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Impact of EEG Rhythm on the Prognosis of Epilepsy

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Abstract: A chronic neurological disorder called epilepsy is characterized by frequent, unplanned seizures. A seizure is an unexpected and uncontrolled electrical disturbance in the brain that can cause a variety of physical and behavioral symptoms. Prognosis of epilepsy can be done based on pre-ictal (prior to seizure) signal variations in Electroencephalogram (EEG) rhythm. EEG rhythm like alpha, beta, theta and delta are substantial for epilepsy analysis. This study aimed to investigate the impact of various features from EEG rhythm and the feature reduction in classification of pre-ictal and inter-ictal (between two seizures) signal. Dataset of CHB-MIT comprises of 23 patients with 23 channels are used to extract Time, Frequency and Time-frequency features from EEG rhythms. Analysis shows that, compared to other bands, beta band features show major variation in pre-ictal and inter-ictal phases, which makes training of a Support Vector Machine (SVM) classifier easy for prediction of seizures. Further reduction in feature size using statistical analysis helped to achieve 75% reduction in computation. Results show average sensitivity of 93% and false positive rate of 0.14 per hour. The proposed method classified pre-ictal signal with maximum accuracy of 95%, sensitivity of 100%, specificity of 93% and false positive rate of 0.07per hour with reduced complexity compare to other state of art methods.

Index Terms: EEG Rhythm; Epilepsy; prediction; SVM; Machine Learning

1. Introduction

The World Health Organization (WHO) estimates that 50 million people worldwide suffer from epilepsy, making it a serious public health issue [1,2]. Epilepsy is caused by certain hereditary factors or abnormalities to the brain or other organs, such as brain tumors, head trauma, birth trauma, damage to the white and gray matter of the brain [3]. The EEG signal detection of epileptic episodes has become a standard approach for epilepsy diagnosis in recent years. Due to the fact that physically diagnosing epileptic seizures by skilled neurologists becomes a labor-intensive, lengthy process that also leads to several mistakes [4,5]. Therefore, it is necessary to detect epileptic seizures quickly and accurately using technology. The condition of patient may be affected by the abnormal brain function causing epileptic seizures. About 20% of epileptics go through the pre-ictal phase, which can be an early warning sign for seizures [6].

Predicting epilepsy depends on the pre-ictal phase because it enables prompt detection and intervention, which may help to avoid seizures and related problems like Sudden Unexpected Death in Epilepsy (SUDEP) [7]. The entrenched information in the pre-ictal phase follows the ictal phase so it is possible to predict epilepsy from the brain waves [8].

If epileptic seizures are anticipated before they occur, medication can successfully prevent them. Through the use of sophisticated computer techniques and machine learning algorithms using EEG signals are used to predict epileptic episodes. Moreover, the extraction of features from EEG signals and the elimination of noise from EEG signals provide two important obstacles that impact both expectancy time and real positive forecast rate. Compared to other brain imaging modalities, the EEG signal has a higher time-based resolution and is utilized to anticipate additional seizures from epilepsy. Since the EEG signal is a multivariate time series of a multidimensional, nonlinear system, only highly-deformed nonlinear functions may fully disclose the intricate link between them [9]. With a certain amount of uncertainty, patients can make an educated decision when they have access to the probabilistic chance of seizures [10].

2. Problem Statement and Literature Review

To predict epilepsy, real time processing of EEG signal is desirable and computational complexity need to reduce. The proposed work focuses on (i) Contribution of EEG band during pre-ictal state for prognosis of epilepsy(ii) Reducing the feature set and computational complexity for real time prediction without incising the sensitivity and false positive rate of machine learning model. To predict epileptic seizures, brain signal activity of patient is classified into two categories: pre-ictal and inter-ictal patterns. The ictal and post-ictal states are excluded from classification since they are used to detect ongoing seizures and provide negligible information about future seizures [11]. Numerous studies have been conducted on seizure prediction. One approach by A. Sharma [12] involves calculating the energy in the beta band of the EEG signal. The brain is divided into zones, and the power is calculated for each zone. The zone with the highest change in power is considered responsible for the seizure [12]. Another method, proposed by M. Z. Parvez et al [13], uses two features—frequency and amplitude—obtained through the Discrete Wavelet Transform (DWT) decomposition technique and classifies them using LS-SVM. Sadaye [14] introduces a new method for predicting seizures by looking at the beta band of EEG signals, which involves analyzing the frequency and amplitude of the brain waves. The method calculates the power spectrum of the beta band in the EEG signal. This helps in understanding the energy distribution across different frequencies in the signal. The power value obtained from the analysis is combined with the amplitude of the EEG signal. To make predictions, a machine learning algorithm called SVM is utilized. SVM is a type of algorithm that classifies data by finding the best line or decision boundary that separates different classes. The proposed method by Sadaye [14] was tested on data from 39 patients during both pre-ictal (before a seizure) and inter-ictal (between seizures) periods. The results showed that the method achieved a prediction accuracy of 70%, indicating a promising ability to forecast seizures in advance.

It has been noted that epilepsy alpha rhythm is linked to mental decline [15]. In the epilepsy group, peak alpha frequency fluctuation has been observed at a lower alpha frequency [16]. When the dependencies on anticonvulsant drugs are excluded, the epilepsy biomarker becomes sensitive to alpha rhythm irregularities [17]. Likewise, the association between theta signals and epilepsy has been shown. It has been observed that in brain tumor patients; theta bands have a positive correlation with the quantity of epileptic episodes [18]. In the rat model of temporal lobe epilepsy, spatial impairments linked with a decrease in theta power but inter-ictal activities were not substantially correlated with theta oscillations when the two were monitored simultaneously [19]. To locate the epileptogenic zone, one can use the irregularity of the delta signals as a biomarker [20]. Hejazi et al. [21] introduced time-variant coefficients based on the standard deviation, showing significant changes near seizure onset, allowing for seizure prediction based on these variations. The performance of the proposed methods by Hejazi et al. indicated an expected seizure occurrence period of approximately 50 minutes, with a maximum sensitivity of around 80% and a false prediction rate of 0.33 FP/h. The findings suggested that the Directed transfer function (DTF) method performed better in the gamma and beta frequency bands, providing greater accuracy and sensitivity compared to other studies under similar conditions [21]. Research suggests that brain networks undergo reorganization prior to seizure onset, characterized by changes in functional connectivity and local circuit dynamics. Increased synchronization and network connectivity, particularly in the seizure onset zone, have been observed in the preictal state [22]. In genetic absence epilepsy models, pre-ictal beta oscillations positively correlate with seizure susceptibility, duration, and intensity, while theta power negatively correlates with these factors [23]. A literature review is done to observe importance of three different bands alpha, theta and beta in classification of pre-ictal and inter-ictal phase. It is observed that pre-ictal phase includes signal variations which can be used to extract features for epilepsy prediction. This paper discusses the significance of beta band(13-30Hz) on feature selection and prediction. Features are further reduced based on p-value without degrading the performance of prediction. While the results showed promising outcomes, they are not yet sufficient for direct clinical applications, indicating the need for further research and refinement of the prediction models.

3. Proposed Method

Preprocessing of raw EEG signal, DWT for decomposition, feature extraction from band, p-value-based feature selection, and SVM for classification are the three well-established components of our methodology, their combined application tailored specifically to beta-band EEG rhythms for real-time seizure prediction represents a novel integration in our proposed method. In order to forecast epilepsy, this article used features trained from the pre-ictal state, which occurs 30 minutes [24] before a seizure starts. Detailed block diagram of proposed method is shown in figure 1. Each block is explained as under.

3.1 Dataset

The CHB-MIT Scalp EEG Database [25-31, 49, 50], which is frequently utilized for epileptic seizure prediction and is openly accessible for research, is employed. It includes scalp EEG records from young patients who had uncontrollable seizures. The MIT Laboratory for Computational Physiology hosts the dataset, which was gathered from Boston Children's Hospital. EEG recordings from 23 participants, aged 1.5 to 22 years, are included in the data. The collection includes EEG recordings that span 24 to 48 hours and have a sampling rate of 256 Hz. Annotation includes the number of seizures, start time, and time and length of the recordings. The International 10-20 system, which has 23 channels, is used to record the EEG data. Pre-ictal signal of 30 minutes before seizure start and inter-ictal of 30 minutes from recording with no seizure of same subject is consider for implementation [24,32].

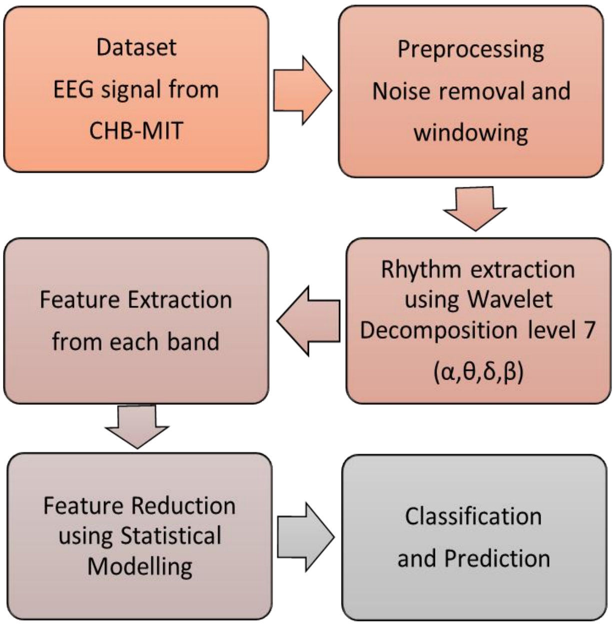


Fig. 1. Proposed Block diagram for Epilepsy prediction.

3.2 Preprocessing

The raw EEG signal includes noises which can lead to wrong prediction. To remove the line frequency noise notch filter is applied, effectively removing the unwanted noise. Additionally, a bandpass filter (BPF) is utilized to extract a specific frequency band of interest from the EEG data. Filtered data is segmented into 4-second intervals with sampling rate of 256 Hz, which captures the signal with adequate precision. The discrete wavelet transform (DWT) method is used to extract various rhythm bands from the EEG data. For this investigation, the Daubechies wavelet with six vanishing moments is specifically selected. The EEG signal can be effectively divided into several frequency bands using this wavelet algorithm. The seven-level Discrete Wavelet Transform (DWT) decomposition of the EEG signal segments is performed in order to precisely capture the various frequency components. The beta, alpha, theta, and delta frequency bands are matched by this decomposition, making it possible to analyze the EEG data in its entirety.

3.3 Feature extraction

Features are very important parameter to train the classifier. For prediction of seizure researchers are using numerous categories like time, frequency, time-frequency, nonlinear and statistical features. In this study, features are extracted after wavelet decomposition so combined time-frequency features are used. Studies on temporal lobe epilepsy have shown that hyper-synchronous neuronal activation before to seizures is reflected in increased spectral energy and slope in the beta band [33]. An increase in accumulated energy within the seizure onset zone can predict epileptic seizures in mesial temporal lobe epilepsy, up to 20–50 minutes prior to seizure onset [34]. Based on review paper [24] four features are extracted as shown below.

Energy of the signal: $\boldsymbol{E_i}$ is the energy of approximation and detail components Ci given by:

$$E_i = \sum_{n=1}^{N} C_i^2[n] \tag{1}$$

Where, N is the length of Ci

Standard deviation:

$$\boldsymbol{S} = \sqrt{\frac{\sum_{i=1}^{N}(Ci-\mu)^2}{N-1}} \tag{2}$$

Where, mean of $\boldsymbol{C_i}$ is μ.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{C_i} \tag{3}$$

where, N is the length of $\boldsymbol{C_i}$.

Signal peaks: The peaks of the pre-ictal and inter-ictal state were calculated by calculating the peaks of each segment.

Derivative of spectrum: The FFT of each rhythm is taken during each 4 sec segment and then derivative of its magnitude is taken for whole segment.

$$D_{\widehat{f}_i} = \sum_{m=1}^{M-1} \widehat{f}_i'[m]^2 \tag{4}$$

Where $\widehat{\boldsymbol{f}}_i'[\boldsymbol{n}] = \widehat{\boldsymbol{f}}_i[\boldsymbol{m}+\boldsymbol{1}] - \widehat{\boldsymbol{f}}_i[\boldsymbol{m}]$ for *m=1,....,M-1, M* is length of $\widehat{\boldsymbol{f}}_i$

3.4 Feature reduction and classification

Feature reduction is a pivotal process in the analysis of high-dimensional data, such as EEG signals used for epileptic seizure prediction. The primary objective of feature reduction is to enhance the performance and efficiency of predictive models by retaining the most relevant features and eliminating redundant or irrelevant ones. Statistical tests play a crucial role in this process by providing a systematic and quantitative means to evaluate and select significant features. Feature selection is crucial for improving the accuracy and efficiency of machine learning models in predicting diseases. Several studies have explored different feature selection techniques, including statistical methods like F-test with p-value < 0.05[35,36,37]. These approaches have demonstrated improved model performance across various classifiers, including logistic regression, decision trees, and support vector machines. Feature selection not only enhances predictive accuracy but also shortens model running time and provides biologically informative insights. This paper discusses the necessity and advantages of employing statistical tests for feature reduction in the context of epileptic seizure prediction. When analysing parametric data that satisfies the requirements of normality and equal variances, the Fisher F-test is utilized to find characteristics that differentiate across groups [27]. To determine variances or means over several populations, this statistical method entails establishing hypotheses, computing the F-statistic, and evaluating the findings. Statistical tests are essential in feature reduction due to their ability to objectively evaluate the relevance of each feature in relation to the target variable. F-test is particularly useful because it directly measures the relationship between features and the target variable. By focusing on the features that have the most substantial impact on the target, the F-test aids in building more accurate predictive models. A mathematical model using the Fisher F-test involves following steps:

a. Formulate Hypotheses

Null Hypothesis (H_0): The variances (or means) of the populations are equal.
Alternative Hypothesis (H_1): The variances (or means) of the populations are not equal.

b. Gather Data

Collect features for which you want to compare variances or means.

c. Calculate Sample Statistics

Sample Variance (S^2): Compute the variance for each sample.
Sample Mean ($\bar{x}$): Compute the mean for each sample if you are comparing means.

d. F-statistic Formula:

For comparing variances:

$$F = \frac{S_1^2}{S_2^2} \tag{5}$$

Where S_1^2 and S_2^2 are the sample variances of the two populations.
For comparing means:

$$F = \frac{MS_{between}}{MS_{within}} \tag{6}$$

Where $MS_{between}$ is the mean square due to treatment (variation between groups) and MS_{within} is the mean square due to error (variation within groups).

e. Degrees of Freedom:

df1 (numerator degrees of freedom) = k−1, where k is the number of groups. (7)

df2 (denominator degrees of freedom) = N−k, where N is the total number of observations. (8)

f. Determine Critical Value or Calculate p-value

Use an F-distribution table to find the critical value for chosen significance level (α)
The two tailed p-value associated with the F-statistic.

$$p = 2 * min(F_{CDF}, 1 - F_{CDF}) \tag{9}$$

where, F_{CDF} is the cumulative distribution function of the F-distribution.

g. Compare p-value and Significance Level (α):

If *p*-value $\leq \alpha$, reject the null hypothesis.
If *p*-val**u**e $> \alpha$, do not reject the null hypothesis.

Outcome of this model helps to select features with *p*-value less than 0.05[35,36,37]. These reduced features are given to SVM classifier for training the data.

3.5 Classification and prediction

This work uses binary classifier to predict pre-ictal and inter-ictal state using SVM classifier. Four features as discussed in eq.1-4 are extracted from each segment after DWT. Data is segmented into 4 sec with sampling rate of 256 Hz. No. of samples per channel=921,600. Using 4 second Segmentation of 30 minutes of inter-ictal and 30 minutes of pre-ictal duration will give total 900 samples. The final feature matrix with 4 features as mention in eq.1-4 of each 4 band (α, β, θ, δ) will have 16 x 900 size as shown in Table 1.

Table 1. Size of feature matrix for one channel with 4 band

Features	**Energy**	**Std. deviation**	**Signal peak**	**Derivative of spectrum**	**Feature matrix**
Matrix size	[4 x 900]	[4 x 900]	[4 x 900]	[4 x 900]	[16 x 900]

For 23 channels using all 4 bands feature matrix size= 23x16x900= 368 x 900
For one band with 23 channels feature matrix size= 23x4x900=92x900

To evaluate the performance of classifier accuracy, sensitivity, specificity and false positive rate is used. Initially training is done by using features of all 4 bands and also using only one band individually. Effect of excluding one band out of four is also tested for the prediction of pre-ictal state. This analysis helped to find out beta band is giving better results and based on those results as shown in Figure. 2 and Figure 3 following approaches are implemented.

In proposed method three approaches are used to train SVM classifier with 10-fold cross validation on CHB-MIT dataset of 23 subjects.

Approach 1: 4 Features from beta band with 23 channels are used to train classifier.

Approach 2: Selected features from approach 1 based on *p*-value for confidence interval *α=0.05* used to train classifier.

Approach 3: Fisher F-test is used to select prominent features based on threshold value of p. Based on that result only 2 prominent features (Energy of signal and derivative of spectrum) from beta band are selected for all 23 channels.

4. Result

Primarily, effect of all four-rhythm alpha, theta, beta and delta was observed using training and testing the SVM model. Based on literature review results are tested for eliminating one out of four bands. When beta band was excluded, performance was degrading compare to another band as shown in Figure.2. These results motivated to work on approach 1. In terms of performance parameters like; Accuracy, Sensitivity and Specificity results are good in approach 1as shown in Figure.3 (a). False positive Rate is also minimum with 0.13 per hour for beta band as shown in Figure.3(b).

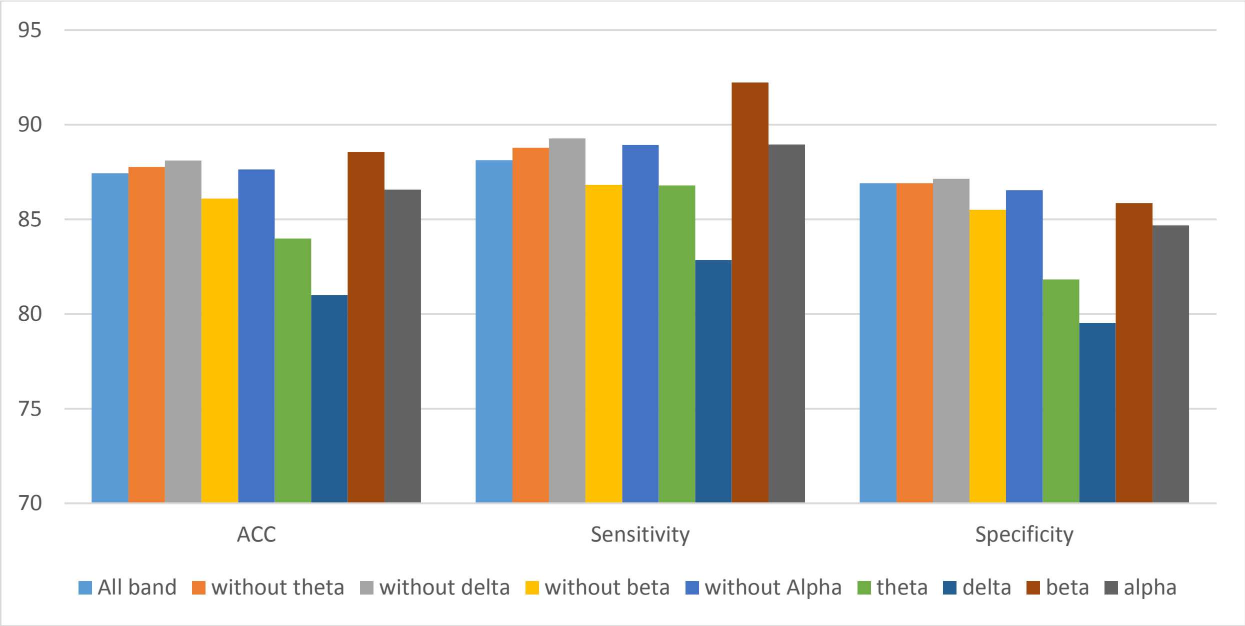
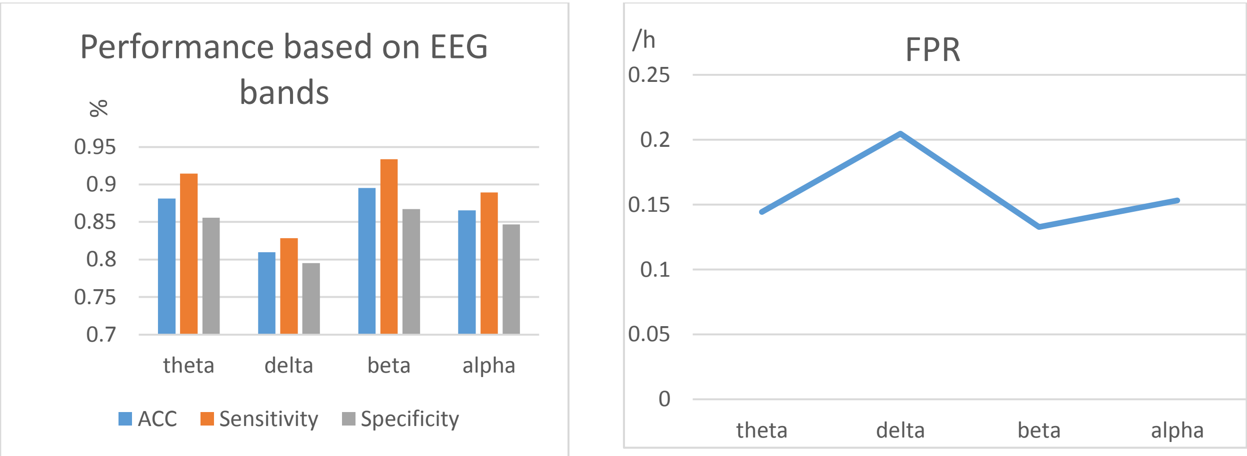


Fig. 2. Performance comparison of various sub band



(a) (b)

Fig. 3. (a)Accuracy, Sensitivity and Specificity of Theta, Delta, Beta and Alpha Rhythms in % (b)False Positive Rate for all four bands.

In approach 2 for feature reduction F-test is used with α=0.05 as a threshold to select the features. Figure 4 and Figure 5 represents p-value for Beta and Theta band respectively for all 23 channels. For all subject p-values are calculated and based on threshold selected features are used to train SVM classifier. Results are shown in Table 2.

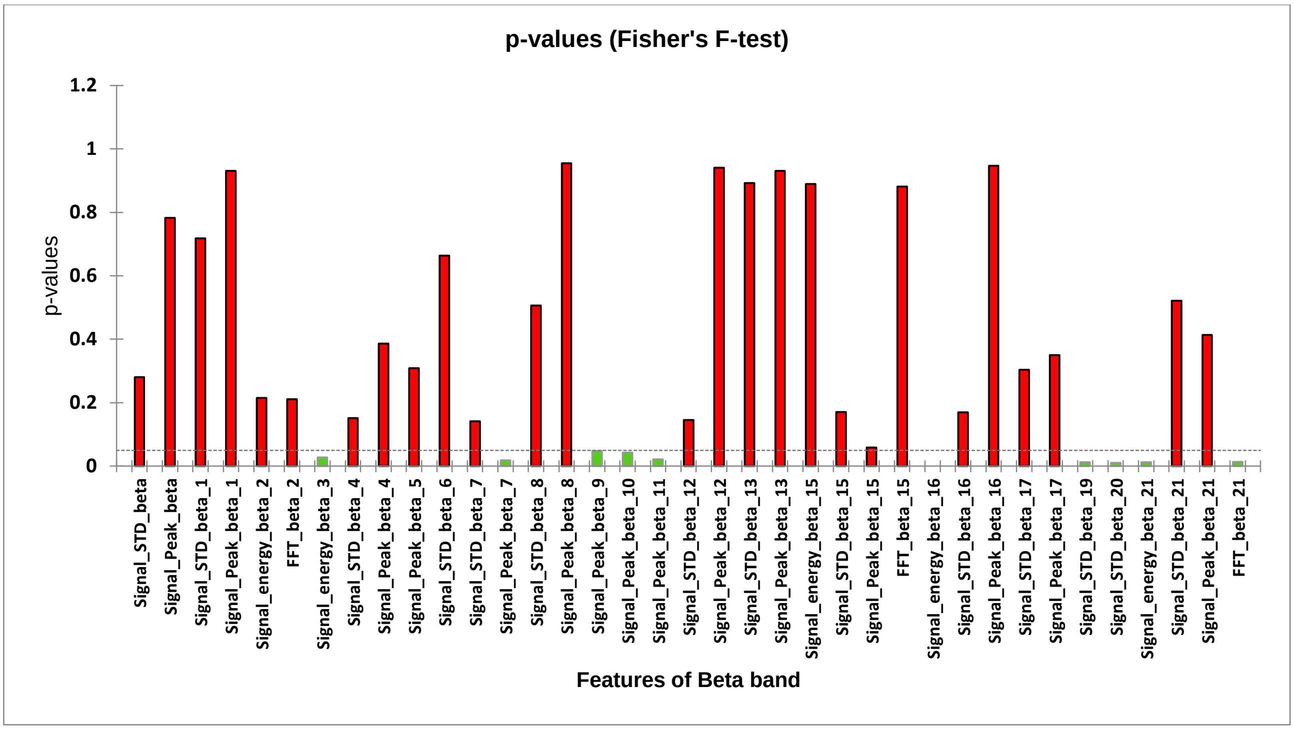


Fig. 4. Result of Fisher F- test for Beta band features showing p-values for all channels

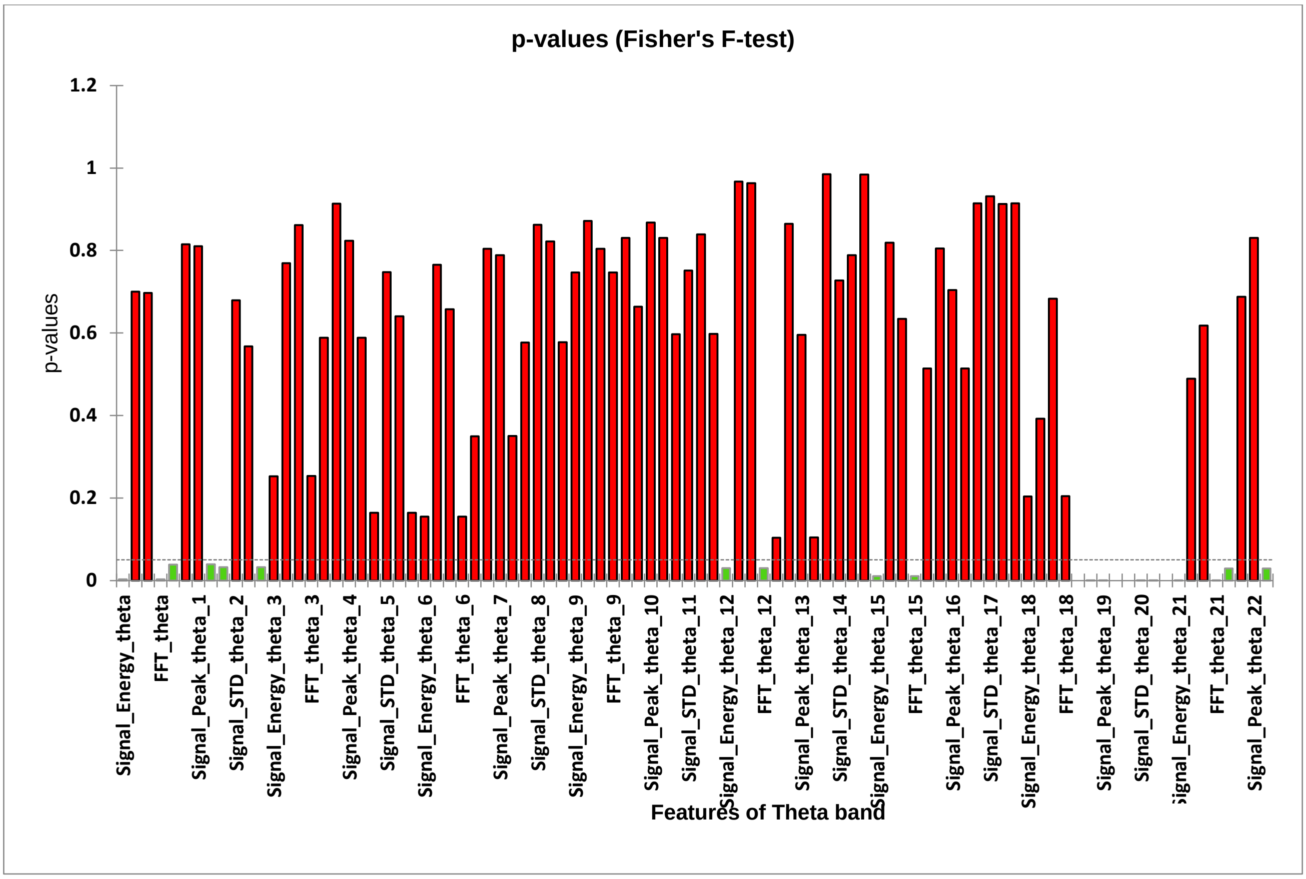


Fig. 5. Result of Fisher F- test for Theta band features showing p-values for all channels

In approach 3: Fisher F-test is used to find the best prominent features out of beta and theta band. Out of all features FFT and energy of beta band shows p-value less than critical as shown in Figure. Comparison of three approaches is evaluated on basis of accuracy, sensitivity and specificity as shown in Figure.7. Results are better for approach 2 with average accuracy of 89%, sensitivity of 93%, specificity of 86% and FPR of 0.14/h.

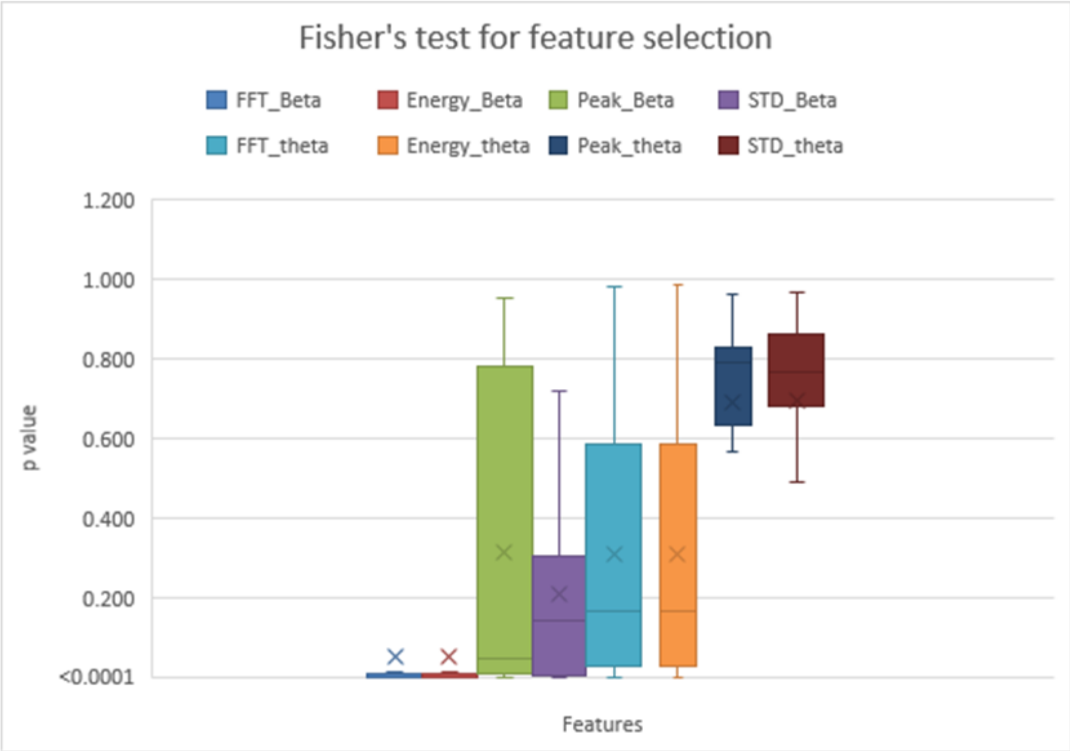


Fig. 6. Comparison of Theta and Beta band features based on p-value

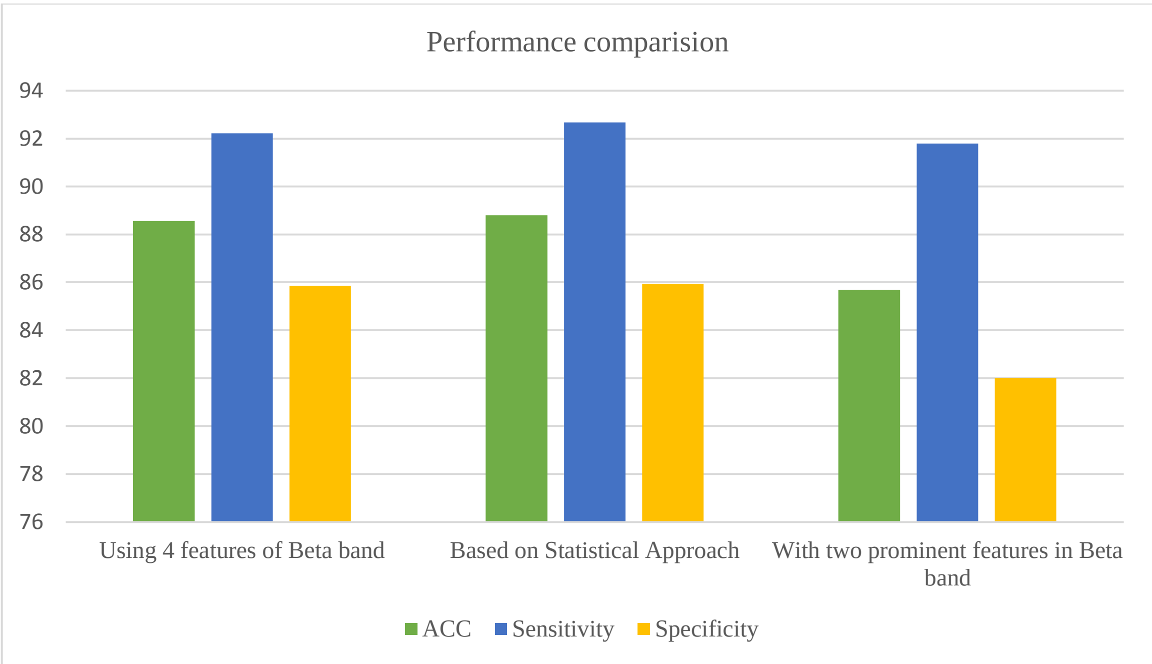


Fig. 7. Comparison of results for three approaches

Patient specific performance for all three approaches is shown in Table 2. Maximum accuracy, sensitivity, specificity and FPR in approach 1: 95%, 100%,93% and 7%; in approach 2 :95%, 100%, 93% and 7%; in approach 3: 95%, 100%, 92 %and 8% respectively. Performance in approach 1 and 2 are almost equal and for third case it is slightly degraded for specificity and FPR. Approach 2 gives better results among all.

Table 2. Comparison of result for three approaches

	Using 4 features of Beta band (Approach 1)				Based on p value threshold (Approach 2)				With two prominent features in Beta band (Approach 3)			
	ACC%	**Sen%**	**Spec%**	**FPR %**	**ACC%**	**Sen%**	**Spec%**	**FPR %**	**ACC%**	**Sen%**	**Spec%**	**FPR %**
chb01	91	95	88	12	92	96	89	11	92	97	88	13
chb02	85	99	77	23	85	99	77	23	83	99	75	25
chb03	93	97	90	10	92	96	90	10	89	91	87	13
chb04	78	87	72	28	78	87	72	28	71	82	63	35
chb05	87	95	81	19	87	95	81	19	81	97	73	27
chb06	80	81	79	21	78	80	76	24	79	80	78	22
chb07	67	67	67	33	67	69	65	35	68	76	64	36
chb08	94	99	90	10	94	99	90	10	92	99	86	14
chb09	74	73	75	25	76	75	78	23	74	75	74	26
chb10	88	86	90	10	88	87	89	11	86	84	89	11
chb11	95	98	93	07	95	99	93	07	95	99	91	09
chb12	94	97	92	08	95	97	93	07	94	97	91	09
chb13	92	94	91	09	92	95	90	10	88	86	90	10
chb14	84	88	81	19	86	90	82	18	83	90	78	22
chb15	94	100	90	10	94	100	90	10	93	98	89	11
chb16	93	93	93	07	93	93	93	07	88	93	84	16
chb17	91	96	87	13	91	96	87	13	88	97	82	18
chb18	90	94	88	12	90	94	87	13	88	88	87	13
chb19	94	99	89	11	94	99	90	11	76	99	68	32
chb20	93	93	93	07	92	92	93	07	91	92	91	09
chb21	93	99	89	11	95	99	92	08	95	99	92	08
chb22	93	99	89	11	94	99	89	11	93	99	89	11
chb23	93	94	92	08	93	94	92	08	85	97	78	22
AVG	**89**	**92**	**86**	**14**	**89**	**93**	**86**	**14**	**86**	**92**	**82**	**18**

Table 3. Pperformance evaluation in relation to previous research work

Author	**CHB-MIT Dataset**	**Method**	**Results**
(Tian et al. 2021) [25]	22 patients	Spiking CNN	Sensitivity 95.1% specificity 99.2%
(Usman, Khalid, and Bashir 2021)[26]	22 patients	EMD for noise removal GAN for class balance (Generative Adversarial Networks) 3 layer CNN	Sensitivity 93% specificity 92.5%
(Wang, Yang, and Sawan et al.2021) [28]	23 patients	Multi-scale Dilated 3D CNN	Sensitivity 85.8% Specificity 75.1% Accuracy 80.5%
(Dissanayake et al. 2020) [29]	23 patients	Feature (MFCCs) 13 bank **Model I:** Convolution Neural Network **Model II**: Siamese Architecture	**Model I:** Sensitivity 93.45 % Specificity 81.64 % ROC-AUC score 0.9273 Accuracy: 88.81% **Model II** Sensitivity 92.45% Specificity 89.94 %. ROC-AUC Score 0.9694 Accuracy 91.54%
(Kalita et al.2024) [30]	24 patients	Deep Learning	Sensitivity 92.54 ±0.41%, Specificity 97.73 ± 0.58% Accuracy 96.15 ±0.45%
(Zhang et al. 2020) [31]	23 patients	Wavelet packet decomposition and common spatial pattern (CSP) for feature extraction and CNN	Sensitivity 92.2% FPR 0.12/h.
(Usman, S. M., Khalid, S., & Aslam, M. H. 2020). [38]	24 patients	CNN Trainable parameters required during training phase of CNN in the proposed method are 32576.	Avg. Sensitivity 92.7% Avg. Specificity 90.8%
(Assali et. al.2023) [39]	22 patients	CNN based prediction	Sensitivity 88.6% to 92.8% Accuracy 90.1% to 94.5% based on the duration of the pre-ictal state.
Jia, M., Liu, W., Duan, J., Chen, L. et. al.2022) [40]	18 patients	Band Energy and Hjorth a general Graph Convolutional Networks (GCN) model architecture	Avg. Sensitivity 96.51% Avg. AUC of 0.92,

Esmaeilpour, A., Tabarestani, S. S., & Niazi, A. (2024) [41]	24 patients	CNN	Sensitivity 90.76%.
Shafiezadeh et. al. 2024 [42]	19 patients	CNN	Sensitivity 70% AUC 0.85
Sadaye, R., Parekh, S., Samuel, J., & Deulkar, K. (2016) [43]	Physionet Dataset	Features power and maxi Amp in Beta band (14-30 Hz)	Sensitivity 66.66% Specificity 25% Accuracy 70%
Altaf, Z., Unar, M. A., Narejo, S., & Zaki, M. A. (2023. [44]	24 patients	Time-frequency features with SVM classifier	The maximum Sensitivity 98% Specificity 84% Accuracy 91 %
Fıçıcı, C., Telatar, Z., & Eroğul, O. (2022) [45]	TLE patient data	Adaptive boosting method Random under sampling boosting (RUS)-boosted trees	The maximum Sensitivity 97.9% Specificity 98.1% Accuracy 97.2% The highest accuracy of 87.1%, sensitivity of 86.0% and specificity of 93.6% (RUS)
Nazari, J., Motie Nasrabadi, A., Menhaj, M. B., & Raiesdana, S. (2022) [46]	3 patients	CNN for features Classifier 1 FCN Classifier 2 SVM	Avg. Sensitivity 95.70% FPR 0.057/h for the 5-min prediction horizon 25-min seizure occurrence period Avg. Sensitivity 98.52% FPR 0.045/h
Tsiouris, K. M. et al. (2019, May) [47]	TUH data in addition	spikes/sharp waves in bands	Avg. Sensitivity 81.15% to 91.35% FPR rate between 5.33/h and 12.15/h
Proposed Method	**23 Patients**	**Time domain and frequency domain features with feature reduction**	**Avg Sensitivity 93%** **Avg. Accuracy 89%** **Avg. Specificity 86%** **Avg. FPR 0.14/h**

5. Discussion and Conclusion

This paper focuses on how to reduce computational complexity in terms of feature reduction without compromising performance of model. In this study comparison of proposed method done with other research work. Selection of papers for performance comparison is based on criteria like dataset used, types of features extracted, method used to train the model and evaluation parameters**.** Table 3 gives comparison of other researcher’s work with proposed method. Usman, Khalid, and FICICI et al. worked on TLE patient data, CHB-MIT and University of Bonn database and accuracy of 97.2% achieved by applying adaptive boosting method. The result shows that only one signal feature which is sub band energy is capable of distinguishing seizure activities. Authors [25,31,38,44] using CNN based model are getting better results but as they need raw data to extract features by training network huge dataset required. Bashir et al. [26] worked on GAN to balance the dataset as pre-ictal data is less compared to inter-ictal. Altaf, Z., Unar et al. [44] works on channel reduction using ICA and trained SVM classifier using only 8 channels with all band got specificity of 84%. Ziwei Wang et al. [48] selected data from sub-zones and sub-bands jointly for Generalized Seizures (GNSZ). As a consequence, the data range was decreased to 0.3% of the entire range, and the performance differed by less than 3% from the findings obtained using the entire data set. In this study the proposed method used with three approaches. Average value of sensitivity, specificity, accuracy and FPR using four features of only Beta band (Approach 1) is 92 %,86%, 89 % and 14% respectively. In approach 2 which uses feature reduction based on two tailed p-value with all channel gives average value of specificity and FPR same as approach 1 while sensitivity and accuracy value increased as 93% and 89 % respectively. Using F- test when only two prominent features of beta band; Energy of the signal and Derivative of spectrum using FFT selected then results degraded by approximately 3.37% in terms of accuracy. It means effect of features along with channels plays a significant role on prediction of epilepsy. Approach 2 outperforms with reduced feature matrix size of 92 x 900 with 75% reduction in computational complexity compare to Approach 1. The limitations of deep learning, such as its high data requirements, computational costs, and interpretability issues, make traditional machine learning methods more appropriate in some situations, especially when working with smaller datasets or when interpretability is critical. Proposed work uses reduced features matrix of beta band and helps to save time with less complexity. In contrast to many deep learning techniques that demand substantial computational resources, the innovation is not in developing a new algorithm but rather in achieving clinically relevant performance (Max 100% sensitivity, 7% FPR) with a highly effective, low-complexity pipeline that is interpretable and hardware-friendly. This work demonstrates that, with the help of statistically substantial feature reduction and targeted rhythm selection, traditional yet optimized strategies can nevertheless perform better than or on par with sophisticated deep learning models. Moreover, the reduction in feature space and computational load demonstrates potential for deployment in embedded or wearable systems, which is critical for practical use in epilepsy monitoring. Though results are good but still need to test on various dataset. In future timing analysis and inclusion of various dataset can be performed for prediction of seizure in real time application.

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