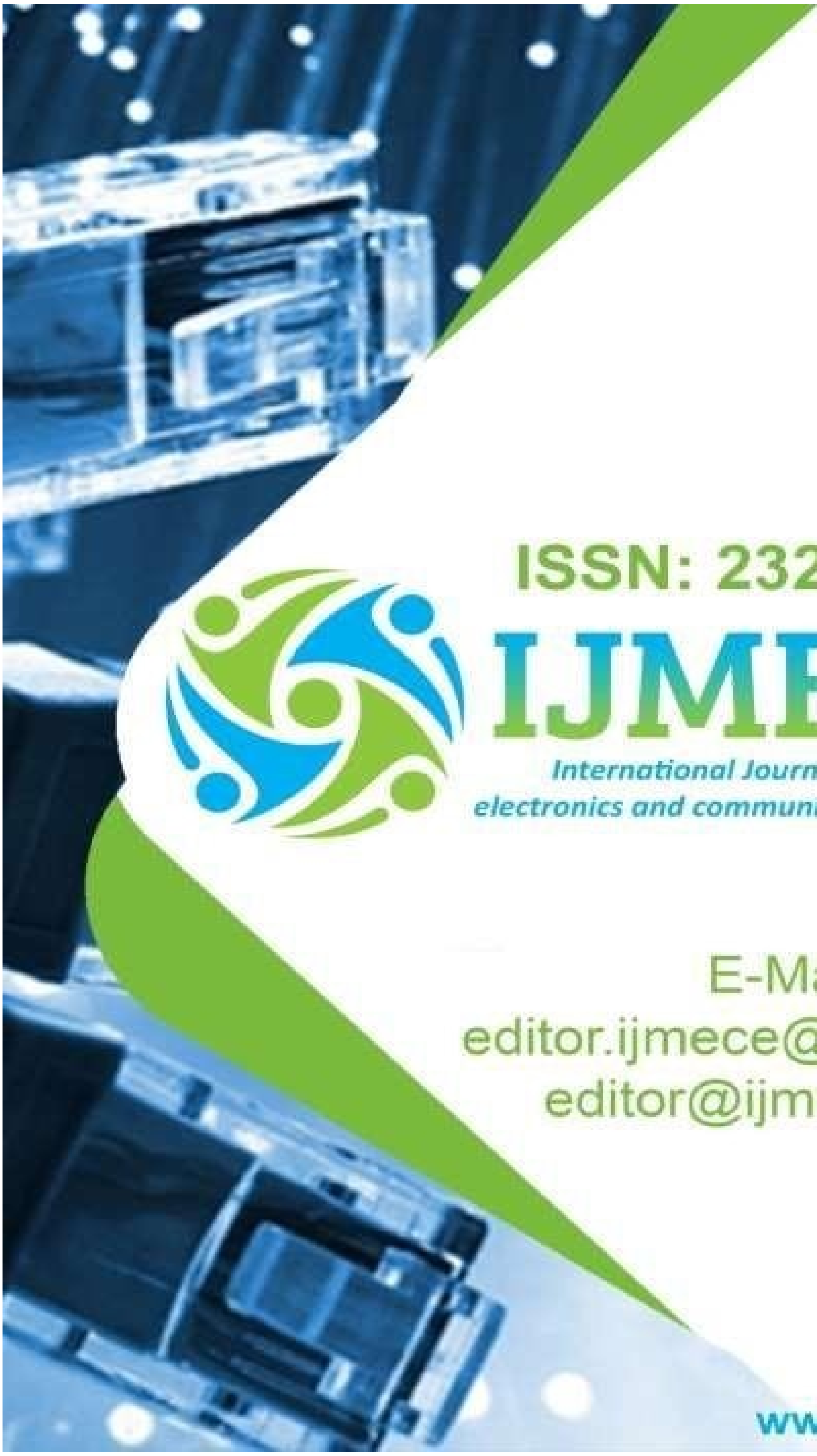

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Analysis of EEG Signal for Epilepsy Seizure Detection Using Machine Learning

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Abstract- The brain is a vital organ responsible for regulating various bodily functions. An electroencephalogram (EEG) is a powerful tool for recording brain activity from the scalp. Analyzing EEG signals plays a key role in diagnosing and treating neurological conditions such as epilepsy, seizures, and other brain disorders. However, these signals are often affected by noise and artifacts, making analysis challenging. Accurate evaluation of EEG signals is critical for reliable diagnosis. Numerous approaches have been developed to achieve high-precision analysis. In this study, Discrete Wavelet Transform (DWT) is utilized to pre-process EEG signals, breaking them down into five distinct frequency bands. Subsequently, features such as mean, standard deviation, root mean square (RMS), entropy, energy, and relative energy are extracted. These features are classified using machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Naive Bayes (NB). The findings reveal that SVM achieves the highest performance, with a classification accuracy of 99.5%, specificity of 100%, and sensitivity of 100% when distinguishing between normal and epileptic subjects.

Keywords: EEG, SVM,Epilepsy, DWT, Artifacts, Classifier

1. INTRODUCTION

Epilepsy, characterized by abnormal neural activity in the brain, affects approximately fifty million people worldwide. In 2015, seizures were responsible for an estimated 125,000 deaths. This condition is more prevalent among the elderly. Epileptic seizures often remain undetectable over extended periods, complicating timely diagnosis. Diagnosing epilepsy involves identifying the onset of seizures and uncovering the underlying causes. An electroencephalogram (EEG) is a valuable tool for monitoring brain activity and assessing the risk of seizures. EEG signals are interpreted by specialists to differentiate and classify various seizure patterns.

However, the visual examination of such signals is time-intensive, demanding, and requires expertise. This manual process can reduce the efficiency of neurologists analyzing patient recordings. To address these challenges and improve the accuracy of seizure diagnosis, computational systems are being developed to create effective models for seizure classification and detection, enhancing diagnostic efficiency.EEG is a method used to capture the brain's electrical activity by placing electrodes on the scalp following the international 10-20 system. These signals are classified into five major frequency bands: delta, theta, alpha, beta, and gamma. EEG testing is painless and involves small sensors attached to the scalp, with signals recorded and analyzed by a computer system before being reviewed by a specialist. Although EEG provides valuable insights into brain function, it is often contaminated by artifacts, which can lead to errors in interpretation and diagnosis. To mitigate these issues, advanced EEG signal processing techniques are employed to intelligently analyze the data, improving the reliability of diagnostic and treatment methods.

2. RELATED WORK

1. The common neurological disorder known as epilepsy is usually diagnosed using EEG data. Visual inspection and interpretation of EEGs is a time-consuming, slow, and subjectivity and human error prone process. Consequently, a great deal of work has been done to develop automatic methods for identifying and classifying epileptic episodes. The current work suggests a novel computer-aided diagnostic technique (CAD) based on the discrete wavelet transform (DWT) and arithmetic coding to identify epileptic seizure signals from normal (seizure- free) signals. The suggested CAD approach consists of three stages. The first stage, which employs DWT to deconstruct EEG signals into approximations and detail coefficients while eliminating non-significant coefficients in light of threshold criteria, places a limit on the number of significant wavelet coefficients.

2. The Electroencephalogram (EEG) provides important information about the many physiological states of the brain. This research presents a methodology for identifying epileptic episodes from EEG recordings of both patients with epilepsy and normal people. The discrete wavelet transform (DWT) analysis of EEG signals utilising linear and nonlinear classifiers forms the foundation of this methodology. With the produced statistical characteristics from DWT, naïve Bayes (NB) and k-nearest neighbour (k-NN) classifiers are used to study the performance of 14 distinct combinations of

two-class epilepsy detection. The individual and combined statistical features derived from the DWT values of normal eyes open and epileptic EEG data provided by the University of Bonn, Germany, have shown that the NB classifier works better and demonstrates an accuracy of 100%. It has been discovered that the NB classifier provides superior accuracy with a shorter computation time than the k-NN method. Therefore, real- time, dependable, automatic epileptic seizure detection systems that improve patient care and quality of life are better suited for the detection of epileptic seizures based on DWT statistical features employing NB classifiers.

3. Research on the identification of epileptic seizures has been done for a number of years in order to facilitate an automated diagnosis system that would ease the burden on physicians. Numerous study papers have been published in this area to identify epileptic episodes. All of these papers need to be thoroughly reviewed. In order to detect epileptic seizures using EEG signals, a study of pattern identification techniques has been attempted. The methods for identifying epileptic seizures have been explored in more than 150 research publications.Additionally, the study of the literature demonstrates that distinct electroencephalogram (EEG) datasets under different settings require different pattern recognition approaches in order to identify epileptic episodes. This is primarily because EEG readings obtained under various circumstances exhibit diverse properties. This subsequently calls for the development of a pattern recognition method to effectively separate EEG data from various disorders from EEG data that is epileptic.

4. An instrument used to assess the electrical activity of the brain caused by variations in brain chemistry is called electroencephalography, or EEG. In feature extraction and classification techniques for identifying and forecasting different brain disorders, the EEG analysis plays a significant role. Seizures, which are a primary symptom of epilepsy, are caused by abrupt, aberrant electrical discharges in the brain. The primary goal of study is to distinguish between normal and epileptic EEG signals. The purpose of the study is to use temporal and frequency aspects to distinguish the pre-seizure and seizure states of the EEG data. Predicting seizures is made easier by employing a fuzzy classifier to categorise various EEG signal states. The approach makes use of pattern-adapted wavelet transform for better classification and hypothetical testing for fine-tuning feature selection. Appropriate feature selection lowers the classifier's computational complexity. The EEG signal artefacts are eliminated with the application of Independent Component Analysis (ICA). For testing, the Children's Hospital in Boston's CHB-MIT EEG scalp dataset is utilised. The classification accuracy for seizures is 96.48%, the True Positive Rate is 96.52%, the False Positive Rate is 0.352, and the classification accuracy for pre-seizure states, which occur 13–110 s before seizures, is 96.02%

5. There are numerous, continual initiatives to develop automatic seizure detection since the manual detection of electrographic seizures in continuous electroencephalogram (EEG) monitoring is exceedingly time-consuming and requires a qualified expert. The capacity of machine learning techniques to categorise seizure diseases from a vast quantity of data and offer neurologists with pre-screened results has led to an aggressive application of these techniques to this problem. To analyse and categorise seizures using EEG signals, a number of characteristics, data transformations, and classifiers have been investigated. Certain jointly applied features that were employed in the classification may have contributed in a similar way throughout the literature, rendering them unnecessary for the learning process. In order to characterise epileptic episodes using EEG signals, this work attempts to thoroughly summarise feature descriptions and their interpretations. It also reviews classification performance metrics. We ran an experiment to look at each feature's quality separately in order to give useful information about feature selection. The non-parametric probability distribution estimation and the Bayesian error were used to assess each feature's significance. Additionally, a correlation-based feature selection was used in a redundancy analysis. The findings shown that the seizures could be significantly captured by the following features: variance, energy, nonlinear energy, and Shannon entropy computed on a raw EEG signal; additionally, variance, energy, kurtosis, and line length calculated on wavelet coefficients. An improvement of 4.77-13.51% in the Bayesian error was obtained when compared to a baseline technique that classified all epochs as normal

6. In this study, an efficient method utilising wavelet-based non-linear analysis and genetic algorithm optimised support vector machine (GA-SVM) is proposed to address five difficult classification problems, aiming to address the issues of low accuracy, poor universality, and functional singleness for seizure detection. We want to investigate if double-density discrete wavelet transform (DD-DWT) can break down the original EEG into distinct sub-bands in place of the conventional discrete wavelet transform (DWT).Two classifiers receive the extracted Hurst exponent (HE) and fuzzy entropy (FuzzyEn) as input features. The GA-SVM configured with less features is found to accomplish the noteworthy classification performance on these ranking non-linear characteristics for a variety of combinations, including AB-CD-E, A-D-E, ABCD-E, C-E, and D-E, with accuracies of 99.36%, 99.60%, 100%, and 100%, respectively. The outcomes show that our technique is not only suitable for handling multiclass problems but also has greater expansibility and lesser complexity. With these qualities, this approach would start to seem like a desirable substitute for a real clinical diagnosis.

7. As a diagnostic decision support tool for the management of epilepsy, we presented a classification model based on a multilayer perceptron neural network (MLPNN). Discrete wavelet transform (DWT) was used to break down EEG signals into frequency sub-bands. For every frequency sub-band, the wavelet coefficients were grouped using the K-means algorithm. The wavelet coefficient distribution to the clusters was utilized to compute the probability distributions, which were then fed into the MLPNN model. To assess how well the suggested model performed in classifying various mixes of healthy segments, epileptic seizure-free segments, and epileptic seizure segments, we ran five separate tests. We demonstrated that the suggested model produced classification accuracy rates that were sufficient.

3. Data Collection and Methodology

1)The proposed classification of the EEG signal is done using following approach 1) pre-processing of EEG signals

2) feature extraction from decomposed signal, and 3) classification using classifier model.

In the present study, EEG data sets (A, B, C, D and E) is preprocessed by DWT to decompose into five sub band signals using seven level decomposition [12]. Next, useful features like Entropy, Mean, Standard deviation, Energy, RMS, and Relative power are derived from each sub-band. Finally, Extracted features are selected and given as input classifier for epilepsy classification.

3.1 Description of EEG Dataset

The publicly available EEG is taken from University of Bonn ([12]. This dataset include five sets labels such as A, B, C, D and E, with each having 100 single- EEG channel of time duration 23.6 sec having f =173.6 Hz sampling rate. In Each segment of data, N=4097 data points are positioned at the intervals of 1/173.61th of 1s.The sets A and B are acquired from scalp EEG recordings of five healthy volunteers subjects using a standard international electrode placement. The subjects were asked to relax in an awake state with eyes open and eyes closed for SET A and SET B respectively [18]. For Interictal and Ictal epileptic activities, the database sets C, D, and E are acquire from the epileptic subjects through intracranial electrodes. The summary of dataset is shown in table 1.

3.2 EEG Pre-processing

In the EEG preprocessing stage, DWT decomposition is employed as a tool to extract five physiological EEG frequency bands: delta (0-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-60 Hz). Initially, the signal is simultaneously passed through low-pass (LP) and high-pass (HP) filters in the first stage of the DWT. The outputs—an approximation (A1) and a detail (D1)—are produced by the low and high pass filters at the first level. Following the Nyquist rule, the output signal is downsampled by two, maintaining half the original signal's bandwidth. This process is repeated for the first-level approximation and detailed coefficients at subsequent levels. During each decomposition step, the frequency resolution is increased and downsampled by splitting its time resolution. Given that the EEG dataset has a sampling frequency of 173.61 Hz, the maximum usable frequency, as per the Nyquist rate, should be half the sampling frequency, or 86.81 Hz [15].

EEG signals are generally classified according to the placement of electrodes on the scalp. In signal processing, distinguishing normal from abnormal rhythms is based on frequency measurements. Similarly, EEG waveforms such as alpha, beta, gamma, theta, and delta are classified by their signal frequency. The continuous rhythm of

brain waves is categorized by frequency bands, which vary based on the brain's mental state. The following details outline the EEG frequency bands:

Delta wave (0.1-4 Hz): The delta wave has the highest amplitude but is the slowest. It is prevalent during all stages of sleep, normal in infants, and abnormal in awake adults.

Theta wave (4-8 Hz): These waves are linked to subconscious activity and are observed during meditation and deep sleep.

Alpha wave (8-13 Hz): Alpha waves are common across all age groups, particularly in adults with closed eyes, and represent the brain's white matter.

Beta wave (13-30 Hz): Symmetrical on both sides of the frontal brain region, these low-amplitude waves occur during mental activity.

Gamma wave (30-100 Hz): Associated with consciousness and perception, gamma waves appear during heightened alertness.

To identify these frequency bands, a method known as the Discrete Wavelet Transform (DWT) is employed. This technique detects the presence of these bands, and additional features are extracted by decomposing the signal using the Daubechies Wavelet.

3.3 Feature Extraction

The below Fig 1 shows the basic methodology for determining the frequency bands of EEG signal. The input EEG signal is taken from Bonn database. The Dataset consist of both normal and epileptic seizure signal. A Sampling rate of 173.61 Hz. is used to sample the signal. MATLAB software is used for analyzing the input EEG signal. As wavelet transform is used for

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analyzing the signal both in time frequency domain, hence the input signal is decomposed to 7levels obtain the various filter coefficient and details vector values. As the EEG signal consist of many artifacts due to interferences, hence using this transformation we are able to obtain the various frequency bands of EEG signal and thus eliminating the unwanted signal frequencies. In the further analysis, we calculate the time frequency domain parameter of these EEG frequency bands like mean, standard deviation, entropy, energy, relative power and RMS.

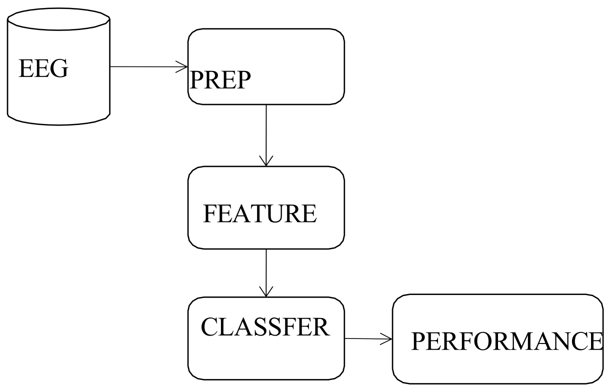

Fig 1: Proposed classification model

(1) The mean of wavelet filter coefficient in different sub band is calculated by

$$ui = \frac{\sum_{i=1}^{n} xi}{n} \qquad i=0,1,2,3,\ldots n \qquad (1)$$

(2) The standard deviation for each sub band is square root of mean give by

$$\sigma^2 = \frac{\sum_{i=1}^{L} (xi-x)^2}{n-1} \qquad (2)$$

(3) The subband energy is obtained by

$$E = \sum_{n=0}^{N-1} |xi|^2 \qquad i=0,1,2,3,\ldots n \qquad (3)$$

(4) The Entropy for each sub-band is given by

$$Entropy\ (EN) = \sum_{i=1}^{N} xilog\ xi^2 \quad i=0,1,2,3,\ldots n \qquad (4)$$

(5) The Relative energy(RE) is calculated by

$$\rho i = \frac{Ei}{Etotal} \qquad i=0,1,2,3,\ldots n \qquad (5)$$

3.4 Classification of different machine Learning algorithms

Several approaches and methods can be used for features extraction and classification of seizure. The differences between normal and abnormal cases are based on these extracted and selected features. The extracted features are given to a classifier model for seizure detection between normal and epileptic patient. In the proposed study we have used three classification model named as SVM, KNN & NB classifier to evaluate the performance proposed model.

Support Vector Machine [SVM]: Support Vector Machines (SVMs) are a popular machine learning algorithm used in seizure detection due to their ability to classify complex patterns in data. In seizure detection, SVMs are employed to analyze features extracted from EEG signals, such as frequency, amplitude, or entropy, and distinguish between seizure and non-seizure states. SVMs work by finding the optimal hyperplane that separates data points of different classes (e.g., seizure vs. non-seizure) in a high-dimensional feature space. If the data is not linearly separable, SVMs use kernel functions (e.g., radial basis function or polynomial) to transform the data into a higher dimension where a linear separation is possible. The advantage of SVMs in seizure detection lies in their robustness, efficiency with small datasets, and ability to handle non-linear data patterns, making them a reliable tool for early and accurate seizure detection in medical applications.

K-Nearest Neighbor (KNN): algorithm is a simple yet effective machine learning technique used in seizure detection. KNN classifies data points based on the majority class of their closest neighbors in the feature space. In seizure detection, features such as frequency, amplitude, or spectral power are extracted from EEG signals, and KNN analyzes these to classify segments as seizure or non-seizure.KNN operates by computing the distance (e.g., Euclidean or Manhattan distance) between a test data point and all points in the training dataset, identifying the k- nearest neighbors, and assigning the most common class among these neighbors to the test point.KNN is advantageous for seizure detection because it is non-parametric, easy to implement, and performs well when the feature space is well-defined. However, it can be computationally intensive for large datasets and may require proper feature scaling to ensure distance metrics are meaningful.

Naive Bayes (NB): Naive Bayes is a probabilistic machine learning algorithm often used in seizure detection because of its simplicity and effectiveness with high-dimensional data like EEG signals. It is based on Bayes' Theorem, which calculates the probability of a class (e.g., seizure or non-seizure) given certain features, assuming that the features are independent. In seizure detection, features such as signal amplitude, frequency, or statistical measures are extracted from EEG data.

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Naive Bayes evaluates the likelihood of these features occurring in seizure or non-seizure states and classifies the data accordingly. Despite its assumption of feature independence, which may not always hold in EEG data, Naive Bayes often performs well due to its computational efficiency and ability to handle noisy or small datasets. Its lightweight computational requirements make Naive Bayes a good choice for real-time seizure detection in portable or resource-constrained medical devices.

4. Results and Discussion

The process of extracting features from EEG signals is carried out in two primary steps. Firstly, the input EEG signal is decomposed into five distinct sub-band signals—alpha, beta, gamma, theta, and delta—using the Discrete Wavelet Transform (DWT). For this decomposition, the Db7 wavelet function is chosen as it provides an appropriate decomposition level. The decomposition is performed at a sampling frequency of 173.6 Hz.In the second step, the wavelet filter coefficients obtained from the decomposition are analyzed further. Relevant statistical features are selected and computed using MATLAB (R2021). This ensures a detailed examination of the EEG signal for different sub-band frequencies.Figures 2 and 3, as well as Figures 4 and 5, illustrate the plots of the input EEG signals for subjects S001 and Z001, showcasing the decomposition across different EEG frequency bands.

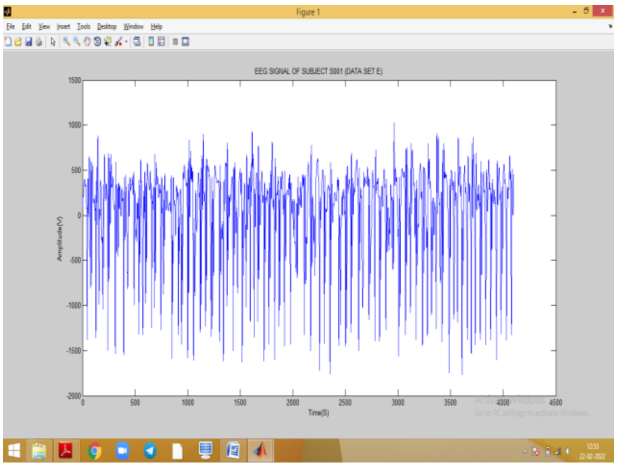

Fig 2: Input EEG signal of subject S001

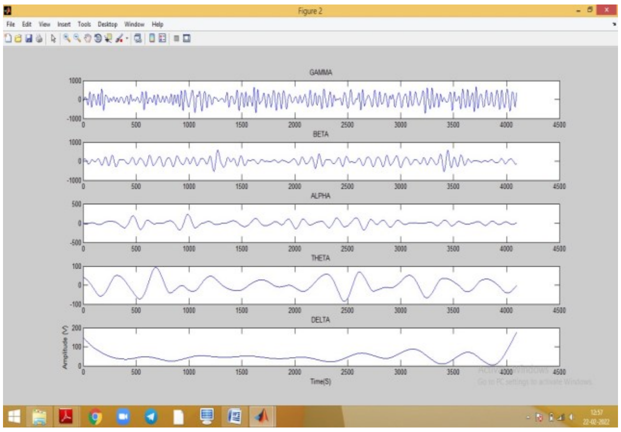

Fig 3: Obtained Frequency bands of subject S001

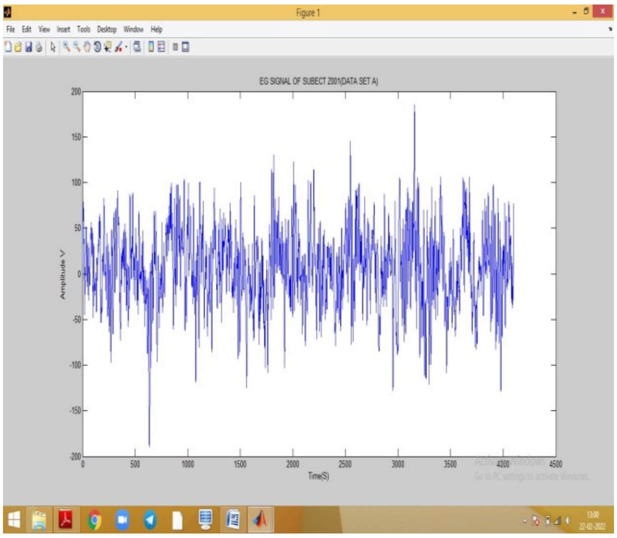

Fig 4: Input EEG signal of subject Z001

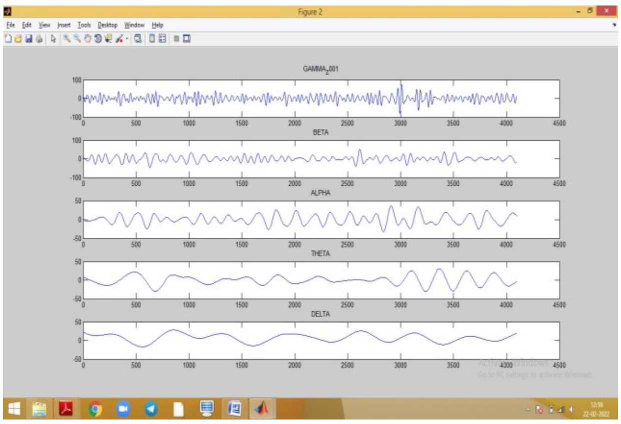

Fig 5: Frequency bands of subject Z001

In the subsequent step, the input EEG signal is decomposed into five distinct sub-signals, and statistical feature values such as Mean, Standard Deviation, Energy, Entropy, Relative Powers, and RMS are computed for each sub- band for both normal and epileptic signals. The features extracted from each sub-band of Datasets A and E are then fed into the classifiers. The performance of the classifiers in seizure detection is evaluated based on specificity, sensitivity, and accuracy, as defined in [19].

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} * 100 \qquad (6)$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}} * 100 \qquad (7)$$

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FN+TN+FP}} * 100 \qquad (8)$$

A sample of test data from SET A and SET E is presented in Table 4. This data illustrates the calculation of statistical parameters for SET A and SET E across six distinct parameters. The classification details of the test cases are outlined in Table 2, while Table 3 displays the performance analysis of the signals, evaluated using various classification models in terms of accuracy, specificity, and sensitivity.

Table 1: A summary of clinical data used

Settings	SET A	SET E
Subjects	5 healthy	5 epileptic
Type of Electrode	surface	Intracranial
Placement of Electrode	International 10-20 system	Epileptogenic zone
Subject condition	Awake, eyes open	Seizure (Ictal)
Number of epochs/ Epoch duration (s)	100 23.6	100 23.6

Table 2: Classification description of test cases.

Test case	Case of Seizure	Classification Description
Case1	SET A VS SETE	Healthy Persons with eye open vs Epileptic patients during seizure activity

Table 3: Assessment of Set A vs Set E Performance Using Various Machine Learning Methods

Method	% in Accuracy	% Specificity	% Sensitivity
KNN	98.5	99	100
SVM	99.5	100	100
NB	98.3	98	98

CONCLUSION

Epilepsy is a neurological disorder characterized by abnormal brain activity leading to seizures. Detecting seizures in EEG signals through visual inspection is challenging, particularly for long-duration recordings, as it can be time- consuming and prone to error. To address this, supervised machine learning techniques have been explored for EEG signal classification. In the proposed method, Discrete Wavelet Transform (DWT) is employed to analyze EEG signals by decomposing them into various sub-bands, extracting detailed and approximate wavelet coefficients. These features are then classified using models such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Naive Bayes (NB), with performance evaluated based on accuracy, sensitivity, and specificity. Among these, SVM demonstrated the highest classification accuracy, delivering more reliable and effective results compared to the other methods.

Table 4: Sample test data

Patient Number	Statistical Parameter	Delta band	Theta band	Alpha band	Beta band	Gamma band
Patient 1 S001	Mean	48.42	-0.832	-0.366	-0.165	0.106
	Standard deviation	24.42	34.49	64.54	156.93	260.06
	Energy	1.03E+08	4.87E+06	1.71E+07	1.01E+08	2.77E+08
	Relative Power	0.089	0.036	0.126	0.748	2.054
	Entropy	0.451	1.552	1.125	1.001	1.055
	RMS	54.24	34.505	64.539	156.909	260.031
Patient 2 S002	Mean	48.4	-0.829	-0.362	-0.167	0.108
	Standard deviation	24.42	34.49	64.54	156.93	260.06
	Energy	1.03E+08	4.87E+06	1.71E+07	1.01E+08	2.77E+08
	Relative Power	0.085	0.035	0.124	0.747	2.052
	Entropy	0.451	1.552	1.125	1.001	1.055
	RMS	54.239	34.503	64.537	156.913	260.035
Patient 1 Z001	Mean	48.44	-0.831	-0.368	-0.167	0.105
	Standard deviation	24.42	34.49	64.54	156.93	260.06
	Energy	1.03E+08	4.87E+06	1.71E+07	1.01E+08	2.77E+08
	Relative Power	0.09	0.037	0.128	0.749	2.057
	Entropy	0.451	1.552	1.125	1.001	1.055
	RMS	54.244	34.504	64.535	156.91	260.036
Patient 2 Z002	Mean	48.41	-0.838	-0.365	-0.168	0.107
	Standard deviation	24.42	34.49	64.54	156.93	260.06
	Energy	1.03E+08	4.87E+06	1.71E+07	1.01E+08	2.77E+08
	Relative Power	0.091	0.038	0.129	0.761	2.057
	Entropy	0.45	1.55	1.123	1	1.054
	RMS	54.241	34.499	64.532	156.91	260.033

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