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TUNABLE-Q WAVELET TRANSFORM BASED ENTROPY MEASURES FOR IDENTIFICATION OF EPILEPTIC SEIZURES

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Abstract: ***The accurate location of epileptic seizures by interpreting an EEG (Electroencephalogram) signal is highly demanding and involves skilled neurologists. In this study, the EEG is analyzed using the Tunable-Q Wavelet Transform (TQWT) method for identifying seizures by splitting an EEG signal into several sub-bands. The entropy computed for each sub-band signifies the nonlinearity in an EEG signal. The other novel parameters viz correntropy, centered correntropy (CCE) and correntropy coefficient assess the nonlinearity of EEG signal and forms the basis for classification. The study has been done on the freely accessible Bonn University EEG database and outperforms in terms of complexity. When contrasted to the existing state-of-the-art methods, 100% accuracy has been achieved in discriminating seizure, seizure-free signals, and non-seizure EEG signals using Random Forest Classifier. Moreover, the computation of the proposed features is fast, and the system is easy to implement.***

Keywords:TQWT, entropy, correntropy, correntropy coefficients, seizures

1. INTRODUCTION

A seizure is a momentary event occurring due to the abrupt firing of millions of neurons. Epilepsy is caused by recurrent unprovoked seizures. Epilepsy has influenced around 65 million people worldwide [Epilepsy, 2019]. The rate of occurrence of epilepsy around the world is around 0.2%. Subsequently, epileptic patients are to be handled carefully to avoid sudden injuries and loss of lives. The conventional techniques for the investigation of epileptic patients are based on analyzing EEG signals. However, over a decade some automated frameworks supported by machine learning have been widely explored by researchers and may replace the existing systems to provide better control of

the problem. Among them, Fourier spectral analysis has been used frequently for feature extraction of the EEG signal assuming the signal to be stationary. However, the available literature [Ghaderyan et al. 2014; Kaur & Singh 2017] manifests the random nature of EEG indicators. In the past, several techniques have been deployed to decompose and analyze the EEG signal by Discrete Wavelet Transform (DWT). The sub-bands and their coefficients obtained by decomposition of EEG are used to extract features to discriminate seizure subjects and healthy subjects [Y. Kumar et al. 2012;O. Faust 2015; R.Sharma et al.2015]. In recent years, the empirical mode decomposition (EMD) method [Huang et al. 1998; R. Pachoriet al. 2014] has gained significant importance for analyzing the EEG signals by its decomposition into simpler modes referred to as intrinsic mode functions (IMF). The mean frequency of IMF computed with Fourier Bessel Expansion is used to discriminate between seizures and non-seizure [Pachori 2008]. However, the number of IMF obtained for every signal is not fixed and the interpretations of results are complex. Using the EMD approach entropy [Acharya et al. 2015]is extracted for each IMF to distinguish focal and non-focal EEG signals.

In literature, several non-linear techniques [Kannathal 2005, A. R. Hassan 2016] have been projected to perceive non-linear characteristics of time-series such as the degree of randomness of EEG signal is measured in terms of entropy. The approximate entropy (ApEn), Sample Entropy (SampEn), Phase Entropy 1 (S1), and Phase Entropy 2 (S2) were separated [U.R. Acharya et al. 2012] to segregate pre-ictal, ictal, and inter-ictal state. The simple features like Pythagorean mean (arithmetic, geometric and harmonic mean) have likewise been utilized to categorize seizures, seizure-free and normal subjects [Shanir, Iqbal, Khan, & Farooq, 2018]. The other non-linear features viz. fractal dimension, correlation dimension [Lehnertz et al. 1995], and Lyapunov exponent [N.F.Guler et al. 2005] provide significant information about the different states of mind used for EEG analysis and classification. The focal EEG signal was recorded for feature extraction to distinguish different classes of EEG signals using the EMD-DWT domain [Das & Bhuiyan 2106]. The epileptic seizure detection has also been done from scalp EEG signals [A. R. Hassan et al 2016]. A non-linear technique for extraction of multi-domain features has also been adopted for epileptic seizure detection [Wang et al., 2017]. The accurate detection of seizure onset /offset has also been done using orthonormal triadic wavelet-based features [Chandel, Upadhyaya, Farooq, & Khan, 2019]. The autoregressive modeling approach adopted [Khan & Farooq, 2009] to detect focal seizures using an artificial neural network (ANN) is also significant.

Recently, a new framework Tunable-Q Wavelet-Transform (TQWT) has been used for the analysis of biomedical signals. This approach adopted for the analysis of the EEG signal provides enhanced sparse signal representation [R. Sharma et al. 2017]. The tuning factor Q affects the accuracy of the system [P.U.Kiran et al. 2018] and with variable Q & J, the signal is decomposed into sub-bands and the sub-bands with maximum energy are utilized for feature extraction. It has been analyzed that in

the TQWT framework, computation of Quality factor-based K-NN entropies was not enough for the classification of different classes of EEG signals. Therefore, multi-scale filtering [Abhijit Bhattacharyya et al. 2017] was applied to discriminate between seizures and non-seizures.

In this study, the TQWT technique has been deployed for the decomposition of the EEG signal into a fixed no. of sub-bands. The four non-linear features namely entropy, correntropy, centered correntropy, and correntropy coefficient is extracted for classification purpose. Entropy, a measure of chaos, used to characterize random EEG signals is computed for sub-bands. The other features extracted based on the Information Theoretic Learning (ITL) toolbox are correntropy, centered correntropy, and correntropy coefficient. Correntropy contains information not only about the distribution of the stochastic process but also about its time structure. Hence, a useful parameter for the analysis of nonlinear EEG signals.

The centered correntropy which is equivalent to the covariance between two random variables is also computed from correntropy. In the ITL toolbox, a parameter analogous to the correlation coefficient i.e. correntropy coefficient is also computed. All these features are used as input to distinguish EEG signals of seizures, non-seizures, seizure-free, and normal subjects.

2. METHOD

The methodology adopted in this study has been shown in the block diagram shown in Figure 1.

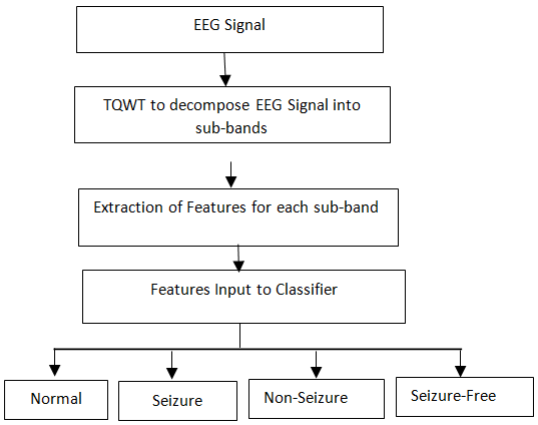


Fig 1: Proposed Methodology

i) Data Availability:

The EEG data for the study has been extracted from a freely obtainable database of Bonn University, Germany [Andrzejak et al. 2001]. The data has been recorded using a sampling frequency of 173.61 Hz for 23.6 sec using100 single-channel EEG electrodes. It has five subsets: Z, O, N, and F for non-seizures and S for seizures, each consisting of 100 single-channel EEG signals. This study has been performed for three groups of EEG signal (i) Seizure and Seizure-free (S-NF)(ii) Seizure and Normal (S-ZO) (iii)Seizure, Normal and Seizure-Free (S-ZO-NF). The EEG signal of each dataset has been represented in Figure 2.

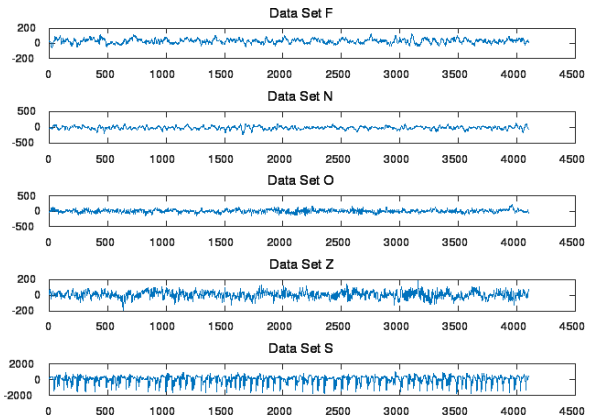


Fig 2 EEG of Seizure-Free (F-N), Non-Seizure (O-Z), and Seizure (S) Dataset

In Fig. 2, it can be observed that the peak amplitude of the seizure signal is much higher as compared to non-seizure.

ii) Tunable Q-Wavelet Transform

TQWT (Tunable-Q Wavelet-Transform) is a powerful tool for the examination of oscillatory signals like EEG, Electromyogram (EMG), and Electrocardiogram (ECG), etc. TQWT (Tunable-Q Wavelet-Transform) is a discrete-time wavelet converted which, unlike other transforms, can adjust the tuning factor Q to provide a better sparse signal representation of the EEG signal. A small value of Q can be chosen for transient evaluation and a higher value of Q for the examination of the oscillatory behavior of the signals. Q can be defined [J. Gubner and W. Chang 1995] as:

$$Q=\frac{f}{B} \qquad [1]$$

Where f is the middle frequency and B is the bandwidth of the signal. Another advantage of TQWT over DWT is that by altering the value of Q, the shape of the wavelet gets altered.

Quality factor (Q), redundancy (r), and no. of decomposition levels (J) are the input parameters for the decomposition of a signal. In the next section, we discussed the extracted features viz entropy, correntropy, centered correntropy, and correntropy coefficient which has been found instrumental in analyzing and distinguishing different EEG signals.

Entropy: Entropy is a measure of chaos or randomness in the signal. The intricacy of a time series is described in terms of entropy and can be computed as:

$$H=-\sum_{i=1}^{M} Xi\ log\ Xi \qquad [2]$$

where Xi is the amplitude of the i^{th} signal and M is the length of the signal.

The entropy plots for S-ZO-NF are shown in Fig. 3

iii) Correntropy

Correntropy is a nonlinear measure of the correlation between two signals. It can transform each signal nonlinearly into a feature space through a positive kernel function that computes the generalized correlation in that space. In the discrete-time domain, CCE can be computed as follows [Melia et al., 2014]:

$$V[k]=\frac{1}{M-k+1}\sum_{n=k}^{M}\kappa\,(y[n]-y[n-k]) \qquad [3]$$

$$\hat{V}=\frac{1}{M^2}\sum_{k=1}^{M}\kappa\widehat{\sum_{n=k}^{M}}(y[n]-y[n-k]) \qquad [4]$$

where $\kappa(\cdot\ ,\ \cdot)$ a shift-invariant Mercer kernel represents the lag, $\hat{V}$ is the mean correntropy and {y[1],y[2],….y[N]} represents a data set having M samples.

The correntropy plots for S-ZO-NF are shown in Fig. 4

iv) Centered Correntropy:

To decrease the effect of dc bias, the mean value$\hat{V}$ of the correntropy can be deducted from the correntropy to acquire centered correntropyVc[k] [Ravi Shankar Reddy & Rao, 2017]given as:

$$Vc[k]=V[k]-\hat{V}[9] \qquad [5]$$

In this study the Gaussian kernel function [Shawe Taylor and Cristianini, 2004]$\kappa(y[n],y[n-k])$ has been used to compute correntropy and defined as:

$$\kappa(y[n],y[n-k])=\frac{1}{\sigma\sqrt{2\pi}}e^{\left\{\frac{-(y[n]-y[n-k])^2}{2\sigma^2}\right\}} \qquad [6]$$

The centered correntropy plots for S-ZO-NF are shown in Fig. 5

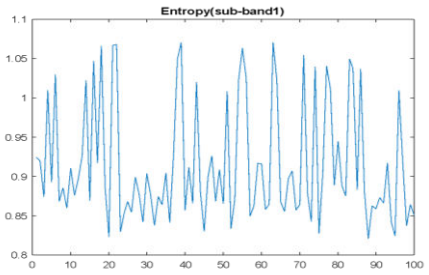
v) *Correntropy Coefficient:*

The correlation between two random variables is measured in terms of the correntropy coefficient[Gunduz and Principe, 2009]. It is equivalent to a well-known parameter, correlation coefficient, which is used to find linear interdependence between two signals x & y. It can be

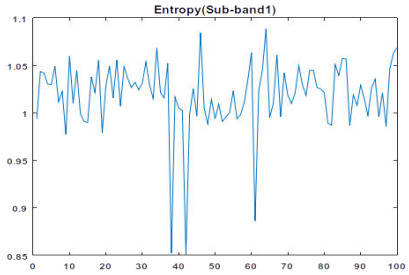
computed as:

$$r=\frac{1}{N}\sum_{p=1}^{M}\frac{(x(p)-\overline{x})}{\sigma_x}\frac{(y(p)-\overline{y})}{\sigma_y}[7]$$

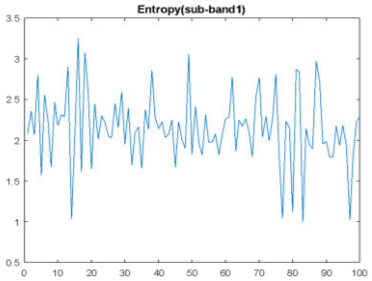
where M is the length of the signal, $\overline{x}\&\sigma_x^2$ are the mean and variance of x whereas $\overline{y}\&\sigma_y^2$ are the mean and variance of y. The ITL toolbox used for computation of correntropy-centered correntropy and correntropy coefficient is accessible at http://www.sohanseth.com/Home/codes.



(a)



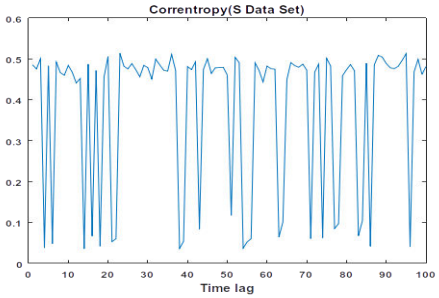
(b)



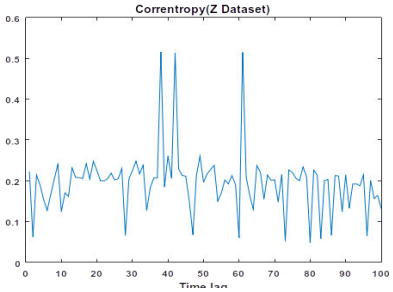
(c)

Fig 3 Entropy (a) Seizure Dataset(S) (b) Normal Dataset (Z-O) (c) Seizure-Free Dataset (N-F)

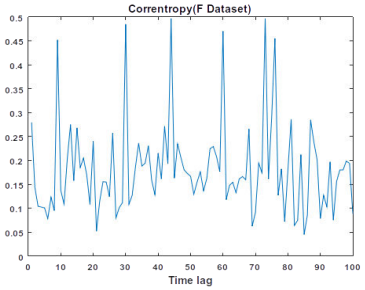
In Fig. 3, the entropy of sub-band 1 has been plotted which depicts that seizure EEG has a large no. of peaks as compared to non-seizure and seizure-free EEG signals.



(a)



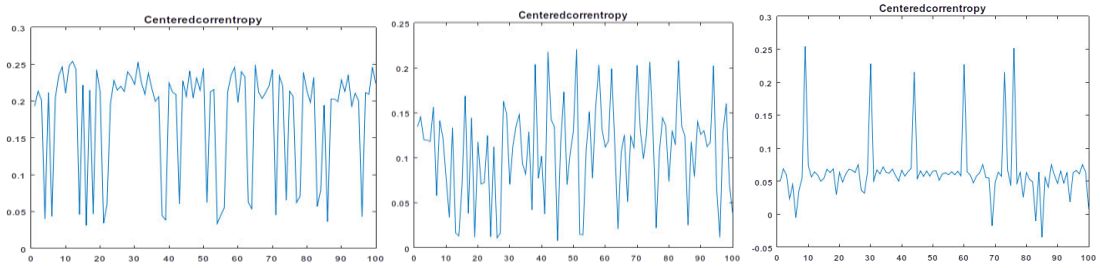
(b)



(c)

Fig 4 Correntropy (a) Seizure Dataset (S) (b) Normal Dataset (Z-O). (c) Seizure-Free Dataset (N-F)

The correntropy plotted in Fig. 4 for seizure,seizure-free and non-seizure EEG signal shows a higher amplitude range for seizure EEG signal.



(a) (b) (c)

Fig 5 Centered Correntropy (a) Seizure Dataset (S) (b) Normal Dataset(Z-O) (c) Seizure-Free Dataset (N-F)

Similarly, in Fig 5, the effect of dc bias has been eliminated and the corresponding seizure-free EEG signal has a wider amplitude range.

3. PERFORMANCE EVALUATION

In this study, the Waikato environment for knowledge analysis (WEKA) [Eibe Frank et al. 2016] software is used for the classification of EEG signals. In the study, it has utilized the Random Forest classifier available in the weka toolbox. Accuracy, specificity, and sensitivity are the performance parameters of the classifier defined as:

$$Accuracy(\%) = \frac{TP + TN}{TP + TN + FP} \, x \, 100$$

$$Sensitivity(\%) = \frac{TP}{TP + FP} \, x \, 100$$

$$Specificity(\%) = \frac{TN}{TN + FP} \, x \, 100$$

where TP, FN, TN, and FP are total numbers of true-positive samples, false-negative samples, true-negative samples, and false-positive samples respectively.

4. RESULTS AND DISCUSSION

TQWT is used to decompose the EEG signals that have been received from the seizure dataset (S). It includes different datasets such as normal dataset (Z, O) and seizure-free dataset (N, F) which are represented as Q=3,r =3, J=9. EEG signal has been decomposed into (J+1) sub-bands. There is the computation of entropy that ranges from sub-band 2 to sub-band 5. Additionally, the ITL toolbox was also used to extract correntropy, centered correntropy, and correntropy coefficients.

To diversify the varied categories of EEG, a commonly used feature selection scheme was executed on the extracted features. The evaluation was performed by using a statistics toolbox that had a confidence level of 95%. It was found that when the p-value was equal to less than 0.5, then the value of the KW test is considered to be discriminately significant. Fig.6- Fig.8 showed that the p-value outcomes were small and discriminated against each class of signals when the p-value was less than 0.05. The comparison in Table 1 shows the accuracy achieved in the proposed technique as compared to existing state-of-art methods.

In the EMD technique, there is a limitation of IMFs signals as they are not fixed and highly dependent on the frequency of the signal. However, in the TQWT approach, there is the presence of a fixed number of sub-bands that help in the extraction process. Thus, it facilitates a comparison between the sub-band and each class of signals. As a result, there is a simplified interpretation of outcomes that can be attained for all the sub-bands.

For the discrimination of each class of signals, different processes such as entropy, correntropy, centered correntropy, and correntropy coefficient are computed. The data that is extracted from each data set acts as an input for the Random Forest classifier. Table 2 represents that each feature exhibits 100% classification accuracy.

Kruskal Wallis Anova Test Results

(1) Seizure Vs Normal

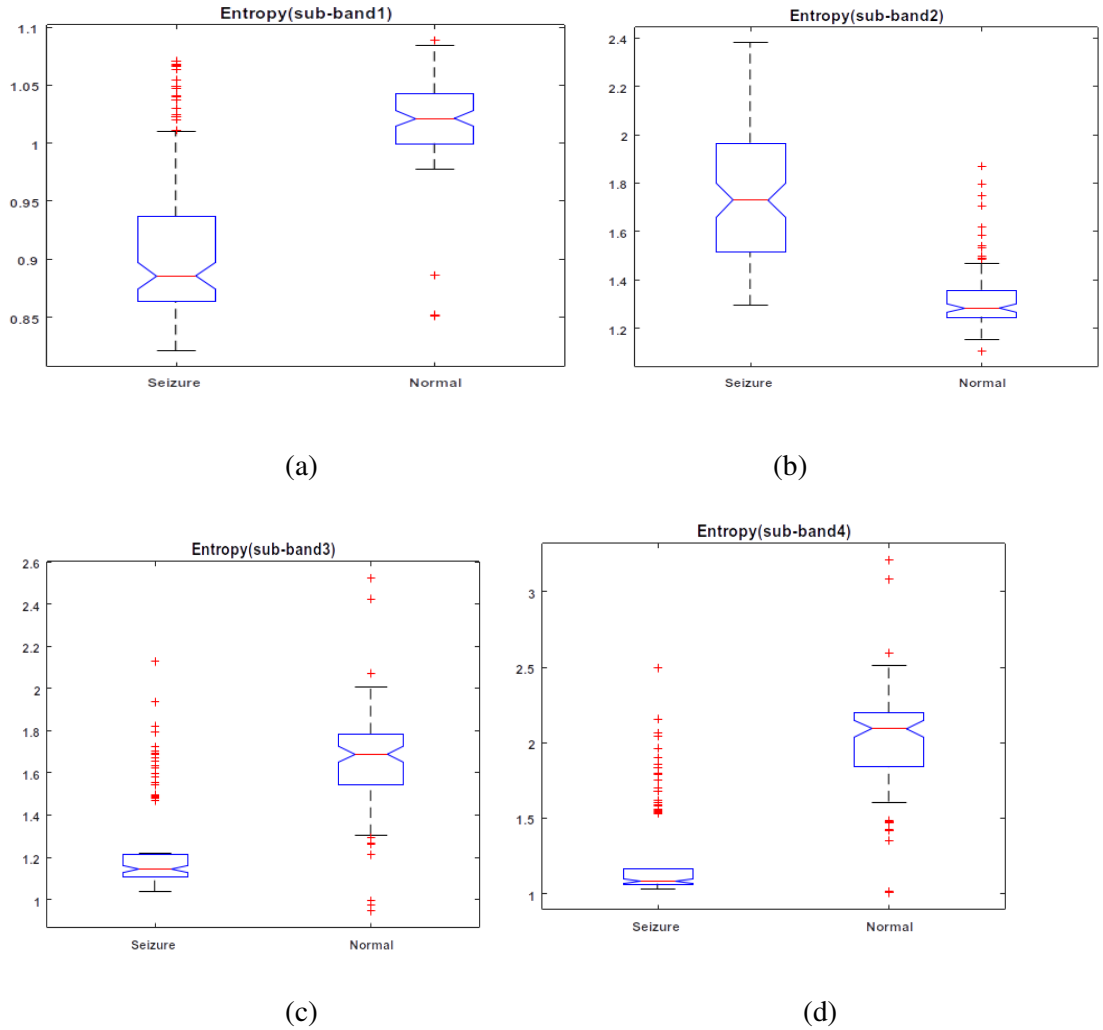


Fig 6 Entropy estimation for different sub-bands: Sub-band 2 ($p=6.1059 \times 10^{-15}$) Sub-band 3 ($p=2.9029 \times 10^{-26}$) Sub-band 4 ($p=6.1634 \times 10^{-19}$) Sub-band 5 ($p=3.2370 \times 10^{-24}$)

Figure 6 includes four graphs a, b, c, and d which were related to the estimation of entropy in different sub-heads. While ascertaining graph a, the value of sub-band 2 was recorded to be p=6.1059 x10-15. In the case of graph b, the value of sub-band 3 was recorded to be p=2.9029x10-26, while in graph c, the value of sub-band 4 was recorded to be p=6.1634x10-19. The graph d showed the sub-band 5 value of p=3.2370x10-24.

(2) Seizure Vs Seizure-Free

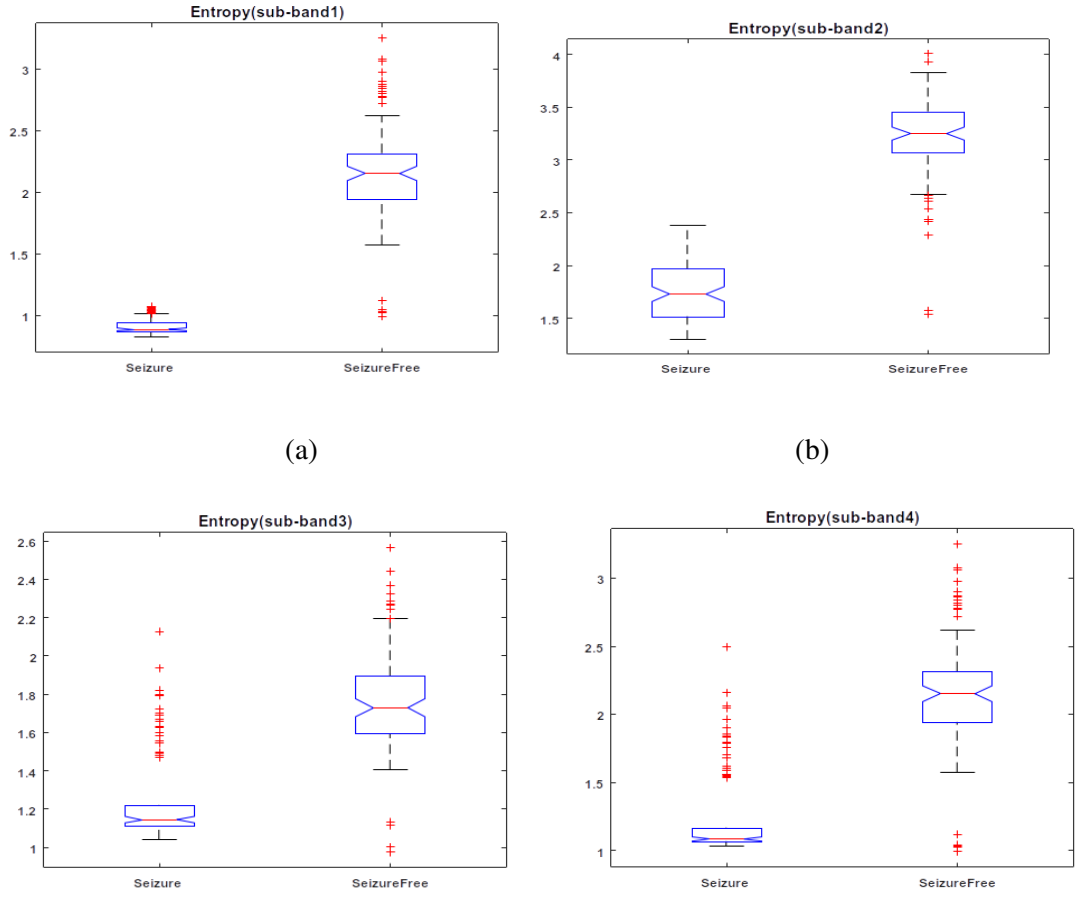


Fig 7 Entropy Estimation or different sub-bands: Sub-band 2($p=1.8647x10^{-33}$) Sub-band 3 ($p=1.6590x10^{-32}$) Sub-band 4 ($p=1.1206x10^{-20}$) Sub-band 5($p=3.4044x10^{-25}$)

Figure 7 includes four graphs a, b, c, and d which were related to the estimation of entropy in different sub-heads. While ascertaining graph a, the value of sub-band 2 was recorded to be p=1.8647x10-33. In the case of graph b, the value of sub-band 3 was recorded to be p=1.6590x10-32, while in graph c, the value of sub-band 4 was recorded to be p=1.1206x10-20. The graph d showed the sub-band 5 value of p=3.4044x10-25

(3)Seizure Vs Seizure-Free Vs Normal

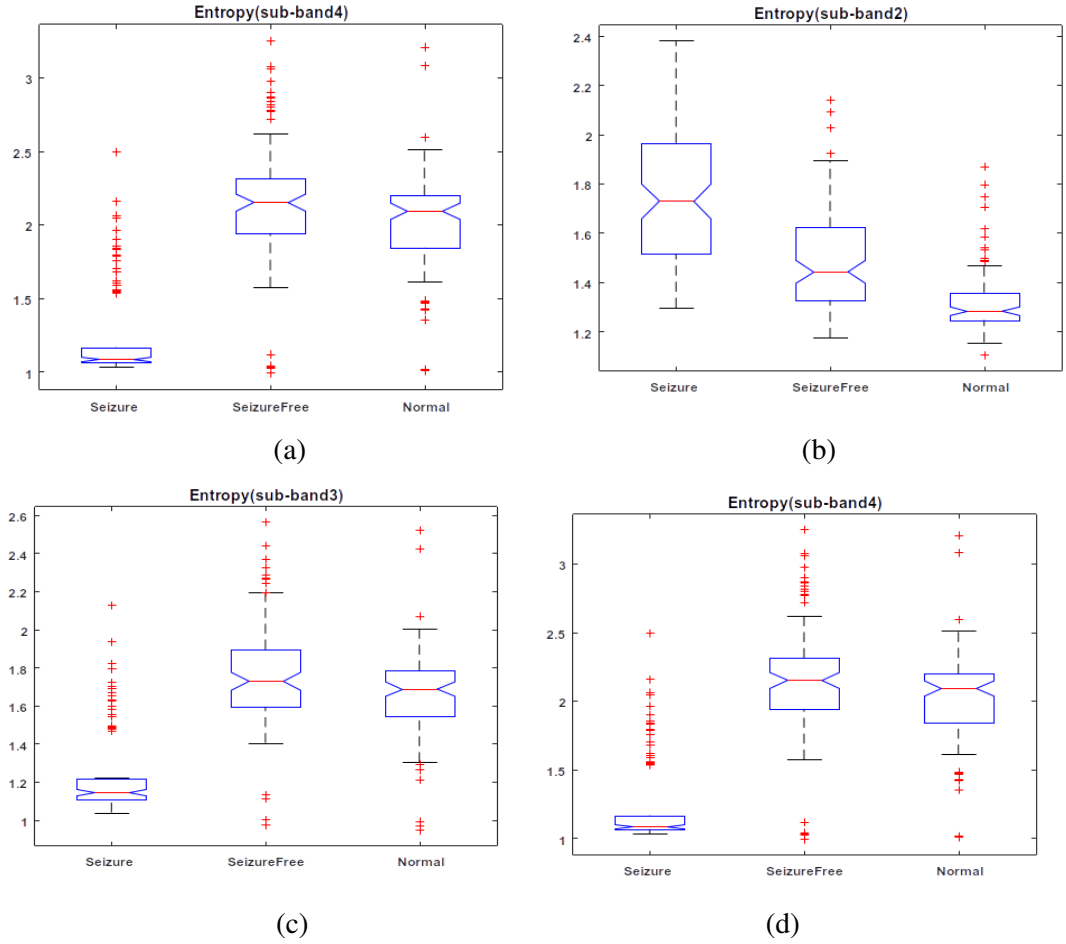


Fig 8 Entropy computation for different sub-bands: Sub-band 2 ($p=6.0674 \times 10^{-20}$) Sub-band 3 ($p=5.5837 \times 10^{-28}$) Sub-band 4 ($p=1.7277 \times 10^{-25}$) Sub-band 5 ($p=7.5962 \times 10^{-32}$)

Figure 8 includes four graphs a, b, c, and d which were related to the estimation of entropy in different sub-heads. While ascertaining graph a, the value of sub-band 2 was recorded to be p=6.0674 x10-20. In the case of graph b, the value of sub-band 3 was recorded to be p=5.5837x10-28, while in graph c, the value of sub-band 4 was recorded to be p=1.7277x10-25. The graph d showed the sub-band 5 value of p=7.5962x10-32.

Table 1: Comparison of the proposed features for classification of normal, seizure-free, and seizure EEG signals with the existing methods studied on the same dataset

Auth or	Method	Dataset	Accuray
Tzallasetal. (2007)	Time-Frequency based features and ANN	S-ZO-NF	97.72%
Acharya et al. (2012)	Approximate entropy, sample entropy, and phase entropy with SVM classifier	S-ZO-NF	98.1%
Peker et al. (2015)	Dual-Tree complex wavelet transform and complex-valued neural networks	S-ZO-NF	98.28%
G.Ravi Shankar Reddy et al. (2017)	TQWT, CCE, RF MLP, and LR	S-ZO-NF	98.2%
Bhattacharya et al. (2019)	TQWT based multiscale k-NN entropy	S-ZO-NF	98.6%
Proposed Method	TQWT, Entropy, Correntropy, Centered Correntropy, Correntropy Coefficient using Random Forest classifier	S-ZO-NF	100%

Table 1 describes the facts related to the comparison between the proposed features for the classification of normal, seizure-free, and seizure EEG signals with the existing methods studied on the same dataset. The table established a comparison between the works of five different researchers were Tzallas etal. (2007), Acharya et al. (2012), Peker et al. (2015), G.Ravi Shankar Reddy et al. (2017), Bhattacharya et al. (2019). As per the comparative analysis, it was found that the most common method that was used by the researchers was TQWT and entropy. The highest S-ZO-NF was recorded to be 98.6% and the lowest S-ZO-NF value was recorded to be 98.1%.

Table 2 Comparison of Accuracy, Sensitivity & Specificity

Parameter	Seizure, Seizure-Free	Seizure, Non-Seizure	Seizure, Non-Seizure, Seizure Free
Entropy	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%
Correntropy	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%
Centered Correntropy	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%
Correntropy coefficient	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%	Accuracy 100% Sensitivity 100% Specificity 100%

5. CONCLUSION:

The revealing of epileptic seizures has been projected and accomplished by utilizing the EEG dataset. The non-linear features viz. entropy, correntropy, centered correntropy, correntropy coefficient forms the basis of classification using Random Forest Classifier. The performance parameters achieved for three classes of signals for different combinations of parameters have been listed in Table 2. The investigational consequences have been replicated that the anticipated parameters are effective for the identification of epileptic EEG signals and can assist epileptologists in the accurate diagnosis and treatment of seizure patients. In comparison with the state-of-the-art methods, the proposed features have given 100% accuracy. Moreover, the computation is fast, and the system can be implemented easily. In the future, this approach may be easily adapted for the detection of other neurological disorders as well.

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