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Detection of Epileptic Seizure in EEG Signals Using Phase Space Reconstruction and Euclidean Distance of First-Order Derivative

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***Abstract*— A most common disorder of human brain "Epilepsy", which is a neurological disorder and is identified as unexpected and transient electrical disturbance of the brain. EEG is a widely used method of signal recording for detection of epileptic seizures. A modified method for classification of ictal (Epileptic seizure) and seizure-free EEG signals is proposed in this paper. The technique is employed for an epoch across the channel for feature extraction. The First order derivative (FOD) shows the rate of variability of the signal while the phase space reconstruction (PSR) shows the evolution of a system and the Euclidean distance measures the dispersion of the points in the 3-D PSR, these shows a better feature for ictal and normal EEG signals classification. The interquartile range of Euclidean distance has been used for feature selection due to its insensitivity towards the outlier. KNN classifier is used for classification of ictal and normal EEG signals. The methodology resulted detection of epileptic seizure in 0.1 second with the degree of performance, sensitivity- 100%, Specificity-100%, and the Accuracy-100%.**

Keywords— Epileptic seizure, EEG, first-order derivative (FOD), phase space reconstruction, Euclidean distance, KNN, artificial neural network (ANN).

I. INTRODUCTION

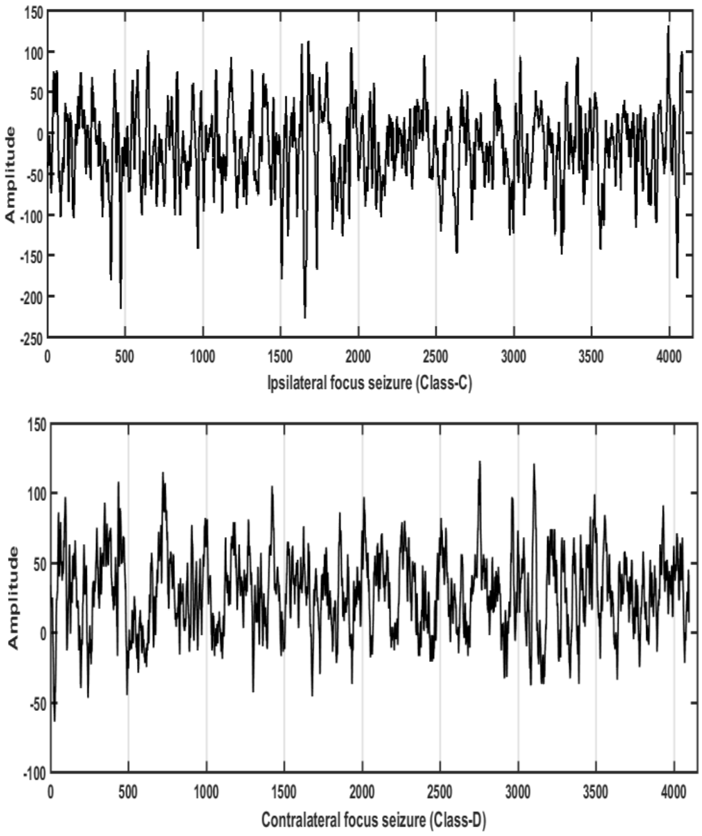
As reported by World Health Organization in 2007, Billions of People affected by neurological disorder[1]. Epilepsy is one of the most chronical neurological disorder amongst people of all ages regardless of their geographical region, age and sex. More than 1% of the world population is affected by epilepsy[2]. The average patient's cost per day for a patient with epilepsy has been estimated to be around $ 6656, with an average length of stay around 5-6 days and the patient used more resources and incurred higher costs than other patients[3]. A few years earlier, the occurrence of epileptic seizure was hard to predict and its behavioral action was little bit understood[4]. Therefore signal analysis of seizure during epilepsy becomes essential to detect the kind of epilepsy and its location in the brain for clinical implementation. Signal recording and its processing and development of algorithm become essential for seizure detection [5]. Electroencephalogram (EEG) is wide, and almost everywhere used for electrophysiological monitoring method for recording brain electrical behavior. The acquired non-invasive EEG signal contains information about physiological states of the brain. The digitally stored data used for detection of Epileptic seizure so that neurologist can treat more patient as compared to without the use of automated seizure detection because reviewing captured graph on a paper takes more time [6].

Several EEG signal processing technique has been developed to gather the essential feature from the impending seizure of epilepsy[7],[5]. These techniques of feature extraction mainly based on dynamics, time and frequency domain of signal[8].

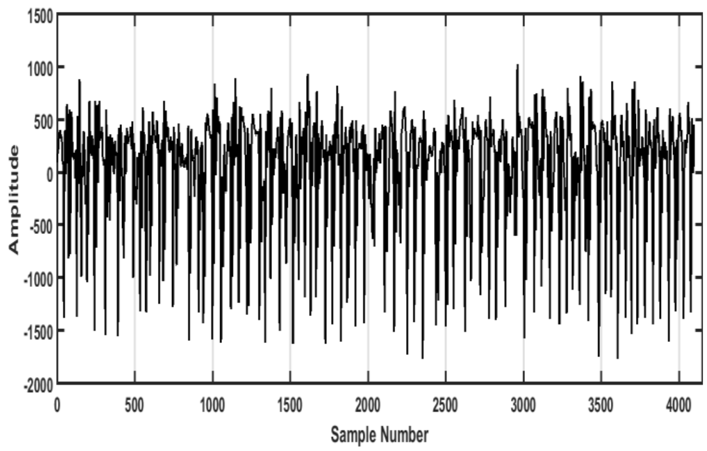
A method of analyzing a non-stationary and non-linear signal is developed in 1996, Using Hilbert transform for automatic detection of Seizure[9]. Using the technique of EMD, different work has been done by R.B Pachori et al[7], [10], [11], presented SODP and Hilbert transformation of Intrinsic mode decomposition(IMF) of EMD for feature extraction of EEG signal has been used, extracted feature found effective for diagnosis of epilepsy. Normalized Time-domain parameters with a coefficient of an autoregressive model are used by L. Tarassen and Y.U Khan in 1998, using Multilayer Perceptron (MLP) for detection of inter-ictal spikes in an epileptic patient.

Due to the nonstationary nature of EEG signal, several methods have been developed in time-frequency domain for epileptic seizure detection and classification based on wavelet transform [5],[12],[14],[15]. A method based on wavelet transform at Daubechies-4 is proposed by Y.U Khan and Gotman in 2003[15] on stereo electroencephalogram (SEEG), the extracted feature from energy and coefficient of variance from the coefficient of wavelet transform used for classification. The Euclidian distance and phase space reconstruction (PSR) based features are extracted on the coefficient of wavelet transform by Song-Hong Lee et al[4] and the coefficient of IMF of empirical mode decomposition by R.B Pachori et al[10] in 2014. A wavelet-based chaos-neural network methodology was presented by Samanwoy Ghosh et al[13] in which decomposed level of wavelet transform used for standard deviation, correlation dimension, and largest Lyapunov.

A two-stage classifier with mixed band wavelet-chaos methodology was proposed by Samanwoy et al[16] in 2008



(a)



(b)

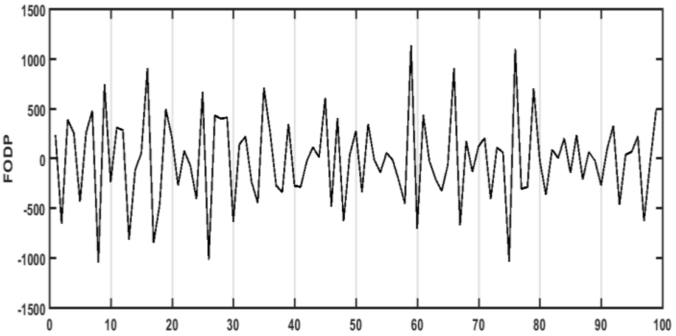
Fig. 1 Plot of Raw EEG Signals of (a) Normal and (b) Ictal

for classification of healthy, ictal, and inter-ictal EEGs. Principle component analysis (PCA) used at first stage of a classifier for improvement in classification accuracy of the cosine radial basis function neural network (RBFNN), shown an excellent accuracy of classification. A new technique for detection of the epileptogenic zone was proposed by Maeike Zijlmans et al[17] in 2010, considered high-frequency oscillation (HFO) for feature extraction. They found HFOs remain confined at the same, possibly epileptogenic area.

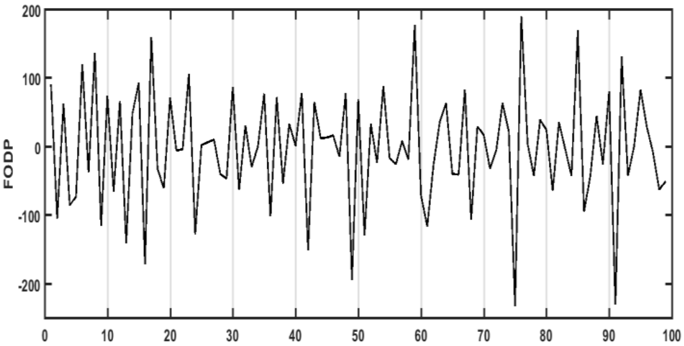
In this paper, our main attention to extract a better feature from the EEG signal than the previous work has been done for classification. A modified technique is proposed; feature extracted for a specific epoch across the channel, not along the channel. This technique gave better feature for detection of epileptic seizure. This extracted feature could be utilized in seizure onset detection because features depend on a very small period of time (i.e. 0.1 second). In this work, first-order derivative (FOD), which measures the rate of variability of the signal strength across each channel is plotted. Three-dimensional phase space reconstruction (PSR) is plotted with a fixed time lag and embedding dimension. From the PSR, Euclidean distance is computed and inter-quartile range (IQR) has been taken of the Euclidean distance. For classification, an artificial neural network classifier KNN (K-nearest neighbor) is used which is a simple and take less time for pattern recognition. Remaining part of the work is described as follows. Section 2 describes about the data sets used for classification. Section 3 describes the Methodology has been used for feature extraction. Section 4 provides the information and principle of working of the classifier. Section 5 includes the results, discussion, and conclusion.

II. ELECTROENCEPHALOGRAM (EEG) DATASETS

This work has been done on the datasets available freely online provided by the University of Bonn (Germany), described in C.E. Elger et al [18] for the classification of normal and epileptic seizure. The dataset was divided into five categorical sets: set A- Normal Eyes Open, set B- Normal Eyes Closed, set C-hippocampal formation of the opposite hemisphere of the brain, set D – epileptogenic zones, and the last set E - seizure Data. Each sets containing 100 files corresponding to a single-channel of EEG signals, of 23.61 seconds in duration. The sampling rate of the EEG data recording was 173.61 Hertz. These datasets signals were segmented from continuous multichannel EEG recording after elimination of artefacts like eyes movements or muscle activity by visual inspection. The datasets A and B is taken from five healthy volunteers using International 10-20 electrode placement scheme[19]. Datasets of C, D, and E originated from an archive of pre-surgical diagnosis. The dataset C were collected by scalp EEG from the hippocampal of opposite hemisphere and that of set D were recorded from the epileptogenic zone of the brain of volunteers. The set E contained only seizure activities while in EEG data set C and D contained activities during normal (seizure free) intervals. The entire EEG signals recorded by the Bonn University using the same 128-channel with amplifier system and the digitalized data where stored at 12-bit resolution. The filters used at settings 0.53-40 Hertz (12dB/octave) were Band pass filter for noise removal. These raw signal (set E, D, and C) have depicted in fig.1.which are used for classification. In this work, for evaluation of performance of the proposed methodology, set E is used as abnormal (Epileptic seizure) class and sets D and C are grouped together to form normal (Seizure-free) class of electroencephalogram signals.



(a)



(b)

Fig.2. First-Order derivative Plot of (a) Siezure signal (b) Normal Signal

III. METHODOLOGY

A. First-order-derivative (FOD)

The First order difference (FOD) gives the rate of variability of the signals, so the FOD of raw EEG signals can provide valuable diagnostic features to distinguish between the class of ictal and seizure-free EEG signals. This FOD is concretely based on the amplitude of the signal and time, therefore it will be easy to implement it in practice. The first order derivative for discrete signals can be express mathematically[10] as

$$a(n) = a(n + 1) - a(n)$$

Where n is the total no of the data point. After the FOD across the channel's sampled data, "n-1" FOD data points came.

The FOD plot is a graphical representation of the rate of change in the strength of EEG signals. Recently, many work have been proposed on the rate of change of variability in the field of costal engineering for water wave simulation[20] and in image processing in developing super-resolution method[21].The first order derivative plot (FODP) has been drawn for the seizure and the seizure-free signals in figure.2. FOD points will be used for distance calculation from one point to another, one by one which shows the separation between two consecutive points of PSR plot.

B. Phase space representation (PSR)

It has been found that some physiologic system behaves in a non-linear and chaotic fashion[22]. Such dynamical system has mainly two parts first one is the dynamic and another one is the state of a system[7]. Dynamics indicates the behavior which shows the evolution of state with time while state relates to the essential information of the signal at an instance of time. Phase space reconstruction (PSR) is quite appropriate and effective tool for non-linear dynamics of a signal which shows evolution of the dynamical behavior with the time. PSR is a method to represent the whole multi-dimension of the dynamics of a system by knowing the behavior of only one component of that system[23]. Therefore only one dimension is required to construct the dynamics of the system with many dimension. This affords interesting application for different problems in various field.

Another application of the PSR, is the classification of attractor, to know the behavior of a system it mandatory to distinguish between chaotic cases and periodic. The digitally recorded EEG signal can be written in time series as

$A = \{a_1, a_2, a_3 \dots\dots\dots\dots\dots\dots a_m\}$,

Where m is the number of data points.

PSR with a very small time delay is frequently used method for reconstructing phase space from its trajectory as explained by F.Taken [24] in 1981. The PSR is written as[4]

$$Z_i = (A_r, A_{r+\tau}, A_{r+2\tau}, A_{r+3\tau} \dots\dots\dots\dots\dots A_{r+(p-1)\tau})$$

Where r = 1, 2, 3…….. m - (p -1) τ, where p is the dimension of phase space and τ is the lagging time. Fig.3. shows the dynamics of the EEG signal plotted by phase space methodology. In this paper we have work on embedding (phase space) dimension at p = 3 i.e. 3-D PSR and the phase space has been constructed as considering lagging time τ =1 as taken by F.Takens. The time lag can be calculated as shown by R.C.Watt et al[22] in 1988 as

$$\tau = \frac{1}{Sampling\ rate} = \frac{1}{173.61} = 0.0057\ sec.$$

Where the sampling rate of EEG data used, is 173.61 Hz.

Therefore the phase lag can be calculated as

$$\varphi = 2\pi\tau$$

The phase lag shows that one-dimensional vector is lagging behind another by φ radian of phase angle. Now the 3-D PSR is a plot of three vectors, where two are delayed vectors A_{r+1}, A_{r+2} of a single vectorA_r, which shows the evolution of the system. In figure.3 which explicitly shows the difference in strength of the EEG signals at different state of the brain.

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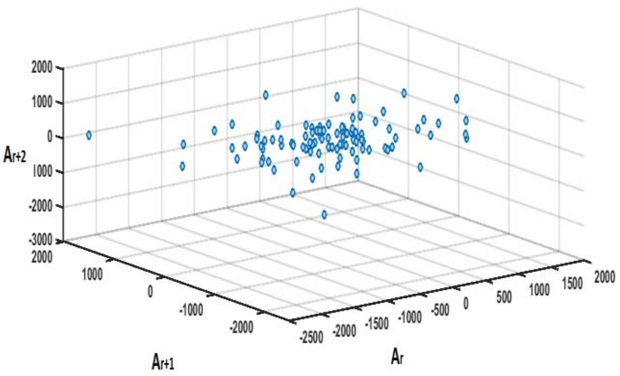
C. Euclidean distance and IQR of Euclidean distance.

The Euclidean distance; from the 3D phase space reconstruction of three delayed vectors A_r, A_{r+1}, A_{r+2} to visualizing the evolution of the system, can be computed as



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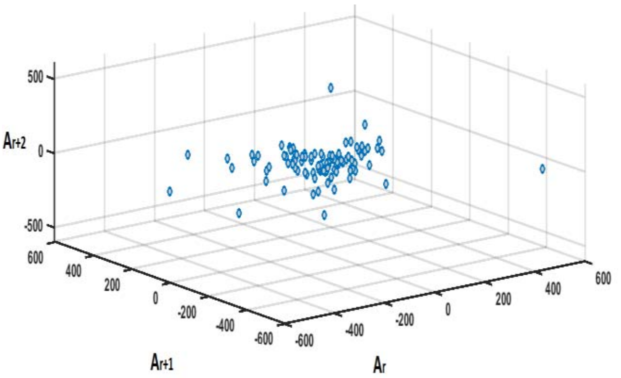

(b)

Fig 3. PSR plot of FOD points (a) Seizure (b) Normal EEG signal

(Let between the points (a_r, a_{r+1}, a_{r+2}) and (a_{r+1}, a_{r+2}, a_r)) as follows[25]:

$$E_r = \sqrt{(a_{r+1} - a_r)^2 + (a_{r+2} - a_{r+1})^2 + (a_r - a_{r+2})^2}$$

Based on the computed Euclidean distance, IQR is computed for the feature of classifier. An IQR is also called middle 50%, is a measure of dispersion. It is a difference between 25th and 75th percentiles, or lower and upper quartiles of the data[26],[5]. The IQR can be expressed mathematically as

$$IQR = Q_3 - Q_1.$$

Therefore it is the measure of variability of 50% of the observation and hence it is not sensitive to outliers of the observations. The outliers are data points in the observation which lies outside of the range of observations[7][26].
Based on the IQR values, 241 feature were extracted which is to be used for classification of normal and seizure class.

IV. K-NEAREST NEIGHBOR (KNN)

A widely used artificial neural network (ANN) has been used for classification. K-nearest neighbor is simplest of all algorithms uses for prediction of class of a test observations. It is based on supervised (teaching) machine learning technique in which the aim is to develop a model which is able to make the decision based on evidence, the algorithm of the classifier “learns” from the previous observations made. The KNN (k-nearest neighborhood) classifier makes the prediction by computing its distance by all training data points and then finding the must K nearest neighbor from that training data vector[27]. The most common distance; is Euclidean distance, which is expressed as

$$d(c,d) = \| c - d \| = \sqrt{(c-d)\cdot(c-d)} = \left(\sum_{i=1}^{m}(c_i - d_i)^2\right)^{1/2}$$

Where c is an instance and d is a label are points in A = $\mathbb{R}^m$ [28]. The classifier predicts the labels of data being tested by finding the more nearest data points in the trained data clusters. In this work K = 5 is used which gave 100% accuracy of classification.

A. Statistical parameters

To evaluate the classifier’s performance: specificity(SPF), accuracy(ACC), and sensitivity(SEN) are the commonly used parameters to evaluate the performance of the classification methods[2],[5],[29]. The evaluation of KNN classifier performance for abnormal (ictal) and normal EEG signals can be carried out by computing the specificity, accuracy, and sensitivity. There are other parameters to evaluate the performance of the classifier are namely: positive predicated value (PPV) and negative predicted value (NPV). Let True negative (TN) and True positive (TP) are the total value of correctly identified true negative and true positive samples and False negative (FN) and False positive (FP) are the total value of incorrectly identified false negative and false positive samples respectively from the confusion matrix[7] shown in table 2. The following terms can be defined as

1. *Positive predicted value (PPV):* It is a truly identified positive test results which are true positives; and the degree of performance of the diagnostic method[29]. It is a ratio of truly identified positive result to the total positive sample. It can be expressed as

$$PPV = \frac{TP}{TP + FP} \times 100\%$$

2. *Negative predicted value (NPV):* This can be defined by the ratio of truly negative value identified to the whole negatives (in this work, seizure-free). It is expressed as

$$NPV = \frac{TN}{TN + FN} \times 100\%$$

3. *Accuracy (ACC):* The accuracy shows the degree of performance of classification. It is a ration of the number of correctly identified samples to the entire predicted samples.

$$ACC = \frac{TN + TP}{TP + FP + TN + FN} \times 100\%$$

Table 1- Comparison of performance for classification of different existing classification methodology for epileptic Seizure and normal with the proposed methodology.

Methodology	Sets	Sensitivity (%)	Specificity (%)	Accuracy (%)
95% of confidence area measure of SODP of IMFs with ANN[10]	C, D and E	96.69	95.27	95.75
Euclidean distance of PSR with NEWFM [4]	A and E	96.33	100	98.17
Euclidean distance and 95% of confidence area of PSR of IMFs with LS-SVM[7]	C, D and E	100	96	98.67
(This work) Euclidean distance of 3D PSR of FOD	C, D and E	100	100	100

Table 2 – Confusion matrix of classification results for KNN

	TP	FP	TN	FN
Epileptic seizure EEG signal	241	0		
Normal EEG Signal			482	0

4. *Sensitivity (SEN):* Sensitivity is the degree of performance of a classifier. It is a degree of proportion of truly positives identified as positive samples [29],[7] and it is defined as

$$SEN = \frac{TP}{TP + FN} \times 100\%$$

5. *Specificity (SPF):* This is a degree of proportion of negatives which are correctly identified sample from the total negative sample and it can be expressed[7],[5],[2] mathematically as

$$SPF = \frac{TN}{TN + FP} \times 100\%$$

The positive and negative patterns represent detected ictal and detected seizure-free EEG signals, respectively.

V. RESULTS, DISCUSSION, AND CONCLUSION

A. Results

In this proposed work, the EEG signals of an epileptic seizure and normal were classified following Rajeev et al. (2015) [7], Lee et al. (2014) [4], and Pachori et al. (2014) [10].The first order derivative of the EEG signals has been utilized for 3-dimensional of phase space reconstruction (PSR). The Euclidean distance from the PSR has been computed and the interquartile range of the Euclidean distance is taken. The feature extraction from the EEG signals has been taken across the channels for an epoch of 0.1 second or 17 samples which shows a very good features (In the database of Bonn University, there are 100 segments of each class). After the FOD of EEG signal across the channel, 99 data points resulted, due to the FOD operator. These points were used for PSR plot from which Euclidean distance was computed from one PSR point to other and then the IQR has taken. In this context, 482 data set of extracted feature for normal and 241 for the seizure EEG signal. The classification performances have shown in table 1. The degree of performance of classifier "KNN" was compared with the SODP (second order derivative plot) with ANN, NEWFM (Neural network with weighted fuzzy membership function), and Least square-SVM have shown in table 1. The extracted feature depends on a very small period of time so this offers a good prospect for onset detection and prediction of the epileptic seizure. It is also important to mention that the proposed work has been done on the state of mind for a particular time and hence this gives a new aspect for future work. From the table 1, it can be observed that the proposed method shows the better result than the existing methodology. The accuracy of this method is better which shows the reliability of this technique.

B. Discussion and Conclusion

The proposed work has used the first order derivative, phase space reconstruction, and the inter-quartile range of Euclidean distance to get the fruitful traits of the EEG signals. As EEG signal is a nonlinear and nonstationary, in this context the derivative of the EEG signal shows the rate of variability of the EEG signals which helps in feature extraction. The 3-dimensional phase space reconstruction shows the evolution of a signal which has been providing an important information about any system under consideration.

The 3-D PSR helps in computation of Euclidean distance between distributed points of FOD of EEG signal for epileptic seizure and normal classification as it can be observed from the plotted figure.3. The Euclidean distance of ictal and normal EEG signals are entirely different: a Euclidean distance of epileptic seizure is quite larger than those of normal EEG signal. The inter-quartile range of Euclidean distance of epileptic seizure and normal EEG signals were computed which measure the degree of dispersion of the points in the 3-D PSR. The most important feature of the IQR is that it is more robust for outlier; reduces the effect of the same when it measures the dispersion of data points. The outlier is an observation point that one distant from the rest of the observation points; which can be characterized by sudden spikes available in the normal and ictal EEG signals. In pattern recognition, the K-nearest neighborhood classifier is being known for simplest among all machine learning algorithm. The KNN algorithm is sensitive to the local structure of the data. An important feature of the KNN algorithm is that it performs very well with multi-modal classes [30] and if compared with the other classifier like SVM, KNN works faster. The extracted feature of the Epileptic seizure and normal was divided into two part; 0.75 parts (542 data set of extracted feature) to train the classifier and rest of the 0.25 part (181 data set of extracted feature) for testing the classifier performance. A label 1 for Epileptic seizure and 0 for normal is used. In the normal class, class C and D are grouped and hence 482 feature extracted points for this grouped class. To check the robustness of the classifier, Ten-fold cross-validation has been used [7]. Using these extracted features for input of KNN classifier, with Ten-fold cross-validation, 100% accuracy, 100% sensitivity, and 100% specificity were achieved. These values of parameters shown a quite better performance when compared to those listed above and confirmed that the proposed outperforms existing. At last, it is come up with that the proposed method with the KNN classifier is very efficient and useful for detecting seizures which will help to the neurologist in diagnosing the epileptic seizure.

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