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Symmetric Source Separation and Improved 1-Dimenstional ResNet Model for Epileptic Seizure Detection

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ABSTRACT

Repeated seizures brought on by irregular electrical activity in the brain characterize epilepsy, a long-term neurological condition. In order to improve outcomes and avoid cognitive decline, early detection is essential. Electroencephalography (EEG) is a key diagnostic tool, but manual interpretation is prone to delays and variability, prompting the need for automated methods using Artificial Intelligence (AI). While Machine Learning (ML) relies on handcrafted features, leading to limitations in complex scenarios, Deep Learning (DL) methods improve performance by extracting features directly from raw data. DL methods often require large training datasets for effective model learning. In the case of epileptic EEG samples, collecting a substantial number of labeled signals is impractical. So, the detection can rely on a few-shot learning scenario, where there are limited labeled samples available. However, directly using raw data in such cases risks local optima, overfitting, and reduced test accuracy. To solve these issues, Empirical mode decomposition with Power Spectral density and One-dimensional Convolutional Neural Network with ResNet (EMD-PSD-CNN1D-5Res) model was introduced for epilepsy detection. However, it suffered from poor generalization issue. This research introduces a Phase-aware Symmetric-Percussive Source Separation (PSPSS) technique as an alternative to the DFT in the EMD-PSD method. PSPSS effectively isolates the harmonic components of EEG signals by eliminating percussive signals, which are treated as noise, thereby enhancing the quality and interpretability of the EEG harmonics. In the classification module, an improved CNN1D-5Res (ICNN1D-5Res) model is introduced where a channel attention block is integrated with the existing CNN1D-5Res model to enhance the accuracy of epilepsy seizure detection. To further improve the accuracy, a novel optimization approach called Adaptive Gradient Descent with Exponential Growth (AGDEG) is used for training the ICNN1D-5Res model. This algorithm offers stable and fast convergence while working with EEG data. The ICNN1D-5Res model is proven to be a strong and effective method for detecting epileptic seizures, as shown by comparative analysis utilizing the CHB-MIT, Bonn EEG, and TUEP datasets. The model achieves an accuracy of 94.51%, 94.62%, and 93.79%, respectively, outperforming existing methods.

Keywords: Epilepsy detection, Harmon Separation, Deep Learning, Electroencephalography, Adaptive Gradient Descent

1. INTRODUCTION

In epilepsy, aberrant electrical activity in the brain causes seizures, which are a chronic neurological condition. Seizures can take many forms, such as convulsions, unconsciousness, or minor alterations in behavior. [1]. Early and accurate detection of epilepsy is crucial, as delayed diagnosis can lead to progressive worsening of the condition, cognitive decline, and reduced quality of life [2]. Electroencephalography (EEG) is widely utilized for the diagnosis and monitoring of epilepsy due to its ability to non-invasively record electrical brain activity. EEG signals contain critical information about normal brain function and abnormalities indicative of epileptic seizures, making them a key diagnostic tool for clinicians [3].

However, traditional EEG analysis often relies on manual interpretation by medical professionals, which can introduce subjectivity, variability, and potential delays in detecting epileptic activity. Additionally, the transient and unpredictable nature of seizures poses a challenge for timely detection. To address these limitations, advancements in automated seizure detection methods have gained significant attention. These methods leverage Artificial intelligence (AI) algorithms to enhance the accuracy and consistency of epilepsy diagnosis [4].

Seizure prediction has been greatly impacted by machine learning. It has provided tools to handle the complicated EEG signals and can quickly identify hidden pre-ictal features. Feature extraction, classification, and pre-processing are the typical processes in a machine learning-based seizure detection technique [5]. When it comes to EEG signal classification, feature extraction is crucial since it influences the final classification performance by reducing the data dimensionality. With its computational advantages, DL has recently found uses in clinical processing, where they outperform more conventional ML methods [6]. Consequently, DL has aimed to use a multi-layer neural network to automatically extract latent characteristics from large datasets, and it has become a research hotspot in ML disciplines [7]. The DL architecture improves feature classification capabilities by converting features into a relative low-dimensional space that can learn features from data on its own [8].

In order to automate the process of seizure identification using scalp EEG, Vidyaratne et al. [9] presented a new design for deep recurrent neural networks (DRNNs). Seizure identification using high-resolution and multi-channel EEG data was tackled by Turner et al. [10] using DBNs. A multi-view deep learning approach is suggested by Yuan et al. [11] to detect seizures in multi-channel epileptic EEG recordings by capturing brain abnormalities.

The combination of EEG signals and DL algorithms has been shown in promising studies, although automatic epilepsy detection still faces obstacles. In order to train and support the network model, deep learning methods often require a huge amount of training examples. When the sample size is small, its performance will be affected to some extent. For epileptic EEG samples, building a large number of tagged samples means that a large number of EEG signals of epileptic patients need to be collected, which is often impractical.

Pan et al. [12] devised a dual-DL based Empirical Mode Decomposition (EMD) approach to detect epilepsy in electroencephalogram (EEG) signals, especially in few-shot situations, in response to these difficulties. The process begins by decomposing EEG signals using EMD, followed by splicing the components, which are then input into CNNs. The EMD-PSD method further processes each component by applying the discrete Fourier transform (DFT), computing the Power Spectral Density (PSD), and feeding the spliced PSD sequences into CNNs for detection.

However, DFT has limitations, including its inability to distinguish between harmonic and percussive components of intrinsic mode functions (IMFs), which can lead to misdetection of seizures due to ignored phase dynamics. Additionally, DFT requires fixed-length EEG signal segments, which increases sample sizes when processing long-duration signals. The CNN1D-5Res model, optimized with Adam for fast convergence, may also suffer from local minima, resulting in poor generalization performance.

To overcome these issues, this research introduces a PVPSS technique as an alternative to the DFT in the EMD-PSD method. PVPSS effectively isolates the harmonic components of EEG signals by eliminating percussive signals, which are treated as noise, thereby enhancing the quality and interpretability of the EEG harmonics. In the classification module, an ICNN1D-5Res model is introduced where a channel attention block is integrated with the existing CNN1D-5Res model to enhance the accuracy of epilepsy seizure detection. In order to train the ICNN1D-5Res model with high convergence speed and stability when working with EEG data, a new optimization algorithm called AGDEG is utilized, which further improves the accuracy. Here is how the rest of the research is structured: The study is organized as follows: Section II provides a review of previous DL models for epilepsy detection; Section III explains out the methodology that will be used; Section IV assesses how well the EEG-FEDNN model performs; and Section V concludes the research.

2. LITERATURE SURVEY

Using EMD's first four high-frequency intrinsic mode functions (IMFs), Parija et al. [13] processed EEG signals. Unfortunately, the method's efficacy may have been hindered due to the absence of a solid theoretical basis in the selection criteria. Lightweight 2D-CNNs were suggested by Pan et al. [14]; these networks could handle raw data as well as data that had been transformed using methods like Discrete Fourier Transform (DFT) and Short-Time Fourier Transform (STFT). The absence of test set data raised concerns about the reliability of the model, even though this hybrid approach improved detection performance with limited data.

In order to distinguish between focal and non-focal EEG signals, Srinath & Gayathri [15] suggested a deep learning-based approach that uses a convolutional neural network (CNN) for classification and empirical mode decomposition (EMD) for signal processing. Nevertheless, the signal severity diagnosing rate is diminished due to the minimal use of external features in this work.

Illias et al. [16] developed STFT and CNN methods for distinguishing healthy, interictal, and ictal EEG cases without feature extraction. However, the process involves tedious feature extraction from both time and frequency domains, followed by training shallow machine learning classifiers. Kaur & Gandhi [17] proposed an automated seizure detection system using EEG image representations and transfer learning, achieving high classification performance. However, this method is computationally expensive and may lack generalization on clinical EEG datasets.

Kunekar et al. [18] LSTM for binary classification of healthy and seizure EEG signals achieved 97% validation accuracy and 2.06% false negatives, outperforming conventional machine learning models. However, the dataset was insufficient and unbalanced, and the system needs improvement in false-negative detection and testing for multiclass classification on other datasets. In order to reduce processing costs through statistical feature extraction and Local Mean Decomposition (LMD), Kumar et al. [19] developed a method for seizure detection that employs a Bidirectional Long Short-Term Memory (Bi-LSTM) network. This network also preserves the nonstationary nature of EEG data. However, further improvements may be needed in handling real-time processing and testing on more diverse datasets.

3. PROPOSED METHODOLOGY

Figure 1 shows the ICNN1D-5Res Model, which is described in this section.

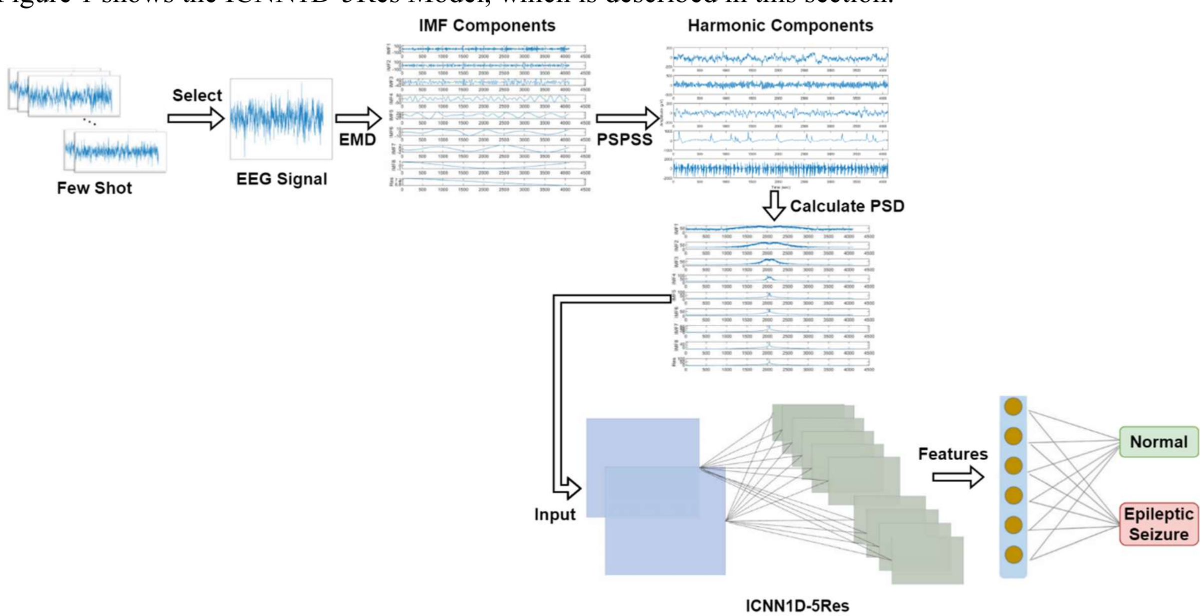

Figure 1. Overall framework of the proposed model

3.1 Dataset Description

(i) CHB-MIT Dataset: At Children's Hospital Boston, researchers obtained multi-channel EEG signals from 24 patients with epilepsy ranging in age from 1.5 to 22 years. This dataset is known as the CHB-MIT Dataset. The sampling rate for these signals was 256 Hz with a resolution of 16 bits and recorded using the international 10-20 system with scalp electrodes under both normal conditions and during epileptic seizures. Most recordings include 18-23 dual electrode channels, and each EEG recording is extensively annotated with the start and end times of epileptic seizures, providing both non-seizure (inter-ictal) and seizure (ictal) EEG segments. The CHB-MIT dataset is detailed in Table 1.

Table 1. CHB-MIT dataset

Parameter	Description
Number of Subjects	24
Number of Channels	23
Recording Type	Scalp EEG
No. of Epileptic Seizures	198
Duration of Each Recording (Hour)	1 (some cases have 2 – 4 hours of recording)
Sampling Frequency (Hz)	256

(ii) Bonn EEG Dataset: The Bonn EEG Dataset contains EEG recordings from both healthy individuals and epilepsy patients. It is divided into five subsets (A-E), each representing distinct brain states, including normal, inter-ictal, and ictal conditions. With a sampling rate of 173.61 Hz and a duration of 23.6 s per segment, each subset contains 100 individual EEG segments. Research on the identification and categorization of epilepsy makes extensive use of this dataset. Data from the Bonn EEG study is detailed in Table 2.

Table 2. Bonn EEG dataset

Parameter	Description
No. of Subjects	25 (5 sets, each with five subjects recorded)
No. of Channels	1(each set contain 100 files of single channel data)
Recording Type	Scalp/ iEEG
No. of Epileptic Seizures	Dataset E contains the ictal stage recordings.
Duration of Each Recording (Hour)	23.6
Sampling Frequency (Hz)	173

(iii) Temple University Hospital EEG Epilepsy Corpus (TUEP) dataset: The TUEP includes EEG signals recorded using the international 10 to 20 system. The majority of these signals were sampled at frequencies of either 256 Hz or 250 Hz.

Table 3. TUEP dataset

Parameter	Description
No. of Subjects	10874
No. of Channels	24-36
Recording Type	iEEG
No. of Epileptic Seizures	≈14777
Duration of Each Recording (Hour)	-
Sampling Frequency (Hz)	250

Typically, training uses up to 80% of the data in all three datasets, while testing uses up to 20%. ensuring a standardized approach to evaluating epilepsy detection algorithms. Table 3 shows the details of the TUEP dataset.

3.2 Overview of the Proposed model

In the existing EMD-PSD approach, each EMD-derived component is processed using the Discrete Fourier Transform

(DFT), followed by the computation of the Power Spectral Density (PSD) for each component. The PSDs of all IMFs and the residual component are concatenated to form a matrix. This matrix is then fed to the CNN1D-5Res model, which uses 5 residual stacks, for learning and detection of epileptic seizures. However, in this research phase, a PVPSS technique is employed as an alternative to the DFT in the EMD-PSD method. PSPSS, originally developed for sound signal processing, is used to separate actual rhythm (harmonic content) from side information (percussive noise). This research uses the same approach on EEG signals' Intrinsic Mode Functions (IMFs). PVPSS effectively isolates the harmonic components of EEG signals by eliminating percussive signals, which are treated as noise, thereby enhancing the quality and interpretability of the EEG harmonics. Additionally, a CNN1D-5Res model that incorporates a channel attention block into the current model is presented, which improves the accuracy of seizure detection in epilepsy. For ICNN1D-5Res model training, a novel AGDEG optimization algorithm is implemented during the training phase to ensure stable and rapid convergence when processing EEG data.

3.3 Empirical Mode Decomposition

An often-used data-driven method for analyzing EEG signals and other nonlinear and non-stationary data is Empirical Mode Decomposition (EMD) [12]. Decomposing the signal into components that represent different scales of fluctuations and trends is how EMD operates in the context of EEG analysis. The components in question are known as Intrinsic Mode Functions (IMFs). If the original signal contains many oscillatory modes, each IMF can be used to analyze each mode independently, providing a more precise and localized picture of the signal. In addition, once all relevant IMFs have been extracted, a residual component is obtained, which stands for the signal's general trend or baseline. This means that the total of K IMFs and a residual component is the EEG signal. For a component can only be considered an IMF if it satisfies two requirements:

1. Within the component, there can be no more than one difference between the number of zero crossings and the number of extrema (maxima and minima combined). This guarantees that the IMF is depicting a genuine oscillatory mode.
2. At every point, the average of the envelopes defined by the signal's local maximum and minimum values must be zero. This ensures that the IMF is symmetric with respect to the local average, reflecting the intrinsic oscillatory behavior without any spurious trends. Figure 2 depicts the basic steps in EMD technique.

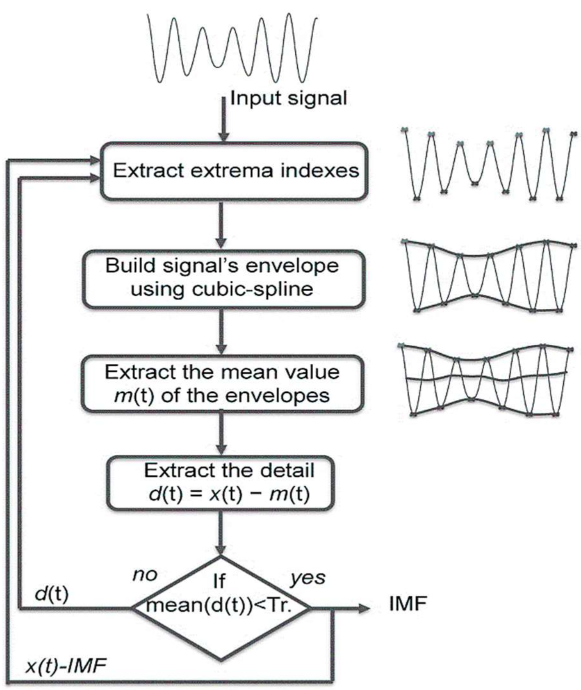

Figure 2. Steps in EMD technique

3.4 Phase-aware Symmetric- Percussive Source Separation (PSPSS) model

EEG signals inherently possess an associated spectrum, which can be decomposed into a series of sine and cosine waves. These spectral characteristics, particularly harmonic patterns (H patterns), are often observed in EEG signals of individuals with focal epilepsy. Multiple high-density frequency bands that evolve over time and are especially prominent in the early and late stages of seizures define H patterns. The percussion components display continuity in the frequency direction, whereas the harmonic components are smooth in the time direction.

(i) Harmonic-Percussive Source Separation

HPSS takes advantage of power spectrograms' anisotropic smoothness. Assumption: The power spectrograms of harmonic components $H \in \mathbb{R}_+^{K\times T}$ and percussive components $P \in \mathbb{R}_+^{K\times T}$ follow these relations:.

For harmonic components, the spectrogram values are approximately smooth along the time axis:

$$H_{\omega,\tau} \approx H_{\omega,\tau\pm1}, \qquad (1)$$

For percussive components, the spectrogram values are approximately smooth along the frequency axis:

$$P_{\omega,\tau} \approx P_{\omega\pm1,\tau}, \qquad (2)$$

where $\omega = 1, \dots, K$ represent frequency $\tau = 1, \dots, T$ represent time, respectively.

To achieve this separation, optimization-based HPSS minimizes the following cost function:

$$\min_{H,P} \frac{1}{2\sigma_h^2} \|D_\tau(H)\|_{Fro}^2 + \frac{1}{2\sigma_p^2} \|D_\omega(P)\|_{Fro}^2 \qquad (3)$$

$$\text{s.t. } H_{\omega,\tau} + P_{\omega,\tau} = \left|X_{\omega,\tau}\right|^{2\gamma}, \qquad H_{\omega,\tau} \geq 0, \qquad P_{\omega,\tau} \geq 0$$

In this context, D_τ and D_ω represent the time and frequency-directional differences, σ_h and σ_p are parameters that can be used to modify the smoothness of the harmonic and percussive spectrograms and $X \in \mathbb{C}^{K\times T}$ is the complex-valued spectrogram of the audio mixture that needs to be separated. For the sake of simplicity, the hyperparameter γ, which is valid for range compression $0 < \gamma \leq 1$, will be set to 1 throughout the remainder of this paper.

It is the sinusoidal model that HPSS is built upon. Assume that the signal $x \in \mathbb{R}^L$ and its short-time Fourier transform (STFT) is

$$\mathcal{F}(x)_{\omega,\tau} = \sum_{l=0}^{L-1} x_{l+a\tau}\, g_l\, e^{-\frac{2\pi j\omega}{L}}, \qquad (4)$$

Index overflow is handled by zero-padding in the following equation: $g \in \mathbb{R}^L$ is a window, , $j = \sqrt{-1}$, a and b are the time and frequency shifting steps.

(ii) Sinusoidal Model in HPSS

Because the sinusoid's amplitude is constant, the following connection holds for its complex-valued spectrogram:

$$\mathcal{F}(x)_{\omega,\tau} = \mathcal{F}(x)_{\omega,\tau-1} e^{2\pi jfa/L} \qquad (5)$$

Hence, when the sinusoid's phase evolution is removed, the complex-valued spectrogram in each sub-band has the same value. The proposal of instantaneous phase corrected STFT (iPC-STFT) aims to eradicate this phase evolution.

$$\mathcal{F}_{iPC}(x) = E \odot \mathcal{F}(x), \qquad (6)$$

The Hadamard product is $\odot$ and E is the instantaneous phase correction matrix defined by $E_{\omega,\tau} = \prod_{\eta=0}^{\tau-1} e^{-2\pi j v_{w,\eta} a/L}$ with $E_{\omega,0} = 1$ for every ω.

(iii) Phase-Aware SPSS

PSPSS extends HPSS by considering both amplitude and phase information. Using iPC-STFT, PSPSS reformulates the optimization problem as:

$$\min_{x_h, x_p} \frac{1}{2} \|W \odot D_\tau(X_h)\|_{Fro}^2 + \lambda \left\|X_p\right\|_{2,1} \qquad (7)$$

$$\text{s.t. } x = x_h + x_p, X_h = \mathcal{F}_{iPC}(x_h), X_p = \mathcal{F}\left(x_p\right)$$

where $W \in \mathbb{R}_+^{K\times T}$ is a weight that is pre-constructed, $\lambda > 0$ is the hyperparameter that modifies the quantity of harmonic and percussive components and x_h, x_p, x are the time-domain signals of harmonic components, percussive components and the EEG signal respectively.

PSPSS formulates the problem as a convex optimization task solved using a primal-dual splitting algorithm. This avoids computationally expensive operations, such as matrix inversion, and iteratively refines harmonic and percussive components. This model specifically includes only harmonic components and removes percussive components. In order to account for harmonic components, PSPSS uses the sinusoidal phase model to infer that the iPC-STFT spectrogram is time-directionally smooth. By simultaneously treating amplitude and phase, PSPSS achieves more accurate separation of harmonic components.

3.5 Density of Power Spectral

As shown by Power Spectral Density (PSD) [12], the distribution of a signal's power across its various frequency components can be described. It offers a method for analyzing a signal's frequency content and calculating the power or energy at each frequency. In the context of EEG signal analysis, PSD helps to understand the contribution of various frequency bands (like alpha, beta, theta, or delta waves) to the overall signal. This is crucial for identifying patterns and abnormalities, such as those seen in epileptic seizures. By breaking down the signal into its frequency components and calculating the power associated with each, PSD allows researchers to create a clear representation of the signal's frequency characteristics, which is then used for further processing and classification tasks.

3.6 Improved CNN1D-5Res model for Few-shot Classification

In the next stage, the separated harmonic component of the EEG signal is processed for epilepsy seizure detection using a classification model. For this purpose, the ICNN1D-5Res model is employed. This model is specifically designed for accurate seizure detection by leveraging channel attention mechanism. Figure 3 depicts the structure of proposed ICNN1D-5Res Model and the residual stack with channel attention.

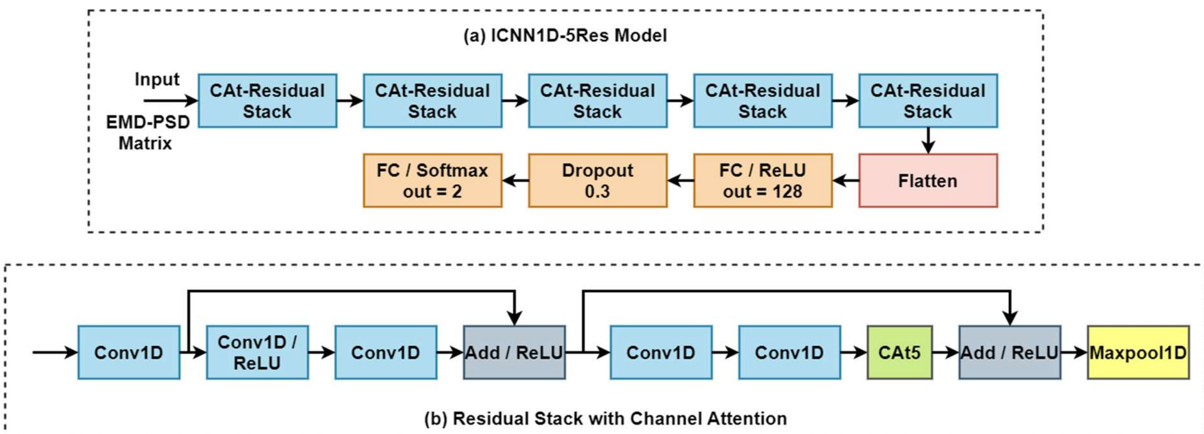

Figure 3. Structure of Proposed (a) ICNN1D-5Res Model and (b) Residual Stack with Channel Attention

3.6.1 Channel Attention Mechanism

To enhance the capability of the CNN1D-5Res model in identifying and prioritizing significant channel features, a channel attention strategy is integrated into its residual stack. This mechanism enables the model to automatically learn the relative importance of features from different channels, thereby improving its performance in tasks like epilepsy seizure detection. The channel attention block, referred to as CAt5, is applied to the features extracted from the residual stack, as illustrated in Figure 4.

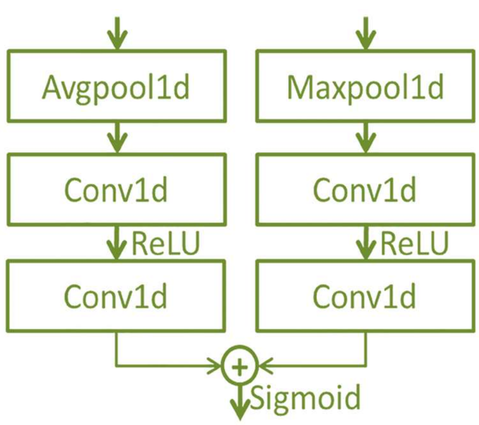

Figure 4. Structure of Cat5 block

Global maximum pooling (GMP) and Global Average Pooling (GAP) are applied to the features generated by the residual stack. Each channel's data is summarized across spatial dimensions by these pooling operations:

Global Average Pooling (GAP): Provides a holistic representation by averaging all pixel values within each channel:

$$z_c^{avg} = \frac{1}{H}\sum_{i=1}^{H} u_c(i)$$

where z_c^{avg} represents the average-pooled value for channel c, $u_c(i)$ denotes the i^{th} element of the feature map in channel c and H is the total number of spatial elements in the channel.

Global Maximum Pooling (GMP): Captures the most significant spatial responses within each channel:

$$z_c^{\max} = \max_{i=1,\dots,H} u_c(i) \quad (8)$$

where $z_c^{\max}$ represents the maximum-pooled value for channel c.

Both pooling operations yield one-dimensional feature vectors $z^{avg} \in \mathbb{R}^C$ and $z^{max} \in \mathbb{R}^C$ \(which C represents the overall count of channels.

The pooled feature vectors, z^{avg} and z^{max}, are independently passed through two convolutional layers to compute intermediate feature representations:

$$s_c^{avg} = \sigma\left(W_2^{avg}.\,\delta\left(W_1^{avg}\,.\,z_c^{avg}\right)\right) \quad (9)$$

$$s_c^{max} = \sigma\left(W_2^{\max}.\,\delta(W_1^{max}\,.\,z_c^{max})\right) \quad (10)$$

where, W_1^{avg} and W_1^{max} are the weights of the first convolutional layers, W_2^{avg} and $W_2^{\max}$ are the weights of the second convolutional layers.

The significance weights for the average pooled and maximum pooled features are denoted by s_c^{avg} and s_c^{max},, respectively, as a result of these two procedures. The final channel attention weights are computed by adding the two feature vectors:

$$s_c = s_c^{avg} + s_c^{max} \quad (11)$$

The channel attention weights s_c are used to scale the original feature map for each channel:

$$F_c' = F_c.\,s_c \quad (12)$$

where, F_c is the original feature map for channel c, s_c is the calculated attention weight for the c^{th} channel.

By incorporating the channel attention mechanism into the residual stack, the ICNN1D-5Res model effectively focuses on critical features across multiple channels. This dual-pooling approach not only improves the ability to learn hierarchical feature representations but also enhances the accuracy of the model in tasks like epilepsy seizure detection. The resulting feature maps are fine-tuned to highlight essential patterns, leading to improved performance and robustness.

3.5 Training the ICNN1D-5Res model using AGDEG optimization algorithm

To ensure effective training of the ICNN1D-5Res model, we employ the Adaptive Gradient Descent with Exponential Growth (AGDEG) optimization algorithm, an advanced technique that combines the strengths of gradient-based methods and evolutionary strategies to balance exploration and exploitation during the learning process.

This novel optimizer incorporates discrete second derivative gradients, parameter adjustment, exponential smoothing and gradient accumulation as part of its adaptive learning process. In order to attain a stable and high convergence rate, the AGDEG optimizer employs a mix of the following techniques:

(1) Exponential Decay: It helps to more accurately adapt to the present optimization conditions by gradually reducing the impact of prior gradients and accumulated values.

(2) Second Order Derivative Discretization: Calculates the discrete second derivative of gradients to estimate the loss function's curvature. To do this, it divides the difference in corresponding parameters $(\theta_t - \theta_{t-1})$ by the difference between the current and previous gradients $(g_t - g_{t-1})$ The outcome is then multiplied by the square of the magnitude of the gradient changes and added to the total value (n_t), which incorporates squares of previous gradients. This

technique offers an effective adjustment of the optimization step and enhances stability by avoiding excessively big or tiny adjustments.
(3) Rate of Adaptive Learning: Improves efficiency in reaching the loss function minimum by adjusting to the present state of gradients and accumulated values. This is achieved through parameter correction mechanisms, such as normalizing moments (m_t) and analogous (n_t) by dividing by $(1 - \beta_{\hat{t}1})$ and $(1 - \beta_{\hat{t}2})$, compensating for initial biases in early iterations and ensuring proper learning rate adaptation.
(4) Exponential Damping: Iteratively decreases the impact of accumulated gradients, improving optimization stability and reducing oscillations. This feature aligns AGDEG with quasi-Newtonian methods but avoids the computational overhead of Hessian calculations, making it efficient while leveraging discrete acceleration principles.
The AGDEG optimizer also includes key parameters such as:
Exponential smoothing coefficients $(\boldsymbol{\beta_1 and\ \beta_2})$: Values range between [0, 1) and decay over iterations.
Learning Rate Coefficient $(\boldsymbol{\eta})$: Usually set to $\eta\ =\ 0.001$ in the initial approximation.
Exponential Damping Factor $(\boldsymbol{k})$: A value in [0, 1) determining the rate of damping.
Smoothing Parameter (ε): A small value (e.g., 10^{-7}) to avoid division by zero.
The choice of hyperparameters is crucial for ensuring a balance between convergence speed and stability. Selecting an appropriate damping factor is particularly important; very small values may cause the algorithm to overshoot the global minima, while very large values could result in premature damping. The optimizer's ability to dynamically adjust gradient influences ensures robust training of the ICNN1D-5Res model. By mitigating oscillations and leveraging gradient accumulation, AGDEG delivers high convergence speed and stability, making it ideal for applications such as epilepsy seizure detection, where precision and robustness are paramount.
Despite its advantages, AGDEG requires storing weights and gradients from the previous iteration, which can increase memory usage for large models. Because of its fast convergence time, reduced oscillations and robust handling of gradient accumulations, however, this drawback is neutralized. These features make AGDEG particularly suitable for training ICNN1D-5Res, ensuring superior performance and stability in epilepsy seizure detection, where precise pattern recognition in EEG data is critical.
Algorithm 1: AGDEG Optimization
1. $g_t \leftarrow \nabla_{\theta_{t-1}} f(\theta_{t-1})$
2. $\hat{\beta}_1 \leftarrow \beta_1 \exp(-kt)$
3. $\hat{\beta}_2 \leftarrow \beta_2 \exp(-kt)$
4. $m_t \leftarrow \beta_1 m_{t-1} + (1-\beta_1) g_t$
5. $n_t \leftarrow \beta_2 n_{t-1} + (1-\beta_2) g_t$
6. $a \leftarrow \sqrt{\left(\frac{g_t - g_{t-1}}{\theta_t - \theta_{t-1} + \epsilon}\right)^2 + n_t}$
7. $\widehat{m}_t \leftarrow \frac{m_t}{1-\beta_1^t}$
8. $\hat{a} \leftarrow \frac{a}{1-\hat{\beta}_2^t}$
9. $\theta_t \leftarrow\ \theta_{t-1} - \eta \frac{\widehat{m}_t}{\hat{a}+\epsilon}$

Algorithm 2: Overall Algorithm for the proposed model
Input: EEG datasets
Output: Normal and Epileptic Seizure Patients
1. **Begin**
2. Split the dataset into training and test sets;
3. **For** training set

4. Apply EMD technique to decompose the given EEG signals into IMFs;
5. **For** each IMF, obtain harmonic and percussive components using PSPSS technique;
6. Determine PSD for all IMF components and concatenate them to obtain a matrix;
7. Initialize the ICNN1D-5Res model;
8. Train the model using AGDEG optimization;
9. **End for**
10. **For** test set
11. Use the trained ICNN1D-5Res model to classify the test EEG signals;
12. Detect normal and epileptic seizure patients;
13. **End for**
14. Evaluate the model performance;
15. **End**

The AGDEG optimization method, with its hybrid gradient-based and evolutionary design, effectively enhances the ICNN1D-5Res model's ability to extract and learn subtle patterns in EEG data. This approach ensures high precision and robustness, making it a suitable solution for detecting epilepsy seizures and distinguishing between normal and abnormal EEG signals.

4. RESULTS AND DISCUSSION

On Windows 10 PCs running version 21H2, with a 64-bit operating system, an Intel(R) Xeon(R) 4.01 GHz processor and 64 GB of RAM, the effectiveness of the ICNN1D-5Res model is measured and evaluated using the existing DL algorithms. MATLAB 2019B is used as the programming language. The EMD-PSD-ICNN1D-5Res model is compared against PS-BiLSTM-Attention [20], SE-TCN-BiGRU [21] and EMD-PSD-CNN1D-5Res [12] highlighting the effectiveness of epilepsy detection. The concepts to be known for predicting the results are as follows:

Seizure detection is to determine whether there is seizure based on the collected EEG signals. There are two possible results: normal (without seizure) or abnormal (with seizure). Therefore, the problem can also be expressed as a binary classification problem.

The most commonly used evaluation metrics for binary classification in deep learning are the accuracy, recall, precision, and F1-score. These metrics are determined using the confusion matrix. A confusion matrix displays the total number of True Positive (TP), False Positives (FP), False Negatives (FN) and True Negatives (TN) in the model's predictions.

- **TP:** It indicates correct identification of seizures
- **TN:** It indicates correct identification of normal activity
- **FP:** It indicates incorrectly identified seizures as normal activity
- **FN:** It indicates incorrectly identified normal activity as seizure

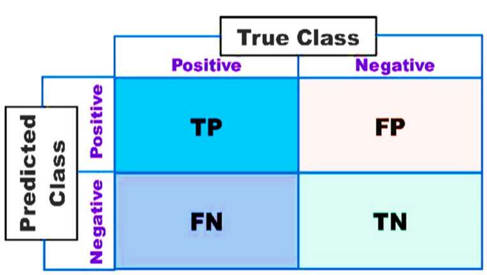

Figure 4. Confusion Matrix

The performance metrics used for evaluating the models are described as:

- **Accuracy:** It is a metric used to assess the overall effectiveness of epileptic seizure detection and is calculated as the ratio of samples that correctly detect epileptic seizures to all samples.

$$Accuracy = \frac{TP+}{TP+TN+FN+F} \quad (13)$$

- **Specificity:** This metric measures how many TNs and misclassified positive detections there were in relation to how many correctly identified negative values.

$$Specificity = \frac{TN}{TN+FP} \quad (14)$$

- **Sensitivity:** It represents the percentage of a specific detection out of the total number of accurate and incorrect detections of disease, that is, among all actual epilepsy patients.

$$Sensitivity = \frac{TP}{FN+T} \quad (15)$$

- **F1-score:** It is calculated as the precision and recall harmonic means.
- $F1-score = \frac{2\times Precision\times Recall}{Precision+Recall}$ (16)

4.1 Comparison of proposed EMD-PSPSS-PSD-ICNN1D-5Res and existing models in different datasets

Table 4 and Figure 5 compares the performance of the proposed EMD-PSPSS -ICNN1D-5Res model with three other methods: PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res, using CHB-MIT dataset.

Table 4. Comparison of proposed and existing models on CHD-MID dataset

Metrics	PS-BiLSTM-Attention	SE-TCN-BiGRU	EMD-PSD-CNN1D-5Res	EMD-PSPSS-PSD-ICNN1D-5Res
Accuracy (%)	92.60	92.97	93.84	94.51
Specificity (%)	91.12	91.70	93.28	94.09
Sensitivity (%)	92.07	92.43	92.91	94.46
F1-score (%)	92.44	92.86	93.15	94.28

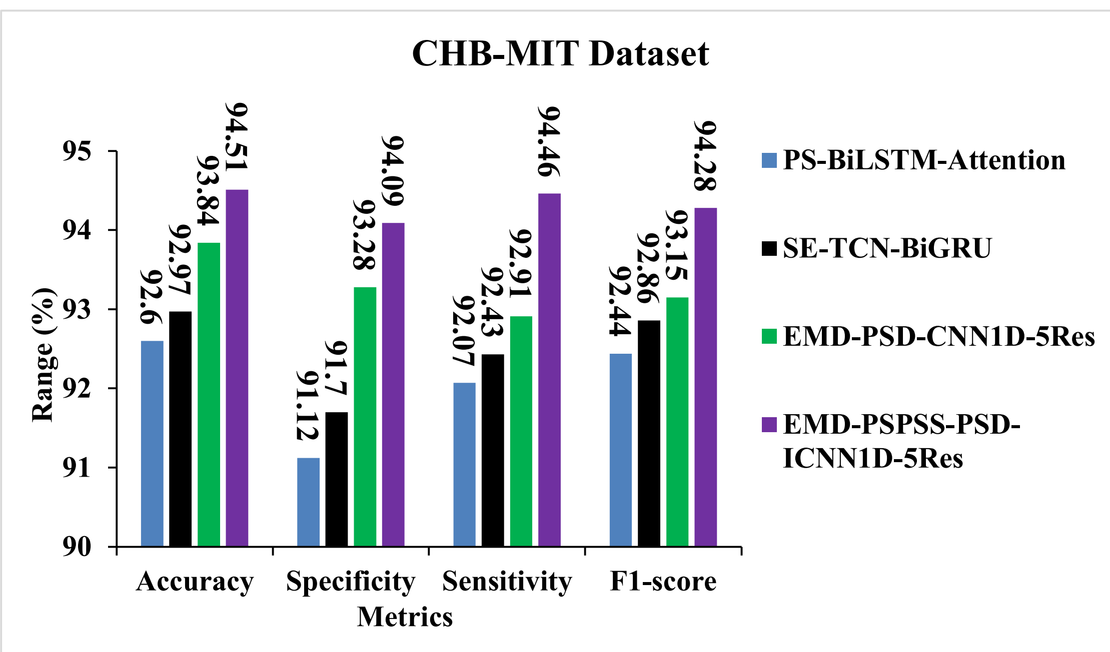

Figure 5 Performance analysis of proposed and existing models on CHB-MIT dataset

The ICNN1D-5Res model demonstrates superior results across key metrics, including Accuracy, Specificity, Sensitivity, and F1-Score. It achieves an Accuracy of 94.51%, outperforming PS-BiLSTM-Attention by 1.91%, SE-TCN-BiGRU by 1.54%, and EMD-PSD-CNN1D-5Res by 0.67%. Similarly, in Specificity, the model records 94.09%, showing an improvement of 2.97%, 2.39%, and 0.81% over PS-BiLSTM-

Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res, respectively. For Sensitivity, ICNN1D-5Res achieves 94.46%, surpassing PS-BiLSTM-Attention by 2.39%, SE-TCN-BiGRU by 2.03%, and EMD-PSD-CNN1D-5Res by 1.55%. Finally, compared to PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res, the model accomplishes an F1-Score of 94.28%, which is an improvement of 1.84%, 1.42%, and 1.13%, respectively. It is clear from these data that the ICNN1D-5Res model is the most trustworthy method for correctly diagnosing epileptic episodes, demonstrating its resilience and effectiveness.

Table 5 Comparison of proposed and existing models on Bonn EEG dataset

Metrics	PS-BiLSTM-Attention	SE-TCN-BiGRU	EMD-PSD-CNN1D-5Res	EMD-PSPSS-PSD-ICNN1D-5Res
Accuracy (%)	93.18	93.54	94.17	94.62
Specificity (%)	92.45	92.92	93.89	94.31
				6
				4

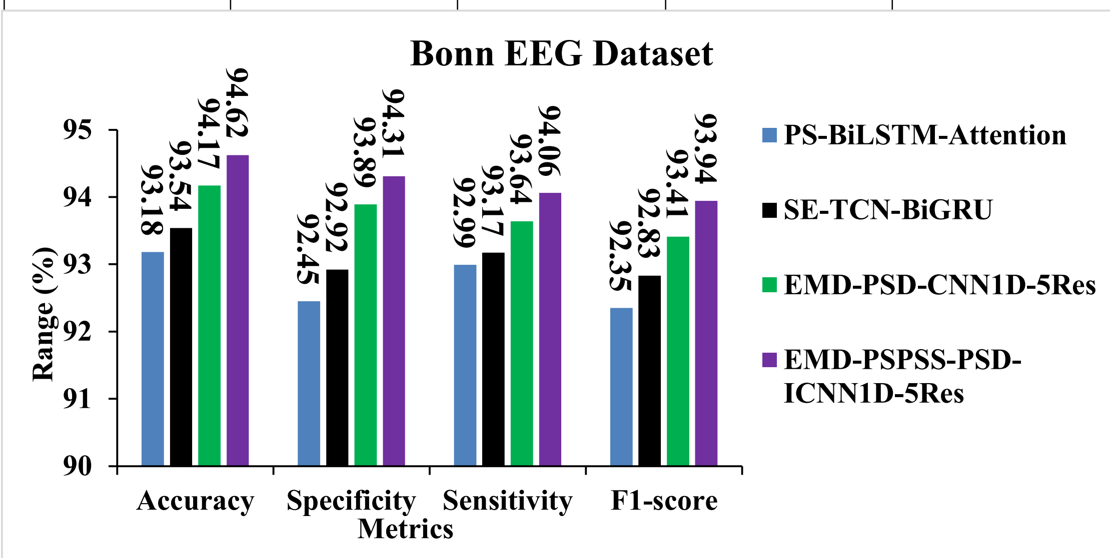

Figure 6 Performance analysis of proposed and existing models on Bonn EEG dataset

Figure 6, which show their respective performances: The Bonn EEG dataset was utilized by PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res. The ICNN1D-5Res model demonstrates superior results across key metrics, including Accuracy, Specificity, Sensitivity, and F1-Score. It achieves an Accuracy of 94.62%, outperforming PS-BiLSTM-Attention by 1.44%, SE-TCN-BiGRU by 1.08%, and EMD-PSD-CNN1D-5Res by 0.45%. In terms of Specificity, the model records 94.31%, showing an improvement of 1.86%, 1.39%, and 0.42% over PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res, respectively. For Sensitivity, ICNN1D-5Res achieves 94.06%, surpassing PS-BiLSTM-Attention by 1.07%, SE-TCN-BiGRU by 0.89%, and EMD-PSD-CNN1D-5Res by 0.42%. In conclusion, the model outperforms PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res with an F1-Score of 93.94%, 1.11%, and 0.53%, respectively. These findings prove that the ICNN1D-5Res model is the most trustworthy method for detecting epileptic seizures, demonstrating its resilience and effectiveness.

Table 6 Comparison of proposed and existing models on TUEP dataset

Metrics	PS-BiLSTM-Attention	SE-TCN-BiGRU	EMD-PSD-CNN1D-5Res	EMD- PSPSS - PSD-ICNN1D-5Res

Accuracy (%)	92.09	92.77	93.14	93.79
Specificity (%)	91.95	92.44	92.90	93.51
Sensitivity (%)	92.28	92.88	93.35	93.67
F1-score (%)	92.24	92.77	93.12	93.60

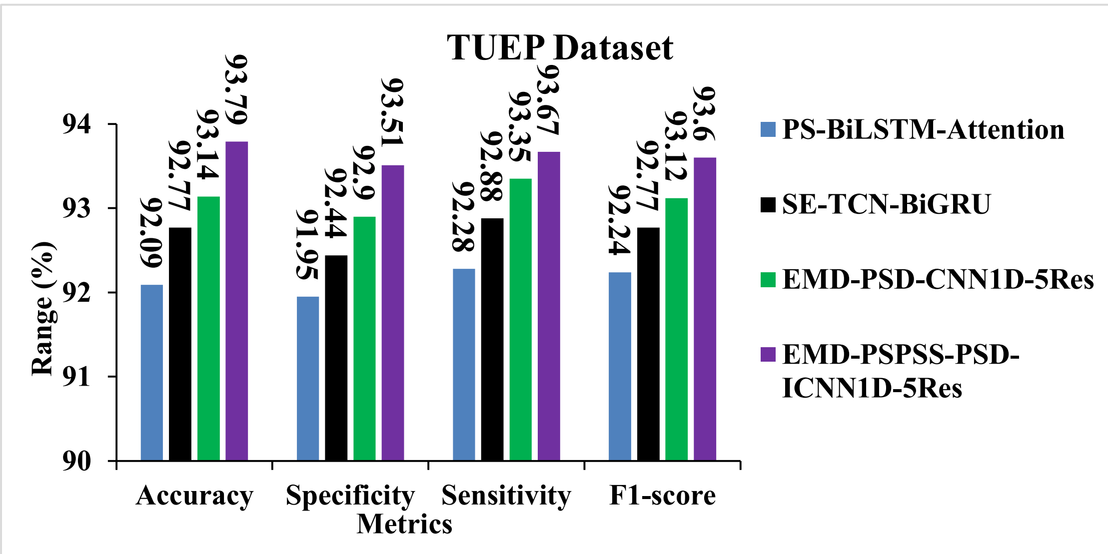

Figure 7 Performance analysis of proposed and existing models on TUEP dataset

Table 6 and Figure 7 shows how the suggested ICNN1D-5Res model compares in terms of performance with three other methods: PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res, evaluated using EEG datasets. The ICNN1D-5Res model exhibits superior performance across critical metrics, including Accuracy, Specificity, Sensitivity, and F1-Score. It achieves an Accuracy of 93.79%, which is 1.70% higher than PS-BiLSTM-Attention, 1.02% higher than SE-TCN-BiGRU, and 0.65% higher than EMD-PSD-CNN1D-5Res. For Specificity, the model attains 93.51%, surpassing PS-BiLSTM-Attention by 1.56%, SE-TCN-BiGRU by 1.07%, and EMD-PSD-CNN1D-5Res by 0.61%. In terms of Sensitivity, ICNN1D-5Res achieves 93.67%, which is 1.39%, 0.79%, and 0.32% higher than PS-BiLSTM-Attention, SE-TCN-BiGRU, and EMD-PSD-CNN1D-5Res, respectively. Finally, for F1-Score, the model records 93.60%, outperforming PS-BiLSTM-Attention by 1.36%, SE-TCN-BiGRU by 0.83%, and EMD-PSD-CNN1D-5Res by 0.48%. These results emphasize the effectiveness and robustness of the ICNN1D-5Res model, solidifying its position as a leading method for epilepsy seizure detection.

5. CONCLUSION

By improving upon prior machine learning models and overcoming the shortcomings of conventional EEG analysis, this study contributes significantly to the science of automated epilepsy detection. The proposed EMD-PSPSS-PSD-ICNN1D-5Res model, which incorporates PSPSS and STFT, enhances feature extraction from EEG signals, effectively overcoming poor generalization issues. Additionally, the introduction of the AGDEG optimization algorithm ensures efficient and stable model training. Comparative evaluations on CHB-MIT, Bonn EEG, and TUEP datasets demonstrate the robustness and superior performance of the proposed model, achieving accuracies of 94.51%, 94.62%, and 93.79%, respectively. These results establish the ICNN1D-5Res model as a reliable and effective solution for epileptic seizure detection, particularly in small dataset scenarios. The results of this study highlight the possibility of improving patient outcomes and diagnostic practices through the use of automated epilepsy diagnosis by incorporating cutting-edge feature extraction and optimization methods.

REFERENCES

[1] Havle, P. A., Pawar, J. M., & Mohite, R. V. (2024, May). Clinical and imaging correlates in the diagnosis and management of seizure disorders. In Obstetrics and Gynaecology Forum (Vol. 34, No. 3s, pp. 626-634).

[2] Operto, F. F., Pastorino, G. M., Viggiano, A., Dell'Isola, G. B., Dini, G., Verrotti, A., & Coppola, G. (2023). Epilepsy and cognitive impairment in childhood and adolescence: a mini-review. Current Neuropharmacology, 21(8), 1646-1665.

[3] Hossen, M. I., Tu, Y., & Hei, X. (2023, July). A first look at the security of EEG-based systems and intelligent algorithms under physical signal injections. In Proceedings of the 2023 Secure and Trustworthy Deep Learning Systems Workshop (pp. 1-8).

[4] Jahan, S., Nowsheen, F., Antik, M. M., Rahman, M. S., Kaiser, M. S., Hosen, A. S., & Ra, I. H. (2023). AI-based epileptic seizure detection and prediction in internet of healthcare things: a systematic review. IEEE Access, 11, 30690-30725.

[5] Y. Shin, S. Lee, M. Ahn, H. Cho, S. C. Jun, and H.-N. Lee, ''Noise robustness analysis of sparse representation based classification method for non-stationary EEG signal classification,'' Biomed. Signal Process. Control, vol. 21, pp. 8–18, Aug. 2015.

[6] S. Min, B. Lee, and S. Yoon, ''Deep learning in bioinformatics,'' Brief Bioinform., vol. 18, no. 5, pp. 851–869, 2016.

[7] G. E. Hinton and R. R. Salakhutdinov, ''Reducing the dimensionality of data with neural networks,'' Science, vol. 313, no. 5786, pp. 504–507, 2006.

[8] Y. Bengio, A. Courville, and P. Vincent, ''Representation learning: A review and new perspectives,'' IEEE Trans. Pattern Anal. Mach. Intell., vol. 35, no. 8, pp. 1798–1828, Aug. 2013.

[9] L. Vidyaratne, A. Glandon, M. Alam, and K. M. Iftekharuddin, ''Deep recurrent neural network for seizure detection,'' in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Jul. 2016, pp. 1202–1207.

[10] J. T. Turner, A. Page, T. Mohsenin, and T. Oates, ''Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection,'' presented at the AAAI Spring Symp., 2014.

[11] Y. Yuan, G. Xun, K. Jia, and A. Zhang, ''A multi-view deep learning method for epileptic seizure detection using short-time Fourier transform,'' presented at the 8th ACM Int. Conf. Bioinf., Comput. Biol., Health Inform., Boston, MA, USA, 2017.

[12] Pan, Y., Dong, F., Yao, W., Meng, X., & Xu, Y. (2024). Empirical mode decomposition for deep learning-based epileptic seizure detection in few-shot scenario. IEEE Access.

[13] Parija, S., Dash, P. K., and Bisoi, R. (2020). Multi-kernel-based random vector functional link network with decomposed features for epileptic EEG signal classification. IET Signal Process. 14, 162–174.

[14] Pan, Y., Zhou, X., Dong, F., Wu, J., Xu, Y., & Zheng, S. (2022). Epileptic Seizure Detection with Hybrid Time-Frequency EEG Input: A Deep Learning Approach. Computational and Mathematical Methods in Medicine, 2022(1), 8724536.

[15] Srinath, R., & Gayathri, R. (2022). Epilepsy disorder detection and diagnosis using empirical mode decomposition and deep learning architecture. Concurrency and Computation: Practice and Experience, 34(11), e6903.

[16] Ilias, L., Askounis, D., & Psarras, J. (2023). Multimodal detection of epilepsy with deep neural networks. Expert Systems with Applications, 213, 119010.

[17] Kaur, T., & Gandhi, T. K. (2023). Automated diagnosis of epileptic seizures using eeg image representations and deep learning. Neuroscience Informatics, 3(3), 100139.

[18] Kunekar, P., Gupta, M. K., & Gaur, P. (2024). Detection of epileptic seizure in EEG signals using machine learning and deep learning techniques. Journal of Engineering and Applied Science, 71(1), 21.

[19] Kumar, P. R., Shilpa, B., Jha, R. K., & Mohanty, S. N. (2023). A novel end-to-end approach for epileptic seizure classification from scalp EEG data using deep learning technique. International Journal of Information Technology, 15(8), 4223-4231.
[20] Tang, Y., Wu, Q., Mao, H., & Guo, L. (2024). Epileptic seizure detection based on path signature and bi-LSTM network with attention mechanism. IEEE Transactions on Neural Systems and Rehabilitation Engineering.
[21] Zhu, P., Zhou, W., Cao, C., Liu, G., Liu, Z., & Shang, W. (2024). A Novel SE-TCN-BiGRU Hybrid Network for Automatic Seizure Detection. IEEE Access.