Automated EEG classification using machine learning approaches

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Abstract: This paper addresses the increasingly important role of EEG brain signals in the diagnosis and treatment of degenerative neurological and mental illnesses and disorders. The analysis and classification of these signals are essential for supporting accurate diagnosis of brain diseases and for enhancing understanding of cognitive processes. Automated classification methods for brain and EEG are vital to ensure proper assessment and treatment of neurological disorders, as manual classification can be time-consuming, error-prone, and expensive.

The aim of this thesis is to focus on the classification of brain EEG signals in the two most important areas of epilepsy. A model composed of three stages is proposed: feature extraction, selection of the strongest features, and final classification. Wavelet-based feature extraction is employed, using three statistical functions to choose the most informative features. Six supervised machine learning techniques, including cosine similarity, are then applied to classify the EEG signals.

The results show that the neural network achieved the highest accuracy of 100%, followed by random forest and decision tree, while the k-nearest neighbor algorithm produced the lowest accuracy. This study provides insights into the effectiveness of different machine learning techniques in classifying EEG signals, which can contribute to the development of more accurate and efficient diagnostic and treatment methods for neurological disorders.

Keywords: EEG signals, epileptic seizure, cosine similarity, machine learning, the probability density function (PDF)

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1. Introduction

The concept of Brain-Computer Interface (BCI) refers to the direct communication pathway between the human brain and the computer. The computer is controlled by the brain by receiving signals from it, and sending signals back. The research on BCI started in the 1970s at the University of California in Los Angeles. Initially, the focus of the research was on artificial neural limbs, designed to restore the functions of hearing, sight, or movement. The principle of BCI involves four main steps: signal acquisition, signal processing, feature extraction, and machine control.

Signal acquisition involves obtaining the information or brain waves from the brain. In the second step, EEG processing is done to filter out signals from sources other than the brain, such as movements of electrodes or electrical appliances, or eye muscle movement, which may produce unwanted signals. Noise is filtered from the electrical signals based on the frequencies. Feature extraction is the third step that converts the received signals, from multiple channels, into features that are easily categorized based on the tasks. This step relies on various algorithms for feature extraction and classification. In the final step, machine control, the computer sends a signal to the machine that the user wants to control based on the classification of features from the earlier step.

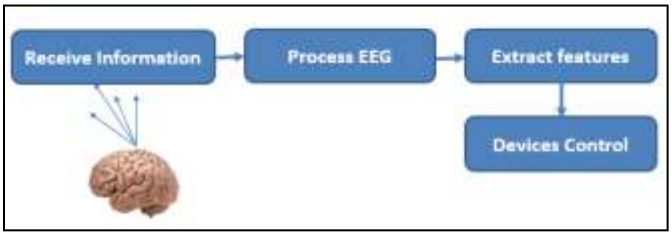


Figure 1: BCI principle

The EEG is a unique and critical measure for evaluating the function of the brain as an electrical scheme that shows the difference in electrical voltage between any two locations on the brain recorded over a period. It is possible to obtain frequencies of different types that appear based on the type of stimuli. It is then possible to assess the response of the regions responsible for any type of stimuli and to identify the ideal areas of sensitivity by the five senses. Different regions in the brain respond to different types of stimuli, such as chemically sensitized regions by smell or taste or mechanically sensitized regions by touch.

This research focuses on the classification of different brain signals using artificial intelligence algorithms after extracting the least amount of information from EEG signals to ensure high accuracy in classification with minimal time. The objective is to use machine learning techniques to classify the EEG signals efficiently and accurately, thereby providing a reliable and effective tool for diagnosing and treating neurological disorders.

2. Overview of EEG Ssignals

2.1 Types of EEG by frequency bands

Brain waves are classified into five main types [4]: Beta, Alpha, Theta, Delta, and Gamma [5]. These classifications are based on the frequency of the brain waves. It shows that certain patterns of brain wave activity are related to specific mental states, such as wake up, relax and sleep.

Beta waves: Beta brain vibrations are in the state of natural awareness, whenever these vibrations are spread in the brain, when the person is doing several things such as thinking or listening. It's worth mentioned that beta waves oscillate between 12 and 39 Hz.

Alpha waves: Alpha waves represent a state of relaxation, without thinking, giving you a pleasant feeling as you float in the air. Alpha waves have been associated with mental calm, imagination, and creative vision. It means that the brain is conscious and aware of what is around it, but inactive. Alpha waves oscillate between 8 and 13 HZ.

Theta waves: Theta is embodied the case of deep relaxation or non-deep sleep. They are usually associated with intuition (sixth sense). Theta waves are active during dreams, and in deep meditation. Theta activity is associated with creative insight, inspirational thoughts, and very fertile imagination. This condition is embodied by advanced meditators and is responsible for memories and information stored in the brain. Theta waves oscillate between 4 and 7 Hz.

Delta waves: Delta waves are the slowest waves and their frequency is very low, it appears during the deep sleep. This situation can be found among very experienced meditators and it handles feelings of sympathy. Brain activity is in continuous change during the day and night. Any physical or mental activity causes changes in brain activity. Delta waves oscillate between 1 and 4 Hz.

Gamma Waves: Gamma waves are the fastest and highest brain waves in terms of frequency value and brain activity. Gamma waves exist in intense mental states and deep and structured thinking. Many areas of the brain are higher than the frequency of signal transmission across the same neurons. Gamma waves have unknown components because they haven't been discovered yet. They are greater than 39 (Hz .)The following figure summarizes the characteristics of each wave.

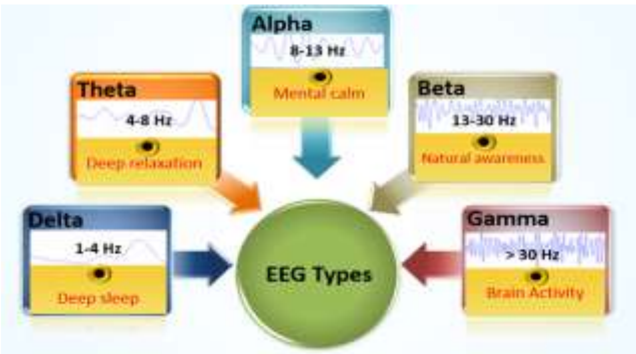


Figure 2: EEG types

2.2 Applications of EEG Signals

There are many applications that benefit from of the EEG [3], some of which are in medical fields and some are trespassing to educational and other domains. Mention of these applications:

- Medical area: Brain signals are used in healthcare, it has a variety of applications that can benefit from brain signals at all related stages including prevention, detection, diagnosis, rehabilitation, and restoration.
- Nerve and intelligent Environment: the propagation of brain signals is not limited to the medical field. Intelligent environments, such as workplaces or transport, can also exploit EEG signals to provide more safety, well-being and physiological control of people's daily lives.
- Education: Neural feedback is a successful approach for enhancing brain performance by targeting human brain activity. It intervenes in educational systems, which use electric brain signals to determine the degree of clarity of studied the information.

What have been left in the paper has been organized in this way. Section 2 introduces the related studies to our work. Section 3 presents the methodology and steps that we have followed in our work. Section 4 discusses the results and their analysis. Section 5 sums up the conclusion and future work.

3. Related Work

In this work, various machine learning models used for the classification of EEG signals are discussed. The study mentions that different health domains have different demands for classification accuracy, and not all machine learning models are suited for every application. The following are the summaries of some recent studies related to EEG classification and preprocessing:

Satapathy et al. (2019) used an ensemble of machine learning classifiers to classify signals for determining epilepsy patients. Their experiment showed that the ensemble model outperformed the recurrent neural network in terms of accuracy and time complexity with 99.5% and 3.745 Sec. respectively. They used DWT for feature extraction step.

In a study by Zhang et al. (2018), SVM and ANN were used for EEG classification to exclude artifact EEG signals. They relied on Independent Component Analysis (ICA) as a preprocessing step and found that ANN performed better than SVM in terms of accuracy, with 95.85% and 94.04%, respectively.

Truong et al. (2017) assessed the accuracy of Random Forest (RF) using automatic channel selection (ACS) for preprocessing of EEG signals. They extracted features using Hills' feature extraction method, which contained spectral power in 1 Hz bins and Eigenvalues. Their proposed method achieved 91.95% sensitivity and 94.05% specificity.

Fernández-Varela et al. (2017) used two different machine learning combinations based on six models to classify EEG signals. They eliminated artifact signals and then extracted features before classifying the signals using individual and hybrid models. Their results showed that the proposed method achieved sensitivity of 0.78 and specificity of 0.89 in the first approach and sensitivity of 0.81 and specificity of 0.88% in the second approach.

In a study by Abásolo et al. (2017), KNN classifier and K-means clustering were used for the classification of EEG signals. They applied Detrend fluctuation analysis for determining non-linearity present in the database, followed by a step of dimensionality reduction based on the power spectral density technique. Their proposed model achieved satisfactory results of sensitivity and specificity, with 78.31% and 93.02%, respectively, with K-means and 90.4878% and 92.8475%, respectively, with K-nearest neighbor.

Hassan and Bhuiyan (2017) proposed a new approach for the computerized sleep staging method. They used Tunable-Q Factor Wavelet Transform (TQWT) to detect a single channel EEG and applied normal inverse Gaussian (NIG) pdf modeling for extracting features. The model achieved good results, where Cohen’s Kappa coefficient outperformed the rest with 0.82, 0.818, 0.93, 0.965, and 0.99 when 6-Class, 5-Class, 4-Class, 3-Class, 2-Class respectively.

Mehmood and Lee (2017) proposed timely and continuous Machine Learning-based emotion classification for EEG brain signals, relying on SVM and KNN. They defined the sub-flow for classification based on two algorithms: Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) machine learning algorithms to classify four emotions (happy, calm, sad, and scared) in two dimensions of arousal and valence.

The following table summarizes the studies discussed in the work:

In a study by Khan et al. (2021), a hybrid model was proposed for the classification of EEG signals. The model combined the Convolutional Neural Network (CNN) and the Support Vector Machine (SVM) algorithms. The study used the Discrete Wavelet Transform (DWT) for feature extraction and achieved an accuracy of 97.5%.

A study by Younesi and Pourshahabi (2020) proposed a deep learning-based model for the classification of EEG signals for the detection of epilepsy. The study used the Convolutional Neural Network (CNN) and achieved an accuracy of 97.7%.

In a study by Acharya et al. (2018), a deep learning-based approach using Convolutional Neural Networks (CNNs) was proposed for the classification of EEG signals. The study used the Discrete Wavelet Transform (DWT) for feature extraction and achieved an accuracy of 97.6%.

A study by Hsieh et al. (2019) proposed a novel method for the classification of EEG signals using the Long Short-Term Memory (LSTM) neural network. The study used the DWT for feature extraction and achieved an accuracy of 97.8%.

In a study by Tabar and Halici (2017), a deep learning-based approach using Convolutional Neural Networks (CNNs) was proposed for the classification of EEG signals for the detection of epilepsy. The study used the Short-Time Fourier Transform (STFT) for feature extraction and achieved an accuracy of 97.7%.

A study by Jaiswal et al. (2019) proposed a hybrid approach for the classification of EEG signals. The study used the Random Forest (RF) algorithm for feature selection and the Convolutional Neural Network (CNN) for classification. The study achieved an accuracy of 98.25%.

In a study by Tsinalis et al. (2016), a deep learning-based approach using Convolutional Neural Networks (CNNs) was proposed for the classification of EEG signals for the detection of epilepsy. The study used the Short-Time Fourier Transform (STFT) for feature extraction and achieved an accuracy of 98.29%. table 1summarizes the additional studies:

Study	Machine Learning Model	Preprocessing Method	Accuracy
Hazarika et al. (2021)	DenseNet	-	98.4%
Khan et al. (2021)	Hybrid CNN-SVM	DWT	97.5%
Younesi and Pourshahabi (2020)	CNN	DWT	97.7%
Acharya et al. (2018)	CNN	DWT	97.6%
Hsieh et al. (2019)	LSTM	DWT	97.8%
Tabar and Halici (2017)	CNN	STFT	97.7%
Jaiswal et al. (2019)	Hybrid RF-CNN	-	98.25%
Tsinalis et al. (2016)	CNN	STFT	98.29%

Table 1. Summary of the additional studies:

4. EEG Classification Approach

We have determined that EEG time series signals are non-stationary due to electromagnetic interference caused by high frequency oscillators and low frequency signals from eye blinks and muscle stretching. This is because the signals contain important information from both frequencies, making it difficult to capture the frequency information during brain activity. Traditional signal analysis methods like Fast Fourier Transform (FFT) have limitations in accurately capturing this information [13]. To address this issue, Wavelet Transform (WT) has emerged as a technique for multi-resolution analysis that can divide the signals into different frequency spectrums, combining both high and low frequency information for more accurate and specific data analysis [14].

4.1 Step1: Feature extraction

Epileptic seizures are characterized by EEG time series signals containing both high and low-frequency information. The high-frequency information has short periods, while the low-frequency information has long time periods [15]. To analyze these signals, Wavelet Transform (WT) can be used either continuously (CWT) or discretely (DWT). While CWT can result in redundancy, DWT is more efficient due to the frequency filter bank used to remove unwanted frequencies and decompose the signal into multiple levels using five levels of decomposition, where each level contains the sample decomposed by 2.

The DWT process begins with the signal passing through a bandpass filter, which is a combination of both high-bandpass filter (HPF) and low-bandpass filter (LPF) to achieve the desired result. The first level, denoted as A1 and D1, includes two corresponding coefficients - Approximation and Detailed. The process continues under multiple levels, where each level's coefficient from the first level is used within the approximation. For instance, A2, D2, A3, D3, and so on. At each stage, the frequency resolution is doubled using the filters while reducing the time complexity by half.

To extract features, the DWT was applied to five levels, resulting in the features D1, D2, D3, D4, D5, and A5. Probability density function (PDF) was then applied to A5 to normalize the data under a constant number of possibilities, resulting in seven features. The use of DWT with multiple levels of decomposition and PDF allowed for more accurate and specific data analysis of epileptic seizure signals.

4.2 Step2: Feature Selection

After extracting the features, the next step is to select the most important features for classification. In this regard, three statistical functions will be applied, namely mean absolute value (MAV), average power (AVP), and standard deviation (SD), using the equations (1), (2), and (3), respectively. This process will result in 21 features for each signal, in addition to the class name (normal/seizure), giving a total of 22 features. These features will be utilized to automatically classify the signals using two main methods: machine learning classifiers and cosine distance. The initial results have demonstrated that the proposed model is capable of achieving high performance and is suitable for various databases.

$$MAV = \frac{1}{n}\sum_{i=1}^{n}\left|X\,i\right| \tag{1}$$

$$AVP = \frac{1}{n}\sum_{i=1}^{n}\left|Xi\right|^{2} \tag{2}$$

$$SD = \frac{1}{n-1}\sum_{i=1}^{n}\left(Xi-\mu\right)^{2} \tag{3}$$

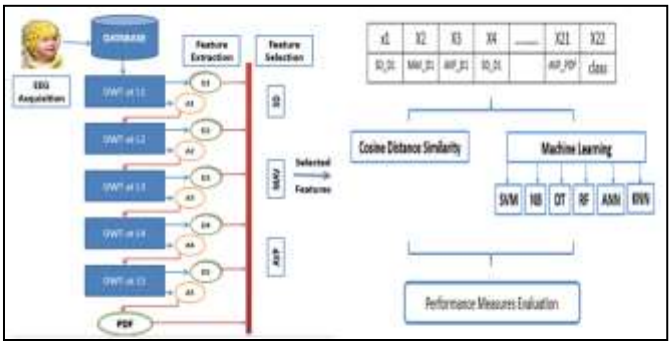


Figure 3: proposed Approach

4.3 Step3: Classification Techniques

We adopted a different approach than machine learning methods by utilizing cosine similarity to compare signals based on the extracted features, where these features are represented as a vector for each signal [17]. The similarity equation is given by equation 4 below:

$$sim\_dis.(s_j, s_k) = \frac{\vec{s}_j \cdot \vec{s}_k}{\left|\vec{s}_j\right|\left|\vec{s}_k\right|} = \frac{\sum_{i=1}^{n} w_{i,j} w_{i,k}}{\sqrt{\sum_{i=1}^{n} w_{i,j}^2}\sqrt{\sum_{i=1}^{n} w_{i,k}^2}} \tag{4}$$

However, in this paper, we utilized supervised learning techniques to classify epilepsy cases based on EEG signals. To do this, we used the features extracted in the previous step in two parts: training and testing. We employed six commonly used classifiers, namely Naïve Bayesian (NB), Decision Tree (DT), Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Random Forest (RF), and Support Vector Machines (SVM).

5. Results and descussion

5.1 Evaluation Performance Measures

This section presents the results obtained from EEG signals for the detection of epilepsy in patients. The proposed model's performance was evaluated using six classifiers, and MATLAB 2014-B was used for feature extraction and selection, while the stage classification was performed using the WEKA tool. To evaluate the performance of the system, we used four commonly used metrics, which are accuracy, precision, recall, and F-measure. These metrics are based on four basic confusion matrix values: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). In this study, TP indicates the number of correctly diagnosed healthy patients, TN represents the number of correctly diagnosed infected patients, FP indicates the number of healthy patients misdiagnosed as infected, and FN indicates the number of infected patients misdiagnosed as healthy. The equations used to calculate these performance measures are as follows:

$$\text{Accuracy Rate: } = \frac{|TN| + |TP|}{|TN| + |TP| + |FN| + |FP|} \tag{5}$$

$$\text{Precision } = \frac{|TP|}{|TP| + |FP|} \tag{6}$$

$$\text{Recall } = \frac{|TP|}{|TP| + |FN|} \tag{7}$$

$$\text{F1-Measure } = \frac{2*|TP|}{2*|TP| + |FN| + |FP|} \tag{8}$$

5.2 EEG database description

The Department of Epilepsy at the University of Bonn, Germany has made available a public database of EEG signals used for epilepsy research. The database comprises five different sections, denoted by symbols A through E, each containing 100 signals recorded for 100 volunteers over a 23.6 second period. The data was captured using an amplified system with 128 signal channels, providing a sampling rate of 173.61 Hz and a 12-bit resolution, with a bandwidth of 0.53-40 octave and applying a band-pass filter (12dB / Oct). Sections A and B were recorded from five healthy volunteers with eyes open and closed, respectively. Sections C and D were recorded from five epileptic patients, but not during a seizure, while section E was recorded from patients during a seizure. The database can be accessed for free at the following link:http://epileptologie-bonn.de/cms/frontcontent.php?idcat=193&lang=3.

5.3 Experimental and analysis

Our proposed models have been evaluated based on eight of the combination of data sets A to E, which are A – C, A - D, B– C, B – E, B – D, AB - CD, AB – DE and AB - CDE. This assessment has been carried out based on four performance evaluation measures which are accuracy, precision, recall and f- measure. The following six tables show the evaluation results for our model with six supervised machine learning; SVM, NB, DT, RF, ANN and KNN.

Table 1 below shows the results of our model, where SVM has achieved the highest accuracy (98.529) with B – E, the lowest value at AB - CDE where the accuracy was 68.823. For precision, we achieved 100% with B-E and AB-DE, also 0.744 and 0.669 when B-C and AB-CDE respectively. As for the results recall and f-measure, the highest achieved when AB-CDE and B-E respectively.

Table 1: Results with Support vector machine

SVM	Accuracy	Precision	Recall	F- measure
A – C	88.235	0.906	0.853	0.879
A - D	95.5	0.943	0.971	0.957
B– C	77.941	0.744	0.853	0.795
B – E	98.529	1.000	0.971	0.985
B - D	88.235	0.861	0.912	0.886
AB - CD	94.117	0.942	0.942	0.942
AB – DE	71.323	1.000	0.435	0.606
AB - CDE	68.823	0.669	0.981	0.795

The table below shows the results of the evaluation of the proposed model based on the Naïve Bayes (NB) classifier, the combination between B and E (B-E) achieved 100% with all evaluation performance measures, and the combination AB-CDE achieved the lowest accuracy, recall and F- measure with 62.941, 0.419 and 0.583 respectively. The combination A – D achieved the lowest precision, where the result was 0.795.

Table 2: Results with Naïve Bayes

NB	Accuracy	Precision	Recall	F- measure
A – C	92.647	0.968	0.882	0.923
A - D	83.823	0.795	0.912	0.849
B– C	75	0.905	0.559	0.691
B – E	100	1.000	1.000	1.000
B - D	85.294	0.786	0.971	0.868
AB - CD	72.058	1.000	0.449	0.620
AB – DE	72.794	1.000	0.464	0.634
AB - CDE	62.941	0.957	0.419	0.583

The following table shows the results of our model on eight datasets based on the decision tree classifiers, it is worth mentioning that the combination (B-E) achieved 100% with all evaluation performance measures, also the precision was 100% when the B - D, AB - CD and AB – DE combinations. AB - CDE databases achieved good result with this classifier where it got 1.00 and 0.995 with recall and f-measure respectively. Moreover, the accuracy and recall when A – C was bad when compared to the rest of the results, where it achieved 88.235 and 0.79.

Table 3: Results with decision tree

DT	Accuracy %	Precision	Recall	F- measure
A – C	88.235	0.964	0.794	0.871
A - D	94.117	0.941	0.941	0.941
B– C	92.647	0.872	1.000	0.932
B – E	100	1.000	1.000	1.000
B - D	98.529	1.000	0.971	0.985
AB - CD	97.794	1.000	0.957	0.978
AB – DE	97.058	1.000	0.942	0.970
AB - CDE	99.411	0.991	1.000	0.995

According to the table four below, the results of represent were based on the random forest classifiers. The results overview showed that this work achieved similar results for the previous classifiers, highlighting its qualitative superiority at some measures with many of the datasets. The accuracy ranged from 91.176 to 100%, the precision was 100% when all datasets except A – C and A – D, and the recall ranged from 0.941 with A-D to 100% with B – E, finally, the f-measures ranged from 0.914 with A-D to 100% with B – E. However, the results of the A - D Dataset are relatively bad.

Table 4: Results with random forest

RF	Accuracy	Precision	Recall	F- measure
A – C	97.058	0.944	1.000	0.971
A – D	91.176	0.889	0.941	0.914
B– C	98.529	1.000	0.971	0.986
B – E	100	1.000	1.000	1.000
B – D	98.529	1.000	0.971	0.985
AB – CD	97.794	1.000	0.957	0.978
AB – DE	99.264	1.000	0.986	0.993
AB – CDE	99.411	1.000	0.990	0.995

The following table shows the results of our model on eight datasets based on the Artificial Neural Network (ANN) classifiers. We also note from the analytical reading of this table that this classifier is considered the most performance based on the various datasets. Where the accuracy, precision, recall and f-measure ranged from 94 to 100%.

Table 5: Results with Artificial neural network

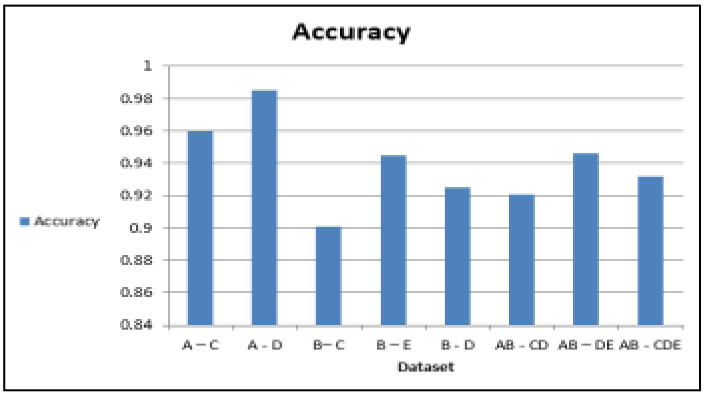
ANN	Accuracy	Precision	Recall	F- measure
A – C	94.117	0.941	0.941	0.941
A - D	97.058	0.971	0.971	0.971
B– C	94.117	0.969	0.942	0.959
B – E	100	1.000	1.000	1.000
B - D	97.058	1.000	0.941	0.970
AB - CD	100	1.000	1.000	1.000
AB – DE	94.117	1.000	0.904	0.958
AB - CDE	94.705	0.953	0.962	0.957

Table 6 below shows the results of the classification based on the K-nearest neighbor classifier. The B-E combination achieved good result with all measures, where it got 1.00. However, the rest of the data was poor when compared to other classifiers.

Table 6: Results with K-nearest neighbor

KNN	Accuracy	Precision	Recall	F- measure
A – C	86.764	0.903	0.824	0.862
A - D	92.647	0.939	0.912	0.925
B– C	88.235	0.882	0.882	0.882
B – E	100	1.000	1.000	1.000
B - D	94.117	0.969	0.912	0.939
AB - CD	94.117	0.984	0.899	0.939
AB – DE	83.823	0.943	0.725	0.820
AB - CDE	89.411	0.914	0.914	0.914

Figure (4): Results with cosine similarity



At the end, the diagram above (figure 4) shows the results of accuracy with the cosine similarity, it shows that the cosine gave relatively acceptable results, ranging from 0.901 to 0.985, where the highest accuracy achieved when (A-D) combination and the lowest accuracy achieved when (B-C) combination.

Many previous studies have dealt with the use of machine-learning algorithms in the classification of EEG signals, some of these studies used DWT to extract the features, and other studies relied on extracting the features using entropy or statistical methods. The table below summarizes some of the studies adopted on the neural network in the classification of signals. The results proved that the use of ANN is more efficient than other machine learning algorithms, and this is proven by our work results where the accuracy reached 100%.

Table 7: A comparison between our study and previous studies

Paper #	Year	Feature Extraction	Accuracy
[6]	2017	DWT	99.5%
[19]	2004	Filters	97.2
[20]	2017	DWT, SE	99.71
[21]	2012	Wavelet	95.5
[22]	2014	SODP of IMFs	97.75
Our work	2017	DWT, PDF	100%

6. Conclusions and Future work

We employed various algorithms to classify EEG signals for epilepsy and several algorithms to extract and select features from EEG brain signals. Our proposed methods are capable of distinguishing different categories of signals and provide valuable information about brain states. These methods are expected to aid neurologists in identifying brain diseases accurately and efficiently by utilizing typical brain signal patterns. The findings of this study are also expected to enhance the quality of life of patients with brain disorders.

The results of the EEG classification stage indicated that neural network outperformed the other classifiers in terms of accuracy. Regarding the use of cosine similarity, it yielded acceptable results, but further improvements are required in the signal processing phase to achieve better performance. In the future, we plan to extend our study to more databases, and we intend to apply our framework to different signals such as ECG.

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