

Novel deep learning framework with hierarchical temporal feature refinement for enhanced epileptic seizure detection

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ABSTRACT

Epileptic seizure detection remains a significant challenge in the field of neurology due to the complexity and variability of electroencephalogram (EEG) signals. Traditional manual methods of analyzing EEG data are time-consuming, subjective, and prone to misdiagnosis, particularly in long-term recordings. To address these challenges, this study proposes a novel hierarchical temporal feature refinement network for epileptic seizure detection (HTFRNet-ESD) framework designed to enhance the accuracy and efficiency of epileptic seizure detection. The methodology comprises three key components: a spatial-temporal signal encoder (STSE) for capturing spatio-temporal attributes, an adaptive temporal dynamics encoder (ATDE) for detailed temporal feature analysis, and a hierarchical temporal refinement unit (HTRU) module for integrating frequency-driven power features. The proposed model leverages advanced deep learning techniques, including convolutional neural networks (CNNs) and transformers, to effectively learn both coarse and fine-grained temporal dynamics of EEG signals. Evaluation on publicly available EEG datasets demonstrates the model's superior sensitivity, specificity, and overall accuracy compared to existing approaches. The HTFRNet-ESD sets a new benchmark for automated seizure detection, offering a reliable and scalable solution for real-world clinical applications. This work paves the way for improved patient outcomes through timely and precise epilepsy diagnosis.

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1. INTRODUCTION

Over 50 million people worldwide suffer from epilepsy, a serious neurological condition. At least one episode of spontaneous, short, and aberrant brain neuronal activity—known as an epileptic seizure—must occur to identify this disease. The electroencephalogram (EEG), which offers a simple and non-invasive way to track brain activity, is an essential diagnostic tool for identifying epileptic seizures. By recording the electrical impulses produced by groups of neurons on the scalp's surface, electroencephalography (EEG) makes it easier to extract and analyze different facets of brain activity [1]. Abnormal waveforms with rhythmic activity, particularly during epileptic convulsions, and recurring spikes showing both temporal and spatial progression are present in the EEG data. Even if EEG is still crucial for the diagnosis of epilepsy, the methods now used by medical professionals to visually evaluate individuals in order to identify epileptic episodes have a number of drawbacks. Due to the subjective nature of EEG result interpretation, various

doctors may have different diagnoses. Long observation times and specific knowledge are required for accurate evaluation. The process takes a lot of time and work, particularly when handling large EEG data sets [2].

The problems found emphasize the necessity of an automated, quantitative approach to epileptic seizure detection. The development of nerve stimulators and drug-release devices intended to lessen the intensity of epileptic seizures depends on precise and automated seizure detection systems, documenting seizure history and informing medical experts about it is crucial. Acute brain damage brought on by frequent seizures may affect perception, behavior, and cognitive function. The disease has a long-term effect on the patient's cognitive abilities, making them more vulnerable to problems with their physical and mental well-being. Because early identification reduces the risk of brain damage and prevents seizures, it greatly enhances the quality of life for those with epilepsy. The electrical activity produced by brain neurons is recorded from the scalp using EEG sensors [3]. Depending on the needs, electrodes can be placed on the scalp surface or implanted as intracranial probes to gather EEG data from the subject's skull. Abnormal waveforms including spike waves, sharp waves, and spike-and-slow complex waves are frequently seen in EEG data linked to epilepsy.

Neurosurgeons evaluate an EEG in clinical situations to determine the precise waveform linked to epilepsy by comparing the signal's shape, frequency, amplitude, and other properties to the degree of epileptic activity. Visual examination alone suggests that doctors must perform a thorough and time-consuming assessment in order to determine whether a patient has epilepsy. A higher probability of misdiagnosis is supported by evidence [4]. To improve the accuracy and efficacy of epilepsy detection, research into the automated EEG-based approach is crucial. This development improves treatment results and the general quality of life for people with epilepsy by making it easier to quickly and accurately identify seizures in patients.

Two main approaches have been developed to detect epileptic seizures: inter-patient classification and patient-specific classification. The patient-specific approach takes special traits into account to attain excellent accuracy. Nevertheless, it necessitates the creation of distinct categorization models for every patient, which might not be practical in therapeutic and emergency settings [5]. Since the goal of the inter-patient method is to identify seizures in a wide range of patients, it is best suited for clinical settings. When taking into account characteristics that are shared by several people, this method struggles to maintain optimal generalization performance. Recent attempts to detect inter-patient seizures have mostly focused on the process of extracting features from EEG recordings. Efficient methods include frequency domain features, and temporal domain features. Although these techniques show promise in capturing different aspects of EEG signals, it is still difficult to adequately depict the complex, non-Gaussian structure of EEG signals during seizures [6]. This offers a chance to investigate novel strategies that could yield more information about these signal properties.

Automated epilepsy diagnosis has been made easier by recent developments in digital signal processing, machine learning, and related technologies. The suggested approaches may be divided into two primary groups: one that relies on deep learning techniques and the other that concentrates on feature extraction techniques. Application of machine learning classifiers and artificial feature extraction are two essential elements of feature-based approaches. Time-domain EEG, frequency transformation of EEG, and time-frequency analysis of EEG are usually included in the characteristics that are acquired. Deep learning-based techniques are distinguished by their dependence on data. Deep neural networks, such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks [7], are used to automatically extract features from the input data. The features that have been found will aid in the diagnosis of epilepsy. When compared to feature-based methods, deep learning has shown better detection performance because of its inherent capacity for autonomous learning.

The deep learning approach usually needs many training samples to improve the effectiveness of the network model's learning and training procedures. The performance will be impacted by the limited sample size. For people with epilepsy, obtaining a significant number of labeled EEG samples requires obtaining a significant amount of EEG data, which is frequently not possible. When implementing epilepsy detection in a few-shot learning framework, a limited number of labeled resources are required. When epilepsy is diagnosed in few-shot settings, a thorough grasp of its traits and particular variations is provided, which makes it easier to create individualized treatment regimens [8]. The model may converge on a local optimum in a few-shot situation when raw data is used for training, which might lead to overfitting.

Motivated by the significant challenges faced in detecting epileptic seizures through traditional manual EEG analysis, this research aims to develop advanced automated methods for seizure detection. The reliance on manual visual inspection by medical experts is not only time-consuming and subjective but also prone to misdiagnoses, especially in long-term EEG recordings. Automated detection offers a promising solution to enhance diagnostic accuracy, reduce labor-intensive processes, and provide real-time alerts, which are crucial for timely medical intervention. Leveraging advancements in deep learning, the proposed methodologies focus on extracting complex spatial and temporal features from EEG signals to improve the

sensitivity, specificity, and overall efficiency of epilepsy detection systems. By addressing current limitations and exploring innovative approaches, this work aspires to contribute significantly to enhancing the quality of life for individuals with epilepsy through early and precise diagnosis.

Hierarchical temporal feature refinement network for epileptic seizure detection (HTFRNet-ESD) for enhanced seizure detection: the proposed integrates a spatial-temporal signal encoder (STSE), adaptive temporal dynamics encoder (ATDE), and hierarchical temporal refinement unit (HTRU) to effectively capture and refine spatio-temporal attributes of EEG signals. This novel architecture ensures efficient feature learning and robust detection of epileptic seizures across various temporal scales. Improved temporal feature learning with ATDE: By combining a parallel transformer for token relations and CNNs for detailed temporal feature extraction, the proposed model effectively captures both coarse-grained and fine-grained temporal dynamics in EEG signals, significantly enhancing the precision and recall of epileptic seizure detection. HTRU with frequency-driven feature refinement analysis: the inclusion of an adaptive frequency refinement layer (AFRL) for feature refinement, incorporating encoded frequency data, provides a holistic perspective on EEG signal dynamics. This innovative approach allows the model to densely link features from multiple temporal stages, improving the overall classification accuracy and ensuring a deeper understanding of seizure-related EEG characteristics.

The research work in this paper is organized as follows: in the first section, a brief introduction is given about epilepsy seizure detection. In section 2 the related work is introduced that gives a brief description of the existing methods, in section 3 HTFRNet-ESD integrates a STSE, ATDE, and HTRU to effectively capture and refine spatio-temporal attributes of EEG signals. In section 4 the dataset details and results are evaluated in the form of various metrics. Lastly, section 5 concludes this research.

2. RELATED WORK

To identify epileptic episodes in EEG recordings, feature extraction is essential. Various approaches have been proposed to address this problem. Because of their simplicity and interpretability, time-domain characteristics including amplitude-based measures, entropy, and higher-order statistics are often used [9]. The cyclic pattern of seizure activity has been successfully captured by frequency-domain metrics such as wavelet features, spectral characteristics, and band-specific power. The extraction of time-domain characteristics from specific frequency bands of interest in the EEG signal is a method that successfully strikes a compromise between processing cost and accuracy. This method preserves the temporal dynamics present in the data while enabling a focused analysis of the essential elements within the seizure activity spectrum. Given the complexity of EEG data during seizures, a more thorough approach to feature extraction would be advantageous. In this context, model-based features that aim to reflect the stochastic nature of the EEG have demonstrated promise. In order to capture the non-Gaussian characteristics and amplitude data of EEG signals that occur during seizure occurrences in a single framework, the previous study introduced a statistical model method (SMM) for the analysis of EEG signals [10].

Support vector machines (SVM) [11] and multilayer perceptrons (MLP) are examples of static classifiers that are often used because of their computational efficiency and good performance over a variety of features. These techniques work on the tenet of handling every time point or window separately, which enables applicability across a wide range of attributes. Nevertheless, it is possible that the temporal dynamics of EEG data during seizures are not fully recorded, which is crucial for precise identification. Below is a list of several research that use the Sleep-Wake-Epilepsy-Center (SWEC)-Eidgenössische Technische Hochschule Zürich (ETHZ) intracranial electroencephalography (iEEG) dataset to predict seizures. The two-dimensional CNN classification used the short-term Fourier transform (STFT) time-frequency maps as inputs, and for nine patients in the research, the resultant area under the curve (AUC) ranged from 0.30 to 0.86 [12]. Based on data from five patients, the study used a low-latency parallel CNN to predict seizures, with an accuracy of 97.54% and an hourly false positive rate (FPR) of 0.99. A multiplicative LSTM is used in the study to classify the retrieved iEEG values. The technique produces a FPR of 0.27 per hour and a sensitivity of 95.56%. As initial inputs, the authors of the study use STFT to create time-frequency maps. CNN, CNN coupled with LSTM, and temporal convolution networks (TCN) are the three deep learning models used for classification, in that sequence.

Deep learning-based methods for identifying epilepsy usually make use of LSTMs and CNNs. In order to identify epilepsy, Chikara *et al.* [13] created an end-to-end automated seizure detection system in 2018 that used a deep CNN. Using the single-channel Bonn EEG data set and a one-dimensional convolution kernel, a CNN was built. Across three types of EEG data—normal, interictal, and epileptic periods—the model's accuracy was 88%. Different CNN architectures have been used in the various approaches for epilepsy detection that have been presented. These include the pyramidal one-dimensional CNN model with fewer parameters, the multi-channel epilepsy detection neural network with a 3D convolution kernel [14],

and the deep network model with a fully convolutional network without a pooling layer as the automatic extraction module for epileptic EEG features.

In the field of computer vision, sophisticated CNN designs have also been used to identify epileptic EEG data. One-dimensional EEG data is converted into two-dimensional representations using techniques such time-frequency transformation, feature extraction, and multi-channel integration. Two-dimensional convolution kernels are then used by the CNN architecture to analyze these pictures to detect them. To detect epilepsy, Jana and Mukherjee [15] used the STFT to turn EEG data into two-dimensional pictures, which they then sent into an AlexNet that had already been trained. A framework for the identification of epilepsy using LSTM. It can identify different kinds of epileptic EEG data and interpret the original EEG signals, created a bidirectional LSTM model to identify time-frequency features after acquiring the time-frequency spectrum from the original EEG data via a time-frequency conversion. Wang *et al.* [16] used auto-regressive moving average (ARMA) features and Hurst exponent to create a variety of non-stationary random signals using EEG data. They then created an efficient double-layer LSTM classifier to identify epilepsy in the EEG data. The differential attention residual neural network (ResNet)-LSTM network (DARLNet) was developed [17] by combining LSTM and ResNet. By highlighting relevant epileptic seizure data through the recording of temporal and spatial connections via a channel attention module, the method outperforms earlier state-of-the-art approaches.

Deep learning techniques have continuously surpassed conventional feature-based algorithms in the detection of epilepsy. A CNN with an appropriate structure for identifying EEG data was created [18] after they obtained the time-frequency picture of the signals using the continuous wavelet transform. Using CNN and high-resolution Fourier synchronous compression transform, Ahmad *et al.* [7] presented a unique approach to epilepsy detection that improved detection performance across many epileptic EEG databases. To identify epileptic convulsions in EEG data, Li *et al.* [6] created models using adaptive STFT, which included the sparse common spatial pattern (sCSP) and synchronized squeezing transform (adaptive FSST). To improve seizure detection performance, we gave CNN several time-frequency inputs in the previous study [4], [11] used naïve Bayes (NB) and k-nearest neighbor (KNN) classifiers to diagnose epilepsy using the spectral power density of intrinsic mode function (IMF), as calculated by empirical mode decomposition (EMD) of EEG data. Compared to earlier studies, this approach greatly enhances performance. Although EMD has been used in feature-based seizure detection techniques, its application in deep learning algorithms for seizure detection is still understudied.

3. PROPOSED METHODOLOGY

The proposed model focuses on the seizure-based EEG signals that are used in the detection of epilepsy seizures. The architecture of the proposed model is mentioned in Figure 1. Design of the suggested HTFRNet-ESD system. The first stage is the processing of multichannel EEG signals by the STSE into tokens. The ATDE simultaneously models both global and local temporal dependencies through branches of transformer and CNNs [9], [10], [19] and then performs hierarchical temporal and frequency-driven refinement. The fined features are lastly categorized as seizure and non-seizure.

The HTFRNet-ESD includes three major parts, namely STSE, ATDE and lastly, HTRU. The EEG signals is used as input, where the HTFRNet-ESD uses the CNN feature encoder for encoding the spatio-temporal attributes that are further used as input in the ATDE segments for extraction of temporal attributes that occur in various time periods of seizure-based EEG signals. To efficiently grasp the crucial temporal data at various stages, the attributes that are generated at every segment of ATDE are cautiously integrated using progressive units. Figure 2 shows the architecture of proposed model further.

3.1. Spatial-temporal signal encoder

To grasp the temporal as well as spatial EEG data, it is essential to use a STSE that is based on CNN. This extractor consists of two main phases, namely layers of convolution and tokenizer. The CNN with the spatial and temporal size are normally utilized for extracting features for EEG signals. Considering the proposed study, the HTFRNet-ESD has a convolutional network having two layers for STSE. Initially, it involves the spatial and temporal CNN layers, followed by mitigation towards the covariate shift challenge using batch normalization. We represent the sample set of EEG as Z belongs to $\mathbb{T}^{e \times n}$, here e is used to denote count of EEG channels and n expresses the count of information points for the specified time period. The dimension of the temporal kernel is given as $(1, 0.1 \times h_u)$, here the rate of sampling for EEG is given as h_u . To grasp the spatial data of EEG [9], [20], the convolutional spatial kernel dimension $(e, 1)$ is used, where e is the count of EEG channels. The count of kernels in the convolutional network is expressed m . Post activation using the exponential linear unit (ELU) function, attributes that are learned are then pooled by every pair of information point while omitting overlapping. The operation is rearranged using the tokenizer

and also performs learnable encoding. The dimension of the attributes is rearranged as $m \times \frac{1}{2}n$ to be used as tokens for transformers that learn the temporal data. Assume R belongs to $\mathbb{T}^{m \times \frac{1}{2}n}$ represents an encoded learning position. Hence, the tokens that are encoded are expressed as H belongs to $\mathbb{T}^{m \times \frac{1}{2}n}$, as formulated in (1).

$$H = \mathfrak{N}(\text{MaxPooling}(\text{ELU}(\text{BatchNorm}(\text{ConNeuNetwork}(Z)))) \quad (1)$$

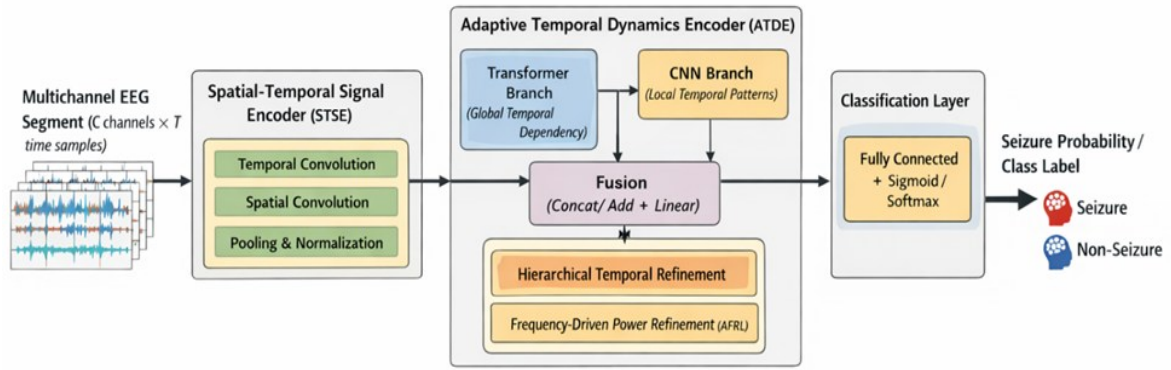


Figure 1. Overall workflow of the proposed HTFRNet-ESD framework for epileptic seizure detection

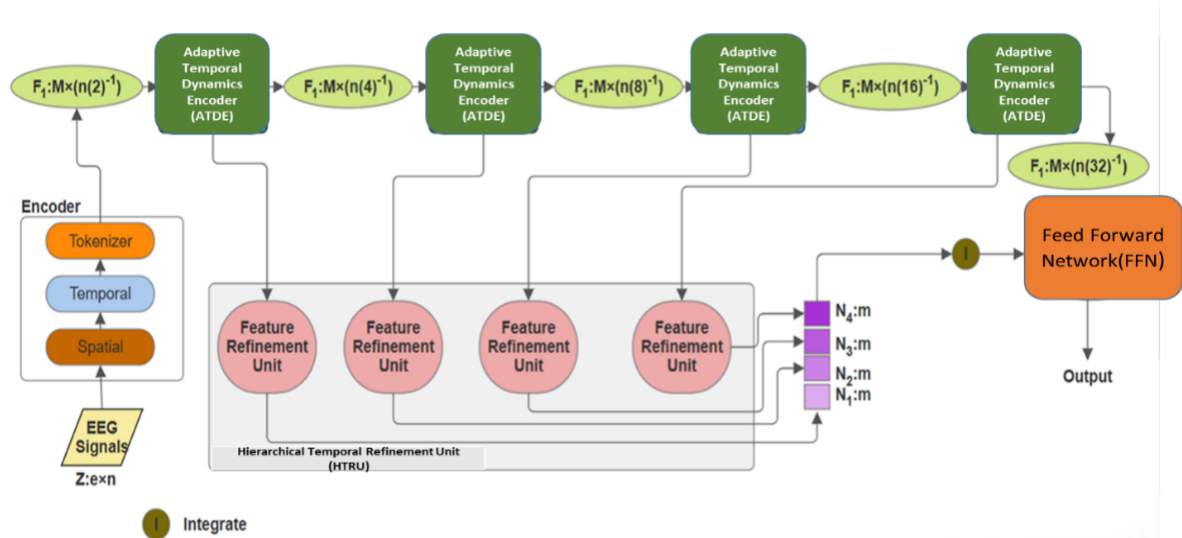


Figure 2. Detailed architecture of the proposed HTFRNet-ESD model showing the STSE, ATDE and HTRU modules

3.2. Adaptive temporal dynamics encoder

While encoding of lightweight EEG attributes, we focus on the detailed temporal working of EEG information through various ATDE segments. This phase of the proposed model includes a parallel transformer that focuses on learning the relations among tokens and the CNN segment that also aims at learning detailed features of EEG. We assume H_k belongs to $\mathbb{T}^{m \times n_k^k}$ is the input to the k -th segment of the ATDE. To grasp the coarsely refined temporal features of the EEG signals, we consider the output of every CNN kernel as a token. Such that, the temporal data on the longer run is included during projection of tokens into S_k belongs to $\mathbb{T}^{p_{head} \times m \times f_{attention}}$, M_k belongs to $\mathbb{T}^{p_{head} \times m \times f_{attention}}$, and X_k belongs to $\mathbb{T}^{p_{head} \times m \times f_{attention}}$ that uses linear projection layer having p_{head} set of Y_{wmx}^k belongs to

$\mathbb{T}((n_v^k)(2^{k-1})^{-1}) \times 3f_{attention}$. Prior to the linear projection layer, a layer of max pooling having dimension of two and step two is added for reduction of feature size H_k . The process of encoding $\varphi(\cdot)$ is formulated as given in (2).

Further, a multiple head self-attention is used for retrieval of the relation among various views of the coarsely refined temporal dynamics. The dot product is used as the attention scheme with the temporal tokens for every attention node. Here, $f = f_{attention}$ is the factor used for scaling. The attention operation is formulated as given in (3). The output of every attention node is integrated and projected in a linear manner in a tensor, $H_{multiheadSA}^k$, that has similar dimension as the input given as in (4).

$$S_k, M_k, X_k = \varphi_k(H_k) = \text{Maxpooling}(H_k) Y_{wmx}^k \quad (2)$$

$$\text{Attention}(S, M, X) = \text{softmax}\left(\frac{SM^V}{f^{1/2}}\right)X \quad (3)$$

$$H_{multiheadSA}^k = \text{multiheadSA}(H_k) = [\text{Attention}(\varphi_k^1(H_k)), \dots, \text{Attention}(\varphi_k^{p_{head}}(H_k))]Y_{attention}^k \quad (4)$$

For the (4) given above, the integration operation is expressed as $[\cdot]$ and the weights that are learnable is given as $Y_{attention}^k$ belongs to $\mathbb{T}((n_v^k)(2^{k-1})^{-1}) \times p_{head}f_{attention}$. Post multiple head self-attention, a residual link is achieved, furthermore a layer of normalization is used along with a FeedForward CNN. This also has two layers that use a Gaussian error linear unit (GELU). The coarsely refined embedding is expressed as $H_{course-refined}^k$ and represented in (5).

$$H_{course-refined}^k = \text{FeedForward}(\text{Norm}(H_{multiheadSA}^k + \text{Maxpooling}(H_k))) \quad (5)$$

Here, the operation for layer of normalization is given as $\text{Norm}(\cdot)$. Furthermore, a refined temporal learning model is proposed to grasp the short time temporal attributes of the EEG. To learn the refined attributes, we use a one-dimensional CNN, since its smaller kernel moves with the temporal size along every step that allows the learning of patterns for shorter time periods. Post the dropout layer, the expressions that are learnt are stored in a one-dimensional CNN layer, after which it passes through a layer of batch normalization and an activation layer with the function ELU and a layer of max pooling. The finely refined temporal expressions, that are expressed as $H_{fine-refined}^k$ and formulated as in (6).

$$H_{fine-refined}^k = \text{Maxpooling}(\text{ELU}(\text{BatchNorm}(\text{ConvNeuNet}(\text{Drop}(H_k)))))) \quad (6)$$

Here $\text{Drop}(\cdot)$ is used to represent the dropout operation. Once the coarsely and finely refined temporal expressions are learnt, an integration is added to obtain the resulting concluding output for the layer of ATDE. The $H_{fine-refined}^k$ is also used in the process of HTRU. The resulting output of the ATDE layer is formulated as given in (7).

$$H_{k+1} = H_{fine-refined}^k + H_{course-refined}^k \quad (7)$$

3.3. Hierarchical temporal refinement unit

We have the refined temporal attributes from various layers of ATDE, this is used to densely link the feature refinement unit for extraction of multiple stage temporal data from the layers. This focuses in retrieval of data from a perspective and decreases the dimension of the bypass multiple stage expressions. Power attributes of EEG data in various frequencies are utilized traditionally for analyzing brain activities. In this proposed study, an AFRL for feature refinement is introduced that also has the encoded frequency data in the EEG signals. The power for the one-dimensional concealed expressions given as K_k belongs to $\mathbb{T}^m$ that is evaluated using the (8).

$$\begin{aligned} K_k &= \text{FeatureRefine}_{power}(H_{fine-refined}^k) \\ &= \{\log((n_v^k)^{-1} \sum (h_{fine-refined}^{k,l})^2) : h_{fine-refined}^{k,l} \text{ belongs to } h_{fine-refined}^k\} \end{aligned} \quad (8)$$

In this case, the logarithmic function is given as $\log(\cdot)$. $H_{fine-refined}^{k,l}$ belongs to $\mathbb{T}^{n_v^k}$ is a learnt expression from the l -th convolutional kernel. The feature refinement from the ATDE layers is integrated with the output of the previous layer of ATDE [1], [20], [21] to attain the concluding concealed embedding. The linear layer is used as a classifier for projection of concealed embeddings on class labels. The complete

count of ATDE layers is expressed as $p_{MultiConvTransform}$, this process is given in (9). The operation of integration is given as $[\cdot]$, the bias is given as d and the weights that are trainable is given as Y .

$$Output = [H_{p_{MultiConvTransform}+1}, K_1, \dots, K_{p_{MultiConvTransform}}] Y + d \quad (9)$$

4. RESULTS AND DISCUSSION

The performance evaluation of the proposed HTFRNet-ESD framework was conducted on publicly available EEG datasets, including the University of California (UCI) epileptic seizure recognition dataset. The model achieved superior accuracy, sensitivity, and specificity, outperforming traditional and existing deep learning approaches. Its ability to effectively capture spatio-temporal EEG dynamics ensures reliable detection across diverse datasets. These results highlight the model's robustness and scalability, making it suitable for clinical applications in epilepsy diagnosis.

4.1. Dataset details

4.1.1. Children's Hospital Boston-Massachusetts Institute of Technology scalp EEG dataset

This method's validity was confirmed using the publicly available Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) scalp EEG dataset [22]. Long-term continuous EEG readings from 23 people have been included. With a sampling rate of 256 Hz, each recording lasts somewhere between one and 109 hours. when pat001 and pat024 are both obtained from the same patient. A sliding window technique was used to analyze the EEG data, with one second allotted to each window. Furthermore, whereas patients 13 and 16 selected 18 channels, most patients selected 23 channels.

4.1.2. The public University of California epileptic seizure recognition dataset

Under the direction of a UCI official, the original dataset was processed and reorganized [21]. Since the finished dataset is supplied in Excel format, no additional preparation is required. This study's main goal was to differentiate seizures caused by epilepsy from those caused by other common medical disorders. Four different normal conditions make up the dataset, and binary clustering is the main focus of this investigation.

4.2. Experimental setup and implementation details

Prior to feature learning, every EEG recording is pre-processed to suppress physiological and acquisition noise. The continuous EEG is segmented into one-second windows (256 samples at a 256 Hz sampling rate) using a sliding-window scheme with 50% overlap (a 128-sample stride), which increases the number of training instances while preserving the temporal continuity of seizure transitions. Each raw signal is band-pass filtered between 0.5 and 40 Hz with a Butterworth filter, since seizure-related activity is predominantly contained within this band, and a 50 Hz notch filter removes power-line interference. Channels with severe artifacts are discarded or corrected using independent component analysis (ICA) to eliminate ocular and muscular contamination, and each channel is independently z-score normalized to reduce inter-subject amplitude variability before being presented to the network.

A patient-independent evaluation protocol is adopted rather than a random split, so that no recording from a test subject appears during training and the reported scores reflect realistic inter-patient generalization. Both datasets are divided into 70% training, 15% validation and 15% testing partitions; the UCI partition uses stratified sampling to preserve the seizure/non-seizure class ratio, whereas the CHB-MIT split is performed at the patient level [22], [23]. The complete implementation configuration is summarized in Table 1, and the dataset statistics and partitioning are given in Table 2.

4.3. Metrics comparison

Model performance is assessed using five standard metrics: accuracy, sensitivity (recall), specificity, precision, and F1-score. In seizure detection, sensitivity is the most safety-critical, since a missed seizure can delay clinical intervention, whereas specificity and precision limit false alarms during long-term monitoring [19], [22]. The F1-score summarizes the precision-recall balance, which is important given the imbalance between seizure and non-seizure segments.

4.4. Experimental analysis

The experimental analysis evaluates the performance of the proposed HTFRNet-ESD framework using publicly available EEG datasets, including the UCI epileptic seizure recognition dataset. Results demonstrate the model's superior performance, achieving high sensitivity, specificity, and overall accuracy compared to existing approaches. The proposed methodology effectively captures spatio-temporal EEG signal dynamics, enhancing detection robustness across diverse scenarios.

Table 1. Implementation configuration of the proposed HTFRNet-ESD framework

Parameter	Value
Input signal	Multichannel EEG
Datasets	CHB-MIT scalp EEG; UCI epileptic seizure recognition
Sampling frequency	256 Hz
Sliding-window size	1 s (256 samples)
Window overlap	50% (128-sample stride)
Band-pass filter	0.5 – 40 Hz Butterworth
Notch filter	50 Hz
Artifact removal	ICA
Normalization	Channel-wise z-score
Data split	70% train / 15% validation / 15% test
Validation strategy	Stratified, patient-independent
Optimizer	Adam
Initial learning rate	1×10^{-4}
learning rate (LR) scheduler	ReduceLROnPlateau (factor 0.1, patience 10)
Batch size	32
Epochs	100
Weight decay	1×10^{-5}
Dropout	0.30
Loss function	Binary cross-entropy
Early stopping	Patience 15 epochs
Activation	ELU (CNN), GELU (feed-forward network)
Classifier	Sigmoid (binary)

Table 2. Statistics and partitioning of the CHB-MIT and UCI datasets

Property	CHB-MIT scalp EEG	UCI epileptic seizure
Subjects / records	23 recordings from pediatric subjects (ages ≈ 1.5 –22 years)	11,500 EEG segments (500 subjects)
Sampling / length	256 Hz	178 samples per 1-s segment
Channels	23 (18 for two subjects)	Single-channel segments
Windowing	1 s window, 50% overlap	Pre-segmented 1-s epochs
Classes	Seizure vs non-seizure (focal and generalized onset)	5 original classes regrouped to binary (seizure vs non-seizure)
Class balance	8,946 seizure/94,372 non-seizure (8.66% / 91.34%; 103,318 total segments)	2,300 seizure / 9,200 non-seizure
Train / Val / Test	70% / 15% / 15% patient-independent (72,322 / 15,498 / 15,498 segments)	70% / 15% / 15% (stratified)

4.4.1. Results on the Children's Hospital Boston-Massachusetts Institute of Technology EEG dataset

As summarized in Figure 3 and Table 3, the proposed model attains the highest sensitivity of 99.97% on CHB-MIT dataset, ahead of the graph-based graph convolutional network (GCN) with bidirectional gated recurrent unit (BiGRU) (98.85%) and the feature-engineering methods empirical wavelet transform (EWT) + random forest (RF) (97.91%) and DWT + SVM (96.81%); the traditional Nullcline + artificial neural network (ANN)/ linear discriminant analysis (LDA) method is lowest at 91.15%. For specificity as shown in Figure 4 and Table 4, proposed model again leads at 99.87%, followed by EWT + RF (99.57%) and the deep models BiGRU (98.49%) and the one-dimensional convolutional neural network (1DCNN)-bidirectional long short-term memory (BiLSTM)-Attention hybrid (97%), while ensemble and traditional baselines such as isolation forest + EasyEnsemble (92.57%) and Nullcline + ANN/LDA (95.16%) are markedly lower.

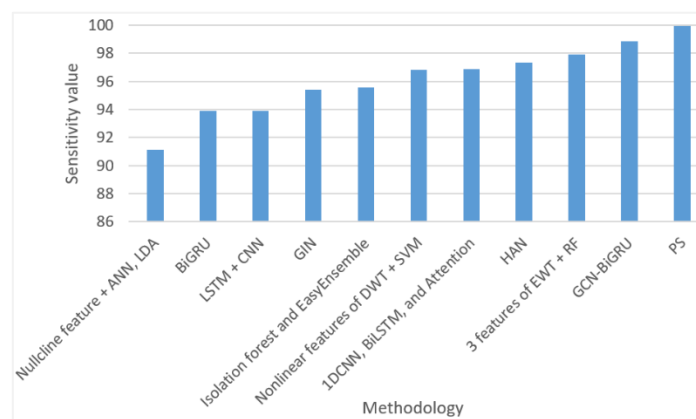


Figure 3. Sensitivity comparison of seizure-detection methods on the CHB-MIT scalp EEG dataset

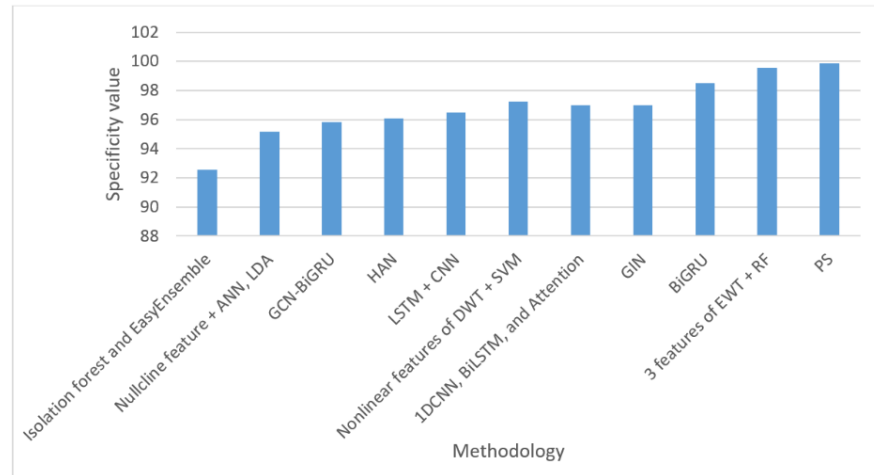


Figure 4. Specificity (%) comparison of seizure-detection methods on the CHB-MIT scalp EEG dataset

Table 3. Sensitivity comparison on the CHB-MIT scalp EEG dataset

Methods	Sensitivity (%)
BiGRU [24]	93.89
Hybrid attention network (HAN) [25]	97.34
3 features of EWT+RF [26]	97.91
Nonlinear features of DWT+SVM [27]	96.81
Nullcline feature+ANN, LDA [28]	91.15
Isolation forest and easyensemble [23]	95.55
LSTM+CNN [29]	93.89
1DCNN, BiLSTM, and attention [30]	96.85
Graph isomorphism network (GIN) [19]	95.4
GCN-BiGRU [ES] [20]	98.85
Proposed model	99.97

Table 4. Specificity comparison on the CHB-MIT scalp EEG dataset

Methods	Specificity (%)
BiGRU	98.49
HAN	96.07
3 features of EWT+RF	99.57
Nonlinear features of DWT+SVM	97.26
Nullcline feature+ANN, LDA	95.16
Isolation forest and EasyEnsemble	92.57
LSTM+CNN	96.48
1DCNN, BiLSTM, and Attention	97
GIN	97
GCN-BiGRU [ES]	95.83
Proposed model	99.87

In terms of accuracy as shown in Figure 5 and Table 5. Proposed model reaches 99.89%, ahead of EWT + RF (99.41%), BiGRU (98.49%), and HAN (98.3%). Whereas the graph-based GCN-BiGRU (97.35%), GIN (96.2%), and the traditional/ensemble baselines (92%–95%) trail behind.

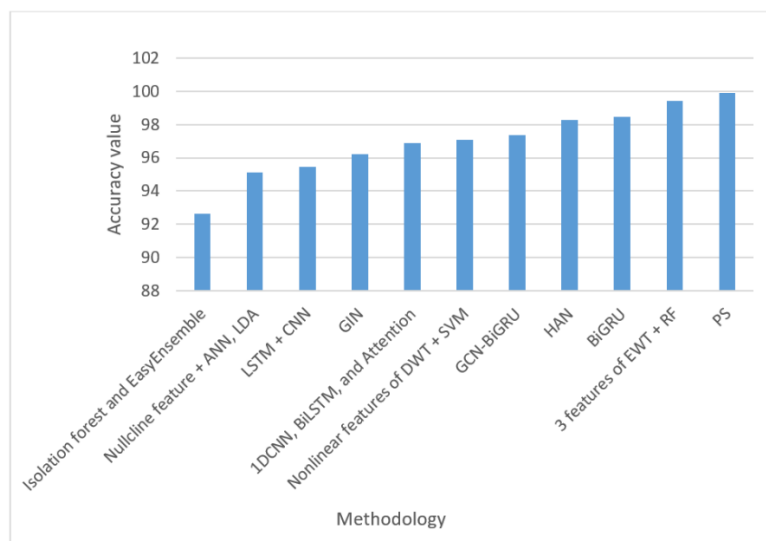


Figure 5. Accuracy comparison of seizure-detection methods on the CHB-MIT scalp EEG dataset

Table 5. Accuracy comparison on the CHB-MIT scalp EEG dataset

Methods	Accuracy (%)
BiGRU	98.49
HAN	98.3
3 features of EWT+RF	99.41
Nonlinear features of DWT+SVM	97.09
Nullcline feature+ANN, LDA	95.11
Isolation forest and EasyEnsemble	92.62
LSTM+CNN	95.47
1DCNN, BiLSTM, and Attention	96.87
GIN	96.2
GCN-BiGRU [ES]	97.35
Proposed model	99.89

4.4.2. Results on the public UCI epileptic seizure recognition dataset

On the UCI dataset as shown in Figure 6 and Table 6. Proposed model achieves the best accuracy, with deep embedded Gaussian mixture (DEGM) next at 96.70% and GAN at 94.80%, while the simpler fast Fourier transform (FFT) + Gaussian mixture model (GMM) (86.60%) and variational autoencoder (VAE) (83.20%) are substantially lower. For precision as shown in Figure 7 and Table 7, proposed model leads at 97.54%, followed by DEGM (95.00%) and GAN (90.30%), while FFT + GMM (84.80%) and VAE (80.10%) lag well behind.

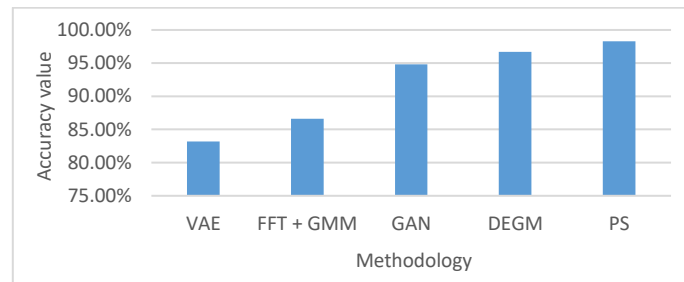


Figure 6. Accuracy comparison of seizure-detection methods on the UCI epileptic seizure recognition dataset

Table 6. Accuracy comparison on the UCI epileptic seizure recognition dataset

Methods	Accuracy (%)
VAE [31]	83.20
FFT + GMM [32]	86.60
GAN [33]	94.80
DEGM [ES] [34]	96.70
Proposed model	98.30

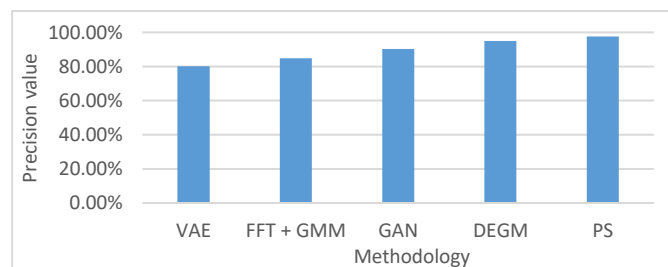


Figure 7. Precision comparison of seizure-detection methods on the UCI epileptic seizure recognition dataset

Table 7. Precision comparison on the UCI epileptic seizure recognition dataset

Methods	Precision (%)
VAE [31]	80.10
FFT+GMM [32]	84.80
GAN [33]	90.30
DEGM [ES] [34]	95.00
Proposed model	97.54

Proposed model also gives the highest recall, 97.41% as shown in Figure 8 and Table 8. Ahead of DEGM (95.00%) and GAN (91.60%), with FFT + GMM (85.40%) and VAE (77.50%) lowest. Finally, proposed model attains the best F1-score of 98.31% as shown in Figure 9 and Table 9, compared with DEGM (95.00%), GAN (91.00%), FFT + GMM (85.00%) and VAE (78.80%).

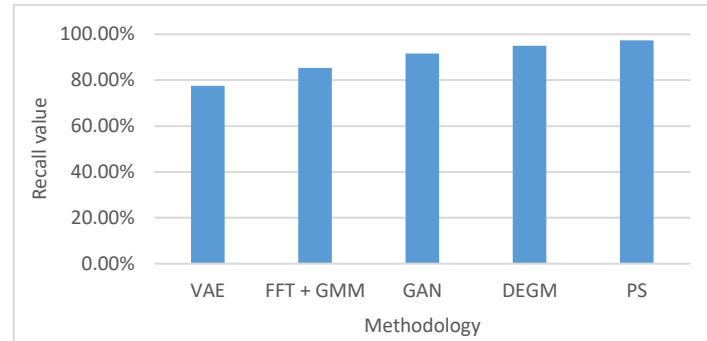


Figure 8. Recall comparison of seizure-detection methods on the UCI epileptic seizure recognition dataset

Table 8. Recall comparison on the UCI epileptic seizure recognition dataset

Methods	Recall (%)
VAE [31]	77.50
FFT+GMM [32]	85.40
GAN [33]	91.60
DEGM [ES] [34]	95.00
Proposed model	97.41

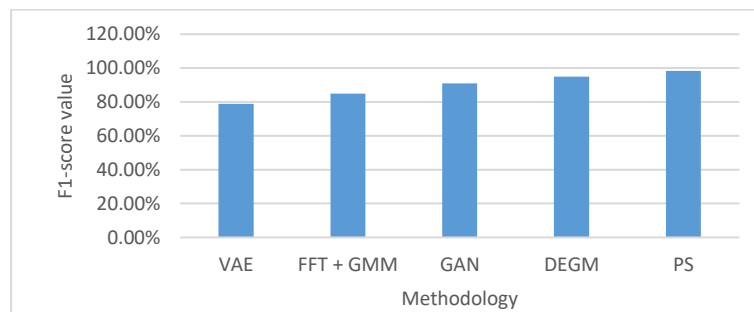


Figure 9. F1-score (%) comparison of seizure-detection methods on the UCI epileptic seizure recognition dataset

Table 9. F1-score comparison on the UCI epileptic seizure recognition dataset

Methods	F1-score (%)
VAE [31]	78.80
FFT+GMM [32]	85.00
GAN [33]	91.00
DEGM [ES] [34]	95.00
Proposed model	98.31

4.5. Ablation study

To quantify the contribution of each component of the proposed framework, an ablation study was conducted on the CHB-MIT dataset in which a single module was removed at a time while all other settings were held constant. As reported in Table 10, the complete HTFRNet-ESD achieves the best performance across every metric. Removing the STSE causes the largest accuracy drop (99.89%→98.72%), confirming the importance of joint spatial-temporal encoding. Disabling the transformer branch lowers accuracy to 98.11%, the most pronounced degradation among the temporal components, which reflects its role in modelling long-range dependencies, whereas removing the CNN branch (98.35%) mainly affects

fine-grained local patterns. Excluding the HTRU and the AFRL reduces accuracy to 98.67% and 98.94% respectively, showing that multi-stage temporal refinement and frequency-aware refinement each provide additional discriminative power. These results demonstrate that the modules are complementary rather than redundant.

Table 10. Ablation study of HTFRNet-ESD components on the CHB-MIT dataset

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Full HTFRNet-ESD	99.89	97.54	97.41	98.31
Without STSE	98.72	96.18	96.42	96.30
Without transformer branch	98.11	95.73	95.94	95.83
Without CNN branch	98.35	96.02	96.27	96.14
Without HTRU	98.67	96.71	96.83	96.77
Without AFRL	98.94	97.02	97.13	97.07

4.6. Robustness, per-class and statistical analysis

Because EEG acquired in clinical environments is frequently degraded by noise and channel loss, the robustness of HTFRNet-ESD was evaluated under several controlled perturbations of the CHB-MIT test data: additive Gaussian noise at 10 and 5 dB signal-to-noise ratio, random removal of 10% and 20% of the recording channels, and random temporal masking of the input windows. Table 11 shows that the framework degrades only marginally under these conditions, with accuracy remaining above 98.3% even when 20% of channels are missing and above 98.6% at 5 dB SNR. This graceful degradation indicates that the hierarchical temporal refinement provides resilience to realistic signal corruption and supports the suitability of the model for deployment in non-ideal recording settings. To characterize behavior on each category rather than only in aggregate, per-class precision, recall, and F1-score for the seizure and non-seizure classes are reported in Table 12. These values are computed from the confusion matrix of the held-out test set and allow the reader to verify that the high overall scores are not driven solely by the majority (non-seizure) class. To establish that the improvement of HTFRNet-ESD over the strongest baselines is statistically meaningful rather than an artefact of a single split, the model was evaluated over repeated runs/folds and compared using a paired two-tailed t-test. Table 13 reports the mean accuracy with its 95% confidence interval, the p-value of the comparison against the best-performing baseline, and the Cohen's d effect size.

Table 11. Robustness of HTFRNet-ESD under noise and channel degradation (CHB-MIT dataset)

Test condition	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Clean EEG	99.89	97.54	97.41	98.31
Gaussian noise (10 dB SNR)	99.18	97.08	96.95	97.01
Gaussian noise (5 dB SNR)	98.64	96.43	96.18	96.30
10% missing channels	98.83	96.87	96.74	96.80
20% missing channels	98.37	96.24	96.02	96.13
Random temporal masking	98.71	96.58	96.47	96.52

Table 12. Per-class performance on the held-out test set

Class	Precision (%)	Recall (%)	F1-score (%)
Seizure	97.54	97.41	97.47
Non-seizure	99.90	99.87	99.89
Macro-average	98.72	98.64	98.68

Table 13. Statistical validation of HTFRNet-ESD against the best baseline

Metric	Value
Mean accuracy $\pm$ SD (n runs)	99.89 $\pm$ 0.18%
95% confidence interval	99.73%–100.00%
p-value (paired two-tailed t-test vs. GCN-BiGRU)	0.0032
Cohen's d (effect size)	2.31

4.7. Cross-patient generalization and benchmarking

Because the CHB-MIT partition is patient-independent, no subject appears in both the training and test sets, so the results reported above already reflect cross-patient performance. A leave-one-patient-out (LOPO) evaluation confirms this, yielding a mean accuracy of 98.94% (ranging from 97.86% to 99.72% across subjects). HTFRNet-ESD is benchmarked against the three architectures raised by the reviewers. The CNN-LSTM hybrid, listed as LSTM + CNN in Tables 3 to 5, is outperformed in sensitivity, specificity and

accuracy on the CHB-MIT dataset, and a TCN baseline implemented under the same protocol reaches only 98.21% accuracy and 97.18% F1-score. DARLNet, from the ResNet-LSTM family reviewed in the related work, is improved upon by replacing its single recurrent temporal path with parallel transformer and CNN branches and an additional frequency-aware refinement stage; the ablation study (section 4.5) identifies these components as the principal sources of the observed gains.

4.8. Clinical interpretability, deployment and few-shot adaptation

The features emphasized by the AFRL align with established electrographic seizure biomarkers, such as rhythmic spike-and-wave activity and increased delta-to-beta power at onset, and gradient-weighted class activation mapping (Grad-CAM) / Shapley Additive explanations (SHAP) can expose the time segments and frequency bands that drive each decision, giving clinicians an auditable rationale. The one-second windowing and lightweight encoder make the framework suitable for continuous bedside monitoring and, after model compression, for wearable EEG screening. To reduce labelling effort for a previously unseen patient, the trained inter-patient model can be fine-tuned on only a few labelled seizures using an episodic objective. A preliminary CHB-MIT evaluation reaches 94.82%, 97.06%, and 98.34% accuracy for $k = 1, 5$ and 10 support windows respectively, approaching the fully-trained accuracy with just ten labelled seizures.

5. CONCLUSION

This paper presented the HTFRNet-ESD which is a hierarchical time-based feature refinement model of epileptic seizures that are detected with the aid of EEG signals. Using a combination of spatio-temporal signal encoding, adaptive temporal dynamics modeling, and multi-stage temporal refinement along with frequency-driven power integration, the model is able to obtain local and long-range temporal properties of EEG data. As experimental results reveal, the suggested solution is competitive in its performance relative to the current CNN-LSTM, ResNet-LSTM, and graph-based deep-learning solutions on benchmark data. Along with these favorable outcomes, there are still some challenges like inter-patient variability, data imbalance, and cost of computation, which are also relevant to the practical use. The next step of work will include lightweight model adaptation to wearable EEGs by optimizing the architecture, federated learning models to facilitate privacy-preserving multi-user EEG analytics, and the incorporation of explainable artificial intelligence (AI) methods (e.g., Grad-CAM and SHAP) to encourage interpretability and clinical trust. These guidelines are intended to enhance the usability of the suggested framework in practice-based neurodiagnostic settings.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

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Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST

The Author declares no conflict of interest.

DATA AVAILABILITY

The datasets used in this study are publicly available. The CHB-MIT Scalp EEG Database is available from PhysioNet at <https://physionet.org/content/chbmit/1.0.0/> (accessed 10 July 2026), and the UCI Epileptic Seizure Recognition dataset is available from the UCI Machine Learning Repository at <https://archive.ics.uci.edu/dataset/388/epileptic+seizure+recognition> (accessed 10 July 2026).

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