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Research Article

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

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ABSTRACT

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 cepstral coefficients and machine learning algorithms. Analysis is carried out using publicly available Bern-Barcelona EEG dataset. Mel Frequency Cepstral Coefficients (MFCC) are calculated from EEG epochs. Feature sets are normalized with z-score and 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 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 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 non-focal 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 non-invasive 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 multi-features [10]–[12] are some of algorithms for focal / non-focal 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.

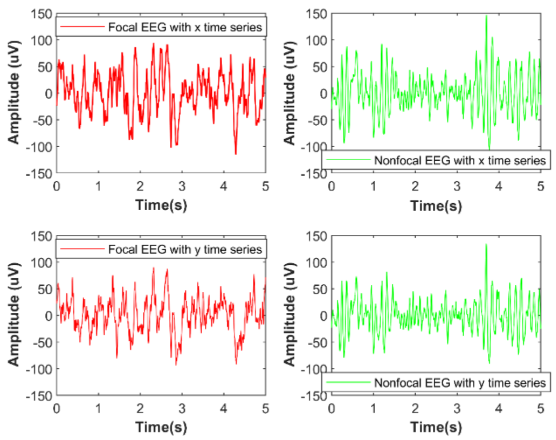

Figure 1. 5 s of sample focal / non-focal EEG records of x-y pairs

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_j, as given in Eq. (1).

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

where c_j refers to jth 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)

$$MF_n[r]=\frac{1}{A_r}\sum_{k=L_r}^{U_r} |V_r[k]X_n[k]|^2 \tag{2}$$

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.

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

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

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

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

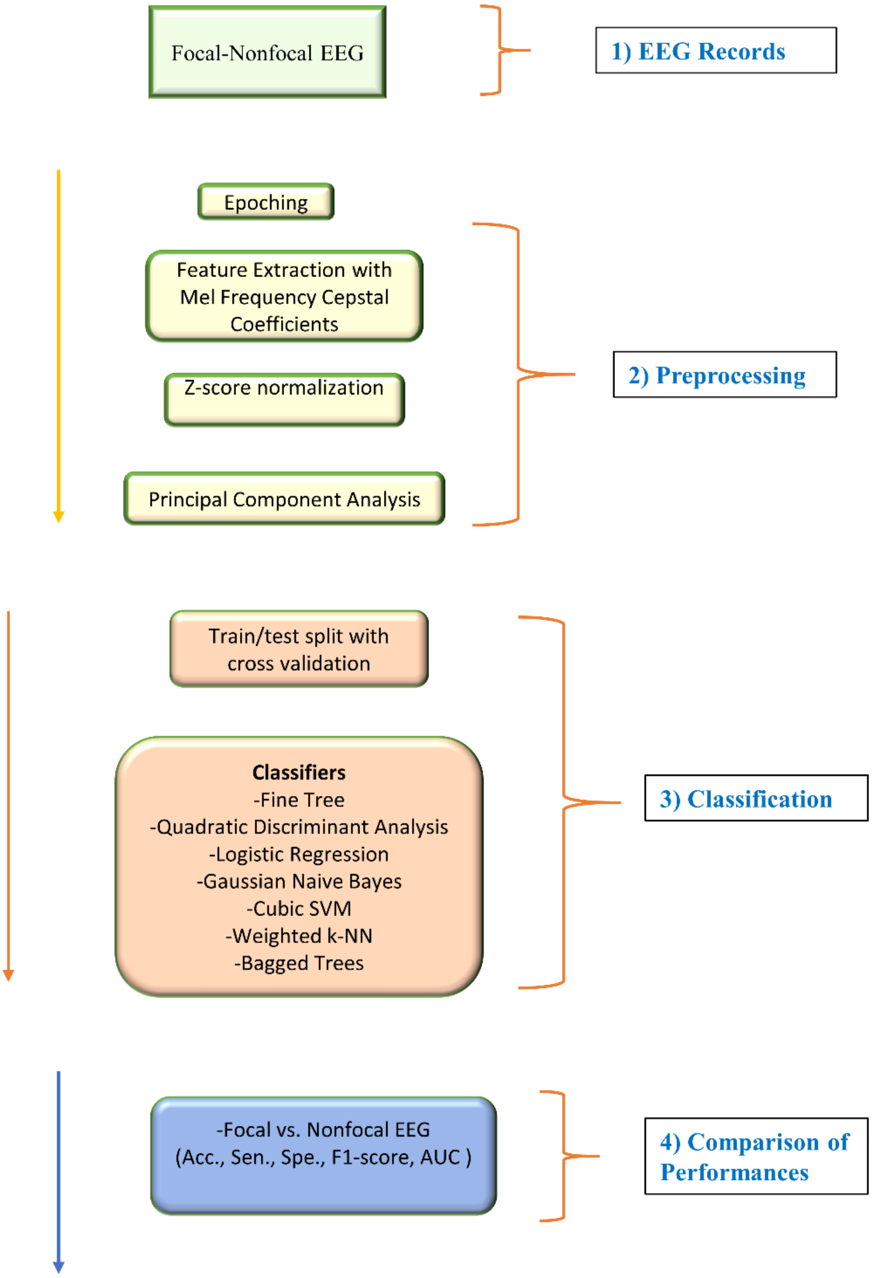

Figure 2. Steps followed in proposed study for focal and non-focal EEG Time Series

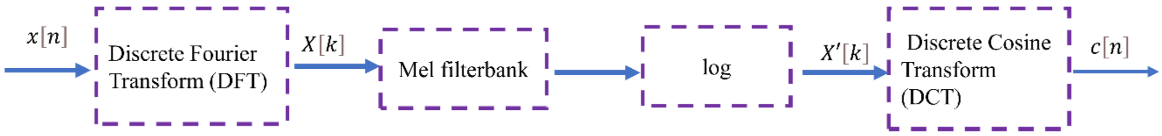

Figure 3. Process for calculation of cepstral coefficients

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.

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

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.

$$\mathrm{R}V_{1:n}=\frac{\sum_{i-1}^{p}\lambda_i}{\sum_{i-1}^{n}\lambda_i} \qquad (6)$$

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 non-focal 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.

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

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 / non-focal 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 / non-focal 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.

Table 1. Performance metrics for classification evaluation

		Predicted		
		Positive	**Negative**	
Actual	**Positive**	True Positive (TP)	False Negative (FN)	Sensitivity $\frac{TP}{TP+FN}$
	Negative	False Positive (FP)	True Negative (TN)	Specificity $\frac{TN}{TN+FP}$
		Precision $\frac{TP}{TP+FP}$	Recall $\frac{TP}{TP+FN}$	Accuracy $\frac{TP+TN}{TP+FP+FN+TN}$

Table 2. Performance metrics for Focal / Non-focal binary EEG Classification before PCA and z-normalization

		Predicted Class		**Performance Metrics**				
Classifier	**Observed Class**	**Focal**	**Non-focal**	**Acc.**	**Sen.**	**Spe.**	**F1-score**	**AUC**
Fine Tree	**Focal**	2499	1251	65.5	66.6	64.2	65.8	0.71
	Non-focal	1338	2412					
Quadratic Discriminant Analysis	**Focal**	1571	2179	57.4	41.8	72.8	49.5	0.63
	Non-focal	1017	2733					
Logistic Regression	**Focal**	2710	1040	69.7	72.2	67.1	70.4	0.76
	Non-focal	1232	2518					
Gaussian Naive Bayes	**Focal**	1571	2179	57.4	41.8	72.8	49.5	0.63
	Non-focal	1017	2733					
Cubic SVM	**Focal**	2912	838	69.3	77.6	60.8	71.5	0.75
	Non-focal	1467	2283					
Weighted k-NN	**Focal**	2194	1556	58.6	58.5	58.7	58.5	0.63
	Non-focal	1548	2202					
Bagged Trees	**Focal**	2653	1097	66.8	70.7	62.8	68	0.74
	Non-focal	1395	2355					

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

		Predicted Class		Performance Metrics				
Classifier	**Observed Class**	**Focal**	**Non-focal**	**Acc.**	**Sen.**	**Spe.**	**F1-score**	**AUC**
Fine Tree	**Focal**	3733	17*	99.6	99.62	99.57	99.58	1
	Non-focal	14*	3736					
Quadratic Discriminant Analysis	**Focal**	3750	0	100	100	100	100	1
	Non-focal	0	3750					
Logistic Regression	**Focal**	3750	0	100	100	100	100	1
	Non-focal	0	3750					
Gaussian Naive Bayes	**Focal**	3750	0	99.9	99.76	100	99.88	1
	Non-focal	9*	3741					
Cubic SVM	**Focal**	3750	0	100	100	100	100	1
	Non-focal	0	3750					
Weighted k-NN	**Focal**	3749	1*	100	99.97	99.97	99.96	1
	Non-focal	1*	3749					
Bagged Trees	**Focal**	3741	9*	99.7	99.62	9975	99.66	1
	Non-focal	14*	3736					

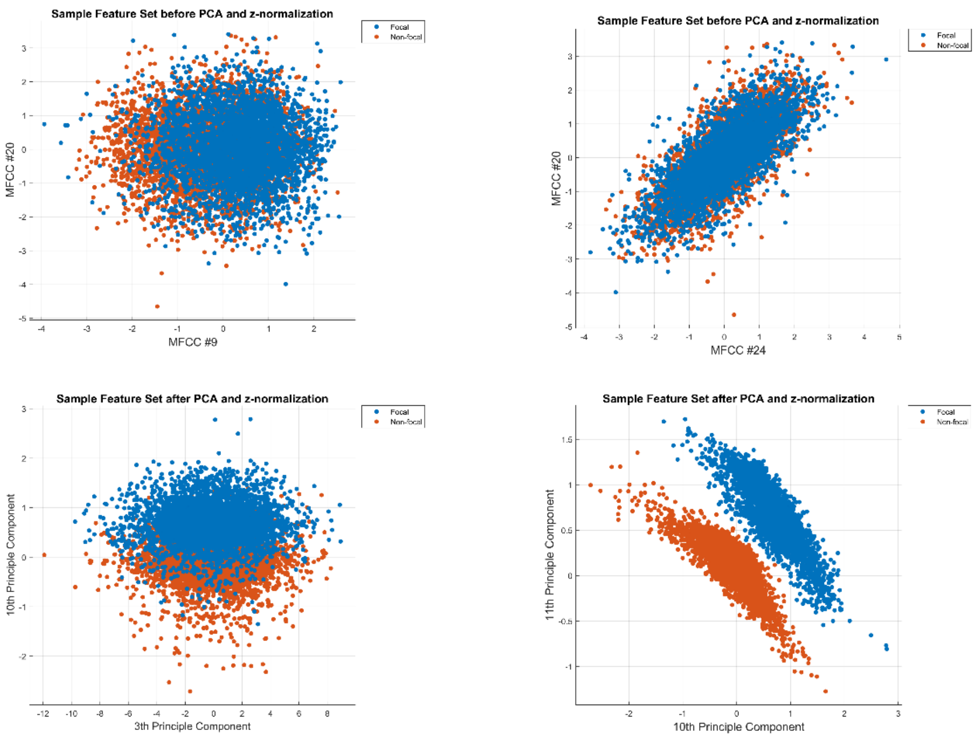

Figure 4. Extracted features before/after PCA and z-normalization given with sample patterns

Table 4. Studies in literature view for focal / non focal EEG Classification

Authors (Year)	EEG Dataset	EEG Markers	Classifiers/ Cross Validation	Performance Metrics
Sairamya et al. (2021) [1]	3750 F 3750 N	Wavelet Package Decomposition, Quad Binary Pattern Entropies	ANN/10-fold cross Validation	Acc. =95.74% Sen. =81.94% Spe. = 78.81%
Sharma et al. (2020) [23]	3750 F 3750 N	Third-order cumulant	SVM with cubic kernel /10-fold cross validation	Acc. =99% Sen. =98.68% Spe. =99.32% F-score =0.99
You et al. (2020) [6]	3750 F 3750 N	Flexible Analytic Wavelet Transform, Log energy entropy, Fuzzy distribution entropy	GRNN, RF, SVM, LS-SVM, KNN, fuzzy KNN/10-fold cross validation	Acc=94.80% Sen. =92.27% Spe. =96.10%
San-Segundo et al. (2019) [4]	3750 F 3750 N/ Bonn	Fourier Transform, Wavelet Transform, Empirical Mode Decomposition	CNN	Healty vs. Ictal Acc=99.8% Non-ictal vs. Ictal Acc=99.5% Healty vs. Interictal Acc=96.5% Healty vs. Interictal vs. Ictal Acc=95.7%
Rahman et al. (2019)[10]	3750 F 3750 N	Variational Mode Decomposition, Discrete Wavelet Transform, Refined Composite Multiscale Dispersion, Refined Composite Multiscale Fuzzy Entropy, Autoregressive Model Coefficient	Stacked SVM/5-fold cross validation	Acc=95.2% Sen. =96.1% Spe. =94.4% AUC=0.989
Raghu and Sriraam (2018) [11]	3750 F 3750 N	NCA with 28 features	SVM, KNN, RF, AdaBoost /10-fold cross validation	Acc=96.1% Sen. =97.6% Spe. =94.4% AUC=0.96
Gupta and Pachori (2020) [24]	3750 F 3750 N	Wavelet Transform, Corr-entropy, Exponential Energy	LS-SVM/10-fold cross validation	Acc=95.85% Sen. =95.47% Spe. =96.24%
Tjepkema-Clostermans et al. (2018) [9]	50 F 50 N	Deep Neural Network Features	Combinations of convolutional and recurrent neural networks	AUC =0.94
Das and Bhuiyan (2016) [3]	3750 F 3750 N	EMD-DWT, log energy entropy	k-NN city block distance	Acc=89.4% Sen. =90.7% Spe. =88.1%
Arunkumar et al. (2018) [7]	50 F 50 N	Entropies	Naive Bayes, Radial Based Function, Best First Decision Tree, KNN, SVM, Non- Nested	Acc=99% Sen. =99%

			Generalized Exemplars/ 10-fold cross validation	Spe. =99%
Fraiwan and Alkhodari (2020) [2]	3750 F 3750 N	Bi-directional Long Short Term Memory	BDLSTM/4,6,10-fold cross validation	Acc. =99.24% Sen. =99.55% Spe. =99.65%
Siddharth et al. (2019) [25]	3750 F 3750 N	Sliding Mode -Singular Spectrum Analysis	Sparse-autoencoder Radial Bases Function Neural Network/10-fold cross validation	Acc=99.11% Sen. =98.52% Spe. =99.70%
Chetterje et al. (2017) [26]	50 F 50 N	Multifractal Detrended Fluctuation Analysis	KNN, SVM/10-fold cross validation	Acc=92.18% Sen. =92.50% Spe. =92.69%
Bajaj et all (2017) [27]	750 F 750 N	Rhythm Based Correlation Features	LS-SVM/10-fold cross validation	Acc=99.20% Sen. =99.73% Spe. =98.68%
Madhavan et al. (2020) [8]	3750 F 3750 N	Synchro-squeezing Transform	2D Deep Convolutional Neural Network/ 5-fold cross validation	Acc=99.94% Sen. =99.94% Spe. =99.94%
Bhattacharrya et al. (2016) [28]	50 F 50 N/ 750 F 750 N	Empirical Wavelet Transform	Least square SVM/10-fold cross validation	Acc=90% Sen. =88% Spe. =92% (50 pairs)
Zeng et al. (2019) [29]	50 F 50 N/ 3750 F 3750 N	Empirical mode Decomposition, Phase Space Reconstruction	Least square SVM/10-fold cross validation	Acc=96% (50 pairs)
Sriraam and Raghu (2017) [12]	3750 F 3750 N	21 Multi features	SVM/10-fold cross validation	Acc. =92.15% Sen. =94.56% Spe. =89.74%
Current Study:	3750 F 3750 N	MFCC	Fine Tree, Quadratic Discriminant Analysis, Logistic Regression, Gaussian Naïve Bayes, Cubic Support Vector Machine, weighted k-NN, Bagged Trees / 10-fold cross validation	Acc. = Sen. = Spe. = F1-score = 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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