

Integration of DWT, FFT, and Spatial domain for the identification of epileptic seizure utilizing electroencephalogram signal

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Abstract

Manual detection of epileptic seizure is a critical task by monitoring electroencephalogram (EEG) signals. It is also a very laborious job and requires highly trained experts. Machine learning-based approaches are widely used to solve the aforementioned problem due to their capability to detect seizures by processing long lengths of data sequences, and they also provide a high detection rate. This study provides a machine learning-based approach to detect epilepsy from the EEG signal by integrating the discrete wavelet transform (DWT), fast Fourier transform (FFT), and the Spatial domain. For the feature selection, two dimensionality reduction techniques, principal component analysis (PCA), and linear discriminant analysis (LDA) have been used. Here, 3 different classifiers, support vector machine (SVM), logistic regression (LR), and K-nearest neighbors (K-NN) have been used to diagnose epilepsy automatically. This proposed method yielded a maximum accuracy of 99% for the combination of PCA with SVM in the transform domain for the feature length of only 10.

Keywords

EEG, support vector machine, logistic regression, K-nearest neighbors, principal component analysis, linear discriminant analysis

1. Introduction and Previous Work

Epileptic seizure is a neurophysiological disease that can be detected via brain signal analysis, which is produced by the neurons in the brain. Diagnosis and treatment help treat epileptic seizures. As per the report of the World Health Organization (WHO), every year, about 2.4 million people are diagnosed with epilepsy. Electroencephalogram (EEG) signals are widely used to detect brain activity and are also used to diagnose epileptic seizure. EEG contains valuable information for studying various aspects of brain function. Analysis of EEG is an active research field for diagnosing brain disorders. But analysis of large amounts of EEG data is a visually challenging and time-consuming task. To address this, various

computational methods have been developed to process and analyze EEG data automatically [1]. For the collection of EEG signals, multiple electrodes are placed above the scalp to record the electrical activity generated by the brain. Those electrodes detect the voltage fluctuations created by the collective activity of neurons in the underlying brain regions [2]. Epilepsy is a neurological disease differentiated by recurrent and unpredictable seizures. Seizures happen when there are occurrences of abnormal electrical impulse transfer activity in the brain, resulting in a temporary disruption of normal brain function.

EEG-based epilepsy detection employs two distinct methods, the spatial domain and transform domain, each focusing on distinct aspects of EEG data. Using raw or pre-processed EEG signals, a

spatial domain-based method analyzes the signal directly in the time or space domain. Spatial domain techniques analyze EEG data by examining the connections between several electrodes (channels), rather than just the time series of each individual channel. This allows for the capturing of spatial correlations and patterns in brain activity associated with epileptic episodes. [3–7] are a few recent studies based on spatial domains. However, spatial domain properties are sensitive to the location of electrodes and may overlook detailed frequency data (like Fourier transform [FT]). On the other hand, several modified techniques, such as frequency, time-frequency (like short-time Fourier transform [STFT]), Multiresolution Analysis (like discrete wavelet transform [DWT]), or other mathematical domains, are widely utilized to uncover the hidden pattern of EEG data. Transient occurrences, such as seizures or spikes, can be easily identified using the transform domain.

The fast Fourier transform (FFT) provides a clear understanding of the frequency components of EEG signals, which makes it possible to pinpoint particular frequency bands showing notable variations during seizures. For example, research has shown that FFT-based features [8] can attain high classification accuracies, with the Bonn and Bern EEG datasets achieving 97.7% and 96.8%, respectively. The simultaneous time and frequency information that STFT offers is crucial for examining non-stationary signals, such as EEG, particularly during epileptic episodes.

STFT is appropriate for real-time processing systems due to its simple structure, which is essential for seizure prediction and epilepsy monitoring. The periodic discharges frequently linked to the development of seizures or interictal spikes are examples of rhythmic activities that STFT records well. Because STFT has a fixed window size, time and frequency resolution must be traded off. Given that EEG waves contain both slow and quick transients, this is not ideal. While STFT is superior to the ordinary FT at handling non-stationary data, its fixed resolution restricts its capacity to adjust to quickly shifting seizure dynamics. To identify epileptic seizures using EEG signals, STFT has been used in many studies [9,10].

Different epilepsy detection methods are available in the literature [11–14]. Some techniques are in the spatial domain [13–14] while some are in the transform domain [15–20]. In [11], the authors reported a wavelet-based approach to detect epilepsy. They have used Mean Absolute Value (MAV) and Mean value as the features. There are so many researchers

who have worked with various types of entropy [13, 14], such as approximate entropy & Fuzzy entropy, etc., to detect epilepsy. On the other hand, [21] presented an epilepsy detection technique by extracting Fourier features in the Wavelet domain. Gajic et al. [22] reported an EEG & Wavelet-based approach to detect epilepsy. Here [22], they utilized scatter matrices for reducing the dimension of features, and then used a quadratic classifier to detect the healthy persons and epileptic patients. Amin et al. [23] also employed DWT for the detection of epilepsy in the wavelet domain. They have used [23] support vector machine (SVM), K-nearest neighbors (K-NN), and Neural Network (NN) different classifiers to compute the performance. Semimetal [24] presented a STFT-based technique to detect epilepsy. For the classification, they have utilized a multilayer NN and achieved a very good accuracy. In [25], authors reported a Q-Q-factor wavelet transform (WT)-based algorithm to extract the features from EEG signals for detecting epilepsy.

Some of the recent works on epilepsy detection are [26–32]. In [26], authors reported a 1D-CNN model to detect epileptic seizure and also provided a good accuracy of 99.1%. Sriraam et al., [27] presented a Multilayer Perceptron Neural Network (MLPNN) to detect epilepsy. They have worked with an EEG dataset of 20 patients. In [28] authors presented a multiway data analysis model by integrating 3 different classifiers to detect epilepsy. They have used the data set of 14 patients and extracted features by applying Block Term Decomposition (BTD), Canonical Polyadic Decomposition (CPD), and WT. Wei et al. [29] presented a 3-dimensional Convolutional Neural Network (CNN) model for the identification of epilepsy. Their method provided a good accuracy for the classification of epileptic and non-epileptic seizures. In [30], authors reported an epilepsy detection method by combining a model of Grid search optimization (GSO) with time frequency analysis and principal component analysis (PCA). To extract the time frequency features, FT, STFT, and Partial Auto Correlation Function (PACF) have been utilized. Their method achieved an accuracy of 96.7%. In another work [31], authors presented an epilepsy detection method by combining continuous wavelet transform (CWT), Artificial Neural Network (ANN), and SVM and achieved a very good accuracy of 99%. Wu et al., [32] presented a machine learning-based epilepsy detection technique by combining Complementary Ensemble Empirical Mode Decomposition (CEEMD) and XGBOOST model. Their method also achieved an accuracy of 99%.

Despite the growing effectiveness, current methods for detecting epilepsy still have several significant drawbacks. Some of important drawbacks are: (i) Computational Complexity: Although promising, deep learning techniques can be computationally demanding and, without additional optimization, inappropriate for wearable or real-time systems, (ii) Low Sensitivity and Specificity: When dealing with noisy EEG data, many detection algorithms continue to generate significant percentages of false positives or false negatives, (iii) Reliance on Manual Feature Extraction: Conventional machine learning techniques frequently call for manually created features, which could miss some important patterns, (iv) Inter-patient Variability: Due to variations in seizure forms, brain anatomy, and comorbidities, models developed on one patient group may not translate well to another, (v) Quantity and Quality of Data: EEG recordings can be noisy, and there is a dearth of high-quality, labeled seizure data, particularly for uncommon seizure forms etc.

In the transform domain, epilepsy detection has demonstrated its potential for evaluating non-stationary EEG signals. This includes methods such as FT, WT, and STFT. The transform domain also has some limitations, like FT's assumption of signal stationarity, making it unsuitable for EEG signals that exhibit significant non-stationarity during seizures [33], while STFT suffers from a trade-off between temporal and frequency resolution [34]. On the other hand, Wavelet decomposition may result in a lot of duplicate coefficients, which can cause overfitting in classification [35, 36].

But most of the methods are time-consuming due to the high dimensionality of the features. In this work, we present 4 different models by integrating DWT and machine learning algorithms to detect epilepsy in a very low-dimensional feature set. It actually reduces the time complexity for classification algorithms. It also provides a very good accuracy for the detection of epilepsy. In this work, we mainly tried to solve the limitations of Computational complexity, and on the other hand we tried to improve the performance by integrating the spatial domain with FT and WT domains.

This research work is constructed as "Introduction and previous work" section, which provides an introduction of EEG signals and epilepsy followed by reviews of the past examinations of seizure or non-seizure detection, The next section "contribution" explains the importance of proposed work, "Proposed method" section describes techniques used in this work, "Results and discussion" section explains the

performance of the technique, and "Conclusion" section concludes the research work.

II. Contribution

The major contributions of this work are presented as follows:

- i) The proposed technique provides an efficient epilepsy detection method by combining the spatial domain and transform domain.
- ii) Here we have tried a multi-perspective study of data by combining the spatial domain, FFT, and DWT for feature extraction. Features that are more robust, discriminative, and informative are generated by combining the distinct qualities that each domain captures. Features in the spatial domain maintain their original intensity and structural information. Though it does not provide temporal localization, FFT provides global frequency information. High-frequency transients and low-frequency trends with temporal localization can both be captured with DWT's multi-resolution time-frequency analysis. When these are combined, the signal is more richly represented in the frequency and time domains. Classifiers can more successfully differentiate between classes when they have access to richer feature sets.
- iii) Here, DWT is used for two reasons: the first one is for dimension reduction, and the second one is to extract low-frequency information, which shows effectiveness for the detection of epilepsy.
- iv) In the proposed technique, a two-step feature dimension reduction method has been used. In the first step, DWT has been applied, and in the next step, PCA and linear discriminant analysis (LDA) has been used to select important features in a low-dimensional feature space.
- v) The performance of the proposed models is evaluated utilizing logistic regression (LR), K-NN, and SVM classifiers. Most of the proposed techniques used a large dimension of features to get good performance, but in these techniques, we have achieved a high accuracy with a small dimension of features, which indirectly decreases the time complexity.
- vi) The proposed work can detect epilepsy with very high accuracy.

III. Proposed Method

This paper aims to present a method to detect epileptic seizures utilizing the EEG. The proposed model architecture is depicted in Figure 1. Here, spatial

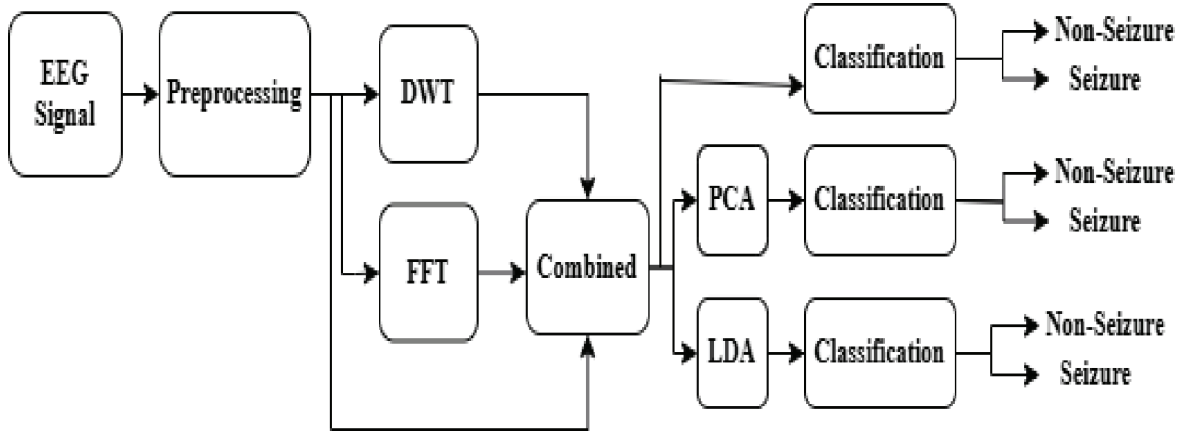


Figure 1: Proposed model of epilepsy detection process. DWT, discrete wavelet transform; EEG, electroencephalogram; FFT, fast Fourier transform; LDA, linear discriminant analysis; PCA, principal component analysis.

domain is integrated with the transform domain, and for the transform domain, FFT and DWT have been used. Features are extracted by applying PCA and LDA to select the important features in low-dimensional feature space. All the 3-models are validated by SVM, K-NN, and LR classifiers.

a. FFT

FFT has several different fields in which it is applied. A mathematical tool called FFT [37–38] is used to translate waveform data from the time domain into the frequency domain [25–26]. The signal that has been analyzed is shown as a succession of sinusoids in the FFT. The “Discrete Fourier Transform (DFT)” is far slower than FFT. With FFT, the presence of various frequencies and, in turn, their magnitudes, may be retrieved. Both discrete and continuous time domains can be used for FT. In real time, FT of a function $z(t)$ is $Z(\omega)$, where, [1, 2]

$$Z(\omega) = \int_{-\infty}^{\infty} z(t)e^{-j\omega t} dt \quad (1)$$

where $j = \sqrt{-1}$ and ω is the frequency. FT inverse of $Z(\omega)$ is $z(t)$, which can be written as

$$z(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} Z(\omega)e^{j\omega t} d\omega \quad (2)$$

where $Z(\omega)$ indicates signal’s spectrum. Discrete domain signal $z(n)$, the DFT is,

$$Z(l) = \sum_{n=0}^{N-1} z(n)e^{-2\pi jln/N}; 0 \leq l \leq N-1 \quad (3)$$

N indicates the number of samples and $n = 0, 1, 2, \dots, N-1$. Eq. (3) is known as the N -point DFT. The FFT algorithm, which reduces the evaluation time and complexity of DFT, was proposed by Cooley and Tukey in 1965. Two basic methods used for calculating the FFT are the decimation in time (DIT) and decimation in frequency (DIF) algorithms. They vary in how they break down the problem and handle the input. DIT essentially performs DIT domain by recursively splitting the input signal into smaller sequences according to even and odd time indices. This indicates that the DIT algorithm computes the output in natural frequency order after starting with the input sequence in bit-reversed order. Following the initial arithmetic operations in each stage, the butterfly operations in DIT apply the twiddle factors. By breaking down the output spectrum into even and odd frequency components, DIF, on the other hand, operates in the frequency domain.

Although it generates the output in bit-reversed order, it processes the incoming data in normal order. Triggered factors are applied before butterfly operations in DIF. Despite the same computational complexity, the two algorithms differ in their structure and functionality. For input-side optimization, DIT is frequently more straightforward, but DIF might be better when the final output needs to be in natural order. Both methods produce the same FFT output in spite of these structural variations, and are selected according to hardware limitations or implementation preferences.

While $N/2 \log_2 N$ complex multiplication is needed to calculate FFT, the total number of N^2 complex multiplications is needed to compute “ N ” point DFT.

These represent FFT's dominance over DFT. In our proposed method, we have used the DIF algorithm. Figure 6 shows the samples of the EEG signal after application of the FFT for 5 different classes of the used dataset.

b. DWT

WT is used to obtain a better time-frequency representation of a signal. For the local representation of non-stationary signals, this mathematical method is employed. WT is separated into two categories: CWT and DWT. Compared to DWT, CWT has far higher computational complexity and generates a lot more data. To extract the frequency information from the signal, a high-pass filter (HPF) and a low-pass filter (LPF) are applied to the signal at each level in the DWT. The output of the LPF is known as approximation or approximate coefficients, which contain lower-order harmonics of the studied signal, and the output of the HPF is known as detail coefficients, which contain higher-order harmonics. Both approximation coefficients (from low-pass filtering) and detail coefficients (from high-pass filtering) are important yet different in DWT-based EEG feature extraction. Their contributions stem from their capacity to depict various frequency components of the EEG signal, which is multi-frequency and intrinsically non-stationary. In this work, we have used approximation coefficients from the first-level decomposition, represented as A1.

The degree of decomposition in DWT analysis is determined by the frequency information needs for the study. "db4" is regarded as the mother wavelet in this work. Although various mother wavelets have also been tested for this purpose, "db4" is the most appropriate in this case for the study. The approximation coefficients ($z_{low}[n]$) and detail coefficients ($z_{high}[n]$) in DWT analysis are computed at each decomposition level using the formula shown below [39, 40].

$$z_{low}[n] = \sum_{k=-\infty}^{\infty} y[k] v[2n-k] \quad (4)$$

$$z_{high}[n] = \sum_{k=-\infty}^{\infty} y[k] w[2n-k] \quad (5)$$

where y is the signal that has been evaluated, k is the number of samples, n is the number of decomposition levels, and v and w are the outputs of the low pass and HPFs, respectively. The frequency range

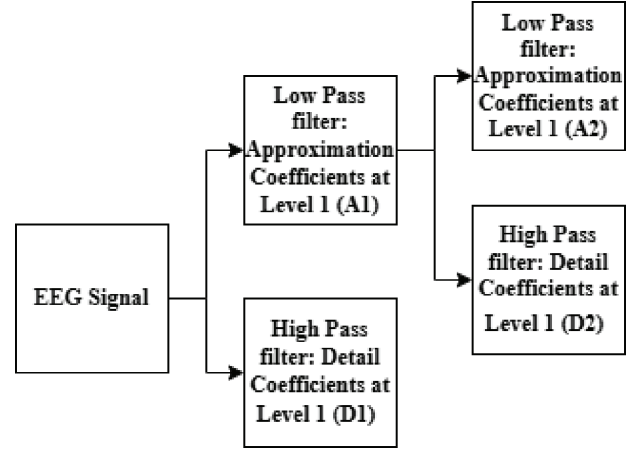


Figure 2: DWT decomposition up to level two (2). DWT, discrete wavelet transform; EEG, electroencephalogram.

of approximation and detail coefficients can be computed using the following formulas.

$$U_{CA} = [0, 2^{-l-1} f_s] \quad (6)$$

$$U_{CD} = [2^{-l-1} f_s, 2^{-l} f_s] \quad (7)$$

where l is DWT decomposition level and f is sampling frequency. Samples of A1 (Approximation Coefficients) after applying DWT of 5 different classes are depicted in Figure 5.

In DWT analysis, the analyzed signal is decomposed at every decomposition level, from where approximation and detail coefficients are extracted. Approximation coefficients consist of lower-order harmonics, whereas detail coefficients consist of higher-order harmonics. Figure 2 depicts DWT decomposition up to decomposition level two (2) though decomposition can be done up to any level, where l is DWT decomposition level and f is sampling frequency. Samples of A1 (Approximation Coefficients) after applying DWT of 5 different classes are depicted in Figure 5.

c. Description of model

In this model as depicted in Figure 1, EEG signals are first pre-processed. Clean EEG signal extraction from a corrupted EEG signal is known as denoising. Savitzky–Golay (SG) finite impulse response (FIR) filter is used here for denoising the EEG signal. In this filter, successive data points are fitted with a low polynomial degree to smooth the noisy signal. In the SG filter, high-frequency components remain unaltered in their

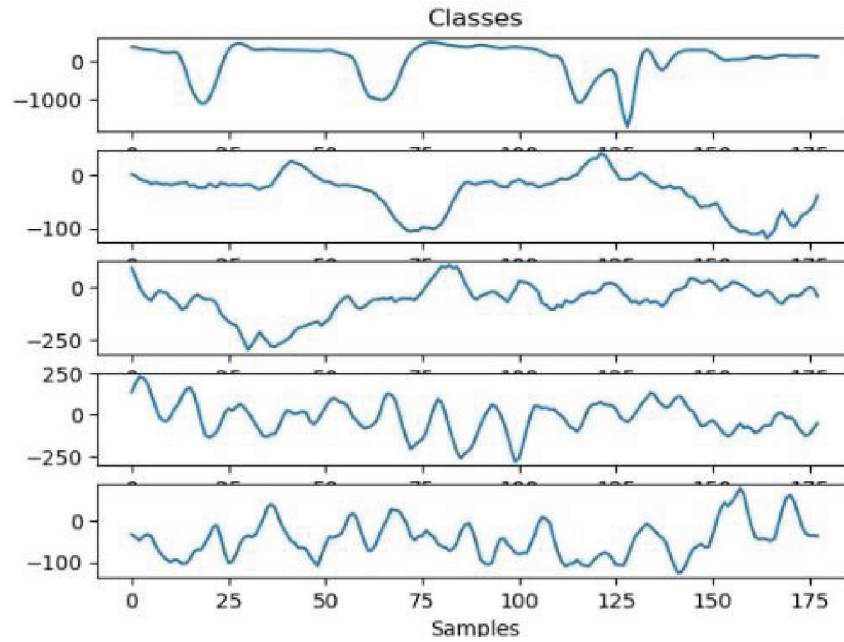


Figure 3: Samples of EEG signals of 5 different classes. EEG, electroencephalogram.

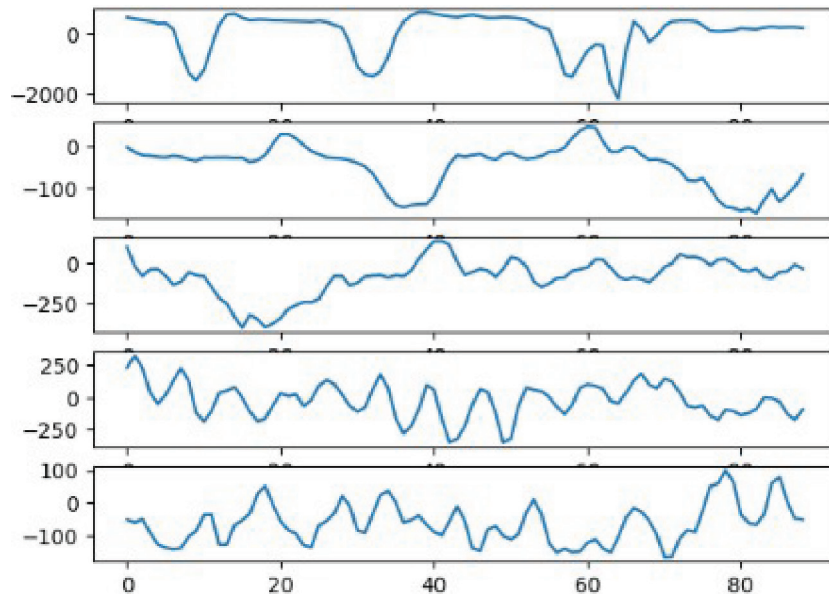


Figure 4: Samples of A1 after applying DWT of 5 different classes. DWT, discrete wavelet transform.

fundamental characteristics. After denoising, EEG signal has been further processed to extract different frequency information by the DIF algorithm-based FFT and DWT.

The samples of EEG signals, of 5 different classes, are depicted in Figure 3. In the next step a DWT has been applied by varying the mother wavelets. DWT divides the pre-processed EEG signal into two

sub-bands. The first one is the approximation (A1) coefficients, and another is the detail coefficients (D1). Here, A1 coefficients are utilized for the next step, as shown in Figure 4. On the other hand, FFT has been applied to the pre-processed EEG signal. FFT coefficients are depicted in Figure 5.

After that, A1, FFT coefficients, and pre-processed spatial domain signals are combined. On

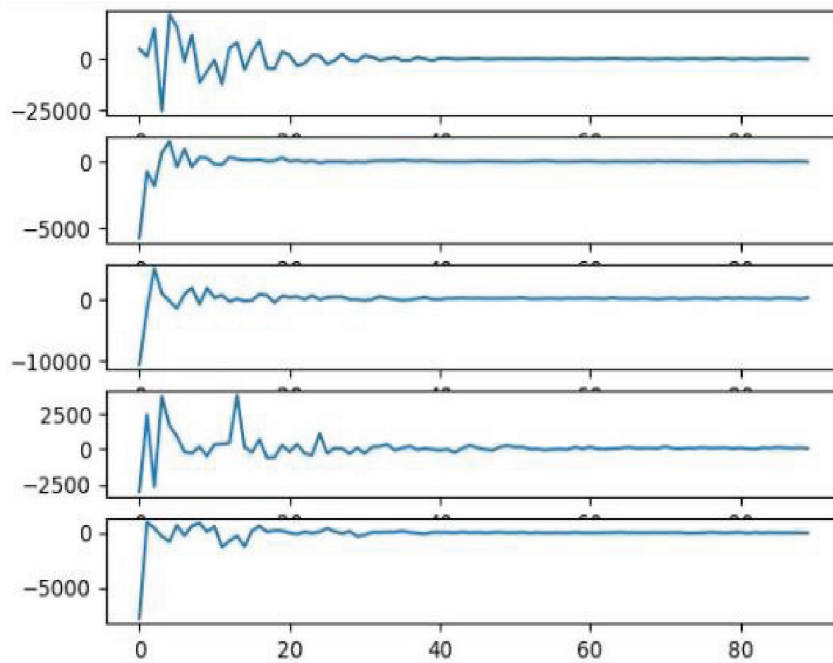


Figure 5: Samples of EEG signal after application of FFT for 5 different classes. EEG, electroencephalogram; FFT, fast Fourier transform.

this combined signal, then PCA and LDA have been applied separately. At the last step, three different classifiers are applied to compute the performance. Here, all the classifiers are applied to compute the importance of combined features.

Here we have calculated the categorization accuracy for three distinct scenarios. In case 1, machine learning-based classification algorithms are first calculated on the combined coefficients (A1 + FFT + spatial), and in case 2, PCA is applied to the combined coefficients to lower the dimension before the performance is calculated. In instance 3, the combined coefficients have been subjected to LDA, another dimensionality reduction technique, and the performance of various classifiers is assessed.

IV. Result and Discussion

This section provides the information about the dataset used in this proposed technique, difference performance measures used, and finally the discussion and comparison of experimental results.

a. Dataset

The actual dataset consists of 5 folders, and each folder contains 100 files of a single subject. Every

file consists of an EEG recording of 23.6 sec. These time series data points are sampled into data points of length 4097 [23]. Since the data points are shuffled and sub-parts into 23 chunks. So, all chunks contain 178 data points. Among 5 folders, first one is for seizure activity, the second one contains the recording of the EEG signal which is extracted from where the tumor was located, and the third one is for the EEG signal which is recorded from a healthy area of the brain, the fourth folder contains the EEG signal which is recorded when the patient's eyes were closed and the last one recorded when patients' eyes were open. Here, only folder 1 contains the EEG recording of epileptic seizure. Here we have performed binary classification, namely class 1 non-seizure and class 2 seizure.

b. Performance measures accuracy

The frequency with which a machine learning model correctly predicts the result is measured by its accuracy. By dividing the total number of predictions by the number of correct predictions, accuracy can be computed. The accuracy can be expressed as a percentage or on a 0–1 scale. The better, the higher the accuracy. Achieving a perfect accuracy of 1.0 requires that each prediction made by the model be accurate. This metric is easy to compute and comprehend. The

ability of the model to accurately classify data points is reflected in the intuitive perception of accuracy that almost everyone possesses.

The accuracy is defined as,

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{All Predictions}} \quad (8)$$

a.i. Precision

The precision metric provides the ratio of actual positive results to the total number of positive results predicted by the model. It provides an answer to the query, “How many of our optimistic predictions came true?” It can be defined as

$$\text{Precision} = \frac{\text{TruePositives}}{\text{Truepositives} + \text{FalsePositives}} \quad (9)$$

a.ii. Recall

Recall focuses on the model’s ability to identify every benefit. The answer to the question “How many of all the data points that should have been predicted as

true did we correctly predict as true?” is provided by recall, also known as the true positive rate.

$$\text{Recall} = \frac{\text{TruePositives}}{\text{Truepositives} + \text{Falsenegatives}} \quad (10)$$

a.iii. F-1 Measure

Recall and precision are combined into one metric called the F1 Score. F1 can be used to gauge how well our models make the trade-off between precision and recall, as we have seen to be necessary. The fact that the F1 score is zero if either precision or recall drop to zero is a crucial component of the score. As a result, it penalizes extremely low values of any component.

It is measured as,

$$\text{F1 Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{recall}} \quad (11)$$

c. Result

The proposed method is simulated by Colab, which is based on the Python programming environment.

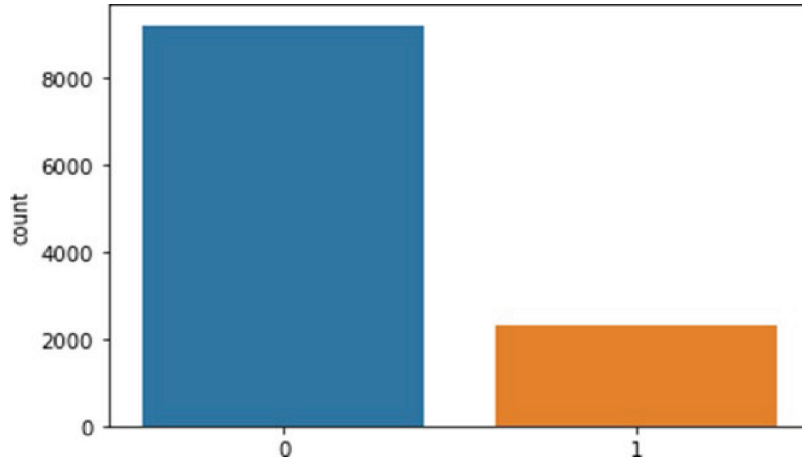


Figure 6: Bar chart of total number of samples non-seizure and seizure.

Table 1: Performance measure of case 3 (combined features)

Algorithm	Accuracy	Precision	Recall	F-1 Score
LR	0.98	0.96	0.96	0.96
K-NN	0.95	0.96	0.89	0.92
SVM	0.95	0.96	0.89	0.92

K-NN, K-nearest neighbors; LR, logistic regression; SVM, support vector machine.

Table 2: Performance measure of case 1 (combined features + PCA)

Algorithm	Accuracy	Precision	Recall	F-1 Score
LR	0.99	0.99	0.97	0.98
K-NN	0.98	0.97	0.96	0.97
SVM	0.98	0.97	0.96	0.97

K-NN, K-nearest neighbors; LR, logistic regression; PCA, principal component analysis; SVM, support vector machine.

Table 3: Performance measure of case 2 (combined features + LDA)

Algorithm	Accuracy	Precision	Recall	F-1 Score
LR	0.97	0.96	0.92	0.94
K-NN	0.96	0.96	0.90	0.92
SVM	0.96	0.96	0.90	0.92

K-NN, K-nearest neighbors; LDA, linear discriminant analysis; LR, logistic regression; SVM, support vector machine.

The number of samples for the non-seizure class is 9200, and for the seizure class is 2300, as depicted in Figure 6.

Performance measures for the three different models are depicted in Tables 1–3, considering the 10-fold Cross-validation (CV) technique.

In this section, results are computed for two-class or binary classification (Epileptic or non- Epileptic). For all the cases, accuracy, precision, Recall, and F-measure are computed for two classes. In the case of DWT, the Daubechies wavelet (db1) has been used to decompose the signal. It is evident from Tables 1–3 that PCA performs well for the combined characteristics and has the highest accuracy of 99% only for 10 principal components. It is also noted that the combination of (spatial domain + FFT + DWT + PCA) produced the best performance for the LR classifier compared to other performance metrics like accuracy recall and F1-Score. This method yields a F1-score of 0.98, a precision value of 0.99, and a recall of 0.97.

Table 4 provides a comparative study with other state-of-the-art epilepsy detection techniques. From Table 4, it is clear that the proposed technique is better compared to Jaiswal and Banka [43], Wang et al. [44], and Shiva Shankar et al. [45]. But recognition accuracy is the same as [41, 42]. It is also observed that our technique is better compared to all other techniques due to its low feature dimension.

Table 4: Comparison with other techniques

References	Classifier	Accuracy (%)
[41]	Decision tree	99
[42]	Multilayer perceptron neural network	99
[43]	ANN	98.30
[44]	SVM	97.98
[45]	PCA with RF	92.69
[45]	PCA with ANN	97.55
Proposed model	LR	99

LR, logistic regression; PCA, principal component analysis; RF, random forest; SVM, support vector machine.

V. Conclusions and Future Scope

This research work presents an efficient epilepsy detection method utilizing EEG data. In this work spatial domain is combined with FFT and DWT. Comparing all the results, it is observed that for all the models, PCA performs well. Here, we achieved the highest accuracy of 99%, F1-score of 0.98, a precision value of 0.99, and a recall value of 0.97 for the LR classifier. The comparison tables reveal that our

proposed technique provides a better accuracy compared to other techniques for a very low dimension of features and provides the maximum accuracy for only to a feature length of 10. Future directions of our work are mentioned below:

The importance of other statistical features, like mean, variance, and different types of entropy, can be studied.

Various feature selection techniques to select the feature can be applied to select the important feature.

In the next work, our proposed algorithm will be applied to different populations and various types of datasets.

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Author Contribution

All authors contributed to the text and the content of the manuscript, including the simulation results.

Data Availability Statement

The used dataset is publicly available.

Research Involving Human and/or Animals

For the preparation of this manuscript, no human subject research was conducted.

Informed Consent

Taken consent from all the authors.

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