Department of Electronic and Telecommunication Engineering

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BM4152 - Biosignal Processing

Paper Implementation

EEG signal classification using PCA, ICA, LDA and support vector machines

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1 Introduction and background

The paper **EEG signal classification using PCA, ICA, LDA, and support vector machines** (1) was published by Subasi and Gursoy in 2010. This work presents a method for analyzing and classifying Electroencephalogram (EEG) signals to detect epileptic seizures, which is a critical diagnostic support for neurologists. The study leverages advanced techniques in signal processing and machine learning. Key steps include:

1. **Signal Decomposition:** EEG signals are decomposed into frequency sub-bands using the Discrete Wavelet Transform (DWT), which is particularly suited for analyzing non-stationary signals.

2. **Feature Extraction and Reduction:** Statistical features are extracted from these sub-bands. Dimension reduction techniques such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) are applied to streamline the data.

3. **Classification with Support Vector Machines (SVM):** The extracted features are classified using SVM into two categories—epileptic and no-epileptic.

The study compares the performance of classifiers built using PCA, ICA, and LDA for feature extraction and demonstrates that SVM with LDA outperforms the others in terms of accuracy. This framework has the potential to enhance automated diagnostic systems for epilepsy, offering a robust approach to EEG signal classification.

In this report, we present our re-implementation of the methodologies outlined in the paper. This includes a detailed account of the procedures we followed, the specific challenges encountered during the implementation, and the results obtained. Furthermore, we provide a comprehensive comparison between the outcomes of our re-implementation and those reported in the original study, offering insights into the reproducibility and practical applicability of the proposed methods. This work not only validates the original findings but also highlights areas for potential enhancement in future EEG classification systems.

2 Overview

2.1 Paper overview

This study explores a systematic approach to classifying EEG signals, leveraging advanced machine learning and signal processing techniques to enhance epilepsy diagnostics. The original paper focused on employing Discrete Wavelet Transform (DWT) to decompose EEG signals, followed by extracting meaningful statistical features from the resulting sub-bands. Dimensionality reduction methods like PCA, ICA, and LDA were then utilized to streamline the feature set and improve computational efficiency. These reduced features were classified using Support Vector Machines (SVM), with LDA-based features achieving the highest classification accuracy.

2.2 Dataset description

The dataset used in the study was sourced from Andrzejak et al.(2) and consists of five distinct sets (A–E), with 100 single-channel EEG segments in each set:

- **Set A & B:** EEG recordings from healthy volunteers (eyes open and closed, respectively).
- **Set C & D:** Seizure-free intervals from epileptic patients (recorded from different regions of the brain).
- **Set E:** EEG segments recorded during epileptic seizures.

In this study, only **Set A** and **Set E** were used:

- **Set A:** Healthy EEG signals.
- **Set E:** Epileptic seizure signals.

Each segment contains 4,096 samples, digitized at 173.61 Hz with a band-pass filter of 0.53–40 Hz. To align with the training and testing needs, each EEG signal was further augmented by splitting and reconstructing to increase the dataset size from 200 signals (original) to 1,600 signals (800 each for training and testing).

3 Methodology

The methodology presented in the original paper outlines a structured approach to EEG signal classification, leveraging a combination of signal processing, feature extraction, dimensionality reduction, and machine learning. This process is designed to classify EEG signals into epileptic and non-epileptic categories effectively. The process involves the following steps.

- Analysis using discrete wavelet transform (DWT)
- Statistical feature extraction
- Dimensionality reduction using (PCA, ICA, LDA)
- Classification using support vector machines (SVM)

As given in the figure[1] the Discrete Wavelet Transform (DWT) is applied to decompose the EEG signals into multiple frequency sub-bands (D1–D5 and A5), capturing both time and frequency characteristics. From these sub-bands, statistical features such as mean absolute value, average power, standard deviation, and the ratio of adjacent sub-band means are extracted to summarize the signal properties. To reduce redundancy and computational complexity, dimensionality reduction techniques—Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA) are applied to the extracted features, retaining only the most critical information. Finally, the reduced features are classified using Support Vector Machines (SVM) with a radial basis function (RBF) kernel. This integrated process efficiently analyzes and categorizes EEG signals into epileptic and non-epileptic classes with high precision.

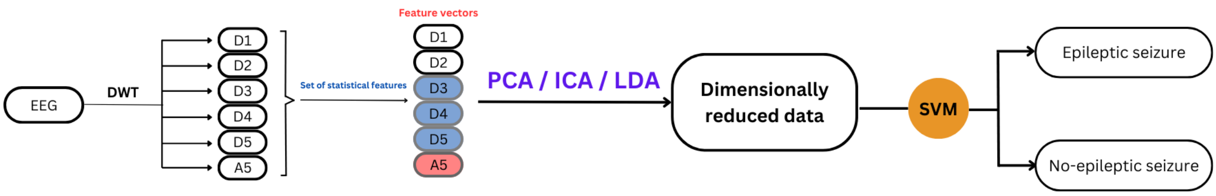


Figure 1: The classification process

3.1 Analysis using discrete wavelet transform (DWT)

If the signal is stationary (i.e. does not change much over time), we can use the Fourier transform to analyze the signal. However, EEG signals may contain non-stationary or transitory characteristics. In such cases, it is not ideal to apply the Fourier transform directly, instead, time-frequency analysis such as wavelet transform must be used.

The DWT lies the foundation over the continuous wavelet transform (CWT) mentioned in the following equation.

$$W_x(s, \tau) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \psi \left(\frac{t - \tau}{a} \right) dt \tag{1}$$

where s = *scaling factor*, τ = *translation* and ψ = *wavelet function*

When it comes to discrete wavelet transform (DWT), it decomposes signal by restricting the variation in translation and scale, usually to the power of 2 as follows.

$$\psi_{m,n}(t) = \frac{1}{\sqrt{s_0^m}}\psi\left(\frac{t - n\tau_0 s_0^m}{s_0^m}\right)$$

where s_0 = scaling step size (usually $s_0 = 2$), τ_0 = translation step size

When we decompose using DWT, the selection of an appropriate number of levels of decomposition is very important. Since EEG signals don't have any useful frequency component above 30Hz, the number of levels was chosen to be 5. Thus, the signal decomposed into the details D1-D5 and the approximation A5 as shown in table[1]. These approximation and details records are reconstructed from the Daubechies 4 (DB4) wavelet filter that is shown in figure[2].

Table 1: Frequencies corresponding to different levels of decomposition (sampling frequency = 173.6 Hz)

Decomposed signal	Frequency range (Hz)
D_1	43.4 - 86.8
D_2	21.7 - 43.4
D_3	10.8 - 21.7
D_4	5.4 - 10.8
D_5	2.7 - 5.4
A_5	0 - 2.7

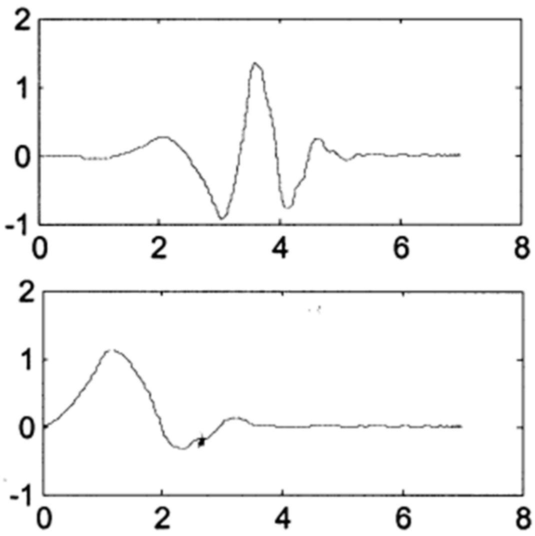


Figure 2: DB4 wavelet function (top) and scaling function (bottom)

3.2 Statistical feature extraction

To further decrease the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients (3) were used.

- Mean of the absolute values of the coefficients in each sub-band.
- Average power of the wavelet coefficients in each sub-band.
- Standard deviation of the coefficients in each sub-band.
- Ratio of the absolute mean values of adjacent sub-bands.

Features 1 and 2 represent the frequency distribution of the signal and features 3 and 4 the amount of changes in frequency distribution. These feature vectors, calculated for the frequency bands **A5** and **D3-D5**, were used for the classification of the EEG signals.

3.3 Dimensionality reduction using (PCA, ICA, LDA)

3.3.1 Principal component analysis (PCA)

Principal component analysis (PCA) is a well-established method for feature extraction and dimensionality reduction. In PCA, we seek to represent the d-dimensional data in a lower-dimensional space. This will reduce the degrees of freedom; and reduce the space and time complexities. The objective is to represent data in a space that best expresses the variation in a sum-squared error sense.

3.3.2 Independent component analysis (ICA)

ICA is a feature extraction method that transforms multivariate random signals into a signal having mutually independent components. Independent components can be extracted from the mixed signals by using this method. In this manner, independence denotes the information carried by one component cannot be inferred from the others. Statistically, this means that the joint probability of independent quantities is obtained as the product of the probability of each of them.

3.3.3 Linear discriminant analysis (LDA)

LDA aims to create a new variable that is a combination of the original predictors. This is accomplished by maximizing the differences between the predefined groups, for the new variable. The goal is to combine the predictor scores in such a way that, a single new composite variable, the discriminant score, is formed. This can be viewed as an excessive data dimension reduction technique that compresses the p-dimensional predictors into a one-dimensional line. At the end of the process, it is hoped that each class will have a normal distribution of discriminant scores but with the largest possible difference in mean scores for the classes.

3.4 Classification using support vector machines (SVM)

Support Vector Machines (SVMs) are advanced classification techniques designed to find an optimal decision boundary, or hyperplane, that separates classes within a dataset as shown in figure[3]. For linearly inseparable data, SVMs leverage a mathematical transformation using kernel functions to project data into a higher-dimensional feature space where linear separation becomes possible.

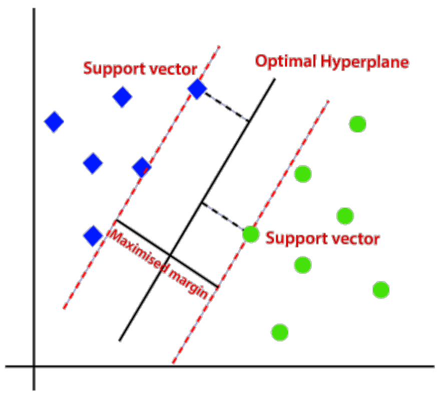


Figure 3: The linear support vector classifier.

4 Implementation details

4.1 Data preparation

As mentioned above, in this study they have only used the **Set A** and the **Set E** from the dataset. Each set contains 100 EEG recordings from subjects. But under their implementation, they have mentioned the train and test set data split as following table[2].

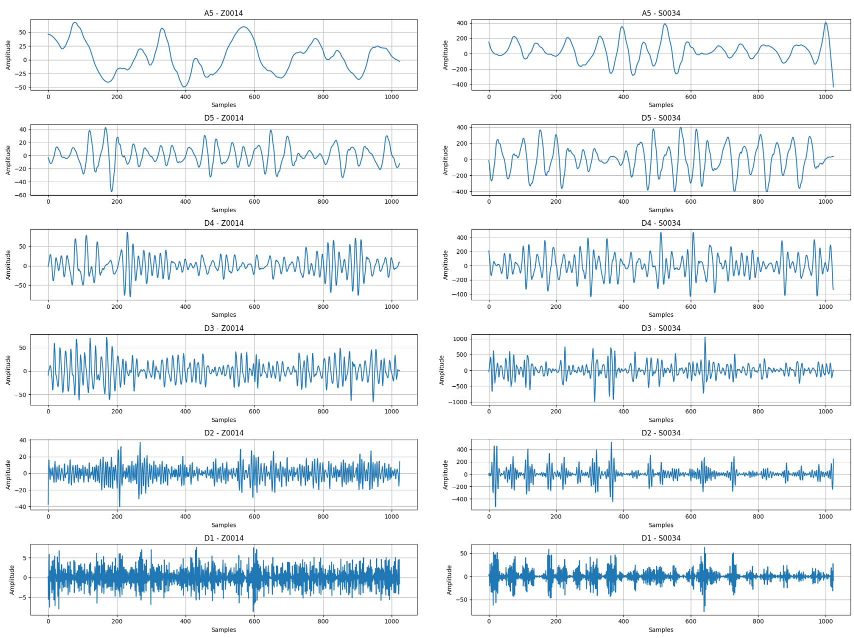
Table 2: Class distribution of the samples in the training and test data sets

Class	Training set	Test set	Total
Epileptic	400	400	800
Normal	400	400	800
Total	800	800	1600

So, we contacted the authors about this and then they said to divide the data into small portions to increase the number of instances. So, we generate 8 signals by using a single EEG as follows.
One EEG has 4096 samples. So first we divided the original EEG into 4 (1024 samples) and took those 4 signals. Next, divided the original EEG into 2 (2048 samples) and took those 2 signals. Finally took 3072 samples from the original signal. Now, there are 8 total signals (1024 signals $\times$ 4 + 2048 signals $\times$ 2 + 3072 signal + Original single).

4.2 Applying wavelet transform

For the above obtained signals, we applied DWT for 5 levels of decompositions and the obtained details and approximations are as follows.



(a) Normal EEG (b) Epileptic seizure EEG

Figure 4: Details and approximation of normal EEG and an epileptic seizure EEG

4.3 Statistical feature extraction

Here, as mentioned in the paper, we extracted 4 statistical features that have been mentioned in the above section 3. So, here we have taken the statistical features only from **A5** and **D3-D5**. The detail coefficients D1 and D2 are neglected because they contain frequencies above the spectrum of interest.
Here, when calculating the statistical features, first we only focused just on the coefficient values of the details and approximation. But when we went through the process, finally we got very low accuracies when we did like that. After that, we reconstructed those details and approximations and extracted statistical features by using those reconstructed data. After that, we got desirable accuracies.
After extracting these statistical features, we had **16 features** for these data.

4.4 Principal component analysis (PCA)

When using PCA to produce a new set of variables with reduced dimensionality through uncorrelatedness, removing mean values from features is mandatory. Standard scaling was used to do that and normalize the data with respect to the variance. The inputs for PCA are the statistical features calculated from individually independent signals. Therefore, to reduce the dimensionality, a single statistical feature across the dataset was used as one feature, and likewise, the rest was used.
Observing the number of components required at the output, we calculated the variance captured when increasing the number of output components. This was done by observing eigenvalues associated with the input array's covariance matrix.

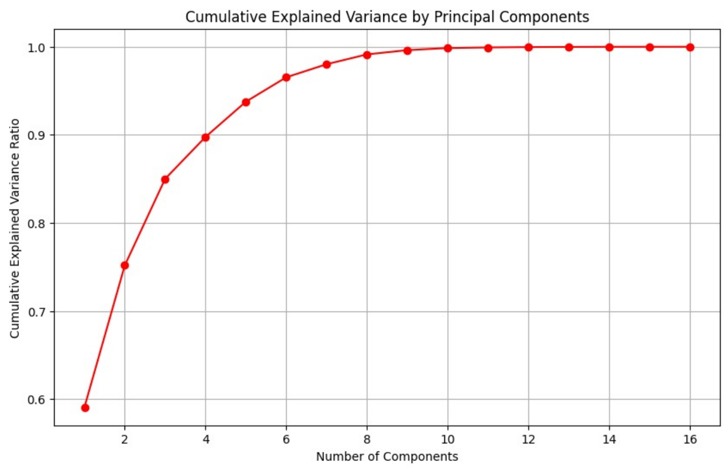
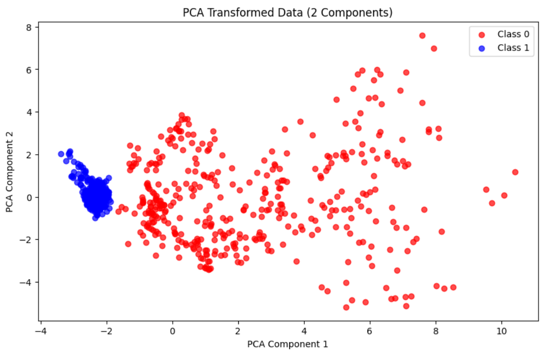


Figure 5: Captured variance with the number of principal components.

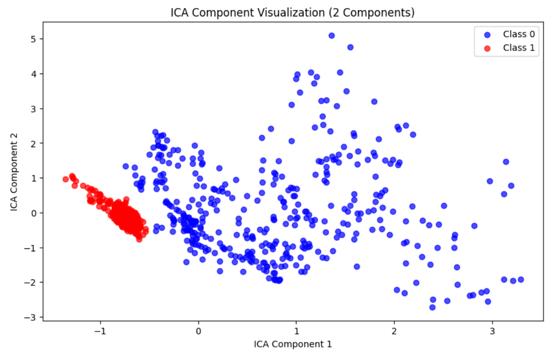
As we can see in the figure[5] almost all variance was captured at 9 components. However, when observing the feature distribution of the two classes before the SVM step, it was observed that two features alone give accurate separability. Therefore, we only had two PCA output components.

4.5 Independent component analysis (ICA)

In ICA, when calculating independent components, a similar normalizing technique was used as PCA, with standard scaling. Here, too similarly a feature across the dataset was used as a single feature to perform ICA. We used two output components since the feature distribution was accurate to separate the two classes. The implemented libraries used fast ICA with a Negentropy-based method to find the independent dimensions.



(a) PCA transformed data



(b) ICA transformed data

Figure 6: PCA transformed data and ICA transformed data for 2 components

4.6 Linear discriminant analysis (LDA)

Linear Discriminant Analysis (LDA) is used for dimensionality reduction to enhance class separability for binary classification. Here we projected high-dimensional data onto a single axis, preserving the most discriminative features between the two classes. The LDA model fits the standardized training data with corresponding labels and is then applied to transform both training and testing datasets, reducing noise and focusing on features critical for classification.

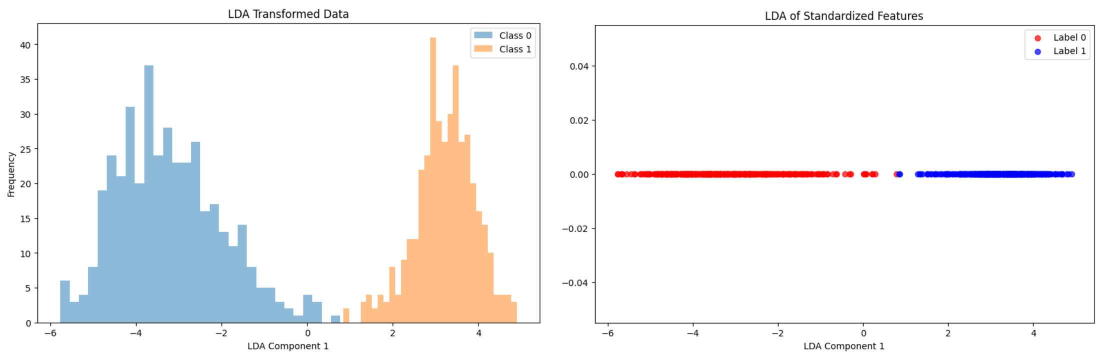


Figure 7: Obtained LDA component (right) and the data frequencies on the component (left)

4.7 Support vector machines (SVM)

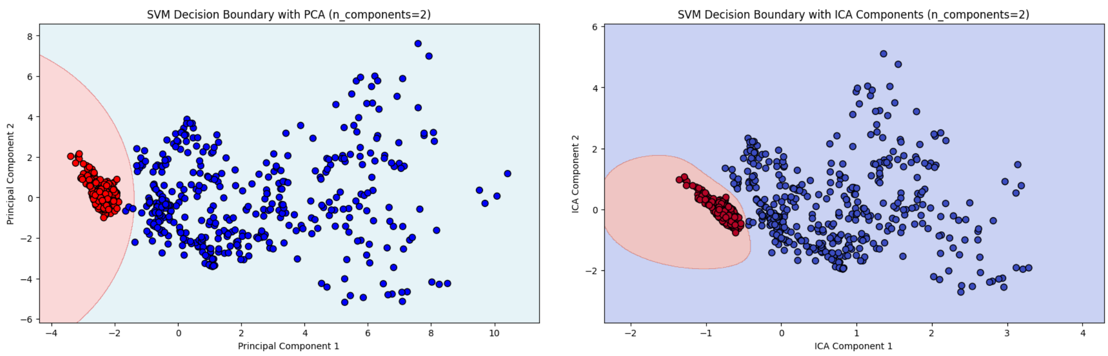
In this work, Support Vector Machines (SVMs) were employed with the Radial Basis Function (RBF) kernel to address non-linear separability in the data. The application of SVM was conducted on datasets transformed by Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA), allowing for a comparative evaluation of feature extraction methods.

To optimize model performance and ensure generalizability, hyperparameter tuning was performed using grid search combined with 10-fold cross-validation. This approach systematically tested all combinations of the kernel parameters γ (penalty term) and C (kernel parameter), selecting the pair that maximized cross-validation accuracy. The penalty term γ influences the trade-off between achieving a low error on the training data and minimizing model complexity to prevent overfitting, while the kernel parameter C governs the flexibility of the decision boundary. Careful optimization of these parameters is crucial, as inappropriate values may lead to underfitting or overfitting. The obtained hyperparameters are shown in Table[3].

Table 3: Obtained optimal hyperparameters (γ and C) for RBF kernel

Method	γ	C
PCA + SVM	1.0	1.0
ICA + SVM	0.2	0.1
LDA + SVM	0.5	0.01

Following the identification of the optimal γ and C parameters, the SVM model was retrained on the entire training dataset to construct the final classifier.



(a) PCA data

(b) ICA data

Figure 8: SVM decision boundary for PCA and ICA transformed data

5 Implementation results

Since this problem involves classification into two classes, **sensitivity** (true positive ratio) and **specificity** (true negative ratio) were used as a performance measure. Table[5] shows the results obtained in the original paper.

Table 4: Results that have been obtained in the original paper

Method	Accuracy (%)	Specificity (%)	Sensitivity (%)
PCA + SVM	98.75	98.5	99.0
ICA + SVM	99.50	99.0	100
LDA + SVM	100	100	100

In our work, we obtained better results for all 3 cases as follows.

Table 5: Results that have been obtained in our work

Method	Accuracy (%)	Specificity (%)	Sensitivity (%)
PCA + SVM	100	99.0	100
ICA + SVM	100	100	100
LDA + SVM	100	100	100

Since these results are somewhat surprising, we did some experiments with our data to confirm our results. First, we did a pair plot of randomly selected features (statistical) as shown in figure[9]. Here we noticed a clear class difference between statistical features as well.

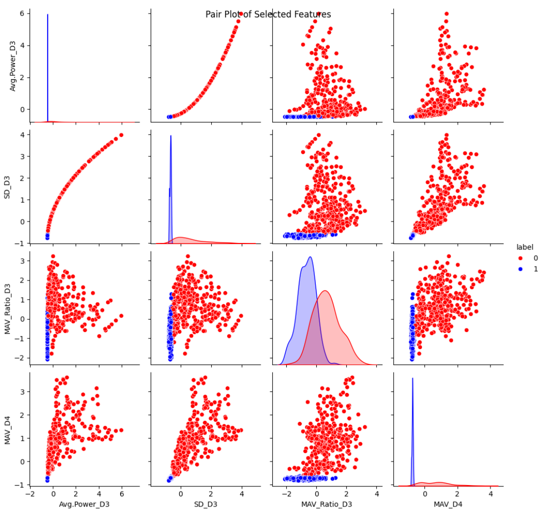


Figure 9: Pair plot of randomly selected statistical features

And also, we plotted the PCA transformed data (figure[6(a)]), ICA transformed data (figure[6(b)]) and LDA transformed data (figure[7]) and observed those plots. Here also we noticed that there is a very clear separation between the two classes with minimum overlap.
After that, we plotted the decision boundaries after applying SVM to each feature extraction method as shown in figure[8(a)] for SVM with PCA and figure[8(b)] for SVM with ICA. There also we noticed that the decision boundary clearly separated the two classes with minimum overlap. (In those figures we have shown PCA and ICA only for 2 components. But in higher dimensions, there is no overlap)

Through these experiments, we can validate and accept our results to some extent.

6 Conclusion

This study highlights the significant advantages of combining statistical features extracted from EEG signals using Discrete Wavelet Transform (DWT) with advanced feature extraction methods— Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA)—for classification using Support Vector Machines (SVMs). The classification performance was assessed using sensitivity and specificity as key metrics, showing that the integration of feature extraction methods consistently improved the SVM's accuracy in distinguishing between epileptic and normal patterns.
Notably, nonlinear feature extraction was found to enhance the SVM's performance by reducing the number of support vectors, which helps optimize the computational efficiency and decision boundary definition. Additionally, dimensionality reduction through PCA, ICA, and LDA proved to improve the generalization of the SVM model, ensuring it performs well on unseen data. When compared with the previous studies (4; 5; 6), the simulation results confirm that SVMs combined with feature extraction consistently outperform those without feature extraction. These findings underscore the potential of leveraging feature extraction and SVMs as a reliable and effective approach for developing intelligent diagnostic systems, particularly for EEG-based epilepsy detection and classification tasks.
When it comes to our implementation, we obtained 100% accuracy for all feature extraction methods (PCA, ICA, and LDA) while outperforming the results obtained from the original paper. Probably this is because of how we perform DWT and extract features.
But to verify these results further, we need to test this trained model with another dataset that contains epileptic seizures and normal EEGs.

In the future, extending this approach to larger, more diverse datasets and exploring the integration of other advanced machine learning techniques, such as deep learning models, could further validate and enhance the robustness of these findings. Moreover, real-time implementation of this method in clinical diagnostic tools could pave the way for more accurate and efficient epilepsy detection systems, ultimately improving patient outcomes and contributing to the advancement of intelligent healthcare technologies.

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