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EPILEPTIC SEIZURE PREDICTION USING HYBRID FEATURE SELECTION

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ABSTRACT

A comprehensive research of Electroencephalography (EEG) is carried out on Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT) domains. In this scenario, the hybrid feature extraction is performed by utilizing entropy features like Shannon entropy, log-energy entropy and Renyi entropy. Generally, the entropy measures are effective in evaluation of non-linear interrelation and complexity of signals. After that, a superior classifier named as Support Vector Machine (SVM) is implemented for classifying the signals. Experimental outcome proves that the advanced method distinguishes the focal and non-focal signals with a superior accuracy.

Keywords: *Empirical Mode Decomposition (EMD), Intrinsic Mode Function (IMF), Support Vector Machine (SVM).*

1. INTRODUCTION

Human brain controls nerve system and have extremely complex arrangement. It collects the instructions from sensory organs and emits the output to muscles and other body parts. In current period, epilepsy is a long lasting disease that affects the all aged people. This disease is the second most neurological syndrome that is affecting 50 million people throughout the world [1]. This disease is occurred by abnormal neuronal activities in the brain as the outcome of formation of seizure. Seizure is an unexpected electrical movement in the brain that commonly begins at all ages [2], [3]. Seizures are commonly defined into two key category: primary seizures and partial seizures. Primary seizures start with an extensive electrical discharge, which implicates in both sides of the brain. Whereas, the partial seizures start with a limited electrical discharge, which comprises in one side of the brain [4]. Several irregular discharges are detected in the brain structures, due to this seizure disorder. These discharges arise either during the seizures or between the two consecutive seizures. It is not easy to identify or detect seizures and Epilepsy disorder. Here, the treatment depends on the accurate diagnosis and exact identification. Numerous methods and inventions are made so far. EEG is an essential test for analyzing epilepsy and also it reports the electrical activity of the brain in a safe and painless manner [5], [6].

Minor metal electrodes are associated to the scalp and the brain activities of the traces are recorded. This is done to get the information regarding physiological states of the brain and body. Partial seizures are detected from the recordings and the defected regions are analyzed using EEG records [7]. The manual examination of EEG by the physicians will not be accurate all the time. Thus, an automatic examination of EEG reports is necessary in the medical enquiry. To differentiate between inter ictal (focal) signals from the ictal (non-focal) EEG signals, many techniques has been developed during the recent times. An efficient and suitable techniques are utilized in this system, to inspect EEG data [8]. In addition, many feature selection schemes (For instant, Different entropy) are added, to define and distinguish the features exists in the signals as per their characteristics. Feature selection is the procedure to obtain the optimal feature subsets from the set of data inputs by the rejection of redundant and irrelevant features [9], [10]. Output of the feature selection process specifies, which features of the EEG signals are essential in describing the data set signals.

In this research, a new hybrid feature combination (Shannon, Log-energy and Renyi entropy) is performed with the superior classifier named as Support Vector Machine (SVM), to perform EEG signal classification (focal and non-focal) signals. In addition, EMD method is also used in this system to process the signal as Intrinsic Mode Function (IMF) and a wavelet transform approach (DWT). Feature extraction is processed from the IMF and DWT band signals. Then, the SVM classifier is employed for the signal classification process.

The remaining portion of the paper is organized as follows. Section II describes background material and related work. Section III describes hybrid feature extraction for epileptic seizure prediction along with DWT and EMD. Section IV illustrates the prediction performance of our method with comparisons to other previous approaches, followed by some concluding remarks in Section V.

2. LITERATURE REVIEW

Gill, et al. [11] has illustrated a scheme of EEG signal detection by employing hybrid feature selection. Initially, the electrical movement was measured for numerous areas of the scalp of EEG signals. This paper evaluated a computerized system, which identified the epileptic seizure without relating an expert opinion. Hence, this computerized system progress in four steps such as, pre-processing, significant feature extraction, selection and hybrid classification. Experimental outcome confirmed that the advanced scheme showed a significant accuracy of 86.93 %.

Zarita, et al. [12] has developed a superior harmony system for feature selection and applied it in the Epileptic seizure detection. In this scenario, a wrapper-based feature selection technique was evaluated by employing evolutionary harmony search algorithm. It helped to determine the optimal solution. The adjustments were accomplished in two ways such as, computation of harmony memory and managing of solutions. Simulation outcome proved that the advanced search algorithm showed a significant result in accuracy than the other traditional search algorithms.

Sriram, et al. [13] has presented a review on seizure detection, and prediction in epilepsy. This review paper described about the advantage of employing EEG, ECG, motion sensors and electro-dermal activities. Also presented an overview of associated prediction schemes for seizure identification. Finally, the researchers confirmed that an effective feature combination and consequent classification can employ a computerized seizure prediction and detection.

Yinxia, et al. [14] has developed an approach for computerized seizure detection by employing SVM and wavelet transform in long-term Intracranial-EEG (I-EEG). Superior features were extracted such as, amplitude, energy, fluctuation index and so on. Then the post-processing was practiced on the classification outcome to attain an extra accurate and stable outcome. Experimental outcome confirmed that the advanced scheme achieved a sensitivity of 94.46% and a specificity of 95.26%.

3. PROPOSED METHODOLOGY

Generally, the EEG signals are examined by applying a suitable well-known classifier. EEG signals are achieved from an openly available EEG database. The respective database consists of two types of signals such as focal and non-focal EEG signals. Focal specifies that the electrical disturbance occurred inside the brain in a limited area. Whereas, non-focal is generalized by seizures, which affects the complete brain.

3.1 Pre-processing

Motivation of implementing pre-processing is to examine the difference of signals between two adjacent channels. Also, the pre-processing technique eliminates the unwanted noise and interference stated in seizure identification. Here, the unwanted noise denotes the frequency range beyond 60 Hz. In this scenario, the frequency over 60 Hz are eliminated by applying 6th order butter worth filter. General equation for butter-worth filter is given in below equation (1),

$$G^2(W) = |H(jw)|^2 = \frac{G_0^2}{1+(\frac{jw}{jw_c})^{2n}} \quad (1)$$

Where, n is specified as the order of filter, w_c is symbolized as the cut-off frequency and G_0 is mentioned as the DC gain.

Once, the order of the filter is increased means the flatness of the output response is also gets increased. Thereby, 6th order butter worth filter shows a superior outcome for removing the noise in EEG signal. After the performance of pre-processing, the frequency with 60Hz is given as the input signal for examining focal and non-focal EEG.

3.2 Examination of focal and non-focal EEG signals

This section analysis, whether these values can distinguish the focal EEG signal from the non-focal

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signal or not. Here, two different Band Limit (BL)-EEG segments are performed such as, EMD and DWT domains. Brief analysis about EMD and DWT domains are specified in below section.

3.2.1 Empirical Mode Decomposition (EMD)

EMD delivers an amplitude and frequency modulated oscillatory configurations, which is noted as IMF. For an $N-point$ data $X\{x_1, x_2 .... x_N\}$, IMFs are attained. Initially, set the input as m_o, such that $m_o = X$, and then $mold = m_o$. After the determination of local maxima and minima of mold, cubic spline interruption is utilized to attain the envelopes.

After that, the mean values (m) of $e_{\min}$ and $e_{\max}$ are determined by employing $p = (e_{\max} + e_{\min})/2$ and successively the values are subtracted,

$$m_{new} = m_{old} - p \tag{2}$$

Finally, mold is set equal to m_{new} and stop the decomposition if SD is denoted as follows,

$$SD = \frac{\Sigma |m_{new} - m_{old}|2}{\Sigma m^2{}_{old}} < \alpha \tag{3}$$

Where, SD determines the spectral density of $0.2 \leq, \leq 0.3$. Otherwise, repeat the steps to get IMFs.

3.2.2 Discrete Wavelet Transform (DWT)

DWT is utilized in engineering practices for solving numerous real-life concerns. Here, an improved low-frequency and high frequency information are achieved by employing short and long time windows. Also, it splits the input 60Hz frequency into five sub-bands with the range of 0-4Hz, 4-8 Hz, 8-15 Hz, 15-30 Hz and 30-60 Hz, respectively. Due to this, DWT is appropriate for investigating the non-stationary signals. General equation of DWT is specified below,

$$DWT(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(N)\psi(\frac{N-2^jk}{2^j})\,dN \tag{4}$$

Where, ψ is denoted as the wavelet function and 2^j, 2^jk are represented as the scaling shifting parameters.

3.3 Hybrid Feature Extraction

After performing suitable BL-EEG segment domain then the both IMFs sub-bands and DWT sub-bands are combined for feature extraction. Here, the entropy based features are utilized as the feature extraction scheme. Generally, entropy is a quantity, which calculates the randomness of the signal and also describes the chaotic system disorder. The non-linear performance of entropy helps to determine the difficulties of the signals. Among numerous categories of entropy, spectral entropy parameters such as, Shannon, log-energy and Renyi entropies are utilized in this work to determine the spectral difficulties of a time sequence.

Due to this concern, the entropy features are anticipated to have an effective discriminate signals. Shannon entropy specifies the uncertainty potential reduction if the result of the probabilistic procedure is recognized. In EEG signals (non-linear signals), the Shannon entropy calculates the average information about Probability Distribution Function (PDF), which helps to reduce the quantization error. Additionally, Renyi entropy is utilized to derive the convolutional mutual information about statistical signals. Besides, the capability of log-energy entropy to characterize the non-linear dynamics of EEG signals helps to describe the electrophysiological behavior of epileptogenic regions successfully. These spectral parameters measure the Power Spectral Density (PSD), which represent the power distribution according to the frequencies.

If the power level of the $i-th$ frequency component is p_i, for a given data-set, with length N and mean, the corresponding Shannon-entropy (H_{SE}), log-energy entropy (H_{LE}) and Renyi entropy (H_{RE}) are expressed as,

$$H_{SE} = -\sum_{i=1}^{N} p_i 2 \times \log_2(p_i 2) \tag{5}$$

$$H_{LE} = \sum_{i=1}^{N} \log_2(p_i 2) \tag{6}$$

$$H_{RE} = \frac{1}{1-\alpha} \log \sum_{i=1}^{N} (p_i)\alpha \tag{7}$$

Where, Renyi entropy is the order of, the value of $\alpha = 0.9$.

3.4 Classification Method

In this scenario, the hybrid features are applied to categorize the EEG signals by implementing SVM classifier. Here, the SVM classifier creates an optimal hyper plane, to distinct the classes by a maximum margin through decision boundary. Here, the partition of two classes stated as focal and non-focal signals. The brief description about the SVM classifier is determined below.

3.4.1 Support Vector Machine (SVM)

SVM is a kind of classifier, it does well in solving two-class problem, which is associated to the theories of VC and structure principles. Significant generalized ability is determined by comprising the model complexity. General formula for linear discriminant function is symbolized as $w.x+b=0$. An optimum hyperplane is required to distinct the samples without noise and also to exploit the gap between two groups. It is satisfied by implementing the below equation,

$$pi[w.x+b]-1\geq 0, i=1,2,.....,N \quad (8)$$

In above formula and diminish $\|w\|^2$, so this optimization issue is solved by the saddle point of a Lagrange function with Lagrange multipliers. Ideal discriminant function is mathematically specified in equation (9),

$$f(x)=\operatorname{sgn}\{(w^*.x)+b^*\}=\operatorname{sgn}\{\sum_{i=1}^{N}\alpha_i{}^*.pi(x_i{}^*.\,x)+b^*\} \quad (9)$$

Then, replace the interior product by a kernel function $K(x,x')$ in formula (10), to solve the large computational complexity fashioned by the high dimensions. In this way, the linear separability of estimated samples are improved and the discriminant function is re-written as follows,

$$f(x)=\operatorname{sgn}\{\sum_{i=1}^{N}\alpha_i{}^*.pi.K(x,x_i)+b^*\} \quad (10)$$

Totally, three dissimilar types of kernel functions are commonly used, they are linear, polynomial and sigmoid kernels in nature.

4. RESULT AND DISCUSSION

In this section, the experimental outcome is specified in detailed. All experiments were implemented on PC with 1.8GHz Pentium IV processor using MATLAB 2015B. Here, the EEG signals were examined in three different domains like EMD, DWT and EMD with DWT, which are briefly discussed below,

4.1 Examination of EEG signals in EMD

EMD delivers amplitude and frequency modified oscillatory designs, which is symbolized as IMF. In figure.1, BL-EEG signals from focal and non-focal of EMD domain are exposed in the first column and second column, respectively. Separation of IMFs sub-bands are based on the equations (2) and (3).

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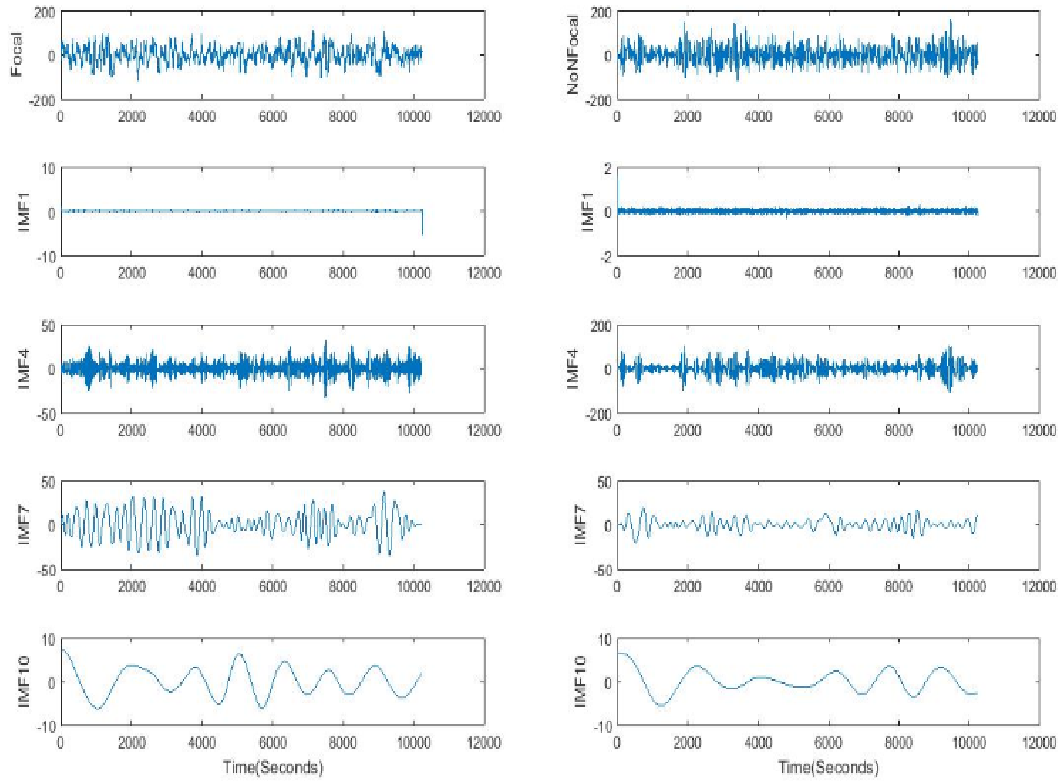

Figure 1: Four random IMFs extracted from EMD for focal (left) and non-focal (right) EEG signals

The box plots in figure.2, 3, and 4 represents the discrimination sub-bands for entropy features in the first, second and third column. Here, F represents the focal signals and N specifies the non-focal signals for EMD domain.

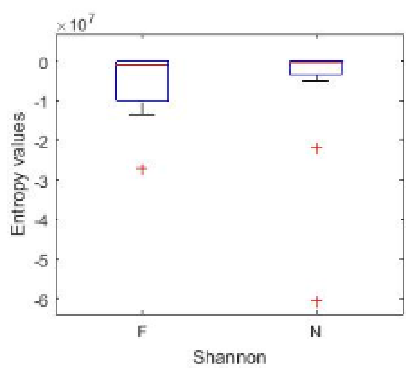

Figure 2: IMF Box plot for Shannon entropy

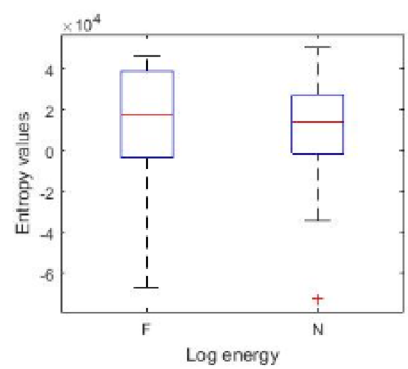

Figure 3: IMF Box plot for Log energy entropy

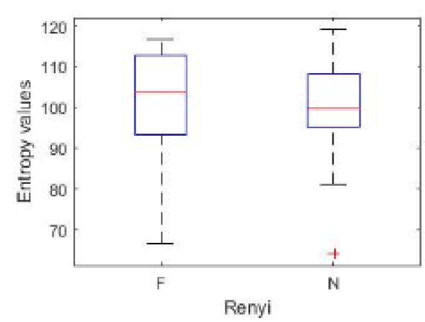

Figure 4: IMF Box plot for Renyi entropy

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Furthermore, in figure 5, the Receiver Operating Characteristic (ROC) curves are shown. The three entropy parameters obtained from the employed IMFs. In EMD domain, the log energy entropy shows a linear enactment in terms of sensitivity and specificity in comparison with other two entropies. Hence, the Shannon and Renyi entropies indicates a slight oscillation in between the range of 0.5 to 0.8 specificity, because of utilizing more number of IMF sub-bands.

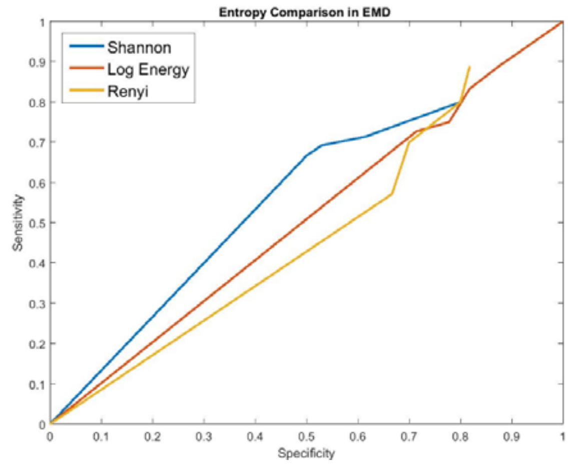

Figure 5: EMD accuracy comparison graph for three entropies

4.2 Examination of EEG signals in DWT

DWT is one of the most enhanced tool in non-stationary signal examination, because of its capability to extract the time and frequency localization from the time domain signals. Figure. 6, represents the BL-EEG signals from focal and non-focal of DWT domain are exposed in the first column and second column. Separation of band frequency (0-60Hz) based on DWT is specified in table 1.

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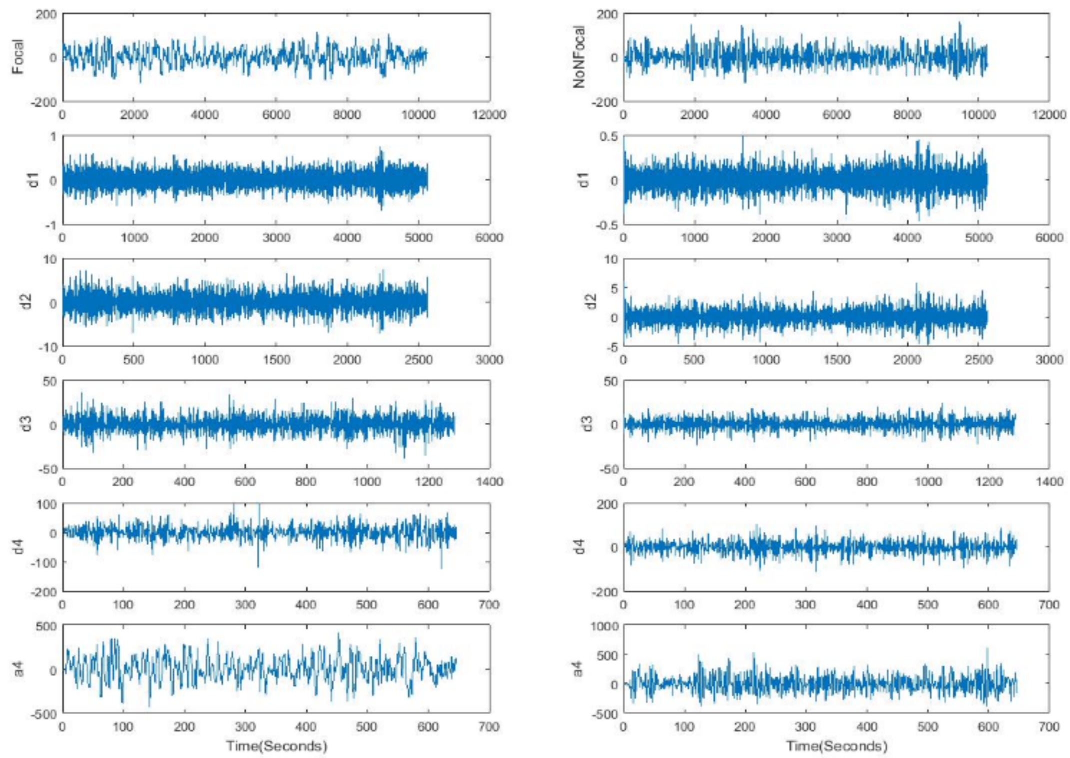

Figure 6: DWT Band-limited signals for focal (left) and non-focal (right) EEG signals

For the purpose of investigation, the BL-EEG signals are exposed to a 5 level DWT sub-bands and the attained sub-bands are exhibited in Table 1,

Table 1: DWT Sub-band Frequency Range

Sub-Band Name	Frequency Range	Physiological EEG sub-bands
a4	0-4 Hz	Delta Band
d4	4-8 Hz	Theta Band
d3	8-15 Hz	Alpha Band
d2	15-30 Hz	Beta Band
d1	30-60 Hz	Gamma Band

Box plots for entropy features are specified in the figure.7, 8, and 9 respectively. Therefore, F represents the focal EEG signals and N specifies the non-focal EEG signals.

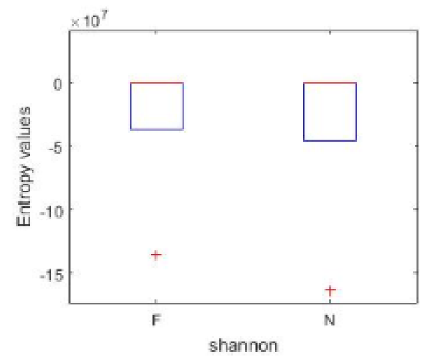

Figure 7: .DWT Box plot for Shannon entropy

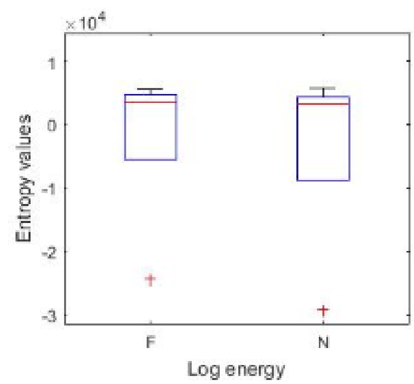

Figure 8: .DWT Box plot for Log energy entropy

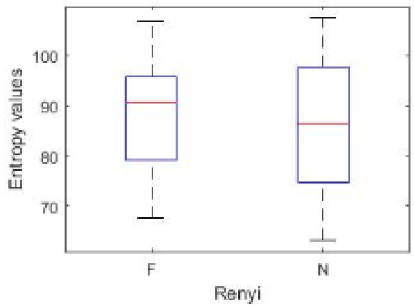

Figure 9: .DWT Box plot for Renyi entropy

ROC curves are displayed for the three entropy parameters attained from the five sub-bands, which is mentioned in table 1. Area under the ROC curves are also increased by a significant level than the case of BL-signals that is determined in the figure 10. Here, the log energy and Renyi entropy shows a gradual improvement in sensitivity, but with the minor oscillation at the end. Nevertheless, the Shannon entropy occurs a high deviation in entropy comparison of DWT domain, because DWT is a low frequency wavelet transform.

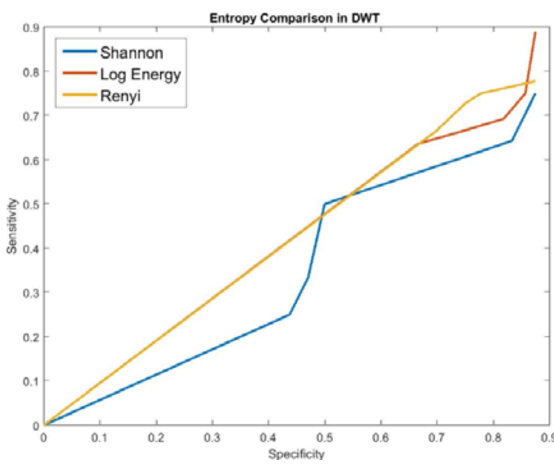

Figure 10: DWT accuracy comparison graph for three entropies

4.3 Examination of EEG signals in EMD-DWT

In this examination, the ROC curves are shown for all the three entropy features. Here, the combination of EMD-DWT, clearly provides a large area under the curves in comparison to the individual EMD and DWT. The comparison is evaluated in terms of specificity, sensitivity and the accuracy. In this domain, all the three entropies show a steady improvement by means of sensitivity and specificity, but with the slight variation in the range of 0.7 to 1.

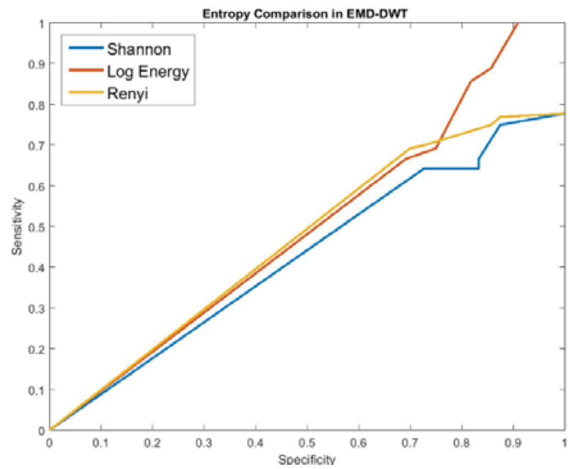

Figure 11: EMD-DWT accuracy comparison graph for three entropies

In table 2, observing the performance of EMD, DWT and the combination of EMD-DWT for the three entropy features. Obviously, the combination of EMD-DWT shows a better enactment by means of accuracy.

Table 2: Performance evaluation for different domains

Domains	Sensitivity	Specificity	Accuracy
DWT [15]	75	87.5	80
EMD [16]	88.88	81.81	85
EMD-DWT(Proposed	94	90.90	90.2

Table 3. represents the performance evaluation of advanced and previous methods, which is based on classification and feature selection.

Table 3: Comparison performance obtained for various algorithm

Method	Classifier method	features	Accuracy %
Sharma, et.al [15]	SVM least square method	DWT, Entropy Measures	84
Sharma, et. al [16]	SVM least square method	EMD, ASE, AVIF	85

Das, et.al [17]	KNN city block distance	EMD- DWT, Log energy Entropy	89.4
Proposed Methodology	SVM linear kernel	EMD- DWT, Log energy Entropy, Shannon entropy and Renyi entropy	90.2

From the Table 3, the advanced method provides the significant performance in comparison to the recent algorithms, which is labelled in the reference [15, 16, and 17]. It is also seen that the combination of entropies (Shannon, log-energy and Renyi) based features shows significant enactment in the combination of EMD-DWT with 0.8% improvement in accuracy. From this study, the accuracy is based on the quality of discriminate between focal and non-focal signals.

5. CONCLUSION

This paper conducted a statistical investigation on EEG signals in the both EMD and DWT domain. The objective of this experiment was to develop a proper feature for categorizing the focal and non-focal EEG signals. In this scenario, the spectral based entropy features like Shannon, log-energy and Renyi entropies were examined in EMD, DWT, and EMD-DWT domain. Associate to the other obtainable approaches for seizure prediction, the advanced scheme delivered an effective performance by means of accuracy 0.8% enhancement than the previous approaches.

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