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Stability Analysis of Multiscale Bubble Entropy and Power Metric based Seizure Detection Technique with MLA

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ABSTRACT
In this paper, we explore the use of multiscale bubble entropy and power metric for feature extraction procedure and extend it with MLA and stability analysis to design a reliable multichannel seizure detection technique. First, we represent the multichannel EEG signal in 2D matrix form and then apply AM FM model to exploit the decomposed form of EEG. Thereafter, we construct the complexity coefficient using multiscale bubble entropy analysis from decomposed EEG wave. Then, second feature set is formed by using simple and efficient power procedure to obtain absolute power index and relative power index. Using two machine learning approaches, classification performance of proposed approach is explored to correctly identify the epileptic seizures. To show the robustness of multiscale bubble entropy, the stability analysis is performed with normal EEG dataset. Experimental results demonstrate that our proposed technique can effectively detect the epileptic seizures and achieve a superior classification performance with the ANN classifier compared to KNN classifier. This method provides higher discriminating capability with greater stability, so that they could detect wider range of seizure and thus help advance the current diagnosis system.

KEYWORDS
ANN; Bubble entropy; EEG; Epilepsy; KNN; Multiscale entropy

1. INTRODUCTION

Epilepsy is prominently characterized by neurological state of diverse etiologies of brain which is known as recurrent debilitating seizures. Symptoms of epilepsy may include disturbed behavior, odd sensation, repetitive rhythmic jerks, and involuntary clonic movements. During epileptic seizure, abnormal electrical activity results from asynchronous firing of electrical signal from different neurons. EEG modality which is essentially a brain activity is the optimal choice for diagnosis of epilepsy implying that EEG provides human brain matrices in terms of electrical signal. EEG signal can be recorded using an array of electrodes positioned on scalp of patient to obtain electric matrices of brain.

Several spectral decomposition methods have been utilized for the extraction of features from different decomposed sub-bands of EEG [1]. These techniques include various frequency spectral features such as energy, absolute power, relative power and power spectral density [1–5]. These features provide significant difference among various classes of EEG which means they have higher discriminating capability. The deficiency of spectral decomposition technique is their inconsistence performance. Many of the researchers are focused on complexity measurement of EEG using entropy analysis, [6–10]. The typical attributes for complexity measurement are Shannon entropy, approximate entropy, and permutation entropy. Several algorithms are also designed to determine the entropy at multiple scale [9,11]. One of the drawbacks of entropy measures, however, is that their performance depends highly on two parameters: embedding dimension and scale factor. Currently, a new algorithm has been designed to improve the performance of entropy analysis using bubble entropy [12]. The counting property of bubble entropy is their stable behavior for larger range of embedding dimension besides removing the necessity of scale factor. Recent efforts have been focused on mixed or combined analysis for the construction of integrated feature set [3, 10, 13].

In our previous proposed approaches [4, 14–16], we have made efforts on the extraction of appropriate features and the combination of these features has proven their efficiency for the detection of epileptic seizure. Advancements in the better understanding of neurological epileptic signal and their modes of information processing have enabled choosing suitable features that can best represent the characteristics of EEG and suitable classifier which can successfully classify wide variety of epileptic seizure

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pattern. Different machine learning approaches are also being used for accurate detection of epileptic seizure. The widely used techniques in machine learning approach are ANN [17, 18], KNN [19–21], SVM [22], and GMM [23]. One prominent technique among them is ANN [6, 17]. However, in biomedical application such as epilepsy associated with sudden occurrence of seizures, it has been found that the choice of classification or machine learning technique plays important role for accurate detection.

Initial results of parts of overall method have been presented in [16] and it achieved effective outcomes with two class classification problems. The proposed study explores it with three class classification problems with different MLAs and extends it with stability analysis to offer the robustness to the seizure detection system. One of the common drawbacks of existing entropy-based feature extraction technique is that its performance highly depends on two parameters: embedding dimension and scale factor. Hence, the entropy features usually show the unstable behavior which in turn adversely affects the seizure detection performance. To address this issue, we proposed a new stabilized entropy feature called multiscale bubble entropy to obtain the stable performance in [16]. Multiscale bubble entropy, a particular variation of bubble entropy, is first performed to yield more effective representation of complexity measures at multiple scale. The multiscale bubble entropy based feature extraction technique explores complexity coefficients at multiple frequency sub-bands, so that it is able to provide more detail seizure information. In this paper, we perform the stability analysis of novel multiscale bubble entropy feature in terms of embedding dimension to obtain stabilized epileptic seizure detection parameters. To the best of our knowledge, this is the first time to perform such analysis for seizure detection of EEG signal. Feature extraction technique is then conducted the power metric analysis to obtain absolute power index and relative power index for discriminative processing of EEG. The proposed algorithm relies on the bubble entropy to obtain stabilized complexity coefficient as one of the feature which is defined as integrated feature set after combining with power analysis. In this paper, we analyzed the performance of our proposed feature extraction technique [16] with three class classification problems using different machine learning approach (MLA) to achieve reliable classification performance. To show the robustness of our proposed multiscale bubble entropy, we also performed the stability analysis of multiscale bubble entropy with various values of embedding dimension. In short, the objective of our proposed technique lies in three aspects described below:

1. The first aspect is that AM-FM model performs decomposition of EEG signal into different subbands such as $\delta, \theta, \alpha, \beta$, and γ.
2. The second one is that both multiscale bubble entropy and power metric (absolute power and relative power) feature vectors possess unique characteristics of EEG that facilitate the stable performance with higher discriminating capability.
3. The integrated feature set is used as input to different machine learning approaches to analyze intelligent classification working programs.
4. Finally, we aim to achieve high level of robustness with respect to the variation of embedding dimension, the stability analysis of multiscale bubble entropy is performed with different values of embedding dimension.

The organization of the rest of the paper is given as follows. Section 2 presents the methodology of the proposed technique. In Section 3, experimental results are discussed and comparative analysis of different machine learning approach is also presented. This section is followed by the conclusion.

2. METHODOLOGY

This study presents a novel seizure detection system to uniquely characterize the seizure pattern with multiscale bubble entropy and power metric analysis and it correctly distinguishes EEG signals into preseizure, seizure, and normal EEG data using different MLAs. Multiscale bubble entropy analysis is used to build stable complexity coefficients of EEG signal. This provides the mapping of complexity coefficients of EEG signal in different frequency sub-bands to achieve stabilized seizure detection performance with high accuracy while maintaining the lower FDR. Afterword the power analysis is used to obtain absolute and relative power coefficients which provide discriminative quality control feature vectors. Power analysis has the ability of built in discrimination of data so that it assures for higher classification accuracy. At the end, our proposed technique combined these two analyses to achieve high accuracy with lower FDR. The proposed feature extraction technique takes advantage of stable multiscale bubble entropy feature and descriptive power feature to characterize the seizure activity. The key feature of our proposed feature extraction technique is their stable behavior for larger range of embedding dimension and it also removes the necessity of scale factor. Figure 1 shows the flowchart of proposed methodology. In our proposed approach, three features are extracted from EEG signal. These three features were

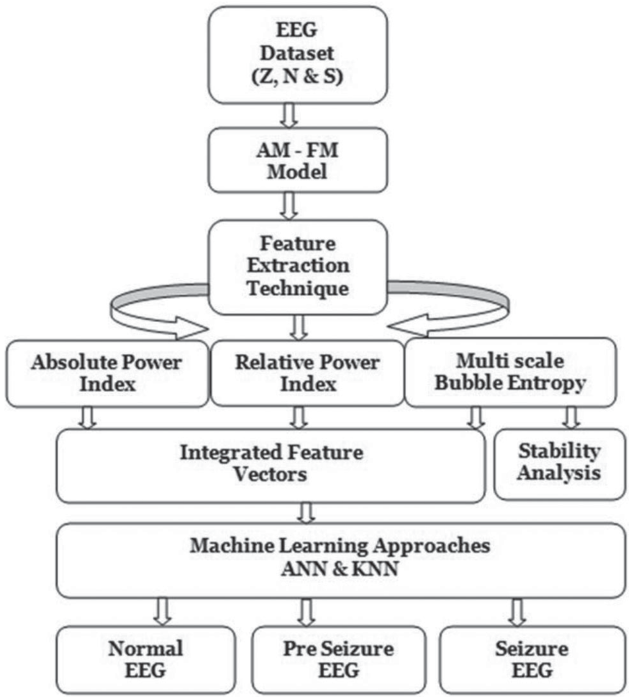

Figure 1: Flowchart of the proposed technique

selected because of their ability to effectively distinguish the seizure activity from normal event.

The proposed technique consists of several consequential steps for the detection of seizures: decomposition of EEG, feature extraction, and more importantly classifier analysis. First, EEG signal is decomposed into different sub-bands using the AM-FM model. Then by applying feature extraction technique, three types of features are extracted for the construction of integrated feature set. Next, the integrated feature set is used as input to different machine learning approaches to classify the EEG into different classes.

2.1 AM-FM Model

AM-FM model is a versatile model to represent the biomedical signal such as EEG wave in terms of their amplitude and phase component. It represents the EEG wave by various decomposed waves such as δ, θ, α, β and γ waves. The spectral range of 0–40 Hz contains the rhythmic characteristic of EEG which is very important for seizure diagnosis task. Each monocomponent wave corresponds to each EEG rhythm or epoch. This model is intended to describe the multichannel EEG wave as summation of monocomponent wave. Each xth rhythm of EEG $E_x(n)$ can be defined as

$$\boldsymbol{E_x} = \boldsymbol{A_x(n)} \cos \boldsymbol{\Psi_x(n)} \tag{1}$$

2.2 Power Metrics

2.2.1 Absolute Power Index

Absolute power index is computed at each electrode from each sub-band. There are 19 electrodes and 4 sub-bands, leading to the estimation of 76 absolute power features from each EEG record. P_{AI} is defined as

$$[P_{AI} = P_{A\delta 1}, P_{A\theta 1}, P_{A\alpha 1}, P_{A\beta 1} \ldots P_{A\delta 19}, P_{A\theta 19}, P_{A\alpha 19}, P_{A\beta 19}] \tag{2}$$

2.2.2 Relative Power Index

The relative power index P_{RI} is determined as

$$\begin{aligned} &\mathrm{P_{RI}} = (P_{ij}/P_i) \\ &i \in \{\delta, \theta, \alpha, \beta\} \\ &j \in \{1, 2, 3 \ldots 19\} \end{aligned} \tag{3}$$

where P_{ij} represents the spectral power at a particular electrode in a specific decomposed wave and P_i is the average spectral power of that specific decomposed wave. This index is also estimated at each of 19 electrodes. P_{RI} is given as

$$[P_{RI} = P_{R\delta 1}, P_{R\theta 1}, P_{R\alpha 1}, P_{R\beta 1} \ldots P_{R\delta 19}, P_{RI\,\theta 19}, P_{R\alpha 19}, P_{R\beta 19}] \tag{4}$$

2.3 Bubble Entropy

In our analysis, we have selected the bubble entropy to measure the complexity of EEG because it provides stable performance. Bubble entropy essentially decreases the dependency of entropy measure on embedding dimension (m) causing it to give consistent entropy measures for large range of embedding dimension and it also removes the requirement of scale factor (r). It is comprised of two entropy measures: conditional permutation entropy and renyi's entropy. Multiscale conditional permutation renyi's entropy (E_{MCPR}) is defined as

$$E_{\mathrm{MCPR}} = \frac{1}{1-\alpha} \log \sum_{i=1}^{m!} p(J_k)^{\alpha} \tag{5}$$

where J_k represent the time series of vectors.

It makes the use of bubble sort algorithm to arrange the feature vectors in ascending order and thereafter counts the number of swaps which decide the value of α for computation of entropy.

$$E_B = [(E_{\mathrm{MCPR}})^{m+1} - (E_{\mathrm{MCPR}})^{m})]/[\log(m + 1/m - 1) \tag{6}$$

Multiscale bubble entropy measures are determined from the five sub-bands (δ, θ, α, β, and γ).

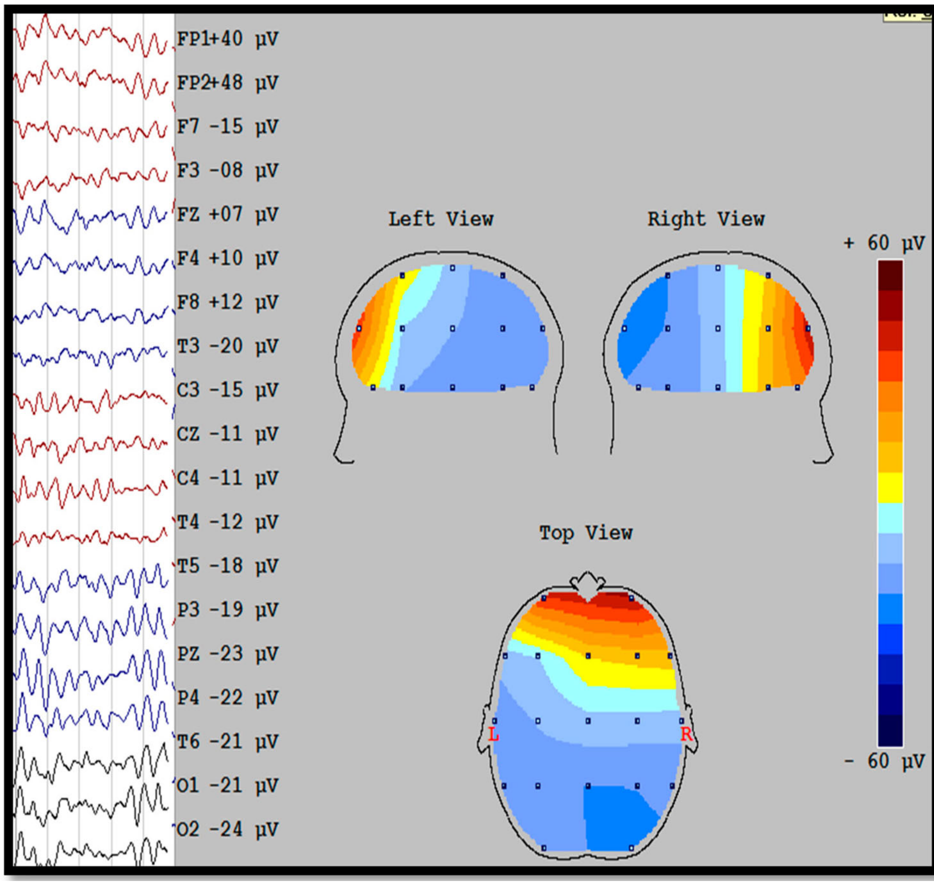

Figure 2: Multichannel EEG signal

Table 1: Absolute power index for normal, preseizure, and seizure patterns

	Absolute power at Delta band			Absolute power at Theta band			Absolute power at Alpha band			Absolute power at Beta band		
Electrodes	NE	PSE	SE	NE	PSE	SE	NE	PSE	SE	NE	PSE	SE
1	22.36	37.07	29.12	0.95	7.73	2.89	1.33	11.59	5.33	1.73	2.21	1.89
2	48.19	58.37	52.53	0.77	10.08	4.42	1.87	15.87	8.23	1.62	2.15	2.12
3	4.33	4.39	4.35	0.69	1.34	0.85	1.08	2.46	1.89	1.04	0.48	0.45
4	8.92	13.47	12.16	0.66	2.34	0.98	0.34	3.46	1.23	0.75	0.47	0.47
5	5.55	112.7	42.82	2.37	14.83	7.46	1.79	15.29	3.26	1.14	2.05	1.18
6	11.05	74.15	61.47	0.81	11.87	3.12	1.6	12.42	5.45	0.74	0.99	0.55
7	25.64	27.22	26.12	0.45	5.08	1.88	0.85	7.53	2.76	0.72	0.42	0.35
8	26.97	51.03	43.76	0.7	5.79	2.86	2.48	6.5	3.84	1.25	0.67	0.42
9	6.88	3.7	2.15	0.41	1.61	0.73	1.94	7.06	4.12	2.03	2.49	1.56
10	16.67	80.78	57.42	1.01	8.17	7.12	1.93	6.88	3.89	1.96	1.24	0.48
11	15.56	29.72	24.11	0.61	2.4	1.33	1.16	3.93	1.58	3.13	0.61	0.13
12	3.67	4.52	3.15	0.39	1.03	0.89	0.45	1.85	0.89	1.14	0.31	0.12
13	7.94	157.2	96.89	1.16	23.54	8.54	4.37	22.12	10.89	1.88	2.2	1.29
14	2.4	216.2	45.62	1.11	33.76	12.6	2.86	42.4	12.74	1.99	3.76	1.46
15	14.31	24.79	21.24	1.6	9.1	4.56	5.06	19.31	8.67	7.17	2.74	0.87
16	19.91	55.94	38.60	0.82	10.08	6.22	1.38	18.56	8.87	2.69	2.39	1.23
17	21.63	151.4	88.45	0.69	15.09	5.87	0.67	23.53	9.58	0.83	2.63	0.92
18	31.53	159	92.57	1.05	29.81	15.5	3.63	30.5	8.54	2.06	2.58	2.16
19	46.3	117.1	78.66	0.98	20.77	8.12	1.78	26.22	15.78	1.15	3.14	1.76

3. EXPERIMENTAL RESULTS AND DISCUSSION

3.1 Database

The epileptic EEG database that is used to demonstrate the performance of our proposed technique was acquired from University of Bonn, Germany. Physiological EEG signals were recorded using RMS advance lab system with 128 channel amplifier configuration. For EEG recording, 19 electrodes were positioned on the scalp of patient according to the international 10–20 system. Band pass filter was used to filter EEG recording with the bandwidth of 0.1–70 Hz. EEG signals are digitalized

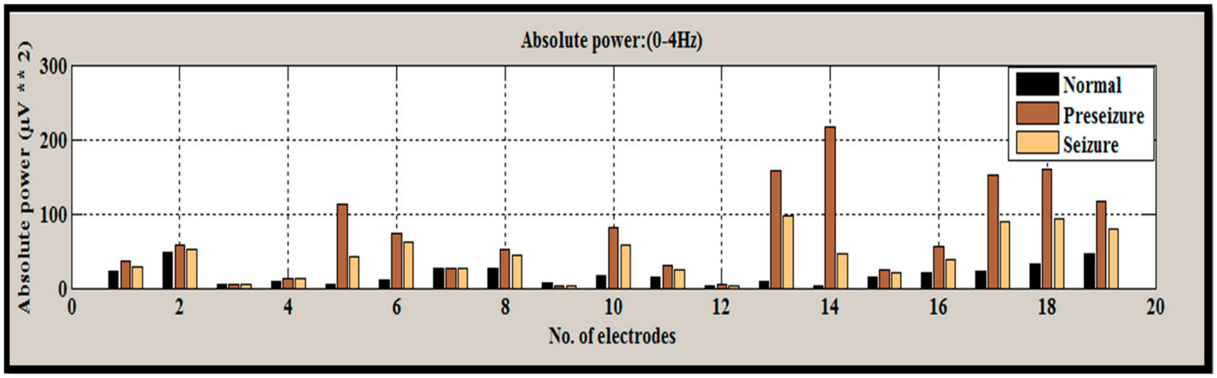

Figure 3: Absolute power index of δ sub-band

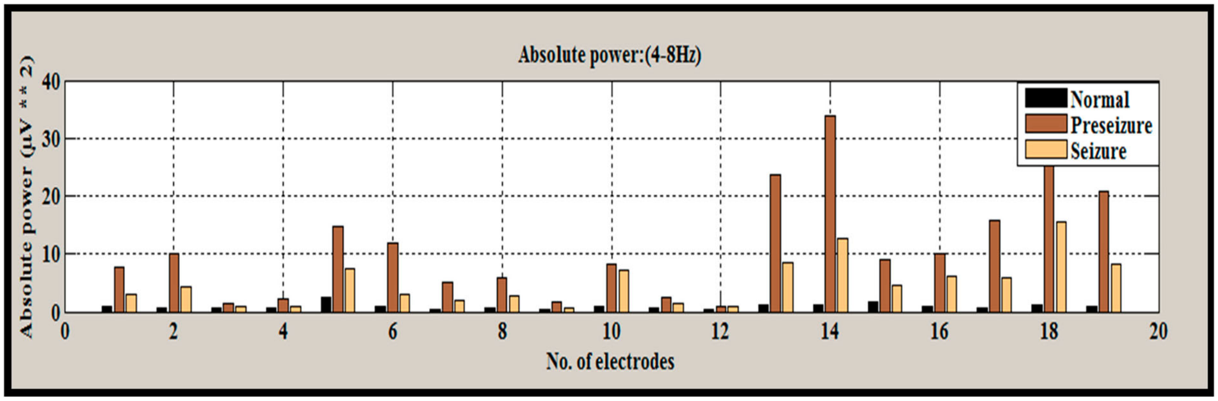

Figure 4: Absolute power index of θ sub-band

with sampling rate of 173.61 Hz and having 12-bit A/D resolution.

Database implementation procedure includes five different sets of EEG recording: Z, O, N, F, S. Each dataset has $N = 100$ EEG recordings with $K = 4097$ data point. Z dataset contains the EEG recording of healthy patients with open eye condition and S dataset has EEG recording of seizure activity. O dataset consists of EEG recording of healthy patients with close eye condition. N and F datasets are the preseizure EEG recording.

3.2 Results

The performance of algorithm is evaluated using Z–S–N classification problem (three class classification). The preseizure event is defined as the initial part of the seizure which is associated with rhythmic jerk cause abrupt changes. This rhythmic jerk gradually down with time.

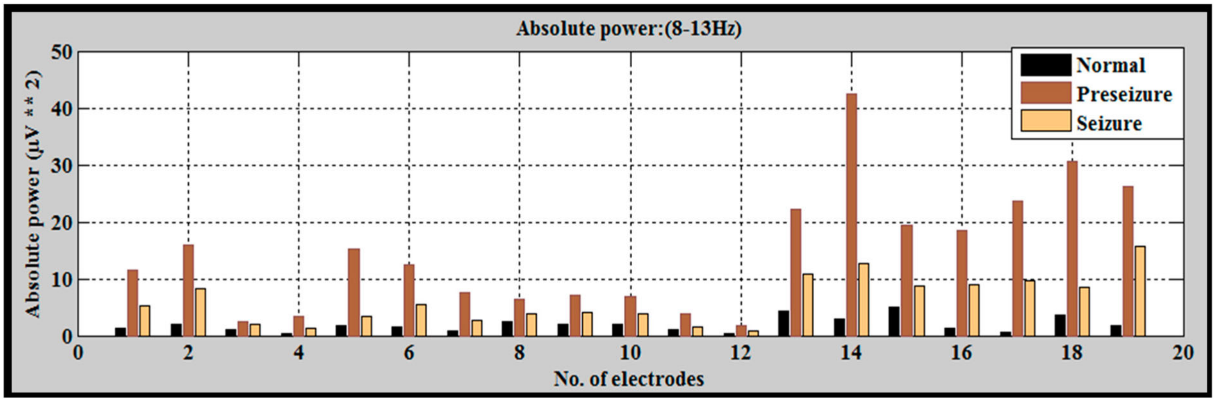

Figure 5: Absolute power index of α sub-band

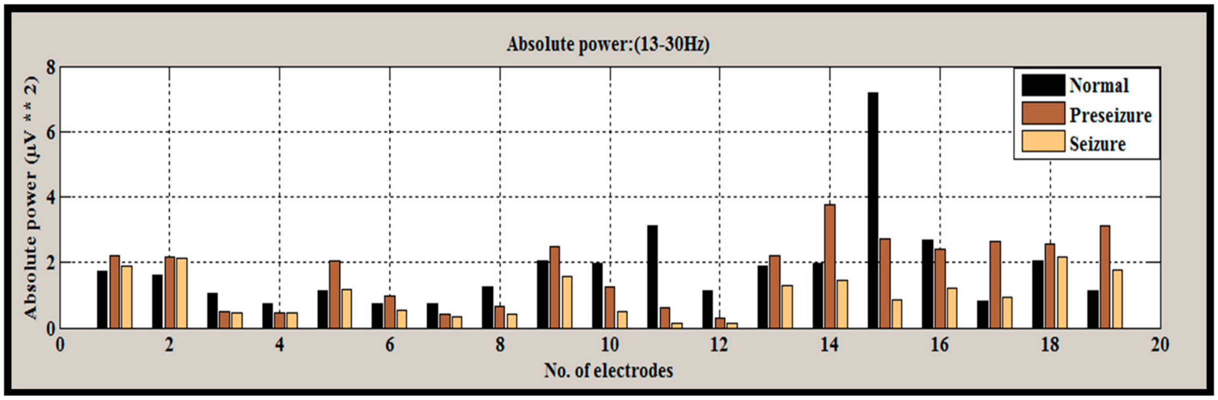

Figure 6: Absolute power index of β sub-band

Table 2: Relative power index for normal, preseizure, and seizure patterns

	Relative power at Delta band			Relative power at Theta band			Relative power at Alpha band			Relative power at Beta band		
Electrodes	NE	PSE	SE	NE	PSE	SE	NE	PSE	SE	NE	PSE	SE
1	84.8	63.3	52.3	3.6	13.2	4.34	5	19.8	6	6.6	3.8	1.26
2	91.9	67.5	43.5	1.5	11.7	2.23	3.6	18.4	5.3	3.1	2.5	2.96
3	60.6	50.7	34.6	9.6	15.4	11.7	15.2	28.4	17.32	14.6	5.5	3.26
4	83.6	68.2	49.6	6.2	11.8	7.45	3.1	17.5	4.89	7.1	2.4	0.33
5	51.1	77.8	56.2	21.8	10.2	3.12	16.5	10.6	6.12	10.5	1.4	0.27
6	77.8	74.6	56.3	5.7	11.9	6.54	11.2	12.5	11.45	5.2	1	0.12
7	92.7	67.6	34.4	1.6	12.6	2.32	3.1	18.7	5.23	2.6	1.1	0.88
8	85.9	79.7	61.2	2.2	9	4.89	7.9	10.2	8.65	4	1.1	0.25
9	61.1	24.9	14.5	3.6	10.8	4.51	17.2	47.5	20.34	18	16.8	0.23
10	77.2	83.2	61.4	4.7	8.4	7.12	9	7.1	5.98	9.1	1.3	1.21
11	76	81.1	55.3	3	6.5	5.22	5.7	10.7	6.87	15.3	1.7	0.44
12	64.9	58.6	47.6	7	13.3	8.44	8	24	9.15	20.1	4	1.38
13	51.8	76.7	56.7	7.6	11.5	6.54	28.4	10.8	8.64	12.2	1.1	0.26
14	28.7	73	54.3	13.3	11.4	23.3	34.2	14.3	9.53	23.8	1.3	0.57
15	50.9	44.3	32.1	5.7	16.3	9.33	18	34.5	22.19	25.5	4.9	1.34
16	80.3	64.3	47.8	3.3	11.6	7.38	5.6	21.3	6.88	10.8	2.7	0.97
17	90.8	78.3	33.8	2.9	8.2	2.16	2.8	12.2	2.32	3.5	1.4	0.34
18	82.4	71.7	56.8	2.7	13.4	4.45	9.5	13.7	8.32	5.4	1.2	0.23
19	92.2	70	23.3	1.9	12.4	3.88	3.5	15.7	5.77	2.3	1.90	0.45

This gradual part of seizer is given as seizure event. We begin this section with the evaluation of absolute power index and relative power index from each electrode. The multichannel EEG signal with 3D view of brain is shown in Figure 2. The numerical results of absolute power index for different sub-bands are illustrated in Table 1 and shown in Figures 3–6. In Tables 1 and 2, the NE stand for normal event, PSE is for preseizure event and SE refers to the seizure event. The θ and α bands present significant difference in their values with respect to preseizure and normal data, with higher absolute power values for the one that carries

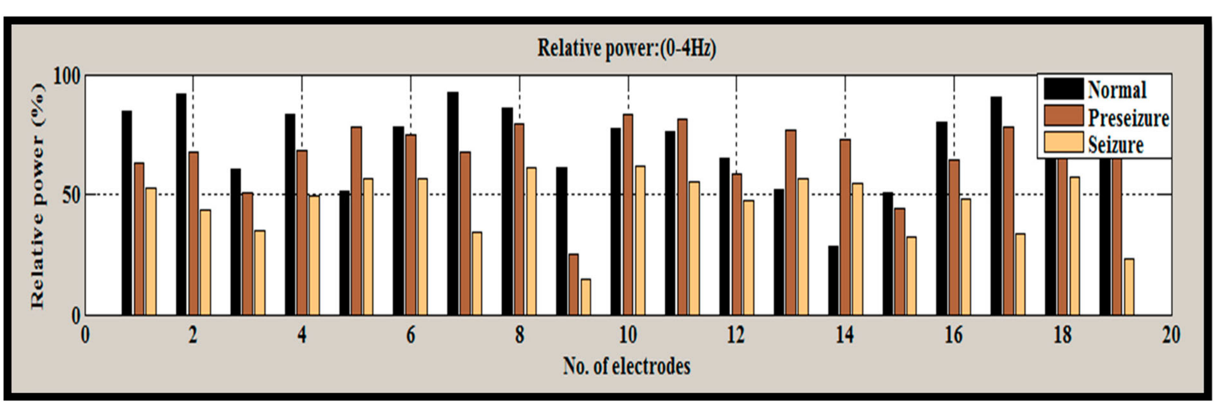

Figure 7: Relative power index of δ sub-band

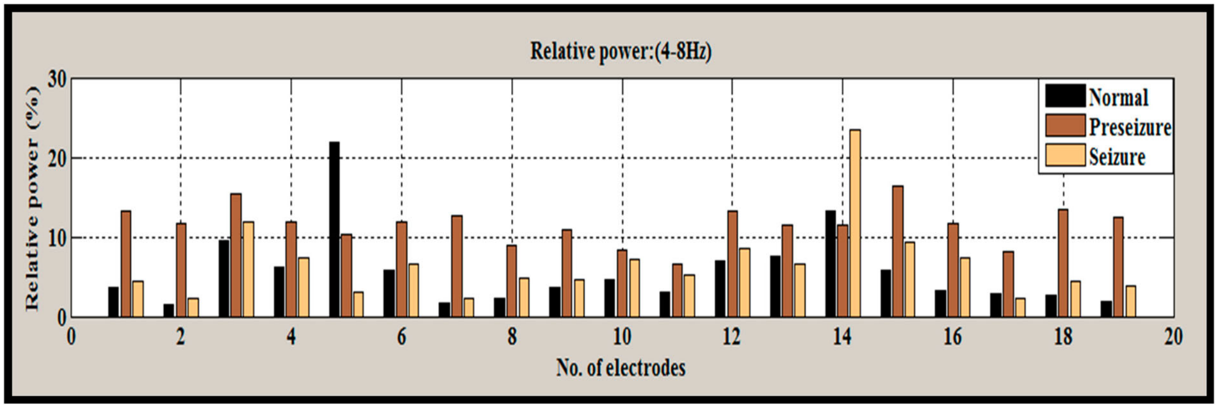

Figure 8: Relative power index of θ sub-band

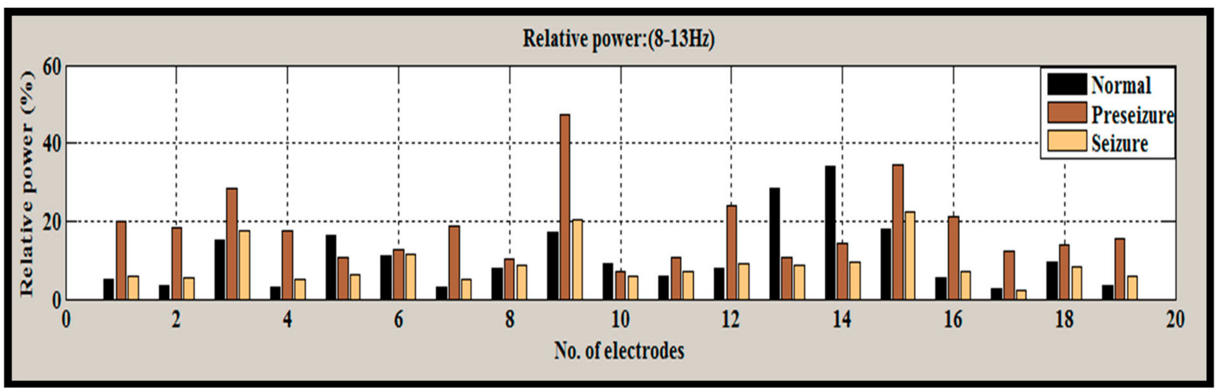

Figure 9: Relative power index of α sub-band

seizure information and lower absolute power values for non-seizure event.

The relative power index values with respect to preseizure, seizure, and normal events are noted in Table 2. Their graphical representation for different sub-bands is illustrated in Figures 7–10. It can be observed that in α band 16 out of 19 values of relative power index achieve higher values for preseizure events and it maintain lower values for normal event. Table 3 shows the numerical results of bubble entropy at multiple scales. The complexity measures exploit the decreasing behavior during seizure activity, so that we obtain the lower values of bubble entropy parameter during preseizure activity, moderate for seizure event and higher for normal EEG rhythm.

Accuracy and false detection rate were used to quantitatively access the performance of our proposed technique. False detection rate is determined as the amount of false

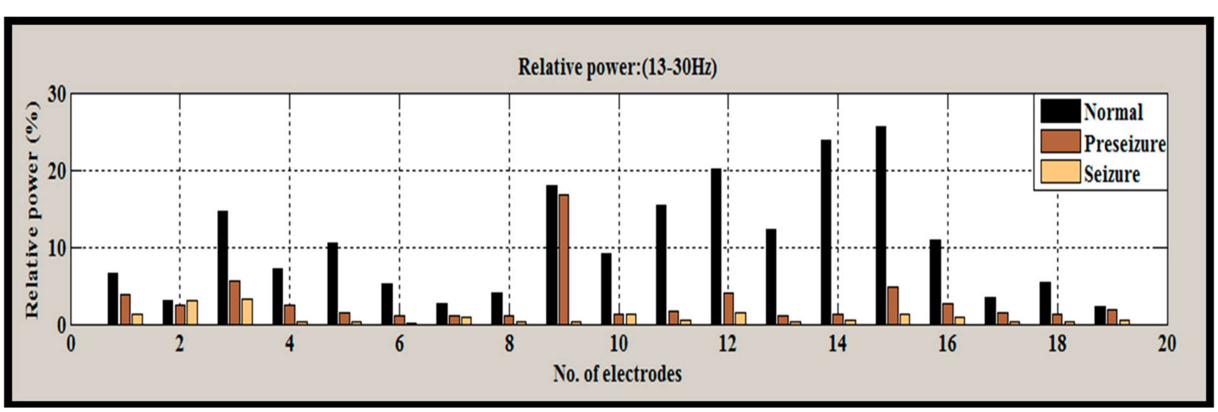

Figure 10: Relative power index of β sub-band

Table 3: Multiscale bubble entropy parameter for preseizure, seizure and normal patterns

Sub-bands	Preseizure pattern	Seizure pattern	Normal pattern
δ (0–4 Hz)	11.52	12.42	14.62
θ (4–8 Hz)	13.17	14.16	17.61
α (8–13 Hz)	11.34	13.47	15.55
β (13–30 Hz)	12.32	12.41	12.45
γ ($f > 30$ Hz)	11.31	11.32	11.38

Table 4: Performance parameter of different MLAs

	Evaluation parameter	
MLA	Accuracy	FDR
ANN	99.73	0.121
KNN	96.10	0.132

detection per hour. Accuracy is determined as follows:

$$\text{ACCURACY} = \frac{(\text{TTP} + \text{TTN})}{(\text{TTP} + \text{TTN} + \text{TFP} + \text{TFN})}$$

where TTP (total true positive) is the number of sick or epileptic event correctly detected as sick and TTN (total true negative) represents healthy events correctly identified as healthy. TFP (total false positive) is the number of healthy event incorrectly detected as sick and TFN (total false negative) is the sick event incorrectly detected as healthy. ANN and KNN classifiers were used to access the performance of proposed technique. The ANN classifier is structured with one input layer, two hidden layers, and one output layer. It uses back propagation learning algorithm with logistic activation function. Input layer

Table 5: Stability analysis of multiscale bubble entropy parameter for different sub-bands

Embedding dimension (m)	MSE at Delta band	MSE at Theta band	MSE at Alpha band	MSE at Beta band	MSE at Gamma band	Permutation entropy
1	14.86	17.56	15.63	12.62	10.85	0.1
3	14.56	17.62	15.6	12.88	11.59	2.02
5	14.78	17.12	15.69	12.5	10.83	5.15
7	14.6	17.34	15.69	12.54	11.59	7.14
9	14.6	17.44	15.73	12.65	11.04	8.32
10	14.62	17.61	15.55	12.35	11.38	9.28
11	14.71	17.74	15.55	12.31	11.4	9.85
13	14.65	17.74	15.89	12.54	11.32	9.65
15	14.54	17.69	15.85	12.55	11.3	9.71
17	14.46	17.62	15.77	12.85	11.27	9.7
19	14.57	17.5	15.7	12.88	11.12	9.8

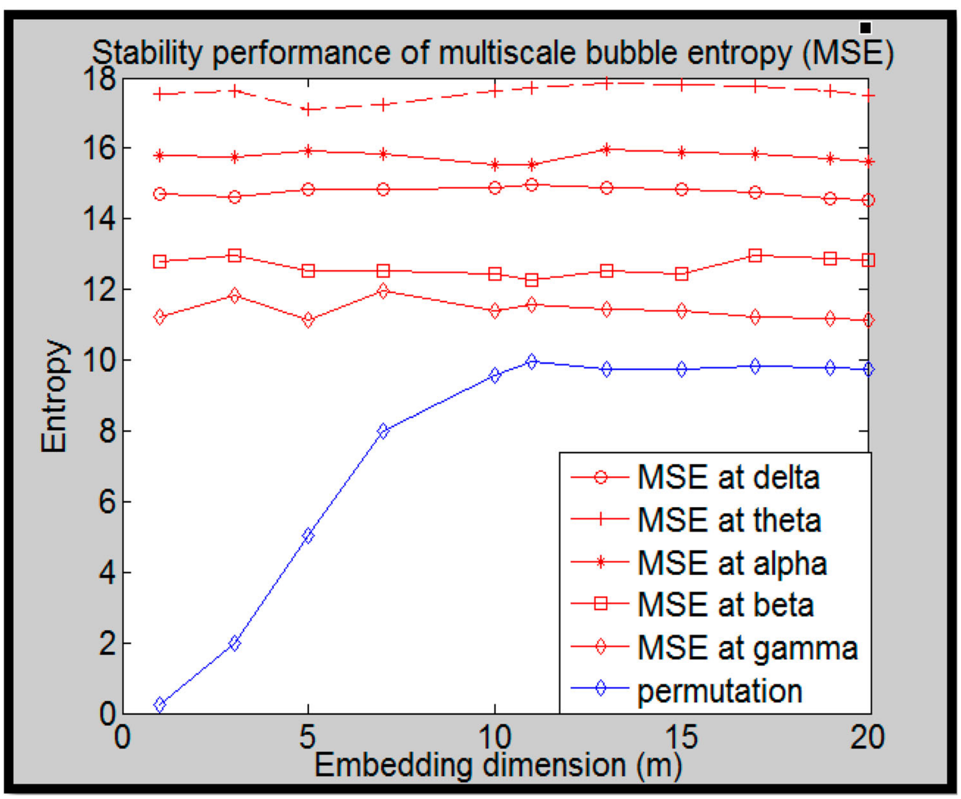

Figure 11: Stability analysis of multiscale bubble entropy

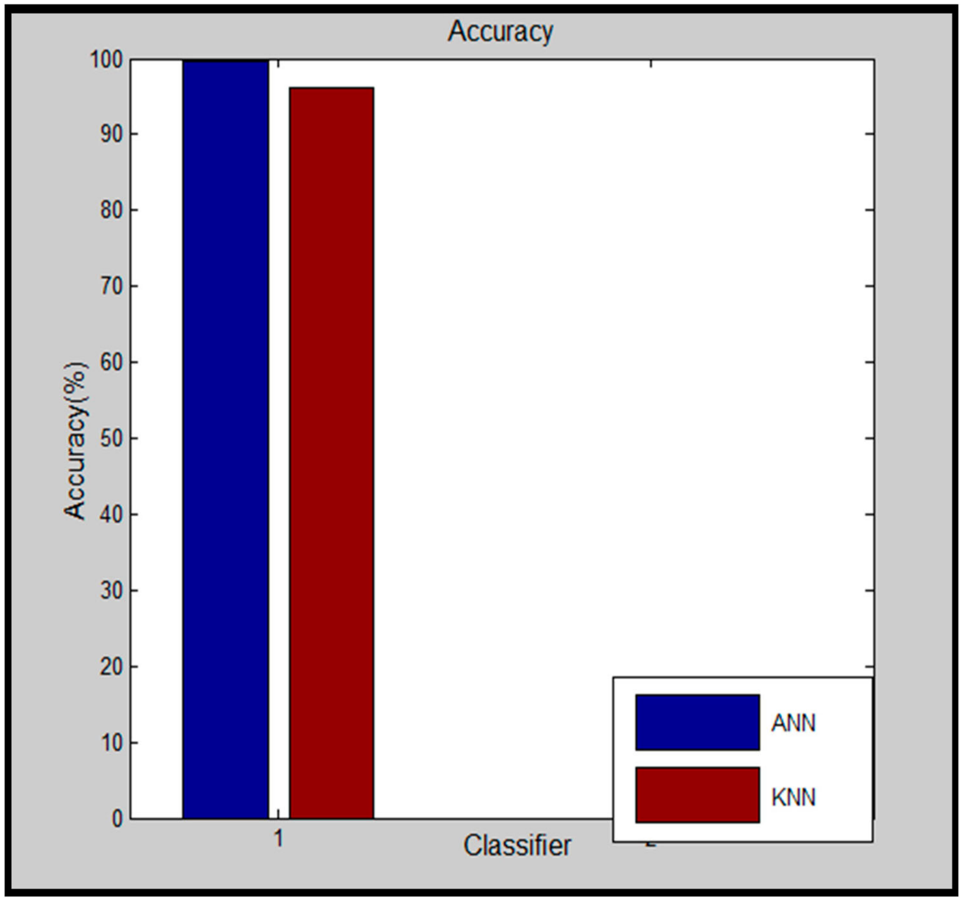

Figure 12: Classifier analysis

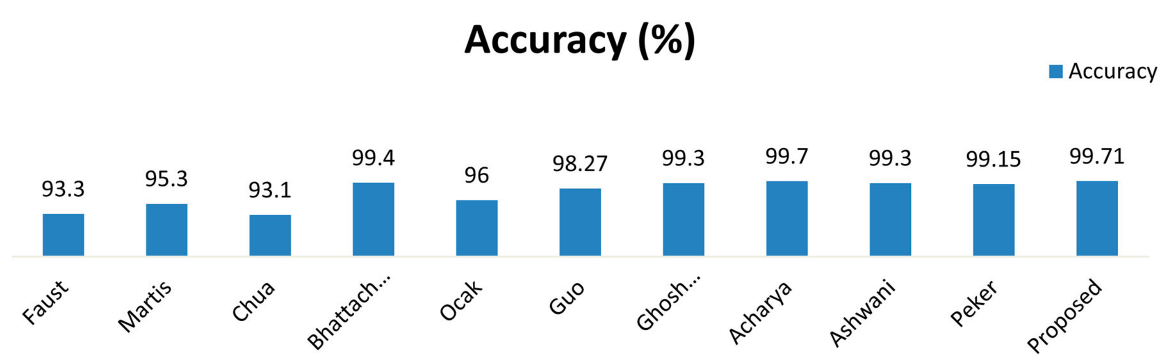

Figure 13: Comparative analysis with the existing technique

has number of neurons equal to number of input features. Training procedure is affected by hidden layer neurons.

The training testing procedure is repeated for $N_R = 20$ times that gave the best classification results with number of neurons in first hidden layer is 15 and in second hidden layer is 10. The training data size is 50 from each group (Z, S, & N). The training testing procedure for $N_R = 20$ repetition is completed for 100 instances. With $N_R = 20$ training repetition and training size $= 50$ from each group yields the best classification accuracy of 99.73% and lower FDR of 0.121 per hour. The significant high accuracy obtained with Z–N–S classification problem that shows the proposed multiscale bubble entropy and power feature well characterize the seizure activity. KNN model utilizes the supervised learning algorithm which determines the set of K nearest neighbors using Euclidean distance measure. The class is assigned to each new testing EEG sample by searching through entire training dataset. Training data size is 50 from each group (Z, S, and N). This searching procedure evaluates K number of training points nearest to the test EEG sample, then it assigned the class to test sample which is most amongst to the K nearest neighbor. It is observed that KNN provides the classification results with lower accuracy of 96.10%. The performance measure of ANN and KNN is given in Table 4. Our proposed study with three class classification problem achieved minor improvement of 0.02 in accuracy with ANN and one more performance attribute (FDR) is computed compared to two class classification technique of [16]. Equipped with specific properties of multiscale bubble entropy and power analysis with MLA analysis achieves higher accuracy and lower false detection rate compared to other state-of-art techniques.

3.3 Discussion

Stabilized classification performance of EEG data relies on the bubble entropy which is determined at different frequency sub-bands. Multiscale bubble entropy enables us to provide stabilized complexity measures of EEG. Bubble entropy analysis is adapted to achieve lower FDR. The power matrices provide significant difference among various classes of EEG that means they have higher discriminating capability. The use of power analysis produces quality control discrimination of EEG signal with the higher accuracy. The correct combination of feature vectors is necessary to achieve higher accuracy with lower FDR. The complexity coefficients and power feature support to form an integrated feature set which represent progressive quality information and guarantee the lower FDR. Therefore our proposed feature extraction technique derives integrated feature vector set using bubble entropy and power analysis.

We also evaluate the stability performance of proposed multiscale bubble entropy feature with increased value of embedding dimension from ($m = 1$–20) with an interval of 2 as noted in Table 5. In Figure 11, the values of multiscale bubble entropy for all different sub-bands at different values of (m) have been plotted. We perform the stability test of multiscale bubble entropy with the normal EEG signal and compare it with the permutation entropy parameter of [12]. We observe that our proposed feature presents stable behavior for all values of (m) and permutation entropy seems to be stable after $m = 10$. The classification accuracy, when using ANN and KNN classifiers were 99.73% and 96.10% respectively. The obtained false detection rate with ANN and KNN was 0.121 and 0.132 respectively. This means that when classify the complex EEG signal, increment of 3.63% in classification accuracy was achieved with ANN, compared to KNN. Their comparative analysis is given in Figure 12. We observe that ANN outperforms KNN, both in terms of accuracy and false detection rate attained while maintaining seizure detection performance. The result shows that the proposed algorithm yields significant improvement compared to several state-of-art techniques. To make this analysis more comprehensive, we have also performed extensive comparative studies of our proposed approach with a few of state-of-art approaches using Table 6 and their comparative analysis is shown in Figure 13. Our proposed technique provides a novel, comprehensive, and comparative approach for the detection of epileptic seizure.

Table 6: Comparative analysis with the existing technique

Authors	Accuracy
Faust[1]	93.3%
Martis [24]	95.3%
Chua [25]	93.1%
Bhattacharyya [26]	99.4%
Ocak [10]	96%
Guo [6]	98.27%
Ghosh Dasidar [13]	96.7%
Acharya [5]	99.70%
Ashwani [2]	99.3%
Peker [27]	99.15%
Proposed approach	99.73%

4. CONCLUSION

This study proposed a combined framework of feature extraction technique for appropriate feature set and comparative analysis of different machine learning approaches for accurate identification of seizures. The feature extraction technique is basically extract bubble entropy, absolute power index, and relative power index features to characterized seizures activity. The counting property of bubble entropy is their stable behavior for larger range of embedding dimension. The proposed technique is an effort to gain better insight into intelligent classification program using classifier analysis. The capability of ANN is to classify EEG into preseizure, seizure, and normal events with higher accuracy of 99.73% and lower false detection rate of 0.121 compared to KNN.

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