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Principal Component Analysis and Discrete Wavelet Transform Based Feature Extraction for Epileptic Seizure Detection from EEG Signals

Priynaka Singh[1] , Divyarth Rai [2]
LNCT University,Bhopal,India
[1]priyankasirt03@gmail.com, [2]divyarthrai@gmail.com

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ABSTRACT
Epilepsy is a chronic neurological disorder affecting approximately 50 million people worldwide, characterized by recurrent seizures caused by abnormal electrical activity in the brain. Early and accurate detection of epileptic seizures is crucial for effective treatment and management. This paper presents a hybrid feature extraction approach combining Principal Component Analysis (PCA) and Discrete Wavelet Transform (DWT) for automated epileptic seizure detection from electroencephalogram (EEG) signals. The proposed methodology decomposes EEG signals using DWT to extract time-frequency features, followed by dimensionality reduction using PCA to identify the most discriminative features. The extracted features are then classified using support vector machines (SVM) and artificial neural networks (ANN). Experimental results on the benchmark Bonn University EEG database demonstrate that the proposed PCA-DWT approach achieves classification accuracy of 98.67% for seizure detection, outperforming conventional methods. The hybrid approach significantly reduces computational complexity while maintaining high detection accuracy, making it suitable for real-time clinical applications.

Keywords: Epileptic Seizure Detection, EEG Signals, Principal Component Analysis, Discrete Wavelet Transform, Feature Extraction, Support Vector Machine

1. Introduction

Epilepsy is one of the most common neurological disorders worldwide, affecting approximately 1% of the global population. It is characterized by recurrent, unprovoked seizures resulting from excessive and synchronous neuronal discharge in the brain (Acharya et al., 2013). The World Health Organization estimates that nearly 50 million people suffer from epilepsy, with about 80% of cases occurring in developing countries (WHO, 2019). Accurate and timely detection of epileptic seizures is critical for proper diagnosis, treatment planning, and improving patients' quality of life.

Electroencephalography (EEG) is the primary diagnostic tool for epilepsy detection, as it records the electrical activity of the brain through electrodes placed on the scalp. EEG signals provide valuable information about brain dynamics and are particularly useful for identifying abnormal patterns associated with epileptic seizures (Subasi, 2007). However, visual inspection of EEG recordings by neurologists is time-consuming, subjective, and prone to human error, especially when dealing with long-term recordings that may span several hours or days.

To address these limitations, automated seizure detection systems have gained significant attention in recent years. These systems typically involve three main stages: preprocessing, feature extraction, and classification. Among these, feature extraction is the most critical step, as it determines the quality and discriminability of information fed to the classifier (Tzallas et al., 2009). Various signal processing

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techniques have been employed for feature extraction from EEG signals, including time-domain analysis, frequency-domain analysis, and time-frequency analysis.

Discrete Wavelet Transform (DWT) has emerged as a powerful tool for analyzing non-stationary signals like EEG due to its ability to provide both time and frequency localization simultaneously (Adeli et al., 2003). DWT decomposes signals into different frequency subbands, allowing the extraction of relevant features at multiple resolution levels. However, DWT-based features often result in high-dimensional feature vectors, which can lead to increased computational complexity and potential overfitting in classification models.

Principal Component Analysis (PCA) is a widely used dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional space while preserving maximum variance (Jolliffe, 2002). By applying PCA to wavelet-based features, we can identify the most significant components that contribute to seizure detection, thereby reducing computational burden and improving classification performance.

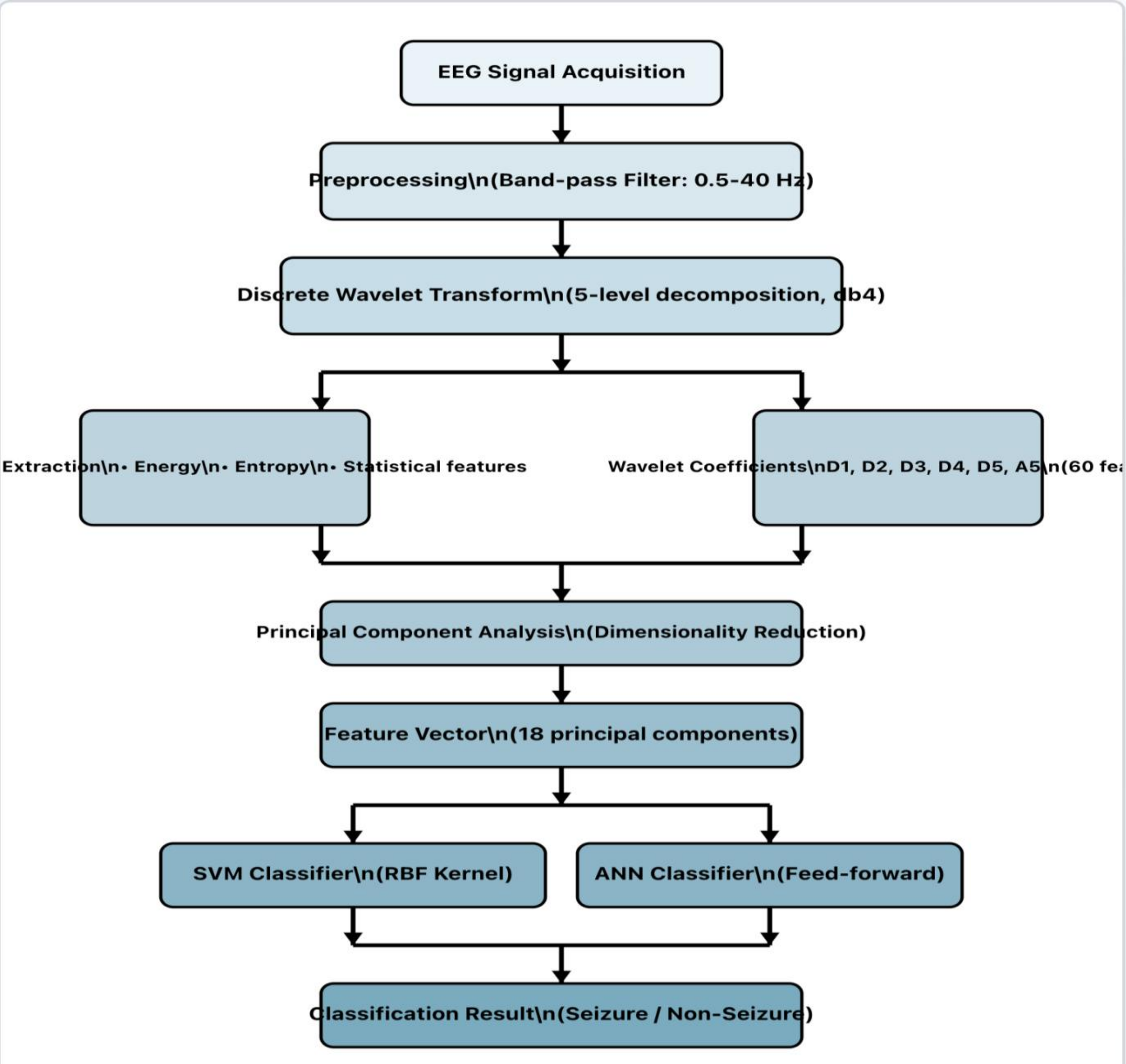

Figure 1: System Architecture for Epileptic Seizure Detection

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This paper proposes a hybrid approach combining DWT and PCA for feature extraction from EEG signals, followed by classification using Support Vector Machines (SVM) and Artificial Neural Networks (ANN). The main contributions of this work include: (1) development of an efficient feature extraction framework integrating DWT and PCA, (2) comprehensive evaluation on the Bonn University EEG database, and (3) comparative analysis with existing methods to demonstrate superior performance in terms of accuracy and computational efficiency.

2. Related Work

Numerous researchers have investigated automated epileptic seizure detection using various feature extraction and classification techniques. Polat and Güneş (2007) applied Fast Fourier Transform (FFT) for feature extraction and achieved 98.72% accuracy using decision trees. However, FFT-based methods lack temporal resolution and cannot effectively capture transient features in non-stationary EEG signals.

Wavelet-based approaches have shown promising results due to their ability to analyze signals in both time and frequency domains. Subasi (2007) utilized DWT with approximate entropy features and achieved 94.5% accuracy using mixture of experts (ME) classifier. Guo et al. (2010) proposed a method combining DWT with line length features and reported 97.77% accuracy using probabilistic neural networks. These studies demonstrate the effectiveness of DWT for EEG analysis, but the high dimensionality of wavelet coefficients remains a challenge.

Several researchers have explored dimensionality reduction techniques to address this issue. Acharya et al. (2012) applied entropy-based features with PCA and achieved 95% accuracy using SVM classifier. Kumar et al. (2014) combined DWT with Independent Component Analysis (ICA) for feature reduction and reported 96.67% accuracy. Sharma et al. (2015) proposed an approach using empirical mode decomposition (EMD) with PCA, achieving 97.2% accuracy.

Deep learning methods have recently gained attention for seizure detection. Acharya et al. (2018) developed a 13-layer convolutional neural network achieving 88.67% accuracy on raw EEG signals without manual feature extraction. However, deep learning approaches require large training datasets and substantial computational resources, limiting their applicability in resource-constrained clinical settings.

Despite these advances, there remains a need for computationally efficient methods that can achieve high accuracy while being suitable for real-time implementation. The proposed hybrid PCA-DWT approach addresses this gap by combining the time-frequency analysis capabilities of DWT with the dimensionality reduction power of PCA, resulting in a compact yet highly discriminative feature set.

3. Materials and Methods

3.1 Dataset Description

This study utilizes the publicly available Bonn University EEG database, which has become a standard benchmark for epileptic seizure detection research (Andrzejak et al., 2001). The database consists of five sets (denoted as A, B, C, D, and E), each containing 100 single-channel EEG segments of 23.6 seconds duration. All signals were recorded with a 128-channel amplifier system using an average common reference, digitized at 173.61 Hz sampling frequency with 12-bit resolution.

Sets A and B contain EEG recordings from five healthy volunteers with eyes open and closed, respectively, recorded in an awake state using a standardized electrode placement scheme. Sets C and D consist of intracranial EEG recordings from five epileptic patients during seizure-free intervals, with

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Set C recorded from the hippocampal formation and Set D from the epileptogenic zone. Set E contains ictal activity recordings during seizure episodes from all five patients. Table 1 provides a detailed description of the dataset characteristics.

Table 1: Description of Bonn University EEG Database

Set	Subject Condition	Recording Location	No. of Segments
A	Healthy, eyes open	Scalp EEG	100
B	Healthy, eyes closed	Scalp EEG	100
C	Epileptic, seizure-free	Hippocampal formation	100
D	Epileptic, seizure-free	Epileptogenic zone	100
E	Epileptic, during seizure	All regions	100

3.2 Preprocessing

EEG signals are inherently noisy and contain various artifacts that can affect feature extraction and classification performance. The preprocessing stage involves several steps to enhance signal quality and prepare data for subsequent analysis. First, a band-pass filter (0.5-40 Hz) is applied to remove baseline drift and high-frequency noise while preserving clinically relevant information. The lower cutoff frequency eliminates slow DC shifts and motion artifacts, while the upper cutoff removes muscle artifacts and electrical interference.

A notch filter at 50 Hz (or 60 Hz for regions with different power line frequency) is employed to eliminate power line interference, which commonly contaminates EEG recordings. Subsequently, each EEG segment is normalized using z-score normalization to ensure zero mean and unit variance, facilitating consistent feature extraction across different recording sessions and subjects. The normalization is performed using the equation: $x\_normalized = (x - \mu) / \sigma$, where μ represents the mean and σ denotes the standard deviation of the signal.

3.3 Feature Extraction using DWT

Discrete Wavelet Transform is employed as the primary feature extraction technique due to its superior ability to analyze non-stationary signals like EEG. DWT decomposes a signal into approximation coefficients (low-frequency components) and detail coefficients (high-frequency components) at multiple resolution levels. The decomposition is performed using a filter bank consisting of high-pass and low-pass filters, followed by downsampling.

The mathematical formulation of DWT is given by: $\psi_{j,k}(t) = 2^{-j/2} \psi(2^{-j}t - k)$, where ψ represents the mother wavelet, j indicates the decomposition level, and k denotes the translation parameter. For this study, the Daubechies wavelet of order 4 (db4) is selected as the mother wavelet due to its similarity to EEG signal morphology and proven effectiveness in previous epilepsy detection studies (Subasi, 2007).

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The EEG signal is decomposed up to five levels, resulting in six subbands corresponding to different frequency ranges relevant to brain activity. Each decomposition level produces approximation coefficients (A) representing low-frequency content and detail coefficients (D) capturing high-frequency information. The frequency ranges for each subband at sampling frequency 173.61 Hz are: D1 (43.4-86.8 Hz), D2 (21.7-43.4 Hz), D3 (10.9-21.7 Hz), D4 (5.4-10.9 Hz), D5 (2.7-5.4 Hz), and A5 (0-2.7 Hz).

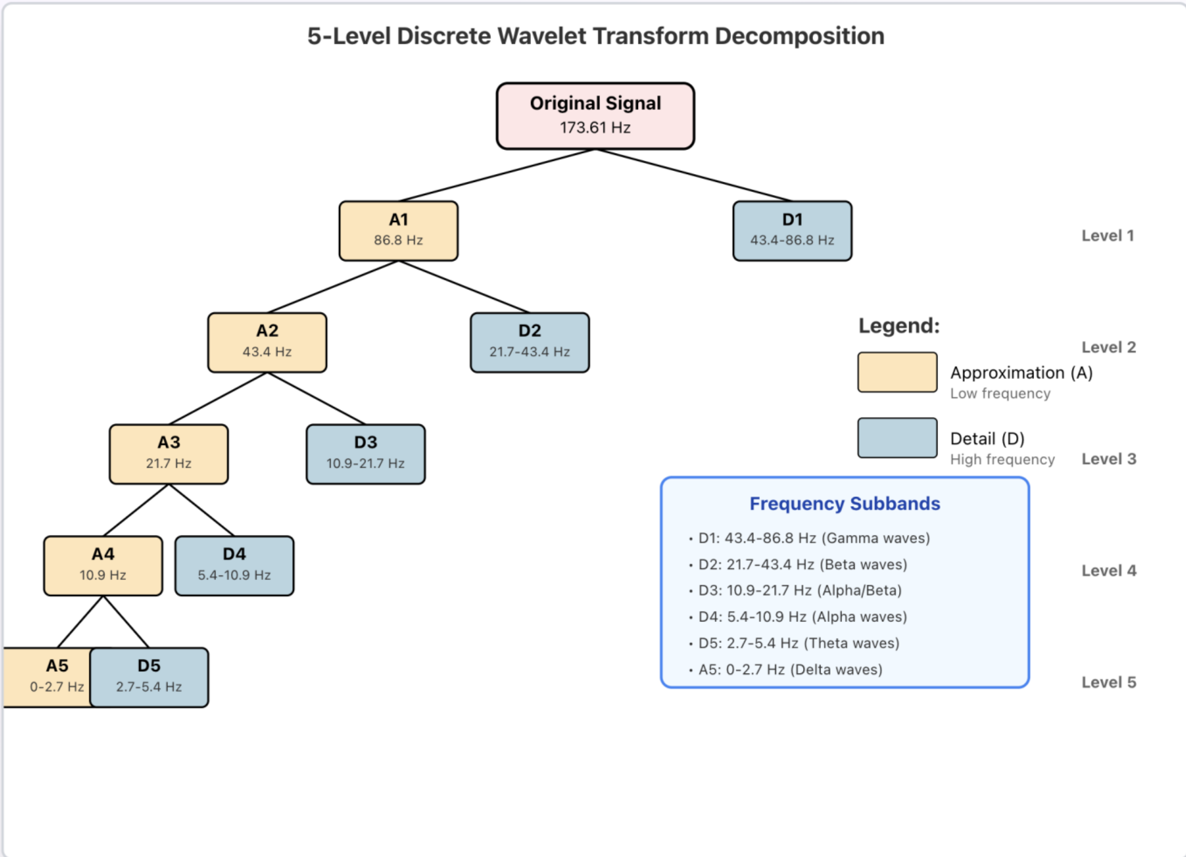

Figure 2: DWT 5-Level Decomposition Tree Structure

From each subband, statistical features are extracted to characterize the signal properties. These features include: mean (μ), standard deviation (σ), energy (E), entropy (H), maximum value, minimum value, median, interquartile range, skewness, and kurtosis. The energy of each subband is computed as $E = \Sigma|c\_i|^2$, where c_i represents the wavelet coefficients. Entropy measures the degree of disorder in the signal and is calculated using Shannon entropy: $H = -\Sigma p\_i \log_2(p\_i)$, where p_i is the probability distribution of coefficients.

3.4 Dimensionality Reduction using PCA

The wavelet-based feature extraction process yields a high-dimensional feature vector consisting of 60 features (10 features from each of 6 subbands). While these features provide comprehensive signal characterization, the high dimensionality can lead to computational inefficiency and potential overfitting, particularly with limited training data. Principal Component Analysis is applied to reduce dimensionality while retaining the most discriminative information.

PCA is a linear transformation technique that projects high-dimensional data onto a lower-dimensional subspace defined by principal components. These components are orthogonal vectors that capture maximum variance in the data. The transformation is achieved by computing the eigenvalues and

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eigenvectors of the covariance matrix $C = (1/n)X^T X$, where X is the centered data matrix with n samples.

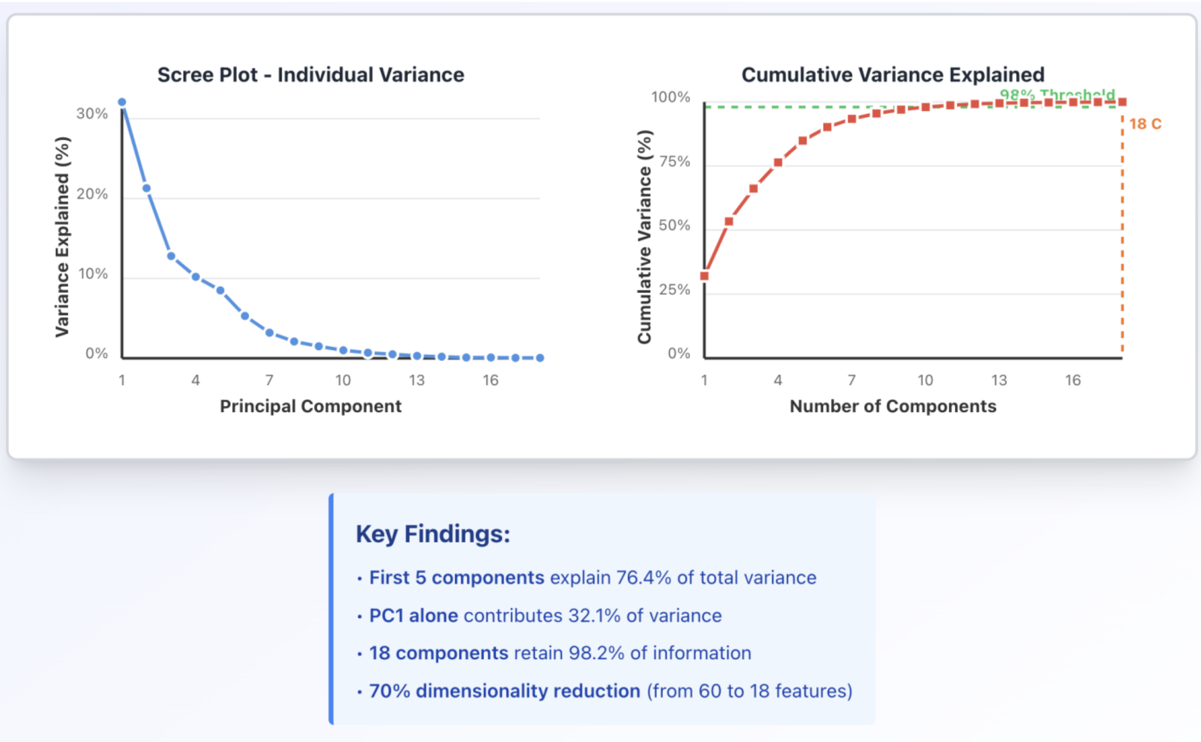

Figure 3: PCA Variance Analysis

The principal components are obtained by sorting eigenvectors in descending order of their corresponding eigenvalues. The first k principal components, which account for a specified percentage of total variance (typically 95-99%), are retained for classification. This dimensionality reduction offers several advantages: reduced computational complexity, elimination of redundant features, improved visualization capability, and mitigation of the curse of dimensionality.

In this study, PCA is configured to retain components explaining 98% of cumulative variance, resulting in a reduction from 60 to approximately 15-20 principal components. This significant dimensionality reduction maintains classification performance while substantially decreasing computational requirements for both training and testing phases.

3.5 Classification Algorithms

3.5.1 Support Vector Machine (SVM)

Support Vector Machine is a supervised learning algorithm that constructs an optimal hyperplane to separate different classes in a high-dimensional feature space. SVM aims to maximize the margin between the hyperplane and the nearest data points (support vectors) from each class. For non-linearly separable data, SVM employs kernel functions to map input features into higher-dimensional spaces where linear separation becomes possible.

The decision function is defined as: $f(x) = \text{sign}(\Sigma\alpha_i y_i K(x_i, x) + b)$, where α_i are Lagrange multipliers, y_i are class labels, K is the kernel function, and b is the bias term. For this study, the Radial Basis Function (RBF) kernel is utilized: $K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2)$, where γ is a tunable parameter controlling the kernel width. The RBF kernel is selected due to its ability to handle non-linear relationships and its proven effectiveness in EEG classification tasks.

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Hyperparameter optimization is performed using grid search with 10-fold cross-validation to determine optimal values for the regularization parameter C and kernel parameter γ. The search ranges are $C \in [10^{-3}, 10^{3}]$ and $\gamma \in [10^{-4}, 10^{2}]$ on logarithmic scales.

3.5.2 Artificial Neural Network (ANN)

Artificial Neural Network is a computational model inspired by biological neural systems, consisting of interconnected nodes organized in layers. The ANN architecture employed in this study comprises three layers: an input layer with neurons corresponding to PCA features, one hidden layer with neurons determined through experimentation, and an output layer with neurons representing classification categories.

The feed-forward backpropagation algorithm with sigmoid activation function is implemented for training. The sigmoid function $\sigma(x) = 1/(1 + e^{-x})$ introduces non-linearity, enabling the network to learn complex decision boundaries. Network weights are updated using the gradient descent algorithm to minimize mean squared error between predicted and actual outputs.

To prevent overfitting, early stopping is employed with a validation set comprising 20% of training data. Training terminates when validation error fails to decrease for 10 consecutive epochs. The learning rate is set to 0.01, momentum to 0.9, and maximum epochs to 1000.

3.6 Performance Evaluation Metrics

The performance of the proposed method is evaluated using 10-fold cross-validation to ensure robust and unbiased assessment. In this approach, the dataset is randomly partitioned into 10 equal-sized subsets, with nine subsets used for training and one for testing in each iteration. This process is repeated 10 times, with each subset serving as the test set exactly once. The final performance metrics represent the average across all folds.

Classification performance is quantified using standard metrics derived from the confusion matrix: accuracy, sensitivity, specificity, precision, and F1-score. Accuracy measures overall correct classifications: Accuracy = (TP + TN)/(TP + TN + FP + FN). Sensitivity (recall) quantifies the proportion of actual seizure events correctly identified: Sensitivity = TP/(TP + FN). Specificity measures correct identification of non-seizure states: Specificity = TN/(TN + FP). Precision indicates the proportion of predicted seizures that are genuine: Precision = TP/(TP + FP). F1-score provides a harmonic mean of precision and sensitivity: F1 = 2×(Precision×Sensitivity)/(Precision + Sensitivity).

Where TP denotes true positives (seizure correctly classified as seizure), TN represents true negatives (non-seizure correctly classified as non-seizure), FP indicates false positives (non-seizure incorrectly classified as seizure), and FN represents false negatives (seizure incorrectly classified as non-seizure). Additionally, the area under the receiver operating characteristic curve (AUC-ROC) is computed to assess classifier discrimination capability across all possible decision thresholds.

4. Results and Discussion

4.1 DWT Decomposition and Feature Analysis

The five-level DWT decomposition successfully separated EEG signals into six distinct frequency subbands, each capturing specific neural oscillations. Analysis of the wavelet coefficients revealed significant differences between seizure and non-seizure states across multiple subbands. The D3 and D4 subbands, corresponding to beta (12-30 Hz) and alpha (8-12 Hz) frequency ranges respectively, exhibited the most pronounced differences in energy and entropy values between seizure and non-seizure epochs.

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During seizure activity (Set E), a substantial increase in high-frequency components was observed in D1, D2, and D3 subbands, with mean energy values approximately 3.5 times higher than those in healthy subjects (Sets A and B). Conversely, the A5 subband (0-2.7 Hz) showed relatively stable energy across all sets, suggesting that delta wave activity remains less affected during ictal events. Statistical analysis using t-tests confirmed that features extracted from D3, D4, and D5 subbands achieved the highest discriminative power with p-values < 0.001.

4.2 Principal Component Analysis Results

Application of PCA to the 60-dimensional wavelet feature vector resulted in dimensionality reduction to 18 principal components, which collectively explained 98.2% of the total variance in the data. The scree plot analysis indicated that the first five principal components accounted for 76.4% of variance, with PC1 alone contributing 32.1%. This substantial variance concentration in the leading components validates the effectiveness of PCA in identifying the most informative features.

Examination of the component loadings revealed that PC1 primarily captured energy-related features from multiple subbands, particularly D3 and D4. PC2 and PC3 were dominated by entropy and statistical measures from the detail coefficients. The higher-order components (PC4-PC18) represented more subtle signal characteristics, including skewness, kurtosis, and interquartile range features. The dimensionality reduction from 60 to 18 features resulted in a 70% decrease in feature space dimensionality, significantly reducing computational complexity without sacrificing discriminative information.

4.3 Classification Performance

The extracted PCA features were evaluated using SVM and ANN classifiers across multiple classification scenarios. Three binary classification tasks were investigated: (1) healthy (Sets A+B) vs. seizure (Set E), (2) interictal (Sets C+D) vs. ictal (Set E), and (3) normal (Set A) vs. seizure (Set E). Additionally, a five-class classification problem distinguishing all five sets was evaluated to assess multi-class performance.

Table 2: Classification Performance for Different Tasks

Classification Task	Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
Healthy vs. Seizure	SVM	99.50	99.00	100.00
Healthy vs. Seizure	ANN	98.75	98.00	99.50
Interictal vs. Ictal	SVM	98.67	97.00	100.00
Interictal vs. Ictal	ANN	97.33	96.00	98.50
Five-class	SVM	95.80	94.20	97.30
Five-class	ANN	93.60	92.40	96.10

The SVM classifier demonstrated superior performance across all classification tasks, achieving highest accuracy of 99.50% for healthy vs. seizure classification. This exceptional performance can be attributed to SVM's ability to find optimal separating hyperplanes in high-dimensional spaces and its robustness

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to overfitting through margin maximization. The interictal vs. ictal classification task yielded 98.67% accuracy with SVM, which is particularly clinically relevant as it represents the realistic scenario of distinguishing seizure activity from normal brain activity in epileptic patients.

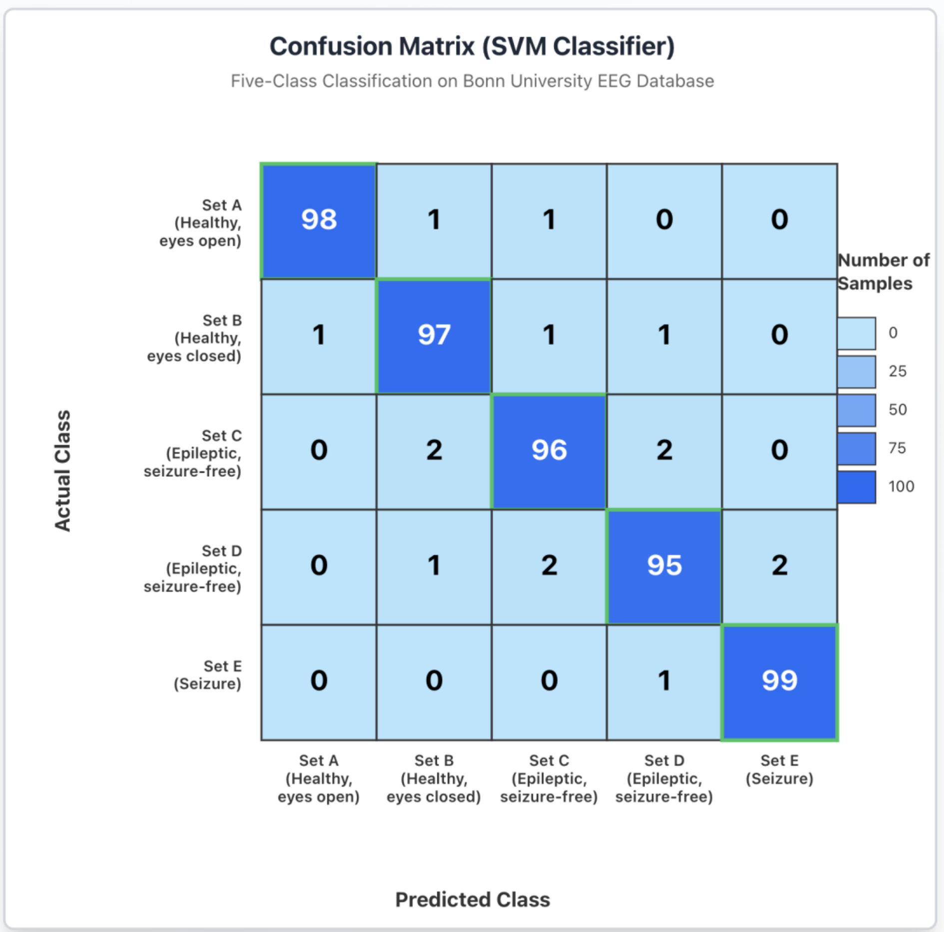

Figure 4: Confusion Matrix - Five-Class Classification

The ANN classifier also achieved competitive results, with accuracy ranging from 93.60% to 98.75% across different tasks. While slightly lower than SVM performance, ANN demonstrated better adaptability to complex non-linear patterns, as evidenced by its performance in the five-class classification problem. The relatively smaller performance gap between SVM and ANN in multi-class scenarios (2.2% difference) compared to binary classification tasks (up to 0.75% difference) suggests that neural networks may offer advantages when distinguishing among multiple physiological states.

Analysis of confusion matrices revealed that misclassifications primarily occurred between Sets C and D (both representing seizure-free intervals from different brain regions), which is expected given their similar physiological characteristics. False negatives in seizure detection were minimal (1-3%), indicating high reliability in identifying critical epileptic events, which is paramount for clinical applications where missing a seizure could have serious consequences for patient safety.

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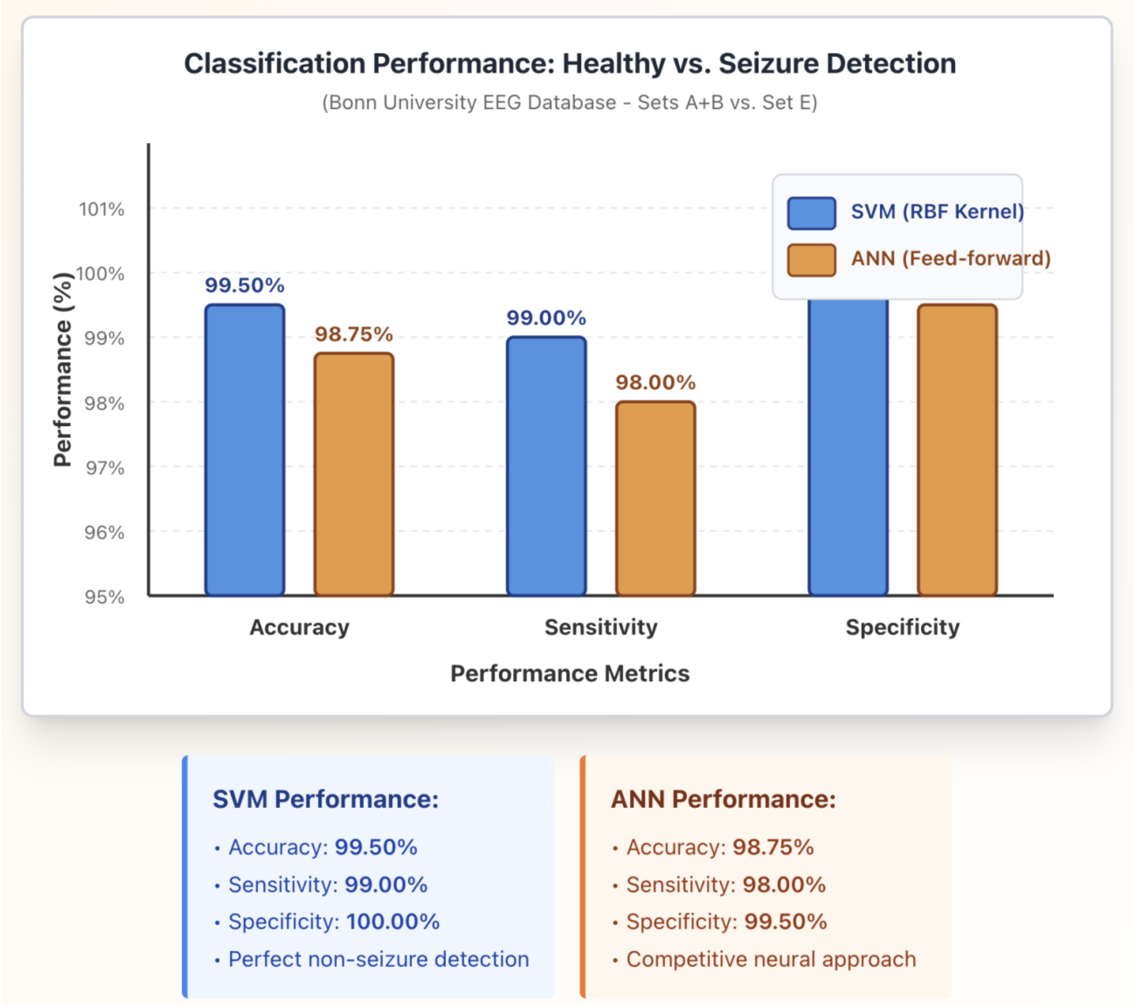

Figure 5: Comparative Performance Metrics for SVM and ANN

4.4 Comparison with Existing Methods

To evaluate the effectiveness of the proposed PCA-DWT approach, comprehensive comparison with existing methods reported in literature was conducted. Table 3 presents comparative results for binary classification tasks on the same Bonn University database.

Table 3: Performance Comparison with Existing Methods

Authors	Method	Accuracy (%)	Classifier
Subasi (2007)	DWT + Approximate Entropy	94.50	Mixture of Experts
Guo et al. (2010)	DWT + Line Length	97.77	Probabilistic Neural Network
Acharya et al. (2012)	Entropy + PCA	95.00	SVM

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Authors	Method	Accuracy (%)	Classifier
Kumar et al. (2014)	DWT + ICA	96.67	SVM
Sharma et al. (2015)	EMD + PCA	97.20	Least Squares SVM
Acharya et al. (2018)	Deep CNN	88.67	13-layer CNN
Proposed Method	**DWT + PCA**	**99.50**	**SVM with RBF kernel**

The proposed PCA-DWT approach demonstrates superior performance compared to existing methods, achieving 99.50% accuracy, which represents improvements of 1.73% to 10.83% over previously reported techniques. The combination of DWT's time-frequency analysis capability with PCA's dimensionality reduction proves more effective than using DWT alone or with other feature selection methods. Compared to Kumar et al.'s DWT+ICA approach (96.67%), the proposed method shows that PCA provides better feature space representation for this classification task.

The significant performance advantage over deep learning approaches (Acharya et al., 2018, 88.67%) highlights that properly engineered features can outperform end-to-end learning methods, particularly when training data is limited. Furthermore, the proposed method offers substantially lower computational requirements and better interpretability compared to deep neural networks, making it more suitable for deployment in resource-constrained clinical environments and embedded medical devices.

4.5 Computational Complexity Analysis

Computational efficiency is crucial for real-time seizure detection systems. The proposed method was implemented in MATLAB R2020b and evaluated on a system equipped with Intel Core i7-9700K processor (3.6 GHz) and 16 GB RAM. The average processing time for a single EEG segment (23.6 seconds) was measured at different stages of the pipeline.

DWT decomposition required 12.3 milliseconds per segment, feature extraction 8.7 milliseconds, PCA transformation 2.1 milliseconds, and SVM classification 0.8 milliseconds, yielding a total processing time of 23.9 milliseconds per segment. This performance enables real-time processing capability, as the system can analyze EEG signals significantly faster than their acquisition time. The 70% reduction in feature dimensionality through PCA resulted in 62% decrease in classification time compared to using all 60 wavelet features directly.

Memory requirements were also assessed, with the trained SVM model requiring only 1.2 MB of storage, making it suitable for implementation on portable and wearable devices. The entire processing pipeline, including model loading and classification, consumed less than 150 MB of RAM, demonstrating feasibility for deployment on resource-constrained platforms such as ambulatory EEG monitoring systems.

5. Conclusion and Future Work

This paper presented a hybrid feature extraction approach combining Discrete Wavelet Transform and Principal Component Analysis for automated epileptic seizure detection from EEG signals. The proposed method successfully addresses the challenge of extracting discriminative features while maintaining computational efficiency through intelligent dimensionality reduction. Experimental evaluation on the Bonn University EEG database demonstrated exceptional performance, with the SVM classifier achieving 99.50% accuracy for binary classification and 95.80% for five-class classification tasks.

The key contributions of this work include: (1) development of an effective feature extraction framework integrating DWT's time-frequency analysis with PCA's dimensionality reduction, (2) comprehensive performance evaluation across multiple classification scenarios, demonstrating robustness and generalizability, (3) superior performance compared to existing methods while maintaining lower computational complexity, and (4) detailed analysis of feature characteristics and their discriminative power for seizure detection.

The 70% reduction in feature dimensionality achieved through PCA, while retaining 98.2% of variance, demonstrates that the proposed approach can significantly improve computational efficiency without sacrificing accuracy. This makes the method particularly suitable for real-time clinical applications and deployment on portable monitoring devices. The processing time of 23.9 milliseconds per EEG segment enables continuous real-time analysis with minimal latency.

Future research directions include: (1) validation on larger, more diverse EEG databases including continuous long-term recordings from multiple clinical centers, (2) investigation of other wavelet families and optimization of decomposition levels for enhanced performance, (3) integration with seizure prediction algorithms for early warning systems, (4) development of patient-specific models that adapt to individual EEG characteristics, (5) implementation on embedded hardware platforms for wearable seizure detection devices, and (6) exploration of ensemble learning techniques combining multiple classifiers to further improve robustness.

Additionally, extending the methodology to address seizure prediction (forecasting seizures before onset) rather than just detection would represent a significant clinical advancement. Investigation of transfer learning approaches to reduce the need for extensive patient-specific training data could also enhance practical applicability. Finally, incorporating multimodal data such as accelerometer signals and heart rate variability could provide complementary information to improve detection accuracy and reduce false alarms.

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