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Research Article

A Classification Approach for Focal/Non-focal EEG Detection Using Cepstral Analysis

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ARTICLE INFO	ABSTRACT
Article history:	
Received 7 August 2021 Received in revised form 21 September 2021 Accepted 22 September 2021 Available online 28 September 2021	Electroencephalogram (EEG) is a convenient neuroimaging technique due to its non-invasive setup, practical usage, and high temporal resolution. EEG allows to detect brain electrical activity to diagnose neurological disorders. Epilepsy is a crucial neurologic disorder that is reasoned from occurrence of sudden and repeated seizures. The goal of this paper is to classify the focal (epileptogenic area) and non-focal (non-epileptogenic area) EEG records with censtral coefficients and machine learning algorithms.
Keywords:	Analysis is carried out using publicly available Bern-Barcelona EEG dataset. Mel Frequency Cepstral Coefficients (MECC) are calculated from EEG apoche. Feature sets are normalized with a score and
cepstrum analysis, classification, EEG, focal and, non- focal	dimension reduction is realized using Principal Component Analysis. Fine Tree, Quadratic Discriminant Analysis, Logistic Regression, Gaussian Naïve Bayes, Cubic Support Vector Machine, weighted k-nearest neighbors, and Bagged Trees are applied for classification stage. A value of k=10 is used for cross validation. All focal and non-focal EEG pairs are perfectly classified with acc., sen., spe., and F1-score of 100% and AUC with 1 via. Quadratic Discriminant Analysis, Logistic Regression, Cubic SVM and Weighted k-NN. Proposed work recommends MFCCs as a single marker and this provides less
Doi: 10.24012/dumf.1002081	computation workload, practicality, and direct processing of focal / non-focal EEG time series. Proposed methodology in this paper serves one of the highest achievements to literature and can assist neurologist
* Corresponding author	and physicians to validate their diagnosis.

Introduction

Epilepsy is one of the common neurological disorders that emerges due to sudden electrical activity in the brain [1]. In accordance with World Health Organization (WHO) reports, there have been about 50 million patients suffering from epilepsy around the world, and 80% of current patients are living in lower income countries [2]. EEG records obtained from epileptogenic area are called as focal EEG, while EEG records sourced from other regions are nonfocal EEG [3]. Some of focal epilepsy patients are drug resistant, and recovery of these patients is feasible with only local brain surgery. Long duration of EEG records needs to be analyzed by neurosurgeons to localize epileptogenic zone prior to surgical operation. This stage is strenuous, time consuming and inclined to errors, therefore, an automatic decision system assists neurologists for examining EEGs via. signal processing methods and machine learning algorithms [4].

EEG records have been preferred as a popular brain screening tool for researchers. This method has noninvasive implementation, higher temporal resolution, and cost-effective solutions [5]. In this regard, there are various methods have been proposed for discrimination of focal and non-focal EEG records. Wavelet based features [6], Empirical Mode Decomposition [4], entropy algorithms [7], deep neural architectures [4], [8], [9], and multifeatures [10]–[12] are some of algorithms for focal / nonfocal EEG identification task in literature studies. The main purpose of the present study is to present an effective method to classify focal / non-focal EEG records. In this context, Mel Frequency Cepstral Coefficients (MFCC) are calculated from related EEG epochs. One of the powerful sides of cepstrum analysis is that any repetitive pattern or harmonic behaviors are emerged as unique component of cepstrum analysis. Yavuz et al. (2018) also reported that there are also a few studies that investigate brain's cognitive behavior using cepstral analysis [13]. According to our research and knowledge, there has been no study that applied cepstral analysis to existing focal / non-focal EEG dataset previously. For further analysis, MFCCs are normalized within z-scores and Principal Component Analysis is applied to normalized feature sets to obtained more relevant subsets of features. Finally, Fine Tree, Quadratic Discriminant Analysis, Logistic Regression, Gaussian Naïve Bayes, Cubic Support Vector Machine, weighted k-nearest neighbors, and Bagged Trees as one of ensemble learning algorithm are applied for classification stage and different performance metrics are calculated.

Moreover, k=10 cross validation is used to split train and test sets.

The remaining of the paper is organized as follows: Section 2 explains proposed methodology, extracted features and classification process. Obtained results are reported and discussed with previous findings in Section 3. Finally, paper is concluded with Section 4.

Material and Methods

Bern-Barcelona Database

In this study, a publicly available Bern-Barcelona EEG dataset is processed for discrimination of focal and non-focal records from Department of Neurology, Bern University [14]. Dataset was recorded from 5 temporal epilepsy patients before brain surgery. Focal EEG records are acquired from the brain regions where appears ictal signals and, non-focal signals are recorded from the lobes that do not exist any seizure. Electrode locations are located according to 10/20 placement. Dataset consists of 3750 focal and 3750 non-focal segment and each segment has X-Y pairs. Signals were recorded with 512 Hz f_s during 20 s. Sample EEG records is given in Fig. 1.



Figure 1. 5 s of sample focal / non-focal EEG records of xy pairs

Method

The current methodology consists of 4 steps: i) obtaining EEG records, ii) dividing EEGs into epochs, feature calculation from epochs, normalization of feature set and dimension reduction to obtain relevant sub-sets, iii) dividing features into train and test sets in order to avoid any bias and overfitting and after that applying machine learning algorithms to compare classification performances, and finally iv) calculating performance metrics for binary classification of focal and non-focal EEGs. The steps followed in related work is illustrated in Fig. 2.

i)Mel Frequency Cepstral Coefficients (MFCC) for Feature Extraction

Cepstrum analysis is mainly used for speech recognition and seismic signals. It can be defined as an inverse Fourier transform of the logarithm of a calculated spectrum. Due a signal has repetitive and harmonic pattern, cepstrum analysis can be utilized as a powerful marker [15]. The steps of how a signal transform to cepstral domain is illustrated in Fig. 3. x[n] is the time domain signal and refers to EEG signal. In addition, X[k] stands for frequency spectrum of x[n]. X'[k] is log magnitude of filter bank energy from calculated spectra. c[n] is the final cepstrum after Discrete Cosine Transform of X'[k]. Cepstrum coefficient, c_i , as given in Eq. (1).

$$c_j = \sqrt{\frac{2}{N}} \sum_{i=1}^{N} A_i \cos\left(\frac{\pi j(i-0.5)}{N}\right) \quad 0 \le j \le N$$
(1)

where c_j refers to *j*th ceptral coefficient, and A_i shows logarithmic value for one of the N channels in filter bank.

Spectrum of mel-frequency during specific time n for r=1,2, ..., R is calculated in Eq. (2)

$$MF_{n}[r] = \frac{1}{A_{r}} \sum_{k=L_{r}}^{U_{r}} |V_{r}[k]X_{n}[k]|^{2}$$
(2)

where $V_r[k]$ stands for the triangular weighting function for order=r filter and index of DFT k is from L_r to U_r . In addition, A_r refers to rth order mel-filter normalization coefficient and given in Eq. 3.

$$A_r = \sum_{k=L_r}^{U_r} |V_r[k]|^2$$
(3)

Mel frequency cepstral coefficients (MFCCs) can be calculated by DCT of logarithm of filter outputs [13]. Details are given in Eq. 4.

$$MFCC_{n}[m] = \frac{1}{R} \sum_{r=1}^{R} \log (MF_{n}[r]) \cos \left[\frac{2\pi}{R} (r + \frac{1}{2})m\right]$$
 (4)

To summarize, the signal is divided into short frames. The reason behind dividing into short frame is to capture statistically stationary segments even if samples are constantly changing. We calculate power spectrum of each frame and identify which frequencies are present in the frames. Then, we apply mel-filter banks to power spectra and, sum the energy in each filter. Thus, one can reach the idea of how much energy exists in different frequencies. Mel scale determines width of the filter banks as the frequency gets higher, filters get wider. After taking logarithm of all filter bank energies, it enables a normalization technique to realize cepstral mean subtraction. This stage is similar with a compression operation to features. Calculated filter bank energies are so correlated because filter banks are all overlapping. DCT uses diagonal covariance matrices to decorrelate the energies. Generally 12 out of 26 DCT coefficients are kept because higher DCT coefficients include fast changes in filter bank energies and possible changes may attenuate performance. For this reason, we drop DCT coefficients after 12th to get more improvement. In this study, 13 number of the static cepstral coefficients including 0th coefficient are calculated. In addition to these static



Figure 2. Steps followed in proposed study for focal and non-focal EEG Time Series



Figure 3. Process for calculation of cepstral coefficients

parameters, 1st order time derivatives ('delta'), also known as differential coefficient, and 2nd order time derivatives ('delta-delta'), also known as acceleration coefficient, are calculated. These 2 parameters are called dynamic parameters. Then, Log-energy coefficients are added to each group. Combining dynamic parameters within static parameters will increase robustness and stability of the study. In order to calculate MFCCs, hamming window in time domain during spectrum calculation and triangular shaped filters in mel-domain is applied as filter banks.

Filters act in absolute magnitude domain. Some of the studies in literature view have obtained higher performance values by analyzing all the coefficients [13]. Finally, 42-coefficient feature vectors are extracted from focal and non-focal EEG segments.

ii)Z-score normalization and Principal Component Analysis (PCA) for dimension reduction

Before applying PCA to feature sets, we normalize the feature vector with z-score. We can use z-scores to put on the features on the same scale prior to further steps. Z-scores are calculated in terms of mean (μ) and standard deviation (σ). Then, normalized feature set has μ =0 and σ =1 as calculated in Eq. 5.

$$Z = \frac{x - \mu}{\sigma}$$
(5)

Processing with high dimensional and redundant features is time consuming and obtained results might be poor. For the purpose of gaining top few features which represent the data set sufficiently and no information to be lost, we applied PCA to feature sets after z-score normalization. If we are given a X:(nxt), where n is number of features and t is the number of observations, PCA can be calculated as eigenvalue of covariance matrix $C_x = XX^T$. The ratio of variance belong to first p components over whole feature set variance is calculated in Eq. 6.

$$\mathbf{R}V_{1:n} = \frac{\sum_{i=1}^{p} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \tag{6}$$

where λ_i is the eigenvalue of i^{th} principal component [16]. Number of principal components is based on explained variance. In this study, 95% of total variance is explained by 11 principal components out of 42 coefficients.

iii)Classifiers

Fine Trees

Decision trees have a framework that divides large number of inputs into small set of records by applying a set of decision rules. A decision tree has a pre-defined target variable and provide a strategy from top to the bottom due to their structure. Decision trees are easily interpretable and can process both numerical and categorical data. They may also produce low predictive performance metrics and result with overfitting. We need to grow simpler trees to solve overfitting problem. Moreover, we may specify the maximum number of splits or branch points to check depth of the tree. In this study, we preferred to use fine tree due to its fast prediction speed, easy interpretation, and flexible model to make fine distinctions among classes[17]. In current model, different set of numbers are selected and maximum number of split is decided as 100 as it gives best classification rate. Moreover, split criterion is Gini's diversity index.

Quadratic Discriminant Analysis

Discriminant analysis uses hyperplanes to separate classes allocated to groups using maximum likelihood rule. It is a multivariate technique to discriminate 2 or more groups and algorithm is fast, precise, and easily interpretable. In addition, discriminant analysis is proper for large datasets. In order to train a classifier, different Gaussian distributions are generated, and fitting function predicts the parameters of those distribution. Linear and Quadratic Discriminant Analysis are commonly used algorithms. Quadratic Discriminant Analysis (QDA) uses quadratic decision boundaries and prediction ability is higher in accordance with Linear Discriminant Analysis (LDA). QDA estimates the covariance matrix for each input classes [18].

Logistic Regression

Logistic Regression (LR) a 2 classes classification algorithm and gives binary solution. LR models the class probabilities uses logistic function that is the linear combination of predictors [5].

Gaussian Naïve Bayes

Naive Bayes (NB) is a classifier that used for pattern recognition problems and based on Bayes theory. In NB classification, a certain amount of trained data is initially applied. The data applied for training should have whether class or category. Within probability operations on trained data, category of the new test data is determined according to probability values. The more the number of trained data, the more accurate it can be to identify the correct category of test data. In this study, Gaussian distributor is used for numeric predictors and multivariate multinomial distribution is applied for categorical predictors [19].

Cubic Support Vector Machine

Statistical learning based SVM was firstly applied by Cortes and Vapnik for binary classification. The purposes within SVM are to the transport nonlinear separable samples to higher dimension by using kernel functions and determine a hyperplane that will separate the samples by help of solving quadratic optimization problems [20]. In current study, cubic kernel function is preferred. Kernel scale is specified as automatic and box constraint level equals to 1. One vs. one multiclass method is applied for discrimination focal and nonfocal EEG records.

Weighted k-Nearest Neighbors

It is parametric, non-linear, and partially simple classification algorithm. k-NN may outperforms for large datasets. Algorithm works according to the similarity of training and test data sets to each other. Assignment of any data point to any class is realized by checking k neighbors close to related data point. If we choose k as very small, the algorithm could be very sensitive. If the k is selected too large, one class can include too many data points from other classes. In weighted k-NN, every neighbor sample has a weight according to its distance to the test sample. Closer points have bigger weights in the voting. In proposed study, number of neighbors is 10, distance metric is 'Euclidean' and distance weight is selected as 'squared inverse', namely weight is $1/distance^2$ [21].

Bagged Trees

Bagged Trees are one of ensemble classifier that use Random Forest Bag with Decision Tree learners. In this study, the algorithm [22] proposed by Breiman is applied to features sets. Bagging is generally preferred to reduce the variance of a decision tree. Several subsets are randomly selected from training sample and each of subsets is used to train its decision trees. Finally, we sum up within an ensemble including different models. Predictions from trees are averaged and a robust prediction is achieved rather than single decision tree. In short, ensemble method is Bag, learner type is Decision tree and number of learners is determined as 30.

Performance Metrics

In order to evaluate the classification performance, accuracy, sensitivity, specificity, F1-score and area under the ROC curve (AUC) are calculated. Calculation of performance metrics is given by Table 1.

Accuracy is the correctly labelled feature sets. Sensitivity is defined as proportion of correctly positive features. Specificity is the ratio of negative instances which are correctly estimated as negative. F1- score is a metric that is combination of TPs, FP, and FN. Calculation of F1-score is given with Eq. 7.

$$F1 - score = 2 * \frac{Precision*Recall}{Precision+Recall}$$
(7)

Results and Discussion

In current study, a single EEG marker of MFCC is utilized for discrimination of focal and non-focal EEG records. 7 different classifiers are performed and confusion matrices for each classifier are given in Table 2-3 in case of before/after PCA and z-normalization process. Extracted features are also compared in Fig. 4 with given sample patterns. Quadratic Discriminant Analysis, Logistic Regression, Cubic SVM and Weighted k-NN performs perfectly with acc., sen., spe., and F1-score of 100% and AUC with 1 as it can be seen in Table 3. Classification performances are all increased with use of PCA and z-normalization. All focal EEG pairs are correctly classified, but some of non-focal EEGs misclassified in Gaussian Naïve Bayes

algorithm. Performance metrics obtained from Fine Tree and Bagged Trees are relatively lower, but still convincing results are achieved.

Most relevant studies published between 2016-2021 based on Bern-Barcelona Dataset are listed in Table 4. Many of studies are included 3750 pairs of focal / non-Focal EEG pairs, and minority of the methods are performed with 50 pairs. EEG markers are composed of wavelet transform, empirical mode decomposition, entropies, Fourier transform, and spectral features. Deep learning-based features are also utilized in previous studies. Support Vector Machines, Neural Network classifiers and k- nearest neighbors are observed as frequently applied as conventional methods besides deep neural networks. 10-fold cross validation is also common method to divide train and test sets. Madhavan et al. [8] achieved best performance with acc., sen., and spe., over 99% using 2D deep CNN within synchro-squeezing transform. Arunkumar et al. [7] proposed entropy algorithms using conventional classifiers and achieved acc., sen., and spe. of 99%. We here achieved highest possible performance withing 100% of acc., sen., spe., and F1-score. Studies in literature included many features and attempted to reach conclusive set of features for a consensus. Proposed work includes MFCCs as a single marker and this provides less computation workload, practicality, and direct processing of EEG time series. Moreover, most of the classifiers performs high and none of algorithms fails to discriminate focal / nonfocal EEGs. This is a good indicator for the robustness of proposed algorithm. z-score normalization and finding relevant subsets of features within PCA are one of crucial steps to increase classification performances.

The current study has some limitations as follows: even if MFCCs provide adequate results, combination of markers suggested by literature studies can also joined within or without MFCCs and contribution of these coefficients can be more clear for discrimination of focal / non-focal EEGs. Parameters for classifiers are chosen empirically; moreover, optimal parameters may be included to observe effects on performance metrics.

Conclusion

In current study, MFCCs are extracted directly from focal / nonfocal EEG time series to analyze unpredictable and non-linear behavior of related signals. All focal and non-focal epochs are fully discriminated. Proposed method serves one of the highest achievements to literature and can assist neurologist and physicians to validate their diagnosis. Same approach can be applied not only to focal / non-focal EEGs but also other types of seizures including preictal, interictal and ictal EEG. Different neurological diseases such as Alzheimer's and Parkinson's disease, schizophrenia, or strokes may be diagnosed within proposed methods. Eventually, treatment stage can be accelerated. In future works, MFCCs feature matrices can be applied directly to input of deep neural networks, or some image conversion methods will be applied to coefficients in frequency domain as another option for evaluation of deep neural architectures.

		Р	redicted	
		Positive	Negative	
				Sensitivity
	Positive	True Positive (TP)	False Negative (FN)	
				$\frac{TP}{TP + FN}$
ctual				Specificity
A	Negative	False Positive (FP)	True Negative (TN)	TN
				$\overline{TN + FP}$
		Precision	Recall	Accuracy
		ТР	ТР	TP + TN
		$\overline{TP + FP}$	$\overline{TP + FN}$	TP + FP + FN + TN

Table 1. Performance metrics for classification evaluation

		Predicted Class Perfo			erformance Metrics			
Classifier	Observed Class	Focal	Non-focal	Acc.	Sen.	Spe.	F1-score	AUC
Fine Tree	Focal	2499	1251	65 5	66.6	64.2	65 9	0.71
	Non-focal	1338	2412	05.5	00.0	04.2	03.8	0.71
Quadratic Discriminant	Focal	1571	2179	57 /	11 0	72 8	40.5	0.62
Analysis	Non-focal	1017	2733	57.4	41.0	12.8	49.5	0.63
Logistic Regression	Focal	2710	1040	60.7	72.2	67 1	70.4	0.76
	Non-focal	1232	2518	09.7	12.2	07.1	70.4	0.70
Gaussian Naive Bayes	Focal	1571	2179	57 1	11 0	72 8	40.5	0.62
	Non-focal	1017	2733	57.4	41.0	12.0	49.3	0.05
Cubic SVM	Focal	2912	838	60.2	776	60.9	71.5	0.75
	Non-focal	1467	2283	09.5	//.0	00.8	/1.3	0.75
Weighted k-NN	Focal	2194	1556	596	595	597	50 5	0.62
	Non-focal	1548	2202	50.0	50.5	30.7	38.3	0.05
Bagged Trees	Focal	2653	1097	66.9	707	62.8	69	0.74
	Non-focal	1395	2355	00.8	/0./	02.8	00	0.74

		Predic	ted Class	Perfo	rmance	Metrics	5	
Classifier	Observed Class	Focal	Non-focal	Acc.	Sen.	Spe.	F1-score	AUC
Fine Tree	Focal	3733	17*	00.6	00.62	00 57	00.59	1
	Non-focal	14*	3736	99.0	99.02	99.37	99.38	1
Quadratic Discriminant	Focal	3750	0	100	100	100	100	1
Analysis	Non-focal	0	3750	100	100	100	100	1
Logistic Regression	Focal	3750	0	100	100	100	100	1
	Non-focal	0	3750	100	100	100	100	1
Gaussian Naive Bayes	Focal	3750	0	00.0	00.76	100	00.00	1
	Non-focal	9*	3741	99.9	99.70	100	99.88	1
Cubic SVM	Focal	3750	0	100	100	100	100	1
	Non-focal	0	3750	- 100	100	100	100	1
Weighted k-NN	Focal	3749	1*	100	00.07	00.07	00.00	1
	Non-focal	1*	3749	100	99.97	99.97	99.90	1
Bagged Trees	Focal	3741	9*	00.7	00.62	0075	00.00	1
	Non-focal	14*	3736	- 99./	99.62	9975	99.00	1

Table 3. Performance metrics for Focal / Non-focal binary EEG Classification after PCA and z-normalization



Figure 4. Extracted features before/after PCA and z-normalization given with sample patterns

Authors (Year)	EEG	EEG Markers	Classifiers/	Performance
	Dataset		Cross Validation	Metrics
Sairamya et al.	3750 F	Wavelet Package	ANN/10-fold cross	Acc. =95.74%
(2021)[1]	3750 N	Decomposition,	Validation	Sen. =81.94%
		Entropies		Spe. = $/8.81\%$
Sharma et al.	3750 F	Third-order cumulant	SVM with cubic kernel	Acc. =99%
(2020) [23]	3750 N		/10-fold cross validation	Sen. =98.68%
				Spe. =99.32%
<u>X</u> (2020)	2750 5	T1 11 A 1 /		F-score =0.99
You et al. (2020)	3750 F	Flexible Analytic	GRINN, KF, SVM, LS SVM KNN furmy KNN/10 fold group	Acc=94.80%
[0]	3750 N	wavelet Transform,	LS-SVM, KINN, IUZZY KINN/10-1010 Cross	Sen. $=92.27\%$
		Log energy entropy,	validation	Spe. =96.10%
		entropy		
San-Segundo et al.	3750 F	Fourier Transform,	CNN	Healty vs. Ictal
(2019) [4]	3750 N/	Wavelet Transform,		Acc=99.8%
	Bonn	Empirical Mode		Non-ictal vs. Ictal
		Decomposition		Acc=99.5%
				Interictal VS.
				Acc=96.5%
				Healty vs.
				Interictal vs. Ictal
				Acc=95.7%
Rahman et al.	3750 F	Variational Mode	Stacked SVM/5-fold cross validation	Acc=95.2%
(2019)[10]	3750 N	Decomposition,		Sen. =96.1%
		Discrete		Spe. =94.4%
		Wavelet Transform,		AUC=0.989
		Multiscale Dispersion		
		Refined Composite		
		Multiscale Fuzzy		
		Entropy,		
		Autoregressive Model		
Dealer and	2750 E	Coefficient	CVM VNN DE AJ-D	A == 06 10/
Sriraam (2018)	5750 Г 3750 N	NCA with 28 features	/10 fold cross validation	Acc=90.1%
[11]	5750 N		/10-1010 cross vanuation	Spe -94.4%
[]				AUC=0.96
Gupta and Pachori	3750 F	Wavelet Transform,	LS-SVM/10-fold cross validation	Acc=95.85%
(2020) [24]	3750 N	Corr-entropy,		Sen. =95.47%
		Exponential Energy		Spe. =96.24%
Tjepkema-	50 F	Deep Neural Network	Combinations of convolutional and recurrent	AUC =0.94
Clostermans et al. (2018) [9]	50 N	Features	neural networks	
Das and Bhuiyan	3750 F	EMD-DWT, log energy	k-NN city block distance	Acc=89.4%
(2016) [3]	3750 N	entropy		Sen. =90.7%
				Spe. =88.1%
Arunkumar et al.	50 F	Entropies	Naive Bayes, Radial Based Function, Best First	Acc=99%
(2018)171	50 N		Decision Tree, KNN, SVM, Non- Nested	Sen. =99%

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			Generalized Exemplars/ 10-fold cross validation	Spe. =99%
Fraiwan and	3750 F	Bi-directional Long	BDLSTM/4,6,10-fold cross validation	Acc. =99.24%
Alkhodari (2020)	3750 N	Short Term Memory		Sen. =99.55%
[2]				Spe. =99.65%
Siddharth et al.	3750 F	Sliding Mode -Singular	Sparse-autoencoder Radial Bases Function	Acc=99.11%
(2019) [25]	3750 N	Spectrum Analysis	Neural Network/10-fold cross validation	Sen. =98.52%
				Spe. =99.70%
Chetterje et al.	50 F	Multifractal Detrended	KNN, SVM/10-fold cross validation	Acc=92.18%
(2017) [26]	50 N	Fluctuation Analysis		Sen. =92.50%
				Spe. =92.69%
Bajaj et all (2017)	750 F	Rhythm Based	LS-SVM/10-fold cross validation	Acc=99.20%
[27]	750 N	Correlation Features		Sen. =99.73%
				Spe. =98.68%
Madhavan et al.	3750 F	Synchro-squeezing	2D Deep Convolutional Neural Network/ 5-	Acc=99.94%
(2020) [8]	3750 N	Transform	fold cross validation	Sen. =99.94%
				Spe. =99.94%
Bhattacharrya et	50 F	Empirical Wavelet	Least square SVM/10-fold cross validation	Acc=90%
al. (2016) [28]	50 N/	Transform		Sen. =88%
	750 F			Spe. =92%
	750 N			(50 pairs)
Zeng et al. (2019)	50 F	Empirical mode	Least square SVM/10-fold cross validation	Acc=96%
[29]	50 N/	Decomposition, Phase		(50 pairs)
	3750 F	Space Reconstruction		
	3750 N			
Sriraam and	3750 F	21 Multi features	SVM/10-fold cross validation	Acc. =92.15%
Raghu (2017) [12]	3750 N			Sen. =94.56%
				Spe. =89.74%
Current Study	2750 E	MECC	Fina Traa Quadratia Disariminant Analysia	$\Lambda_{00} = S_{00} = S_{00}$
Current Study.	3750 F	MITCU	Logistic Regression Gaussian Naïva Pavas	- El scoro $-$
	5750 IN		Cubic Support Vector Machine weighted k	- 1 ⁻¹⁻⁵⁰⁰¹⁰ -
			NN Bagged Trees / 10-fold cross validation	AUC-1
			Cubic Support Vector Machine, weighted k- NN, Bagged Trees / 10-fold cross validation	100% AUC=1

Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared

There is no conflict of interest with any person / institution in the article prepared

Authors' Contributions

Seker D: Study conception and design, visualization, analysis, and interpretation of data, drafting of manuscript

Ozerdem MS: conceived the original idea, supervised the project, critical revision

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