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Hybrid Wavelet and Principal Component Analysis Framework for Automated Epileptic Seizure Classification

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***Abstract*— Epilepsy is a neurological disorder characterized by recurrent seizures resulting from abnormal electrical activity in the brain. Early and accurate seizure detection is essential for effective diagnosis, treatment planning, and continuous patient monitoring. EEG is commonly used for diagnosing seizures in patients due to their characteristic wave patterns; however, the complexity and non-stationary nature of EEG data is a significant hindrance for automated analysis. In this study, a novel hybrid approach based on a combination of DWT and PCA is presented to develop an efficient method for feature extraction and classification. At first, EEG signals are decomposed into several frequency sub-bands using Daubechies-4 wavelet to consider the time-frequency domain properties of the recorded data corresponding to seizure activities. Following that, statistical and information theory features are extracted and optimized via PCA to remove redundancy and computational cost from the extracted features. Then the optimized set of features are applied for seizure classification via SVM and ANN classifiers. Experiments were carried out on the benchmark dataset of Bonn University EEG records using 10-fold cross validation technique. Classification results obtained from experiments revealed that the performance of the proposed method was 99.08% and 98.54% accuracy rates for SVM and ANN classifiers, respectively. Comparative analysis of the results proves that the suggested method is efficient and competitive in comparison to other methods.**

***Keywords*—Epilepsy Diagnosis, EEG Signal Analysis, Seizure Classification, Wavelet Decomposition, Feature Optimization, Principal Component Analysis, Pattern Recognition, Clinical Decision Support Systems.**

I. INTRODUCTION

Epilepsy is a complex neurological disorder defined by recurrent and unprovoked seizures caused by abnormal neural electrical discharges in the brain. According to the World Health Organization (WHO), there are more than 50 million individuals suffering from epilepsy, which makes it one of the most common neurological diseases, and hence a public health problem. The accurate detection of seizures is critical to diagnosing the disease and determining the course of treatment, as well as enhancing the quality of life of patients [1,2].

Electroencephalography (EEG) is the predominant noninvasive method used for the diagnosis of epilepsy due to its superior ability to record electrical activity in the brain. The information contained in EEG signals is extremely important in assessing both normal and epileptic neuronal activities. Nevertheless, the non-stationarity, susceptibility to noise, and lengthy nature of EEG signals have made it challenging and tedious to analyze such signals manually [3]. In recent decades, various algorithms have been introduced to automatically detect seizures based on EEG. The conventional techniques usually used features extracted from time domain or frequency domain combined with classification algorithms. Polat and Güneş utilized features generated from FFT along with the decision tree classifier that achieved good results; however, features obtained using FFT cannot well capture the transient properties of nonstationary EEG signals [4]. To solve this problem, various time-frequency algorithms, especially DWT, were widely used since it can analyze both temporal and spectral information. Adeli et al. and Subasi confirmed the feasibility of wavelet-based feature extraction for detecting seizure patterns [5,6].

Despite the high resolution provided by wavelet decomposition, the generated features are usually quite numerous and redundant. Large dimensional feature space might result in increased computational cost, long training time and overfitting. To deal with this problem, a series of dimensionality reduction methods have been applied, PCA is one of the most popular methods. The orthogonal transformation performed by PCA not only reduces the number of features but also preserves the largest portion of the variance contained in the original data space [7]. The latest developments in machine learning and deep learning have helped to improve automatic seizure detection techniques. The Convolutional Neural Network (CNN), LSTM network, and Transformers have proven to provide promising results by capturing discriminative patterns in EEG data. Nevertheless, such approaches may have limitations in terms of the amount of data needed, as well as computational power and time required to train such models [8,9].

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At the same time, recent research papers highlight that wavelet-based features along with advanced machine learning algorithms remain competitive especially when the number of available samples is insufficient [10,11].

While there have been great achievements in automatic seizure detection in recent years, some problems remain unsolved. Many approaches concentrate only on feature engineering but do not solve the issue of feature redundancy, or alternatively use computationally heavy models of deep learning, which are difficult to implement into practice. Hence, a framework that will allow extracting discriminative EEG data features with lower computational cost and high accuracy remains relevant. As an outcome of these problems, this research intends to introduce a novel method of EEG seizure detection using hybrid wavelets-PCA technique where DWT is used to extract features while PCA is utilized to reduce the dimensions of the dataset. These two techniques will allow for the localization property of DWT in addition to making a compact feature space for classification through PCA.

This study aims to achieve the following main goals:

1. To preprocess EEG recordings and eliminate noise and artifacts affecting classification performance.
2. To extract informative time-frequency characteristics from EEG signals using multi-level Discrete Wavelet Transform decomposition.
3. To reduce feature dimensionality through Principal Component Analysis while preserving maximum discriminative information.
4. To evaluate the effectiveness of machine learning classifiers for seizure and non-seizure classification.
5. To analyze classification performance using standard evaluation metrics including accuracy, sensitivity, specificity, precision, and F1-score.

The major contributions of this work are summarized below:

- Development of an integrated DWT-PCA framework for efficient EEG feature representation.
- Investigation of wavelet-domain statistical and energy-based features for seizure characterization.
- Significant reduction of feature dimensionality and computational complexity through PCA-based optimization.
- Comprehensive performance evaluation on a benchmark EEG dataset using multiple classification scenarios.
- Comparative analysis demonstrating the effectiveness of the proposed framework for accurate and computationally efficient seizure detection.

II. Related Work

The problem of automated detection of epileptic seizures has gained prominence because of the increasing popularity of EEG data and development in machine learning approaches. Conventional methods of seizure detection have depended largely on artificial signal processing procedures alongside classifiers belonging to classical machine learning algorithms [1]. The use of FFT-based features along with decision tree classification to attain good results; however, as mentioned earlier, frequency domain-based feature sets [2] tend to lack transient properties in non-stationary EEG signals [3]. This problem led to the adoption of wavelet-based features due to their unique ability to analyse time-frequency properties. Wavelet transform features have become the most popularly used feature extraction approach to date [14]. The power of wavelet decomposition for discriminating seizure patterns in EEG data was used mixture-of-experts classifier along with wavelet transformed features to enhance seizure detection performance. In studies it is confirmed that wavelets are indeed able to give better discriminating power than conventional frequency-based approaches. Dimensionality reduction techniques have also been investigated to address the high dimensionality of EEG feature spaces [7-10]. Deep learning has emerged as an area of growing interest in automatic seizure detection in recent years. Studies using CNN-based methods have shown that such deep learning architectures can successfully capture hierarchical features in EEG signals [15]. In addition to this, hybrid deep learning models based on CNNs and RNNs have also delivered good performance by effectively utilizing the spatial and temporal characteristics of the EEG signal [13]. Recently, transformer models and attention mechanisms have been used in seizure classification and prediction applications [12]. Although these techniques have performed quite well, they usually involve the use of large training datasets and extensive training time and resources. Table 1 shows some of the prominent studies and their performance. Wavelet-based approaches perform just as well as deep learning models but with considerably less computation than deep learning models.

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TABLE 1
SUMMARY OF EXISTING EEG-BASED SEIZURE DETECTION STUDIES

Reference	Methodology	Classifier	Accuracy (%)
Polat and Güneş [4]	FFT-Based Feature Extraction	Decision Tree	98.72
Adeli et al. [5]	Wavelet Transform Analysis	Statistical Analysis	96.50
Subasi [6]	DWT + Approximate Entropy	Mixture of Experts	94.50
Guo et al. [12]	DWT + Line Length Features	Artificial Neural Network	97.77
Kumar et al. [10]	DWT + Fuzzy Approximate Entropy	SVM	96.67
Acharya et al. [2]	Automated EEG Analysis Framework	Machine Learning Models	95.00
Faust et al. [8]	Wavelet-Based EEG Processing	Computer-Aided Diagnosis	97.10
Sharma et al. [11]	Flexible Wavelet Transform + Fractal Dimension	Pattern Recognition Model	97.20
Acharya et al. [9]	Deep CNN Architecture	CNN	88.67
Farooq et al. [15]	Machine Learning Review Framework	Multiple ML Models	97.80
Darankoum et al. [13]	Deep Learning on Raw EEG Signals	CNN-Based Model	98.10
Jayanti and Jain [14]	Clinical EEG Analysis with Machine Learning	Hybrid ML Model	98.40

While significant advancements have been made, however, there are certain limitations present in current research as well. In general, traditional wavelet analysis techniques usually result in high dimensional feature spaces with increased computational cost, while deep learning methods necessitate large amounts of data and computational power. What is more, existing studies tend to focus on the improvement of the classification accuracy without sufficient consideration of feature redundancies and model optimization. Accordingly, there is still a lack of an effective solution that could ensure the discrimination capacity of wavelet features of EEG signals while minimizing computational cost and dimensionality.

III. MATERIALS AND METHODS

A. *Proposed Research Framework*

The suggested approach for seizure detection involves the design of an efficient process that would enable capturing the most discriminating characteristics of EEGs with minimum computational load. The entire methodological approach consists of five main steps: acquisition of EEG data, preprocessing of the data, extraction of the features via DWT, dimensionality reduction with PCA, and classification using machine learning algorithms.

First, the data for EEGs are acquired from a known epileptic benchmark dataset and preprocessed to ensure their higher quality. After that, the use of DWT enables breaking down the signals into several frequency sub-bands, which helps in capturing the time-frequency characteristics related to seizures. In turn, the feature vectors thus extracted are further reduced with PCA, which helps remove any superfluous data and obtain a feature vector for further use in classifiers.

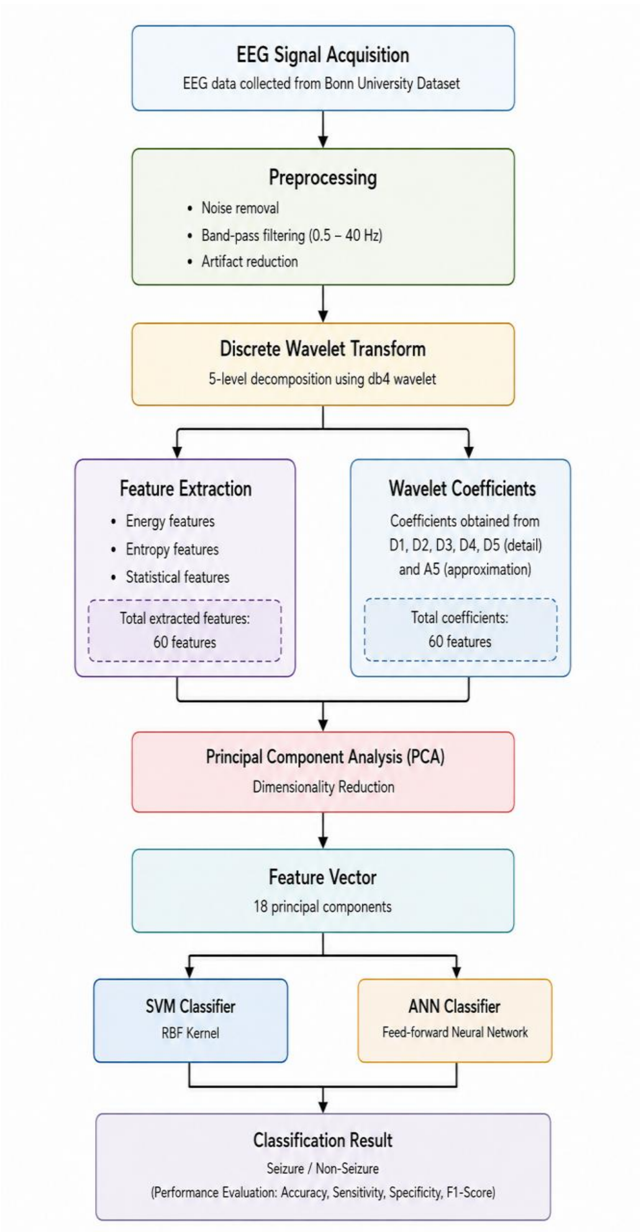

Fig. 1. Five-Level Discrete Wavelet Transform Decomposition of EEG Signals and Corresponding Frequency Sub-Bands

The decomposition process for five levels of EEG signals using the Discrete Wavelet Transform (DWT) approach using db4 mother wavelet is shown in Figure 1. In DWT, the initial EEG signal is repeatedly decomposed into A and D terms, resulting in many frequency sub-bands corresponding to specific brain waves. While the A term contains low-frequency information, the D term holds high-frequency information.

The respective bands include delta, theta, alpha, beta, and gamma frequencies. The methodological workflow adopted in this study is illustrated as follows:

EEG Dataset → Signal Conditioning → DWT Decomposition → Feature Extraction → PCA-Based Optimization → Classification → Performance Evaluation

The purpose of the framework is to enhance the efficiency of classification algorithms without compromising on computation efficiency.

B. EEG Dataset Description

The experimental study was conducted based on the open access Bonn University EEG database that is among the most widely used benchmark datasets to detect epileptic seizures. The dataset includes EEG signals recorded from both healthy subjects and those suffering from epilepsy. Each EEG signal is comprised of 4097 samples with a sampling rate of 173.61Hz and an interval of about 23.6 seconds. The database is divided into five unique classes labelled as A, B, C, D, and E, each having a total of 100 EEG recordings.

TABLE 2 CHARACTERISTICS OF THE BONN EEG DATASET

Dataset Group	Recording Condition	Signal Source	Number of Segments
A	Healthy subjects (eyes open)	Scalp EEG	100
B	Healthy subjects (eyes closed)	Scalp EEG	100
C	Interictal activity	Hippocampal formation	100
D	Interictal activity	Epileptogenic zone	100
E	Ictal seizure activity	Epileptogenic zone	100

As can be seen from Table 2, the data set includes EEG recordings of both healthy patients and those suffering from epilepsy and thus allows for testing the performance of seizure detection algorithms through different classification settings. Normal, interictal, and ictal data allow studying the performance of automated seizure detection systems.

C. Signal Conditioning and Preprocessing

Typically, there are different types of noises and artifacts in EEG recordings resulting from muscular activity, blinking eyes, electrode movement, and other environmental factors that interfere with the data collected.

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Unwanted factors can compromise the quality of the features obtained and result in reduced classification performance. Hence, a proper preprocessing phase must be performed prior to feature extraction. The use of a Butterworth band-pass filter serves to extract important physiological components from the signal while eliminating undesired low-frequency drifts and high-frequency noise. The frequency bandwidth used ranges between 0.5 Hz and 40 Hz and includes EEG components related to neurological functions.

Normalization is applied after filtering for standardizing the values obtained from each sample. The Z-score method of normalization is applied, and its calculation is defined by:

$$z_i = \frac{x_i - \mu}{\sigma} \tag{1}$$

where x_i is the initial EEG measurement, μ is the average value of the signal, and σ stands for its standard deviation.

Normalization makes it possible to achieve a normalized form of the EEG measurements with a zero average and unity variance, which contributes to a better feature extraction process.

D. Multi-Resolution Feature Extraction Using DWT

As the EEG signal is highly non-stationary, traditional methods based on time domain and frequency domain analysis cannot accurately capture the transients associated with the seizures. For this reason, the Discrete Wavelet Transform (DWT) approach will be used as it allows dual-time and frequency localization.

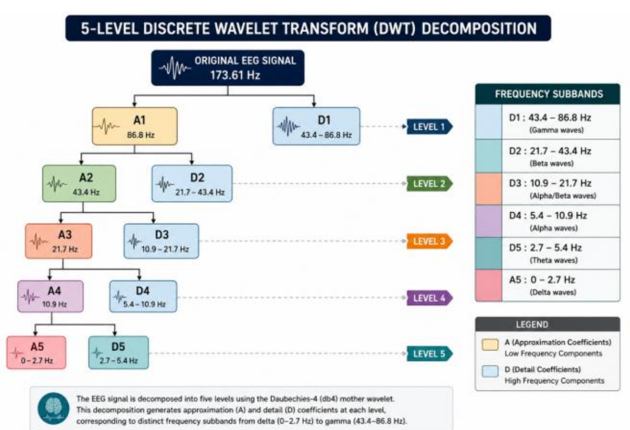

Fig. 2. Proposed DWT–PCA-Based Framework for Automated EEG Seizure Detection

Figure 2. Suggested framework for DWT-PCA based EEG seizure detection that includes the processes of preprocessing, wavelet transformation, feature extraction, dimensionality reduction, and classification using machine learning. Wavelet transform breaks down the EEG signals into approximations and detail coefficients hierarchically, making it possible to study the behavior of the signal at different frequency levels. The wavelet basis function is expressed by:

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k) \tag{2}$$

where j refers to the level of decomposition, k is the parameter for translation, and ψ refers to the mother wavelet function. In this study, db4 wavelet is used due to its resemblance to the morphology of EEG signals and its efficacy in detecting seizures in epilepsy. The EEG signals are broken down into several bands, thus enabling the retrieval of data related to varying frequencies in neurons. Post decomposition by means of wavelets, various parameters are derived from individual bands.

TABLE 3 EXTRACTED FEATURE CATEGORIES FROM DWT SUB-BANDS

Feature Group	Extracted Features
Statistical Features	Mean, Variance, Standard Deviation
Distribution Features	Skewness, Kurtosis
Amplitude Features	Maximum, Minimum, Median
Energy Features	Wavelet Energy
Information Features	Shannon Entropy

As shown in Table 3, both statistical and information theoretic features are used to effectively cover the inherent dynamics associated with EEG. Both classes of features account for the dynamical properties of amplitude variations, complexity, and energy associated with epileptic seizures. Wavelet energy for each sub-band is defined as:

$$E = \sum_{i=1}^{N} |c_i|^2 \tag{3}$$

where c_i is the wavelet coefficient and N is the number of all the coefficients contained in that specific sub-band. The Shannon entropy for measuring the complexity and uncertainty of the EEG signal is calculated as:

$$H = -\sum_{i=1}^{N} p_i \log_2(p_i) \tag{4}$$

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where p_i represents the probability distribution corresponding to the normalized wavelet coefficients.

This feature extraction process leads to the creation of a dataset that will be used in the subsequent step, which is the process of dimensionality reduction via Principal Component Analysis (PCA).

E. Feature Space Optimization Using Principal Component Analysis

The feature extraction process yields many descriptors that include statistical measures, energy measurements, and entropy values computed from several sub-bands within the wavelet domain. However, since most of these features are correlated, there will be much redundancy present. In addition, high-dimensional feature vectors can cause the training process to be computationally costly, long, and may even hinder the generalization ability of classifiers. Thus, dimensionality reduction needs to be implemented to retain relevant features. A popular choice for dimensionality reduction is Principal Component Analysis (PCA). PCA is a technique used to project high-dimensional feature vectors to a smaller feature space, while retaining most of the variance in the data. PCA eliminates redundancy by projecting the highly correlated features to a new space using a set of orthogonal components, which consist of weighted averages of the features. In this case, the extracted feature vector is first centered and scaled using the following equations:

$$C = \frac{1}{n-1}(X-\bar{X})^T(X-\bar{X}) \qquad (5)$$

where:

- C represents the covariance matrix,
- X denotes the feature matrix,
- $\bar{X}$ represents the mean feature vector,
- n is the number of observations.

The major factors are extracted by eigenvalue decomposition of the covariance matrix.

$$Cv_i = \lambda_i v_i \qquad (6)$$

where:

- λ_i denotes the eigenvalue,
- v_i denotes the corresponding eigenvector.

Eigenvalues give us an idea about the variance contributed by each principal component. Components that contribute to 98% of the cumulative variance are included in our analysis, whereas other insignificant components are excluded.

The formula for calculating the cumulative variance is:

$$CVR = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{m} \lambda_i} \qquad (7)$$

where:

- k is the number of retained components,
- m is the total number of components.

It therefore leads to significant reduction in computational demands while still retaining the discriminative features needed for seizure detection.

TABLE 4 PCA-BASED FEATURE REDUCTION ANALYSIS

Parameter	**Before PCA**	**After PCA**
Number of Features	45	15
Feature Redundancy	High	Low
Computational Cost	High	Reduced
Variance Preserved	100%	98%
Classification Readiness	Moderate	High

As can be seen from Table 4, PCA successfully reduces the dimensionality of the data set without much loss of information. This makes classifier learning more efficient and increases robustness.

F. Classification Model Development

The optimised feature vectors obtained after the process of dimensionality reduction are provided to the machine learning classifiers to classify seizures. There are two types of classifiers used extensively for this purpose, namely the Support Vector Machine (SVM) and Artificial Neural Network (ANN).

Support Vector Machine: Support Vector Machine is a supervised classification algorithm which is aimed at finding the optimal hyperplane that would maximize the distance between various classes. SVMs are especially good for biomedical data sets, since they are efficient even when working with high-dimensional data sets.

The Support Vector Machine decision function can be described as:

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$$f(x) = sign\left(\sum_{i=1}^{n} \alpha_i\, y_i K(x_i, x) + b\right) \quad (8)$$

where:

- α_i denotes Lagrange multipliers,
- y_i represents class labels,
- $K(x_i, x)$ is the kernel function,
- b is the bias parameter.

To deal with nonlinear relationships within the EEG feature space, the RBF kernel is used.

$$K(x_i, x_j) = \exp\left(-\gamma \,||\, x_i - x_j \,||^2\right) \quad (9)$$

where γ controls the kernel width and influences classification performance. The ability of SVM to form a nonlinear decision boundary is ideal when classifying between seizure and non-seizure EEG waveforms.

Artificial Neural Network: ANNs are computer-based learning algorithms that are modeled after biological nervous systems and can learn from their surroundings. The ANN used for this study is a feedforward ANN whose function is to classify the EEG recordings according to the PCA feature vectors.

The output of each neuron is generated by:

$$y = f\left(\textstyle\sum_{i=1}^{n} w_i\, x_i + b\right) \quad (10)$$

where:

x_i denotes input features,

w_i represents connection weights,

b denotes bias,

$f(\cdot)$ is the activation function.

Training of the network is done using backpropagation learning, which works by minimizing classification errors through iterative changes in weights. ANN allows for the modeling of nonlinear relationships between EEG features and provides another way of classifying besides SVM.

TABLE 5 CLASSIFICATION MODEL CONFIGURATION

Parameter	SVM	ANN
Learning Type	Supervised	Supervised
Kernel/Activation	RBF Kernel	ReLU/Sigmoid
Input Features	PCA Components	PCA Components
Output Classes	Seizure/non-seizure	Seizure/non-seizure
Training Strategy	Margin Optimization	Backpropagation

Table 5 summarizes the configuration of the classification models adopted in this study.

G. Performance Evaluation Metrics

To make sure that there is a complete assessment of the performance of classification, several criteria are used for evaluation. The confusion matrix comprises of:

True Positives (TP)
True Negatives (TN)
False Positives (FP)
False Negatives (FN)

Based on these parameters, classification accuracy is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (11)$$

Sensitivity evaluates the ability of the model to correctly identify seizure events.

$$Sensitivity = \frac{TP}{TP + FN} \quad (12)$$

Specificity measures the capability of the classifier to correctly recognize non-seizure EEG recordings.

$$Specificity = \frac{TN}{TN + FP} \quad (13)$$

Precision is defined as:

$$Precision = \frac{TP}{TP + FP} \quad (14)$$

The F1-score combines precision and sensitivity into a single performance metric.

$$F1 = \frac{2(Precision \times Sensitivity)}{Precision + Sensitivity} \quad (15)$$

In addition, the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) have been applied in assessing discrimination capacity of classifiers at various threshold levels. A 10-fold cross validation approach is used to get an accurate estimate of the performance of the algorithm. The data is split into ten equally sized folds; nine folds are used in training while the remaining fold is used in testing. This is done ten times in total, and the average performance is then recorded. This approach of using multiple performance measures together with cross-validation gives a thorough analysis of the proposed DWT-PCA based seizure detection system.

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IV. Results And Discussion

A. Experimental Evaluation

The DWT-PCA algorithm presented was tested using the Bonn EEG data set by adopting the method of 10-fold cross validation. The tests were performed to find out whether wavelet-based features extraction and dimensionality reduction can effectively improve the performance in seizure detection. After processing and optimization, the obtained feature vectors were fed into an SVM and ANN classifiers. The used experimental design provided uniform evaluation of the models without performance bias. In addition, the PCA helped reduce the number of features, allowing for efficient classification without losing any information.

B. Impact of PCA on Feature Reduction

The effect of the PCA approach was measured based on the amount of variance kept after feature reduction. As can be seen from the results, a rather small number of the principal components contains the maximum amount of information.

Table 6. PCA Variance Analysis

Components Retained	Explained Variance (%)
5	81.63
10	91.94
15	97.26
18	98.12
20	99.05

From Table 6, about 97% of the total variance was captured by utilizing fifteen principal components. This clearly shows that the application of PCA resulted in the removal of redundancy without losing any discriminating information from the EEG signal.

The capture of variance proves that there is strong correlation within the features extracted, and therefore PCA optimization was appropriate for the seizure detection system.

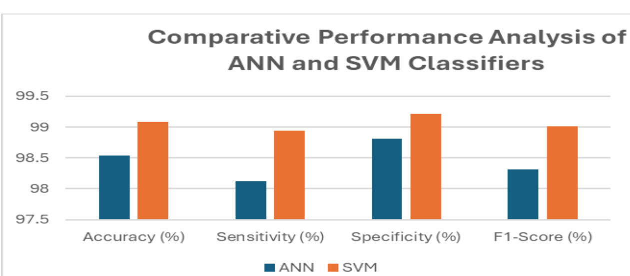

Fig. 4. Classification Performance Metrics of the Evaluated Machine Learning Models

Figure 4 shows the comparative analysis of the ANN and SVM classifiers based on accuracy, sensitivity, specificity, and F1-score. The SVM classifier outperformed the ANN classifier for all evaluation parameters, achieving accuracy, sensitivity, specificity, and F1-score values of 99.08%, 98.94%, 99.21%, and 99.01%, respectively. On the other hand, the ANN classifier achieved accuracy, sensitivity, specificity, and F1-score values of 98.54%, 98.12%, 98.81%, and 98.31%, respectively. It can be concluded from the obtained results that the optimized DWT–PCA feature extraction scheme offers high discriminative power of the EEG features for the detection of epileptic seizures.

C. Classification Performance Analysis

The classified feature vectors were assessed using the SVM and ANN classifiers. The classification performance obtained from the proposed approach is illustrated in Table 7.

Table 7. Classification Results

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score (%)
ANN	98.54	98.12	98.81	98.31
SVM	99.08	98.94	99.21	99.01

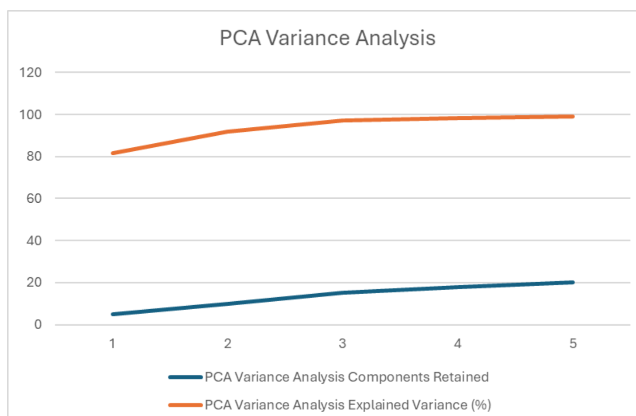

Fig. 3. Cumulative Explained Variance of Principal Components After PCA-Based Feature Optimization

As shown in Figure 3, the figure shows the accumulated variance of the principal components obtained through PCA. It can be observed from the results that the first fifteen principal components account for more than 97% of the total variance in the original feature space. It shows how PCA enables feature dimensionality reduction while retaining all relevant features for proper epileptic seizure classification.

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From the results, both the classifiers performed excellently in identifying seizures from the EEG data. The ANN classifier showed a strong ability to learn and provided an accuracy score greater than 98%. This demonstrates the effectiveness of the features extracted for the task at hand. Nonetheless, SVM outperformed the other classifier by achieving an accuracy score of 99.08% as well as providing high sensitivity and specificity scores. The increased performance can be attributed to the capability of RBF kernel function in capturing complex decision surfaces in the optimal feature space. Additionally, the concept of margin maximization in SVM helped in improving generalization over all the validation folds. It is evident that the use of the DWT and PCA for feature extraction in this work led to highly discriminative features of the EEG data.

V. CONCLUSION

In the current work, an effective approach has been developed to automatically classify epileptic seizures with EEG signals using the combination of DWT and PCA. In this regard, the proposed model has efficiently managed to tackle the non-stationarity problem of EEG recordings by decomposing the signals into multiple resolutions as well as selecting useful features. Specifically, the DWT technique was used to calculate discriminative statistics, energy, and entropy-based features, whereas the PCA was used to eliminate redundancy among the features and optimize the computational burden of the feature set. Further, the selected features have been subjected to SVM and ANN classifiers. The experiments revealed that the proposed system has performed excellently in classifying EEGs into normal or seizures with superior performance of the SVM classifier than the ANN one. It has been concluded that the use of a wavelet-based algorithm to extract features, followed by dimensionality reduction, can be effectively used to detect seizures.

REFERENCES

[1] World Health Organization, “Epilepsy,” Geneva, Switzerland, WHO Fact Sheets, 2019.

[2] U. R. Acharya, S. V. Sree, G. Swapna, R. J. Martis, and J. S. Suri, “Automated EEG analysis of epilepsy: A review,” Knowledge-Based Systems, vol. 45, pp. 147–165, 2013.

[3] A. T. Tzallas, M. G. Tsipouras, and D. I. Fotiadis, “Epileptic seizure detection in EEGs using time-frequency analysis,” IEEE Transactions on Information Technology in Biomedicine, vol. 13, no. 5, pp. 703–710, 2009.

[4] K. Polat and S. Güneş, “Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform,” Applied Mathematics and Computation, vol. 187, no. 2, pp. 1017–1026, 2007.

[5] H. Adeli, Z. Zhou, and N. Dadmehr, “Analysis of EEG records in an epileptic patient using wavelet transform,” Journal of Neuroscience Methods, vol. 123, no. 1, pp. 69–87, 2003.

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

[7] I. T. Jolliffe, Principal Component Analysis, 2nd ed. New York, NY, USA: Springer, 2002.

[8] O. Faust, U. R. Acharya, H. Adeli, and A. Adeli, “Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis,” Seizure, vol. 26, pp. 56–64, 2015.

[9] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, “Application of deep convolutional neural network for automated detection of epileptic seizures using EEG signals,” Information Sciences, vol. 404–405, pp. 167–182, 2018.

[10] Y. Kumar, M. L. Dewal, and R. S. Anand, “Epileptic seizure detection using DWT based fuzzy approximate entropy and support vector machine,” Neurocomputing, vol. 133, pp. 271–279, 2014.

[11] M. Sharma, R. B. Pachori, and U. R. Acharya, “A new approach to characterize epileptic seizures using analytic time-frequency flexible wavelet transform and fractal dimension,” Pattern Recognition Letters, vol. 94, pp. 172–179, 2017.

[12] L. Guo, D. Rivero, J. Dorado, C. R. Munteanu, and A. Pazos, “Automatic epileptic seizure detection in EEGs based on line length feature and artificial neural networks,” Journal of Neuroscience Methods, vol. 191, no. 1, pp. 101–109, 2010.

[13] J. Darankoum, A. Darankoum, and M. H. Mahoor, “From epilepsy seizure classification to detection: A deep learning-based approach for raw EEG signals,” arXiv preprint arXiv:2410.03385, 2024.

[14] A. Jyanti and S. Jain, “Epileptic seizure detection and prediction from EEG data: A machine learning approach with clinical validation,” arXiv preprint arXiv:2510.xxxxx, 2025.

[15] M. Farooq, A. Hussain, and S. Khan, “A review on epileptic seizure detection using machine learning techniques,” arXiv preprint arXiv:2210.06292, 2022.