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Investigate Schizophrenia Classification Based on EEG Electrode Reduction Using Machine Learning Techniques

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ABSTRACT

Schizophrenia is a mental disorder condition that causes patients to become distracted from reality. Over time, the patient loses his cognitive and social abilities to communicate with the outside world. Due to machine learning's strong ability to analyze complicated brain data, it has become an increasingly important tool in recent years. This study considers the brain's neurologic signals in the resting state in two scenarios to classify schizophrenia disease by electroencephalography (EEG). The performed scenarios were to investigate the impact of selecting electrodes randomly (5 electrodes and 8 electrodes) and comparing it with applying the principal component analysis (PCA), utilizing four algorithms to extract features: Fast Fourier Transform (FFT), Approximate Entropy (ApEn), Log Energy Entropy (LogEn), and Shannon Entropy (ShnEn). We used publicly available datasets with 19 EEG channels consisting of two classes, which are schizophrenia and health control, using a one-second epoch window size. We applied a band-pass filter to decompose the EEG signals into five sub-bands. Also, the L2-normalization method has been applied to the derived features, which positively impacted the outcomes. The features were applied to three classifiers named K-nearest neighbor (KNN), support vector machine (SVM), and quadratic discriminant analysis (QDA). From all the scenarios, the five-electrode with random selection showed remarkable results of 99% using the SVM classifier in all evaluation metrics with LogEn+ Bandpass features.

1. INTRODUCTION

The human nervous system is the main system that determines lifestyle and general behaviour, including decisions and emotional control. The brain may be exposed to various accidents or diseases that lead to abnormalities in the brain's neural structure. The severity of the abnormalities varies depending on many factors, such as the patient's age, the family's medical history, or the brain injury's location, which leads to multiple differences occurring between one patient and another in the behaviour and diagnoses. Neurological diseases that affect the neural cells, for instance, epilepsy, schizophrenia (SZ), Parkinson's, and Alzheimer's, effect different locations of the brain and have a specific effect on brain function that is discovered and diagnosed through symptoms, tests, and using different tools. One of the worst diseases that may completely destroy the neural system in the brain is schizophrenia.

Delusions, hallucinations, depression, and anxiety are just a few of the symptoms that come along with schizophrenia, which causes a severe behavioral change in character [1]. These symptoms can be clearly seen and distinguished between the ages of 16 and 30 and can be utilized to determine the patient's state, where timely detection is a crucial part of the patient's healing process [2, 3]. Besides, according to the official data of the World Health Organization, there are around 21 million patients, which is around 1% of people worldwide who are afflicted with this illness [4]. The traditional process of diagnosing schizophrenia is considered a complex process, according to some factors such as the psychiatrists' experience and the different case responses between one patient and another.

Indeed, the neuroimaging techniques field provided help in discovering various brain disorders like schizophrenia, which is considered a time-consuming process, encouraging scientific researchers to accomplish new medical aims.

Electroencephalography (EEG) devices have made tremendous strides in the diagnosis of nervous system disorders in recent years, including epilepsy [5], Alzheimer's disease [6-9], and schizophrenia [10, 11]. The non-invasive nature of EEG has led to its adoption as the ideal tool for recording and collecting the electrical activity of the brain, which in turn provides brain dimensions that contain huge amounts of data, which gives the capability to diagnose different brain diseases. Meanwhile, deep learning and machine learning (ML) are the most important methods in the medical domain that offer advanced processing and evaluation of diverse medical datasets, including brain signals [12].

ML used the feature extraction approach to retrieve the hidden information of signals from the data, where these features provide the possibility of obtaining clearer signals and identifying and measuring the most relevant data, which will be used with the frequency domain or the time domain [13, 14].

Many studies have addressed the subject of classifying schizophrenia based on EEG and analyzing the brain signals captured using the global 10-20 electrode system. The analysis of the relationship between these electrodes represents the nature of neural communication in the brain, which in turn leads to the detection of a person's mental health. According to the brain regions and the different functions and channels associated with them, the features in each channel of EEG are analyzed and extracted separately, and these features are subsequently linked and then classified.

Consequently, this study investigates the feasibility and importance of electrodes through the model's ability to classify schizophrenia without compromising classification accuracy by reducing electrodes and selecting electrodes randomly.

This approach supports the ability of electrodes for non-sophisticated devices as well as for devices with few electrodes, such as Emotiv Insights (5 channels), Muse EEG (4-6 channels), Neurosky Mindwave (1 channel), and InteraXon Muse S (4 channels). Clinically, random electrode reduction offers advantages by mitigating bias related to electrode type and placement. Furthermore, the proposed methodology simplifies traditionally employed techniques.

The manuscript is written in the following format: related work in Section 2, which included a comparison with the literature that has classified schizophrenia using different datasets and techniques. In Section 3, we illustrated the materials and methods: Firstly, we described the EEG dataset; secondly, we mentioned the preprocessing methods used; thirdly, we summarized the techniques of feature extraction; and finally, the normalization techniques applied to the dataset. In Section 4, we explained the classification through the description of machine learning classifiers; then in Section 5, we presented and discussed the results, and finally, the conclusion is clarified in Section 6.

2. RELATED WORK

Researchers in the last era increased their work that aimed to classify schizophrenia disorder utilizing a variety of methods, including MRI [15], eye tracking [16], facial features [17, 18], tracking handwriting [19], and schizophrenia EEG signal [20]. Various studies have been done on the use of several characteristics in machine learning to classify EEG data for the diagnosis of schizophrenia. They employed several ML models and achieved differing degrees of accuracy. Depending on the topic and the data utilized for classification, popular machine learning models in these investigations include SVM, RF, and Artificial Neural Networks (ANNs), with accuracy varying from 70% to over 90% [21].

One of these published papers that aimed to classify schizophrenia was done by Krishnan et al. [20], using datasets obtained from the Repository for Open Data (RepOD) with two classes: schizophrenia patients and healthy controls with 28 subjects. The EEG signals were recorded for 15 minutes, using 19 channels. The highest result achieved was by the SVM with Radial Basis Function, with an accuracy of up to 93%. Siuly et al. [22] used an EEG dataset including two groups: patients diagnosed with schizophrenia and healthy controls.

The signals underwent empirical mode decomposition, and the most significant features were then selected using the Kruskal-Wallis test. The SVM was then provided with all the attributes for classification. The highest percentage achieved was 93.21%. De Miras et al. [23] evaluated if machine learning methods may be helpful in the diagnosis of the condition. Additionally, they have created a pipeline for processing. Support vector machines (SVM), k-nearest neighbors (KNN), logistic regression (LR), decision trees (DT), and random forest (RF), were the five machine-learning techniques that they examined. SVM yielded the greatest results 89%.

Hartini and Rustam [24] proposed fuzzy kernel c-means using data from Northwestern University, including 171 schizophrenia and 221 non-schizophrenia samples. Using RBF and polynomial kernel functions, k-fold cross-validation was used for evaluation. Results showed that the RBF kernel with σ=0.01 and σ=1 performed better than the polynomial kernel with similar running time. Furthermore, among the five classification strategies employed by Khare et al. [25]-including SVM, KNN, DA, ensemble methods, and decision trees — SVM achieved the highest accuracy of 88%. They divide nonstationary EEG signals into Fourier spectrum modes, pull out linear and nonlinear time domain features, and use the Kruskal-Wallis test to choose highly discriminant features. This helps them put people into two groups: healthy and those with schizophrenia.

Hassan et al. [26] used a publicly available EEG signals dataset from Warsaw's Institute of Psychiatry and Neurology to automate the identification of schizophrenia using a channel selection mechanism based on a rigorous performance analysis of the Convolutional Neural Network. They used CNN in conjunction with other ML classifiers to train the classification model. Their highest findings reveal that LR and CNN yield 98% accuracy. Supakar et al. [27] proposed a DL model using RNN-LSTM to analyze the EEG signal data to diagnose schizophrenia. EEG signal data of 45 SZ patients and 39 healthy subjects. They had two scenarios: a complete feature set and a reduced feature set, which achieved an accuracy of 98% and 93%, respectively.

Moreover, Li et al. [28] introduced an innovative EEG data mapping technique using Vision Transformer (LeViT) as both a feature extractor and classifier for the early detection of schizophrenia. Their data was private, and they achieved 98%.

Table 1 presents and compares studies using various datasets, when all channels are used, with different techniques to classify EEG signals with SZ and healthy controls.

Previous studies have explored the researchers' utilization of various methods to categorize schizophrenia disorder and various datasets, and the outcomes were inconsistent and fell short of expectations. As a result, we examine and compare the possibility of improving the diagnostic precision of schizophrenia by using an electrode reduction technique with PCA as a traditional technique.

Table 1. Classifying schizophrenia utilizing various datasets

Ref.	Chan.	Dataset		Methods	Acc%	Spe%	Sen%
		SZ	Free				
[29]	64	49	32	RF	81	NA	NA
[30]	16	37M, 10F	14M, 11F	SVM	90	91	89
[31]	NA	31M, 19F	32M, 18F	non-linear SVM	73	56	62
[32]	16	39	45	MDC-CNN	93	93	93
[33]	8	48	24	RF	68	NA	NA
[34]	256	33M, 37F	47M, 28F	SVM	82	81	82

Note: M refers to male and F refers to female, chan. refers to channel

Table 1. Classifying schizophrenia utilizing various datasets (continue)

Ref.	Chan.	Dataset SZ	Dataset Free	Methods	Acc%	Spe%	Sen%
[35]	64	36M, 18F	3 M, 24F	Hybrid DNN	99	NA	NA
[36]	10	49	32	KNN	99	90	95
[37]	64	49	32	CNN	92	NA	NA
[38]	20	37M, 25F	38M, 32F	KNN	96	98	95
[39]	NA	158	76	Ensemble	87	65	98
[40]	64	41M, 8F	67M, 14F	HDSS	92	91	97
[2]	16	39	45	CNN	98	NA	NA
[41]	64	13	11	SVM	89	90	88
[42]	32	310	205	XGB	94	NA	NA
[43]	16	39	45	AdaBoost	99	100	98
[44]	64	49	32	DT	99	95	95
[23]	31	9M, 20F	13M, 7F	SVM	89	90	63
[45]	32	215M, 97F	176M, 144F	RBF	93	NA	NA
[46]	19	626	516	KNN	97	NA	NA
[47]	16	39	45	CNN	99	99	100
[48]	64	36	22	CNN	98	98	98

Note: M refers to male and F refers to female, chan. refers to channel

3. MATERIALS AND METHODS

3.1 Dataset

The EEG dataset used was accessible to the public [49]. Table 2 presents the details of the total signal used containing 28 subjects, 14 from each group: schizophrenia and healthy controls. The sampling frequency of the EEG dataset recording is 250Hz. The montage was executed with a conventional 10-20 system. Moreover, the dataset was assembled utilizing the subsequent 19 EEG channels: Fp1, Fp2, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2 [50].

Table 2. The used datasets details

Features		Values
SZ	♂	7
	♀	7
HC	♂	7
	♀	7
Mean age (SZ)		28.1±3.7 years
Mean age (HC)		27.75±3.15 years
SZ	Mean age (♂)	27.9±3.3 years
	Mean age (♀)	28.3±4.1 years
HC	Mean age (♂)	26.8±2.9 years
	Mean age (♀)	28.7±3.4 years
EEG segment		15min
No. of segments		21702
No. of segments without artefacts		30

3.2 Preprocessing

Preprocessing is a crucial step in ML due to EEG signals often containing a combination of noise resulting from several different factors, which in turn affects classification accuracy. There are several ways to reduce the noise and improve the EEG signals, for instance, by applying filters to enhance the signal quality.

Thus, the bandpass filter was utilized to decompose the EEG data into five frequency sub-bands: beta rhythm (31-31Hz), alpha rhythm (10-14Hz), theta rhythm (5-9Hz), delta rhythm (0.1-4Hz), and gamma rhythm (32-100Hz).

The bandpass filter works on filtering out very high or low frequencies, as presented in Figure 1 with the 19 channels of the EEG signal after the band-pass filter was applied.

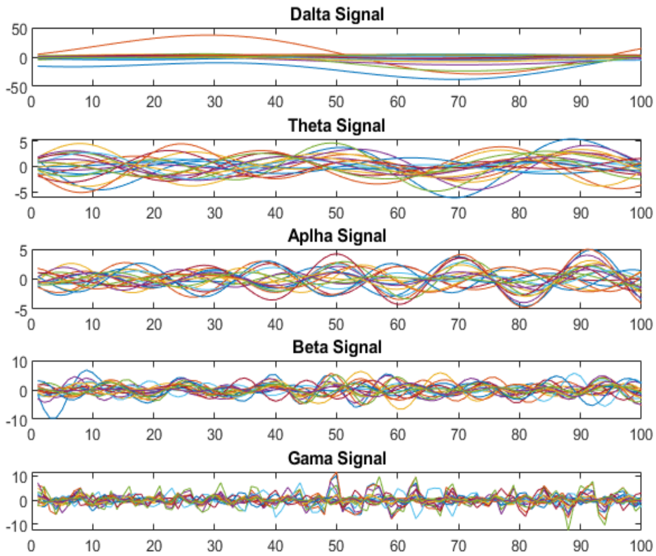

Figure 1. The impact of band-pass filtering on EEG signals

The brain's electrical activity generates billions of signals, so a multitude of electrodes are used to record these signals; adding more electrodes has a positive impact on the classification outcomes. It is important to note that there is no defined minimum or maximum number of electrodes, rules, or specific standards that should be used, as this varies depending on the kind of disorder being dealt with.

Hence, we examined our proposed models by the two electrode scenarios (8 and 5 electrodes); the electrodes were selected randomly to assess the suggested approach and determine whether or not it might yield encouraging outcomes. Additionally, we evaluated the computational efficiency of the classifier's final output, as well as estimated the training and speed time.

3.3 Feature extraction techniques

Different feature extraction techniques have been put out in the literature, such as entropy, approximate entropy, Shannon entropy, fuzzy entropy, fast Fourier transform, etc. Each one of these methods has a special mechanism for obtaining the feature from the signal. We identified the most commonly used methods with brain signals that helped identify subtle abnormalities associated with schizophrenia and combined these methods with our proposed approach to evaluate their effectiveness with varying constraints.

In this study, four extraction methods were calculated to extract the hidden features as presented in the following equations: Eq. (1) represents the mathematical formulation of Fast Fourier Transform (FFT), approximate entropy (ApEn) as shown in Eq. (2), log energy entropy (LogEn) by Eq. (3), and Shannon entropy (ShEn) as shown in Eq. (4).

FFT, LogEn, and ShEn were implemented with the band-pass filter; ApEn was applied in both cases with and without the band-pass filter. We selected these four techniques due to their established applications in EEG research and their accurate dealing with brain signals, which are explained in the following paragraphs.

FFT is one of the most important algorithms developed of all time, and the real reason for depending on FFT is its quick and effective method of denoising data. The FFT features have been implemented on the SZ EEG signals to convert the time domain to the frequency domain. Thus, it allows one to see the most prominent frequencies in the EEG signal and identify abnormalities or patterns that may appear in the brain wave frequencies [51].

$$X(K) = \sum_{n=0}^{N-1} X[n] W_N^{kn} = \sum_{n\ even} x(n) n w_N^{kn} + \sum_{n\ odd} x(n) w_N^{kn} \qquad (1)$$
$$K = 0,1 \dots\dots, N-1,$$

$$ApEn(E, r, N) = \frac{1}{(N-e+1)} \sum_{i-1}^{N-e+1} \log\ C_i^e\,(r) - \frac{1}{N-e} \sum_{i=1}^{N-e} log\ C_i^{e+1}\,(r) \qquad (2)$$

$$\text{ShEn}=\frac{HSh}{og\ k} \qquad (3)$$

$$\text{E}=\sum\nolimits_n log\left(w_{i,j}^{n2}\right) \qquad (4)$$

Entropy is the most frequently used feature to measure time-domain features. It is also widely used in disease detection by capturing any slight or subtle change in the brain signal, which assists when dealing with small data sizes. ApEn is defined as a measurement of the regularity or randomness of data in a time series and is used for short-length data due to its lower sensitivity to noise.

ShnEn is a time-domain complexity metric that does not rely on the signal spectrum and is similar to ApEn functionality. Since entropy may be used to ascertain the degree of randomness in the information, it is employed as the feature approach for schizophrenia due to ShEn decreasing with decreased neural complexity [52].

In signal processing, a common measure called LogEn, is used to extract relevant information. Since the frequency bands specific to schizophrenia have been identified, these bands can provide insights into the underlying neural systems. All these feature extraction methods are computed using a MATLAB routine.

3.4 Normalization

In general, normalization is the most common technique that deals with data in linear transformations. Its role is to rescale numerical features to a standard range to avoid larger values that may affect and bias the machine learning results. Although applying any normalization method is easy to implement, each method has strengths and weaknesses. Selecting the appropriate normalization method depends on some factors, such as the data and what is required from machine learning to obtain optimal results. In our work, we used L2 normalization to increase and enhance our accuracy results.

4. CLASSIFICATION

We used three machine learning (ML) classifiers, namely SVM, KNN, and QDA, together to classify the features computed by four different methods from the EEG signal using two scenarios for identifying a patient with schizophrenia (SZ). The main goal of our research is to achieve the highest possible accuracy regardless of the number and the location of the electrodes concerning different brain regions and prove that all channels are not necessary to achieve satisfactory results. Therefore, we implemented the 5 electrodes and 8 electrodes first by random selection, and then we implemented a traditional method, which is the PCA, as shown in Figure 2.

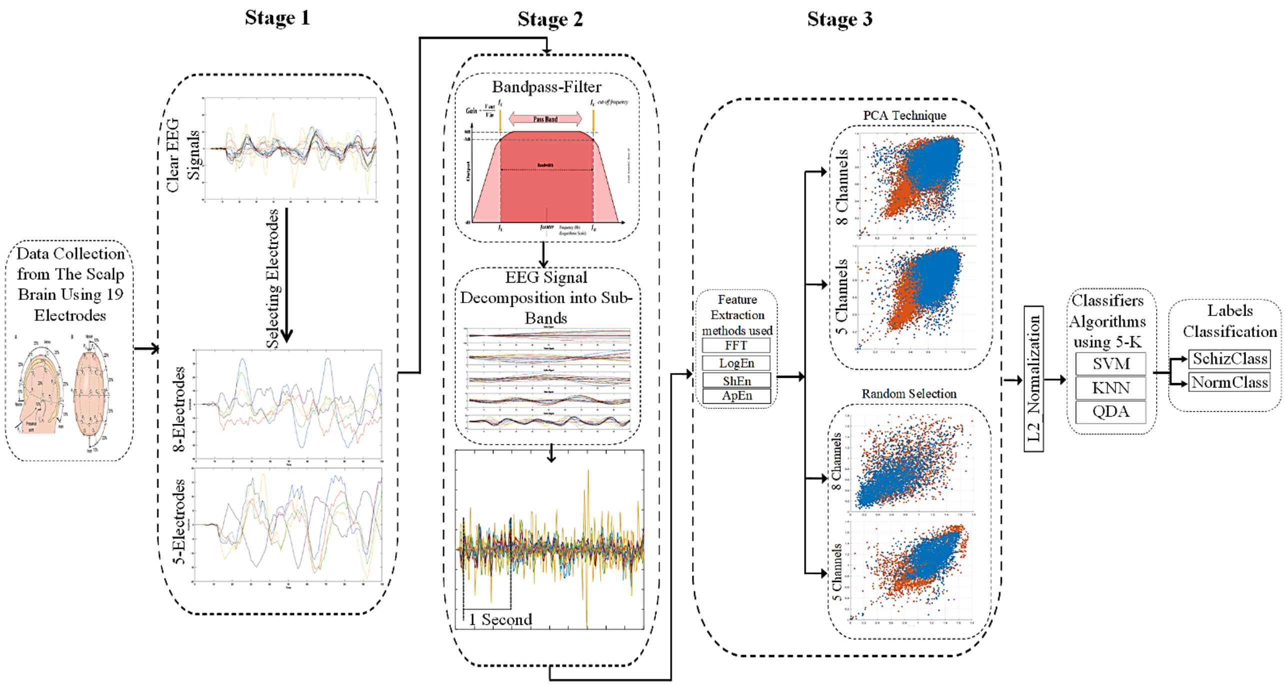

Figure 2. EEG signal data classification for schizophrenia with two classes: Healthy control and schizophrenia

4.1 SVM

In the field of machine learning, SVM is a popular choice for dealing with and processing various problems, most notably classification, as the strength of this approach lies in maximizing the margin separating the different classes, which leads to obtaining ideal accuracy in classification regardless of the type of data being dealt with. To lower classification error, certain unnecessary data are eliminated from the training data set at the ultra-optimal level, which affects the class borders. Multiple kernel tricks, such as polynomial, Gaussian, radial basis function (RBF), Laplace RBF, sigmoid, and Anove RBF, are used in SVM, making it a versatile tool.

4.2 K-nearest neighbors (KNN)

KNN is a non-parametric classification technique that finds the classifier's nearest neighbors by performing a distance check. Distance is calculated using the Euclidean Distance equation. During the training phase, the classifier check calculates the distance between the specific and the other data to categorize it. It gives it a unique label denoting its class, and KNN applies this to all of the data until all of the data is.

4.3 Quadratic discriminant analysis (QDA)

A machine learning and statistical classification classifier called QDA uses quadric surfaces to categorize two or more classes of disparate kinds of data. Compared to a linear classifier, this version is more suited. For every class, QDA specifically uses a Gaussian distribution.

5. RESULTS AND DISCUSSION

By using the public database [49], we explore how bandwidth filtering and electrode reduction affect our ability to find schizophrenia-related EEG signals. We selected electrodes randomly, unlike previous studies that focused on identifying brain regions and selecting effective electrodes, which introduced monotony into the work and repeated the results. Most current studies now use all channels to obtain the highest possible classification accuracy to achieve the best computational efficiency in less time, which is often not the case when the electrodes are reduced. Therefore, our study investigates the effect of minimizing the data channel numbers in two different scenarios to achieve comparable results to studies that used all data channels.

Random channel selection is computationally inexpensive when compared to the traditional method (algorithms used that have the ability to rank channels or feature importance analysis), which is considered computationally expensive and helps to influence without prior knowledge of which are the most important channels.

Our experiments were based on 14 subjects for SZ and 14 subjects for healthy, so to maximize the data, we used one epoch window size for our two scenarios.

We examined the efficacy of four feature extraction methods: FFT, ApEn, LogEn, and ShnEn. Among the features, ApEn was applied twice: with and without the band-pass filter on the data. Then, the data was standardized using the L2-normalization approach and fed to three ML classifiers: SVM, KNN, and QDA. The original signals were recorded with 19 channels and a 250Hz frequency.

5.1 Experiment I: EEG classification based on five randomly selected electrodes

The brain's electrical activity generates billions of signals, so a multitude of electrodes are used to record these signals, and using more electrodes has a favourable impact on the classification outcomes. It is important to note that there is no defined minimum or maximum number of electrodes that should be used, as this varies depending on the kind of disorder being dealt with. As a result, there is no guideline, rule or specific standard for this. Therefore, we first tested the proposed models to evaluate our approach by reducing the number of electrodes to five, as the goal of choosing this number was to determine whether or not it could lead to encouraging results using a very limited electrode setup. And demonstrate the ability of the approach to extract and obtain information contained in a small set of EEG channels.

Classification was performed using the SVM, KNN, and QDA algorithms on the five electrodes for each class; the obtained confusion matrix values for the three classifiers are presented in Table 3, and the performance values are listed in Table 4.

Based on Table 4, the results show that when randomly selecting five electrodes, EEG signal classification with KNN with implementing LogEn outperformed the other two classifiers with results of 98%, 98%, and 99% for accuracy, sensitivity, and specificity, respectively.

Table 3. The confusion matrix obtained by the three classifiers with random 5-electrodes

Feature Name	**Classes Name**		**SVM**	
			Predicted Class	
FFT+Bandpass	**Actual class**	Sch	1042	13703
		Healthy	12160	869
ApEn		Sch	4337	11496
		Healthy	10225	2804
ApEn+Bandpass		Sch	5093	10740
		Healthy	11247	1782
ShnEn+Bandpass		Sch	7176	8657
		Healthy	13181	963
LogEn+Bandpass		Sch	166	15666
		Healthy	12856	174
Feature Name	**Classes Name**		**KNN**	
			Predicted Class	
FFT+ Bandpass	**Actual Class**	Sch	1402	13343
		Healthy	12184	845
ApEn		Sch	4095	11738
		Healthy	9782	3247
ApEn+Bandpass		Sch	8401	7432
		Healthy	12411	588
ShnEn+Bandpass		Sch	1297	14536
		Healthy	13312	832
LogEn+Bandpass		Sch	196	15636
		Healthy	12872	158
Feature Name	**Classes Name**		**QDA**	
			Predicted Class	
FFT+ Bandpass	**Actual Class**	Sch	3580	11165
		Healthy	11804	1225
ApEn		Sch	7047	8786
		Healthy	10691	2338
ApEn+Bandpass		Sch	8072	7761
		Healthy	12667	362
ShnEn+Bandpass		Sch	9355	6478
		Healthy	11342	2802
LogEn+Bandpass		Sch	1910	13922
		Healthy	12781	249

Table 4. Classification performance results utilizing five random electrodes

Filter Condition	Classifiers	Feature Extraction Methods	Evaluation Metrics		
			Acc	Sen	Spe
With Bandpass	SVM	FFT	93	92	94
	KNN		91	89	94
	QDA		82	76	90
	SVM	ApEn	76	68	85
	KNN		68	59	92
	QDA		70	61	95
	SVM	ShEn	72	64	89
	KNN		92	91	94
	QDA		59	54	69
	SVM	LogEn	98	98	98
	KNN		98	98	99
	QDA		92	87	98
Without Bandpass	SVM	ApEn	75	70	80
	KNN		74	70	78
	QDA		67	60	78

In contrast, SVM scored 98%, 98%, and 98%, and QDA scored 92%, 87%, and 98%, respectively, for accuracy, sensitivity, and specificity.

5.2 Experiment II: EEG classification based on eight randomly selected electrodes

Table 5. The confusion matrix was obtained by the three classifiers with random 8-electrodes

Feature Name	Classes Name		SVM Predicted Class	
FFT+ Bandpass	Actual Class	Sch	504	15328
		Healthy	12543	486
ApEn		Sch	2753	13080
		Healthy	10997	2032
ApEn+Bandpass		Sch	1651	11379
		Healthy	11157	4676
ShnEn+Bandpass		Sch	4160	11673
		Healthy	12001	1028
LogEn+Bandpass		Sch	64	15768
		Healthy	12970	60
Feature Name	**Classes Name**		**KNN Predicted Class**	
FFT+ Bandpass	Actual Class	Sch	576	15256
		Healthy	12341	688
ApEn		Sch	2838	12995
		Healthy	10767	2262
ApEn+Bandpass		Sch	1053	11977
		Healthy	8763	7070
ShnEn+Bandpass		Sch	644	15189
		Healthy	12352	677
LogEn+Bandpass		Sch	96	15736
		Healthy	12979	51
Feature Name	**Classes Name**		**QDA Predicted Class**	
FFT+ Bandpass	Actual Class	Sch	1511	14321
		Healthy	1192	1037
ApEn		Sch	6675	9158
		Healthy	11285	1744
ApEn+Bandpass		Sch	216	12814
		Healthy	7386	8447
ShnEn+Bandpass		Sch	11097	4736
		Healthy	12858	171
LogEn+Bandpass		Sch	1381	14451
		Healthy	12969	61

Table 6. Classification performance results utilizing eight random electrodes

Filter Condition	Classifiers	Feature Extraction Methods	Evaluation Metrics		
			Acc	Sen	Spe
With Bandpass	SVM	FFT	96	96	96
	KNN		95	95	95
	QDA		91	88	93
	SVM	ApEn	78	87	70
	KNN		71	89	62
	QDA		69	97	60
	SVM	ShEn	82	74	91
	KNN		95	95	95
	QDA		61	53	96
	SVM	LogEn	99	99	99
	KNN		99	99	99
	QDA		95	90	99
Without Bandpass	SVM	ApEn	83	79	86
	KNN		82	79	85
	QDA		70	62	84

In this scenario, we chose eight electrodes as an intermediate step between the first scenario of five electrodes and the previous studies mentioned in Section 2, which include more comprehensive electrodes. Here we verify the proposed approach to see if a small increase in the number of electrodes leads to a significant improvement in classification performance. Table 5 displays the confusion matrix obtained by using 8 electrodes, and Table 6 displays the performance values.

For this scenario reduction, the classification accuracy rates were 99%, 99%, and 95% for SVM, KNN, and QDA, respectively. The corresponding sensitivity and specificity of the SVM and KNN classifiers were identical at 99%, while QDA got 90% and 99%, respectively. Consequently, SVM outperformed the other classifiers.

5.3 Experiment III: EEG classification based on PCA

Finally, we applied the principal component analysis (PCA); it preserves the most important features and reduces the dimensionality of the data by its formula illustrated in Eq. (5), but at the same time, these features may not be the most relevant or important for classifying the EEG data. This belongs to the PCA's lack of knowledge of the patterns that are important and required to function.

Tables 7 and 8 compare and demonstrate classifying EEG data for schizophrenia disorder by the confusion matrix for the two PCA scenarios, while Tables 9 and 10 show the performance results.

$$cov_{x,y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{N-1} \tag{5}$$

Given the earlier studies mentioned in section 2 and our study that investigated the limitations of random electrode selection and compared them to the PCA feature selection methods, this work stands out as a real demonstration of the validity of achieving impressive and unexpected results with fewer electrodes than expected, which demonstrates the existence of substantial discriminative information within this restricted grouping. This highlights the need to further explore the potential of EEG systems and the extent to which they can be extended.

Table 7. The confusion matrix was obtained using PCA with the 5-electrodes

Feature Name	Classes Name		SVM Predicted Class	
FFT+ Bandpass	Actual Class	Sch	10929	2100
		Healthy	3061	11684
ApEn		Sch	7521	5508
		Healthy	4357	11476
ApEn+Bandpass		Sch	12744	285
		Healthy	7308	8525
ShnEn+Bandpass		Sch	7	14137
		Healthy	6	15827
LogEn+Bandpass		Sch	11447	1583
		Healthy	1978	13854
Feature Name	**Classes Name**		**KNN Predicted Class**	
FFT+ Bandpass	Actual Class	Sch	12274	755
		Healthy	1849	12896
ApEn		Sch	9782	3247
		Healthy	5357	10476
ApEn+Bandpass		Sch	11659	1370
		Healthy	7762	8071
ShnEn+Bandpass		Sch	8937	5207
		Healthy	5494	10339
LogEn+Bandpass		Sch	12689	341
		Healthy	448	15384
Feature Name	**Classes Name**		**QDA Predicted Class**	
FFT+ Bandpass	Actual Class	Sch	11660	1369
		Healthy	6675	8070
ApEn		Sch	10587	2442
		Healthy	7190	8643
ApEn+Bandpass		Sch	12946	83
		Healthy	8950	6883
ShnEn+Bandpass		Sch	14106	38
		Healthy	15797	36
LogEn+Bandpass		Sch	11988	1042
		Healthy	4658	11174

By comparing all the results obtained using 8 electrodes with the results using 5 electrodes in the two scenarios, our proposed methods result confirmed an acceptable balance between classification accuracy and the number of effective electrodes, taking into account the limited amount of data. We can set this random selection of electrodes in small numbers as a benchmark for comparison with more advanced electrode selection techniques. Where, the model based on PCA achieved a lower level of accuracy in identifying individuals with schizophrenia based on their EEG data, demonstrating the potential of our proposed approach as a valuable tool in the automated diagnosis of this mental disorder.

On the other hand, the datasets used are open-source data for all, and the number of subjects from whom data were collected was equal, which is an important factor in not biasing one group over another in our work. In addition, numerous previous studies have utilized the same dataset, as shown in Table 11.

To add reliability and achieve appropriate robustness to our approach, we calculated the prediction speed and training time, as computational efficiency is one of the indicators relied upon to determine the effectiveness of systems. Tables 12 and 13 show the prediction speed and training time for our approach when using 5 electrodes and 8 electrodes, while Tables 14 and 15 include the PCA prediction speed and training time.

These values are affected by several factors, such as the size of the medical dataset to be classified and the complexity of the model used. The model's prediction speed was significantly slower using 5 electrodes, indicating faster classification and lower computational complexity. In the 8-electrode scenario, increasing the number of electrodes collected more features, enabled the model to make faster decisions. Thus, the 5-electrode model is faster in prediction but takes longer to train. This is a trade-off between performance speed and the actual time required by the system.

Table 8. The confusion matrix was obtained using PCA with the 8-electrodes

Feature Name	Classes Name		SVM Predicted Class	
FFT+ Bandpass	Actual Class	Sch	10342	2687
		Healthy	1915	13917
ApEn		Sch	10269	2760
		Healthy	5510	10323
ApEn+Bandpass		Sch	8471	7361
		Healthy	128	12902
ShnEn+Bandpass		Sch	5212	7817
		Healthy	6332	9501
LogEn+Bandpass		Sch	10827	2203
		Healthy	5549	10283
Feature Name	**Classes Name**		**KNN Predicted Class**	
FFT+ Bandpass	Actual Class	Sch	11966	1063
		Healthy	427	15405
ApEn		Sch	10915	2114
		Healthy	3592	12241
ApEn+Bandpass		Sch	8632	7200
		Healthy	1199	11831
ShnEn+Bandpass		Sch	7500	5529
		Healthy	3201	12632
LogEn+Bandpass		Sch	12806	224
		Healthy	322	15510
Feature Name	**Classes Name**		**QDA Predicted Class**	
FFT+ Bandpass	Actual Class	Sch	11278	1751
		Healthy	4934	10898
ApEn		Sch	10916	2113
		Healthy	7482	8351
ApEn+Bandpass		Sch	7152	8680
		Healthy	171	12859
ShnEn+Bandpass		Sch	12942	87
		Healthy	15629	204
LogEn+Bandpass		Sch	12826	204
		Healthy	10258	5574

Table 9. Classification performance results with PCA for 5-electrodes

Filter Condition	Classifiers	Feature Extraction Methods	Evaluation Metrics Acc	Sen	Spe
With Bandpass	SVM	FFT	81	78	84
	KNN		90	86	94
	QDA		71	63	85
	SVM	ApEn	73	63	96
	KNN		68	60	85
	QDA		68	59	98
	SVM	ShEn	52	53	52
	KNN		64	61	66
	QDA		47	47	48
	SVM	LogEn	87	85	89
	KNN		97	96	97
	QDA		80	72	91
Without Bandpass	SVM	ApEn	65	63	67
	KNN		70	64	76
	QDA		66	59	77

Table 10. Classification performance results with PCA for 8-electrodes

Filter Condition	Classifiers	Feature Extraction Methods	Evaluation Metrics		
			Acc	Sen	Spe
With Bandpass	SVM	FFT	84	84	83
	KNN		94	96	93
	QDA		76	69	86
	SVM	ApEn	74	98	63
	KNN		70	87	62
	QDA		69	97	59
	SVM	ShEn	50	45	54
	KNN		69	70	69
	QDA		45	45	70
	SVM	LogEn	73	66	82
	KNN		98	97	98
	QDA		63	55	96
Without Bandpass	SVM	ApEn	71	65	78
	KNN		80	75	85
	QDA		66	59	79

Table 11. Comparing the sensitivity (Sen), specificity (Spe), and accuracy (Acc) values of the studies using the same dataset, where Chan. Refer to channels

Study	Year	Chan.	Preprocessing	Time	Features	Cross-Validation	Methods	Acc%	Sen%	Spe%
[53]	2019	19	Butterworth filter	25 S	Nonlinear	Unspecified	SVM(RBF)	92.91	NA	NA
[54]	2019	19	Z-score	25 S	11-layer CNN	10	SoftMax	98.07	97.32	98.17
[55]	2020	19	Independent Component Analysis	Unspecified	nonlinear features	10	AdaBoost	98.77	NA	NA
[56]	2020	19	CWT	Unspecified	Pre-trained CNNs	10	SVM	98.60	99.65	96.92
[57]	2020	19	Independent Component Analysis	Unspecified	Fast Fourier Transformation	10	RF	96.77	NA	NA
[20]	2020	19	Multivariate Empirical Mode Decomposition	2 S	Several Entropies	10	SVM(RBF)	93	98	93.33
[58]	2020	19	Band-pass filtered	Unspecified	Entropy	Unspecified	RF	89.29	NA	NA
[59]	2021	19	Z-score and L2	25 S	13-layer 1D-CNN-LSTM	5	Sigmoid	99.25	NA	NA
[60]	2021	19	Phase space dynamic	255 S	Graphical features	10	KNN	94.8	94.3	95.2
[61]	2021	19	Iterative Filtering	25 S	Several features	5&10	SVM (Cubic)	98.9	99.1	98.8
[62]	2021	19	Katz fractal dimension (KFD), approximate entropy (ApEn), and time-domain	Unspecified	Several Nonlinear features	2	SVM	99	99	NA
[63]	2021	19	Wavelet-based	25 S	Fourier transform	10	KNN	97.20	96.49	98.06
[36]	2021	19	Collatz pattern	15 S	INCA-based	10	KNN	99	99.20	99.80
[64]	2022	19	Transfer Entropy		EfficientNetB0-LSTM	10	BT	96.26	95.48	97.02
[2]	2022	19	CWT	5 S	Pre-trained CNNs	Unspecified	SoftMax	99.5	NA	NA
[65]	2022	19	Bandpass filtering	Unspecified	Entropy measures	10	KNN	93	NA	NA
[26]	2023	19	2 nd order Butterworth filter	20 S	CNN+ML	10	LR	98	99	97
[14]	2023	19	Wavelet Scattering Transform	5 S & 1 S	12 Statistical features	10	DT	97.98	98.2	97.72
[43]	2023	19	Histogram of local variance (HLV)	1 Min (60 S)	Weighted local binary patterns (SLBP)	10	AdaBoost	99.36	98.8	100
[44]	2023	19	Fourier transform	4 S	look ahead pattern	Unspecified	boosted trees	96.12	95.20	96.99
[66]	2024	19	Min–max normalization	Unspecified	Marine predator algorithm (MPA)	10	DT	99	NA	NA
[67]	2024	6	Artifact subspace reconstruction (ASR) and fast, independent component analysis (Fast ICA)	Unspecified	Selected channels (Penalized sequential dictionary learning (PSDL))	Unspecified	PSDL	89.12	NA	NA
Ours	**2025**	**5**	Bandpass filter	**1 S**	**FFT, ApEn, LogEn, and ShEn**	**10**	**SVM**	**98**	**98**	**98**
							KNN	**98**	**98**	**99**
							QDA	**92**	**87**	**98**
		8					**SVM**	**99**	**99**	**99**
							KNN	**99**	**99**	**99**
							QDA	**95**	**90**	**99**

Table 12. The computational efficiency utilizing 5 electrodes

Filter Condition	Classifiers	Feature Extraction	Prediction Speed (sec)	Training Time (sec)
With Bandpass	SVM	FFT	21892	445.2
	KNN		1561.5	701.5
	QDA		198823.6	2.8
	SVM	ApEn	5095.1	820.3
	KNN		2679.4	2679.4
	QDA		259110.1	2.6
	SVM	ShEn	4463.7	2725.7
	KNN		2099.7	2791.5
	QDA		221274.4	14.1
	SVM	LogEn	36298	27454.4
	KNN		1262.8	1120.5
	QDA		67659.2	23.1
Without Bandpass	SVM	ApEn	4826.5	446.9
	KNN		15037.7	728.7
	QDA		315467.5	21.6

Table 13. The computational efficiency utilizing 8 electrodes

Filter Condition	Classifiers	Feature Extraction	Prediction Speed (sec)	Training Time (sec)
With Bandpass	SVM	FFT	39702.4	218.4
	KNN		936	673.9
	QDA		162248.9	17
	SVM	ApEn	3550.2	1202.3
	KNN		915.3	1727.3
	QDA		97039.2	28.1
	SVM	ShEn	7728.6	858.4
	KNN		2131.6	1789.2
	QDA		173752.5	3
	SVM	LogEn	79433.4	197.3
	KNN		2924.3	383
	QDA		176420.4	4.44
Without Bandpass	SVM	ApEn	6937.4	553.12
	KNN		14667.6	591.23
	QDA		272336.9	28.24

Table 14. PCA computational efficiency utilizing 5 electrodes

Filter Condition	Classifiers	Feature Extraction	Prediction Speed (sec)	Training Time (sec)
With Bandpass	SVM	FFT	8653.217	91.90725
	KNN		3795.987	77.97983
	QDA		47966.05	9.484103
	SVM	ApEn	5288.737	137.3424
	KNN		3286.784	80.33712
	QDA		33422.95	12.59305
	SVM	ShEn	4394.708	113.8068
	KNN		25778.1	93.64905
	QDA		63068.43	8.791682
	SVM	LogEn	13111.01	79.90283
	KNN		4923.825	73.03309
	QDA		50694.2	11.28417
Without Bandpass	SVM	ApEn	4538.36	121.9812
	KNN		9167.939	97.13916
	QDA		50401.99	11.33394

It is important to note that successful classification of machine learning-based data in MATLAB, such as neuroimaging, also depends on memory management, as dealing with such data is a challenge due to the large memory resources required for loading, preprocessing, feature extraction, and model training. Tables 16 and 17 show the memory utilization in megabytes for the random selection for each of the three ML models (SVM, KNN, and QDA) during the execution. In contrast, Tables 18 and 19 present the memory utilization values by PCA.

Upon calculating both M.A for all arrays and M.U by MATLAB for the model, the SVM model with random selection showed the highest memory usage when using five electrodes at 7356MB, while the KNN model with eight random electrodes required the most memory at 320MB. These results strengthen our conclusions and provide a more comprehensive understanding of the approaches for EEG-based schizophrenia classification.

Table 15. PCA computational efficiency utilizing 8 electrodes

Filter Condition	Classifiers	Feature Extraction	Prediction Speed (sec)	Training Time (sec)
With Bandpass	SVM	FFT	5216.988	150.1511
	KNN		1679.254	128.1679
	QDA		27115.5	16.29031
	SVM	ApEn	2520.788	87.73264
	KNN		4312.89	171.1056
	QDA		45278.55	13.39469
	SVM	ShEn	3378.736	143.4718
	KNN		15538.8	106.7791
	QDA		37936.46	12.65391
	SVM	LogEn	9768.915	102.6538
	KNN		2490.387	97.01666
	QDA		37183.76	13.4246
Without Bandpass	SVM	ApEn	5196.502	136.0106
	KNN		5977.845	102.8758
	QDA		46429.98	10.30246

Table 16. Summarizing the memory usage for the five electrodes, where M.A refers to memory availability and M.U refers to memory usage

Memory Usage (MB)	Features Used	5 Electrodes		
		SVM	KNN	QDA
M.A for all arrays	FFT+Bandpass	5284	3708	4389
M.U / MATLAB		6979	6920	6899
M.A for all arrays	ApEn	4634	4326	3979
M.U / MATLAB		6157	6251	6325
M.A for all arrays	ApEn+Bandpass	4914	3582	3902
M.U / MATLAB		6804	6752	6749
M.A for all arrays	ShEn+Bandpass	8101	4965	5056
M.U / MATLAB		7356	7269	7233
M.A for all arrays	LogEn+Bandpass	5249	5216	5513
M.U / MATLAB		7144	7105	7094

Table 17. Summarizing the memory usage for the eight electrodes, where M.A refers to memory availability, and M.U refers to memory usage

Memory Usage (MB)	Features Used	8 Electrodes		
		SVM	KNN	QDA
M.A for all arrays	FFT+Bandpass	5541	5374	5490
M.U / MATLAB		6888	6936	6957
M.A for all arrays	ApEn	6097	5991	6242
M.U / MATLAB		6046	6281	6133
M.A for all arrays	ApEn+Bandpass	6196	6046	5857
M.U / MATLAB		6652	6694	6696
M.A for all arrays	ShEn+Bandpass	5238	4820	5306
M.U / MATLAB		7358	7409	7368
M.A for all arrays	LogEn+Bandpass	5352	5268	5188
M.U / MATLAB		7134	7160	7172

Lastly, the visual examination aids clinicians in identifying the disorder's signal and location inside the brain. Figure 3 displays the power spectral density, highlighting the disparity between the signals of a patient with schizophrenia and those of a healthy individual. The healthy signals are mostly uniform and stable, whereas the patient signals display irregularities and unusual rhythms. Furthermore, a topographical picture delineates the electrode's position, enabling physicians to ascertain the etiology of the neurological issue more precisely and identify the indicators of schizophrenia.

Above all, the five random electrodes using KNN with LogEn features outperformed the performances of the two other classifiers (SVM and QDA). Whereas SVM with LogEn achieved the best performance compared with KNN and QDA in the eight-electrode scenario. To conclude, the two random scenarios, based on the findings, indicate that superior outcomes may be achieved with a reduced number of electrodes.

In this study, some limitations are listed below:

(1) The dataset used was publicly available and not privately collected for this study.

(2) The one-epoch window size technique was an advantage that allowed us to cover and provide a much bigger amount of the data, with an overlap was 50%, which was fed into the machine-learning models.

Table 18. PCA memory usage with the five electrodes, where M.A refers to memory availability, and M.U refers to memory usage

Memory Usage (MB)	Features Used	5 Electrodes		
		SVM	KNN	QDA
M.A for all arrays	FFT+ Bandpass	4409	4473	4173
M.U / MATLAB		6139	6143	6135
M.A for all arrays	ApEn	4711	4744	4470
M.U / MATLAB		5795	5876	5919
M.A for all arrays	ApEn+Bandpass	3881	3877	4075
M.U / MATLAB		6321	6320	6327
M.A for all arrays	ShEn+Bandpass	4227	4088	4346
M.U / MATLAB		6489	6497	6491
M.A for all arrays	LogEn+Bandpass	4298	4266	4179
M.U / MATLAB		6423	6413	6426

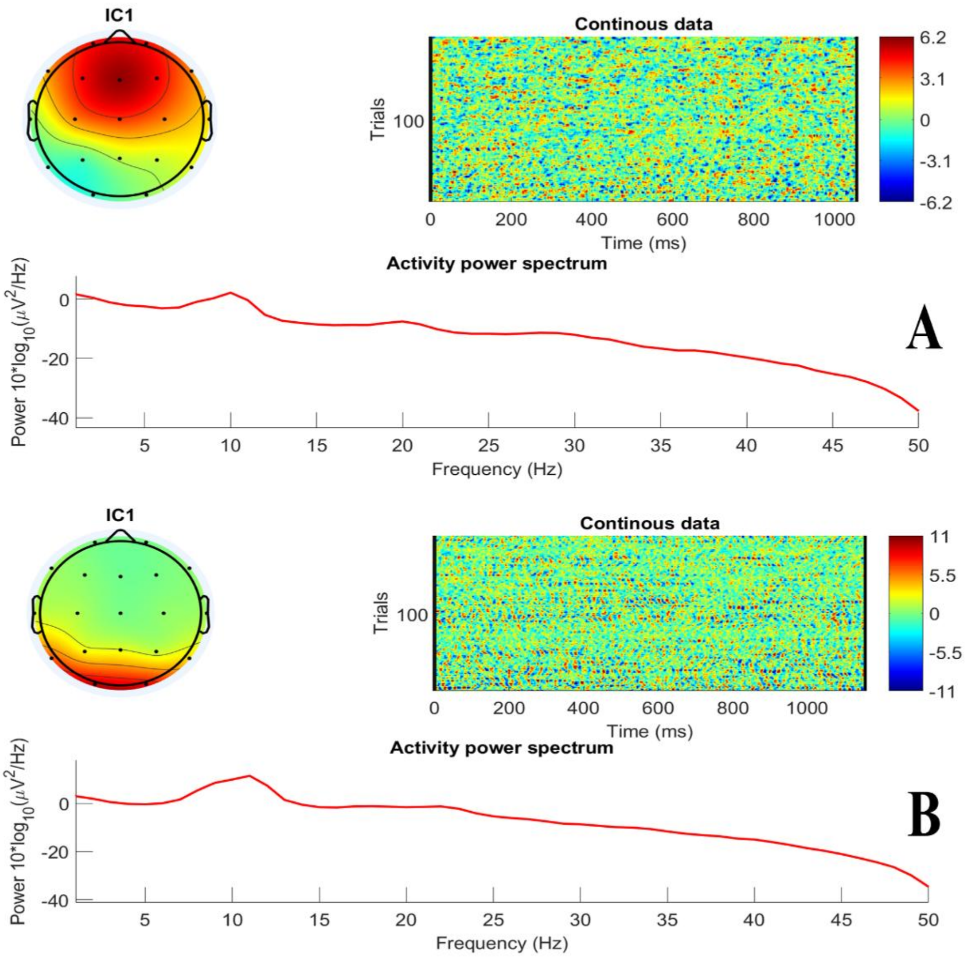

Figure 3. Visualisation method for power spectrum density and topography image, whereas A represents the Schizophrenia person and B represents the patient

(3) The model processed the data and diagnosed schizophrenia, not its three severity stages (early, active, or residual).

(4) The study results may lack the ability to generalize to patients with schizophrenia for several reasons that may be due to some characteristics of the data, such as age and gender.

Table 19. PCA memory usage with the eight electrodes, where M.A refers to memory availability and M.U refers to memory usage

Memory Usage (MB)	Features Used	8 Electrodes		
		SVM	KNN	QDA
M.A for all arrays	FFT+Bandpass	4773	4796	4931
M.U / MATLAB		6717	6712	6722
M.A for all arrays	ApEn	4002	4009	4065
M.U / MATLAB		6505	6499	6515
M.A for all arrays	ApEn+Bandpass	5059	4834	3829
M.U / MATLAB		6666	6661	6679
M.A for all arrays	ShEn+Bandpass	5597	5270	4755
M.U / MATLAB		6777	6777	6787
M.A for all arrays	LogEn+ Bandpass	4773	4660	4874
M.U / MATLAB		6762	6752	6754

6. CONCLUSION

The person's life and behavior are influenced by the changing electrical activity of the brain, which can be observed through an electroencephalogram (EEG). It can be asserted that a healthy brain functions more actively compared to a brain affected by schizophrenia. In this study, we proposed a method to classify schizophrenia using an EEG signal dataset containing 28 subjects: 14 individuals suffering from schizophrenia and 14 healthy controls. Due to the variations in the EEG signal, we applied a band-pass filter to decompose the EEG signal into five sub-bands. Next, we implemented four feature extraction methodologies. We applied the first three methods (FFT, ApEn, LogEn, and ShnEn) to the band-pass filter, and then we used ApEn again without band-pass filters to compare the impact of the filter on the results.

Normalization was applied to all features to ensure they were on the same scale, using the L2 normalization technique. Consequently, we fed the features into the SVM, KNN, and QDA classifiers.

The hypothesis in this work demonstrates the ability to use a smaller number of electrodes, a randomly selected subset, that can achieve classification accuracy similar to all data electrodes. We provide support to EEG-based diagnostic tools that are less sophisticated and have fewer electrode numbers, such as Emotiv Insight, Muse EEG, Neurosky Mindwave, and InteraXon Muse S.

Our proposed approach was simple and effective with the most imposed constraints. First, we reduced the number of channels to 5 electrodes, which means we decreased by (5/19=73.68%). Then, we used 8 electrodes to 8, which means increased by (8/19=57.89%), which in turn increased the accuracy by 1% using the random channel selection. Thus, both experiments showed remarkable classification performance despite reducing the number of electrodes.

The results show that our approach provides a clear and significant improvement in accuracy compared to the PCA conventional methods. In addition, recent advances indicate that using EEG with fewer electrodes could completely transform the usability and affordability of the technology. This technique simplifies electrode preparation, which not only saves time and reduces complexity but also improves mobility, allowing EEG to be used in a variety of contexts outside of clinical laboratories.

According to the study limitation mentioned above, future work may include:

(1) Combining EEG data with other neuroimaging methods (such as fMRI and PET) may provide a more comprehensive understanding of brain changes caused by schizophrenia.

(2) Implement techniques to enhance the dataset, improve model robustness, and mitigate overfitting.

(3) Utilize the Graph Neural Networks (GNNs) for analyzing brain networks.

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