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DISCRIMINATION OF FOCAL AND NON-FOCAL EPILEPTIC EEG SIGNALS USING DIFFERENT TYPES OF CLASSIFIERS

BY

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Abstract. Epilepsy is a neurological disorder characterized by recurrent seizures and has a high incidence rate. The aim of this research is to classify EEG signals as either focal and non-focal in order to identify the epileptogenic area of the brain, which can be surgically treated to manage epilepsy. In this paper, was proposed a classification method based on higher order spectra (HOS) parameters and four different classifiers: linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), k-Nearest neighbors (KNN), and Mahalanobis distance (MD). The method was evaluated using a public dataset that consists in EEG recordings from epileptic patients. The classifiers performances were evaluated and it was shown that KNN classifier achieves a maximum classification rate of 99.55%, sensitivity of 100%, and specificity of 99.09%. The data classification was performed with maximum values of 0.96 for F1-score, and 0.91 for both Kappa and Matthews Coefficient. The results demonstrate the efficiency of the proposed method to identify the type of EEG signals.

Keywords: epilepsy; focal EEG; non-focal EEG; classification method; signal.

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1. Introduction

Approximately 50 million people worldwide are affected by epilepsy, which is a type of neurological disorder that affects the brain. In epilepsy, the brain activity is abnormal, intermittent, paroxysmal and excessive discharges occur. As a result of this condition, the patients experience uncontrollable muscle convulsions that can result in loss of consciousness (Cherian and Kanaga, 2022).

Epilepsy has a significantly impact to the quality of life for people affected by the disorder and can, in severe cases, even lead to death. Therefore, it is essential to analyze, accurately detect, properly classify, and effectively treat this condition with a high degree of efficiency (Who, 2017).

The activity of the human body is evaluated by biological signals captured by means of medical devices that provide information about the health status.

In the diagnosis stage of epilepsy, the most commonly used technique is electroencephalography, which provides an excellent tool for investigating brain activity. The process of electroencephalographic (EEG) recording involves the measurement of electrical fluctuations in the brain, which represent the rhythmic oscillations of neural activity (Seyed and Sankar, 2020).

According to Subasi *et al*. (2019), identifying the sources of seizures in EEG recordings is not a straightforward task based on visual analysis alone. Compared to EEG signals recorded from non-epileptogenic brain areas, those from epileptogenic areas tend to exhibit a higher degree of non-linearity and non-stationarity. Hence, the detection of seizures is a challenging task and therefore it appears the necessity of developing intelligent system of identifying the type of epilepsy (Lim *et al*., 2010).

The diagnosis of epilepsy typically requires the occurrence of at least two unprovoked seizures with a time interval of more than 24 hours, as well as an assessment of the possibility of further seizures, which are triggered by certain stimuli, (flashing lights, noises). Also, this possibility is typically similar to the general risk of recurrence after two unprovoked seizures, which is at least 60% (International League Against Epilepsy - ILAE), (Fisher et *al*., 2005).

The classification of epileptic seizures is constantly evolving, so we present the most commonly used classifications and a brief history of them.

In 1985, the ILAE, published an approach to the classification of epilepsy, addressing semiology and etiology. In terms of semiology, epilepsy has been classified into epilepsy with focal seizures and generalized seizures. Alternatively, it can also be classified based on its cause, with idiopathic epilepsy and symptomatic epilepsy.

In 2005, the ILAE, has classified seizures (epileptic syndromes), and published that those epileptic seizures fulfil the following conditions: the period before a seizure is referred to as the pre-ictal phase during which there may be

changes in neurological activity. The period during which the seizure occurs is known as the ictal phase. The interictal phase refers to abnormal neurological activity that occurs between seizures, while the post-ictal phase refers to the period of neurological activity that occurs after a seizure (Fisher *et al.*, 2005).

A more recent classification of epilepsy was published in 2010, which updated previous classifications with more current terminology and concepts. The terms "generalized" and "focal" are used to describe seizures. Thus, seizures are classified into three distinct categories: focal (previously called partial), generalized, and unknown seizures (Berg and Millichap, 2013).

Focal crises are defined as abnormal activities present in only one area of the brain. Focal discharges in epilepsy can spread locally through synaptic and asynaptic mechanisms, while they can also extent distally to subcortical structures or affect the entire cortex involving through commissural pathways.

Focal crises are divided into two categories:

• focal seizures that affect consciousness (complex partial crises), and involve changes in consciousness or even loss of consciousness;

• focal seizures that do not affect consciousness, and may cause alterations in emotional state or change the shape, smell, taste or sound of other objects (Berg and Millichap, 2013).

In addition to the presence of focal signals that are recorded in focal epilepsy, in (Andrzejak *et al*., 2012), another type of signals known as non-focal signal are presented.

Generalized seizures occur throughout the neocortex and are seen on the EEG recording of generalized peak waves in all brain lobes.

Epileptic seizures that are difficult to evaluate can be classified as unknown, which can refer to both focal or generalized seizures and therefore need some more investigations (Steriade *et al*., 2021).

Accurately discriminating between focal and non-focal groups of EEG signals is essential for determining the epileptic focus in cases of pharmaco-resistant focal epilepsy, as it enables effective treatment. As such, an automated system capable of detecting and distinguishing between focal (F) and non-focal (NF) EEG signals can be a valuable tool to assist clinicians in their diagnosis (Oliva et *al*., 2019).

EEG signals recorded from specific areas of the brain where abnormalities in brain activity are initially observed are referred to as focal EEG signals (Hosseini, 2017).

According to (Narin, 2022), non-focal EEG signals are captured from brain regions that are not initially affected during the onset of a seizure. Non-focal areas are adjacent to the focal areas.

In cases of focal epilepsy, medication alone may not be sufficient to handle seizures, making it decisive to accurately identify the location of the focal epileptic area.

Creating classification systems that meet the rigorous standards set by the ILAE is a lengthy and complex process. The new classifications of seizures and epilepsy were announced by the ILAE in March 2017 (Chang *et al*., 2017) and involve three levels of classification: types of seizures, types of epilepsy, and epileptic syndromes.

Detecting and distinguishing between focal and non-focal EEG signals is a significant research area, as accurately localizing epileptogenic areas is essential for successful epilepsy surgery treatment. To determine the type of EEG signal, a comprehensive literature review was conducted. The aim of the following presented papers is to provide clinicians with a reliable and efficient tool for identifying the epileptogenic zone and guiding the surgical resection of the affected brain tissue.

Numerous algorithms have been proposed, linear and non-linear methods have been employed mainly due to their simplicity and versatility. One common method for identifying epileptic seizures is through analyzing EEG signals in either the time domain, frequency domain, or time-frequency domain (Cherian and Kanaga, 2022).

A system of detecting epilepsy is detailed in (Ullah *et al.*, 2018). A deep learning method comprised of a series of one-dimensional pyramidal convolutional neural network (P-1D-CNN) models helps neurologists to detect the type of epilepsy and, provides an accuracy of $99.1 \pm 0.9\%$.

A study conducted by Sharma and Pachori in 2014, used the empirical mode decomposition (EMD) method along with the least square support vector machine (LS-SVM) classifier to classify EEG data from epileptic patients into focal and non-focal categories. The study achieved an accuracy of 87%.

In (Gupta *et al*., 2017), an approach based on the flexible analytic Wavelet transform (FAWT) and the LS-SVM classifier is applied on EEG epileptic signals. The focal EEG data are classified with a classification accuracy of 94.41%.

In (Gupta and Pachori, 2020) is introduced an automated method for classifying focal EEG signals. This method comprises two components: a flexible time-frequency coverage wavelet transform based on Fourier-Bessel series expansion and an LS-SVM classifier. Results showed that the EEG signals are classified with a high accuracy rate of 95.47%.

In (Arunkumara *et al*., 2018), a classification approach is developed to identify different types of EEG signals using the following entropies, approximate entropy (ApEn), sample entropy (SampEn), and fuzzy entropy (FuzzyEn), as features. The extracted features are then used in the classification stage. Naïve Bayes (NB), radial basis function (RBF), best-first decision tree (BFDT), k-Nearest neighbor (KNN), support vector machines (SVM), and non-nested generalized exemplars (NNge) decision rule classifiers, are used to differentiate the focal and non-focal EEG signals. It was reported that the NNge

classifier gave the highest classification accuracy of 99% in differentiating between focal and non-focal EEG signals.

The objective of this study is to identify the most suitable classifier for distinguishing and categorizing the EEG epileptic signals. This information is important in surgery to treat drug-resistant patients by rejecting epileptic foci in the brain (Hosseini, 2017).

In this paper, a classification method is proposed for discriminating between focal and non-focal EEG signals. The approach is applied on a free database from the Department of Neurology, University of Bern. Higher order statistics are used in combination with four classifiers. The classifiers employed include linear linear discriminant analysis (LDA) as proposed by (Prendergast and Smith, 2022), quadratic discriminant analysis (QDA), (Rezaei and Abbari, 2022), Mahalanobis distance-based (MD), and k-Nearest neighbors, (Martinez-del-Rincon *et al*., 2017). In order to determine the optimal classifier, their performances are evaluated based on metrics such as classification rate, sensitivity, specificity, F1-Score, Kappa Coefficient, and Mathews Coefficient Correlation (MCC), (Vries *et al*., 2021).

This paper is structured in five sections: the theoretical background is detailed in Section 2, the EEG dataset is described in Section 3, the methods used are presented in Section 4, Section 5 shown the results, and Section 6 concludes the paper.

2. Theoretical background

The field of Higher Order Spectra (HOS) in signal processing has numerous practical applications in various domains, such as brain-computer interfaces, vibration analysis, neural data processing, and speech processing (Hrisca-Eva *et al.*, 2021).

Higher Order Spectra are defined as spectral moments with orders greater than two and are described using higher-order statistics such as cumulants and moments (Swami *et al.,* 2001).

In this paper the bispectrum and the bicoherence are used as parameters in the features vector extraction. The indexes extracted by these HOS parameters are used in classification stage of EEG epileptic signals.

The bispectrum, also known as the third-order spectrum, is a signal processing technique that quantifies the skewness of a signal over frequency. It provides a way to detect and analyze asymmetric nonlinearities in signals (Hosseini, 2017). The bicoherence is a normalized version of the bispectrum, which is a tool used to measure the presence of quadratic phase coupling. This type of coupling arises when a signal passes through systems with quadratic non-linearities, and it can be detected by analyzing the frequency-domain skewness of the signal (Rivola and White, 2002).

The bispectrum is defined in the bivariate frequency domain and its expression is given in Eq. (1).

$$B(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)] \tag{1}$$

The bispectrum is calculated using the Fourier transform $X(f)$ of the signal $x(nT)$, where n is an integer index, and T is the sampling period. The complex conjugate of X is represented by X^*. Additionally, the expectation operation is represented by the symbol $E[.]$ (Chua *et al*., 2009).

Bicoherence is provided by:

$$B_{norm}(f_1, f_2) = \frac{E[X(f_1)X(f_2)X^*(f_1+f_2)]}{\sqrt{P(f_1)P(f_2)P(f_1+f_2)}}, \tag{2}$$

Where $P(f)$ is the power spectrum of the signal $x(nT)$ (Chua *et al*., 2007).

3. Database

The database used in this paper is available on Internet and can be downloaded from https://www.upf.edu/web/mdm-dtic/datasets.

This dataset consists in intracranial EEG recordings obtained from five patients who had temporal lobe epilepsy and underwent due to lack of response to drug treatments. The recordings were conducted as a component of the patients' epilepsy diagnosis.

The database comprises a total of 3750 EEG signals, with an equal number of focal and non-focal signals. Each pair of EEG signals, denoted by x and y, consists of one signal recorded in the focal or non-focal area, and the other signal recorded on an adjacent channel. The sampling rate of the signals was either 512 Hz or 1024 Hz, depending on the number of acquisition channels. Signals with greater than 64 acquisition channels were sampled at 1024 Hz, while those with fewer than or equal to 64 channels were sampled at 512 Hz. To minimize phase distortion, a 4th order Butterworth filter was used to digitally band-pass filter the signals between 0.5 and 150 Hz (Chua *et al.*, 2009). The term "focal EEG channels" refers to the channels that detected the ictal EEG signal changes first, while the other channels are referred to as "non-focal EEG channels".

In this paper, the proposed classification approach is applied on a dataset consisting of 100 EEG focal signals and 100 EEG non-focal signals, sampled at 512 Hz.

4. Methods

The MATLAB programming environment was used to implement the offline classification method based on HOS features, using the Higher-Order Spectral Analysis Toolbox (Swami *et al.*, 2001).

To ensure stationarity, the signals were segmented, resulting in 1024 samples, and each segment was filtered using a low-pass filter with a cutoff frequency of 60 Hz. The filter used was a sixth-order infinite impulse response (IIR) filter.

A segment of the filtered EEG signals for the focal and non-focal channels is shown in Fig. 1a) and Fig. 1b), respectively.

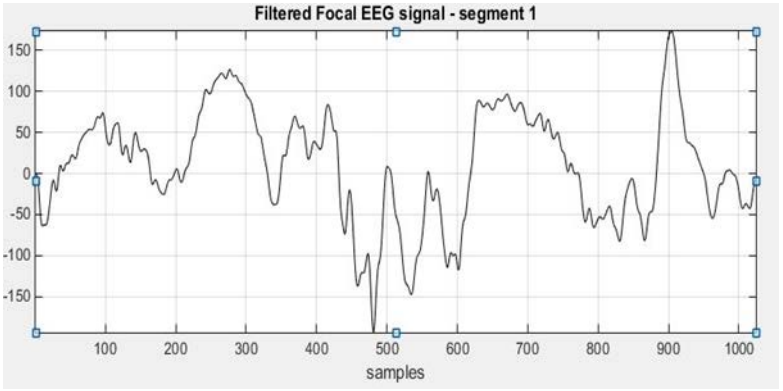


Fig. 1a) – Segmented and filtered focal EEG signal.

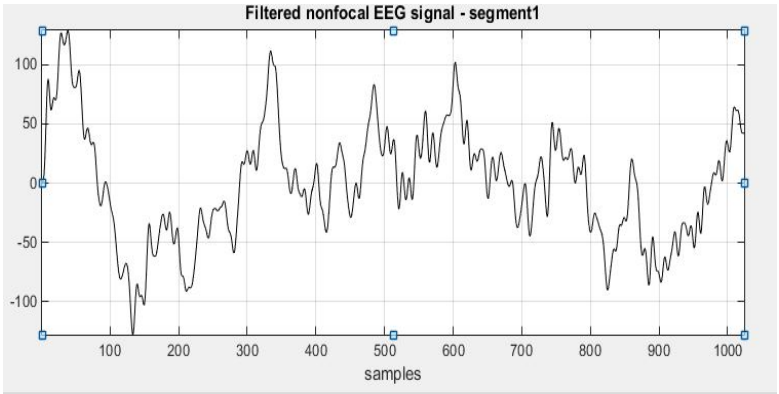
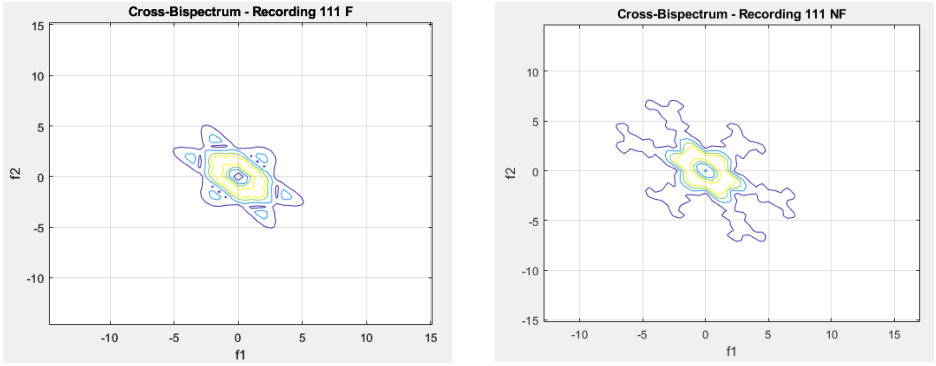


Fig. 1b) – Segmented and filtered non-focal EEG signal.

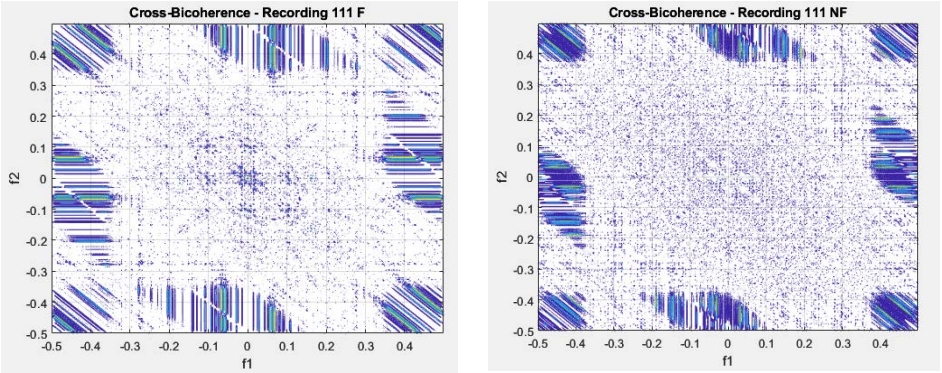
Further, the fast Fourier transform (FFT) was used to compute the bispectrum and bicoherence via the direct method (Swami *et al*, 2001). In Fig.

2a) and b) is represent the bispectrum of the focal and non-focal EEG signals, respectively. In Fig. 3a) and b) is represent the bicoherence of the focal and non-focal EEG signals, respectively.



a) b)

Fig. 2 – a) Bispectrum representation of an EEG focal signal; b) Bispectrum representation of an EEG non-focal signal.



a) b)

Fig. 3 – a) Bicoherence representation of an EEG focal signal; b) Bicoherence representation of an EEG non-focal signal.

The feature vector was defined in order to be used in the classification stage. The frequency axis (f_1 and f_2), were divided into four intervals, denoted as δ (0-4 Hz), θ (4-8 Hz), α (8-13 Hz), and β (13-30 Hz), each representing a different brain rhythm. This results in a total of 10 distinct cases. Fig. 4 illustrates the axes and the intervals cases used (Hosseini, 2017).

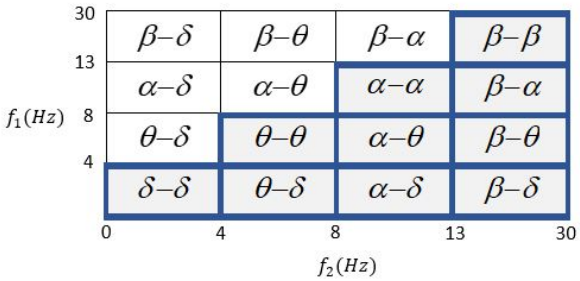


Fig. 4 − Frequency bands for bispectral analysis of EEG signals.

The magnitudes of the bispectrum and the bicoherence were calculated for these cases. Four quantitative indexes were obtained by computing the sum of the bispectrum modules, the sum of the squares of the bispectrum modules, the sum of the bicoherence modules, and the sum of the squares of the bicoherence modules, for each of the 10 frequency intervals as well as for the whole frequency range.

The signals were classified using the before mentioned classifiers.

The LDA classifier is a statistical method of selecting the characteristics contained in the EEG signal, and is used to find a linear combination of features that can best separate two or more classes (Prendergast and Smith, 2022).

The QDA classifier is suitable for separating two or more classes of objects, being a more general version of the linear classifier. The difference between the QDA and LDA classifier is given by the covariance matrices, which must be estimated for each class independently (Hasan and Tatum, 2021).

The MD classifier relies on identifying and comparing correlations between different patterns and variables with a reference population (Lai *et al.*, 2012).

The KNN classifier is a simple method of classifying classes using the closest k classes in the training set (Subasi *et al.*, 2019).

The classifiers performances were evaluated using several metrics such as classification rate (CR), sensitivity, specificity, F1-score, MCC, and Kappa. The formulas for calculating these metrics are presented below:

$$CR = \frac{TP+TN}{TN+FP+TP+FN} \times 100 \tag{3}$$

$$Sensitivity = \frac{TP}{TN+FN} \times 100 \tag{4}$$

$$Specificity = \frac{TN}{TN+FP} \times 100 \tag{5}$$

$$F1-score=\frac{TP}{TP+\frac{1}{2}(FP+FN)} \tag{6}$$

$$MCC=\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)\times(TP+FN)\times(TN+FP)\times(TN+FN)}} \tag{7}$$

$$Kappa=\frac{2\times(TP\times TN-FP\times FN)}{(TP+FP)\times(TP+FN)\times(TN+FP)\times(TN+FN)} \tag{8}$$

Where true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) represent the number of correctly classified instances, correctly rejected instances, instances falsely classified as positive, and instances falsely classified as negative, respectively (Goutte and Gaussier, 2005; Seyed and Sankar, 2020).

Fig. 5 illustrates the steps followed for differentiating between F and NF EEG signals, with the proposed approach.

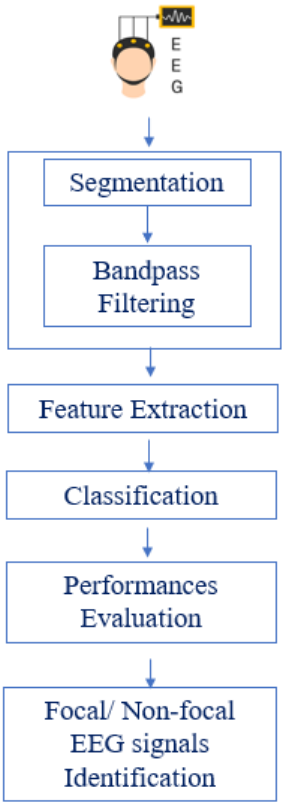


Fig. 5 – Flow chart of the proposed method.

5. Results

In this section are presented the outcomes of the proposed classifier method, obtained by assessing the performance of different classification algorithms on the task of differentiating between focal and non-focal EEG signals.

Table 1
Classification Rates Results

	LDA(%)	**QDA(%)**	**MD(%)**	**KNN(%)**
min	40.48	52.05	43.94	67.72
max	88.61	98.59	96.53	99.55
medie	62.38	76.97	72.14	88.53
median	62.23	77.29	69.42	89.67

Table 1 presents the results achieved with all classifiers by means of classification rate. The range of classification rates is from 40.48% to 99.55% with the proposed classifiers. The KNN classifier performed best comparatively to the rest of the classifiers, according to the quantitative result reported. The LDA, QDA, and MD classifiers led to good performances for some recordings, but overall, the quantitative results were lower.

Table 2
Sensitivity Results

	LDA(%)	**QDA(%)**	**MD(%)**	**KNN(%)**
Min	11.04	34.67	63.29	52.10
Max	89.79	100	100	100
Medie	34.08	79.02	89.74	84.99
Median	30.69	81.14	92.09	88.36

The sensitivity metric reflects the capacity of the classifiers to accurately identify focal EEG signals in contrast to non-focal EEG signals. The sensitivity obtained with the proposed classifiers are given in Table 2. The MD and KNN classifiers showed the best performance with a maximum sensitivity of 100%, indicating that these classifiers are most effective in identifying the focal EEG signals. Based on the results obtained with LDA classifier, we concluded that this classifier is not appropriate to classify the dataset types used in this study.

Table 3
Specificity Results

	LDA(%)	**QDA(%)**	**MD(%)**	**KNN(%)**
Min	71.23	38.15	18.06	71.23
Max	100	97.18	97.18	99.09
Medie	92.34	75.40	55.48	92.22
Median	94.30	78.93	52.26	94.30

Table 3 presents the performances of the proposed classifiers evaluated through the specificity metric, which measures their ability to correctly identify the non-focal EEG signals compared to the focal EEG signals.

In the study conducted, the ranges were found to be from 71.23% to 100% with LDA classifier, and from 71.23% to 99.09% with KNN classifier, that demonstrate good performances in identifying the non-focal EEG signals. The other two classifiers, QDA and MD, performed well for several recordings, but in terms of the minimum values obtained we can conclude that they are not accurate in identifying non-focal signals.

Table 4
F1 – Score Results

	LDA	**QDA**	**MD**	**KNN**
Min	0.67	0.64	0.64	0.67
Max	0.90	0.92	0.96	0.96
Medie	0.80	0.81	0.81	0.84
Median	0.81	0.82	0.82	0.85

As stated in (Delgado and Tibau, 2019), signals are correctly classified only if the value of the F1 – Score is greater than 0.5. Table 4 summarizes the F1-score achieved with the four classifiers. The results indicate that the KNN classifier performed best, obtaining a minimum value of 0.67, while the LDA, QDA, and MD classifiers yielded lower minimum values of 0.64. This means that the data was correctly classified into focal and non-focal with the proposed classification approach. The maximum range values of 0.90-0.96 indicate a good performance of the classifiers, and the KNN and the MD classifiers were attained the highest performances in data classification.

Table 5
Mathews Coefficient Correlation Results

	LDA	**QDA**	**MD**	**KNN**
Min	0.37	0.27	0.27	0.37
Max	0.91	0.83	0.91	0.91
Medie	0.62	0.65	0.64	0.64
Median	0.64	0.65	0.65	0.66

Table 6
Kappa Coefficient Results

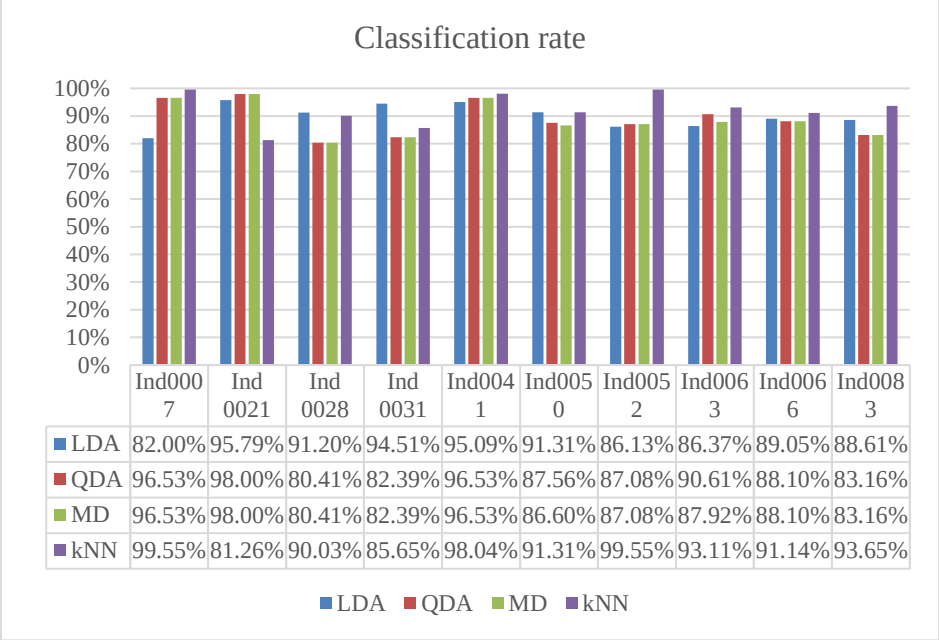
	LDA	**QD**	**MD**	**KNN**
Min	0.36	0.27	0.27	0.36
Max	0.91	0.82	0.91	0.91
Medie	0.63	0.63	0.63	0.64
Median	0.64	0.64	0.64	0.64

The evaluation of the classifiers performances was conducted also, using the Matthews Correlation Coefficient and Kappa Coefficient, which are presented in Table 5 and Table 6, respectively.

As noted in (Delgado and Tibau, 2019), when the results for both the Matthews Correlation Coefficient and Kappa Coefficient are similar, it indicates that the classifier performs effectively. In our case, the maximum values reached with MCC and Kappa are close, about 0.91 and demonstrates the applicability of the proposed classification method.

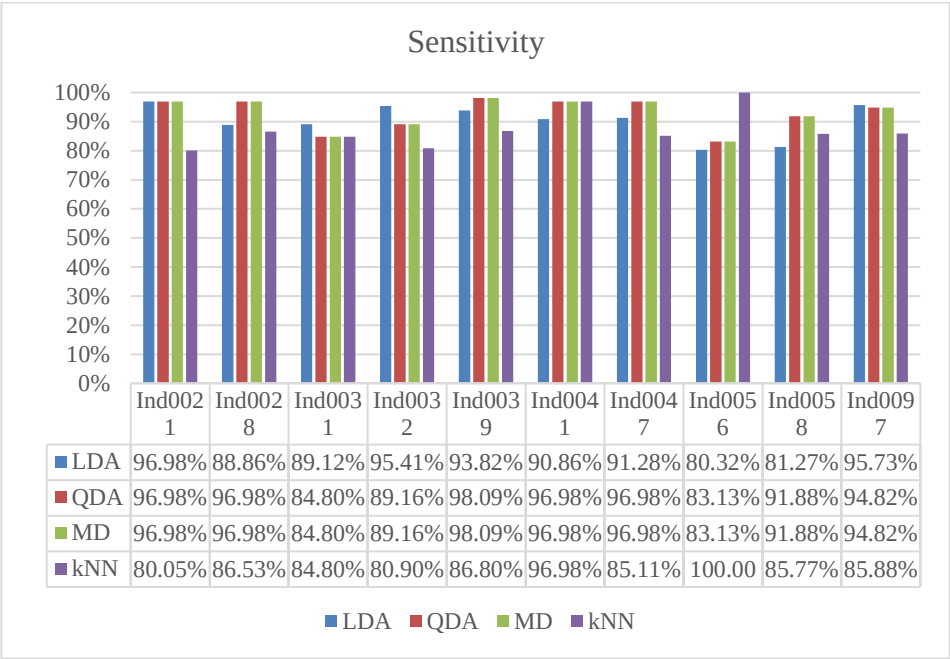
We observed that for some of the recordings, all four classifiers showed good performance, despite the fact that the data was randomly selected. As a result, we have chosen several such instances to demonstrate the versatility of our method in various types of data.

The charts presented in Figs. 6-8 illustrate the best performances achieved by all classifiers in identifying the type of EEG signal.



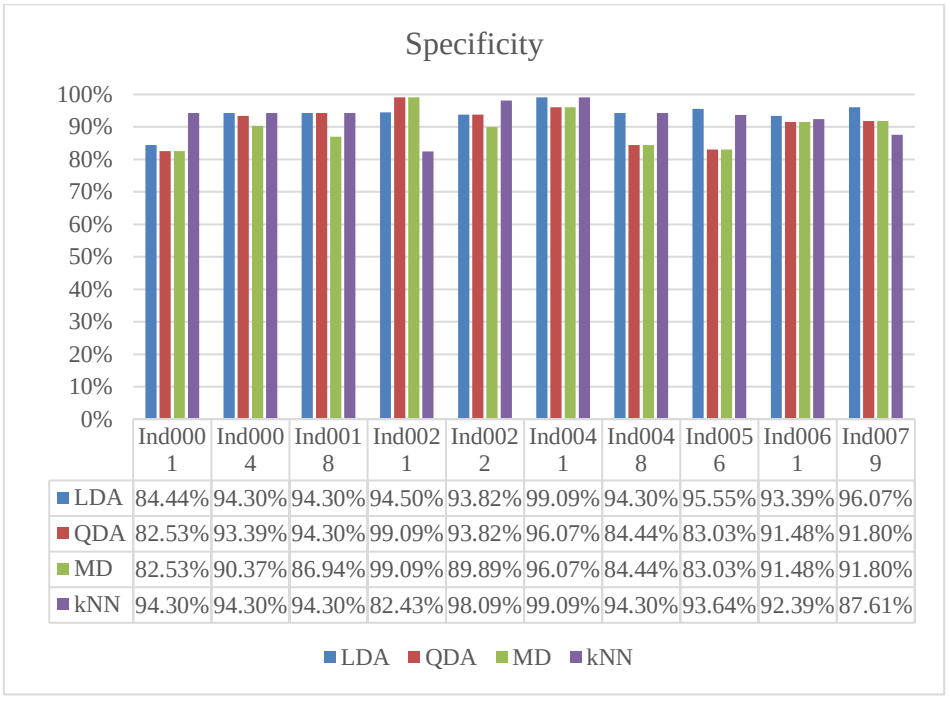
	Ind0007	Ind0021	Ind0028	Ind0031	Ind0041	Ind0050	Ind0052	Ind0063	Ind0066	Ind0083
LDA	82.00%	95.79%	91.20%	94.51%	95.09%	91.31%	86.13%	86.37%	89.05%	88.61%
QDA	96.53%	98.00%	80.41%	82.39%	96.53%	87.56%	87.08%	90.61%	88.10%	83.16%
MD	96.53%	98.00%	80.41%	82.39%	96.53%	86.60%	87.08%	87.92%	88.10%	83.16%
kNN	99.55%	81.26%	90.03%	85.65%	98.04%	91.31%	99.55%	93.11%	91.14%	93.65%

Fig. 6 – The highest classification rate quantities achieved by all classifiers.



	Ind0021	Ind0028	Ind0031	Ind0032	Ind0039	Ind0041	Ind0047	Ind0056	Ind0058	Ind0097
LDA	96.98%	88.86%	89.12%	95.41%	93.82%	90.86%	91.28%	80.32%	81.27%	95.73%
QDA	96.98%	96.98%	84.80%	89.16%	98.09%	96.98%	96.98%	83.13%	91.88%	94.82%
MD	96.98%	96.98%	84.80%	89.16%	98.09%	96.98%	96.98%	83.13%	91.88%	94.82%
kNN	80.05%	86.53%	84.80%	80.90%	86.80%	96.98%	85.11%	100.00	85.77%	85.88%

Fig. 7 – The highest sensitivity quantities achieved by all classifiers.



	Ind0001	Ind0004	Ind0018	Ind0021	Ind0022	Ind0041	Ind0048	Ind0056	Ind0061	Ind0079
LDA	84.44%	94.30%	94.30%	94.50%	93.82%	99.09%	94.30%	95.55%	93.39%	96.07%
QDA	82.53%	93.39%	94.30%	99.09%	93.82%	96.07%	84.44%	83.03%	91.48%	91.80%
MD	82.53%	90.37%	86.94%	99.09%	89.89%	96.07%	84.44%	83.03%	91.48%	91.80%
kNN	94.30%	94.30%	94.30%	82.43%	98.09%	99.09%	94.30%	93.64%	92.39%	87.61%

Fig. 8 – The highest specificity quantities achieved by all classifiers.

Based on the results obtained, it can be concluded that for a specific type of data, an appropriate classifier can be applied to differentiate between focal and non-focal EEG signals.

The KNN classifier performed very well and lead to good results in the classification stage.

To demonstrate that the method and the classifiers we have applied on this database are validated, we perform a comparison with other similar applications described in the literature that employed the same database. The comparisons presented in Table 7 were reported, according to the maximum values obtained.

Table 7
Comparisons with Other Papers that Used the Same Dataset

References	Methods/ Classifiers	Results (%)
Sharma et al., 2014	*Empirical Mode Decomposition (EMD)/ The least square support vector machine (LS-SVM)*	*Classification rate: 85*
Rai et al., 2015	*Empirical Mode Decomposition/ Neural network*	*Classification rate: 98.33*
Das and Bhuiyan, 2016	*EMD/ SVM and KNN*	*Classification rate: 89.4 Sensitivity: 91.95 Specificity: 96.56 (KNN)*
Sriraam and Raghu, 2017	*Statistical, frequency-based, fractal dimension entropy/ SVM*	*Classification rate: 92.15 Sensitivity: 94.56 Specificity: 89.74*
Arunkumara et al., 2018	*Approximate entropy (ApEn), Sample entropy (SampEn), and Fuzzy entropy (FuzzyEn)/ Non-Nested Generalized, Exemplers (NNge)*	*Classification rate: 99 Sensitivity: 99 Specificity: 99 MCC: 0.92 (NNge)*
This work	*HOS/ LDA, QDA, MD, KNN*	*Classification rate 99.55 Sensitivity: 100 Specificity: 99.09 MCC:0.91 (KNN)*

Considering these comparisons, we can conclude that there is a real need for systems that indicate as accurate as possible the type of epilepsy, and the epileptic area. These comparisons give us the certainty that the method we have applied on epileptic dataset led to good results, depending on the type of data, a certain combination of method and classifier can be applied for identifying the epileptic brain area.

6. Conclusions

In conclusion, the results obtained from this study demonstrate the efficacy of the proposed approach in accurately identifying the brain areas responsible for epileptic seizures through the proper discrimination of focal and non-focal EEG signals.

The results suggest that the KNN classifier is the optimal choice for accurately identifying the epileptic area by correctly classifying focal and non-focal EEG signals. The performance of the LDA classifier appeared to be inconsistent as its outcomes varied across different EEG recordings. The MD and QDA classifiers demonstrated good performance for some recordings, but overall, their quantitative results were lower compared to those of the KNN classifier.

Given the fluctuations in the results obtained with all four different classifiers, it can be concluded that testing several classifiers is useful in finding a suitable classification method for each recording.

The proposed approach is effective due to the good results obtained, and all these results are used for drawing new directions in the field of research.

The accurate classification of epileptic areas proved to be an essential factor in predicting signal types and automatically identifying the brain area that needs to be surgically removed for epileptic patients.

Future research directions will aim to explore new combinations of methods, feature vectors, and classifiers to further improve the accuracy of the classification results. Additionally, the investigation of other databases will be pursued to evaluate the generalizability and robustness of the proposed approach.

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DIFERENȚIEREA SEMNALELOR EEG EPILEPTICE FOCALE ȘI NON-FOCALE FOLOSIND DIFERITE TIPURI DE CLASIFICATORI

(Rezumat)

Epilepsia este o tulburare neurologică caracterizată prin apariția crizelor recurente și are o incidență ridicată. Scopul acestei cercetări este de a clasifica semnalele EEG focale și non-focale, pentru a identifica zona epileptogenă a creierului, care poate fi tratată chirurgical pentru a gestiona epilepsia.

În această lucrare, a fost propusă o metodă de clasificare bazată pe parametrii spectrului de ordin superior (HOS) și pe patru clasificatori diferiți: analiza discriminantă liniară (LDA), analiza discriminantă pătratică (QDA), distanța Mahalanobis (MD) și cei mai apropiați k vecini (KNN).

Metoda de clasificare propusă a fost evaluată folosind un set de date public care constă în înregistrări EEG de la pacienți epileptici.

Au fost evaluate performanțele clasificatorilor și s-a demonstrat că, cele mai bune rezultate au fost obținute cu clasificatorul KNN. Cu clasificatorul KNN, clasificarea datelor s-a efectuat cu o valoare maximă a ratei de clasificare de 99,55%, a sensitivității de 100% și a specificității de 99,09%. Clasificarea datelor a fost efectuată cu valori maxime de 0,96 pentru scorul-F1 și 0,91 pentru coeficientul Kappa și Matthews. Rezultatele demonstrează eficiența metodei propuse de a identifica tipul de semnal EEG și aplicabilitatea sa în epilepsie.