Journal of Computer Science

Research Article

Epileptic Seizure Detection from EEG Signal Using Progressive Channel Selection and Deep Learning

Suraiya Akter Mumu[1], Shupta Das[1], M. A. H. Akhand[1], Abdus Salam[2] and Md Abdus Samad Kamal[3]

[1]Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh
[2]Department of Neurology, Khulna Specialized Hospital, Khulna, Bangladesh
[3]Graduate School of Science and Technology, Gunma University, Kiryu 376-8515, Japan

Article history
Received: 02-02-2026
Revised: 07-05-2026
Accepted: 22-05-2026

Corresponding Author:
M. A. H. Akhand
Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh
Email: akhand@cse.kuet.ac.bd

Abstract: Epileptic Seizures (ES), marked by abrupt abnormal electrical discharges in the brain, represent the primary symptom of epilepsy, making timely and accurate detection critical because of their unpredictable recurrence and potentially severe consequences. The Electroencephalogram (EEG), a widely used, non-invasive, and economical method for monitoring brain activity, plays a key role in automated ES detection through Machine Learning (ML) and Deep Learning (DL) techniques. Most existing ML/DL approaches typically utilize all available EEG channels or apply patient-specific channel selection to maximize detection performance. This study investigates a novel Progressive Channel Selection (PCS) framework designed to identify and retain only the most informative EEG channels across patients. The proposed method progressively selects channels in multiple stages according to their contribution to classification accuracy, ensuring that only the most influential channels are preserved. Experimental evaluation was performed using both Neural Network (NN) and Convolutional Neural Network (CNN) models on the CHB-MIT dataset. The CNN model achieved an accuracy of 98.99% while utilizing fewer than half of the available EEG channels. Although some existing approaches report slightly higher accuracy by employing all channels, the proposed method provides a more effective trade-off between detection accuracy and channel efficiency. The identification of informative EEG channels could support hardware simplification and may facilitate low-cost EEG-based ES detection systems.

Keywords: Epileptic Seizure, Electroencephalogram, Empirical Mode Decomposition, Progressive Channel Selection, Convolutional Neural Network

Introduction

Epileptic Seizures (ES) occur when abnormal synchronized neuronal activity disrupts normal brain function and produces changes in consciousness, behavior, sensation, or motor activity (Epilepsy, 2022). Electroencephalography (EEG) is widely used for seizure assessment because it records brain activity non-invasively with high temporal resolution (Asadzadeh et al., 2020). EEG signals contain temporal and spectral changes that are useful for automatic seizure detection, but these signals are difficult to analyze because they are noisy, nonlinear, and non-stationary (Yan et al., 2022; Acharya et al., 2013).

For several decades, epilepsy research has remained a prominent topic in computational intelligence and biomedical signal processing, with extensive efforts focused on developing automated epileptic seizure detection systems using EEG signals (OK and Rajesh, 2020; Pattnaik et al., 2022; Sameer and Gupta, 2022; (Nogay and Adeli, 2020; He et al., 2022). EEG is widely regarded as one of the most reliable and commonly utilized signals for seizure detection because of its high temporal resolution, non-invasive acquisition process, and cost-effectiveness (Hassan et al., 2022). Automated EEG-based seizure detection has therefore become an important research topic in biomedical signal processing and computational intelligence. Recent work has used machine learning and deep learning to support diagnosis not only for epilepsy, but also for other EEG-related applications such as autism-spectrum analysis and emotion recognition (Peya et al., 2020; Akhand et al., 2023). In seizure EEG, abnormal rhythmic events may appear as spikes, sharp waves, or spike-and-wave complexes. However, seizure and non-seizure segments can have overlapping frequency and amplitude characteristics, and recordings may also contain artifacts (Dikanev et al., 2005). These issues require preprocessing, feature extraction, and classification methods that can generalize across patients and seizure patterns (Aayesha et al., 2022).

Existing EEG-based seizure-detection studies can be grouped into several broad directions. Some studies train deep models directly on raw EEG so that feature learning is handled internally by the network (Nogay and Adeli, 2020; Sameer and Gupta, 2022; Gao et al., 2022; He et al., 2022; Gómez et al., 2020; Kaziha and Bonny, 2020). Other studies rely on handcrafted or statistical descriptors to make the seizure and non-seizure classes more separable (Pattnaik et al., 2022; Gao et al., 2022; Mahmoodian et al., 2019; Nandini et al., 2022; Tapani et al., 2019). A further group uses signal transformations, filtering, or decomposition methods to obtain more informative representations before classification (Hassan et al., 2019; OK and Rajesh, 2020; Pattnaik et al., 2022).

Many existing approaches depend on utilizing all available EEG channels in order to obtain high classification accuracy. Limited attention has been given to identifying and reducing redundancy among EEG channels while preserving or enhancing detection performance. A recent work has shown that single- or few-channel detectors can achieve sensitivity comparable to full-cap montage when channels are chosen based on seizure focus (Chung et al., 2024). This study investigates an EEG-based ES detection framework that uses selected EEG channels while maintaining high detection performance. An initial conference version of this work introduced a rank-based channel-selection strategy using neural-network classifiers (Mumu et al., 2025). The present paper extends that preliminary work by reformulating the procedure as Progressive Channel Selection (PCS), incorporating CNN-based models, expanding the literature comparison, and evaluating the selected-channel framework in a broader experimental setting. The major contributions of this study are summarized as follows:

1. Performance-driven ranking of individual EEG channels: The performance of each EEG channel is evaluated individually to determine its standalone effectiveness for ES detection. Ranking of the channels is done based on performance to determine the importance of a channel over others
2. Progressive channel selection: A novel channel selection approach, called progressive channel selection, is investigated, where EEG channels are progressively selected based on improvements in accuracy, ensuring that only the most informative channels are retained for model development
3. Develop ML and DL models with selected channels for ES detection: NN and CNN are considered to develop an ES detection model with selected channels and achieved strong classification accuracy, demonstrating their potential for an efficient ES detection system
4. Performance of the proposed ES detection model compared to existing methods: The proposed approach achieves high epileptic seizure detection accuracy while utilizing a reduced set of EEG channels and demonstrates competitive performance relative to existing EEG-based seizure detection methods

Related Work

Several EEG seizure-detection studies use all available channels and focus on improving feature extraction or classification accuracy. Pattnaik et al., (2022) decomposed EEG data using a configurable Q-wavelet transform, then extracted statistical, temporal, and nonlinear properties for classification using SVM and RF techniques. Nandini et al.(2022) investigated a method that relied on temporal-domain attributes and assessed their effectiveness using multiple classical machine learning models, namely nearest-neighbor, probabilistic, tree-structured, ensemble-based, regression-driven, and hyperplane-based classification methods. Salafian et al. (2022) used Mutual Information (MI) to represent inter-channel relationships and applied a 2D CNN so that discriminative patterns could be learned directly from EEG data. He et al. (2022) combined Graph Attention Networks (GAT) with Bi-directional Long Short-Term Memory (BiLSTM) layers to model spatial and temporal dependencies in raw EEG.

Other work has similarly emphasized feature engineering across the full channel set. Hassan et al. (2022) developed a seizure recognition methodology that incorporated empirical mode decomposition for signal analysis, followed by a mutual information–guided selection process to retain informative attributes. The selected feature subset, obtained through the MIBIF procedure, was subsequently processed using a multilayer perceptron neural network for classification. Liu et al. (2024) used interpretable clinical and statistical features with dataset-specific coefficients of variation for spectral-feature selection. Al-Adhaileh et al. (2025) designed an EEG-driven classification pipeline for identifying seizure states by analyzing data collected from 102 individuals. Feature engineering involved the extraction of entropy measures and frequency-domain characteristics, while dataset imbalance was mitigated using SMOTE prior to benchmarking a collection of machine learning and deep learning approaches, including RF, GB, KNN, LSTM, and LRCN. Mohammadpoory et al. (2025) developed a patient-independent seizure detection approach that integrated wavelet decomposition with weighted visibility graph (WVG) features derived from EEG signals. Graph-based features from EEG sub-bands were extracted and optimized through feature selection prior to classification.

Some studies likewise focused on all available EEG channels. Kong et al. (2024) proposed a multi-domain feature fusion framework for seizure detection using EEG signals. They applied DWT and Welch's method to extract diverse features, then used an enhanced PSO with a shrinkage factor for feature selection, followed by Pearson correlation to remove redundancy. The refined features were classified using SVM, RF, ANN, and XGBoost on the Bonn and CHB-MIT datasets. Das et al. (2024a). An EEG-based seizure identification framework by generating 1D and 2D features from EMD-processed signals. Characteristics computed from intrinsic mode functions, including variance, fluctuation index, and ellipse-area metrics, were employed, with the 2D convolutional architecture outperforming the 1D-CNN in classification effectiveness. Additionally, Das et al. (2024b) introduced an epileptic seizure detection approach based on an integrated feature representation derived from EMD-decomposed EEG signals. Antonoudiou et al. (2025) developed SeizyML, an open-source application for semi-automated seizure detection from electrographic recordings. The system integrates machine learning-based detection with manual validation of detected events. Four interpretable classifiers, like a decision tree, Gaussian naïve Bayes, passive-aggressive classifier, and stochastic gradient descent classifier, were implemented, and their performance was first tested on chronically epileptic mice and then on humans for seizure detection.

Recent studies on EEG-based epileptic seizure detection have increasingly adopted deep learning and hybrid feature-learning strategies to improve classification performance. Assali et al. (2023) used a CNN-based model for epileptic-state classification by combining temporal and spectral EEG features, showing that deep networks can benefit from richer signal representations for seizure prediction. Mallick and Baths (2024) proposed a deep learning framework integrating 1D-CNN, BiLSTM, GRU, and average-pooling units for seizure and non-seizure EEG classification as well as multiclass seizure-state classification. Jibon et al. (2024) introduced a hybrid architecture combining sequential graph convolutional networks and DeepRNN to exploit both spatial relationships and temporal dependencies in EEG signals. Similarly, Sagga et al. (2025) compared several deep learning models, including 1D-CNN, VGGNet, ResNet, Xception, and WaveNet, demonstrating the effectiveness of CNN-based architectures for automated seizure detection. These studies indicate that recent EEG seizure-detection models are moving toward deeper architectures capable of learning spatial, temporal, and spectral patterns directly from EEG signals.

More recent studies have further emphasized feature fusion, multiband representation, and multimodal learning to improve seizure-detection robustness. Zhang et al. (2024) combined DWT-based feature fusion with a CNN-GRU-attention model for seizure detection and prediction, showing the benefit of integrating time-frequency and nonlinear features before deep classification. Cao et al. (2025) proposed a hybrid CNN-BiLSTM model with feature fusion to capture both local and sequential EEG characteristics. Thakare and Ranawat (2025) investigated multimodal deep learning fusion using EEG and ECG inputs to reduce false positives. Recent review work by Huang et al. (2026) also reports that CNNs, RNNs, graph neural networks, Transformers, and hybrid architectures are now dominant approaches in EEG-based seizure prediction. However, most of these methods primarily focus on improving detection accuracy through complex architectures or richer feature representations, while the issue of reducing the number of required EEG channels remains comparatively less explored.

Unlike approaches that rely on all EEG channels, several recent studies have emphasized reducing feature dimensionality or choosing the most relevant channels to enhance interpretability and lower processing expense while preserving strong classification performance. Such strategies are particularly important for developing practical and hardware-efficient seizure detection systems. Consequently, increasing attention has been directed toward channel selection techniques designed to retain only the most relevant EEG signals. Ferrara et al. (2025) developed a patient-tailored seizure detection approach in which EEG channels are selected through a lightweight CNN-based framework. A subject-adaptive seizure classification strategy was introduced in which principal component analysis was applied to rank EEG channels and retain two participant-specific signals. These selected channels were subsequently utilized as inputs to a CNN for prediction. Dokare and Gupta (2025) presented a seizure identification framework that employs MI and RF to determine informative EEG channels, followed by DWT-based extraction of ten frequency-band features and SVM-based classification using the CHB-MIT dataset. To address EEG channel reduction in seizure detection, Moctezuma and Molinas (2020) implemented a multi-objective optimization process employing NSGA-II/III algorithms. Signal representations obtained through wavelet-based and mode-based decomposition, combined with energetic and fractal characteristics, were utilized to balance predictive performance against channel minimization.

Most existing EEG-based epileptic seizure detection studies that consider channel reduction use patient-specific channel selection, where a small subset of channels is chosen separately for each patient. Although such methods can achieve strong performance for individual patients, the selected channels may differ across cases, making it difficult to define a uniform channel configuration for generalized seizure detection systems. To address this issue, the present study proposes a validation-driven, performance-based channel selection strategy that aims to identify a common set of informative EEG channels capable of maintaining high detection performance across patients without patient-specific tuning.

Materials and Methods

This work presents a structured methodology for detecting ES from EEG recordings with reduced channel requirements. The overall workflow, including preprocessing, decomposition, feature extraction, progressive channel selection, and classification, is summarized in Fig. 1.

EEG Data Preprocessing

EEG data preprocessing is the first stage of the proposed method. EEG data used in this study were obtained from the publicly available CHB-MIT Scalp EEG Database (Guttag, 2010), which is one of the most widely used benchmark datasets for EEG-based epileptic seizure detection (Das et al., 2024a; Ferrara et al., 2025; Dokare and Gupta, 2025). The database was collected at Children's Hospital Boston and contains long-term scalp EEG recordings from pediatric subjects with intractable seizures. A detailed description of the dataset is available on the dataset website (https://physionet.org/content/chbmit/) and in prior studies.

This study followed the preprocessing strategy adopted in prior studies (Das, et al., 2024b). A total of 22 common EEG channels available across the selected 23 cases were considered to ensure a consistent channel configuration. To maintain a uniform input configuration, 22 common channels from the selected cases were used. The channel indices correspond to the following bipolar leads: (1) FP1-F7, (2) F7-T7, (3) T7-P7, (4) P7-O1, (5) FP1-F3, (6) F3-C3, (7) C3-P3, (8) P3-O1, (9) FP2-F4, (10) F4-C4, (11) C4-P4, (12) P4-O2, (13) FP2-F8, (14) F8-T8, (15) T8-P8, (16) P8-O2, (17) FZ-CZ, (18) CZ-PZ, (19) P7-T7, (20) T7-FT9, (21) FT9-FT10, and (22) FT10-T8. The sampling rate was 256 Hz. No additional filtering was applied. Each recording was divided into 10-second windows with 70% overlap, giving a 3-second step between consecutive segments. Segment labels were assigned from the seizure annotations supplied with the database, producing 7414 labelled EEG samples for the experiments.

Decomposition by Empirical Mode Decomposition (EMD)

The next stage is signal decomposition. To address the nonlinear and non-stationary nature of EEG signals, each windowed segment was decomposed using EMD. EMD was used to decompose the EEG windows because it is suitable for complex and dynamic signals. For each 10-second segment, EMD separates the signal into intrinsic mode functions that represent oscillatory components at different time scales (Huang et al., 1998). For this investigation, the initial six IMFs were retained because earlier EEG seizure-detection studies showed that they contain useful seizure-related information (Das et al., 2024a). The decomposition was performed separately for each of the 22 channels.

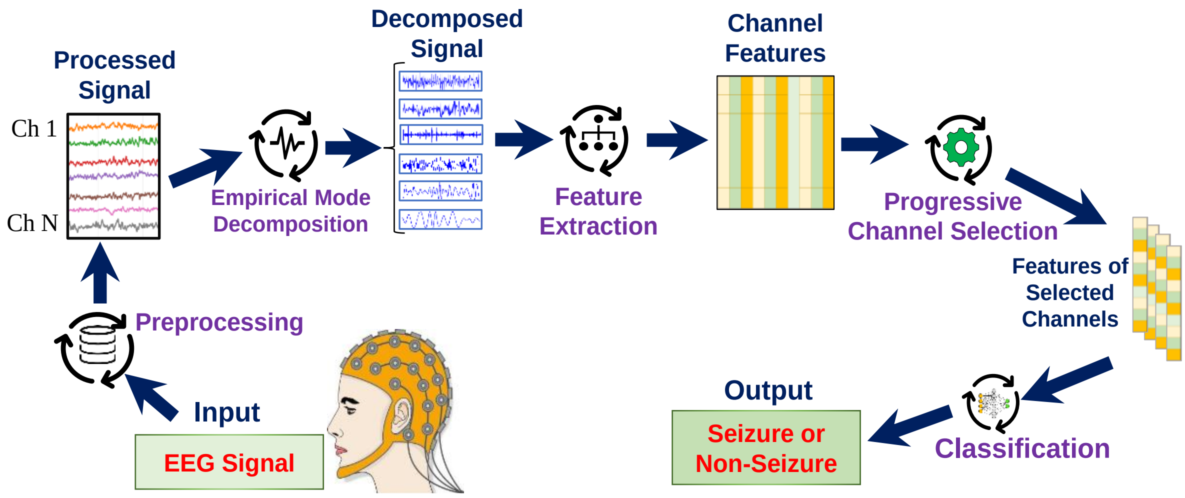


Fig. 1: Schematic representation of the proposed framework for epileptic seizure detection from EEG recordings

DOI: 10.3844/jcssp.2026.2006.2021

Channel-Wise Feature Extraction

The feature extraction stage is performed after decomposition. For each IMF, three features were calculated:

(i) Variance (V), which reflects signal energy
(ii) Fluctuation Index (F), which measures signal instability and fluctuation magnitude
(iii) Ellipse Area (EA) from the second-order difference plot, which captures the geometric spread of the signal in a phase space that is nonlinear

These descriptors have been used in prior EEG studies to capture temporal and nonlinear signal behavior (Li et al., 2013; Du et al., 2019; Ullal and Pachori, 2020). Since six IMFs and three features were used, each channel generated 18 features (6 IMFs × 3 features). Therefore, one selected channel produced an 18-dimensional feature vector, two channels produced 36 features, and the dimension increased by 18 for each added channel (Das et al., 2024).

Progressive Channel Selection (PCS)

The main methodological contribution of this study is the PCS strategy, which is illustrated in Fig. 2. Algorithm 1 also shows the major steps of PCS. PCS progressively incorporates EEG channels according to their contribution to validation accuracy, ensuring that only the most informative channels are preserved. The effectiveness of each channel is evaluated independently using separate models, allowing channels (RC1–RC22) to be ranked based on their classification performance. The key stage of PCS lies in selecting the optimal subset of channels from this ranking. Initially, RC1 is chosen as the reference channel for the model. The remaining ranked channels (RC2–RC22) are then assessed sequentially in descending order of performance contribution. For each step, a temporary model is created by adding the candidate channel to the currently selected set. If the temporary model achieves better performance than the existing model, the channel is retained; otherwise, it is excluded.

The PCS method is designed for EEG channel selection. In the case of the CHB-MIT dataset, channels are progressively evaluated up to RC22, and the final PCS denotes the channel subset. Each added channel contributes 18 new features, which are aggregated with the existing feature pool. Although the temporary model is learned using the training set, its evaluation is carried out on a distinct dataset, namely the validation set used in this study.

Algorithm 1: Progressive Channel Selection (PCS)

1. Train one model for each individual channel.// 22 for CHB-MIT
2. Calculate the validation accuracy of each channel.
3. Rank the channels from highest accuracy to lowest accuracy.
4. Select the best-ranked channel as the first selected channel.
S = {best channel}
5. For each remaining ranked channel:
a. Add the channel temporarily with the selected channels.
b. Train a temporary model using this temporary channel set.
c. Compare its validation accuracy with the previous best accuracy.
d. If accuracy improves:
Keep the channel in S.
Otherwise:
Discard the channel.
6. Repeat **Step 5** until all channels are checked.
7. Return S as the final selected channel set.

PCS is related to feature selection, but it is narrower because it selects EEG channels, not constructed features. Therefore, PCS differs from simple feature ranking because the final decision depends on the combined contribution of a channel rather than its individual performance alone.

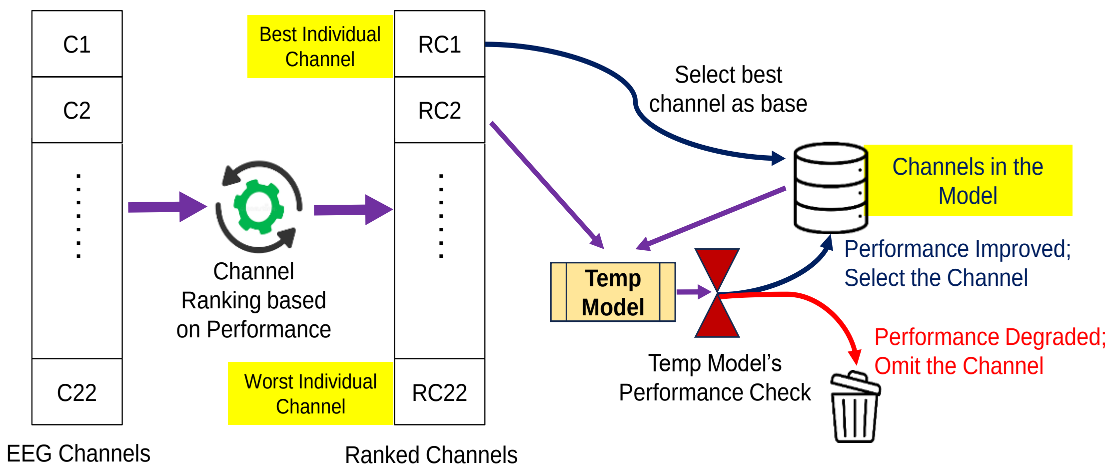


Fig. 2: Progressive Channel Selection (PCS) procedure for identifying informative EEG channels

DOI: 10.3844/jcssp.2026.2006.2021

Methodologically, PCS is related to ranking-guided sequential forward selection, as discussed in prior feature selection studies (Liu and Lei, 2005; Isabelle and André, 2003).

Compared with existing channel-selection methods, PCS provides a simpler and more generalized strategy for epileptic seizure detection. Ferrara et al. (2025) used PCA-based ranking to select two patient-specific channels with a lightweight CNN, while Dokare and Gupta (2025) combined MI and RF for patient-dependent channel selection, followed by DWT and SVM classification. Moctezuma and Molinas (2020) achieved strong performance using multi-objective optimization with NSGA-II and NSGA-III, but their approach involves higher computational and methodological complexity. In contrast, PCS progressively retains a channel only when it improves validation accuracy with the already selected channels. Thus, PCS is straightforward, interpretable, and suitable for identifying a common informative channel subset across patients while maintaining a strong balance between detection accuracy and channel efficiency.

Classification With NN and CNN

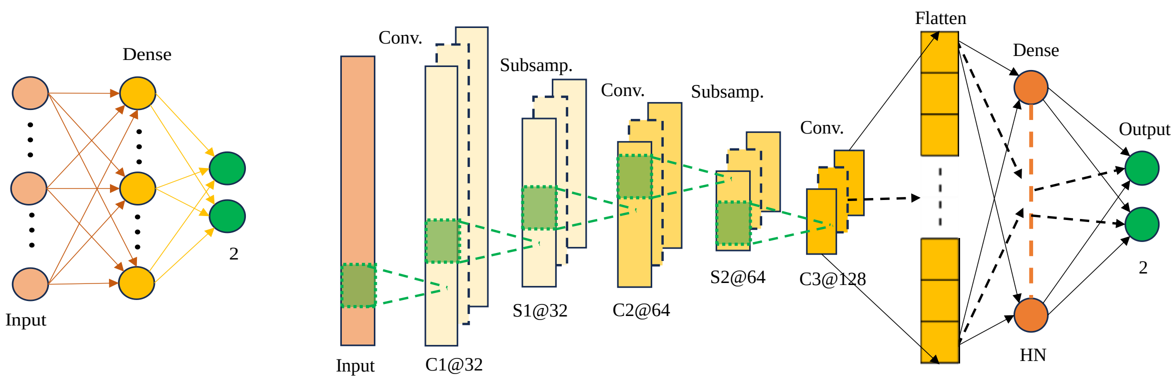
The final classification stage, shown in Fig. 3, uses both NN and CNN models for binary seizure detection (Seizure vs. Non-Seizure). Two different NN models with 10 and 50 Hidden Neurons (HN) are considered. Two one-dimensional (i.e., 1D) Convolutional Neural Networks (CNNs) with 10 and 50 HNs in the dense layer are also evaluated. Unlike traditional 2D CNNs, our 1D CNN architecture operated directly on the 1D feature vectors without any need for spatial transformation. The 1D-CNN begins with a Conv1D layer using 32 filters to extract local patterns from the input sequence, followed by batch normalization for training stability and a max pooling layer to reduce the sequence length. Two more Conv1D layers with 64 and 128 filters, respectively, are added, each followed by a pooling layer (only after the second), to learn deeper hierarchical features. The output is then flattened and passed through a dense layer with 10 neurons, and finally through a *softmax*-activated dense layer with two neurons for binary classification. As an example, for a total of 54 features from three selected channels, the CNN model with HN=10 is shown below.

$$I_{54x1} \rightarrow \{32K1_{3x1}C1_{52x1} - S_{2x1}32S1_{26x1}\} \rightarrow \{64K2_{3x1}C2_{24x1} - S_{2x1}64S2_{12x1}\} \rightarrow \{128K3_{3x1}C3_{10x1}\} \rightarrow \{Wo_{1280x10}\} \rightarrow \{Wo_{10x2}\} \rightarrow O_2.$$

Models of a similar nature have been reported in prior studies, with detailed methodological explanations available in (Das et al., 2024b). In this work, all four models were trained using the same training and validation data partitions, while performance assessment was carried out on a separate reserved test set. Comparative analysis was performed based on final test accuracy, representing generalization performance, as well as the number of selected channels used by each model.

Experimental Studies

The main objective was to identify a compact subset of channels that could maintain classification performance, thereby minimizing hardware and electrode complexity, while also examining how varying model capacities influenced channel selection. To achieve this, a progressive channel selection approach was applied. Initially, each channel was assessed independently using validation accuracy, after which the channels were ranked according to their performance. This procedure was carried out using four classification architectures: A neural network with a single hidden layer containing 10 hidden neurons (NN-10), a comparable neural network with 50 hidden neurons (NN-50), and two convolutional neural network models with dense layers consisting of 10 hidden neurons (CNN-10) and 50 hidden neurons (CNN-50). For every model, channels were added sequentially using a greedy strategy that selected the channel yielding the greatest improvement in validation accuracy at each stage.



(a) NN (b) CNN

Fig. 3: Architectures of the (a) NN and (b) CNN models used for classification

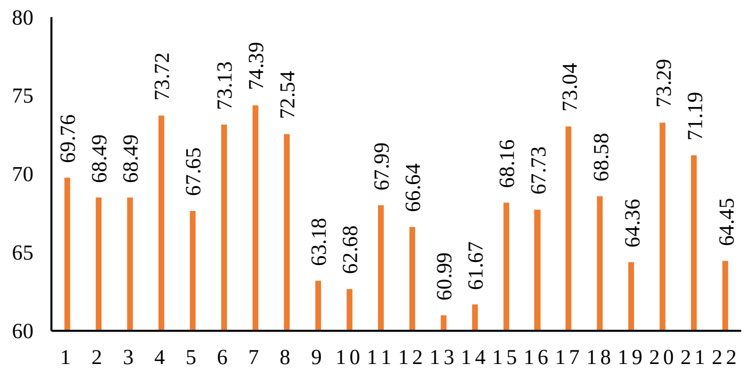
DOI: 10.3844/jcssp.2026.2006.2021

To assess the performance of the proposed greedy-based progressive channel selection method, experiments were conducted using the CHB-MIT Scalp EEG Database. A total of 18 features were extracted from each EEG channel segment, meaning that the feature dimensionality increased by 18 with every additional channel (e.g., one channel corresponds to 18 features, two channels to 36 features, and so on). The dataset contained 7,414 samples in total. All experimental procedures, including feature extraction and classification, were implemented in Python.

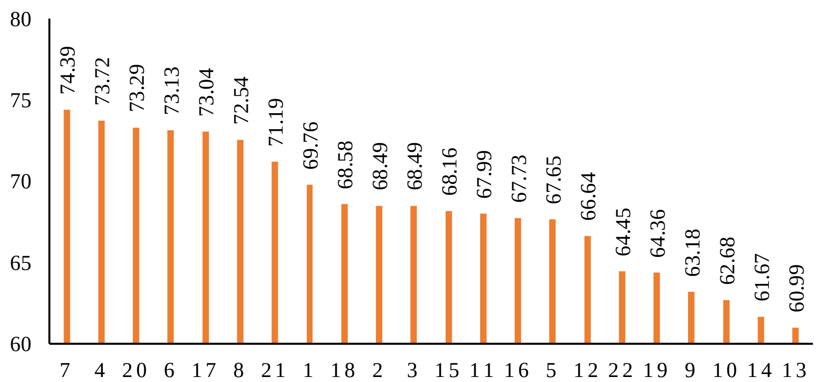
Initially, comprehensive experimental analyses were performed to illustrate the proposed method in a step-by-step manner. For the experimental setup, 20% of the 7,414 samples were set aside as an independent test set, which was excluded from all stages of model development and used solely to evaluate the generalization capability of the final model. From the remaining 80% of the data, 60% was allocated for model training, while 20% was used as a validation set to monitor intermediate model performance. The neural network models were trained using the well-known Adam optimization algorithm with a learning rate of 0.001. Finally, the performance of the most suitable model was further evaluated using a 5-fold cross-validation scheme.

Performance With Individual Channel

The histogram in Fig. 4 presents the validation accuracy obtained from each individual EEG channel (ch1–ch22) separately using NN-10 for ES detection. The y-axis denotes the accuracy percentage, ranging from 60% to 75%. Among the channels, ch4, ch6, ch7, ch8, ch17, ch20, and ch21 demonstrate comparatively higher validation accuracies, suggesting their greater effectiveness in capturing seizure-related discriminative patterns. In contrast, channels such as ch9, ch10, ch13, and ch14 showed comparatively lower individual validation accuracy, indicating weaker standalone discriminative ability for ES classification. Fig. 4(a) shows the accuracy according to channel serial, and Fig. 4(b) shows the accuracy according to the achieved accuracy. The results indicate that channel ch7 achieves the highest accuracy of 74.39%, whereas channel ch13 shows the lowest accuracy of 60.99%. These findings demonstrate that the effectiveness of EEG channels differs significantly for seizure detection, emphasizing the importance of channel selection strategies. Selecting only the most informative channels may further improve the overall performance of the model.



(a) Accuracy of Individual Channels



(a) Channels according to Rank based on Accuracy

Fig. 4: Validation accuracy of individual EEG channels using the NN-10 model: (a) According to Channel Serial and (b) According to Channel Rank

Results Analysis With NN Model

Starting with the best-performing individual channel, namely ch7 with a validation accuracy of 74.39%, the progressive addition of channels is examined for both NN-10 and NN-50 models. Table 1 presents the validation accuracy of the NN-10 model using the ranked channel sequence illustrated in Fig. 4(b): ch7, ch4, ch20, ch6, ch17, ch8, ch21, ch1, ch18, ch2, ch3, ch15, ch11, ch16, ch5, ch12, ch22, ch19, ch9, ch10, ch14, and ch13. Ch7 is used as the baseline channel in the model due to its superior individual performance.

The addition of channels ch4, ch20, and ch6 improves the model performance, increasing the validation accuracy to 85.26% using channels ch7, ch4, ch20, and ch6. However, incorporating channels ch17 and ch8 reduces performance, so these channels are discarded, and ch21 is considered instead. Overall, the NN-10 model achieves a validation accuracy of 96.97% using 12 selected channels (ch7, ch4, ch20, ch6, ch21, ch1, ch3, ch15, ch16, ch5, ch19, and ch14), while 10 channels are excluded. Similarly, Table 2 presents the NN-50 model performance following the same channel selection procedure.

Table 1: PCS-Based Performance of the NN-10 Model

Ranked Channel	Validation Accuracy (VA)	Notes on VA	Selected Channels	Omitted Channels
ch07	74.39	Set as Baseline	ch07	-
ch04	78.85	Increased	ch04	-
ch20	83.49	Increased	ch20	-
ch06	85.26	Increased	ch06	-
ch17	85.03	Decreased	-	ch17
ch08	80.23	Decreased	-	ch08
ch21	86.60	Increased	ch21	-
ch01	92.08	Increased	ch01	-
ch18	91.98	Decreased	-	ch18
ch02	91.90	Decreased	-	ch02
ch03	92.33	Increased	ch03	-
ch15	92.67	Increased	ch15	-
ch11	92.50	Decreased	-	ch11
ch16	92.67	Increased	ch16	-
ch05	93.34	Increased	ch05	-
ch12	92.60	Decreased	-	ch12
ch22	93.08	Decreased	-	ch22
ch19	95.20	Increased	ch19	-
ch09	95.11	Decreased	-	ch09
ch10	94.30	Decreased	-	ch10
ch14	96.97	Increased	ch14	-
ch13	95.90	Decreased	-	ch13

Table 2: PCS-Based Performance of the NN-50 Model

Ranked Channel	Validation Accuracy (VA)	Notes on VA	Selected Channels	Omitted Channels
ch07	78.22	Set as Baseline	ch07	-
ch04	88.67	Increased	ch04	-
ch20	93.86	Increased	ch20	-
ch06	96.42	Increased	ch06	-
ch17	96.83	Increased	ch17	-
ch08	97.10	Increased	ch08	-
ch21	97.52	Increased	ch21	-
ch01	98.04	Increased	ch01	-
ch18	97.64	Decreased	-	ch18
ch02	97.64	Decreased	-	ch02
ch03	98.44	Increased	ch03	
ch15	98.51	Increased	ch15	
ch11	97.47	Decreased	-	ch11
ch16	97.47	Decreased	-	ch16
ch05	97.30	Decreased	-	ch05
ch12	97.13	Decreased	-	ch12
ch22	97.89	Decreased	-	ch22
ch19	97.81	Decreased	-	ch19
ch09	98.56	Increased	ch09	
ch10	96.29	Decreased	-	ch10
ch14	96.96	Decreased	-	ch14
ch13	97.81	Decreased	-	ch13

Starting with ch7 (78.22% validation accuracy), the model performance improves further with additional channels. The highest validation accuracy of 98.56% is achieved using 11 selected channels (ch7, ch4, ch20, ch6, ch17, ch8, ch21, ch1, ch3, ch15, and ch9), while the remaining channels are discarded. Overall, the NN-50 model outperforms NN-10 despite using fewer channels.

Figure 5 presents the accuracy trends on both the test and validation sets for the two neural network models, illustrating the progressive channel selection strategy based on validation performance. Overall, both models show a consistent improvement in performance as additional channels are incrementally selected. However, when comparing NN-10 and NN-50, the NN-50 model exhibits a more pronounced gain, achieving stronger performance even with a relatively smaller number of selected channels, as shown in Fig. 5(b). With only three channels, the NN-10 and NN-50 models achieve test accuracies of 80.47% and 93.86%, respectively. When the number of channels increases to 10, NN-50 reaches a test accuracy of 98.52%, while NN-10 achieves 95.68%. These results indicate that the NN-50 model consistently outperforms NN-10 across different channel subsets while relying on a comparable or slightly reduced feature set. This suggests that the larger hidden layer in NN-50 is more effective in capturing and leveraging discriminative information from the selected EEG channels, leading to improved classification performance without the need for additional input channels. Overall, the findings highlight that increasing model capacity can enhance epileptic seizure detection performance, particularly when it is combined with a carefully designed channel selection strategy that minimizes redundancy and preserves informative features.

Result Analysis With CNN Model

Similar to NN models, the validation set accuracy was evaluated for the incremental addition of channels progressively for two CNN models, namely CNN-10 and CNN-50. A CNN model applied a 1D convolution over the sequential feature vectors obtained from the selected EEG channels. The CNN-10 model achieved a baseline validation accuracy of 88.46% with ch7, as shown in Table 3. On the other hand, the baseline accuracy of CNN-50 is 90.56% as presented in Table 4.

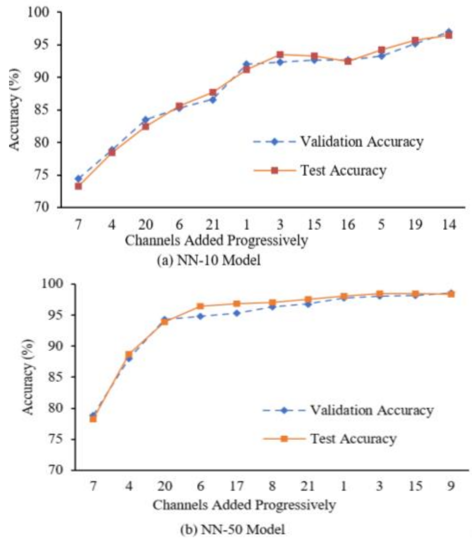


Fig. 5: Accuracy trends of (a) NN-10 and (b) NN-50 models with progressive channel selection

Table 3: PCS-Based Performance of the CNN-10 Model

Ranked Channel	Validation Accuracy (VA)	Notes on VA	Selected Channels	Omitted Channels
ch07	88.46	Set as Baseline	ch07	-
ch04	94.43	Increased	ch04	-
ch20	86.01	Decreased	-	ch20
ch06	95.36	Increased	ch06	-
ch17	97.39	Increased	ch17	-
ch08	95.70	Decreased	-	ch08
ch21	97.97	Increased	ch21	-
ch01	96.46	Decreased	-	ch01
ch18	97.89	Decreased	-	ch18
ch02	96.79	Decreased	-	ch02
ch03	96.80	Decreased	-	ch03
ch15	97.47	Decreased	-	ch15
ch11	97.72	Decreased	-	ch11
ch16	98.40	Increased	ch16	-
ch05	93.34	Decreased	-	ch05
ch12	98.14	Decreased	-	ch12
ch22	98.14	Decreased	-	ch22
ch19	98.06	Decreased	-	ch19
ch09	97.21	Decreased	-	ch09
ch10	98.40	Increased	ch10	-
ch14	96.63	Decreased	-	ch14
ch13	97.13	Decreased	-	ch13

DOI: 10.3844/jcssp.2026.2006.2021

Table 4: PCS-Based Performance of the CNN-50 Model

Ranked Channel	Validation Accuracy (VA)	Notes on VA	Selected Channels	Omitted Channels
ch07	90.56	Set as Baseline	ch07	-
ch04	94.69	Increased	ch04	-
ch20	94.50	Decreased	-	ch20
ch06	93.20	Decreased	-	ch06
ch17	97.39	Increased	ch17	-
ch08	96.64	Decreased	-	ch08
ch21	94.26	Decreased	-	ch21
ch01	96.21	Decreased	-	ch01
ch18	97.47	Increased	ch18	-
ch02	97.11	Decreased	-	ch02
ch03	97.73	Increased	ch03	-
ch15	98.23	Increased	ch15	-
ch11	98.65	Increased	ch11	-
ch16	98.65	Increased	ch16	-
ch05	97.30	Decreased	-	ch05
ch12	98.74	Increased	ch12	-
ch22	99.16	Increased	ch22	-
ch19	98.98	Decreased	-	ch19
ch09	97.65	Decreased	-	ch09
ch10	98.01	Decreased	-	ch10
ch14	97.56	Decreased	-	ch14
ch13	98.66	Decreased	-	ch13

The performance of the two CNN architectures was evaluated on both validation and test datasets, as illustrated in Fig. 6, while also reflecting the impact of progressively increasing EEG channel selection guided by validation feedback. The results indicate a consistent improvement in classification accuracy as additional channels are incorporated into the model. In the early stage, using only three selected channels, the CNN-10 and CNN-50 models achieve test accuracies of 95.82% and 96.76%, respectively. With continued progressive channel inclusion, performance further improves, reaching 98.79% for CNN-10 and 98.99% for CNN-50 when the selected channel counts reach 7 and 10, respectively. Overall, CNN-50 demonstrates more efficient utilization of the selected feature space and achieves marginally higher accuracy across all stages.

This improvement can be attributed to its larger hidden-layer capacity, which enables more effective representation learning compared to CNN-10.

Comparative Discussion and Observations from Model Outcomes

Table 5 compares NN-10, NN-50, CNN-10, and CNN-50 under the proposed progressive channel selection framework. Across all models, validation and test accuracies show close agreement, indicating that the greedy selection strategy yields stable and generalizable channel subsets. Among the evaluated methods, CNN-50 consistently achieves the best balance between performance and channel efficiency. It reaches a maximum validation accuracy of 99.16% using 10 selected channels (ch7, ch4, ch17, ch18, ch3, ch15, ch11, ch16, ch12, ch22) and a peak test accuracy of 98.99%. Compared to other models, CNN-50 attains near-optimal performance with fewer channels while maintaining consistently superior results throughout the selection process, highlighting the advantage of deeper convolutional architectures for EEG-based seizure detection.

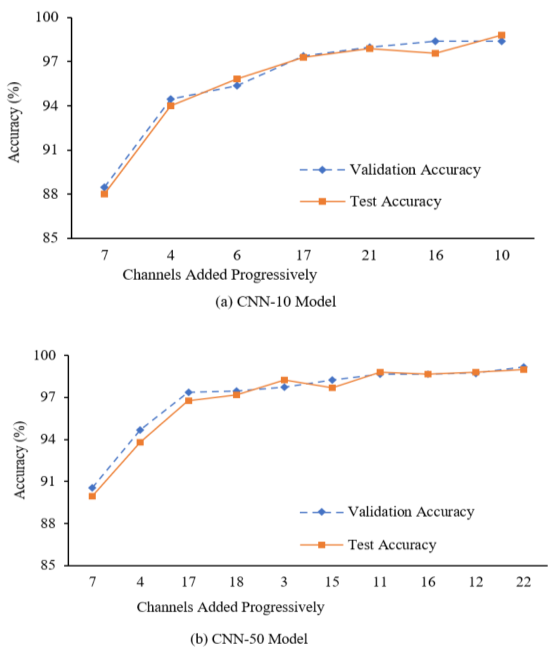


Fig. 6: Accuracy trends of (a) CNN-10 and (b) CNN-50 models with progressive channel selection

Furthermore, comparative analysis across the four models reveals that deeper convolutional architectures achieve high performance with even fewer channels, underscoring the synergy between model capacity and channel efficiency.

Another important finding from Table 5 is the repeated selection of specific EEG channels across all models. In particular, ch4 (P7–O1) consistently appears throughout the selection process, highlighting its strong contribution to seizure detection performance. Additionally, ch17 (FZ-CZ) and ch18 (CZ-PZ) were frequently selected, particularly in CNN-based models, demonstrating their importance in capturing central brain region dynamics. Again, ch21 (FT9-FT10), ch3 (T7-P7), ch6 (F3-C3), ch11 (C4-P4), and ch16 (P8-O2) also recurrently appeared in optimal channel subsets, emphasizing their complementary role in achieving high accuracy. The repeated occurrence of these channels across different model architectures highlights their importance as key EEG leads for practical use, improving both detection performance and computational efficiency.

Experiments in a 5-fold cross-validation setting, i.e., 20% samples were maintained as the test set by turn, have also been conducted for the four models. While 20% samples were reserved as a test set, the remaining 80% samples were divided into a training set and a validation set, having 60% and 20% samples, respectively. The Precision (= TP/(TP + FP)), Recall (= TP/(TP + FN)), and F1-Score (= 2 Precision * Recall/(Precision + Recall)) performance metrics were also measured, counting True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). Table 6 presents the average results of the 5-fold cross-validation on the test set for the four models. The values in the table justify the effectiveness of the proposed models in achieving strong and balanced ES detection performance using a reduced number of EEG channels. The CNN-based models performed better than the NN models, with CNN-10 and CNN-50 achieving 98.47% and 98.53% accuracy, respectively. The precision, recall, and F1-score values further confirm that the models are not only accurate but also balanced in detecting ES and non-ES classes. For all models, these values are close to their corresponding accuracy values, indicating stable classification without major bias toward either class. Overall, the results demonstrate that high ES detection performance can be maintained with approximately 10 selected channels, supporting the effectiveness of PCS for channel-efficient EEG-based seizure detection.

Performance Comparison With Existing Studies

This section compares the performance of the proposed method with prominent existing EEG-based ES detection strategies, focusing on test set accuracy as a measure of generalization ability. The CHB-MIT dataset has been used in a number of recent studies to detect epileptic seizures using different machine learning and deep learning techniques. A comparative overview of this research is given in Table 7, which covers topics including claimed accuracies, channel selection methods, signal decomposition and feature engineering techniques, data segmentation methodologies, and classification models. The results of the existing methods are reported as presented in their respective publications. Additionally, it should be mentioned that many of these studies did not use channel selection; as a result, the stated performance is based on all 22 EEG channels. In this category, Hassan et al. (2022); Kong et al. (2024) achieved 99.57% and 99.32% accuracy, respectively, by combining signal decomposition methods like EMD and DWT with manually created feature extraction and machine learning classifiers. In our previous studies (Das et al., 2024 a-b), EMD-derived features were utilized with NN and CNN architectures without performing channel selection and achieved a near state-of-the-art performance of approximately 99.8%. In contrast, the proposed approach attains competitive test accuracy using only 10 selected channels, comparable to existing methods that rely on all 22 EEG channels.

Table 5: Comparison of outcomes across the evaluation of NN-10, NN-50, CNN-10, and CNN-50 models

Model	Selected Channels	Number of Channels	Max Validation Accuracy Raised (%)	Test Accuracy (%)
NN-10	7, 4, 20, 6, 21, 1, 3, 15, 16, 5, 19, 14	12	96.97	96.43
NN-50	7, 4, 20, 6, 17, 8, 21, 1, 3, 15, 9	11	98.56	98.38
CNN-10	7, 4, 6, 17, 21, 16, 10	07	98.40	98.79
CNN-50	7, 4, 17, 18, 3, 15, 11, 16, 12, 22	10	99.16	98.99

Table 6: Summary of 5-fold cross-validation experimental results on the test set

Model	Avg. Num. of Channels	Accuracy (%)	Precision	Recall	F1-Score
NN-10	10.80	96.29	0.9609	0.9633	0.9620
NN-50	10.40	98.15	0.9830	0.9798	0.9814
CNN-10	9.80	98.47	0.9858	0.9838	0.9848
CNN-50	10.00	98.53	0.9834	0.9854	0.9844

Table 7: Experimental comparison of the proposed method with prior approaches on the CHB-MIT dataset

Study [Ref.], Year	Segment Time (Overlap %)	Train-Test Split	Decomposition + Feature Extraction + Feature Selection	Channel Selection (CS) Method: Number of Selected Channels	Classification using ML/DL	Accuracy (%)
Hassan et al., 2022	10 sec (70% overlap)	K-fold cross-validation (CV) K = 2, 5, 10	EMD + Ellipse area, variance, Fluctuation Index + MI	[No CS]: 22	MLPNN	99.57
Mohammadpoory et al., 2025	3 sec & 6 sec (no overlap)	Leave-One-Patient-Out (24-fold CV)	DWT + Weighted Visibility Graph	[No CS]: 22	RF, SVM, KNN, NB, LDA	94.02
Kong et al., 2024	1024 data points (64 points overlap)	10-fold cross-validation	DWT + Welch + PMPSO	[No CS]: 22	SVM, ANN, RF, and XGBoost	99.32
Das et al., 2024a	10 sec (70% overlap)	5-fold cross-validation	EMD + Fluctuation Index, Variance, Ellipse area + [No FS]	[No CS]: 22	CNN	99.78
Das et al., 2024b	10 sec (70% overlap)	80-20	EMD + Fluctuation Index, Variance, Ellipse area + [No FS]	[No CS]: 22	NN	99.80
Ferrara et al., 2025	4 sec (50% overlap)	Leave-one-record-out (LORO) cross-validation	[No Decomposition] + PCC + [No FS]	PCA: 2 channels (per patient, not fixed, which two channels)	CNN	83.00
Dokare and Gupta, 2025	4 sec (no overlap)	70/30 split, then on 70% 5-fold cross-validation	DWT + [No FE] + [No FS]	MI and RF: Channel number varies with patient	SVM	97.70
Moctezuma and Molinas, 2020	6 sec (no overlap)	10-fold cross-validation	EMD/DWT + [No FS]	Backward-elimination algorithm and NSGA-III: 1 to 3	SVM, KNN, RF	1 Channel: 97 2 Channel: 98 3 Channel: 99
Proposed Method	10s (70% overlap)	80-20	EMD + FI, V, Ellipse area SODP + [No FS]	Rank-based Progressive: 10	CNN	98.99

Table 7 shows that the proposed approach delivers competitive results when compared with existing channel-selection-based methods. Selecting an effective subset of EEG channels without compromising classification performance is a crucial challenge. In general, there exists a trade-off between model complexity, the number of EEG channels used, and overall predictive performance. Preserving strong generalization ability on the test set after channel reduction is particularly important, since channel selection is typically performed using training or validation data. Moctezuma and Molinas (2020) applied evolutionary optimization-based channel selection methods, which are relatively complex, reducing the number of channels significantly (to as few as 1–3 channels) while still achieving reasonable accuracies between 97% and 99% using 10-fold cross-validation with 10% test data. The recent method adopted by Ferrara et al. (2025) proposed a patient-specific PCA-based channel selection approach, which achieved a comparatively lower accuracy of 83.00% using only two channels. Another recent method, Dokare and Gupta (2025), used MI and RF-based channel selection and obtained 97.70% accuracy.

In comparison, the proposed method introduces a straightforward progressive channel selection approach that yields a compact yet informative set of EEG channels. With only 10 channels and a CNN classifier, it achieves 98.99% accuracy, reflecting a strong trade-off between performance and efficiency. This comparison underscores the importance of effective channel selection for developing practical and computationally efficient seizure detection systems.

In summary, while several existing studies achieve slightly higher accuracies using all 22 channels, they do so at the cost of increased complexity and limited practical deployment. In contrast, the proposed PCS framework achieves competitive performance with less than half the channels. The identification of informative EEG channels can enable simpler hardware design and reduce the cost of EEG devices used for ES detection.

Conclusion

The major contribution of this study is the development of a Progressive Channel Selection (PCS) strategy for EEG-based epileptic seizure detection. Unlike many existing approaches that use all available EEG channels or select patient-specific channels, PCS identifies a compact set of informative channels through a validation-driven process. Initially, each channel is assessed separately, and then channels are progressively added only when they improve the validation accuracy of the model. This makes the channel selection process simple, interpretable, and directly connected to classification performance.

Another important contribution is the demonstration that high seizure detection accuracy can be maintained with fewer EEG channels. By combining EMD-based feature extraction with NN and CNN classifiers, the proposed framework achieved approximately 98%–99% test accuracy using fewer than half of the available CHB-MIT channels. These findings show that several EEG channels are not important for seizure detection, and carefully selected important channels can support lightweight and low-cost EEG monitoring devices without significantly compromising detection efficiency.

This study may be expanded in a number of ways by future research. Other signal decomposition techniques, such as Discrete Wavelet Transform, Variational Mode Decomposition, or hybrid decomposition methods, can be investigated with PCS to examine whether alternative signal representations improve seizure detection performance. Feature selection methods may also be integrated with PCS to further reduce the feature dimension after channel selection. Since PCS follows a greedy progressive strategy and does not exhaustively explore all possible channel combinations, advanced optimization techniques may be considered to identify potentially better channel subsets. In addition, future studies will include a comprehensive evaluation of inference time, training overhead, and PCS computational complexity to better assess the practical suitability of the proposed method for real-time and resource-constrained EEG-based seizure detection systems. Finally, PCS may be validated on additional EEG datasets and extended to other EEG-based applications, such as autism detection, emotion recognition, and sleep-stage classification.

Acknowledgment

The authors wish to thank the authority of the CHB-MIT Scalp EEG Database for preparing the dataset and making it publicly available for research.

Funding Information

This research received no external funding.

Author’s Contributions

Suraiya Akter Mumu: Developed the concept; conducted the experiments and contributed to editing and reviewing the manuscript.

Shupta Das: Developed the concept; conducted the experiments and result analysis; prepared the initial manuscript and contributed to editing and reviewed the manuscript.

M. A. H. Akhand: Developed the concept and contributed to result analysis; suggested initial manuscript preparation and contributed to editing and reviewed the manuscript.

Abdus Salam: Contributed to result analysis and suggested in initial manuscript preparation.

Md Abdus Samad Kamal: Contributed to result analysis, edited and reviewed the manuscript.

Ethics

The authors confirm that this article has not been submitted elsewhere and have no conflicts of interest or ethical issues.

References

Aayesha, B. Q. M., Afzaal, M., Shuaib Qureshi, M., & Gwak, J. (2022). Fuzzy-Based Automatic Epileptic Seizure Detection Framework. *Computers, Materials & Continua*, *70*(3), 5601–5630. https://doi.org/10.32604/cmc.2022.020348

Acharya, U. R., Vinitha Sree, S., Swapna, G., Martis, R. J., & Suri, J. S. (2013). Automated EEG Analysis of Epilepsy: A Review. *Knowledge-Based Systems*, *45*, 147–165. https://doi.org/10.1016/j.knosys.2013.02.014

Akhand, M. A. H., Maria, M. A., Kamal, M. A. S., & Murase, K. (2023). Improved EEG-based emotion recognition through information enhancement in connectivity feature map. *Scientific Reports*, *13*(1), 13804. https://doi.org/10.1038/s41598-023-40786-2

Al-Adhaileh, M. H., Ahmad, S., Alharbi, A. A., Alarfaj, M., Dhopeshwarkar, M., & Aldhyani, T. H. H. (2025). Diagnosis of epileptic seizure neurological condition using EEG signal: a multi-model algorithm. *Frontiers in Medicine*, *12*, 1577474. https://doi.org/10.3389/fmed.2025.1577474

Antonoudiou, P., Basu, T., & Maguire, J. (2025). SeizyML: An Application for Semi-Automated Seizure Detection Using Interpretable Machine Learning Models. *Neuroinformatics*, *23*(2), 23. https://doi.org/10.1007/s12021-025-09719-4

Asadzadeh, S., Yousefi Rezaii, T., Beheshti, S., Delpak, A., & Meshgini, S. (2020). A systematic review of EEG source localization techniques and their applications on diagnosis of brain abnormalities. *Journal of Neuroscience Methods*, *339*, 108740. https://doi.org/10.1016/j.jneumeth.2020.108740

Assali, I., Ghazi Blaiech, A., Ben Abdallah, A., Ben Khalifa, K., Carrère, M., & Hédi Bedoui, M. (2023). CNN-based classification of epileptic states for seizure prediction using combined temporal and spectral features. *Biomedical Signal Processing and Control*, *82*, 104519. https://doi.org/10.1016/j.bspc.2022.104519

Cao, X., Zheng, S., Zhang, J., Chen, W., & Du, G. (2025). A hybrid CNN-Bi-LSTM model with feature fusion for accurate epilepsy seizure detection. *BMC Medical Informatics and Decision Making*, *25*(1), 6. https://doi.org/10.1186/s12911-024-02845-0

Chung, Y. G., Cho, A., Kim, H., & Kim, K. J. (2024). Single-channel seizure detection with clinical confirmation of seizure locations using CHB-MIT dataset. *Frontiers in Neurology*, *15*, 1389731. https://doi.org/10.3389/fneur.2024.1389731

Das, S., Mumu, S. A., Akhand, M. A. H., & Kamal, M. A. S. (2024a). Epileptic Seizure Detection Using Integrated Decomposed Features from EEG Signal. *Journal of Computer Science*, *20*(10), 1270–1280. https://doi.org/10.3844/jcssp.2024.1270.1280

Das, S., Mumu, S. A., Akhand, M. A. H., Salam, A., & Kamal, M. A. S. (2024b). Epileptic Seizure Detection from Decomposed EEG Signal through 1D and 2D Feature Representation and Convolutional Neural Network. *Information*, *15*(5), 256. https://doi.org/10.3390/info15050256

Dikanev, T., Smirnov, D., Wennberg, R., Velazquez, J. L. P., & Bezruchko, B. (2005). EEG nonstationarity during intracranially recorded seizures: statistical and dynamical analysis. *Clinical Neurophysiology*, *116*(8), 1796–1807. https://doi.org/10.1016/j.clinph.2005.04.013

Dokare, I., & Gupta, S. (2025). Optimized seizure detection leveraging band-specific insights from limited EEG channels. *Health Information Science and Systems*, *13*(1), 30. https://doi.org/10.1007/s13755-025-00348-4

Du, L., Zhang, Y., Meng, Q., Zhang, H., & Li, Y. (2019). Automatic Seizure Detection Based on a Novel Multi-feature Fusion Method and EMD. *Advances in Neural Networks – ISNN 2019 (16th International Symposium on Neural Networks, Proceedings, Part II)*, 512–521. https://doi.org/10.1007/978-3-030-22808-8_50

Epilepsy. (2022). World Health Organisation. *World Health Organization Newsroom*. https://www.who.int/news-room/fact-sheets/detail/epilepsy

Ferrara, R., Giaquinto, M., Percannella, G., Rundo, L., & Saggese, A. (2025). Personalizing Seizure Detection for Individual Patients by Optimal Selection of EEG Signals. *Sensors*, *25*(9), 2715. https://doi.org/10.3390/s25092715

Gao, B., Zhou, J., Yang, Y., Chi, J., & Yuan, Q. (2022). Generative adversarial network and convolutional neural network-based EEG imbalanced classification model for seizure detection. *Biocybernetics and Biomedical Engineering*, *42*(1), 1–15. https://doi.org/10.1016/j.bbe.2021.11.002

Gómez, C., Arbeláez, P., Navarrete, M., Alvarado-Rojas, C., Le Van Quyen, M., & Valderrama, M. (2020). Automatic seizure detection based on imaged-EEG signals through fully convolutional networks. *Scientific Reports*, *10*(1), 21833. https://doi.org/10.1038/s41598-020-78784-3

Guttag, J. (2010). CHB-MIT Scalp EEG Database. *PhysioNet*. https://doi.org/10.13026/C2K01R

Hassan, K. M., Islam, Md. R., Nguyen, T. T., & Molla, Md. K. I. (2022). Epileptic seizure detection in EEG using mutual information-based best individual feature selection. *Expert Systems with Applications*, *193*, 116414. https://doi.org/10.1016/j.eswa.2021.116414

Hassan, K. M., Islam, Md. R., Tanaka, T., & Molla, Md. K. I. (2019). Epileptic Seizure Detection from EEG Signals Using Multiband Features with Feedforward Neural Network. *2019 International Conference on Cyberworlds (CW)*, 231–238. https://doi.org/10.1109/cw.2019.00046

He, J., Cui, J., Zhang, G., Xue, M., Chu, D., & Zhao, Y. (2022). Spatial–temporal seizure detection with graph attention network and bi-directional LSTM architecture. *Biomedical Signal Processing and Control*, *78*, 103908. https://doi.org/10.1016/j.bspc.2022.103908

Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., Yen, N.-C., Tung, C. C., & Liu, H. H. (1998). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, *454*(1971), 903–995. https://doi.org/10.1098/rspa.1998.0193

Huang, X., Meng, H., & Li, Z. (2026). Deep learning for epileptic seizure prediction from EEG signals: A review. *Biomedical Signal Processing and Control*, *117*, 109518. https://doi.org/10.1016/j.bspc.2026.109518

Isabelle, G., & Elisseeff, A. (2003). An introduction to variable and feature selection. *The Journal of Machine Learning Research*, *3*, 1157–1182.

Jibon, F. A., Chowdhury, A. R. J., Miraz, M. H., Jin, H. H., Khandaker, M. U., Sultana, S., Nur, S., Siddiqui, F. H., Kamal, A. H., Salman, M., & Youssef, A. A. F. (2024). Sequential graph convolutional network and DeepRNN based hybrid framework for epileptic seizure detection from EEG signal. *DIGITAL HEALTH*, *10*, 20552076241249870. https://doi.org/10.1177/20552076241249874

Kaziha, O., & Bonny, T. (2020). A Convolutional Neural Network for Seizure Detection. *2020 Advances in Science and Engineering Technology International Conferences (ASET)*, 1–5. https://doi.org/10.1109/aset48392.2020.9118362

Kong, G., Ma, S., Zhao, W., Wang, H., Fu, Q., & Wang, J. (2024). A novel method for optimizing epilepsy detection features through multi-domain feature fusion and selection. *Frontiers in Computational Neuroscience*, *18*, 1416838. https://doi.org/10.3389/fncom.2024.1416838

Li, S., Zhou, W., Yuan, Q., Geng, S., & Cai, D. (2013). Feature extraction and recognition of ictal EEG using EMD and SVM. *Computers in Biology and Medicine*, *43*(7), 807–816. https://doi.org/10.1016/j.compbiomed.2013.04.002

Liu, H., & Yu, L. (2005). Toward integrating feature selection algorithms for classification and clustering. *IEEE Transactions on Knowledge and Data Engineering*, *17*(4), 491–502. https://doi.org/10.1109/tkde.2005.66

Liu, S., Zhou, Y., Yang, X., Wang, X., & Yin, J. (2024). A Robust Automatic Epilepsy Seizure Detection Algorithm Based on Interpretable Features and Machine Learning. *Electronics*, *13*(14), 2727. https://doi.org/10.3390/electronics13142727

Mahmoodian, N., Boese, A., Friebe, M., & Haddadnia, J. (2019). Epileptic seizure detection using cross-bispectrum of electroencephalogram signal. *Seizure*, *66*, 4–11. https://doi.org/10.1016/j.seizure.2019.02.001

Mallick, S., & Baths, V. (2024). Novel deep learning framework for detection of epileptic seizures using EEG signals. *Frontiers in Computational Neuroscience*, *18*, 1340251. https://doi.org/10.3389/fncom.2024.1340251

Moctezuma, L. A., & Molinas, M. (2020). EEG Channel-Selection Method for Epileptic-Seizure Classification Based on Multi-Objective Optimization. *Frontiers in Neuroscience*, *14*, 593. https://doi.org/10.3389/fnins.2020.00593

Mohammadpoory, Z., Nasrolahzadeh, M., & Amiri, S. A. (2025). Patient-independent epileptic seizure detection using weighted visibility graph features and wavelet decomposition. *Multimedia Tools and Applications*, *84*(6), 3197–3221. https://doi.org/10.1007/s11042-025-20594-8

Mumu, S. A., Das, S., Akhand, M. A. H., Salam, A., & Kamal, M. A. S. (2025). Epileptic Seizure Detection from EEG Using Rank-Based Channel Selection and Neural Networks. *Proceedings of the 2025 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON)*, 106–111. https://doi.org/10.1109/becithcon69222.2025.11504077

Nandini, D., Yadav, J., Rani, A., & Singh, V. (2022). Improved Patient-Independent Seizure Detection System Using Novel Feature Extraction Techniques. *Proceedings of Second Doctoral Symposium on Computational Intelligence*, 879–888. https://doi.org/10.1007/978-981-16-3346-1_71

Nogay, H. S., & Adeli, H. (2020). Detection of Epileptic Seizure Using Pretrained Deep Convolutional Neural Network and Transfer Learning. *European Neurology*, *83*(6), 602–614. https://doi.org/10.1159/000512985

OK, F., & Rajesh, R. (2020). Empirical Mode Decomposition of EEG Signals for the Effectual Classification of Seizures. *Advances in Neural Signal Processing*. https://doi.org/10.5772/intechopen.89017

Pattnaik, S., Rout, N., & Sabut, S. (2022). Machine learning approach for epileptic seizure detection using the tunable-Q wavelet transform based time–frequency features. *International Journal of Information Technology*, *14*(7), 3495–3505. https://doi.org/10.1007/s41870-022-00877-1

Peya, Z. J., Peya, Z. J., Akhand, M. A. H., Ferdous Srabonee, J., & Siddique, N. (2020). EEG Based Autism Detection Using CNN Through Correlation Based Transformation of Channels' Data. *Proceedings of the 2020 IEEE Region 10 Symposium (TENSYMP)*, 1278–1281. https://doi.org/10.1109/tensymp50017.2020.9230928

Sagga, D., Echtioui, A., & Kallel, F. (2024). Comparative analysis of deep learning algorithms for seizure detection. *Multimedia Tools and Applications*, *84*(25), 29351–29370. https://doi.org/10.1007/s11042-024-20330-8

Salafian, B., Ben-Knaan, E. F., Shlezinger, N., Ribaupierre, S. de, & Farsad, N. (2022). CNN-Aided Factor Graphs with Estimated Mutual Information Features for Seizure Detection. *Proceedings of the ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 8677–8681. https://doi.org/10.1109/icassp43922.2022.9746730

Sameer, M., & Gupta, B. (2022). CNN based framework for detection of epileptic seizures. *Multimedia Tools and Applications*, *81*(12), 17057–17070. https://doi.org/10.1007/s11042-022-12702-9

DOI: 10.3844/jcssp.2026.2006.2021

Tapani, K. T., Vanhatalo, S., & Stevenson, N. J. (2019). Time-Varying EEG Correlations Improve Automated Neonatal Seizure Detection. *International Journal of Neural Systems*, *29*(04), 1850030. https://doi.org/10.1142/s0129065718500302

Thakare, V. S., & Ranawat, R. (2025). Multimodality Deep Learning Fusion Based Epileptic Seizure Detection. *International Journal of Intelligent Engineering and Systems*, *18*(2), 679–691. https://doi.org/10.22266/ijies2025.0331.49

Ullal, A., & Pachori, R. B. (2020). EEG Signal Classification using Variational Mode Decomposition. *ArXiv*. https://doi.org/10.48550/arXiv.2003.12690

Yan, X., Yang, D., Lin, Z., & Vucetic, B. (2022). Significant Low-Dimensional Spectral-Temporal Features for Seizure Detection. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 668–677. https://doi.org/10.1109/tnsre.2022.3156931

Zhang, J., Zheng, S., Chen, W., Du, G., Fu, Q., & Jiang, H. (2024). A scheme combining feature fusion and hybrid deep learning models for epileptic seizure detection and prediction. *Scientific Reports*, *14*(1), 16916. https://doi.org/10.1038/s41598-024-67855-4