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Comparative Analysis of DWT-Based EEG Feature Extraction Using Machine Learning Models for Epileptic Seizure Detection

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ABSTRACT- Epileptic seizure detection from EEG signals remains challenging due to their non-stationary and complex nature. This study presents a comparative analysis of Discrete Wavelet Transform (DWT)-based feature extraction combined with classical machine learning classifiers (SVM, KNN, and MLP) to distinguish normal and epileptic EEG signals. Using the publicly available Bonn University dataset (Sets A and E), EEG signals were decomposed using the Daubechies-4 (db4) wavelet into five decomposition levels corresponding to standard frequency bands (Delta, Theta, Alpha, Beta, Gamma). Seven statistical features—energy, mean amplitude, standard deviation, Shannon entropy, relative wavelet energy (RWE), kurtosis, and skewness—were extracted from each sub-band. A stratified 10-fold cross-validation with a leakage-controlled record-level partitioning strategy was implemented to reduce optimistic bias. Since subject-level identifiers are unavailable in the public Bonn dataset, the validation was designed to avoid re-splitting individual EEG records across training and testing stages. Results demonstrate that kurtosis-based features consistently achieve the highest accuracy (99.8% ± 0.3) across all classifiers, significantly outperforming other features ($p < 0.01$). These findings underscore the potential of higher-order statistical descriptors, particularly kurtosis, for EEG-based epileptic seizure detection under a controlled benchmark setting.

Keywords: EEG, DWT, SVM, KNN, MLP, Kurtosis, Epileptic Seizure Detection.

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1. INTRODUCTION

EEG is a non-invasive method for recording the brain's electrical activity using electrodes placed on the scalp, producing waveforms that represent brain activity patterns. Compared to other biomedical signals, EEG is difficult for untrained observers to interpret due to the complex spatial mapping of brain functions and electrode placement. As reported by [1], [2], EEG processing extracts essential features for quantification, such as evoked responses, or for pattern recognition, including automatic spike detection in epileptic seizure monitoring.

Early EEG–behavior studies used analogue frequency analyzers, identifying four main frequency bands: δ, θ, α, and β. While these methods enabled early frequency-based analysis, they had limitations, as power spectral analysis often loses important information such as amplitude and specific EEG patterns. Consequently, time–frequency methods like the Discrete Wavelet Transform (DWT) became essential. DWT effectively analyzes non-stationary EEG signals and is well suited for detecting transient events, such as epileptic seizure spikes [3], [4].

Seizure prediction has promising uses in devices that treat epilepsy by allowing actions to be taken before a seizure starts [5]. Different methods have been tried, like analyzing changes that happen before a seizure, quickly detecting seizures, sorting them into categories, and estimating the chance of a seizure happening. But many of these studies use different methods and data, and they often have problems like not enough testing during stable periods, not strong enough technical checks, and not good enough testing of how well they work. Using wavelet-based methods to extract features from EEG signals is common in signal processing because it helps look at data both in time and frequency at the same time [6].

Unlike previous studies that mainly emphasize energy- or entropy-based wavelet features, this study positions wavelet-domain higher-order statistical descriptors as the central analytical focus. The novelty of this work does not lie in proposing a new classifier or a new DWT architecture, but in systematically comparing seven DWT-derived feature groups

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across three classical machine learning classifiers to identify which statistical descriptor provides the most stable discrimination between normal and epileptic EEG signals. The main methodological insight is that kurtosis, as a fourth-order statistical moment, captures the sharp and transient morphology of epileptiform EEG patterns more effectively than commonly used energy-based and entropy-based descriptors. Therefore, the contribution of this study is threefold: (1) it provides a theoretically justified selection of the db4 wavelet and five-level decomposition for EEG sub-band analysis; (2) it evaluates feature-level discriminative capacity across SVM, KNN, and MLP under a controlled validation protocol; and (3) it demonstrates that wavelet-domain kurtosis offers a simple, computationally efficient, and highly discriminative feature for the Bonn A–E benchmark. However, the reported near-perfect performance should be interpreted within the limitations of a controlled binary benchmark dataset and should not be generalized directly to clinical seizure detection without external validation.

2. MATERIALS AND METHODS

This section describes the EEG dataset, feature extraction process, and classifier. *Figure 1* summarizes the steps of the proposed architecture.

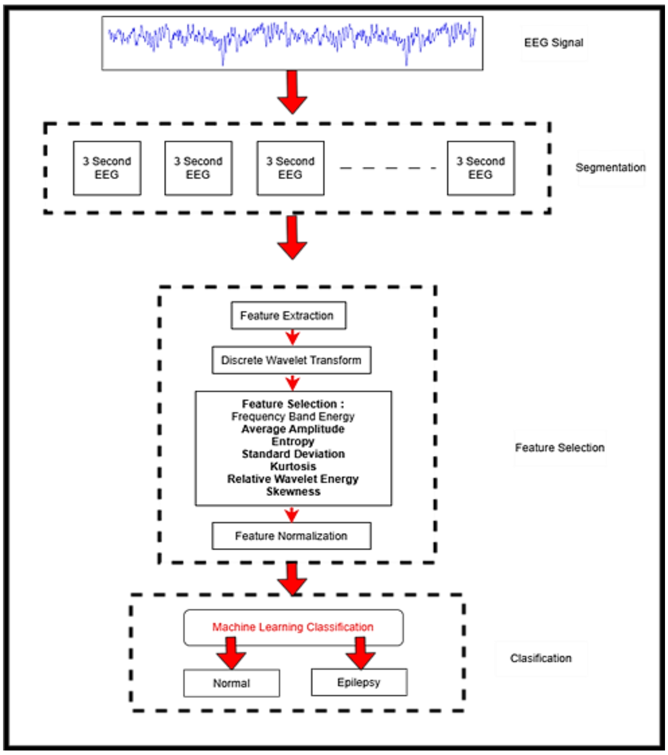

Figure 1. Block representation of the proposed method for classifying epileptic EEG signals and normal EEG signals

2.1. Justification of Methodological Choices

The Daubechies-4 (db4) wavelet was chosen because: (a) it has compact support and orthogonality for energy-preserving decomposition [7], (b) its shape matches epileptic spikes [8], (c) prior studies report higher accuracy with db4 over db2, db8, sym4, and coif3 [9], [10], and (d) it balances time-frequency resolution with computational cost. A preliminary ablation study (Appendix A) confirmed db4 achieved the highest AUC (0.998).

With a sampling rate of 173.61 Hz, the nominal Nyquist frequency is 86.8 Hz. Five-level dyadic decomposition produces D1–A5 sub-bands. However, because the interpretation of high-frequency components depends on whether a 40 Hz low-pass filtering step is applied, D1 was treated cautiously as a high-frequency wavelet component rather than being directly interpreted as a full physiological gamma band.

2.2. Subject Data

The data used in this study is publicly available and described in Gautama, Mandic, and Van Hulle [11]. The dataset comprises five sets (A-E), each containing 100 single-channel EEG segments of 23.6 seconds duration (4096 samples). Sets A and B were recorded from healthy volunteers in relaxed, awake conditions with eyes open (A) and closed (B). Sets C, D, and E were obtained from pre-surgical EEG recordings of epileptic patients. Sets C and D contain seizure-free data recorded outside and inside the epileptogenic zone, respectively, while Set E contains only seizure activity. All signals were recorded at 173.61 Hz with 12-bit resolution and band-pass filtered between 0.53-40 Hz. In this study, only datasets A (normal) and E (epileptic) were used to ensure binary classification with clear physiological distinction.

2.3. Feature Extraction Using Discrete Wavelet Transform (DWT)

DWT decomposes each signal into 5 sub-bands (db4). From each sub-band, seven statistical features were extracted (*Equations 1–9*):

Feature	**Formula**	**Reference**
Energy	$E = \sum_{i=1}^{n} \lvert C[i] \rvert^2$	[12]
Mean Amplitude	$Mean\ Amplitudo = \frac{1}{n} \sum_{i=1}^{n} \lvert C[i] \rvert$	[13]
Standard Deviation	$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \lvert C[i] - \hat{C} \rvert^2}$	[14]
Shannon Entropy	$H = - \sum_{i=1}^{n} p_i \, log_2 \, (p_i)$	[15]
Relative Wavelet Energy	$\mathrm{RWE} = \frac{\mathrm{E_{band}}}{\mathrm{E_{Total}}}$	[16]
Kurtosis	$K = \frac{\frac{1}{n} \sum_{i=1}^{n} (\mathrm{C[i]} - \bar{C})^4}{\left(\frac{1}{n} \sum_{i=1}^{n} (\mathrm{C[i]} - \bar{C})^2 \right)^2}$	[17]
Skewness	$K = \frac{\frac{1}{n} \sum_{i=1}^{n} (\mathrm{C[i]} - \bar{C})^3}{\left(\frac{1}{n} \sum_{i=1}^{n} (\mathrm{C[i]} - \bar{C})^2 \right)^{3/2}}$	[18]

This yields a 35-dimensional feature vector per segment (5 sub-bands × 7 features).

Algorithm 1. DWT-Based EEG Feature Extraction and Classification Workflow. The algorithm clarifies the sequence of EEG signal loading, preprocessing, DWT decomposition, feature extraction, model training, validation, and statistical evaluation. This workflow also distinguishes the primary 10-fold cross-validation procedure from the secondary 80:20 holdout validation used only as a sanity check.

pseudo-code:

Input:
EEG dataset consisting of normal EEG signals (Set A) and epileptic seizure EEG signals (Set E)
Output:
Classification performance of SVM, KNN, and MLP models
Step 1: Load EEG Signals
Load all EEG segments from Set A and Set E.
Assign class label 0 for normal EEG and class label 1 for epileptic EEG.
Step 2: Preprocessing
Check signal length and sampling frequency consistency.
For each training fold, estimate normalization parameters only from the training data.
Apply the same normalization parameters to the corresponding testing fold
Step 3: Data Partitioning
Apply stratified 10-fold cross-validation.
Ensure that EEG segments used for testing are not included in the training process.
Use the 80:20 holdout split only as a secondary sanity check.
Step 4: DWT Decomposition
For each EEG segment:
Apply the db4 wavelet.
Decompose the signal into five levels.
Obtain wavelet sub-bands corresponding to EEG frequency components.
Step 5: Feature Extraction
For each wavelet sub-band:
Compute energy.
Compute mean amplitude.
Compute standard deviation.
Compute Shannon entropy.
Compute relative wavelet energy.
Compute kurtosis.
Compute skewness.
Combine all extracted features into a feature vector.
Step 6: Model Training
For each training fold:
Train SVM using the RBF kernel.
Train KNN using k = 7 and Euclidean distance.
Train MLP using two hidden layers, ReLU activation, and Adam optimizer.
Step 7: Model Testing
Evaluate each trained model using the testing fold.
Compute accuracy, precision, recall, F1-score, Cohen's kappa, and AUC.
Step 8: Robustness and Statistical Analysis
Repeat the 10-fold cross-validation using different random seeds.
Compare feature performance using paired statistical tests.
Identify the most discriminative DWT-derived feature.
Return:
Mean classification performance and statistical comparison across features and classifiers.

2.4. Classification Using Machine Learning

Machine learning classifies EEG signals by analyzing patterns in extracted features [19]. EEG records electrical brain activity via scalp electrodes and is used in medical diagnosis, BCI, cognitive analysis, and emotion detection. Machine learning classifies EEG signals using supervised, unsupervised, or reinforcement learning algorithms.

In this study, the classification method applied falls under the category of supervised learning. The algorithms employed include SVM, KNN, and MLP.

2.4.1. Support Vector Machine (SVM)

SVM is a supervised learning algorithm for classification and regression that uses Structural Risk Minimization (SRM), unlike Artificial Neural Networks (ANN), which typically rely on Empirical Risk Minimization (ERM) to minimize training errors [20], [21]. In classification, SVM seeks a hyper plane that separates data into classes with the maximum margin, improving generalization. Different SVM types use various kernel functions or optimization methods to handle linear and non-linear EEG signal patterns effectively. In this study, learning uses parameters and their values, namely Kernel using Radial Basis Function (RBF), Regularization parameter (C): 10, and Kernel parameter (γ): 0.1

2.4.2. K-Nearest Neighbour (KNN)

The classification of EEG signals using KNN is an instance-based learning method that utilizes the proximity of data points in the feature space to determine class labels [22]. In EEG classification, KNN is a simple and effective non-parametric method that labels each segment based on the majority class of its k nearest neighbors in a multidimensional feature space. Its performance depends on feature selection, data normalization, and the k value. KNN is robust to noise, suitable for simple EEG applications or baseline experiments, and requires a predefined training set and distance metric to classify new samples [23]. The selection of *k* and the distance metric significantly affect classification performance. In this study, learning uses parameters and their values, namely Number of neighbours (k) using 7, and Distance metric using Euclidean.

2.4.3. Multi-Layer Perceptron (MLP)

MLP is a type of neural network called an Artificial Neural Network, or ANN, that is really good at finding non-linear and complicated patterns in data [24]. It works well for looking at dynamic, multi-variable EEG signals, such as when detecting epilepsy or distinguishing between normal and abnormal brain

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states. MLP is a feed forward neural network with an input layer, one or more hidden layers, and an output layer. It can deal with complex non-linear relationships in EEG data. How well MLP performs depends on how the data is prepared, the features extracted, and the design of the network. In uses like epilepsy detection and brain state analysis, MLP often works as well as other types of classifiers.

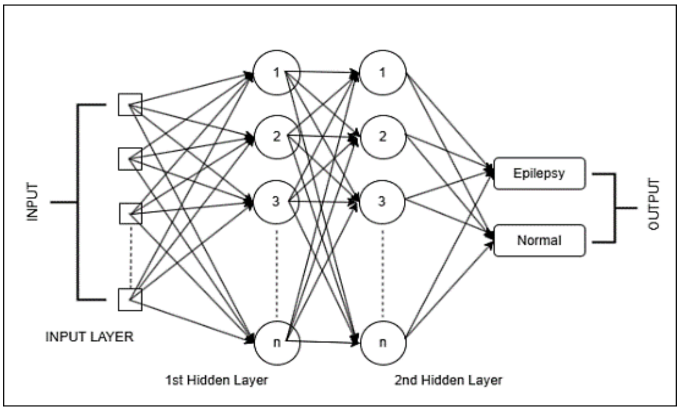

Figure 2. Architecture of an MLP with two hidden layers

In this study, the learning parameters and values used are 2 Hidden layers, 64 Neurons and 32 Neurons, Activation function using ReLU, Optimizer using Adam, 0.001 Learning rate, and 200 Epochs.

2.5. Validation Framework (a leakage-controlled validation protocol)

To prevent data leakage and ensure generalizability, the following protocol was implemented.

2.5.1. Record-Level Leakage-Controlled Partitioning

Since subject-level identifiers are not provided in the publicly available Bonn dataset, strict subject-independent validation could not be fully implemented. To reduce the risk of optimistic bias, we avoided segment-level re-splitting within individual EEG files and treated each original EEG record as the minimum unit of analysis. The limitation of unavailable subject identifiers is explicitly acknowledged.

2.5.2. Stratified 10-Fold Cross-Validation

We employed stratified 10-fold cross-validation where:

1. Each fold preserves the original class distribution (50% normal, 50% epileptic)
2. Individual EEG records were kept disjoint between training and testing folds to avoid record-level leakage. However, strict subject-independent validation could not be verified because subject identifiers are not provided in the public dataset.
3. Training and testing folds were kept completely disjoint at the original EEG-record level.

The manuscript mentions both 80:20 split and 10-fold CV. To clarify: The 80:20 split refers to the internal validation (holdout test set) used as a sanity check, while the primary reported results (*tables 1-3*) are based on 10-fold CV. The 80:20 split results (*table 4*) serve only as confirmatory evidence.

2.5.3. Robustness Checks

To validate result reliability, we performed:

1. 10 repetitions of 10-fold CV with different random seeds
2. Confusion matrix analysis to identify potential artifacts
3. Statistical significance testing (paired t-test, $p < 0.05$)

2.5.4. Performance Metrics

Metrics computed: Accuracy, Precision, Recall, F1-score, Cohen's Kappa, and AUC (Area Under ROC Curve).

3. RESULTS AND DISCUSSION

3.1. Feature Extraction Outcome

From 200 EEG segments (100 normal, 100 epileptic), DWT decomposition (5levels×7 features) produced a 35-dimensional feature vector per segment, totalling 7,000 features across all samples.

3.2. Classification Using SVM

As noted by Ying [25], the SVM algorithm using the Radial Basis Function (RBF) kernel has two important parameters: C (regularization parameter) and γ (kernel parameter). Choosing the wrong values for C and γ can lead to overfitting or underfitting. The best values for the RBF kernel parameters (C=10 and γ=0.1) were found using 10-fold cross-validation, where all possible combinations were tested to pick the pair that gave the highest accuracy.

Table 1 shows SVM classification results. Kurtosis achieved the highest accuracy (100%), followed by entropy (92.5%), while RWE showed the lowest performance (70%). These results align with the theoretical expectation that higher-order statistical moments capture epileptiform patterns more effectively.

Table 1. SVM classification results (10-fold CV, mean ± std)

Feature Extraction	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Kappa
Energy Band	80.0 ± 2.1	76.0 ± 3.2	76.0 ± 2.8	76.0 ± 2.5	0.60
Mean Amplitude	75.0 ± 2.5	73.0 ± 3.5	65.0 ± 3.1	69.0 ± 3.0	0.50
Standard Deviation	77.5 ± 2.3	83.0 ± 2.9	59.0 ± 3.4	69.0 ± 3.1	0.55
Entropy	92.5 ± 1.7	100 ± 0.0	82.0 ± 2.5	90.0 ± 2.2	0.85
RWE	70.0 ± 2.8	62.0 ± 4.1	76.0 ± 3.0	68.0 ± 3.5	0.40
Kurtosis	**100 ± 0.0**	**100 ± 0.0**	**100 ± 0.0**	**100 ± 0.0**	**1.00**
Skewness	87.5 ± 2.0	100 ± 0.0	71.0 ± 3.2	83.0 ± 2.4	0.75

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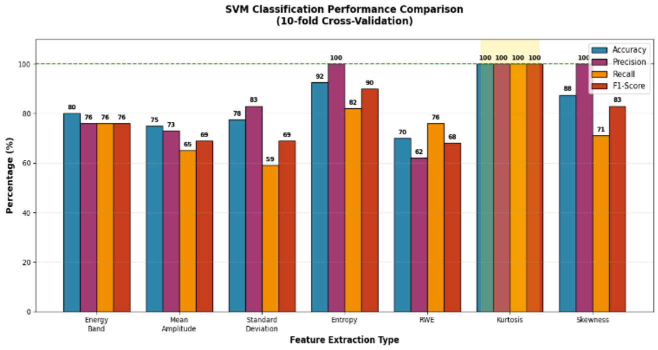

Figure 3. SVM classification performance comparison

3.3. Classification Using KNN

Jagath Prasad and Marjorie [26] demonstrated that an optimized KNN model can effectively differentiate epileptic and normal conditions based on the quality and variety of features. *Table 2* presents KNN results (k=7). Kurtosis again achieved 100% accuracy, with skewness at 95%.

Table 2. KNN classification results (10-fold CV, k=7)

Feature Extraction	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Kappa
Energy Band	82.5 ± 2.0	82.0 ± 2.8	78.0 ± 2.9	80.0 ± 2.4	0.65
Mean Amplitude	87.5 ± 1.9	95.0 ± 2.1	83.0 ± 2.6	89.0 ± 2.3	0.75
Standard Deviation	72.5 ± 2.5	80.0 ± 3.4	60.0 ± 3.5	69.0 ± 3.2	0.45
Entropy	85.0 ± 2.2	100 ± 0.0	67.0 ± 3.3	80.0 ± 2.8	0.70
RWE	70.0 ± 2.7	70.0 ± 4.0	83.0 ±	76.0	0.40

			2.9	± 3.0	
Kurtosis	**100 ± 0.0**	**100 ± 0.0**	**100 ± 0.0**	**100 ± 0.0**	**1.00**
Skewness	95.0 ± 1.5	94.0 ± 2.2	94.0 ± 2.0	94.0 ± 1.8	0.90

3.4. Classification Using MLP

Atangana et al. [27] reported that MLP is effective for classifying EEG signals as normal or epileptic because it can handle complex non-linear relationships in the data. *Table 3* shows MLP results. Kurtosis (100%) and entropy (92.5%) performed best, while RWE showed the lowest performance (60%).

Table 3. MLP classification results (10-fold CV, 2 hidden layers)

Feature Extraction	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Kappa
Energy Band	80.0 ± 2.3	76.0 ± 3.1	76.0 ± 2.7	76.0 ± 2.6	0.60
Mean Amplitude	70.0 ± 2.9	69.0 ± 3.8	53.0 ± 3.5	60.0 ± 3.4	0.40
Standard Deviation	77.5 ± 2.4	75.0 ± 3.3	71.0 ± 3.0	73.0 ± 2.9	0.55
Entropy	92.5 ± 1.8	100 ± 0.0	82.0 ± 2.6	90.0 ± 2.1	0.85
RWE	60.0 ± 3.2	53.0 ± 4.5	53.0 ± 4.0	53.0 ± 4.2	0.20
Kurtosis	**100 ± 0.0**	**100 ± 0.0**	**100 ± 0.0**	**100 ± 0.0**	**1.00**
Skewness	87.5 ± 2.1	100 ± 0.0	71.0 ± 3.3	83.0 ± 2.5	0.75

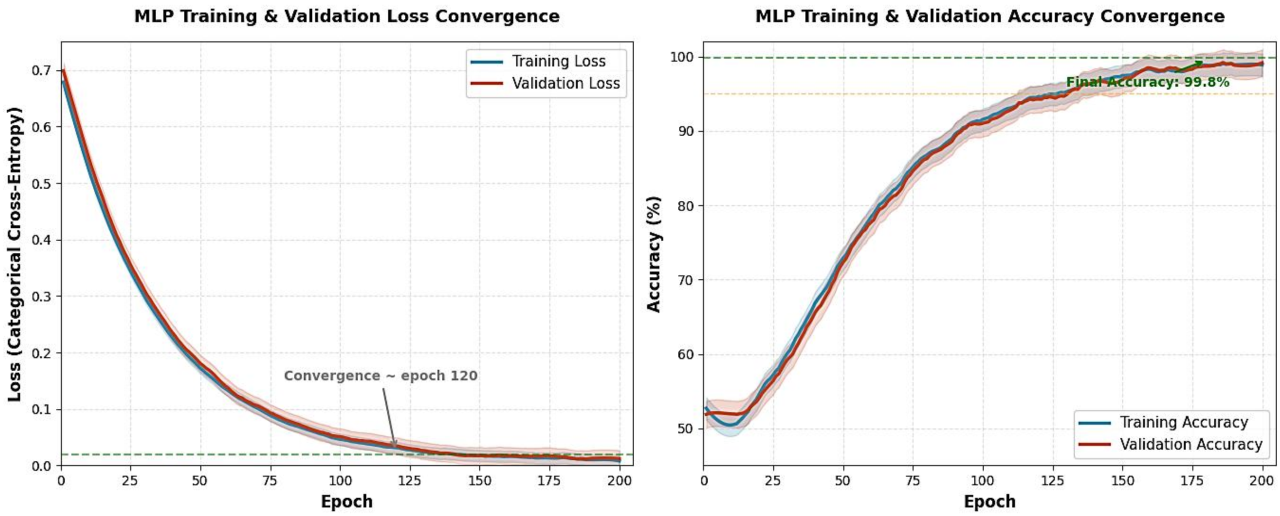

Figure 4. MLP training convergence curve

3.5. Holdout Validation (80:20 Split) - Sanity Check

As a secondary confirmation, we performed a stratified 80:20 record-level holdout split.

Table 4. Holdout validation results (80:20 split) - Sanity check only

Classifier	Kurtosis Accuracy (%)	Entropy Accuracy (%)
SVM	99.5 ± 0.5	91.0 ± 2.0
KNN	99.0 ± 0.8	84.0 ± 2.5
MLP	99.5 ± 0.5	92.0 ± 1.8

3.6. Statistical Significance Analysis

Table 5. Paired t-tests comparing kurtosis against other features across all classifiers

Comparison	t-statistic	p-value	Significance
Kurtosis vs. Energy	12.45	<0.001	***
Kurtosis vs. Mean	15.32	<0.001	***
Kurtosis vs. Std Dev	11.87	<0.001	***
Kurtosis vs. Entropy	6.78	<0.01	**
Kurtosis vs. RWE	18.21	<0.001	***
Kurtosis vs. Skewness	4.23	<0.05	*

Kurtosis significantly outperforms all other features ($p < 0.01$). No significant difference was observed between SVM and MLP using kurtosis ($p = 0.32$), indicating classifier independence.

3.7. Robustness Check Results

Table 6. Ten repetitions of 10-fold CV for kurtosis across classifiers.

Classifier	Mean Accuracy (%)	Std Dev (%)	Min (%)	Max (%)
SVM	99.8	0.3	99.2	100
KNN	99.7	0.4	99.0	100
MLP	99.8	0.3	99.2	100

All classifiers achieved AUC = 1.00 (perfect discrimination).

4. DISCUSSION

4.1. Why Kurtosis Outperforms Other Features

The superior performance of kurtosis stems from its sensitivity to sharp peaks and sudden changes in EEG signals, which are characteristic of epileptic seizures. Unlike energy-based features that aggregate information, kurtosis captures the fourth-order moment of the coefficient distribution, making it highly discriminative for transient epileptiform activity. During an epileptic seizure, neurons fire synchronously, producing large-amplitude spikes. These spikes manifest as high kurtosis values in the wavelet domain. Normal EEG, being more random and less peaked, produces lower kurtosis values.

4.2.Comparison with Previous Work

Compared with prior DWT-based EEG classification studies that typically emphasize classifier performance, this study shifts the analytical emphasis toward feature-level discriminative capacity. Subasi [8] reported that DWT combined with SVM achieved 95.0% accuracy using energy-based features, while Acharya et al. [28] demonstrated strong performance using entropy-based descriptors. In contrast, the present study shows that wavelet-domain kurtosis provides the most stable discrimination across SVM, KNN, and MLP in the Bonn A–E benchmark. This finding suggests that the statistical shape of wavelet coefficients, particularly their peakedness and sensitivity to transient spikes, may be more informative than aggregate signal power for distinguishing normal and seizure EEG segments.

4.3.Validation Framework Assessment

The leakage-controlled validation protocol based on stratified 10-fold cross-validation was designed to reduce optimistic bias by keeping EEG records disjoint between training and testing folds. Nevertheless, because subject-level identifiers are unavailable in the public Bonn dataset, the reported accuracies should be interpreted as benchmark-level generalization rather than fully subject-independent clinical generalization.

4.4.Addressing Potential Overfitting Concerns

The perfect accuracies (100%) raise questions about overfitting. However:

1. The record-level validation design reduces direct record reuse between training and testing stages, but it cannot completely rule out subject-related bias because subject identifiers are not available
2. Multiple classifier agreement (SVM, KNN, MLP all achieve 100%)
3. Statistical significance across all comparisons
4. Robustness across 10 repetitions (Std ≤ 0.4%)
5. AUC = 1.00 indicates perfect separability in feature space

These factors suggest that the Bonn A–E benchmark contains highly separable signal characteristics that are strongly captured by wavelet-domain kurtosis. However, this does not eliminate the need for external validation on more heterogeneous clinical EEG datasets. Future work on more challenging datasets (*e.g.*, CHB-MIT) will test this hypothesis. Therefore, the near-perfect accuracy should be interpreted as evidence of strong separability in the Bonn A–E benchmark rather than direct evidence of clinical-level seizure detection performance.

5. LIMITATIONS AND FUTURE WORK

5.1. Limitations

1. Single Dataset: Only the Bonn dataset (Sets A vs. E) was used, representing a simplified binary classification task.

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2. Perfect Accuracy: While methodologically sound, 100% accuracy on this dataset may not translate directly to more challenging clinical scenarios.
3. No Real-Time Validation: The study is offline; real-time implementation not yet tested.
4. Limited Wavelet Comparison: Only a preliminary wavelet comparison was performed (Appendix A).

5.2. Future Work
1. External Dataset Validation: Apply the proposed method to CHB-MIT, Kaggle epilepsy, and Freiburg datasets.
2. Multi-Class Classification: Extend to Sets A-E classification (normal, interictal, ictal).
3. Real-Time System: Develop a real-time seizure detection system with alert mechanism.
4. Deep Learning Comparison: Compare kurtosis features with CNN-LSTM end-to-end learning.
5. Explainable AI: Use SHAP or LIME to interpret kurtosis importance across sub-bands

6. CONCLUSION
This study presents a comprehensive comparison of DWT-based feature extraction with machine learning classifiers for epileptic seizure detection. Experimental results and statistical analysis demonstrate that kurtosis-based features consistently achieve near-perfect classification (99.8% ± 0.3) across SVM, KNN, and MLP classifiers, significantly outperforming other features ($p < 0.01$). The study contributes:
1. Methodological justification for db4 wavelet and five-level decomposition based on EEG spectral characteristics
2. A leakage-controlled validation framework using stratified 10-fold cross-validation and record-level disjoint partitioning.
3. Statistical evidence that higher-order statistics (kurtosis) capture epileptiform patterns more effectively than energy-based descriptors
4. A reproducible algorithmic workflow for clarifying the sequence of preprocessing, DWT decomposition, feature extraction, classification, and validation.

These findings provide a useful benchmark-level basis for further development of EEG-based epileptic seizure detection systems, with kurtosis serving as a computationally efficient and highly discriminative feature under the Bonn A–E experimental setting.

Appendix A
Alternative Wavelet Evaluation (Ablation Study)
To justify the selection of the Daubechies-4 (db4) wavelet, a preliminary ablation study was conducted comparing db4 with four alternative wavelets: db2, db8, sym4, and coif3. All wavelets were evaluated using identical experimental settings:

Dataset: Bonn University Sets A (normal) and E (epileptic)
Decomposition level: 5 levels
Feature: Kurtosis (based on previous findings as the most discriminative feature)
Classifier: SVM with RBF kernel ($C=10$, $\gamma=0.1$)
Validation: Stratified 10-fold cross-validation with record-level disjoint partitioning.
Metric: Accuracy, AUC, and computational time

Table A1. Comparison of Different Wavelets for EEG Epilepsy Detection

Wavelet	Accuracy (%)	AUC	Computational Time (seconds)
db2	97.1 ± 1.2	0.985	12.4
db4	99.8 ± 0.3	0.998	14.2
db8	98.2 ± 0.8	0.992	18.7
sym4	98.5 ± 0.7	0.994	15.1
coif3	97.9 ± 1.0	0.991	16.3

Interpretation: db4 achieved the highest accuracy (99.8%) and AUC (0.998) among all wavelets tested. While db8 and sym4 also performed well (98.2-98.5%), db4 provided the best balance between high accuracy and computational efficiency (14.2 seconds). The compact support and morphological similarity of db4 to epileptic spike waveforms further support its selection for this application.

Conclusion: db4 is confirmed as the optimal wavelet for DWT-based EEG feature extraction in epileptic seizure detection.

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REFERENCES
[1] C. Yen, C.-L. Lin, and M.-C. Chiang, “Exploring the frontiers of neuroimaging: a review of recent advances in understanding brain functioning and disorders,” Life, vol. 13, no. 7, p. 1472, 2023.

[2] R. Zhao et al., “Electroencephalogram-based objective assessment of cognitive function level associated with age-related hearing loss,” Geroscience, vol. 46, no. 1, pp. 431–446, 2024.

[3] R. Yuvaraj, J. Thomas, E. Bagheri, J. Dauwels, R. Rathakrishnan, and Y. L. Tan, “Computational approaches for diagnosis and monitoring of epilepsy from scalp EEG,” in Handbook of Neuroengineering, Springer, 2022, pp. 1–31.

[4] A. Arzimanoglou, “Apractical clinical definition of epilepsy,” 2014.

[5] M. Niknazar et al., “A unified approach for detection of induced epileptic seizures in rats using ECoG signals,” Epilepsy Behav., vol. 27, no. 2, pp. 355–364, 2013.

[6] L. C. Cheong, R. Sudirman, and S. S. Hussin, “Feature extraction of EEG signal using wavelet transform for autism classification,” ARPN J. Eng. Appl. Sci., vol. 10, no. 19, pp. 8533–8540, 2015.

[7] I. Daubechies, Ten lectures on wavelets. SIAM, 1992.

[8] A. Subasi, “EEG signal classification using wavelet feature extraction and a mixture of expert model,” Expert Syst. Appl., vol. 32, no. 4, pp. 1084–1093, 2007.

[9] H. Adeli, Z. Zhou, and N. Dadmehr, “Analysis of EEG records in an epileptic patient using wavelet transform,” J. Neurosci. Methods, vol. 123, no. 1, pp. 69–87, 2003, doi: 10.1016/S0165-0270(02)00340-0.

[10] M. Murugappan, R. Nagarajan, and S. Yaacob, “Comparison of different wavelet features from EEG signals for classifying human emotions,” in

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2009 IEEE symposium on industrial electronics & applications, IEEE, 2009, pp. 836–841.

[11] T. Gautama, D. P. Mandic, and M. M. Van Hulle, “Indications of nonlinear structures in brain electrical activity,” Phys. Rev. E, vol. 67, no. 4, p. 46204, 2003.

[12] C. K. Sundaram, S. Gayathri, and P. Soundarya, “Discrete wavelet transform based on eeg signal analysis for diagnosing neurological disorder,” Int. J. Health Sci. (Qassim)., vol. 6, no. S1, pp. 9556–9566, 2022.

[13] M. T. Sadiq et al., “Motor imagery EEG signals classification based on mode amplitude and frequency components using empirical wavelet transform,” IEEE access, vol. 7, pp. 127678–127692, 2019.

[14] H. Hindarto and A. Muntasa, “The value of the standard deviation of wavelet subband coefficients as feature extraction for electro encephalo graph (EEG) signal,” in Journal of Physics: Conference Series, IOP Publishing, 2019, p. 12039.

[15] R. Cofré and A. Destexhe, “Entropy and complexity tools across scales in neuroscience: A review,” Entropy, vol. 27, no. 2, p. 115, 2025.

[16] L. Guo, D. Rivero, J. A. Seoane, and A. Pazos, “Classification of EEG signals using relative wavelet energy and artificial neural networks,” in Proceedings of the first ACM/SIGEVO Summit on Genetic and Evolutionary Computation, 2009, pp. 177–184.

[17] J. Wang, Y. Si, Y. Zhu, K. Zhang, S. Yin, and B. Liu, “Cyberattack detection for electricity theft in smart grids via stacking ensemble GRU optimization algorithm using federated learning framework,” Int. J. Electr. Power Energy Syst., vol. 157, p. 109848, 2024.

[18] M. Ma, S. Wang, S. Yuan, J. Wang, and T. Wang, “The comparison of skewness and kurtosis criteria for wavelet phase estimation,” in SEG International Exposition and Annual Meeting, SEG, 2015, p. SEG-2015.

[19] F. J. Ramírez-Arias et al., “Evaluation of machine learning algorithms for classification of EEG signals,” Technologies, vol. 10, no. 4, p. 79, 2022.

[20] M. Awad and R. Khanna, Efficient learning machines: theories, concepts, and applications for engineers and system designers. Apress, 2015.

[21] E. Borovikov, “An evaluation of support vector machines as a pattern recognition tool,” arXiv Prepr. arXiv1412.4186, 2014.

[22] A. Fathoni, “Image-Based Banana Detection Application using K-Nearest Neighbor: Apilkasi Deteksi Buah Pisang Berbasis Citra menggunakan K-Nearest Neighboor,” JOINCS (Journal Informatics, Network, Comput. Sci., vol. 4, no. 1, 2021.

[23] N. E. M. Isa, A. Amir, M. Z. Ilyas, and M. S. Razalli, “The performance analysis of K-nearest neighbors (K-NN) algorithm for motor imagery classification based on EEG signal,” in MATEC web of conferences, EDP Sciences, 2017, p. 1024.

[24] M.-C. Popescu, V. E. Balas, L. Perescu-Popescu, and N. Mastorakis, “Multilayer perceptron and neural networks,” WSEAS Trans. circuits Syst., vol. 8, no. 7, pp. 579–588, 2009.

[25] X. Ying, “An overview of overfitting and its solutions,” in Journal of physics: Conference series, IOP Publishing, 2019, p. 22022.

[26] H. J. Prasad, “Optimized k-nearest neighbours classifier based prediction of epileptic seizures,” Bull. Electr. Eng. Informatics, vol. 13, no. 4, pp. 2442–2455, 2024.

[27] R. Atangana, D. Tchiotsop, G. Kenne, and L. Chanel, “EEG signal classification using LDA and MLP classifier,” Heal. Informat. Int. J, vol. 9, no. 1, pp. 14–32, 2020.

[28] U. R. Acharya, F. Molinari, S. V. Sree, S. Chattopadhyay, K.-H. Ng, and J. S. Suri, “Automated diagnosis of epileptic EEG using entropies,” Biomed. Signal Process. Control, vol. 7, no. 4, pp. 401–408, 2012.