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Classification of Focal and Non-Focal EEG Signal using an Area of Octagon Method

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Abstract: ***Epilepsy, a neurological syndrome can be detected via the electroencephalogram (EEG) signal with the help of sensors placing in the human cranium. This article introduces a fresh method known as the Area of Octagon (AOO), used for Focal (F) and Non-Focal (NF) EEG Signal classification. Initially, both class signals are putrefied into many intrinsic mode functions (IMF) with the help of Empirical mode decomposition (EMD) algorithm. The AOO can be computed with the help of decomposed IMFs. The AOO is now used as an input feature set for the classifier. This research aims to discriminate the F and NF EEG measurements for the therapy resistance. The proposed method attained an average classification accuracy of 97.9% with Linear, polynomial and an RBF kernel.***

Keywords: Area of octagon (AOO), Electroencephalogram (EEG), Empirical Mode Decomposition (EMD), Intrinsic Mode Function (IMF).

I. INTRODUCTION

Epilepsy is a central nervous system disease that makes brain activity an abnormal condition that causes an attack or unusual behaviour, sensation or, occasionally, lack of consciousness. Focal seizures come from just one portion of the brain whereas Non-focal seizures come from the whole brain rather than from one portion of the brain. Many scientists attempted, by various algorithms, to classify the F and NF EEG signals. IMF's average variance of instantaneous frequency (AVIF) and Average sample entropy (ASE) are used as an input feature set for the F and NF EEG signal classification (1). Although anti-epileptic drugs are appropriate, nearly one-third of individuals with epileptic seizures remain at high risk of cognitive and psychosocial dysfunctions and death (2). The Electroencephalogram signals in epileptogenic regions are less random, less non-linear, and more stationary than signals in non-epileptogenic regions (3). Many trials were carried out with the stimulus treatment method in order to further analyse, detect and classify EEG cell measurements. The identification of the onset of an attack involves peaks in the EEG measurements (4). A different neural network type called Elman network is used to detect and diagnose epilepsy automatically (5). The EEG seizure signals have been spontaneously detected and assessed with a hybrid approach (6). Various methods to identifying an epileptic seizure were created depending on linear prediction (7) and linear fraction predictions (8). The Focal and Non-focal EEG Signals were classed by methodologies such as Short Time Fourier Transform (9, 10). The EEG signals are analysed using EMD and Fourier-Bessel expansion (12). Hilbert huang transform technique seeks to help doctors discriminate between normal and seizure EEG signals (13). An Automatic System has been designed with the flexible analytical wavelet transform method for the detection of the Focal and Non-Focal EEG signal (14). A different method is presented with entropy measures for classifying F and NF EEG signals (15). A new class of orthogonal wavelet filters has been implemented for automatically detecting the F and NF EEG signals in the time – frequency domain (16). On the basis of an integrated index, a new method was developed for the detection of F and NF EEG signals with the aid of discrete wavelet transform and entropy features (17). The intra-cranial EEG with various time delays, depending on the Focal epileptogenic zone is measured using the Delay permutation entropy methodology (18). The remaining document is structured as follows: Section 2 describes the dataset used, EMD, computation of AOO and SVM classifier. Outcomes are provided and discussed in Section 3 and finally concluded in Section 4.

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II. METHODOLOGY

A. *Dataset*

This work uses the EEG dataset that can be accessed internet and outlined in (3). EEG multichannel samples were obtained from five individuals with pharmacoresistant temporal lobe epilepsy and were surgical applicants. Samples of EEG signals at 512 Hz were taken. The records contain EEG signals marked with the "x" and "y" indications. The dataset includes 3750 pairs of Focal and Non focal EEG signals each. Fig (1) shows the flowchart to process the EEG signal. The Focal and Non-Focal EEG signals are randomly collected from 3750 pairs which is shown in fig.2 and 3 respectively.

B. *Empirical Mode Decomposition*

The Empirical Mode Decomposition (11) is an adaptive signal decomposition method that signifies time-domain frequency into a definite set of amplitude and frequency modulated oscillating components which are the sources of putrefaction that is termed as IMF.

It is found that the decomposition of an EEG signal does not require any limitations on linearity and stationary properties of the frequency.

Fig.4 explains the process involved in the EEG decomposition using EMD.

C. Computation of Area of Octagon

The Area of octagon of the intrinsic mode functions of EEG signals can give useful diagnostic features for Focal and Non-focal EEG signal classification. The AOO of EEG signal can achieved with the X(n) versus Y(n). The Area of octagon can be computed as follows:

$$X(n)=x(n+1)-x(n) \tag{1}$$

$$Y(n)=x(n+2)-x(n+1) \tag{2}$$

$$Mx^2 = (1/N)\sum_{n=0}^{N-1}[X(n)]^2 \tag{3}$$

$$My^2 = (1/N)\sum_{n=0}^{N-1}[Y(n)]^2 \tag{4}$$

$$M_{xy} = (1/N) \sum X(n)\, Y(n) \tag{5}$$

$$M_{sum}^2 = M_y^2 + M_x^2 \tag{6}$$

$$M_{prd}^2 = M_x^2 * My^2 \tag{7}$$

$$D= [M_{sum}^2-4(M_{prd}^2-M_{xy}^2)]^{1/2} \tag{8}$$

$$Dia= [3(M_{sum}^2 +D)]^{1/2} \tag{9}$$

The area of octagon is obtained from Fig.5 as given below
In the above figure, From ΔABC
As all sides are equal in an octagon,

$$S^2 = |AC|^2 + |BC|^2 \tag{10}$$

Therefore,

$$|AC|=S/\sqrt{2} \tag{11}$$

Where ‘S’ is the sides of the octagon
In general, Diameter of the octagon is given by

$$Diameter=S+2(S/\sqrt{2}) \tag{12}$$

Since, $$S=Diameter/ (1+\sqrt{2}) \tag{13}$$

$$Area\ of\ octagon=2(1+\sqrt{2}) * S^2 \tag{14}$$

On substituting ‘S’ value in Area of octagon

$$Area\ of\ octagon\ (AOO) = \frac{2}{1+\sqrt{2}} * Dia^2 \tag{15}$$

[Here the Dia value is obtained from (9)]

D. *Support Vector Machine (SVM) based classification*

one SVM is used here for classifying the F and NF EEG signals. SVM classifies two different data by discovering the finest hyper plane. In this paper, Linear, RBF/Gaussian and polynomial kernels are used to classify Electroencephalogram signals. Let us consider X1 and X2 are the two different data points of different classes. The different kernels used are defined as:

1. Linear Kernel: It is the simplest form of kernel function.

$$K(X_1, X_2)= (X_1^T * X_2) + C$$

Where, C is a constant.

2. RBF/Gaussian kernel: RBF kernel is a function that relies on the distance to or from the starting point.

$$K(X_1, X_2)= e^{-\|X1-X2\|/2\sigma 2}$$

Where, $\|X_1-X_2\|$ is the euclidean distance between X_1 and X_2.

3. Polynomial kernel: It is a non-stationary kernel function.

$$K(X_1, X_2)= [(a+ X_1^T)* X_2]^b$$

Where ‘a’ is a constant and ‘b’ is the degree of the kernel. The classifier efficiency can be evaluated with different efficiency parameters such as Sensitivity (SENS), Specificity (SPEC), Accuracy (ACC), Error Rate Detection (ERD), Positive predictive value (PPV), Negative predictive value(NPV) and Matthews correlation coefficient(MCC). The properly recognized focal EEG signals are denoted as C_F and the properly recognized Non focal EEG signals are denoted as C_{NF}. Correspondingly the wrongly detected focal EEG signals are denoted as W_F and the wrongly detected Non focal EEG signals are denoted as W_{NF} then the performance parameters can be defined as (Azar et al., 2014):

$$SENS = \frac{CF}{CF+WNF}*100$$

$$SPEC = \frac{CNF}{CNF+WF}*100$$

$$ACC = \frac{CF+CNF}{CF+CNF+WF+WNF}*100$$

$$ERD = \frac{WF+WNF}{CF+WNF}*100$$

$$PPV = \frac{CF}{CF+WF}*100$$

$$NPV = \frac{CNF}{CNF+WNF}*100$$

$$MCC = \frac{CF.CNF-WNF.WF}{\sqrt{(CF+WNF)(CF+WF)(CNF+WNF)(CNF+WF)}}$$

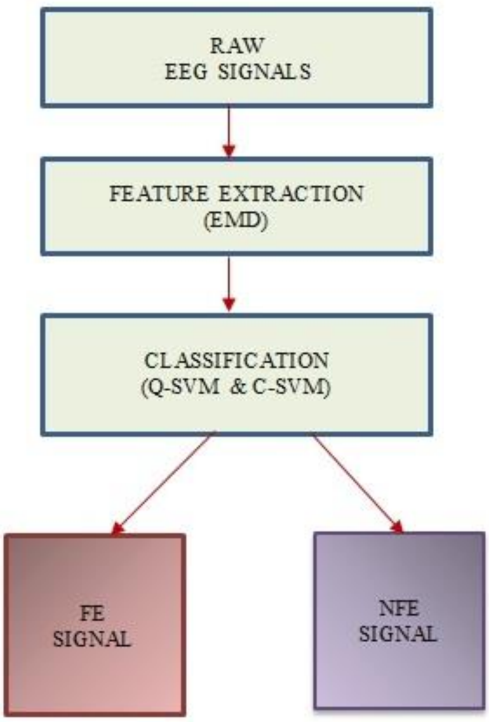

Fig. 1. Processing of signal- Flowchart

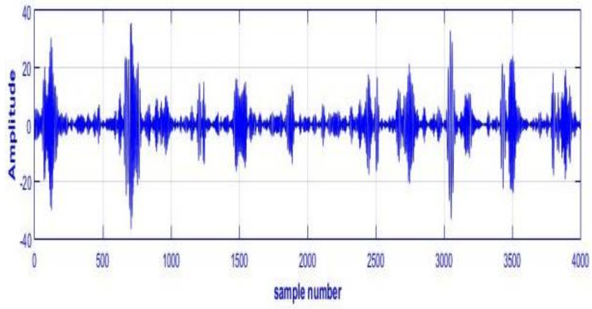

Fig.2. Focal EEG Signal

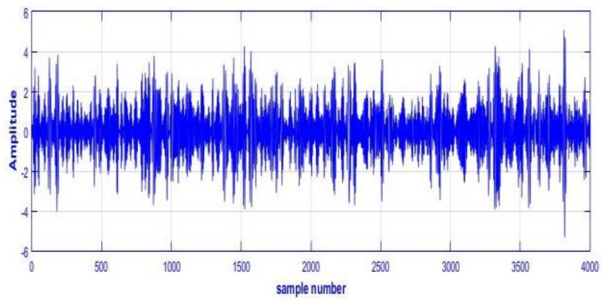

Fig.3. Non-Focal EEG Signal

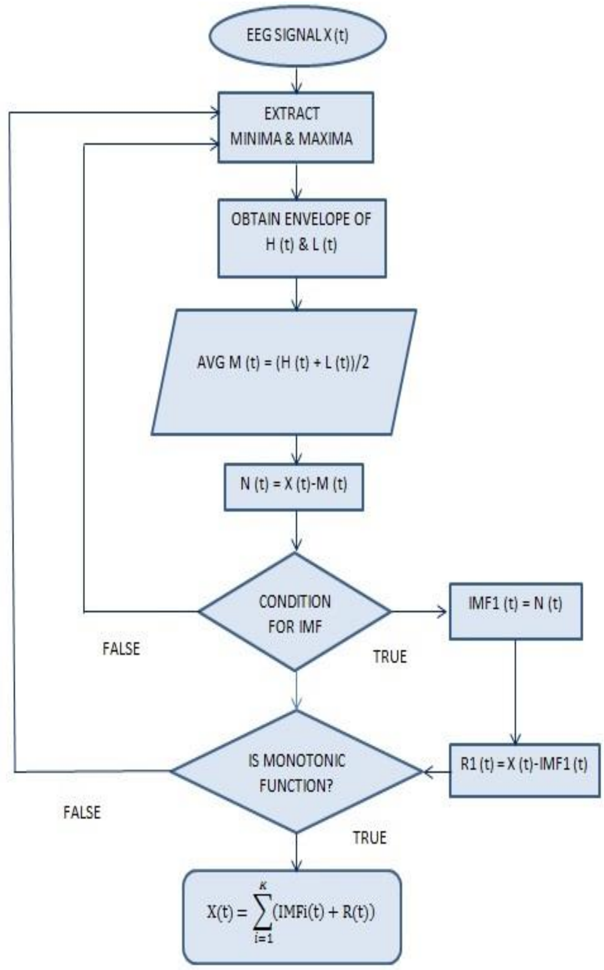

Fig.4. Flow chart of Empirical Mode Decomposition

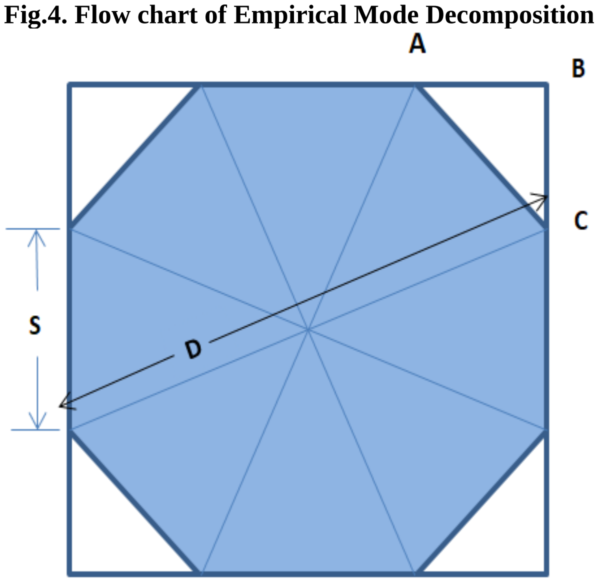

Fig.5. Octagon for AOO calculation

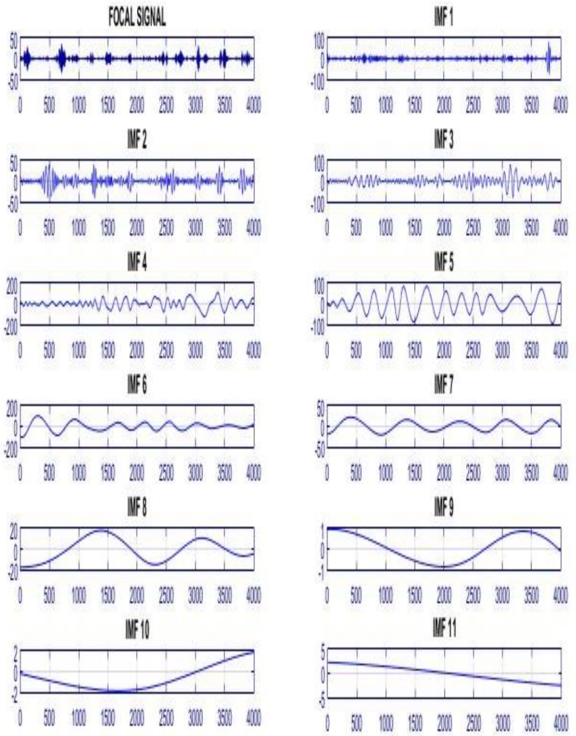

Fig.6.Intrinsic Mode functions of Focal EEG signal

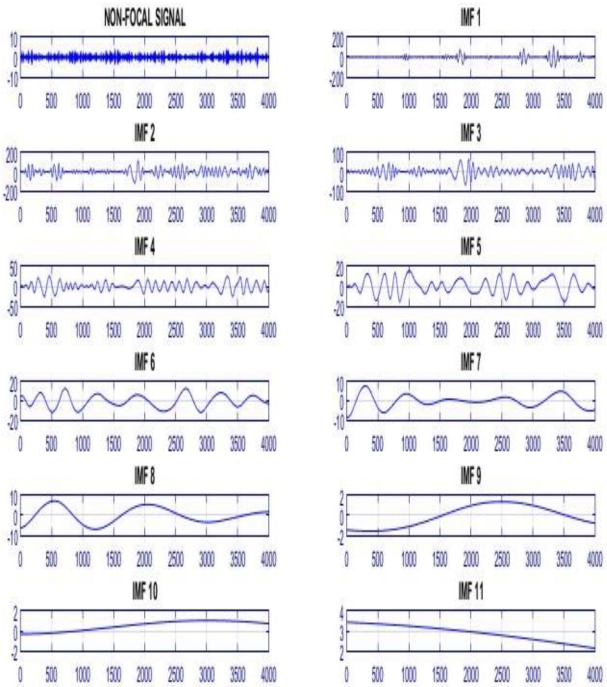

Fig.7.Intrinsic Mode functions of Non-Focal EEG signal

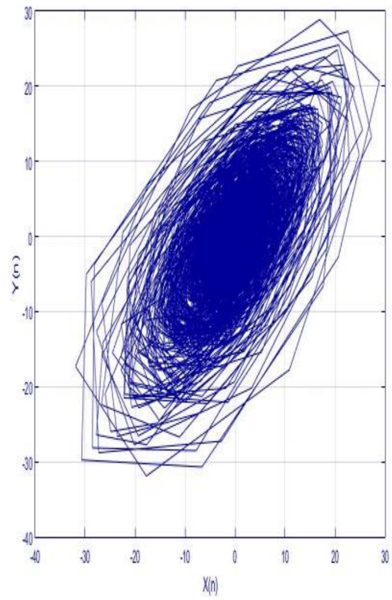

Fig.8.AOO-Focal EEG Signal

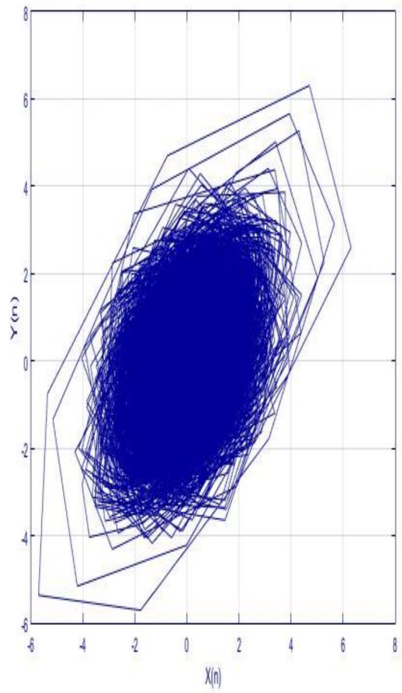

Fig.9.AOO-Non Focal EEG Signal

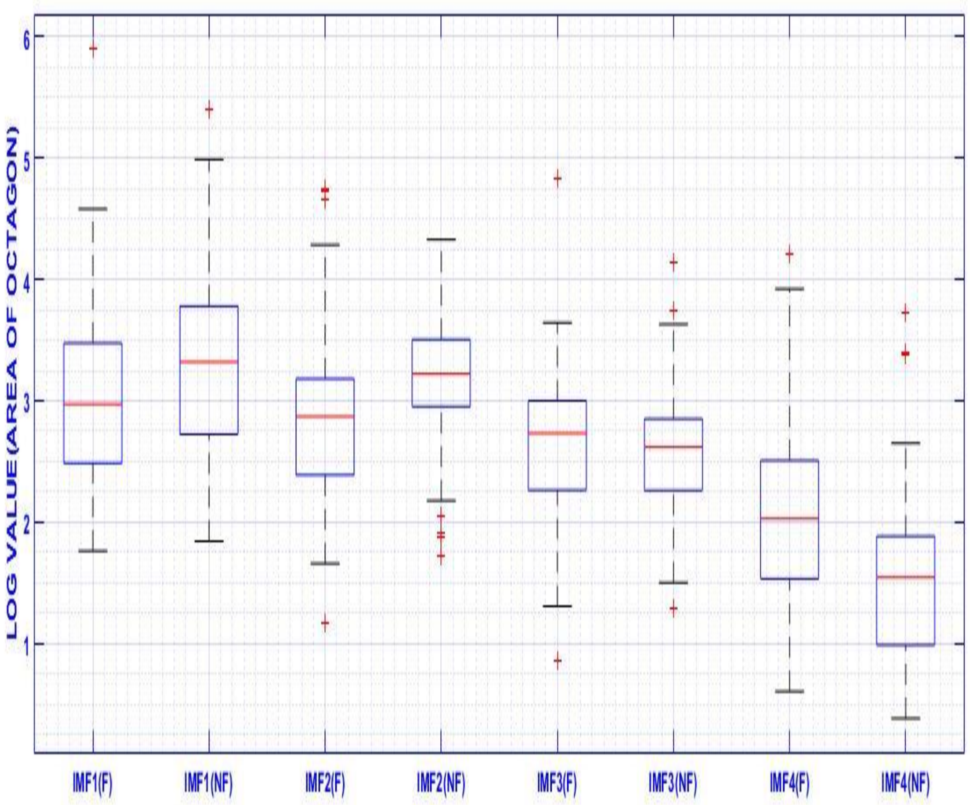

Fig.10. Comparison of AOO for IMFs (1-4) of Focal and Non Focal EEG signal (window size- 4000)

III. Results and Discussion

Using EMD, Electroencephalogram signal is putrefied into many IMF which is shown in fig (6) and (7) respectively. The decomposed IMF has been reconstructed using the equations (1-13) and its representation for the first four IMF of F and NF Electroencephalogram signals have been presented in Fig (8) and (9) respectively. The discriminating ability of the AOO has been measured using kruskal wallis test for 4000 window size. Fig (10) clearly shows that this proposed method is a promising technique which can produce good discrimination ability between F and NF EEG signals for 4000 window size ($p<0.01$).In this paper the classification of F and NF EEG signals have been implemented in Matlab.

The feature set obtained using AOO has been given as input to the SVM classifier. SVM classifier has been evaluated using linear, RBF and Polynomial kernels.10 cross validation has been employed to warrant the stability of the classifier. Table 1 shows the classifier performance with different kernels for IMF (1-4) for 4000 window size. From the Table 1, It is clearly understood that most of the maximum value is attained from IMF 2.It is also found that the overall classification accuracy attained is 97.9% through this proposed method.

It is also to point out here that in IMF 2, all the statistical parameters have attained the maximum value of 100% through Linear and RBF kernel. Table 2 demonstrates that the
classification accuracy of the suggested technique is greater than any other existing work.

IV. CONCLUSION

In day today life, it is a very challenging task for a doctor to inspect each and every patient regularly. So to reduce the burden of doctors, an automatic diagnosis of focal epilepsy is required. In this research work, a new technique called Area of octagon (AOO) is used to classify the Focal and Non focal EEG signals. Primarily, EEG signals are putrefied into many IMF. Later, the decomposed IMF has been reconstructed with AOO method. The Calculated AOO is used as Feature set in this work. The feature set is given as input to the SVM classifier which produces an average classification accuracy of 97.9% which is better than all other existing methods. This suggested technique could also be examined in the future for other illnesses such as sleep disorder, Alzheimer's disease, etc…

Table- I: classifier performance with different kernels for 4000 window size

Decomposed Signal	SVM	Sens(%)	spec(%)	Acc(%)	PPV(%)	NPV(%)	MCC	ERD
IMF 1	**Linear**	100	91.83673	96	92.72727	100	0.922809	7.843137
	Polynomial	100	93.87755	97	94.47684	100	0.941766	5.882353
	RBF	98.69281	95.2381	97	95.72391	98.69281	0.941733	5.882353
IMF 2	**Linear**	100	100	100	100	100	1	0
	Polynomial	100	100	100	100	100	1	0
	RBF	99.31973	99.34641	99.33333	99.31973	99.34641	0.986661	1.360544
IMF 3	**Linear**	94.23077	100	97	100	94.11765	0.941742	5.769231
	Polynomial	95.19231	100	97.5	100	95.05882	0.951255	4.807692
	RBF	98.07692	93.75	96	94.91453	97.97222	0.923514	7.692308
IMF 4	**Linear**	100	97.67442	99	98.27586	100	0.979747	1.754386
	Polynomial	100	97.67442	99	98.27586	100	0.979747	1.754386
	RBF	100	93.02326	97	95.12074	100	0.940619	5.263158
	Min. value	94.23077	91.83673	96	92.72727	94.11765	0.922809	0
	Max. value	100	100	100	100	100	1	7.843137
	Avg. value	**98.79271**	**96.86841**	**97.90278**	**97.4029**	**98.76566**	**0.959133**	**4.000796**

Table- II: Comparison of proposed work with existing works

METHODS	CLASSIFIER	ACCURACY (%)
Delay permutation entropy (18)	SVM classifier with RBF kernel	84
Discrete Wavelet Transform, Entropy measures (17)	LS-SVM classifier	84
EMD, Entropy measures (15)	LS-SVM classifier	87
EMD, ASE,AVIF (1)	LS-SVM classifier	85
EMD-DWT, log-energy entropy (19)	KNN city-block distance	89.4
Orthogonal wavelet filter banks, entropy measures (16)	LS-SVM classifier	94.25
FAWT method, log energy entropy (14)	LS-SVM with RBF kernel	94.41
Proposed method (EMD, Area of Octagon)	SVM with Linear, RBF, polynomial	**97.9**

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