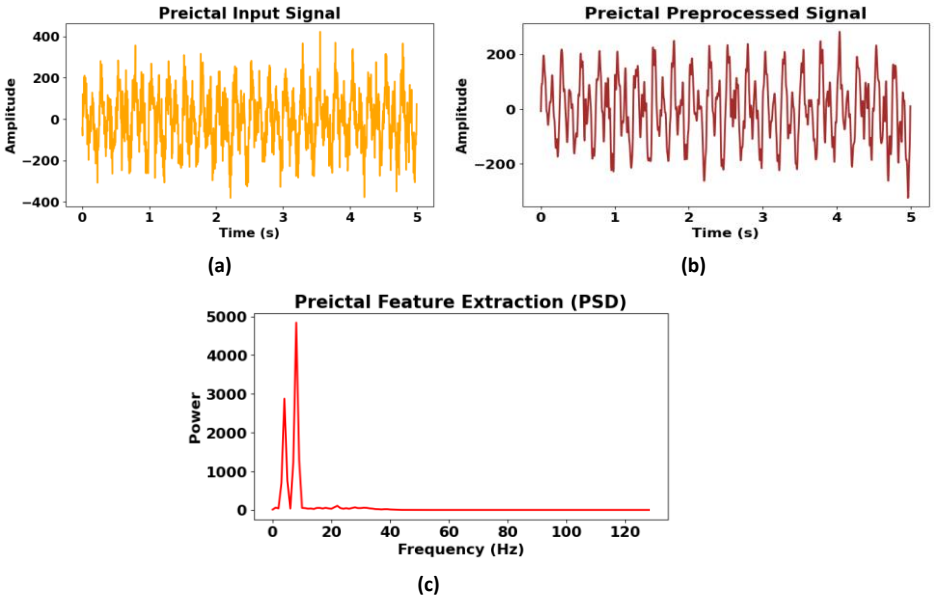


Figure 7: Preictal EEG Signal Analysis: a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD)

Figure 7 shows the analysis of the preictal EEG signal with a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD). Figure 7(a) illustrates the preictal original EEG signal over a 5 s period, during which the amplitude varies between about -350 and 350 µV, representing the transition phase before the seizure. The post-processing signal is shown in Figure 7(b), and the noise has been reduced, with the amplitude leveling off at -250 250 mu V. Figure 7(c) shows the PSD, where the main frequency peak is observed at 812Hz with a power of about 5000.

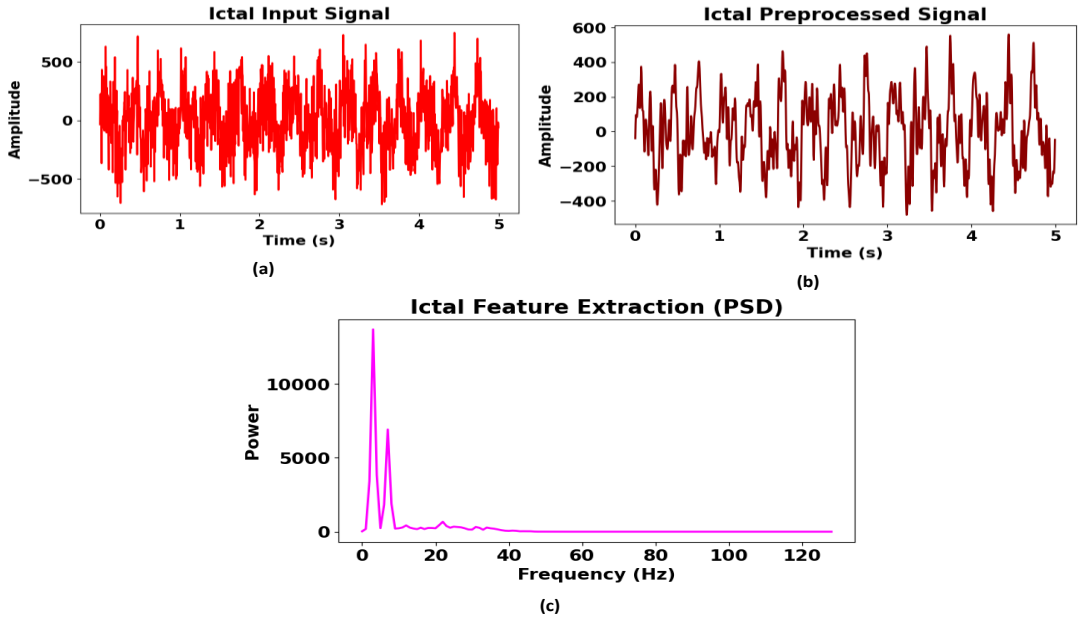


Figure 8: Ictal EEG Signal Analysis: a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD)
Figure 8 shows the analysis of the Ictal EEG signal with a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD). The raw ictal EEG signal over a duration of 5 s, as depicted in Figure 8(a), exhibits amplitude variation of up to -600/600umV -1 and therefore suggests the presence of a seizure. Figure 8(b) shows the signal after noise removal, which is in the form of a preprocessed signal, and the amplitude is minimized to approximately -450 to 450 00 V. Figure 8(c) shows the PSD characteristics with the strong frequency maps at the range of 6-10 Hz with power values of about 14,000.

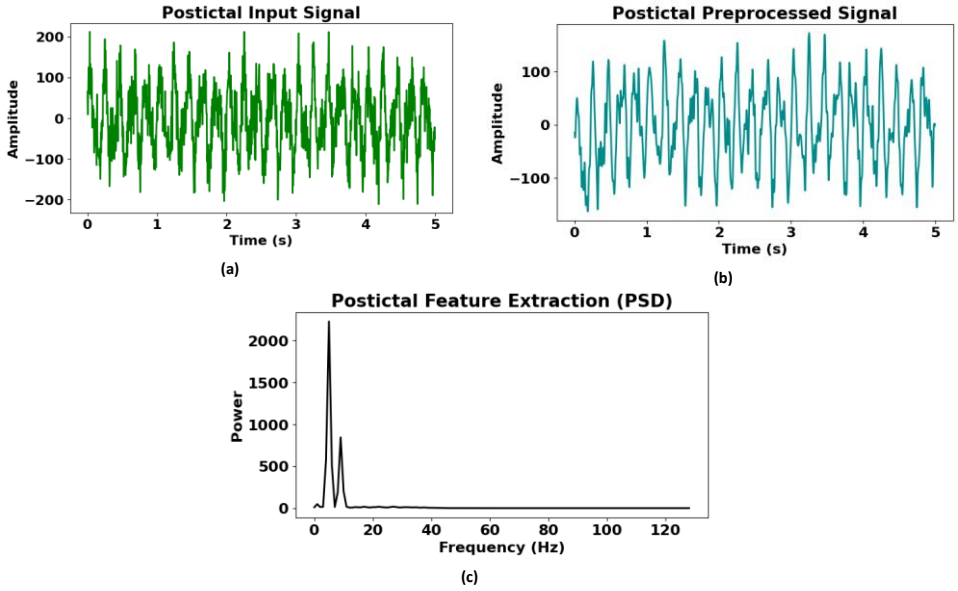


Figure 9: Postictal EEG Signal Analysis: a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD)
The postictal EEG signal analysis in Figure 9 contains a) Raw Input, b) Preprocessed Signal, and c) Feature Extraction (PSD). Figure 9(a) depicts the raw EEG signal (postictal) in a 5 s time interval. In this case, irregular amplitude changes and noise are due to artifacts and sensor interference. Filtering the signal yields the preprocessed signal (Figure 9(b)), in which the noise components are minimized, and smoother patterns of brain activity are observed. The PSD-based feature extraction, as represented in Figure 9(c), shows that the major peaks in the feature extraction are located in the range of 4 10 Hz with a power reading of approximately 2000-3000, which reflects high theta and alpha bands.

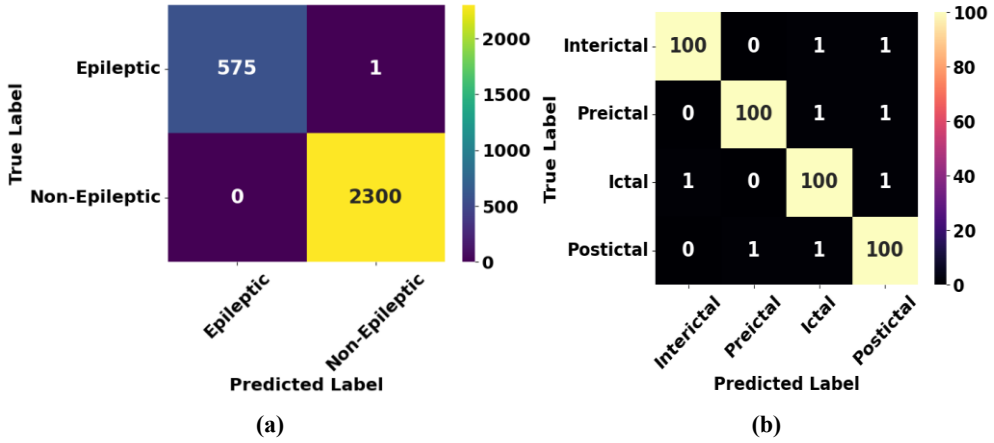


Figure 10: Classification Performance using Confusion Matrices: a) Dataset 1, and b) Dataset 2

Figure 10 illustrates the classification results of the proposed model on two data sets using confusion matrices. The results on the Bonn EEG dataset are shown in Figure 10(a), with 575 epileptic samples and a total of 2300 non-epileptic samples correctly classified, resulting in a high detection rate. Figure 10(b) presents the results on the CHB-MIT dataset, where the four classes Interictal, Preictal, Ictal, and Postictal achieve close to 100 correct predictions, providing evidence of effective multiclass seizure stage classification.

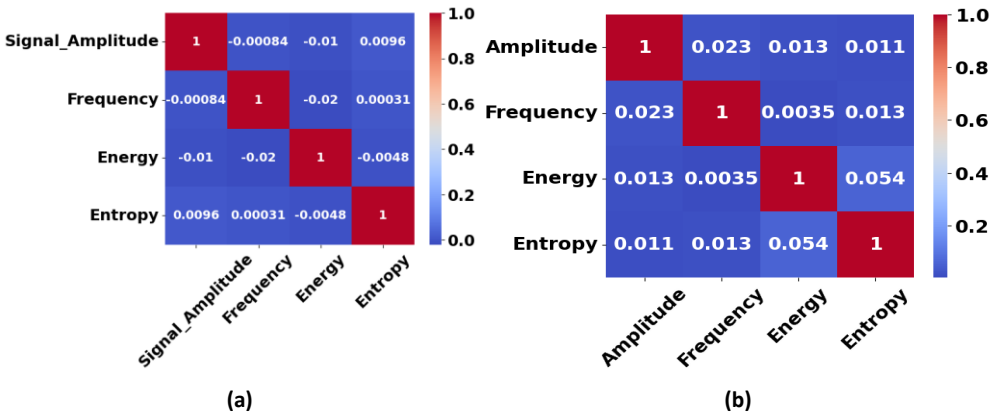


Figure 11: Feature Correlation Analysis: a) Dataset 1, and b) Dataset 2

The correlation analysis of the features with extracted EEG such as amplitude, frequency, energy and entropy are shown in figure 11. Figure 11(a) represents the correlation heatmap of Bonn EEG dataset, most of the correlation values are close to 0, which even includes the correlation between energy and entropy = -0.0048, which shows that there is not much dependency between the features. The same analysis shown in Figure 11 (b) is applied to the CHB-MIT data, revealing that the extracted features are mostly independent and can be used to classify seizures effectively.

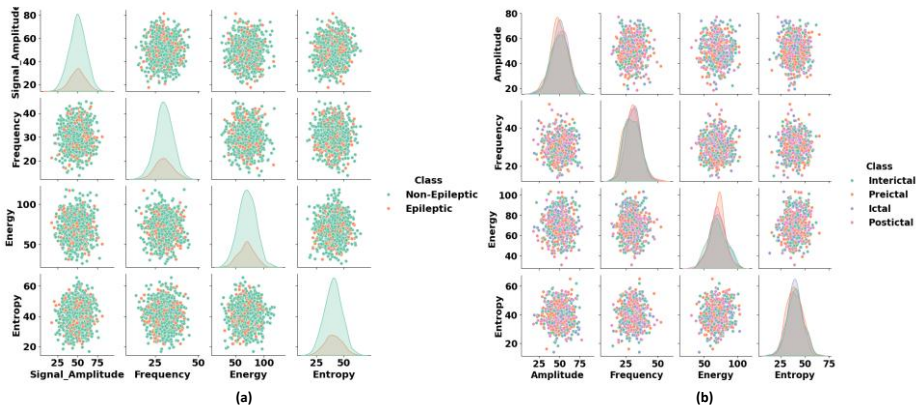


Figure 12: Pairwise Feature Distribution Analysis:a) Dataset 1, and b) Dataset 2

In Figure 12, the pairwise distribution of EEG features is plotted to identify the features used for seizure detection. Figure 12(a) depicts the relationships between the features in the Bonn EEG dataset, and it can be observed in Figure 12(a) that feature pairs overlap, making it clear that individual feature pairs do not give clear

linear separation between epileptic and non-epileptic signals. Figure 12(b) shows the same trends in the CHB-MIT data, where feature combinations consisting of amplitude, frequency, energy, and entropy follow complex distributions, making it necessary to use nonlinear deep learning networks.

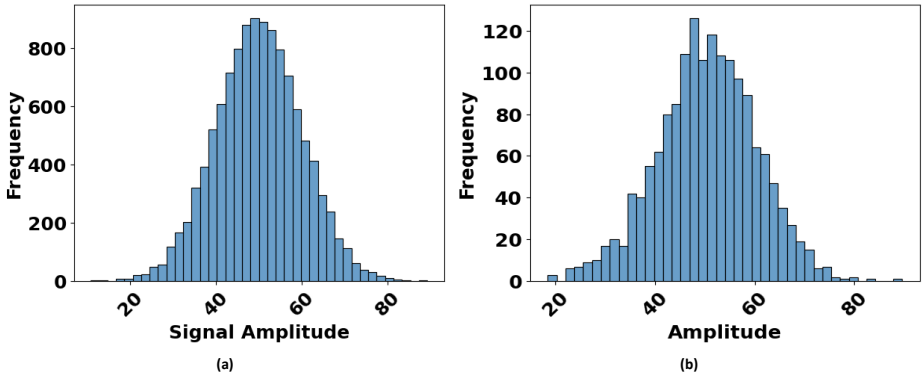


Figure 13: Signal Amplitude Distribution: a) Dataset 1, and b) Dataset 2

Figure 13 shows the amplitude distributions of the two EEG samples. Figure 13(a) shows the amplitude distribution for the Bonn EEG case, which is a Gaussian-like curve with a mean of 50, indicating normal EEG amplitude levels. The amplitude distribution in the CHB-MIT dataset is shown in Figure 13(b),with most values falling between 40 and 60, indicating that the amplitude patterns are similar across various stages of seizures.

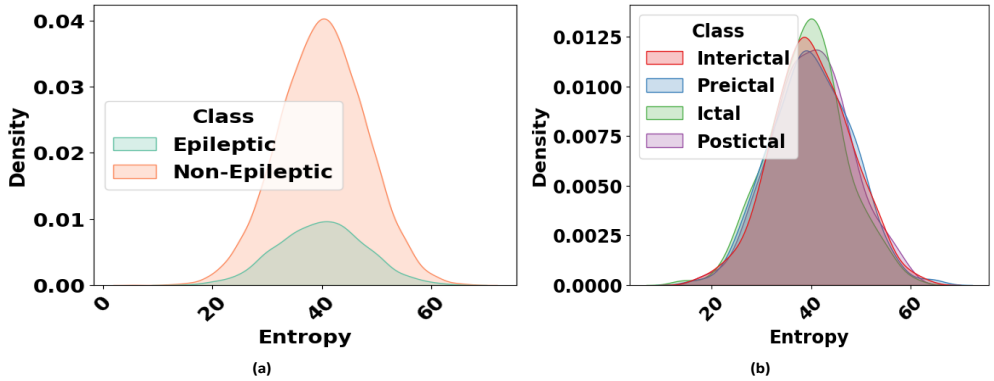


Figure 14: Entropy Density Distribution: a) Dataset 1, and b) Dataset 2

Figure 14 shows the entropy density distribution of both datasets of EEG signals. The entropy distribution of the Bonn EEG dataset is shown in Figure 14(a), where non-epileptic signals exhibit higher peak density than epileptic signals, indicating a higher signal complexity. Figure 14(b) shows the entropy distribution of the CHB-MIT dataset, where curve clusters are most concentrated across various stages of seizures, with slightly higher-density, peaked values during seizure activity.

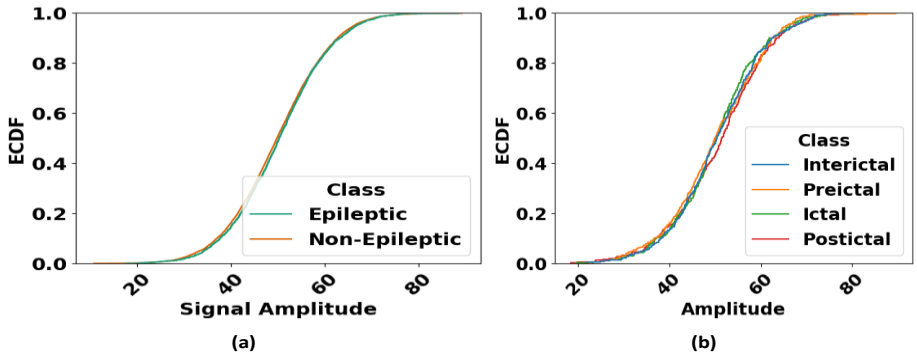


Figure 15: Empirical Cumulative Distribution of Signal Amplitude: a) Dataset 1, and b) Dataset 2

Figure 15 shows the empirical cumulative distribution functions (ECDFs) of the signal amplitudes for both datasets. The ECDF curves of epileptic and non-epileptic in the Bonn EEG dataset are shown in Figure 15(a),

where the two curves are nearly the same, meaning that the cumulative amplitude distributions are the same. Figure 15(b) shows the ECDF of the CHB-MIT data, where minor changes in the curves are evident between Interictal, Preictal, Ictal, and Postictal states, with the postictal curve having a slight shift in higher amplitude values.

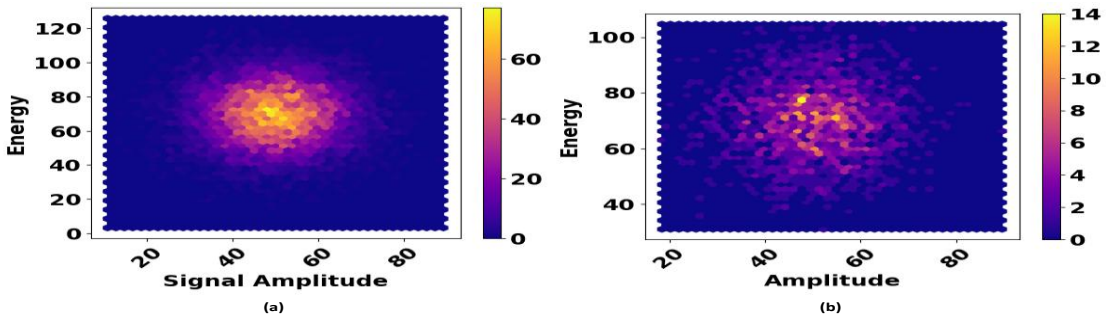


Figure 16: Energy vs Signal Amplitude Density Distribution: a) Dataset 1, and b) Dataset 2

Figure 16 presents the joint distribution between energy and signal amplitude using hexbin density plots. Figure 16(a) shows a dense cluster in the Bonn EEG dataset, where most samples concentrate around 60–80 energy and 40–60 amplitude, with counts exceeding 60 per bin. Figure 16(b) shows a more dispersed distribution for the CHB-MIT dataset, with peak density decreasing to around 14 instances per bin, indicating greater variability in EEG signal characteristics.

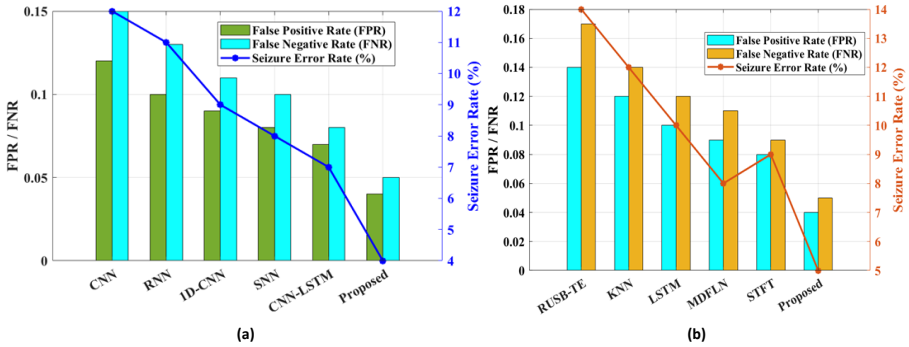


Figure 17: Comparative Error Analysis of Seizure Detection Models: a) Dataset 1, and b) Dataset 2

The error rates of the proposed model were compared with those of current methodologies on two datasets used in Figure 17. In Figure 17(a), it is demonstrated that the error rate of seizures reduces in the Bonn EEG dataset as the model reduces the error rate by a factor of 4 to 12, which is the error rate in the CNN. Figure 17(b) depicts the findings from the CHB-MIT data, where the error rate decreases to approximately 5% with the proposed approach,h, compared to almost 14% with RUSB-TE, demonstrating improved performance.

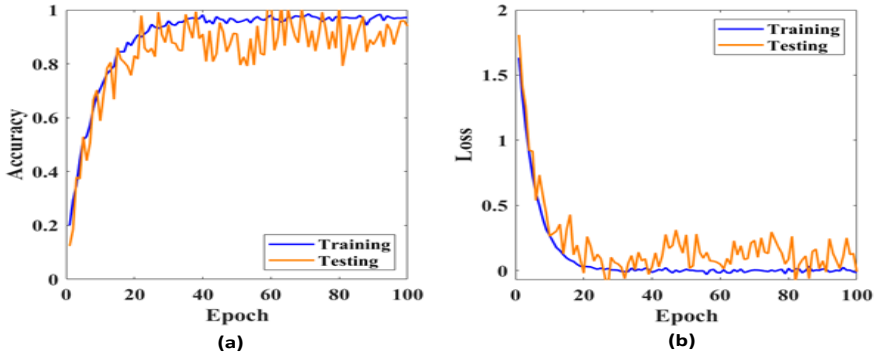


Figure 18: Training Dynamics of the Proposed Model on Dataset 1: a) Accuracy Curve, and b) Loss Curve

Figure 18 shows the training curves of the proposed model on Dataset 1 (Bonn EEG) in relation to 100 epochs. Figure 18(a) shows the training and testing accuracy curve and it increases rapidly and reaches 95% accuracy after the 20th epoch which shows rapid convergence. Figure 18(b) shows the loss curve, which reduces rapidly in the initial epochs and levels off near zero, indicating a stable training process with low overfitting.

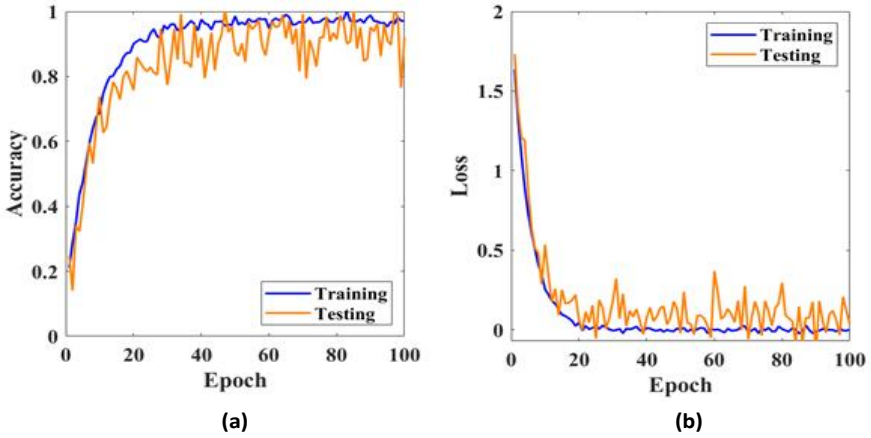


Figure 19: Training Dynamics of the Proposed Model on Dataset 2: a) Accuracy Curve, and b) Loss Curve

Figure 19 show that the proposed model trained on Dataset 2 (CHB-MIT EEG) achieves high training performance after 100 epochs. Figure 19(a) illustrates the learning curve: the training accuracy rises quickly and levels off at about 100% at approximately 40 epochs, whereas the testing accuracy attains a relatively high value of about 95%, indicating good generalization. The loss curve in Figure 19(b) shows that the loss decreases rapidly from approximately 1.7 to almost 0.01 over the first 20 epochs, indicating that the training process is successful.

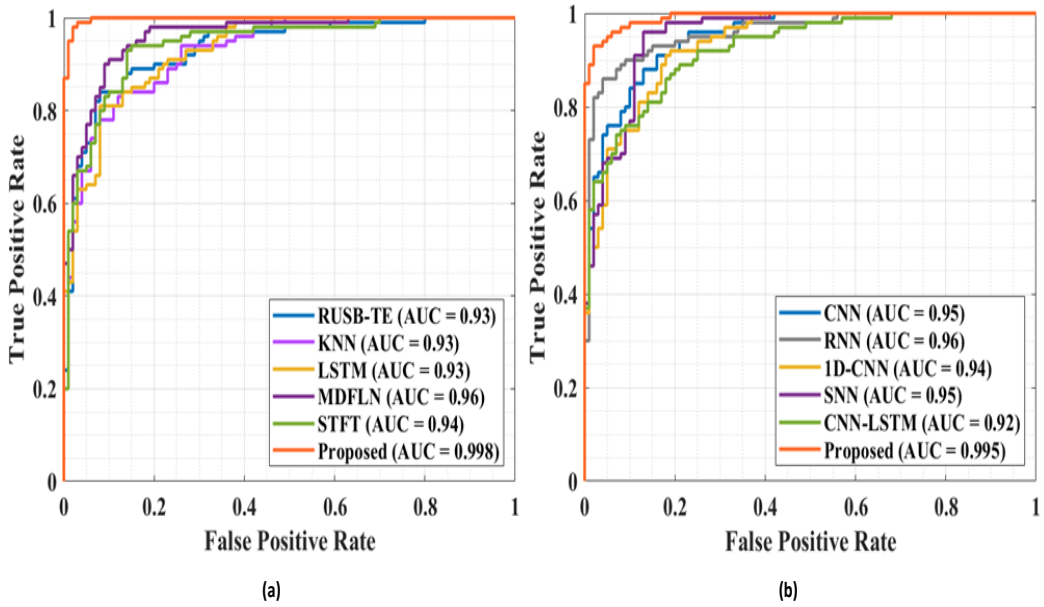


Figure 20:ROC Curve and AUC Comparison: a) Dataset 1 and b) Dataset 2

The various seizure detection models show their performance through their ROC curves and AUC values which Figure 20 presents. The proposed model achieved an AUC of 0.998 which it attained on the Bonn EEG dataset whereas MDFLN and STFT achieved respective AUCs of 0.96 and 0.94. The results on the CHB-MIT dataset show that the proposed method achieved the highest AUC of 0.995 while RNN and CNN-LSTM achieved respective AUCs of 0.96 and 0.92. The proposed method shows improved classification performance according to these results.

4.4. Performance Analysis with Comparison of Existing Methods

The proposed DG-IANN-CAO model is contrasted with some of the existing models, namely CNN [16], RNN [17], 1D-CNN [18], SNN [19], CNN-LSTM [20], RUSB-TE [21], KNN [22], LSTM [23], MDFLN [24], and STFT [25], to test its performance in EEG-based seizure detection. The comparative analysis indicates that the proposed model has a greater classification accuracy, a greater representation of features, and more stable performance in different seizure detection scenarios.

Table 6: Comparative Performance Analysis of Different Methods on dataset 1

Methods	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)	Error Rate (%)
CNN [16]	88.6	87.9	88.2	89.1	88.0	11.4
RNN [17]	90.4	89.7	90.1	91.2	89.9	9.6
1D-CNN [18]	91.8	91.2	91.0	92.5	91.1	8.2
SNN [19]	93.5	92.9	92.7	94.0	92.8	6.5
CNN–LSTM [20]	94.3	93.8	93.5	94.8	93.6	5.7
DG-IANN-CAO (Proposed)	99.1	98.7	98.5	98.9	98.6	0.9

Table 6 shows how the proposed DG-IANN-CAO model performs in comparison to existing EEG-based seizure detection methods. The performance assessment will use six evaluation metrics which include accuracy and precision and recall and specificity and F1-score and error rate. The research shows that the proposed model demonstrates superior performance because it achieved 99.1 accuracy and 0.9 error rate which establishes its superiority over the other base methods.

Table 7: Comparative Performance Analysis of Different Methods on dataset 2

Methods	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)	Error Rate (%)
RUSB-TE [21]	92.6	91.9	91.7	93.1	91.8	7.4
KNN [22]	89.9	89.1	88.8	90.2	88.9	10.1
LSTM [23]	95.8	95.3	95.0	96.2	95.1	4.2
MDFLN [24]	96.7	96.1	95.8	97.0	95.9	3.3
STFT [25]	94.9	94.3	94.0	95.2	94.1	5.1
DG-IANN-CAO (Proposed)	98.9	98.5	98.4	98.6	98.3	0.89

Table 7 displays the evaluation results which compare different approaches for Dataset 2 through six assessment metrics: accuracy, precision, recall, and specificity together with the F1-score and error rate. The results show that the proposed DG-IANN-CAO model has maximum accuracy of 98.9 and minimum error rate of 0.89 relative to the other techniques MDFLN, LSTM, STFT, KNN and RUSB-TE. Thus, it is useful in the seizure detection.

4.5 Statistical Analysis

The three statistical tests employed to evaluate the efficacy of the proposed DG-IANN-CAO framework are the Wilcoxon Signed-Rank Test (WSR), the Friedman Test (FT), and the Nemenyi Post-hoc Test (NPT). These tests help assess statistical significance, ranking performance, and compare the proposed model with existing approaches. The statistical analysis can prove that the provided framework provides stable and significant enhancements in seizure detection performance in comparison with other methods.

Table 8: Statistical Test Comparison of GV-MNN-DSA with Existing Approaches

Methods	**WSR Test p-Value**	**FT p-Value**	**NPT p-Value**	**Mean Rank**
CNN	0.052	0.041	0.048	7.8
RNN	0.060	0.038	0.042	7.1
1D-CNN	0.045	0.034	0.039	6.5
SNN	0.040	0.031	0.036	5.9
CNN–LSTM	0.038	0.028	0.032	5.3
RUSB-TE	0.042	0.030	0.035	6.0
KNN	0.055	0.037	0.041	7.3
LSTM	0.035	0.026	0.030	4.8
MDFLN	0.031	0.024	0.028	4.1
STFT	0.048	0.033	0.037	6.7
DG-IANN-CAO (Proposed)	**0.021**	**0.018**	**0.020**	**2.0**

Table 8 shows that the proposed DG-IANN-CAO framework has the lowest mean rank of 2.0, as it is statistically more effective than the current methods. The results of WSR (0.021), FT (0.018), and NPT (0.020) confirm that the model yields a statistically significant improvement and is more stable, accurate, and robust in detecting seizures using EEG signals.

4.6 Ablation Study of the Proposed DG-IANN-CAO Approach

The researchers perform an ablation study to evaluate the significance of each element in the DG-IANN-CAO framework through its progressive component installation process. The study evaluates the performance of different model variants on Dataset 1 and Dataset 2 by using accuracy and F1-score as measurement tools.

Table 9: Ablation Study of the Proposed Framework

Model Variant	**Dataset 1**		**Dataset 2**	
	Accuracy	**F1-Score**	**Accuracy**	**F1-Score**
Without MVI-FKMV (No preprocessing)	93.21	92.48	92.64	91.92
With MVI-FKMV	94.76	94.05	94.12	93.46
With DQQPFT (Time–Frequency Representation)	95.88	95.12	95.43	94.98
With ML-CTN Feature Extraction	97.02	96.58	96.67	96.11
With DG-IANN Classification	98.11	97.72	97.85	97.34
With CAO Optimization	98.63	98.14	98.32	97.95
Full Model (DG-IANN-CAO)	**99.10**	**98.60**	**98.90**	**98.30**

Table 9 presents the results of the ablation experiment of the proposed DG-IANN-CAO framework. All the modules improve the overall performance, according to the findings. The entire model attains 99.10 and 98.65

accuracy and F1-score respectively on Dataset 1 and Dataset 2, and these scores indicate the appropriateness of the holistic model in the context of EEG-based seizure detection.

4.7 Discussion

The experiment findings reveal the usefulness of the suggested DG-IANN-CAO framework in detecting EEG-based seizure in both datasets. Datasets 1 and 2: Accuracy of 99.1 and 98.9 percent in classification, respectively. The enhanced performance can be described through the combination of a number of elements into the framework. The MVI-FKMV preprocessing technique is effective in EEG values missing or corrupted and also improves the quality of the signal. DQQPFT time-frequency representation represents the temporal and spectral content of the EEG signals, thus making it easier to describe the patterns of seizures. Moreover, the ML-CTN feature extraction module acquires multiscale contextual features, thereby increasing the discriminative power of various seizure states. The combination of domain adaptation and graph-based neural networks is evident in the DG-IANN classifier, which enhances a model's ability to capture complex connections among EEG features. Moreover, the CAO optimization algorithm also modulates network parameters resulting in improved convergence and classification stability. Altogether, the experimental results and statistical data indicate that the proposed DG-IANN-CAO model is a reliable and robust intervention to use automated EEG-based seizure detection with greater precision and stability compared to the existing machine learning and deep learning methods.

4.8. Interpretability and Explainable Artificial Intelligence (XAI)

In medical decision-support systems, especially automated epileptic seizure detection with EEG signals, interpretability is a very important aspect. As deep learning models tend to be black-box systems, an opportunity arises to add Explainable Artificial Intelligence (XAI) components to increase transparency and reliability in clinical use. In the suggested framework, interpretation is based on the contributions of extracted time-frequency EEG features and their effects on seizure classification. XAI techniques are applied to identify the most significant signal segments and feature patterns that drive a model's predictions. The clinicians would be better informed of how the model differentiates between the seizure and non-seizure states by pointing to the significant areas on the EEG time-frequency representation. Furthermore, DG-IANN incorporates graph-based feature relationships, thus, allowing the model to learn important structural dependencies between EEG features, and, therefore, provides increased classification accuracy and interpretability. The diagram of feature importance and the decision plan offers the data concerning the inner workings of the proposed model. The interpretability framework can improve transparency and clinical reliability of the models, allowing the neurologists to verify the automated predictions and helping the practical enactment of the proposed seizure detection model into the actual healthcare environment.

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5. Conclusion

This paper establishes the framework for effective seizure detection with EEG, the DG-IANN-CAO, which uses time-frequency deep learning. The proposed approach combines MVI-FKMV preprocessing, DQQPFT-based time-frequency representation, ML-CTN feature extraction, and DG-IANN classification, which is optimized using CAO. The experimental results demonstrate superior performance over multiple existing methods through testing results which achieved 99.1% accuracy and 98.7% precision and 98.6% F1-score and 0.9% error rate. The registration of seizure detection through statistical examination and ablation studies demonstrate the framework maintains high-performance capability.

Although the proposed framework has high performance, it is still limited in some way. The model delays feature extraction, and the classification stage involves numerous processing steps, including preprocessing, time-frequency transformation, feature extraction, and classification, making the model's overall computational nature a limitation for real-time and resource-constrained implementations. The detection performance depends on three factors which are the EEG datasets used for training and their different characteristics and their actual quality. The various conditions of recording and the patient attributes in the datasets may influence the generalization performance of the model. Future studies will focus on developing more computationally efficient and lightweight models to run clinical applications in real-time, enhancing cross-dataset generalization by utilizing advanced domain adaptation methods and more robust XAI methods to make automated seizure detection systems more understandable, more transparent, and more clinically dependable.

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