International Journal of Mathematics, Statistics, and Computer Science
Vol. 3
ISSN: 2704-1077 eISSN 2704-1069, DOI: 10.59543/ijmscs.v3i.14771

EEG Feature Selection Techniques for Epileptic Seizure Detection: Performance and Evaluation Study

Ali Al Farawn[1,2], Salam Al-Khammasi[1,3], Ahmed Hazim Alhilali[4], Nabeel Salih Ali1[5]*
[1]Information Technology Research and Development Centre, University of Kufa, Najaf Governorate, Iraq
[2]Faculty of Engineering, University of Kiel, Kiel, Germany
[3]College of Engineering, University of Bridgeport, Bridgeport, CT, USA 06604
[4]Faculty of Engineering and Information Technology , University of Technology Sydney, Ultimo, NSW 2007, Australia
[5]Faculty of Information and Communication Technology, University Technical Malaysia Melaka, , Melaka , Malaysia
*nabeel@uokufa.edu.iq

Received 15.05.2025, Revised 17.06.2025, Accepted 20.06.2025

Abstract: Epilepsy poses a significant challenge for people around the world, particularly in third-world countries. Hence, over 80 million people are suffering from this disease. Therefore, the detection of epileptic seizures plays a vital role in diagnosis by measuring the activity of the brain, like the Electroencephalography (EEG) instrument. Nowadays, Data variety, attributes and size are growing increasingly, causing high dimensions and high preprocessing, which requires high computational resources. Therefore, reduce the data dimension to eliminate posing high computational resources in data preprocessing in the classification techniques. To address these issues, different feature selection techniques are used for high-dimensional data reduction by selecting the most relevant features in the classification process, which aim to detect disease faster and accurately. These techniques include Mean Decrease in Impurity (MDI), Correlation Coefficient, Sequential Forward Selection (SFS), and Sequential Backwards Selection (SBS). The results have registered diverse classification accuracy ratios for the mentioned method when using random forest classification, where MDI has 98.313% to 98.1% accuracy ranges for the selected features, whilst it achieved 98.504% in the case of using all the features. Moreover, the highest percentage, 98.4% accuracy, was achieved with the correlation method when extracting two features. On the other hand, SFS has an accuracy range from 98.6% to 98.212% after extracting nine features. A satisfactory classification accuracy was maintained by the SBS method, with accuracy from 98.6% to 98.2% after deleting ten features. Classification performance results show their impact in reducing dataset dimension, complexity, and computational resources cost, respectively.

Keywords: Feature Selection; Filter Methods; Wrapper Methods; Epileptic Seizure; RF Classification;

1. Introduction

Epilepsy is one of the most common and potentially life-threatening neurological disorders. It affects people of every age, race, and socioeconomic background, with incidence peaks in early childhood and after the age of sixty [1]. Although epilepsy is a frequent neurological disorder, many patients do not receive an early and correct diagnosis, and some do not have access to suitable treatment.

According to data from 2020, the number of people living with epilepsy reached about 50 million worldwide [2]. The number of deaths related to epilepsy is increasing and 80% of these cases are found in developing countries.

In 2019, The World Health Organization reported that the proportion of people affected by this disease is between 4 and 10 per 1,000 individuals especially those with severe conditions who need medical care. This percentage can be higher in developing countries with medium or low income [3]. Electroencephalography (EEG) is a method for diagnosing epilepsy.

To perform this test, electrodes are placed on the scalp to record the electrical activity of the brain. This technique is non-invasive and allows for the extraction and analysis of wave signals from the brain, these signals are essential for identifying abnormal patterns related to epilepsy [4].

Past studies have discussed this trend. Authors in [4] have combined feature ranking with an artificial-neural-network (ANN) classifier and they achieved 96.9 % accuracy. Another study by authors in [5] assesst independent component analysis for artefact deletion, ANOVA-based feature selection, and a fuzzy classifier, reporting 96.48 % accuracy.

In another work by [6] applied the ReliefF algorithm to 52 time-, frequency-, and time–frequency-domain features and showed competitive results. A research by [7] conducted a prediction methods using EEG signal processing and deep learning and comprehensive review of epilepsy detection. Their models can achieve accuracy rates above 95% on benchmark datasets such as CHB-MIT.

Work by [8] proposed a novel approach that combines hybrid deep learning model (CNN-GRU-Attention Mechanism) with a multi-class feature fusion for seizure prediction and detection. Their method achieved an accuracy of 99.35% for seizure detection and 95.16% for seizure prediction, demonstrating the value of integrating time frequency and nonlinear features with attention-based deep learning by using the CHB-MIT dataset.

In addition, to detect automated EEG-based epilepsy, authors in [9] enhanced a dual-attention mechanism model. Their spatio-temporal feature fusion framework (STFFDA) directly processes raw EEG signals, eliminating the need for extensive preprocessing. Their model achieved a single-validation accuracy of 95.18% and a 10-fold cross-validation accuracy of 92.42%, confirming the potential of attention mechanisms for robust and efficient seizure detection on the CHB-MIT dataset. The present studies are concerned with reducing the number of features used for classification by applying feature selection techniques.

In this proposed approach, only the features that have the strongest relationship with the classification task are kept, while features that are not relevant are removed.

The main contrubutions of this paper are:

1- Employing an optimization strategy of four methods (Mean Decrease in Impurity (MDI), Correlation Coefficient, Sequential Forward Selection (SFS), and Sequential Backward Selection (SBS)).

2- Determine the accuracy for each method after removing the irrelevent feautres. deleting up to five features has reduced accuracy marginally to ~ 98%.

According to the methodology of recent studies, the research includes five main phases:

1- Acquisition

2- The EEG signal is filtered.

3- Features are extracted from the signal.

4- Feature selection is performed to keep only those features that are important and have a significant effect in diagnosing epilepsy and evaluating the patient’s condition.

5- Classification: This method makes it easier to detect epilepsy, allowing patients to receive an accurate and approved diagnosis in a short period and to start suitable treatment before the disease becomes more severe by focusing on the most reliable features.

The paper is organized as follows:

- Section 1 is the introcution.
- Section 2 details the proposed approach methodology.
- Section 3 expalins the experimental results.
- Section 4 compares those results with state-of-the-art studies from recent years.
- Section 5 presents the conclusions of this paper.

2. Methodology

Due to the inherent variability in clinical manifestations among individuals with epilepsy, the classification of seizure episodes presents a significant challenge in clinical research. This heterogeneity complicates the differentiation between epileptic and non-epileptic events, as noted in prior studies [10]. To address this issue, the current study emphasizes the optimization of classification models through dimensionality reduction strategies. While excluding non-informative or redundant features, feature selection methodologies are applied to retain and identify variables with the highest discriminative power for seizure classification. This approach improves computational efficiency by reducing data complexity, which may contribute to speeding up diagnostic processes and improved classification accuracy. Figure 1 illustrates the methodological flowchart of this research and is structured into distinct phases. Each phase in the proposed framework is structured to perform a distinct task, with the primary objective of evaluating the influence of feature selection techniques on the performance of the classification model for distinguishing between different seizure types.

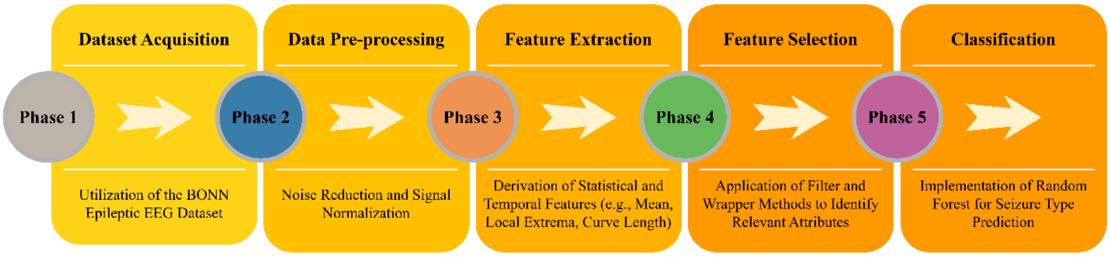

Figure 1. Five-phases framework (Methodology Flowchart)

2.1. Acquisition

The Bonn Epilepsy Seizure Detection Dataset, developed by the University of Bonn, serves as a foundational resource for investigating electroencephalogram (EEG) based identification of epileptic seizures. The dataset comprises five distinct subsets labeled (A, B, C, D, and E), each containing 100 EEG channels. Each channel encompasses 123,500 data samples acquired over a temporal window of 23.6 seconds, totaling approximately 178 seconds of recording time.

Subsets A and B originate from surface EEG recordings of five healthy participants without epilepsy. Subset A captures neural activity during wakeful relaxation with open eyes, while subset B corresponds to the same state with closed eyes. Both subsets utilize non-invasive electrode placement. In contrast, subsets C, D, and E derive from intracranial EEG data archived during pre-surgical evaluations of epilepsy patients. Subset C contains interictal (non-seizure) activity recorded from the hippocampal formation in the hemisphere contralateral to the epileptogenic focus. Subset D similarly represents seizure-free intervals but is sourced directly from the epileptogenic zone. Subset E exclusively features ictal (seizure) activity recorded from the hippocampal focus.

All EEG signals were acquired using the standardized 10–20 electrode configuration system, ensuring consistent spatial resolution across recordings [11]. The dataset’s structure facilitates comparative analysis between healthy and pathological brain activity, with subsets A and B serving as controls, while C, D, and E enable examination of epileptogenic regions during interictal and ictal states. This hierarchical organization supports methodological development in seizure detection algorithms, particularly in distinguishing baseline activity from pre-seizure and seizure events.

2.2. Data Pre-processing

Although filtering the EEG signal can introduce temporal distortions, it is a critical step for eliminating artifacts and reducing noise that may interfere with the detection of meaningful brain activity. As EEG signals are acquired directly from the brain, they generally require less extensive pre-processing; however, the selection of filtering techniques must be done with care. Conventionally, a low-pass filter is used to eliminate high-frequency components above 40–50 Hz, while a high-pass filter is employed to suppress slow drifts below 0.1 Hz.

In addition to basic filtering, several advanced signal processing methods have been developed to further improve EEG signal quality and remove thermal noise and physiological artifacts. Techniques such as Wavelet Transform (WT), Empirical Mode Decomposition (EMD), and Blind Source Separation (BSS) are commonly utilized for this purpose. WT-based denoising, for example, operates by decomposing the signal into wavelet coefficients using a selected basis function. A threshold is then applied to discard coefficients likely to represent noise, and the signal is reconstructed using the remaining coefficients. In [12] authors introduced a dynamic thresholding approach using Discrete Wavelet Transform (DWT), which demonstrated effective artifact removal and signal enhancement. Also they applied DWT in combination with adaptive filtering to suppress low-frequency physiological artifacts, preserving relevant neural information more accurately.

2.3. Feature Extraction

This section outlines the critical features extracted from EEG signals to enable efficient classification of epileptic activity. Most feauters were extracted from [13].Feature extraction serves two primary objectives: (1) preserving diagnostically relevant information during signal processing, and (2) reducing computational complexity by minimizing redundant data representation [5].

The following features were evaluated across all experimental cases, derived from preprocessed EEG data:

- Mean Value: represents the arithmetic average of signal amplitudes within a time window. Calculated as:

$$\bar{x} = \frac{\sum x_n}{N} \tag{1}$$

Where:
x_n : Signal amplitude
N : The number of samples [6].

For enhanced discriminative power, mean values were computed for both the raw signal and its first/second derivatives.

- Zero-Crossing Rate: Quantifies sign changes in the signal waveform, calculated for both the raw signal and its first/second derivatives. This metric reflects signal oscillatory behavior.
- Local Minima: Number of amplitude troughs within a defined interval.
- Local Maxima: Number of amplitude peaks within the same interval.
- Curve Length: Measures cumulative waveform variability using the integral:

$$curve\ length = \int_a^b \sqrt{1 + \frac{dx}{dt}^2}\ dt \tag{2}$$

- Absolute Value: Computes the mean absolute value of the signal's first and second derivatives to quantify rate-of-change patterns.
- Hjorth Parameters: Three statistical descriptors for time-domain signal analysis [14]:
    1- Activity is the signal variance:

$$activity = variance\big(x(t)\big) \tag{3}$$

    2- Mobility is the ratio of derivative variance to signal variance:

$$mobility = \sqrt{\frac{variance(\frac{dx}{dt})}{variance(x(t))}} \tag{4}$$

    3- Complexity: Compares mobility of the signal to its derivative:

$$complexity = \frac{mobility(\frac{dx}{dt})}{mobility(x(t))} \tag{5}$$

- Amplitude Range:
    1- Maximum: Peak amplitude value in the window.
    2- Minimum: Trough amplitude value in the window [5].
- Energy Duration:

The time required to compute the energy content within each analysis window. These time and frequency domain features collectively characterize EEG patterns associated with healthy versus epileptic states. Subsequent feature selection will identify the most discriminative features, eliminating redundant variables to enhance computational efficiency and classification accuracy.

2.4.Feature Selection

Feature selection constitutes an essential preprocessing step to address the challenges of high-dimensional datasets, where irrelevant or redundant features frequently compromise computational efficiency and model performance. Such superfluous variables not only increase processing time but also impose excessive storage requirements [15].
In this study, a comparative evaluation of multiple feature selection methodologies was conducted to identify the optimal feature subset that keep classification accuracy while minimizing dimensionality.

These techniques, schematically illustrated in Figure 2, enable systematically eliminating non-discriminative features, thereby enhancing algorithmic robustness and reducing resource demands.

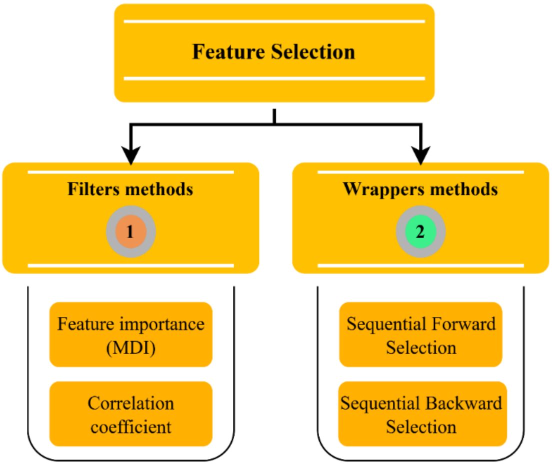

Figure 2. Feature Selection Methods (Filters and Wrappers)

2.5. Filter Methods

Filter-based feature selection methods demonstrate computational efficiency when processing high-dimensional data due to their independent model approach [15]. Unlike wrapper techniques that require iterative model training, these methods evaluate feature relevance through statistical measures prior to classification, significantly reducing processing time and resource consumption. Common implementations include the Chi-square test, Fisher's Score, Variance Threshold, ANOVA, and Correlation Coefficient.
This study employs the Correlation Coefficient method to quantify linear dependencies between features. By identifying strongly correlated variables (where one feature reliably predicts another), redundant attributes can be systematically eliminated without compromising informational integrity. The evaluation metric for pairwise correlation is defined as:

$$MS = \frac{K}{\sqrt{k+k(k-1)\overline{r_{ff}}}} \qquad (6)$$

The heuristic value *MS* is used to evaluate the quality of a feature subset *S* that contains *K* features. The term $\overline{r_{cf}}$ denotes the mean correlation between features and the class, and $\overline{r_{ff}}$ represents the average correlation among the features themselves, as described in [14].
This heuristic is designed to reduce the selection of features that are not relevant or carry redundant information; as such, features do not contribute effectively to the classification task.

Besides applying the feature importance method, this work also uses two additional techniques. One of them is known as Gini Importance or Mean Decrease in Impurity (MDI) [16]. The MDI approach calculates feature importance by counting how often a feature is used to split decision nodes in the model, with the contribution weighted by the number of data samples involved in each split. The total importance of a feature is obtained by summing these contributions across all trees in the ensemble.

2.6. Wrapper Methods

Wrapper methods provide high level feature selection capability compared to filter techniques, achieving enhanced predictive accuracy through iterative model-based evaluation of feature subsets. On other hands, this performance advantage comes at substantial computational expense, as wrappers systematically explore all potential feature combinations to identify optimal subsets—a process requiring repeated model validation and training[15]. Common implementations include recursive feature elimination (RFE), exhaustive feature selection (EFS), Sequential Forward Selection (SFS), and Sequential Backward Selection (SBS), all of which integrate classifier feedback during the selection process.

In this paper, Sequential Forward Selection (SFS), and Sequential Backward Selection (SBS) and recursive feature elimination (RFE) were implemented to balance classification accuracy with computational efficiency. FFS constructs feature subsets incrementally by adding the most discriminative attributes, while BFE iteratively eliminates the least contributive features from the full feature set. RFE extends this approach by recursively pruning features rely on model weights (e.g., tree importance scores or SVM coefficients).

3. Results

Different research studies use different performance metrics to measure feature performance and classification accuracy. The study within reference [6] used multiple performance measures, including True Positive Rate (TPR), False Positive Rate (FPR), and accuracy. Another study [14] also applies sensitivity, specificity, and accuracy as performance metrics to benchmark a feature selection method. Among all measures, accuracy is the most common metric for evaluating classification performance simply because it is the ratio between the amount of correctly classified EEG signals over the total amount of EEG signals. Accordingly, this study proposed using accuracy as the primary evaluation metric of classification accuracy and the F1-score as it is a balance of precision and recall.

Accuracy was computed using the following definition:

$$accuracy = \frac{TPn + TNn}{TPn + FNn + TNn + FPn} \times 100\% \qquad (9)$$

Where *TPn* is the true positive, *TNn* the true negative, *FNn* the false negative, and the *FPn* is the false positive.
And *F1- Score* defined as:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \times 100\% \qquad (10)$$

Where Precision is a metric that measures how accurate a classifier is when it predicts the positive class

$$Precision = \frac{TPn}{TPn + FPn} \times 100\% \qquad (11)$$

and Recall measures how well a model can identify all actual positive cases.

$$Recall = \frac{TPn}{TPn + FNn} \times 100\% \qquad (12)$$

The data for all features without features selection (15 features) have an accuracy of 98.4%. Figure 3. shows the confusion matrix for the data before applying feature selection methods.

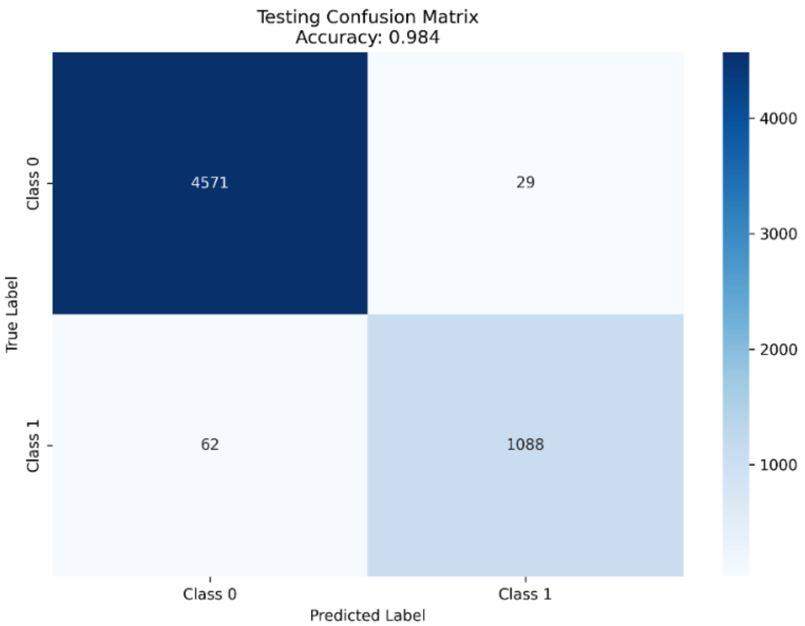

Figure 3. Testing Confusing Matrix for all features (15 features).

The outcome of this project is to apply both wrapper-based and filter-based selection techniques for classifying epileptic seizure activity using EEG signals have been shown. The main evaluation metrics were classification accuracy and F1-score, both of which demonstrate the predictive performance of the random forest (RF) classifier under different feature selection scenarios.

3.1. Result of Filter methods

3.1.1. Mean Decrease in Impurity (MDI)

Figure 4. represents the significance of each of the fifteen extracted features that were extracted from the EEG data after applying random forest classifier.

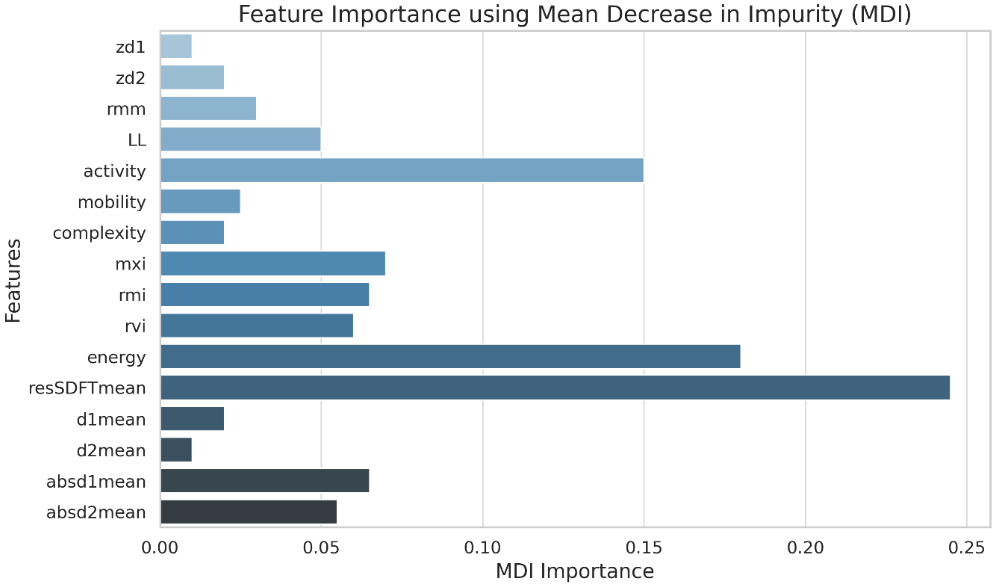

Figure 4. Shows the Significance of Each Feature Using MDI Method

The MDI method used feature importance based on their contribution to node impurity reduction in the random forest classifier. As shown in Figure 4., features such as SDFTmean, activity, and energy had the highest importance scores, while others like d1mean, d2mean, and zd1 were less influential.
Table 1 illustrates the real impact of iterative feature removal on the accuracy of the model. deleting up to five features reduced the accuracy marginally to 98.102%. The best trade-off was noticed after removing three features (d1mean, d2mean, zd1), yielding 98.469% accuracy and a 96.12% F1-score.

Table 1. Change the accuracy percentage by selecting the features in MDI method

N.Features	*The Deleted features*	*Accuracy%*	*F1 Score %*
13	d1mean ,d2mean	98.313%	95.69%
12	D1mean,d2mean,zd1	98.469%	96.12%
11	D1mean,d2mean,zd1,mobility	98.260%	95.57%
10	D1mean,d2mean,zd1,mobility ,complexity	98.173%	95.15%
9	D1mean,d2mean,zd1,mobility ,complexity ,zd2	**98.102%**	**94.90%**
8	D1mean,d2mean,zd1,mobility ,complexity ,zd2,nmm	98.0%	94.96%
7	D1mean,d2mean,zd1,mobility ,complexity ,zd2,nmm,ll	98.19%	95.45%
6	D1mean, d2mean, zd1, mobility, complexity, zd2, nmm, LL, absd2mean	98.03%	95.05%
5	D1mean, d2mean, zd1, mobility, complexity, zd2, nmm, LL, absd2mean, absd1mean	97.57%	93.95%

3.1.2. Correlation Coefficient Method

The correlation-based filter approach deleted redundant features based on inter-feature correlation exceeding a predefined threshold (ranging from 0.7 to 0.95). When eight highly correlated features were removed using a 0.95 threshold, the highest classification accuracy of 98.33% was obtained as shown in Table 2.

As illustrated in Figure 5 this method is based on assessing the degree of similarity among the fifteen extracted features, and between each feature and the target variable, as shown in Figure 6. Features exhibiting high inter-correlation and indicating redundancy can be selectively removed by applying a correlation threshold. Specifically, the feature with the lower correlation to the target is excluded from the dataset if two features demonstrate a correlation exceeding the defined threshold.

It is crucial to note that the threshold value in this approach can be adjusted, allowing for precise control over the level of permissible similarity among features. Classification accuracy differs according to the number and identity of features removed under different threshold values as demonstrated in Table 2.

The analysis indicates that keeping a threshold below 0.8 leads to a noticeable decline in classification performance. Consequently, to enable the removal of six redundant features while achieving an accuracy of 98.10%, a threshold value of 0.9 was found to offer the most favorable balance. This shows the method's effectiveness in optimizing feature selection without significantly corrupting model performance.

Table 2. Change the accuracy percentage with the threshold by selecting the features in correlation method

Threshold	*Selected Features*	*Accuracy%*	*F1 Score %*
0.7	zd2, nmm, complexity', resSDFTmean	97.8%	94.45%
0.75	zd2, nmm, complexity', resSDFTmean	98.03%	95%
0.8	zd2, nmm, complexity, resSDFTmean	98.03%	95%
0.85	zd2, nmm, complexity, mxi, mni, resSDFTmean	**98.29%**	**95.69%**
0.9	zd2, nmm, complexity, mxi, mni, resSDFTmean	98.29%	95.69%
0.95	zd2, nmm, activity, complexity, mxi, mni, resSDFTmea', absd1mean	98.33%	95.79%

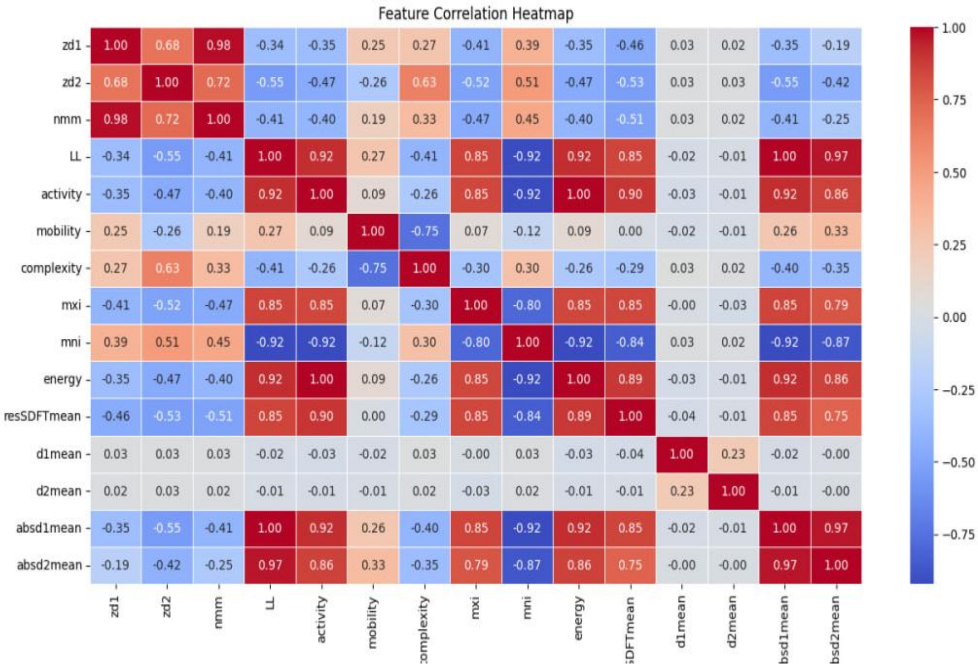

Figure 5. Heat Map Demonstration of the Correlation Method Shows the Similarity Ratio Between 15 Features,

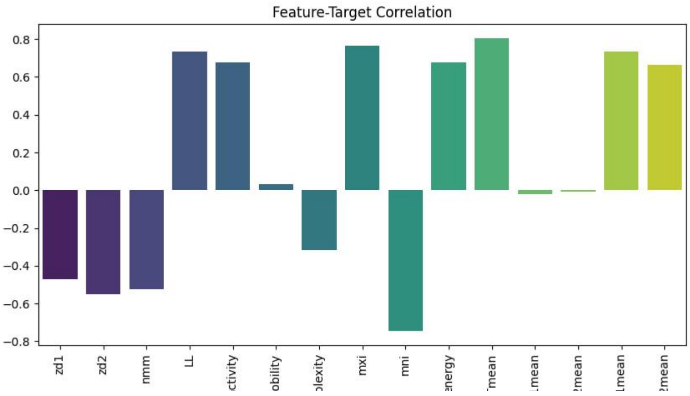

Figure 6. The similarity Between 15 Features and Target using Correlation Method.

3.2. Result of Wrapper methods

In contrast to the filter-based techniques, the wrapper methods result specifically Sequential Backward Selection (SBS and Sequential Forward Selection (SFS) are summarized in Tables 3 and 4, respectively. As previously discussed, wrapper methods operate in conjunction with a predictive model, allowing the algorithm to retain those that optimize classification performance and iteratively evaluate feature subsets. This method varies from filter methods, which depend on statistical measures independent of model feedback.

3.2.1. SFS method

Table 3 presents the outcomes of the SFS method, which sequentially adds features that most improve the model's accuracy. The accuracy is 98.4% when selecting the top thirteen features, the model automatically excluded *zd1* and *absd1mean*. When all features were included, this performance is nearly equivalent to the baseline accuracy of 98.44% achieved. Notably, the highest classification accuracy of 98.6% appeared using twelve features. Further reductions to eleven and ten features yielded slightly lower, yet comparable, accuracies of 98.5%. A gradual decline was noticed as the feature count dropped less than six, with accuracy reduced to 98.2% or lower, showing the importance of maintaining an adequate number of informative features.

Table 3. Change the accuracy percentage by selecting the features in SFS method

N.features	***The Deleted features***	***Accuracy%***	***F1 Score %***
13	Zd1 ,absd1mean	98.4%	96%
12	Zd1 ,absd1mean ,LL	98.6%	96.43%
11	Zd1 ,absd1mean ,LL,d1mean	98.512%	96.17%
10	Zd1 ,absd1mean ,LL,d1mean,activity	98.5%	95.9%
9	Zd1 ,absd1mean ,LL,d1mean,activity ,mni	98.40%	95.96%
8	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean	98.4%	95.85%
7	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean ,d2mean	**98.50%**	**96.1%**
6	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean ,d2mean,zd2	98.212%	95.7%
5	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean ,d2mean,zd2,max	97.96%	94.82%
4	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean,d2mean,zd2,max,energy	97.90%	95.3%
3	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean,d2mean,zd2,max,energy,nmm	97.78%	95.03%
2	Zd1 ,absd1mean ,LL,d1mean,activity ,mni,absd2mean,d2mean,zd2,max,energy,nmm,mobility	97.75%	93.63%

3.2.2. SBS method

Similarly, Table 4 summrize the performance of the SBS method, which begins with the full feature set and removes the least contributive features in a stepwise manner. The results show strong consistency with the SFS method, albeit with slight differences in feature selection and resulting accuracy. For example, eliminating *d1mean* and *d2mean* while retaining thirteen features yielded an accuracy of 98.4%, mirroring the performance seen in SFS. The model maintained high accuracy98.5% with twelve features and peaking at 98.6% with ten features. As features were progressively removed.
Interestingly, the SBS method demonstrated high performance in some cases. SBS maintained an accuracy of 98.4%, which was marginally higher than that of SFS for the same feature count when using eight or seven features. However, the accuracy declined to 98.2%, which was deemed suboptimal when the number of features was reduced to five or fewer. Thus, it was determined that the minimum number of features should not fall below five or six to preserve model performance.
While preserving classification accuracy, with SBS demonstrating slightly greater resilience in scenarios involving more aggressive feature reduction, these results confirm that both SFS and SBS are effective at reducing dimensionality.

Table 4. Change the accuracy percentage by selecting the features in SBS method

N.features	***The Deleted features***	***Accuracy%***	***F1 Score %***
13	d1mean ,d2mean	98.4%	95.78%
12	d1mean ,d2mean ,nmm	98.5%	96.2%
11	d1mean ,d2mean ,nmm, energy	98.50%	95.25%
10	d1mean ,d2mean ,nmm, energy ,max	98,6%	95.38%
9	d1mean ,d2mean ,nmm, energy ,max ,mobility	98.5%	96.31%
8	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1	98.4%	95.92%
7	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1 ,absd2mean	98.4%	95.82%
6	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1 ,absd2mean ,mni	**98.41%**	**95.44%**
5	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1 ,absd2mean ,mni ,absd1mean	98.20%	95.52%
4	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1 ,absd2mean ,mni ,absd1mean,activity	98.2%	95.38%
3	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1 ,absd2mean ,mni ,absd1mean,ll,energy	97.8%	94.99%
2	d1mean ,d2mean ,nmm, energy ,max ,mobility,zd1 ,absd2mean ,mni ,absd1mean,ll,activity,energy	97.77%	94.12%

4. Discussion

In this section, a critical evaluation of the feature selection methods employed, focusing on their effectiveness in maintaining high classification accuracy while reducing feature dimensionality. The analysis of this section inlcudes a comparative review of both wrapper and filter methods, reaching the highest development in the design of a hybrid model based on the most frequently retained features. Additionally, the performance of the proposed approach which is benchmarked against existing state-of-the-art studies in literature.

4.1. Comparative Analysis of Feature Selection Techniques

The filter-based methods, Mean Decrease in Impurity (MDI) and Correlation Coefficient, produced satisfactory outcomes based on the results presented in Tables 1 and 2. After the removal of three features (d1mean, d2mean, zd1), The MDI method achieved a maximum classification accuracy of 98.469% while maintaining 98.173% accuracy even after excluding up to five features. By adjusting the similarity threshold, the Correlation Coefficient method allowed the elimination of two to five redundant features with minimal impact on accuracy with a highest accuracy of 98.4%, particularly when absd1mean and energy were excluded at a threshold of 0.99.

In comparison, Tables 3 and 4 show that the wrapper-based methods, Sequential Forward Selection (SFS), and Sequential Backward Selection (SBS) demonstrated superior performance. These methods integrate the feature selection process with the learning model to enable automatic identification of feature subsets that optimize classification performance. Even after removing nine features, the SFS method retained high accuracy (98.212%) and achieved a maximum of 98.6% when absd1mean, zd1, and LL were excluded. In the same way, upon removal of d1mean, d2mean, nmm, energy, and max, the SBS method yielded comparable results, attaining a peak accuracy of 98.6%. Notably, even with fewer features, highlighting its robustness in dimensionality reduction, SBS maintained high accuracy levels.

These observations affirm the advantages of wrapper methods over filter methods in terms of feature reduction efficiency and classification accuracy. This can be attributed to the model-based selection mechanism inherent in wrapper approaches, which evaluates feature importance dynamically during training. In contrast, filter methods rely on static, threshold-based metrics, and manual intervention, which may overlook complex feature interactions. However, it is also important to note that wrapper methods are time-consuming and computationally more intensive.

4.2. Optimized Hybrid Model Development

A hybrid model was developed using the most frequently excluded features across all approaches to capitalize on the strengths of all evaluated methods.The features commonly identified as redundant (d1mean, d2mean, zd1, energy, and absd1mean) were removed as shown in Table 5, resulting in a streamlined model containing ten features. This hybrid configuration achieved a classification accuracy of 98.539%, showing the ability of constructing a compact yet high-performing model through integrative feature selection.

Table 5. Highest accuracy for each method

Method	***The Deleted features***	***Accuracy%***
Filter methods		
MDI	**D1mean,d2mean,zd1**	98.469%
Correlation	**energy, absd1mean**	98.4%
wrapper methods		
SFS	**Zd1 ,absd1mean** ,LL	98.6%
SBS	**d1mean ,d2mean** ,nmm, **energy** ,**max**	98,6%

4.3. Comparison with Existing Studies

The performance of the proposed methods relative to previous researchs is summarizesd in Table 6. Dawa et al. [5] implemented ranking techniques followed by an artificial neural network classifier, reporting an accuracy of 96.9%. These figures are notably lower than the results achieved in the present study. Similarly, Varsha and Vinayak [6], utilized ANOVA-based selection with a fuzzy classifier and achieved 96.48% accuracy.

In another works, Sanchez et al. [10], using the RELIEF algorithm with a 52-feature input and multiple classifiers including QDA, RF, and SVM, achieved an average accuracy of approximately 94.25%. Tawfik et al. [12], who adopted Weighted Permutation Entropy and Support Vector Machines, reached 91.65% and 93.75% for linear and non-linear SVMs, respectively.

Mursalin et al. [14], who also employed wrapper methods in this study consistently achieved higher accuracy, exceeding 98.6% in optimal cases. However, the correlation-based selection in conjunction with a Random Forest classifier int this study, reported an average accuracy of 98.45%, which is comparable to our correlation method at its optimal threshold.

Chua K. C [17] employed HOS-based features and GMM classification, reporting accuracy values ranging from 88% to 93.1%. These outcomes further illustrate the performance advantage of the proposed wrapper-based and hybrid methods.

Tzallas et al. [18], applied an artificial neural network and time-frequency analysis on the same dataset. His work achieved an accuracy of approximately 89%, which is considerably lower than the performance of the methods explored in this paper.

Fergus et al. [19] used a machine learning system to discover automatic whole-brain seizures from EEG signals. They utilized K-Nearest Neighbors classifier which obtained a classification score for accuracy of 93 % with the CHB-MIT dataset. This is meaningful but is relatively moderate compared to the subsequent deep learning-based, or hybrid feature selection.

Guharoy et al. [20], used DWT for feature extraction and then used Principal Component Analysis for dimensionality. His results were an admirable 98.0% accuracy using the Bonn EEG dataset. The feature dimensionality was successfully reduced while achieving relatively high classification performance.

Alzamili et al. [21], applied a Ruzicka Similarity-based filter method for feature selection, and then explored the results with an additional set of classifiers: KNN, SVM, Decision Tree, Naive Bayes, and Random Forest. His study achieved an impressive accuracy level of 97.5% with the Bonn EEG dataset and confirmed the use of filter-based feature selection within the context of EEG signal classification.

Finallay, our proposed method employed a new optimization strategy based on mimizing the complexity of the model by reducing the number of features and keeping the accuracy rate at ~98% which is acceptable compared to relevant studies in the same field.

Table 6. Compared to the methods used in recent research and the classification accuracy.

Authors (year)	***Methods***	***Dataset***	***Accuracy***
S & Dawa, 2017 [5]	ranking techniques with artificial neural networks classifier	From neurology & sleep centre	96.9%
Varsha & Vinayak , 2021 [6]	ANOVA based feature selection with fuzzy classifier	CHB-MIT dataset	96.48%
D, L, E, & O, 2018 [10]	RELIELF methods, with several classification QDA &RF & SVM and RBF	Bonn Dataset	94.25%
Noha S. Tawfika [12]	Weighted Permutation Entropy with Support Vector Machine classification	Bonn Dataset	Linear SVM :91.65% Nonlinear :93.75%
Md Mursalin, 2017 [14]	correlation-based feature with RF classification	Bonn dataset	98.45%
Chua K. C, 2008 [17]	HOS based features with GMM classification	Bonn Dataset	88%-93%
A. Tzallas, M. G. Tsipouras,2007 [18]	time frequency analysis for feature extracted with artificial neural network classification	Bonn Dataset	89%
P. Fergus, A. Hussain,2016 [19]	Machin learning platform ,KNN classifier	CHB-MIT Dataset	93%
Guharoy, 2021 [20]	Discrete Wavelet Transform (DWT, Principal Component Analysis (PCA), and feature-level fusion	Bonn Dataset	98%
Alzamili, 2023 [21]	Ruzicka Similarity-based feature selection	Bonn Dataset	97.5%
Our proposed method	**wrapper-based and filter-based with RF classification**	**Bonn dataset**	**98.5%**

5. Conclusion

Generally, most epilepsy patients suffer from sudden epileptic seizures, putting them at a higher risk of getting serious injuries which leads sometimes to sudden death. The EEG-based seizure monitoring method with a low level of complexity is critical for everyday use. Therefore, this study introduced a tailored approach to EEG feature selection techniques, which is vital for attaining effective seizure management at low computing cost.

The objective of the paper is to reduce the dimensions of the data used in classification by studying and using the feature selection method when selecting the features that are most relevant to the classification process, by removing irrelevant features, which leads to improved computational efficiency. Thus, it helps to detect disease faster and accurately.

To achieve the research goals, two MDI and correlation filter methods were adopted, which work in conjunction with a random forest (RF) classification. These methods were able to delete up to three or four features while maintaining a classification accuracy of not less than 98.469%, In addition to suggesting two SFS and SBS methods as well as wrapper methods, which work with a model for selection the features accurately, these methods were able to delete about nine or ten features out of the fifteen features used and to maintain a classification accuracy of not less than 98.20%, which is a satisfactory percentage. The outcome of the feature selection techniques opens the door for researchers to use suitable methods for epileptic seizure detection.

In the future steps, the methodologies employed in this study can be extended to more complex datasets or a larger number of features to facilitate the process of analyzing patient data, supporting precise diagnosis and treatment.

Acknowledgements.

This work was supported by the Electronic and Communications Department, Faculty of Engineering, and ITRDC University of Kufa, Iraq. We extend our sincere gratitude to the engineers, Bushra abd al Sahib and Zahraa Mohammed, for thier exceptional efforts in bringing this work to completion.

Funding: This research received no external funding.
Conflict of interest: The authors declare no conflicts of interest.

References.

[1] C. E. Vote, “Report by the numbers,” *Development*, vol. 1, no. May, pp. 1–41, 2016.

[2] World Health Organization, “Epilepsy: A public health imperative,” 2019. [Online]. Available: https://www.who.int/about/licensing

[3] World Federation of Neurology and World Health Organization, *Atlas: Country resources for neurological disorders*. Geneva, Switzerland: WHO, Dept. of Mental Health and Substance Abuse.

[4] I. Ullah, M. Hussain, E.-U.-H. Qazi, and H. Aboalsamh, “An automated system for epilepsy detection using EEG brain signals based on deep learning approach,” unpublished.

[5] SKR Engineering College and IEEE Madras Section, *Proc. Int. Conf. Energy, Commun., Data Analytics Soft Comput. (ICECDS)*, Chennai, India, Aug. 2017.

[6] V. Harpale and V. Bairagi, “An adaptive method for feature selection and extraction for classification of epileptic EEG signal in significant states,” *J. King Saud Univ. – Comput. Inf. Sci.*, 2018, doi: 10.1016/j.jksuci.2018.04.014.

[7] H. Zhang *et al*., “Interpretable seizure prediction using adaptive Graph Neural Networks,” *Front. Neurosci.*, vol. 18, Art. no. 1468967, 2024. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2024.1468967/full

[8] A. Ghosh *et al*., “A high-precision deep neural model for real-time epilepsy prediction using raw EEG,” *Sci. Rep.*, vol. 14, Art. no. 67855, 2024. [Online]. Available: https://www.nature.com/articles/s41598-024-67855-4

[9] L. Xu *et al*., “Deep multi-scale attention fusion network for seizure prediction,” *Sci. Rep.*, vol. 15, Art. no. 90315, 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-90315-6

[10] M. A. Sanchez, L. Aguilar, M. Castañón-Puga, and A. Rodríguez-Díaz, Eds., *Studies in Systems, Decision and Control*, vol. 143. Cham, Switzerland: Springer, 2018. [Online]. Available: http://www.springer.com/series/13304

[11] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E*, vol. 64, no. 6, p. 061907, Dec. 2001, doi: 10.1103/PhysRevE.64.061907.

[12] N. S. Tawfik, S. M. Youssef, and M. Kholief, "A hybrid automated detection of epileptic seizures in EEG records," *Comput. Electr. Eng.*, vol. 53, pp. 177–190, Jul. 2016, doi: 10.1016/j.compeleceng.2015.09.001.

[13] A. S. Abdulhussien, A. T. AbdulSaddaa, and K. Iqbal, "Automatic seizure detection with different time delays using SDFT and time-domain feature extraction," *J. Biomed. Res.*, vol. 36, no. 1, pp. 48, Jan. 2022.

[14] M. Mursalin, Y. Zhang, Y. Chen, and N. V. Chawla, "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier," *Neurocomputing*, vol. 241, pp. 204–214, Jun. 2017, doi: 10.1016/j.neucom.2017.02.053.

[15] A. J. Ferreira and M. A. T. Figueiredo, "Efficient feature selection filters for high-dimensional data," *Pattern Recognit. Lett.*, vol. 33, no. 13, pp. 1794–1804, Oct. 2012, doi: 10.1016/j.patrec.2012.05.019.

[16] E. Scornet, "Trees, forests, and impurity-based variable importance," *arXiv preprint*, Jan. 2020. [Online]. Available: http://arxiv.org/abs/2001.04295

[17] K. C. Chua, "HOS-based features with GMM classification for epileptic EEG analysis," in *Proc. 2008 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Vancouver, BC, Canada, 2008.

[18] A. Tzallas, M. G. Tsipouras, and D. I. Fotiadis, "The use of time-frequency distributions for epileptic seizure detection in EEG recordings," *Int. J. Med. Inform.*, vol. 76, pp. 93–103, 2007.

[19] P. Fergus, A. Hussain, D. Hignett, D. Al-Jumeily, K. Abdel-Aziz, and H. Hamdan, "A machine learning system for automated whole-brain seizure detection," *Appl. Comput. Inform.*, vol. 12, no. 1, pp. 70–89, Jan. 2016, doi: 10.1016/j.aci.2015.01.001.

[20] S. Guharoy, D. Bhattacharjee, and M. Nasipuri, "EEG-based epileptic seizure detection using PCA and DWT-based feature extraction," *Procedia Computer Science*, vol. 185, pp. 540–547, 2021, doi: 10.1016/j.procs.2021.05.057.

[21] A. Alzamili, H. Mahdi, and Z. A. Jalab, "EEG epileptic seizure detection using Ruzicka similarity-based feature selection with different classifiers," *International Journal of Cognitive Computing in Engineering*, vol. 4, pp. 115–122, 2023, doi: 10.1016/j.ijcce.2022.12.011.