

Electroencephalography-based epileptic seizure classification using a sparse iterative recursive-gated recurrent unit

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ABSTRACT

Epileptic seizure classification using electroencephalography (EEG) plays a significant role in clinical diagnosis, long-term patient monitoring, and treatment planning. However, accurate seizure classification remains challenging due to its high complex and non-stationary nature of brain signal, which leads to misdiagnosis. This research proposes a sparse iterative recursive (SIR)-gated recurrent unit (GRU) to classify epileptic seizures accurately. By incorporating GRU into SIR, the model effectively learns and retains significant temporal patterns in EEG signals over long sequences. The gated structure minimizes the vanishing gradient, resulting in effective learning from sequential seizure patterns. Sparsity and recursion enhance the feature representation with lesser computational complexity for accurate seizure classification. Time- and frequency domain feature extract with sparsity and iterative recursion enables the model to selectively concentrate on seizure relevant temporal patterns, which minimizes redundant and noisy information. Hence, SIR-GRU achieves higher accuracies of 99.75% and 99.54% on the Bonn EEG as well as Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) dataset, respectively, compared to the existing method including spatio-temporal feature fusion dual attention (STFFDA). These findings indicate that SIR-GRU provides rapid and reliable performance, which improves accuracy in clinical practice.

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1. INTRODUCTION

According to a report by the World Health Organization (WHO), epilepsy is the second most prevalent primary neurological disorder after stroke. Epilepsy affects approximately 1% of the global population and individuals of all ages and backgrounds, while posing challenges to quality of life, thereby emphasizing the need of accurate detection for effective treatment and management [1]. Typically, epileptic seizures are represented by sharp and spike-wave patterns in electroencephalography (EEG) signals. Additionally, the epilepsy diagnosis involves a detailed EEG evaluation by medical staff, which compares data with patient symptoms to identify abnormal brain activity [2]. EEG is non-invasive and records the

brain's electrical activity by measuring voltage fluctuations generated by ionic currents of neurons that capture the brain's bioelectrical signals [3]–[5]. Furthermore, non-focal and focal epilepsy are the two categories of epilepsy. In focal epilepsy, only a certain region or one hemisphere of the brain is affected [6], whereas non-focal epilepsy affects diverse brain regions, even those which are not directly involved in seizure activity.

Various seizure detection methods have been developed by employing classical signal-processing methods [7]. The overall process has three primary stages: preprocessing, feature extraction, and classification that differentiate between seizure and non-seizure [8], [9]. Moreover, inter-patient significantly complicates the diagnostic process and affects external factors [10]. Recent advancements in artificial intelligence (AI), especially through machine learning (ML) [11] and deep learning (DL) [12], [13] offers a significant approach to solve these challenges effectively. These technologies significantly improve clinicians' workloads, while enhancing diagnostic accuracy and efficiency in classifying epileptic seizures [14], [15]. DL is chosen over ML because it automatically extracts high-level and complex features without the need for manual feature engineering [16]. This greatly reduces human intervention and ensures that the learned features are more discriminative and representative [17], [18]. Unlike ML, which is based on domain expertise for designing features, DL learns hierarchical feature representations directly from the data, which enhances scalability, accuracy, and adaptability over different and complex datasets by developing an efficient seizure detection system [19], [20].

Pandey *et al.* [21] established a hybrid convolutional neural network (CNN) with long short-term memory (LSTM) to classify epileptic seizures that used EEG signals. In CNN-LSTM, the processes of feature extraction, selection, and classification were performed to eliminate the requirement for handcrafted feature extraction. Huang *et al.* [22] developed spatio-temporal feature fusion dual attention (STFFDA) to classify epileptic seizures. Initially, spatio-temporal fusion enabled CNN to capture spatial features and channel weights, whereas, bidirectional long short-term memory (BiLSTM) effectively captured temporal dependencies. This feature representation increased the model's capability to distinguish between normal EEG patterns and epileptic seizures using CNN, whereas BiLSTM adapted to diverse EEG channel data.

Ahmad *et al.* [23] suggested a bagged tree-based classifier (BTBC) and explainable artificial intelligence (XAI) to detect epileptic seizures. At first, a Butterworth filter was used to remove different artifacts and a discrete wavelet transform (DWT) was employed to decompose EEG signals to extract different eigenvalue features. Optimal features were then determined by correlation coefficient and distance coefficient evaluation. The selected discriminative features were fed into BTBC for classification. Rani and Kavitha [24] presented an LSTM with a zebra optimization algorithm (ZOA) for hyperparameter tuning to classify epileptic seizures. Features such as frequency, statistics, entropy, multiscale wavelet, and power spectrum were extracted from the signal decomposition. Subsequently, the extracted features were fed into hyperparameter tuning, which used ZOA with LSTM after feature selection.

Prasanna *et al.* [25] introduced a brain epilepsy seizure detection network (BESD-Net) by employing a CNN with a recurrent neural network (RNN)-BiLSTM. A customized CNN was trained on pre-processed data to extract features, and an exhaustive random forest (ERF) selected the features that were greatly correlated with disease-dependent properties. Finally, the RNN with BiLSTM effectively detected seizures. Zhu *et al.* [26] presented a squeeze and excitation (SE)-temporal convolutional network (TCN)-bidirectional gated recurrent unit (BiGRU) for seizure detection. An attention mechanism assigned weight to each input channel, thereby indicating the channel that exhibited more discriminative and seizure-relevant features. Then, the TCN extracted weight features and transmitted directly into BiGRU to learn long-term relevant data. Finally, fully connected (FC) predicted seizure possibility based on the BiGRU output. Kumar *et al.* [27] established a BiLSTM model for classified epileptic seizures. BiLSTM effectively classified epileptic seizures by distinguished seizure from non-seizure data, which reduced the computational burden. Sun *et al.* [28] introduced a multi-input deep feature learning network (MDFLN) by considering features from time-frequency (TF) and time domains using EEG signals. MDFLN extracted features automatically and BiLSTM distinguished between non-seizure and seizure events. The introduced method minimized time consumption, which effectively helped the expert to diagnose clinical and treatment issues.

From the overall evaluation, the existing methods have a research gap, such as higher computational complexity, difficulty in capturing temporal patterns, and feature redundancy. In addition, accurately classified epileptic seizures from EEG signals remained a challenge due to the complex and non-stationary nature of brain signals. To overcome this issue, a sparse iterative recursive (SIR)-gated recurrent unit (GRU) was proposed to classify epileptic seizures accurately by sparsity and iterative recursive mechanisms in GRU selectively processed only the most informative neurons. This selective refinement decreased redundant computations and concentrated the learning on seizure-relevant temporal features. As a result, the model attained efficient training, lesser complexity, and improved accuracy in classifying epileptic seizures.

A major contribution of this research is as follows:

- i) GRU captures long-term dependencies with fewer parameters than LSTM, which enables rapid convergence, lesser computational complexity, and stable learning for sequential analysis.
- ii) SIR mechanism updates informative hidden states and minimizes redundant activation, which enhances feature discrimination, improves robustness to noise, and solves overfitting by concentrating on salient temporal patterns.
- iii) Time-domain features such as mean, variance, kurtosis, and skewness capture statistical and amplitude variations in EEG signals. Frequency-domain features, including fast fourier transform (FFT) captures spectral information that enables the comprehensive characterization of seizure patterns for accurate classification.

This research paper is structured as follows. Section 2 illustrates the proposed method. Section 3 represents the research method. Section 4 analyzes the results with discussion. Lastly, section 5 summarizes the conclusion.

2. PROPOSED METHOD

This research proposed SIR-GRU to effectively classify epileptic seizures. Initially, the Bonn EEG and Children's Hospital Boston-Massachusetts Institute of Technology (CHB-MIT) datasets are used to evaluate the efficiency of the proposed method. The gathered EEG signals underwent a filtering process using 8th order Butterworth filter to remove unwanted noise. Furthermore, time-domain and frequency-domain methods are used to extract the features from the pre-processed signal. Finally, the proposed SIR-GRU used to classify the epileptic seizures accurately. Figure 1 illustrates a block diagram of the proposed epileptic seizure classification method that utilizes the EEG signal, which represents the flow from the dataset, pre-processing, feature extraction, and classification.

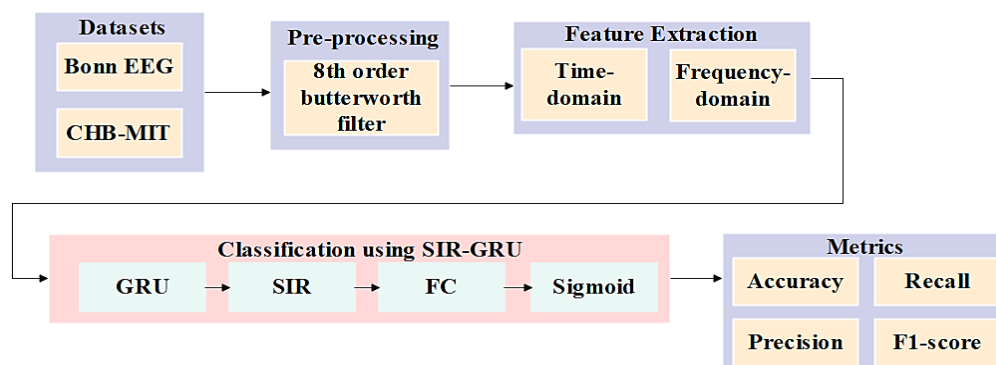


Figure 1. Block diagram of the proposed epileptic seizure classification method using EEG signal

2.1. Dataset

In this research, Bonn EEG [22] and CHB-MIT [23] are used to evaluate the model performance. The UCI-EEG [23] dataset is used to evaluate the generalization performance of the proposed method. Bonn EEG is gathered from five patients and classified it into five sets labeled as (A) to (E), which has 100 single-channel EEG signals acquired over 23.6 seconds. Bonn EEG dataset contains 4097 samples with a 173.61 Hz sampling rate. CHB-MIT dataset consists of multichannel EEG signals from 23 patients of Children's Hospital in Boston. All EEG signals are sampled at a 256 Hz sampling rate with 16-bit resolution and the recordings are gathered by utilizing scalp electrodes based on the international 10-20 system. UCI-EEG dataset is gathered from five subjects, which has 100 files with 4097 data points recorded over 23.5 seconds. All samples presented in this dataset are split into 23 chunks with one second of EEG signal. Table 1 presents a detailed description of the Bonn EEG and CHB-MIT datasets, and the signals are fed into the preprocessing stage, which emphasizes characteristics and relevance for epileptic seizure classification.

Table 1. Detailed description of Bonn EEG and CHB-MIT

Datasets	No. of patients	Channels	Sampling rate (Hz)
Bonn EEG	5	Single-channel	173.61
CHB-MIT	23	Multi-channel	256

2.2. Pre-processing

The gathered EEG signal underwent a filtering process to eliminate noise and artifacts introduced by electromyography (EMG), limb movements, and eye blinking during recording. The 8th-order Butterworth filter is selected due to EEG signals are affected by power-line interference and high-frequency noise produced from muscle movements and recording equipment. This filter provides a flat passband response with attenuation after the cutoff frequency which preserves EEG information and eliminates unwanted noise. Compared to lower-order filters, the 8th-order Butterworth filter provides better noise suppression with less signal distortion. Hence, it enhance the quality of EEG signals for accurate seizure classification. To enable clean and reliable signals, an 8th-order Butterworth filter [24] is used with a cutoff frequency of 60 Hz at -3 dB to minimize both the electrical and high-frequency noise components. The sampling frequency of the EEG recording is employed to normalize the cutoff frequency. A higher-order filter is chosen for its ability to provide robust attenuation beyond the desired bandwidth, which ensures minimal distortion in the passband. The continuous response of the 8th-order Butterworth filter is formulated in (1), which represents the frequency characteristics and stability.

$$G^2(\omega) = \frac{G_0^2}{1 + \left(\frac{j\omega}{j\omega_c}\right)^{2n}} \quad (1)$$

Where G_0 is the direct current gain, ω_c is the cutoff frequency, n is the filter order, ω is the angular frequency of the input signal, and j is the imaginary part. This effectively suppresses unwanted noise while retaining significant EEG signals for accurate classification of epileptic seizures. The pre-processed outputs are passed through the feature extraction stage using time-domain and frequency-domain methods.

2.3. Feature extraction

After pre-processing, both the time-domain and frequency-domain features are extracted to capture spectral characteristics of the EEG signals. Time-domain features, such as variance, mean, kurtosis, and skewness, are selected due to effectively describe the statistical properties and amplitude variations of EEG signals. These features assist to capture changes in signal distribution and enable rapid model training. Hence, the time-domain feature offer informative characteristics for distinguishing seizure and non-seizure EEG signals. Moreover, frequency-domain features include FFT that is used to provide the spectral components of the EEG signals. Handcrafted features are utilized instead of DL method because EEG signals are high on-stationary, noisy, and limited in size, which degrade end-to-end DL learning. FFT transforms the EEG signal from the time domain into frequency domain which enable seizure-related spectral components easier to identify. FFT effectively extracts frequency information with low computational complexity compared to other spectral analysis methods. Therefore, FFT method provides spectral features that help to improve seizure detection accuracy. This feature engineering methods minimizes dimensionality and noise resulting in stable as well as rapid convergence. A detailed explanation of these methods are provided as follows.

2.3.1. Time-domain

Mean measures the average of all EEG segments depending on the information generated by the intrinsic mode function (IMF) using (2). Variance calculates the degree deviation of the EEG segment from the mean value using (3). Kurtosis method is employed for locating peak points in EEG data using (4). Skewness is a measuring rate at which the EEG signals shift using (5).

$$\mu_t = \frac{1}{N} \sum_{i=1}^N (x_i) \quad (2)$$

$$\sigma_t^2 = \frac{1}{N} \sum_{i=1}^N (x_i - \mu_t)^2 \quad (3)$$

$$K_t = E \left[\left(\frac{x_i - \mu_t}{\sigma_t} \right)^4 \right] \quad (4)$$

$$\beta_t = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i - \mu_t}{\sigma_t} \right)^3 \quad (5)$$

Where σ denotes the standard deviation, N denotes the IMF length, μ represents the mean of the IMF, μ_t is the mean at time t , σ_t^2 is the standard deviation at time t , K_t is the kurtosis at time t , and β_t is the skewness at time t .

2.3.2. Frequency-domain

The FFT is used to transform EEG signals from the time domain to the frequency domain, which enables the identification of spectral components related to epileptic activity. FFT effectively enhances the model's ability to discriminate between seizure and non-seizure EEG segments. From the resulting frequency spectrum, the primary spectral features, such as spectral power, dominant frequency, and band-specific energy, are computed. These frequency domain features capture the EEG signal behavior, which is indicative of seizure activity. Finally, the extracted features are compiled into a feature vector that acts as an input for the classification method, thereby enabling effective discrimination between both seizure and non-seizure EEG patterns.

3. RESEARCH METHOD

After extracting the features, SIR-GRU is used to classify epileptic seizures by focusing on the most informative temporal dependencies. The proposed SIR-GRU is selected due to EEG signals contain complex temporal patterns and accurately learning these sequential relationships is significant to distinguish seizure and non-seizures. GRU [29] effectively capture these temporal dependencies with fewer parameters than LSTM which leads to rapid training and lower computational complexity. The introduced SIR mechanism eliminates irrelevant features by minimizing noise. Therefore, SIR-GRU achieves more feature learning and high seizure classification accuracy than the traditional GRU method. Figure 2 demonstrates layer diagram of the proposed SIR-GRU and its explanation, which shows that temporal and frequency-domain features are processed with sparsity and a recursive mechanism for epileptic seizure classification.

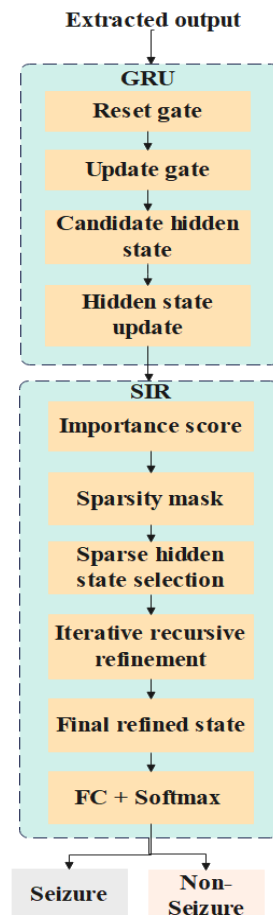


Figure 2. Layer-wise diagram of the proposed SIR-GRU

GRU: it effectively captures long-term dependencies with fewer gates and minimizes vanishing gradient issues, which leads to lower computational costs and rapid training compared to the RNN and

LSTM. This balances efficiency and model performance, which makes the GRU appropriate for classifying epileptic seizures. In a conventional GRU, the hidden state h_t at time step t is processed using reset gate r_t and update gate z_t , which is expressed in (6) and (7). The reset gate is used for regulating the influence of the hidden state from prior time step h_{t-1} using (8), whereas the candidate hidden state $\tilde{h}_t$ is formulated in (9).

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (6)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (7)$$

$$\tilde{h}_t = \tanh(W_h x_t + r_t \odot (U_h h_{t-1}) + b_h) \quad (8)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (9)$$

Where x_t represents input at present time step, W_z, W_r, U_r, U_z, W_h determines weight, b_r, b_h indicates bias, σ demonstrates activation function, and $\odot$ denotes element-wise multiplication.

SIR: GRU output is fed into SIR, where it undergoes sparse recursive refinement to concentrate on the most informative neurons. This selective updating enhances seizure-associated features, which increases classification accuracy and minimizes computational overhead. The standard recursive mechanism continuously updates all hidden neurons, including irrelevant features, which increases the computational cost. To solve this issue, SIR introduces selective updates during recursion, which enhances efficiency and concentrates learning on epileptically relevant dynamics. The mathematical formula for recursive SIR is given in (10) and (11).

$$x_b = G \left(G \left(\dots \left(G(f_b(x_{b-1})) \right) \dots \right) \right) \quad (10)$$

$$x_b^{(k+1)} = x_b^{(k)} + M_b \odot G(x_b^{(k)}) \quad (11)$$

Where $f_b(x_{b-1})$ indicates the transformed input of $(b-1)$ block, $G(.)$ determines the GRU function, M_b denotes sparse, and k denotes recursive iterations. A sparsity mask M_b is generated using (12) based on the magnitude of GRU hidden state activation to minimize redundancy and noisy activation. Where τ demonstrates a sparsity threshold, h_t represents the hidden state at time step t , $M_b(i) = 1$ determines i^{th} neuron is active, and $M_b(i) = 0$ represents the neuron is not updated. Activation below τ are suppressed to enforce structured sparsity by preserving salient temporal features. The mask is iteratively refined for k iterations, which is formulated in (13) to stabilize sparsity patterns and avoid abrupt information loss.

$$M_b(i) = \begin{cases} 1, & \text{if } |h_t(i)| > \tau \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

$$x_b = x_b^{(k)} \odot M_b \quad (13)$$

The sparsity mechanism contributes better performance by selectively activating only seizure relevant neurons, which minimize noisy signals. This decreases redundant feature updates and avoids inappropriate background activity from the learning process. By concentrating GRU on salient temporal patterns, sparsity improves discriminative learning and robustness. Moreover, it solves overfitting by limiting unwanted neuron co-adaptation, which leads to improve generalization. The hyperparameters $k = 5$ recursive iterations and the sparsity threshold $\tau = 0.02$ are selected to balance performance and computational efficiency. Fewer iterations $k < 5$ results insufficient refinement of salient temporal features, which leads to underfitting higher values $k > 5$, also provide marginal accuracy and gains the cost of increasing computation. Similarly, sparsity threshold τ manage retention of informative neuron activation; higher values retained redundant activation while lower values cause excessive sparsification and loss of seizure relevant information. The selected $\tau = 0.02$ offers optimal trade-off among feature preservation and noise suppression. Thus, $k = 5$ and $\tau = 0.02$ are employed to provide stable convergence and superior validation performance across dataset. The hyperparameter values are chosen based on grid search to determine the optimal configuration for seizure classification. Adam optimizer is used due to effective and adaptive gradient updates, whereas the tanh activation function effectively modeled nonlinear temporal dependencies. The 0.0001 learning rate ensures stable convergence and the 0.5 dropout rate prevents overfitting by regularizing the model. The categorical cross-entropy loss function measures the difference between predicted and true class probabilities. Training over 100 epoch assist to attain stable convergence of loss function. Integrating

SIR in the GRU selectively refines only the seizure-relevant neurons across recursive iterations. This enables effective learning, enhances robustness, and robust feature discrimination in the classification of epileptic seizures. Algorithm 1 provides the pseudocode for the proposed methodology to ensure reproducibility and Table 2 represents notation and records all the symbols, variables, and descriptions employed in the proposed seizure classification for better clarity.

Algorithm 1. Proposed SIR-GRU

```

Input: EEG signal datasets  $D$ 
Output: seizure classification result
Step 1: dataset and pre-processing
Load datasets  $D = \{\text{Bonn EEG, CHB-MIT}\}$ 
For each EEG signal  $x$  in  $D$  do
     $x_{\text{filtered}}$  = Butterworth filter ( $x$ , order = 8, cutoff = 60 Hz)
    Store  $x_{\text{filtered}}$ 
End For
Step 2: feature extraction
For each  $x_{\text{filtered}}$  in  $D$  do
    i) Compute time domain features
    ii) Determine frequency-domain features
    iii) Concatenate time domain and frequency domain features
    iv) Store feature vector
End for
Step 3: classification
i) Initialize hidden state  $h_t$ 
ii) Set number of recursive iterations  $k=5$  and set sparsity threshold  $\tau = 0.02$ 
For each feature vector in sequence do
    i) Utilize GRU to learn long-range dependencies using reset gate, update gate,
        candidate activation, and hidden state update
    ii) Sparse iterative recursion
        For  $r=1$  to  $R$  do
            Compute importance =  $|h_t|/\max(|h_t|)$ 
            Generate sparsity mask = (importance >  $\tau$ )
            Refine hidden state  $h_t = h_t \odot M_b$ 
        End for
    iii) Apply softmax for final classification
    iv) Obtain seizure class label
End for
Return  $y$ 

```

Table 2. Notation table for symbols, variables, and descriptions in seizure classification

Symbols	Description	Symbols	Description
G_0	direct current gain	z_t	update gate
ω_c	cutoff frequency	h_{t-1}	hidden state from prior time step
n	filter order	$\hat{h}_t$	candidate hidden state at the present time step
ω	angular frequency of the input signal	x_t	input at present time set
j	imaginary part	W_z, W_r, U_r, U_h, W_h	weight
σ	standard deviation,	b_r, b_h	bias
N	IMF length	σ	activation function
μ	mean of the IMF	$\odot$	element-wise multiplication
μ_t	mean at time t	$f_b(x_{b-1})$	transformed input of $(b-1)$ block
σ_t^2	standard deviation at time t	$G(\cdot)$	GRU function
K_t	kurtosis at time t	M_b	sparse
β_t	skewness at time t	k	recursive iterations
h_t	hidden state at time step t	M_b	sparsity mask
r_t	reset gate	τ	sparsity threshold

4. RESULTS AND DISCUSSION

The proposed SIR-GRU is simulated using the MATLAB 2020 environment with Intel i5 processor, 64 GB random access memory (RAM), and Windows 10 operating system. The system has libraries, such as Keras 3.4.1, TensorFlow 2.17.0, TorchVision 0.19.1+cu121, PyTorch 2.4.1+cu121, Pandas 2.1.4, NumPy 1.26.4, OpenCV-Python 4.10.0, scikit-learn 1.2.2, SciPy 1.13.1, Matplotlib 3.7.1, and OpenCV (cv2) version: 4.10.0. The baseline methods used in section 4.1 and 4.2 are reimplemented based on proposed method settings like hyperparameters, pre-processing methods, and feature extraction methods to ensure fair

comparison. Moreover, existing method values are directly adopted from respective papers to ensure reproducibility. Accuracy, precision, Matthews correlation coefficient (MCC), specificity, recall, and F1-score are used to calculate model performance using (14) to (19). Where TN is demonstrates a true negative, FP indicates a false positive, TP represents a true positive, and FN denotes a false negative.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (14)$$

$$\text{Precision} = \frac{TP}{TP+FP} \times 100 \quad (15)$$

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \times 100 \quad (16)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100 \quad (17)$$

$$\text{Recall} = \frac{TP}{TP+FN} \times 100 \quad (18)$$

$$\text{F1-score} = \frac{2TP}{2TP+FP+FN} \times 100 \quad (19)$$

4.1. Performance analysis

Table 3 demonstrates the performance analysis of different classification methods applied for epileptic seizures, which demonstrates superior accuracy and robustness of proposed method. Compared to existing methods, such as vision transformer (ViT), LSTM, GRU, CNN, LSTM, CNN + LSTM, and adversarial spatio-temporal attention network (STAN), the proposed SIR-GRU achieves higher accuracy of 99.75% and 99.54% on the Bonn EEG as well as CHB-MIT dataset, respectively, owing to its ability to capture long-term temporal dependencies, which minimizes redundant information via sparsity. The iterative recursive mechanism enables progressive feature refinement across multiple passes, which enhances the discrimination between seizure and non-seizure patterns. Moreover, GRU's gated structure enables effective gradient flow, which preserves significant temporal correlations. Hence, the integration of sparsity and recursion enhances the robustness of the seizure classification.

Table 3. Performance analysis of different classification methods applied for epileptic seizure

Datasets	Methods	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
Bonn EEG	ViT	88.48	85.58	86.15	85.03	84.28	85.17
	LSTM	90.75	88.33	88.20	88.47	85.31	86.03
	GRU	92.36	91.15	90.48	91.85	88.06	88.62
	CNN	93.40	91.44	91.05	91.85	91.96	89.30
	LSTM	94.26	91.99	91.85	92.15	92.30	90.12
	CNN + LSTM	95.63	93.01	92.36	93.68	93.48	91.78
	STAN	95.89	93.89	93.78	94.02	94.08	92.38
	SIR-GRU	99.75	99.49	99.51	99.49	99.52	95.78
CHB-MIT	ViT	86.30	85.33	84.30	86.39	85.03	89.36
	LSTM	89.48	85.42	86.87	84.02	89.31	92.38
	GRU	92.36	92.80	93.26	92.36	93.68	95.63
	CNN	93.89	93.36	93.85	92.89	93.89	95.87
	LSTM	94.02	93.51	94.02	93.02	94.05	96.02
	CNN + LSTM	95.63	94.00	94.56	93.45	95.36	96.87
	STAN	95.87	94.94	95.03	94.87	95.89	96.96
	SIR-GRU	99.54	99.18	99.15	99.23	98.84	99.50

Table 4 presents the ablation study, which provides performance evaluation for each component in the proposed method. This table represents the impact of sparsity, recursion, and feature integration on classification performance. Compared to recursive-gated recurrent unit (R-GRU), iterative recursive-gated recurrent unit (IR-GRU), and raw EEG + SIR-GRU, the proposed SIR-GRU obtains higher accuracy by integrating the sparsity mechanism that eliminates redundant performance and concentrates on salient temporal features. This selective feature refinement improves representation learning from EEG signals. Moreover, iterative recursive further enhances the temporal pattern dependencies, thereby achieving superior performance.

Table 4. Ablation study showing individual contribution of each component in the proposed method

Datasets	Methods	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
Bonn EEG	R-GRU	89.48	87.62	88.23	87.03	89.61	91.25
	IR-GRU	91.56	89.89	90.48	89.32	92.65	93.84
	Raw EEG + SIR-GRU	95.08	93.01	92.15	93.89	94.28	94.06
	Handcrafted + SIR-GRU	99.75	99.49	99.51	99.49	99.52	95.78
CHB-MIT	R-GRU	92.36	90.97	89.36	92.64	93.48	92.48
	IR-GRU	95.78	93.85	92.38	95.37	95.36	93.73
	Raw EEG + SIR-GRU	96.32	95.79	94.80	96.82	97.03	95.02
	Handcrafted + SIR-GRU	99.54	99.18	99.15	99.23	98.84	99.50

Table 5 illustrates the evaluation of the computational complexity and statistical analysis, which demonstrates effectiveness and reliability for EEG-based seizure classification. The proposed SIR-GRU requires lesser training time of 196 s and 205 s on the Bonn EEG and CHB-MIT datasets, respectively, because the sparsity mechanism minimizes unnecessary neuron activation and computations. Although SIR-GRU utilize an iterative recursive mechanism, the number of iterations is fixed as $k = 5$, and the sparsity mechanism minimizes the number of active neurons during training. Moreover, analysis of params, training time, inference time, and memory consumption shows that the SIR-GRU attains superior accuracy with lesser computational complexity, which makes appropriate for large-scale applications. The p-value from McNemar's test is determined statistically by verifying whether the difference in classification performance among existing and proposed method is significant. Since, this analysis operates on paired prediction results, which is appropriate for evaluating the enhancement in classification tasks using the same test samples.

Table 5. Evaluation of computational complexity and statistical analysis for the proposed method

Datasets	Methods	Training time (s)	Inference time (s)	Memory consumption (MB)	Params (millions)	p-value from t-test	p-value from McNemar's test	Floating point operations (s)
Bonn EEG	ViT	269	236	325	24.68	32.06	0.041	187.26
	LSTM	241	225	304	22.79	30.48	0.038	175.68
	GRU	228	203	294	21.78	29.25	0.035	163.29
	CNN	221	214	285	23.58	28.36	0.033	175.36
	LSTM	219	208	274	25.36	27.36	0.031	179.05
	CNN + LSTM	248	221	296	29.05	32.05	0.039	185.36
	STAN	231	203	263	27.35	31.05	0.026	181.58
	SIR-GRU	196	185	256	18.36	25.39	0.012	143.89
	ViT	296	247	326	30.45	29.45	0.043	163.54
	LSTM	248	221	315	28.36	28.48	0.039	157.64
CHB-MIT	GRU	236	203	254	25.41	26.34	0.036	149.36
	CNN	241	221	265	26.87	28.36	0.034	151.02
	LSTM	248	214	278	28.05	30.35	0.032	153.87
	CNN + LSTM	256	263	296	29.63	31.54	0.037	156.68
	STAN	220	258	281	31.25	33.89	0.029	159.38
	SIR-GRU	205	198	202	21.56	23.15	0.025	141.74

Table 6 presents a performance evaluation of the proposed method using k-fold validation for the classification of epileptic seizures, which shows consistency over different datasets. The k-fold validation obtains higher accuracy owing to the optimal balance between variance and bias. Therefore, the $k = 3$ model attains higher bias because of limited training data, whereas $k = 7$ and 9 increase the variance and computational cost. Thus, $k = 5$ ensures sufficient training data per fold, which results in reliable and stable performance.

Figure 3 illustrates confusion matrix of the proposed SIR-GRU for the classification process, where Figure 3(a) corresponds to Bonn EEG and Figure 3(b) corresponds to the CHB-MIT dataset. This figure shows accurate and misclassifications across seizure and non-seizure classes. For Bonn EEG, the model achieves better classification over five classes (A-E), with misclassification in class C. In the CHB-MIT dataset, the model accurately distinguished between the normal, preictal, and ictal states with lower misclassification rates. These matrices represent the model's robust ability to capture both long- and short-term temporal patterns. As a result, the model achieves robustness and higher reliability of SIR-GRU for classifying epileptic seizures over the two dataset.

Table 6. Performance evaluation of the proposed method using k-fold validation for seizure classification

Datasets	k-fold	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
Bonn EEG	k = 3	87.45	85.87	85.36	86.39	89.48	51.96
	k = 5	99.75	99.49	99.51	99.49	99.52	61.78
	k = 7	89.36	89.62	89.48	89.78	92.36	53.69
	k = 9	92.56	93.57	93.58	93.57	95.48	56.48
CHB-MIT	k = 3	89.47	89.40	89.45	89.36	91.58	84.29
	k = 5	99.54	99.18	99.15	99.23	98.84	99.50
	k = 7	92.65	92.57	92.68	92.48	93.58	92.36
	k = 9	94.28	95.28	95.89	94.68	95.79	95.84

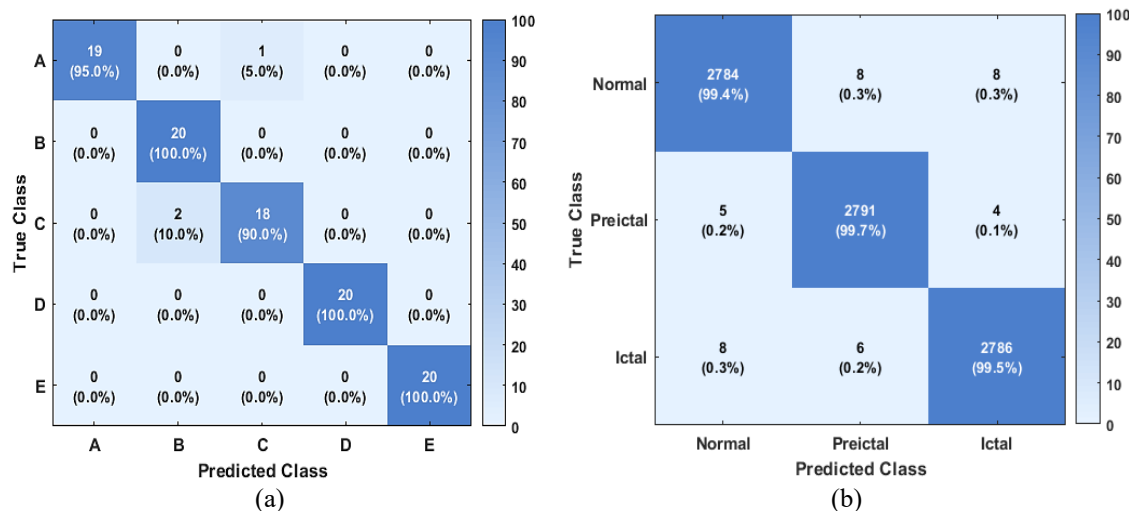


Figure 3. Confusion matrix of the classification performance of the proposed method: (a) Bonn EEG and (b) CHB-MIT dataset

Figure 4 depicts the analysis of the receiver operating characteristic (ROC) curve for the proposed seizure classification method, where Figure 4(a) corresponds to Bonn EEG and Figure 4(b) corresponds to CHB-MIT dataset. Figure 4 shows the model's discriminative ability and reliability. The Bonn EEG curves associated with different classes (A to E), which obtains better classification performance with area under the curve (AUC), which provides higher TP in over all classes. Similarly, the ROC curve for normal, preictal, and ictal classes exhibited higher AUC values, which represent the robustness of the model in differentiating among seizure states. As a result, the proposed method achieved accurate seizure classification across both datasets.

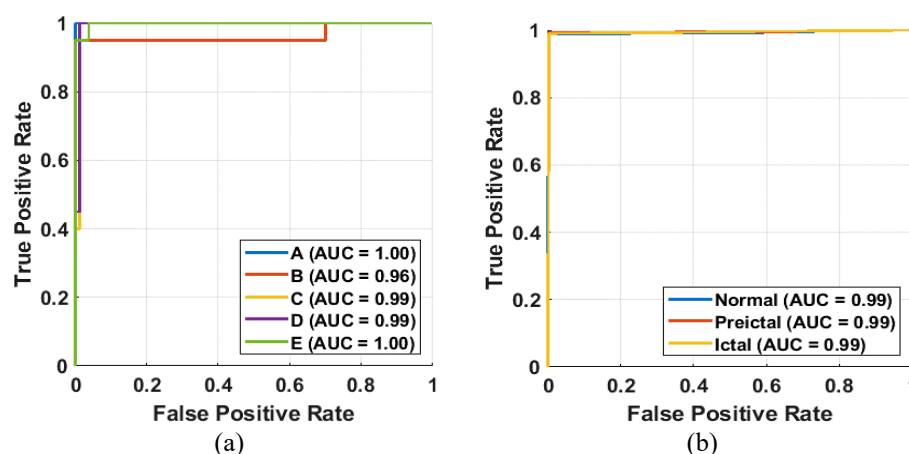


Figure 4. Analysis of ROC curve for proposed seizure classification method: (a) Bonn EEG and (b) CHB-MIT

Figure 5 provides the visualization of gradient-weighted class activation mapping++ (Grad CAM++), which represents discriminative EEG regions and temporal behavior learned by SIR-GRU for classification, where Figure 5(a) corresponds to Bonn EEG and Figure 5(b) corresponds to CHB-MIT. High-activation regions align with amplitude variations represent efficient localization of discriminative seizure-related patterns. Lower attention with lesser informative indicates suppression for redundant temporal signal. This represents the model's ability to learn robust and meaningful representations to classify accurate seizure.

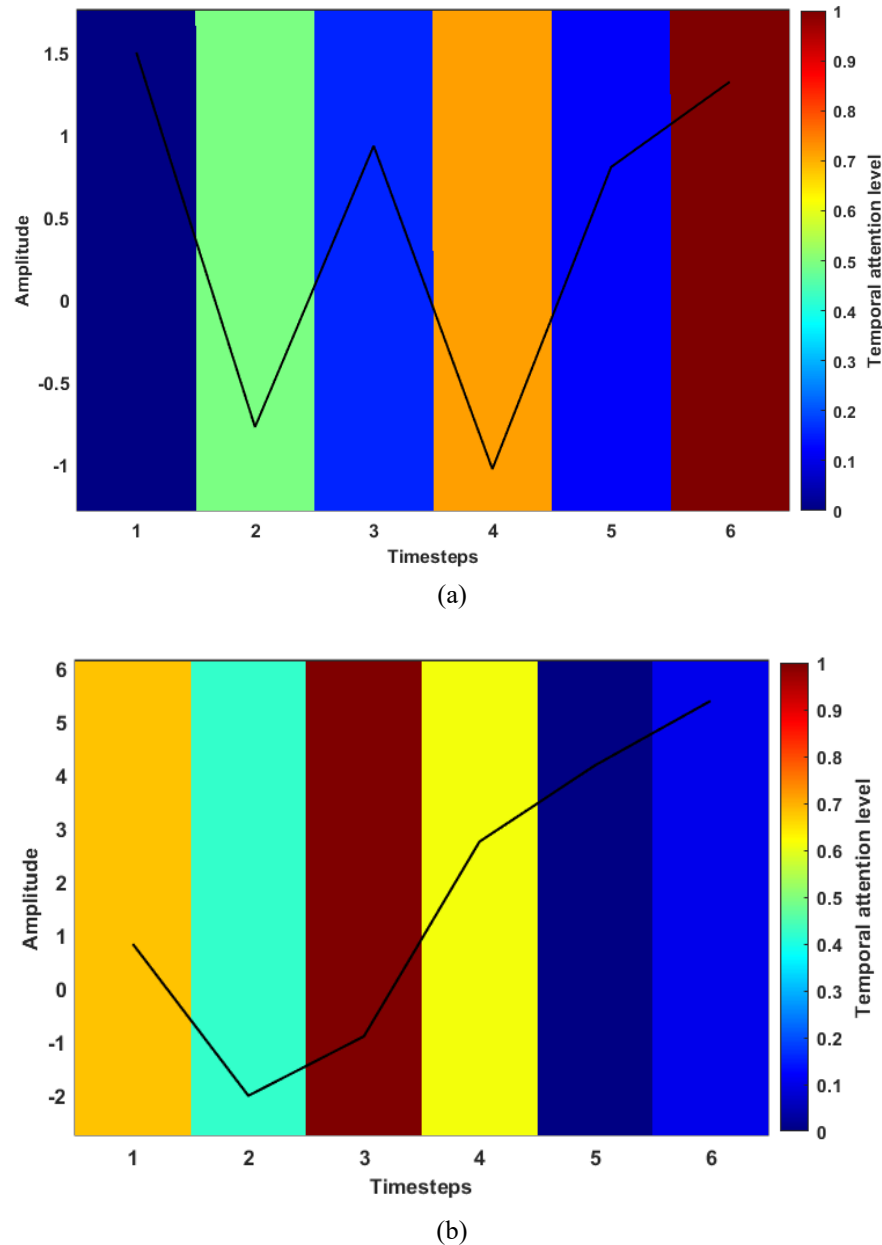


Figure 5. Visualization of Grad CAM++ representing discriminative EEG regions learned by the proposed method: (a) Bonn EEG and (b) CHB-MIT

Tables 7 and 8 represent the performance analysis of learning rate and optimizer for the proposed method on both datasets. The learning rate of 0.0001 ensures stable fine-grained weight updates and provides a dropout of 0.5. This minimizes overfitting through neuron co-adaptation to improve generalization and overall performance.

Table 7. Performance analysis of learning rate for proposed method on both datasets

Dataset	Learning rate	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
Bonn EEG	0.1	87.96	87.17	86.30	88.06	89.36	89.20
	0.01	89.05	88.61	87.04	90.25	89.75	89.75
	0.001	89.85	89.08	87.36	90.87	92.35	92.48
	0.0001	99.75	99.49	99.51	99.49	99.52	95.78
CHB-MIT	0.1	86.02	87.53	85.78	89.36	90.25	87.06
	0.01	86.74	87.52	85.39	89.78	90.57	87.96
	0.001	87.06	89.80	89.36	90.25	91.30	89.32
	0.0001	99.54	99.18	99.15	99.23	98.84	99.50

Table 8. Performance evaluation of optimizer for proposed method on both datasets

Dataset	Optimizer	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
Bonn EEG	0.2	87.25	88.45	89.57	87.36	89.36	89.75
	0.3	87.96	89.48	89.68	89.30	89.74	89.87
	0.4	91.25	91.26	92.31	90.25	92.30	92.36
	0.5	99.75	99.49	99.51	99.49	99.52	95.78
CHB-MIT	0.2	89.50	88.79	89.48	88.12	89.75	87.02
	0.3	89.85	90.83	92.36	89.36	92.15	89.31
	0.4	92.36	90.18	93.48	87.12	92.36	92.35
	0.5	99.54	99.18	99.15	99.23	98.84	99.50

4.2. Generalization analysis

Table 9 illustrates the performance of cross-dataset validation with training on CHB-MIT dataset and testing on Bonn EEG dataset to evaluate unseen data, which demonstrates the proposed method's robustness and generalization ability. CHB-MIT is chosen for training due to its higher number of patients and Bonn EEG is selected for testing due to lesser number of patients. The proposed method obtains superior performance due to sparsity-guided iterative process that minimizes noise and focus seizure relevant features compared to the existing methods. Table 10 illustrates generalization and evaluation for different classification methods in epileptic seizure on UCI-EEG dataset. Compared to exiting methods, SIR-GRU obtains higher accuracy of 94.58% due to sparsity mechanism, which minimize redundant information and preserves seizure-relevant temporal features. Moreover, iterative recursive learning refines long-term dependencies that makes robust feature generalization across unseen EEG patterns.

Table 9. Cross-dataset validation results with training on CHB-MIT and testing on Bonn EEG

Methods	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
ViT	81.02	79.37	78.52	80.25	80.48	78.45
LSTM	83.69	80.80	79.30	82.36	81.69	80.21
GRU	85.74	82.19	81.35	83.05	82.34	81.36
CNN	86.35	84.21	83.65	84.79	83.69	83.05
LSTM	86.89	86.09	85.39	86.81	84.05	85.69
CNN+LSTM	87.02	87.70	86.17	89.30	86.79	86.18
STAN	90.25	90.96	91.58	90.35	89.58	88.15
SIR-GRU	97.02	96.63	96.48	96.80	93.58	91.05

Table 10. Generalization evaluation of different classification methods for epileptic seizure on UCI-EEG dataset

Methods	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
ViT	78.05	76.53	76.03	77.05	79.63	80.25
LSTM	79.30	78.49	78.36	78.63	82.34	81.48
GRU	80.24	79.50	80.25	78.78	85.02	81.97
CNN	82.31	79.83	80.69	78.99	85.87	82.36
LSTM	83.06	80.23	81.24	79.25	86.30	82.69
CNN+LSTM	85.69	80.52	81.39	79.68	86.98	83.48
STAN	86.32	82.36	82.38	82.36	87.25	85.06
SIR-GRU	94.58	93.72	93.60	93.85	94.25	94.03

4.3. Comparative analysis

Tables 11 and 12 present a comparative evaluation of existing methods using Bonn EEG and CHB-MIT dataset. Compared to existing methods, SIR-GRU achieves higher accuracies of 99.75% and 99.54% on different datasets by effectively capturing long-term temporal dependencies that minimize redundant computation via sparsity connectivity. Moreover, iterative recursive refinement of feature representations across time steps enhances the discriminative ability to obtain higher accuracy.

Table 11. Comparative evaluation of existing methods with proposed method using Bonn EEG dataset

Methods	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	Specificity (%)	MCC (%)
Hybrid CNN-LSTM [21]	99.33	N/A	N/A	N/A	N/A	N/A
STFFDA [22]	67.24	67.13	67.11	67.36	N/A	58.95
BTBC [23]	99.50	99.40	99.40	99.42	99.42	N/A
ZOA-LSTM [24]	98.43	97.09	98.04	N/A	97.88	N/A
MDFLN [28]	98.4	N/A	97.02	N/A	98.71	N/A
Proposed SIR-GRU	99.75	99.49	99.51	99.49	99.52	61.78

Table 12. Comparative evaluation of existing methods with proposed method using CHB-MIT dataset

Methods	Accuracy (%)	F1-score (%)	Recall (%)	Precision (%)	MCC (%)	Specificity (%)
STFFDA [22]	92.42	92.42	92.42	92.47	88.66	N/A
BESD-Net [25]	98	97.91	97.54	98.36	N/A	95.08
SE-TCN-BiGRU [26]	98.77	96.77	95.88	N/A	96.08	99.44
BiLSTM [27]	97.00	N/A	95.70	N/A	N/A	93.90
MDFLN [28]	98.09	N/A	98.42	N/A	N/A	97.77
Proposed SIR-GRU	99.54	99.18	99.15	99.23	98.84	99.50

4.4. Discussion

The benefits of the proposed method and the limitations of existing methods are discussed in detail in this section. The existing methods, such as hybrid CNN-LSTM [21] suffers from higher computational complexity, while the dual attention mechanism [22] is sensitive to noisy channels, which adversely affects classification accuracy. BTBC [23] struggles to capture temporal patterns because it operates primarily on static feature sets, which reduces effectiveness. LSTM with ZOA [24] is also sensitive to noisy EEG data owing to noise distorting temporal patterns, which leads to inaccurate feature learning. SE-TCN-BiGRU [26] overly relies on SE module that amplifies noisy channel features and reduces robustness. The proposed SIR-GRU overcomes these limitations by effectively modeling temporal dependencies that maintain computational efficiency through sparse connectivity. Its iterative mechanism improves feature representation by progressively refining hidden states to assist in capturing subtle seizure patterns. This minimizes overfitting and enhances generalization in different patients. In addition, the proposed SIR-GRU has fewer parameters than the RNN, LSTM, and GRU, which leads to rapid training and lesser memory usage.

5. CONCLUSION

This research proposed SIR-GRU to accurately classify epileptic seizures. The model integrates a sparsity mechanism and recursive learning to selectively refine seizure-relevant neurons, which minimizes redundant updates and enhances feature representations. This integration enhances robustness, reduces overfitting, and obtains superior accuracy with lesser training time and memory consumption through selective refinement as well as efficient gradient flow. The experimental analysis on the Bonn EEG and CHB-MIT datasets demonstrates the proposed SIR-GRU achieves superior accuracy of 99.75% and 99.54%, respectively, compared to existing methods such as, STFFDA. Therefore, the proposed SIR-GRU method ensures rapid, reliable, and efficient seizure classification for clinical diagnosis. Although SIR-GRU obtains higher accuracy, Bonn EEG dataset has a smaller number of samples, which affects robustness. Also, the higher accuracy obtained in this dataset raises overfitting risk. Moreover, real-time settings is not included in the present research because its primary objective is to establish model effectiveness under a benchmark dataset, which ensure fair comparison with existing methods. Hence, the proposed method has been extended to real-time settings by incorporating robust, noise-aware, imbalance methods, and enriched feature representation including spatial and wavelet-based features to enable comprehensive evaluation in future. The overfitting risk will be mitigated using a regularization method by validating the model on larger and multi-model EEG dataset with clinical metadata to improve diagnostic ability. Also, an adaptive and data-driven sparsity thresholding mechanism is investigated to improve generalization across different patient.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

I : Investigation

Vi : Visualization

M : Methodology

R : Resources

Su : Supervision

So : Software

D : Data Curation

P : Project administration

Va : Validation

O : Writing - Original Draft

Fu : Funding acquisition

Fo : Formal analysis

E : Writing - Review & Editing

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are publicly available from Kaggle: <https://www.kaggle.com/datasets/amnaxt/bonn-eeg-dataset> and PhysioNet: <https://physionet.org/content/chbmit/1.0.0/>.

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