Research Article BEU Fen Bilimleri Dergisi 15(1): 423-437 (2026) DOI: 10.17798/bitlisfen.1831933

BİTLİS EREN UNIVERSITY
FEN BİLİMLERİ DERGİSİ
ISSN: 2147-3129 / e-ISSN: 2147-3188

AUTOMATIC EPILEPTIC SEIZURE DETECTION WITH MUSIC AND CROSS-CORRELATION METHODS: PERFORMANCE ENHANCEMENT WITH ENSEMBLE LEARNING-VOTING

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Article Info

Received: *November 28, 2025*
Revised: *January 5, 2026*
Accepted: *January 23, 2026*

Keywords
Epileptic seizure detection,
Cross-correlation technique,
MUSIC method,
Machine learning,
Ensemble learning-voting.

ABSTRACT

Epileptic seizures are characterized by abnormal neuronal discharges that generate distinctive patterns in EEG signals, requiring accurate and fast detection for clinical decision support. This study proposes a high-resolution spectral approach that integrates the Multiple Signal Classification (MUSIC) algorithm with cross-correlation-based feature extraction for automated seizure detection. High-resolution spectral estimates of reference EEG signals and individual segments were obtained using the MUSIC algorithm, and six correlation-driven statistical features were computed to capture both spectral similarity and phase relationships. These features were classified using Random Forest, k-Nearest Neighbor, Multilayer Perceptron, and an Ensemble Learning-Voting model. Experiments were conducted on the Bonn University EEG dataset across 14 binary and multi-class tasks. The Ensemble Learning-Voting classifier achieved the best overall performance with an average accuracy of 99.17%, outperforming individual classifiers. The proposed methodology provides high frequency resolution, low computational cost, and robust classification capability, demonstrating strong potential for real-time epileptic seizure detection and integration into clinical EEG monitoring systems.

1. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by abnormal electrical discharges in the brain that cause recurrent seizures. Under normal conditions, neurons communicate through electrical and chemical signals to regulate cognitive, emotional, and physiological functions. During a seizure, excessive and synchronous neuronal firing disrupts this normal activity, leading to involuntary movements, sensory disturbances, emotional and behavioral changes, and impaired consciousness. Recovery after a seizure varies among individuals and may include fatigue, confusion, and weakness [1]. It is estimated that more than 70 million people worldwide live with epilepsy, with approximately 80% of cases occurring in developing countries, and nearly 2.4 million new cases reported annually [2], [3].

Epilepsy diagnosis and monitoring rely heavily on electroencephalography (EEG), which can be acquired as non-invasive scalp EEG or invasive intracranial EEG (i-EEG) [4]. Seizures are classified as generalized or partial and are typically divided into four phases: pre-ictal, ictal, post-ictal, and inter-ictal [5]. Long-duration EEG recordings and the need for expert visual inspection make manual identification of seizure events time-consuming and impractical. Therefore, reliable automatic seizure detection systems are essential for both clinical monitoring and patient safety.

Due to the invasive nature of i-EEG, most studies focus on scalp EEG recordings and publicly available databases [6]. Among these, the Bonn University EEG Database is widely preferred because of its well-structured, balanced, and artifact-free design. It consists of five distinct classes (A–E), each containing 100 EEG segments of 23.6 seconds, enabling controlled experimental conditions and reliable benchmarking of classification methods.

Research on automatic epileptic seizure detection shows that some studies apply classification methods using specific groups of features from EEG signals. In other studies, classifiers use feature vectors obtained from analyses in time, frequency, or time-frequency domains. Studies using the public CHB-MIT scalp EEG database for automatic epileptic seizure detection have shown successful results [7], [8]. Various feature extraction and classification methods, including Wavelet Transforms (WT), Empirical Mode Decomposition (EMD), Artificial Neural Networks (ANN), Support Vector Machines (SVM), and k-Nearest Neighbor (k-NN), have been applied with high accuracy rates [9–11]. Similarly, studies using the Bonn University dataset have demonstrated the effectiveness of feature extraction techniques such as Fast Fourier Transform (FFT), Local Binary Patterns (LBP), and Deep Learning (DL) models, achieving classification accuracies exceeding 99% in some cases [12–14]. Additionally, other studies using frequency or time-frequency domain features from the Bonn University dataset have reported accuracies of 99.75%, 99.40%, 100%, 99.80%, and 98.87%, respectively [15–19].

A limited number of studies have explored Cross-Correlation Analysis (CCA) and Dynamic Time Warping (DTW) for seizure detection. DTW-based approaches have shown moderate to high performance in magnetoencephalography (MEG) and EEG datasets [20-21], while cross-correlation-based feature extraction combined with SVM classifiers has achieved promising results on the Bonn dataset [22]. Other studies using long-term i-EEG recordings have successfully combined cross-correlation features with machine learning classifiers such as AdaBoost, Radial Basis Function Kernel Support Vector Machine (RBF-SVM), and ANN [23].

Despite these efforts, the combined use of high-resolution subspace-based spectral estimation and correlation-based similarity analysis has not been sufficiently investigated in the context of epileptic seizure detection.

To address this gap, this study introduces a distinctively novel framework that integrates the Multiple Signal Classification (MUSIC) algorithm for high-resolution spectral estimation with cross-correlation–based feature extraction. Unlike conventional approaches that rely on classical spectral estimators such as FFT and Welch or use similarity measures in isolation, the proposed framework jointly exploits subspace-based spectral resolution and correlation-driven similarity modeling within a unified structure.

In the proposed approach, EEG segments from the Bonn University dataset are processed by computing their MUSIC-based spectral representations and comparing them with class-specific reference spectra via cross-correlation analysis. The resulting parameters are used to construct feature vectors, which are then classified using Random Forest (RF), k-Nearest Neighbor (k-NN), Multilayer Perceptron (MLP), and Ensemble Learning-Voting (EL-V) algorithms.

This framework captures subtle and discriminative spectral similarities that conventional methods fail to resolve, while simultaneously reducing feature dimensionality and computational burden. The results demonstrate that the integration of MUSIC-based high-resolution spectral estimation with cross-correlation analysis provides an efficient and reliable solution for automatic epileptic seizure detection, offering a meaningful and novel contribution to existing literature.

2. MATERIAL AND METHOD

Figure 1 presents a high-level overview of the proposed epileptic seizure detection framework and summarizes the sequential structure of the analysis pipeline. As detailed in Sections 2.1–2.5, the method includes the construction of class-specific reference signals, high-resolution spectral estimation with the MUSIC algorithm, cross-correlation–based comparison of each EEG segment with its corresponding reference spectrum, and the extraction of statistical descriptors used for classification. Mathematically, the problem can be expressed as assigning each EEG segment $x_i[n]$ to one of the predefined classes $C = \{A, B, C, D, E\}$ by quantifying the spectral similarity between its MUSIC-based spectral estimation $P_i(f)$ and the class-dependent reference spectrum $P_{ref,c}(f)$. The cross-correlation distribution between these two spectra provides a compact statistical representation that forms the feature vector D_i, which is then used by machine learning and ensemble classifiers to make the final decision. This structure provides a coherent, interpretable, and mathematically well-defined basis for the overall methodology illustrated in Figure 1.

2.1. Bonn University Epileptology Department Datasets

The publicly available EEG dataset from the Department of Epileptology at the University of Bonn used in this study is detailed in Table 1 and Table 2.

The Bonn University EEG database comprises 500 data segments distributed across sets A, B, C, D, and E, with 100 segments per set. In this study, each segment of 4096 samples is divided into two segments of 2048 samples, resulting in a total of 1000 segments (200 per set). After splitting, the segments are labeled as follows: Set A as Z0001-Z0200.txt, Set B as O0001-O0200.txt, Set C as N0001-N0200.txt, Set D as F0001-F0200.txt, and Set E as S0001-S0200.txt.

Splitting the signals into two segments is critical. This segmentation plays an important role in the frequency and time analysis of the signals. Dividing the signal into 200 segments, as opposed to 100, provides more data points, allowing for a finer capture of the signal's frequency components. This is particularly useful for gaining a better understanding and analysis of low-frequency components. In classification algorithms, using a greater number of examples can enhance the model's generalization ability. By providing more data, the 200-segment approach allows machine learning algorithms to achieve better performance compared to 100 segments. Additionally, dividing the signal into smaller segments offers a better opportunity to examine how the signal changes over time, which is beneficial for identifying significant patterns within the signal.

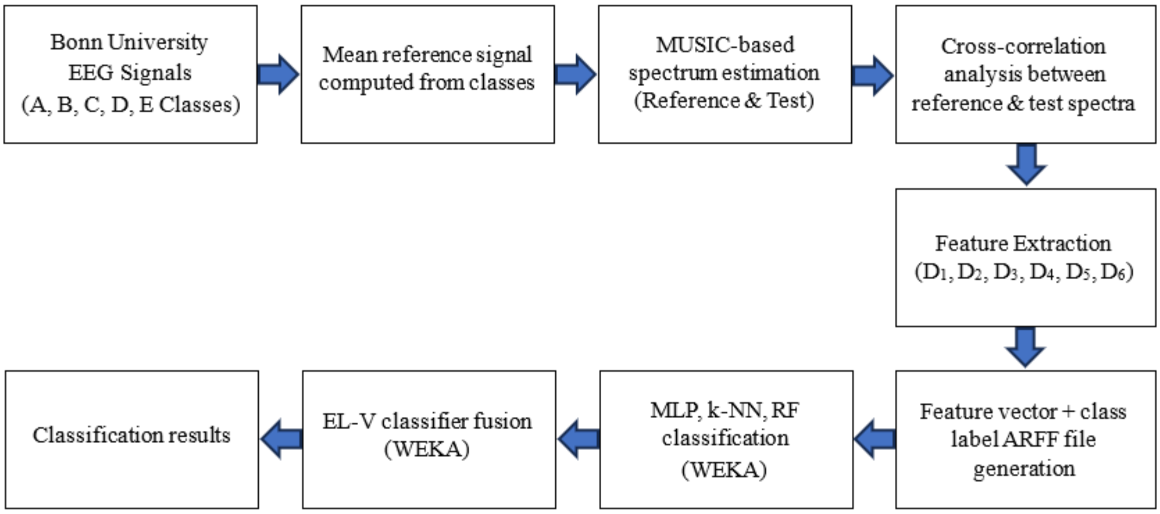

Figure 1. Proposed epileptic seizure decision block diagram.

Table 1. EEG dataset from Department of Epileptology at the University of Bonn

EEG Dataset Information	
Recording System	128-channel, 12-bit EEG system
Sampling Frequency	173.61 Hz
Channel Averaging	128 channels averaged into a single channel
Segment Length	Each segment is 23.6 seconds long
Number of Segments	100 single-channel EEG segments per dataset
Sample Sets per Segment	4096 sample sets (A, B, C, D, E)
Frequency Band	Low pass filtered within 0-40 Hz
Artifact Removal	Data cleaned of distortions caused by eye and muscle movements
Electrode System	International 10-20 electrode system
Datasets	**Description**
Set A	Surface EEG recordings from 5 healthy volunteers with eyes open
Set B	Surface EEG recordings from 5 healthy volunteers with eyes closed in a calm, awake state
Set C	i-EEG recordings from 5 epileptic patients during non-seizure periods
Set D	i-EEG recordings from 5 epileptic patients during non-seizure periods
Set E	i-EEG recordings from the same 5 patients during seizure periods

Table 1. Statistical properties of the EEG database from the University of Bonn

	Set A	Set B	Set C	Set D	Set E
Average	-6.26	-12.51	-8.87	-6.20	-4.73
Median	-6	-12	-7	-6	-5
Standard Deviation	48.33	70.68	59.38	90.34	341.12
Minimum	-288	-424	-412	-1147	-1885
Maximum	294	360	623	2047	2047
Skewness	0.03	-0.03	-0.04	3.97	-0.38
Kurtosis	3.28	3.58	4.82	79.67	5.88

2.2. Reference Signal

The purpose of the reference signal is to create a representative signal by averaging the signals in each dataset. This reference signal serves as a baseline for comparing other signals, providing significant advantages, especially in distinguishing between seizure and non-seizure states. The reference signal represents the common characteristics of each dataset, which simplifies the comparison of different EEG segments and enhances classification accuracy.

During seizures, the abnormalities become more prominent when contrasted with the typical patterns observed in non-seizure states. Obtaining an average signal reduces random noise and helps capture the characteristic features of the signals more effectively. This reference signal provides a more general and reliable foundation for the model, supporting classifiers in learning the overall characteristics of the dataset rather than just specific signals.

The reference signal is used with metrics like cross-correlation to measure the similarity of other signals in the dataset to this baseline. This process generates a robust feature set for distinguishing between seizure and non-seizure signals. For instance, seizure signals may show significant deviations from the reference signal, making these analyses substantially improve classification accuracy.

In line with this objective, a reference signal will be calculated for each of the sets A, B, C, D, and E in the database of the Department of Epileptology at the University of Bonn by averaging 200 signals in each set.

2.3. The Multiple Signal Classification (MUSIC) Method

The MUSIC method is a high-resolution spectral estimation technique that detects the frequencies of narrowband signals by performing eigenvalue decomposition. The algorithm separates the signal and noise subspaces to accurately estimate the frequency components of a given signal [24,25].

The MUSIC spectral estimation is defined by the following formula,

$$P_{MUSIC}(f) = \frac{1}{\sum_{i=p+1}^{M} \left| e_i^H v(f) \right|^2} \tag{1}$$

Here, $P_{MUSIC}(f)$: Spectral estimation function at frequency *f*, *M*: Number of antenna elements or sampled data points, e_i: Eigenvectors corresponding to the noise subspace (obtained via eigenvalue decomposition), $v(f)$: Steering vector at frequency *f*, $(\cdot)^H$: Hermitian (complex conjugate transpose) operation.

MUSIC-based spectral representations of the reference signals for Sets A, B, C, D, E are shown in Figure 2.

2.4. Cross-Correlation Analysis (CCA) and Feature Vector Extraction

Correlation analysis quantifies the degree of similarity between two signals using a single scalar value known as the correlation coefficient. In this study, Cross-Correlation Analysis (CCA) is employed to evaluate the similarity and relative alignment between two spectral waveforms by relating the observation values of one series to those of another at various time delays. CCA is particularly effective in identifying leading–lagging relationships and estimating how one signal varies relative to another over time [26]. Mathematically, the cross-correlation function represents the sum of the products of two signals shifted with respect to each other.

In CCA, in-phase waveforms yield positive correlation values, whereas out-of-phase waveforms result in negative correlations. A correlation coefficient of ±1 indicates a perfect relationship, while values approaching zero indicate weak or no similarity. High symmetry of the cross-correlation coefficients around zero lag implies a stable and strong similarity between the compared signals. As the lag increases beyond zero, decreasing correlation values indicate reduced similarity and stability between the signals [27].

Mathematically, consider two series $x(i)$ and $y(i)$ where $i = 0,1,2,\cdots,N$. The normalized cross-correlation ϕ_{xy} at delay k is defined as

$$\phi_{xy}(k) = \frac{\sum_i[(x(i)-m_x)\cdot(y(i-k)-m_y)]}{\sqrt{\sum_i(x(i)-m_x)^2}\sqrt{\sum_i\left(y(i-k)-m_y\right)^2}} \tag{2}$$

Where m_x and m_y represent the mean values of $x(i)$ and $y(i)$, respectively. The cross-correlation coefficients are calculated for $k = 0,1,2,\cdots,N-1$, and the resulting $\phi_{xy}(k)$ values form the cross-correlation coefficient graph between the two waveforms.

The time delay corresponding to the maximum value of the cross-correlation function indicates the point at which the two signals best align. This optimal alignment occurs when $\phi_{xy}(k)$ reaches its peak. As the time delay between the signal's increases, the cross-correlation value decreases, reflecting a reduction in similarity. If two signals are identical or highly similar, the maximum correlation occurs at *k=0*. Any shift of this peak away from zero or a decrease in $\phi_{xy}(0)$ implies reduced similarity between the signals.

In this study, CCA is applied to the MUSIC-based spectra of EEG signals. First, a reference signal is obtained by averaging the EEG segments within each dataset in the time domain. The spectrum of this reference signal is then computed using the MUSIC method. Similarly, the MUSIC spectra of all individual EEG segments in each dataset are obtained. Each segment's spectrum is subsequently compared with the reference spectrum of the corresponding dataset using CCA.

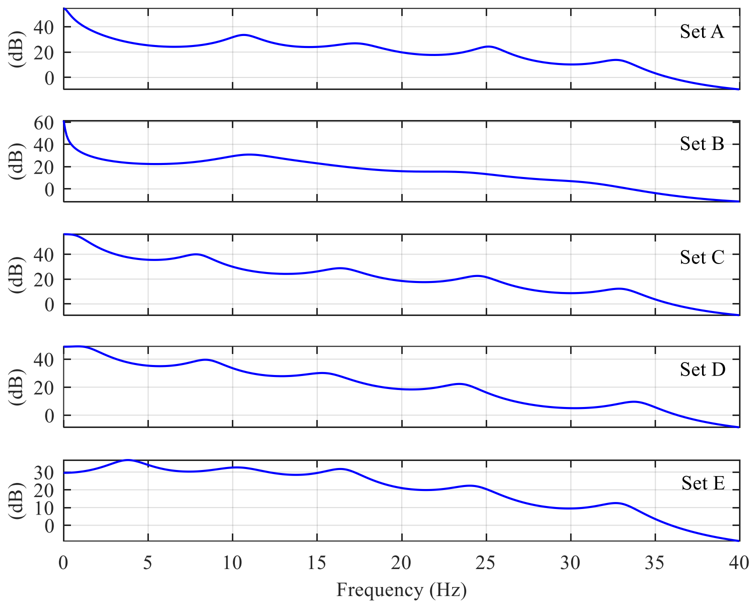

Figure 2. MUSIC pseudo-spectrum of the reference EEG signals for Sets A–E, obtained by averaging all signals within each set and analyzed over the 0-40 Hz frequency range.

For each dataset (A, B, C, D, E), the cross-correlation coefficients between the MUSIC spectrum of each segment and the reference spectrum are computed. For example, for Set A, the resulting cross-correlation matrix is expressed as

$$Set\ A = \left[\phi_{1,ref}(k) \cdots \phi_{200,ref}(k)\right] \tag{3}$$

where each $\phi_{i,ref}(k)$ represents the cross-correlation coefficients between the i-th segment and the reference signal for $k = 0,1,2,\cdots,N$. Each column contains the full cross-correlation coefficient sequence corresponding to one EEG segment.

Representative CCA graphs obtained from the MUSIC spectra of two similar and two different EEG segments are illustrated in Figure 3. As observed in the figure, identical or highly similar segments exhibit a pronounced peak at $k = 0$ and a symmetric distribution of correlation coefficients around this point. In contrast, dissimilar segments show reduced peak values, shifted maxima, and asymmetric distributions.

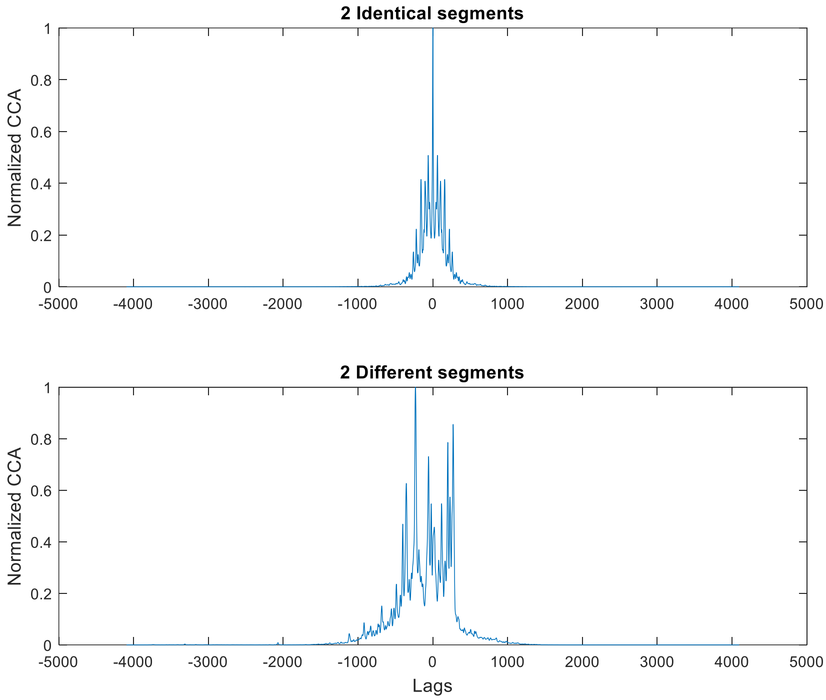

Figure 3. CCA graphs of spectra for identical or different segments from set A, B, C, D, E.

Based on the statistical characteristics of the cross-correlation coefficients, a six-dimensional feature vector is extracted for each EEG segment as follows:

- D_1: The lag value k at which $\phi_{xy}(k)$ attains its maximum. For identical segments, this peak occurs at $k = 0$; increasing k values indicate decreasing similarity.
- D_2: The absolute value of the zero-lag correlation coefficient $|\phi_{xy}(0)|$. Values closer to 1 indicate a higher degree of similarity.
- D_3: Skewness of the cross-correlation coefficient distribution. Identical segments exhibit symmetry around $k = 0$, whereas asymmetry increases as similarity decreases.
- D_4: Kurtosis of the distribution, representing the degree of peakedness or tail heaviness. Similar segments show lower kurtosis values, while dissimilar segments result in higher kurtosis.
- D_5: Mean value of the cross-correlation coefficients.
- D_6: Standard deviation of the cross-correlation coefficients, indicating the dispersion of the distribution.

By replacing each $\phi_{i,ref}(k)$ sequence with its corresponding feature vector, the feature matrix for *Set A* is obtained as

$$D_{SetA} = \left[(D_1, D_2, D_3, D_4, D_5, D_6)_{1,ref} \cdots (D_1, D_2, D_3, D_4, D_5, D_6)_{200,ref}\right] \quad (4)$$

The same procedure is applied to all datasets. The resulting feature vectors are then used to train and test the RF, MLP and k-NN classifiers as described below.

2.5. Classification Methods and Classification Performance Evaluation

In our study, RF [28], MLP [29], and k-NN [30] were selected as base classifiers for EL-V [31] due to their diverse learning mechanisms and strong performance in EEG classification tasks. RF is effective in handling high-dimensional data and mitigating overfitting through its ensemble structure, while MLP captures complex nonlinear relationships, making it well-suited for EEG signal analysis. k-NN, being a non-parametric method, provides robustness in capturing local patterns. SVM and Logistic Model Trees (LMT) were not included due to their computational complexity and sensitivity to parameter tuning, which can limit their adaptability in heterogeneous EEG datasets. Additionally, SVM may struggle with large datasets due to its reliance on kernel computations, and LMT, although interpretable, may not generalize as well as ensemble-based methods in multi-class classification scenarios.

In all classification experiments, the hyperparameters of the RF, MLP, and k-NN classifiers were not manually tuned; instead, the default settings provided by the WEKA software were employed to ensure methodological consistency and reproducibility. Specifically, RF was executed with 100 trees and default feature-subset selection per split, MLP was trained using a single hidden layer configured as “a=(number of attributes+classes)/2”, with a learning rate of 0.3, momentum of 0.2, and 500 training epochs, k-NN was implemented with k = 3, Euclidean distance, and uniform weighting. For the EL-V classifier, an equal-weight majority voting strategy was adopted, meaning each base classifier (RF, MLP, k-NN) contributed one vote to the final decision without any priority weighting. This design ensures a fair and unbiased combination of classifiers while preserving the complementary learning behavior of the individual models.

To evaluate the epileptic seizure detection performance of the model, we used three typical classification indicators. These indicators are accuracy, sensitivity and F1 score. These metrics are defined in Equations (5) – (8). Here, TP and TN denote the numbers of true positive and true negative samples, respectively, while FP and FN represent the numbers of false positive and false negative samples, respectively.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (7)$$

$$F1\ Score = 2 \times \frac{Precision \times Sensitivity}{Precision + Sensitivity} \quad (8)$$

3. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed MUSIC and cross-correlation framework, four classifiers RF, k-NN, MLP and EL-V model were tested across various EEG classification tasks. Experiments employed 10-fold cross-validation to ensure robust assessment, with EEG segments from different classes analyzed in each task. All analyses were performed using MATLAB and WEKA on a laptop equipped with an Intel Core i5-12535U CPU at 1.3 GHz, 16 GB RAM, and a 64-bit Windows 11 operating system, and the resulting performance metrics are summarized in Table 3.

As shown in Table 3 and Figure 4, most binary classification tasks involving healthy (A, B) and epileptic seizure (E) EEG segments achieved near-perfect accuracy. MLP, k-NN, and EL-V reached 100% in A-E, B-E, and A-D tasks, with RF slightly lower at 99.75%.

For multi-class tasks, accuracy ranged from 96.83% to 99.50%, with EL-V and RF consistently outperforming other classifiers. Even in complex scenarios mixing healthy and seizure EEG recordings, classification remained highly accurate.

In the full five-class task (A-B-C-D-E), EL-V and RF achieved 98.00% accuracy, while MLP and k-NN reached 95.50–95.80%, demonstrating the framework's robustness in complex multi-class scenarios.

Overall, EL-V achieved the highest average accuracy (99.17%), followed by RF (98.90%), k-NN (98.32%), and MLP (97.85%). EL-V's superior performance illustrates the benefits of ensemble learning, while RF shows stability across tasks, and k-NN excels mainly in binary classifications.

Table 3. Accuracy, sensitivity and F1 score values of RF, MLP, k-NN and EL-V classifiers for different classification tasks

Classification Task	MLP			RF			k-NN			EL-V		
	Acc (%)	Sens	F1 Score	Acc (%)	Sens	F1 Score	Acc (%)	Sens	F1 Score	Acc (%)	Sens	F1 Score
A-E	100	1.000	1.000	99.75	0.998	0.997	100	1.000	1.000	100	1.000	1.000
C-E	99.50	0.995	0.995	99.50	0.995	0.995	99.75	0.998	0.997	99.75	0.998	0.997
A-B-C	97.00	0.970	0.970	99.33	0.993	0.993	99.00	0.990	0.990	99.50	0.995	0.995
A-B-C-D	96.25	0.963	0.962	97.62	0.976	0.976	97.37	0.974	0.974	98.12	0.981	0.981
A-B-C-D-E	95.50	0.955	0.955	98.00	0.980	0.980	95.80	0.958	0.958	98.10	0.981	0.981
A-B-C-E	97.50	0.975	0.975	99.25	0.993	0.993	96.37	0.964	0.964	99.50	0.995	0.995
A-B-E	97.00	0.970	0.970	99.66	0.997	0.997	95.66	0.957	0.957	99.33	0.993	0.993
A-C	98.75	0.988	0.987	99.75	0.998	0.997	100	1.000	1.000	99.75	0.998	0.997
A-C-E	99.00	0.990	0.990	99.33	0.993	0.993	99.83	0.998	0.998	99.50	0.995	0.995
A-D	99.75	0.998	0.997	99.75	0.998	0.997	100	1.000	1.000	100	1.000	1.000
B-C-D-E	97.25	0.973	0.972	98.25	0.983	0.982	97.75	0.978	0.978	98.62	0.986	0.986
B-E	100	1.000	1.000	100	1.000	1.000	100	1.000	1.000	100	1.000	1.000
C-D	95.50	0.955	0.955	97.00	0.970	0.970	98.00	0.980	0.980	98.00	0.980	0.980
C-D-E	96.83	0.968	0.968	97.50	0.975	0.975	97.00	0.970	0.970	98.33	0.983	0.983
Averaged	97.85	0.978	0.978	98.90	0.989	0.989	98.32	0.983	0.983	99.17	0.991	0.991

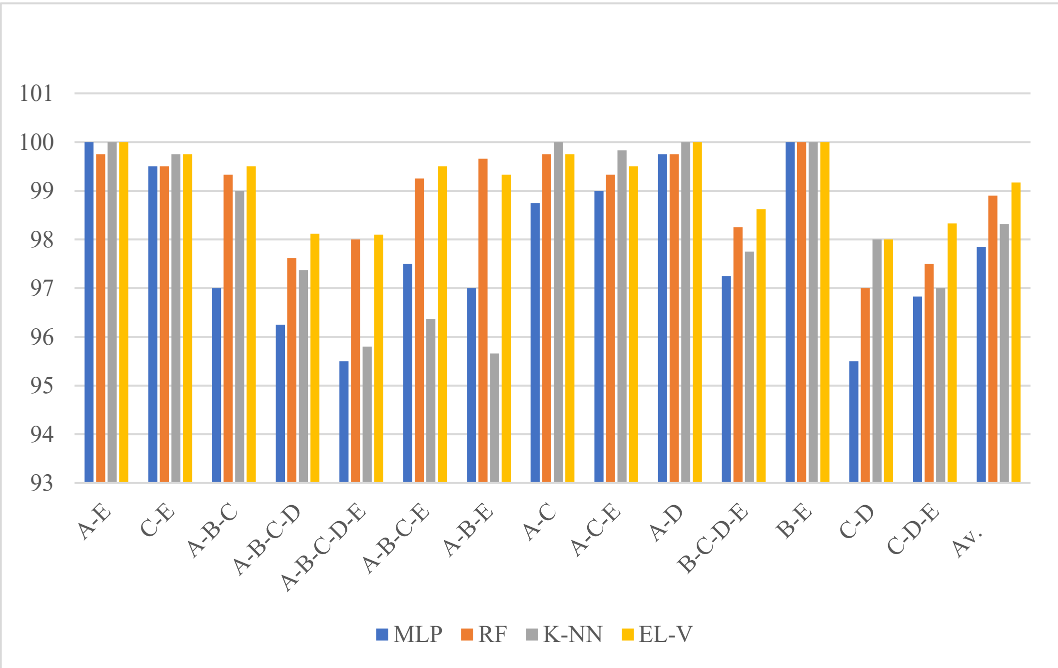

Figure 4. Classifier comparison based on accuracy (%).

These findings confirm that the integration of high-resolution spectral analysis with cross-correlation-based feature extraction significantly enhances the accuracy of epileptic seizure detection, making it a reliable and effective approach for automated EEG classification.

Table 4 summarizes the confusion matrices for the C-D-E and A-B-C-D-E classification tasks using EL-V. Notably, class E (epileptic seizure segments) was perfectly classified in both sets. PCA results for the A-B-C-D-E task (Table 5) rank the features according to their contribution to the principal components.

Feature ranking based on eigenvalues and contributions is as follows:

- First Principal Component (V_1): This component has the highest eigenvalue (4.36761) and accounts for 39.70% of the variance. It is most influenced by mean, D_6, and D_3, with coefficients like 0.441 (D_5), 0.444 (D_6), and 0.386 (D_3). These features have the greatest contribution to the classification of class E and other features like D_4 and D_1 also contribute.
- Second Principal Component (V_2): The second highest eigenvalue (2.00476) explains 18.20% of the variance. It is influenced by D_2, D_1, class B, and class D.
- Third Principal Component (V_3): This component has an eigenvalue of 1.4074 and explains 12.80% of the variance. It is mainly associated with class A, class B, D_4, and other features like D_2.
- Fourth Principal Component (V_4): With an eigenvalue of 1.25597 (11.40% of the variance), it contributes to the classification of class D, class C, and class E.
- Fifth Principal Component (V_5): This component accounts for 10.80% of the variance and is linked with class C, class A, D_4, and class E.
- Sixth Principal Component (V_6): The last principal component, with an eigenvalue of 0.4193 (3.80% of the variance), is influenced by D_1, class B, D_6, and D_4.

Ranking the features by contribution to the principal components:

- D_5 (0.441) and D_6 (0.444) are the most important features, appearing in the highest eigenvalue component (V_1), which captures the majority of variance.

Table 4. Confusion matrix of sets C-D-E and sets A-B-C-D-E classifications by EL-V

True Label \ Predicted Label	C	D	E
C	200	0	0
D	10	190	0
E	0	0	200

True Label \ Predicted Label	A	B	C	D	E
A	198	2	0	0	0
B	1	199	0	0	0
C	0	4	196	0	0
D	2	0	10	188	0
E	0	0	0	0	200

Table 5. PCA eigenvectors and A-B-C-D-E class separation features

	V_1	V_2	V_3	V_4	V_5	V_6
D_1	-0.2312	-0.4943	-0.1400	0.0602	-0.1834	0.5709
D_2	0.1744	0.5532	-0.2379	0.0121	0.1858	-0.1761
D_3	-0.3863	0.2639	-0.2363	-0.0659	0.2638	0.2768
D_4	-0.3557	0.2063	-0.3012	-0.0767	0.3877	0.2979
D_5	0.4410	-0.1629	-0.1272	-0.0342	0.1807	0.1507
D_6	0.4442	0.0208	-0.2111	-0.0337	0.0678	0.3187
class=A	-0.1330	0.0353	0.6921	0.1479	0.4035	0.1278
class=B	-0.2914	-0.3451	-0.4236	0.0012	0.0602	-0.5254
class=C	-0.0259	0.2613	0.0600	-0.6757	-0.4767	0.1597
class=D	0.0769	0.2699	-0.1802	0.6914	-0.3683	0.1794
class=E	0.3733	-0.2215	-0.1483	-0.1649	0.3813	0.0585

- D_2 (0.553) is highly influential in V_2.
- D_3 and D_4 are important in multiple components, particularly V_1 and V_3.
- D_1 has significant weights in V_1, V_2, and V_6, indicating a noteworthy role across several principal components.

Based on these eigenvectors and contributions, the features can be ranked in terms of importance; D_5 (most important), D_6, D_2, D_3, D_4, D_1. Thus, the most significant features for classification tasks are D_5 and D_6, with D_2, D_3, and D_4 also contributing significantly. D_1 follows, but with less contribution compared to the others.

The findings of this study confirm that EEG signals from the Bonn University dataset can be effectively used for the automatic detection of epileptic seizures by combining high-resolution spectral estimation and correlation-based feature extraction. Unlike conventional approaches that rely solely on time–frequency transforms, the proposed framework integrates MUSIC-based spectrum estimation with cross-correlation analysis to capture both spectral and phase-related characteristics of EEG signals.

A key contribution of this study is the application of cross-correlation analysis after generating class-specific reference signals. The use of cross-correlation coefficients and lag values enables the modeling of temporal alignment and phase-shift information, which plays a critical role in distinguishing seizure and non-seizure EEG patterns. The inclusion of higher-order statistical descriptors in the feature vector further enhances class separability, as supported by the PCA findings.

The comparative results presented in Table 6 demonstrate that the proposed MUSIC + CCA framework provides competitive and, in many cases, superior performance when compared with existing methods reported in the literature [32–46]. For instance, Bandil et al. [32] and Chen et al. [33] achieved high accuracies using DWT and entropy-based features with ANN and Least Squares Support Vector Machines (LS-SVM) classifiers. However, DWT-based approaches often involve higher computational complexity, whereas the MUSIC method used in this study provides improved frequency resolution at a lower computational cost.

Similarly, Li et al. [34] reported strong performance using STFT-based representations with SVM classifiers, but STFT suffers from limited time–frequency resolution. In contrast, the MUSIC algorithm can resolve closely spaced low-amplitude frequency components, making it more suitable for analyzing the transient characteristics of epileptic EEG signals. Mahjoub et al. [35] employed EMD, which is sensitive to noise and computationally expensive, while the proposed approach demonstrates robustness to noise through correlation-based similarity modeling.

Table 6. Some studies conducted using the Bonn University datasets [6]

Authors	**Feature Extraction**	**Classification**	**Classification Task**	**Results (Acc %)**
Bandil et al. [32]	DWT, entropy features	ANN	A-D-E	99.00
Chen et al. [33]	DWT, entropy features	LS-SVM	D-E	99.50
Li et al. [34]	STFT, spectrogram, scalogram	SVM	AB-CD-E	99.60
Mahjoub et al. [35]	EMD	SVM	ABCD-E	97.00
Choubey et al. [36]	FFT	k-NN	AD-E	97.00
Acharya et al. [37]	Z-score normalization	CNN	B-A-E	88.67
Li et al. [38]	PSD, autoregressive model	SVM	CA-E	98.73
Sharmila et al. [39]	DWT	k-NN	A-E	100
Amin et al. [40]	DWT, arithmetic coding	SVM, k-NN, MLP	A-E ABCD-E	100 99.33
Baykara et al. [41]	Stockwell Transform	ELM	AB-CD-E	90.00
Eltrass et al. [42]	Signal Energy	QKLMS	A-B-C-D-E	97.88
Dehuri at al. [43]	DWT	SVD, EL-M	A-B-C-D-E	95.00
Zeng at al. [44]	Decomposition, DWT	MLP	A-B-C-D-E	94.01
Polat et al. [45]	FFT, time features	SVM	A-B-C-D-E	82.50
Jana et al. [46]	STFT	SVM	ABCD-E	97.63
Proposed Work	MUSIC, CCA	MLP, RF, k-NN, EL-V	14 Different Tasks	Averaged 99.17

On the other hand, the suitability of different feature extraction methods for real-time applications varies significantly. DWT-based approaches compute a large number of wavelet coefficients, typically resulting in relatively large feature vectors per EEG segment. Similarly, STFT-based methods generate time-frequency matrices and extract tens of features per segment, leading to higher computational demands, especially for long EEG recordings or multi-channel data. In contrast, the proposed MUSIC+CCA framework focuses on estimating only the dominant frequency components and computes just 6 features per EEG segment through cross-correlation analysis. Consequently, while DWT and STFT approaches are limited in their suitability for real-time or embedded applications due to higher complexity and larger feature sets, MUSIC+CCA is highly suitable for such applications, making it particularly advantageous for real-time EEG monitoring and portable healthcare systems.

In terms of classification performance, several studies have relied on SVM, ANN, k-NN, and MLP classifiers [36–40]. Although some works reported very high accuracies for binary classification tasks, performance generally decreased in more complex multi-class problems. In this study, the proposed framework was evaluated across 14 different classification tasks, achieving an average accuracy of 99.17%, while maintaining strong performance in multi-class (A–B–C–D–E) settings. The EL-V strategy consistently outperformed individual classifiers by combining their complementary strengths.

In binary, ternary, quaternary, and quinary classification problems, class separability, sample distributions, and the degree of class overlap vary inherently. Consequently, it is expected that the optimal classifier parameters, such as the number of neighbors in k-NN, the training time (number of epochs) in MLP, or the number of trees in Random Forest, may differ depending on the specific class combination. Additional experiments conducted in this study explicitly examined the effect of training time in the MLP classifier. When the training time was set to 500 and 1000 epochs, the classification accuracy reached 95.50% and 95.90%, respectively. Increasing the training time to 15000 epochs further improved the accuracy to 97.2% for the ABCDE classification task. Similarly, for the same task, the k-NN classifier achieved higher accuracy with $k = 1$ compared to the commonly used $k = 3$. These results clearly indicate that parameter optimization can improve numerical performance. However, performing extensive, class-specific parameter tuning for each classification scenario may reduce comparability and increase the risk of overfitting, particularly in limited-data settings. Therefore, rather than focusing on achieving the maximum possible accuracy through exhaustive tuning, this study emphasizes the intrinsic discriminative capability and stability of the proposed CCA+MUSIC-based spectral similarity approach across different classification scenarios.

The high accuracy obtained even with WEKA's default parameter settings demonstrates that the proposed method produces robust and classifier-independent features. Comprehensive parameter optimization for individual classifiers (MLP, k-NN, RF), as well as their ensemble-based EL-V configuration, is identified as an important direction for future work.

Studies focusing on full multi-class classification using the Bonn dataset have reported accuracies of 97.88% [42], 95.00% [43], and 94.01% [44]. Compared with these works, the proposed method achieved higher performance, as summarized in Table 6. Furthermore, the limitations of conventional FFT-based approaches, as reported by Polat et al. [45], highlight the importance of high-resolution spectral estimation provided by the MUSIC method.

Beyond classification performance, the proposed framework also offers practical advantages for real-world applications. Conventional techniques such as FFT, DWT, and EMD typically require high computational resources, which limits their use in wearable and portable EEG systems. The relatively low computational complexity of the MUSIC and cross-correlation stages makes the proposed method more suitable for low-power, real-time seizure monitoring applications and embedded healthcare systems.

While the proposed framework demonstrates high performance on the Bonn EEG dataset, it should be noted that real-world clinical EEG recordings can exhibit greater variability. Factors such as multi-channel configurations, long-term monitoring sessions, and the presence of various artifacts (e.g., muscle activity, eye movements, and environmental noise) may affect the generalizability of the model. Future studies on larger and more heterogeneous datasets will be necessary to validate the framework under these realistic clinical conditions.

Overall, the results confirm that the combination of MUSIC-based spectral analysis and cross-correlation–based feature extraction provides a robust, efficient, and scalable framework for automatic epileptic seizure detection. The method not only achieves competitive performance when compared with existing studies (Table 6) but also demonstrates strong potential for deployment in clinical and wearable EEG monitoring systems.

4. CONCLUSION AND SUGGESTIONS

This study proposed and validated an automated epileptic seizure detection framework based on the integration of high-resolution MUSIC spectral estimation and cross-correlation–driven feature extraction. The experimental results confirm that the proposed methodology can reliably distinguish seizure and non-seizure EEG activity across diverse classification scenarios. The extracted statistical and correlation-based features demonstrated strong discriminatory capability, supporting the effectiveness of the proposed signal processing strategy.

The findings indicate that the combined use of subspace-based spectral estimation and correlation-oriented statistical analysis provides a practical and efficient alternative to conventional time–frequency techniques. The framework achieves high detection performance while maintaining low feature complexity, which is particularly valuable for developing efficient and scalable EEG-based diagnostic tools.

Overall, the proposed approach contributes to the field of automated seizure detection by offering a stable, interpretable, and computationally efficient framework that is suitable for real-world EEG analysis and clinical decision-support applications.

Future research will focus on extending the proposed framework in several directions. First, validation on larger and more heterogeneous EEG datasets, including long-term scalp EEG and sleep EEG recordings, will be necessary to further assess generalizability and robustness in real clinical environments. Second, integrating MUSIC-based spectral features with modern deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (LSTMs), and attention-based temporal models may enhance the detection of complex temporal patterns.

In addition, future work will explore adaptive reference signal generation to enable patient-specific and dynamically updated feature extraction, which may encounter challenges due to inter-patient variability, signal noise, and changes in seizure patterns over time. Finally, optimizing the proposed framework for wearable and embedded hardware platforms will be a critical step toward real-time, continuous seizure monitoring, with expected challenges including limited computational resources, power consumption, and reliable data transmission in portable healthcare systems.

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

Artificial Intelligence (AI) Contribution Statement

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

Contributions of the Authors

G.E.: Conceptualization, investigation, methodology, validation, writing, data curation, formal analysis, review & editing.

N.İ.: Conceptualization, investigation, methodology, validation, writing, data curation, formal analysis, software, review & editing.

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