



# Performance evaluation of DWT based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using SVM classifier

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## ABSTRACT

The electroencephalogram (EEG) signal contains useful information on physiological states of the brain and has proven to be a potential biomarker to realize the complex dynamic behavior of the brain. Epilepsy is a brain disorder described by recurrent and unpredictable interruption of healthy brain function. Diagnosis of patients with epilepsy requires monitoring and visual inspection of long-term EEG by the neurologist, which is found to be a time-consuming procedure. Therefore, this study proposes an automated seizure detection model using a novel computationally efficient feature named sigmoid entropy derived from discrete wavelet transforms. The sigmoid entropy was estimated from the wavelet coefficients in each sub-band and classified using a non-linear support vector machine classifier with leave-one-subject-out cross-validation. The performance of the proposed method was tested with the Ramaiah Medical College and Hospital (RMCH) database, which consists of the 58 Hours of EEG from 115 subjects, the University of Bonn (UBonn), and CHB-MIT databases. Results showed that sigmoid entropy exhibits lower values for epileptic EEG in contrary to other existing entropy methods. We observe a seizure detection rate of 96.34%, a false detection rate of 0.5/h and a mean detection delay of 1.2 s for the RMCH database. The highest sensitivity of 100% and 94.21% were achieved for UBonn and CHB-MIT databases respectively. The performance comparison confirms that sigmoid entropy was found to be better and computationally efficient as compared to other entropy methods. It can be concluded that the proposed sigmoid entropy could be used as a potential biomarker for recognition and detection of epileptic seizures.

## 1. Introduction

Epilepsy is a neurological disorder that affects the brain and will have a profound influence on patients' daily lives. A sudden discharge of electrical activity in the brain causes temporary brain dysfunction, which is referred to as a seizure, and recurrent seizures lead to epilepsy [1,2]. The World Health Organization (WHO) estimated that epilepsy affects 50 million people worldwide [2]. The electroencephalogram (EEG) signals have proven to be a potential biomarker for detection and recognition of epilepsy [1]. A thorough inspection of the long-term EEG recordings is necessary to recognize the abnormal EEG patterns, which are found to be time-consuming, costly and leading to human errors.

Though several automated, computer-aided algorithms for seizure detection were proposed earlier, there is still scope for identifying better biomarkers for real-time seizure detection.

Neurological disorders cause changes in EEG patterns, which could be used as a marker for the diagnosis. It was shown that non-linear methods could provide potential markers for EEG analysis over conventional methods [1,3,4] however, several limitations exist which needs to be solved. To design an automated seizure detection system, it is essential to extract features that describe the morphology of the epileptic seizures from EEG signals in a better manner. Studies have reported that the best feature significantly improves the algorithm performance [5–7]. Thus, we propose a novel feature named sigmoid

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entropy derived from the sigmoid function that offers a significant non-linear behavior to capture robust markers for seizure detection.

For epileptic seizure detection, studies based on non-linear entropy have shown significant results in terms of sensitivity as compared to other known EEG derived features. It can be observed from the literature that variations of entropy methods have been applied for seizure detection [5–14]. Different entropy methods such as approximation entropy (ApEn), sample entropy, phase entropy 1 and phase entropy 2 have been used for the automatic detection of normal, pre-ictal, and the ictal conditions [5]. Among the seven different classifiers described in Ref. [5], fuzzy classifier showed the highest accuracy of 98.1%. Permutation entropy was used to identify the changes in EEG signals during absence seizures [8,11]. A method based on discrete wavelet transforms (DWT), and ApEn obtained 100% classification accuracy using an artificial neural network [12]. Srinivasan et al. showed a classification accuracy of 100% between normal and epileptic EEG using ApEn and artificial neural network classifier [9]. Optimized sample entropy with extreme learning machine method showed a high accuracy of 99.0% [10]. Fuzzy entropy and support vector machine (SVM) based approach for the detection of epileptic seizures showed acceptable results [13]. Acharya et al. [15] gave a systematic review of the application of various entropy methods to differentiate normal, interictal, and ictal EEG signals. A patient non-specific algorithm showed a specificity of 99.9%, sensitivity of 87.5% and a false positive rate 0.9/h [16].

In Ref. [17], weighted permutation entropy showed distinguishable band for seizure and normal EEG segments. An accuracy of 99.0% was achieved using SVM classifier between healthy subjects (with eyes open and closed) and epileptic patients [17]. Automated threshold-based detection of epileptic seizures was proposed using a novel feature called minimum variance modified fuzzy entropy [18]. In this study, relative energy was used as a membership function to estimate fuzzy entropy and an accuracy of 100% was obtained using the threshold method. In Refs. [17,18], lower entropy was observed for epileptic seizures EEG, which were in contrary to other entropy methods proposed in Refs. [9,12,19,20]. Wavelet packet transforms followed by log energy and norm entropy showed an accuracy of 99.7% using recurrent Elman neural network [20]. Further, Renyi, spectral, Shannon and wavelet entropy methods were explored for the classification of epileptic seizures [19,21–23]. The above-mentioned entropy-based studies demonstrated promising classification results for epileptic seizure detection.

On the other hand, a framework using DWT and SVM was proposed for the epileptic focus localization problem [24]. In this study, seven commonly used wavelet families (Coiflets, Daubechies, Discrete Meyer, Haar, Biorthogonal, Reverse biorthogonal, Symlets) were considered for the EEG signal decomposition. An accuracy of 88.0% was obtained using optimal frequency bands and wavelet coefficient features. Statistical features extracted from wavelet decomposed EEG were classified using the relevance vector machine (RVM) classifier [25]. Similarly, statistical features estimated from DWT showed an accuracy of 97.83% using combined neural network model [26]. Faust et al. [27] proposed a review on wavelet-based EEG processing for seizure detection. Further, signal energy [28], Eigenvalues [29], and 21 different features [30] were investigated for the classification of epileptic seizures and promising results were reported. Transfer learning semi-supervised learning fuzzy system based model was found to be computationally intensive for solving real-time seizure detection [31]. A deep convolution neural network-based approach was introduced recently for automated seizure detection using EEG signals [32,33]. The SVM classifier has been extensively used for epileptic seizure detection due to its efficient generalization ability and promising results [24,30,34,35].

A specific study on the prediction of epileptic seizures using long-short-term memory network was reported, wherein 185 seizures were predicted correctly [36]. Signal energy in the time-frequency domain

achieved a classification accuracy of 98.25% [37]. Multivariate empirical mode decomposition along with artificial neural network was used to classify ictal and non-ictal EEG signals [38]. In another study, non-linear dimension technique was used to reduce the frequency domain features and the seizure/non-seizure events were classified using KNN classifier [39].

A number of studies [12,20,22,24,26–28,34,40–46] have employed wavelet transforms for seizure detection and have reported promising results. Therefore, in this study, EEG signal was decomposed using DWT with five different wavelet functions.

The thorough literature survey suggests that the classification results could be further improved through an optimal selection of the feature extraction method and classifier. It is essential that the algorithm computation time should be very short for real-time seizure detection. Hence, in this study, in order to achieve better performance over existing methods, a novel feature referred to as sigmoid entropy derived from DWT coefficients was introduced. A SVM model was later employed to classify seizure and non seizure patterns.

The rest of the paper is organized as follows. In Section 2, a brief description of the sigmoid entropy and the database used for the study is described. The results of the study are presented in Section 3 and performance comparison is discussed in Section 4. Finally, Section 5 concludes the paper.

## 2. Methodology

### 2.1. Proposed method

Fig. 1 depicts the block diagram of the proposed seizure detection algorithm that uses a DWT based sigmoid entropy and SVM classifier. The EEG recordings were pre-processed using a notch filter and a bandpass filter to remove any noise. An independent component analysis was performed to remove any artifacts. The EEG was segmented into 1 s length to maintain the stationarity of the signal. Further, the EEG signal was decomposed using DWT consisting of five different

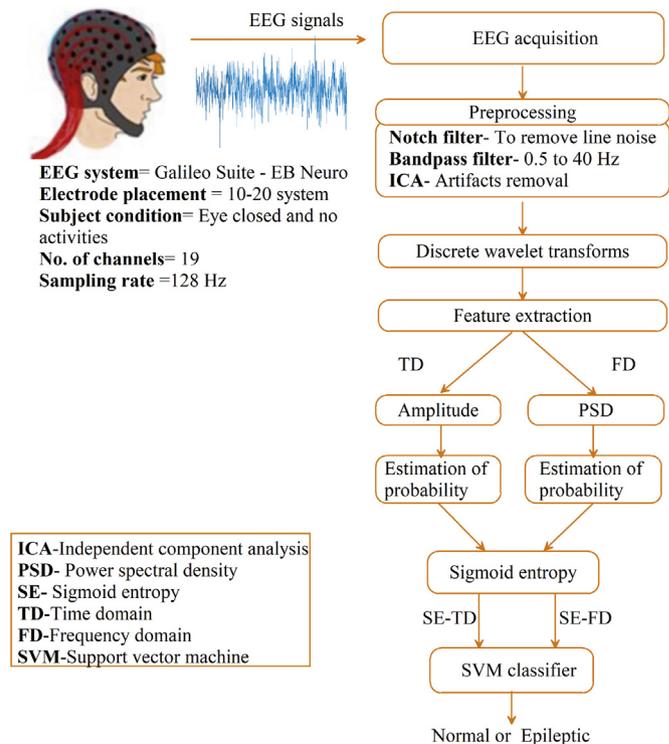


Fig. 1. Block diagram of the proposed seizure detection algorithm using DWT based sigmoid entropy and SVM classifier for the RMCH database.

mother wavelets. Subsequently, sigmoid entropy was estimated in both time and frequency domain using amplitude and power spectral density of the EEG signal. Finally, the extracted features were classified using SVM classifier with the segment and event-based approaches and the performance of the algorithm was evaluated using three databases.

## 2.2. Clinical data

In this study, three EEG databases were used to validate the proposed seizure detection algorithm. The first database was obtained from the Ramaiah Medical College and Hospitals (RMCH), Bengaluru, India. Ethical clearance was obtained from the RMCH ethics committee to study EEG recordings for research purpose. The unipolar scalp EEG was recorded using 19 electrodes placed according to the International 10–20 system of configuration at a sampling rate of 128 Hz using Galileo Suite-EB Neuro EEG system. The database comprises of 115 subjects, which include 67 male and 48 female, ranging between 2.5 and 75 years of age. Among the 115 subjects, 38 were suffered from epilepsy and 77 were healthy subjects. The scalp EEG was recorded from the following electrode positions: Fp1, Fp2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, and O2. Two experts with the same display setting were visually labeled the EEG recordings as normal and epileptic events. The seizure activities with a minimum duration of 6 s and a maximum of any period were considered for the study.

The second database used in our study was a publicly available database from the University of Bonn (UBonn)<sup>1</sup> [47]. The EEG recordings were obtained from Five different patients who have undergone presurgical evaluations. The EEG recordings in UBonn database were divided into five sets (A-E), each set consisting of 100 single channel EEG segments of 23.6 s duration recorded at a sampling rate of 173.61 Hz. Each subset A, B, C, D, and E represent the states of normal with eyes open, normal with eyes closed, pre-ictal, post-ictal and ictal respectively. For this study, classification problems, namely {A}-{E}, {ACD}-{E}, {ABCD}-{E}, and {AB}-{CD}-{E} were formed using five different subsets [12,29,46,48].

The third database was collected from CHB-MIT [49], an open-source EEG available in Physionet repository.<sup>2</sup> This database consists of 844 h of EEG recordings, which comprises of 182 seizures recorded from 23 patients. The recordings were obtained from 23 channels placed according to 10–20 International system bipolar montage electrode placement and recorded at a sampling rate of 256 Hz. One can refer to the [49,50] for more details on the EEG database and patient information.

## 2.3. Preprocessing

For the RMCH database, EEG was pre-processed using suitable signal processing techniques. A 50 Hz notch filter was used to attenuate the power line interference. Further, EEG time series were filtered using a bandpass filter with the lower and a higher cut-off frequency of 0.5 Hz and 40 Hz respectively. An independent component analysis was applied to the EEG signal to remove artifacts such as eye blinks, chewing, muscular artifacts, etc [51]. In our study, filtering techniques were not employed on UBonn and CHB-MIT databases as the available data was already pre-processed.

## 2.4. Discrete wavelet transform

DWT is a spectral analysis technique that provides a multi-resolution and time-frequency analysis of non-stationary EEG signal [52,53]. DWT has been used extensively for seizure detection and promising

results were achieved [12,20,22,24,26–28,34,40–45]. DWT comprises pairs of low pass filter (approximation coefficients) and high pass filter (detail coefficients). At each level of DWT, the signal is simultaneously passed through a set of low pass filter and high pass filter followed by downsampler (refer Fig. 2). The selection of the decomposition level depends on the dominant frequency components of the signals [40,52–54].

The wavelet  $\psi^i$  can be obtained from the following relationship [52]:

$$\psi^{2i} = \frac{1}{\sqrt{2}} \sum_{k=-\infty}^{\infty} h(k) \psi^i \left( \frac{t}{2} - k \right) \quad (1)$$

$$\psi^{2i+1} = \frac{1}{\sqrt{2}} \sum_{k=-\infty}^{\infty} g(k) \psi^i \left( \frac{t}{2} - k \right) \quad (2)$$

Here,  $i$  is the modulation parameter,  $k$  is the translation parameter,  $\psi^i$  is the mother wavelet,  $h(k)$  is the low pass filter and  $g(k)$  is the high pass filter associated with the scaling function and the mother wavelet function [52,53].

The wavelet coefficient  $c_{j,k}^i$  ( $j$  is the dilation parameter) corresponding to a signal  $s(t)$  can be obtained as [52],

$$c_{j,k}^i = \int_{-\infty}^{\infty} s(t) \psi_{j,k}^i(t) dt \quad (3)$$

Based on the previous studies reported on seizure detection [12,22,27,28,34,40–42,44,45], we have selected five most commonly used wavelets, namely Haar, Coiflets (Coif4), Discrete Meyer (Dmey), Biorthogonal (Bior3.1) and Reverse Biorthogonal (Rbio3.1). These studies have proved that above-mentioned mother wavelets were well suited for EEG signal analysis.

Fig. 2 shows the structure of wavelet decomposition of an EEG signal up to the fifth level. The decomposition levels until the fourth, fifth, and fifth levels were considered for RMCH, UBonn, and CHB-MIT databases respectively. The levels of decomposition selected were different as each database has a different sampling frequency. The EEG sub-bands were selected, ensuring different frequency ranges as it would reveal information associated with that EEG band. The frequency ranges of approximation and detail coefficients in each level were given in Table 1.

## 2.5. Sigmoid entropy

The latest improvements in non-linear dynamics theory or chaos theory provided a new concept to analyze EEG time series due to its high versatility. It is a well-known fact that EEG contains nonlinear elements, which is a reflection of the neuronal activity in the brain. The sigmoid function is one of the most widely used activation functions in neural networks. The advantage of this activation function is, unlike the linear function is that its output is always in the range of 0 and 1. Therefore, we propose sigmoid entropy to analyze EEG time series data by exploiting the nonlinear characteristics of the sigmoid function.

### 2.5.1. Definition

A sigmoid function is a particular case of the logistic function having “S” shaped curve (refer Fig. 3) defined by (4)

$$\sigma(t) = \frac{1}{1 + e^{-t}} \quad (4)$$

### 2.5.2. Sigmoid entropy

The sigmoid function is used as a feature for epileptic seizure detection as it is widely used in the artificial neural networks as a non-linear complex function. Assuming that  $n$  is the number of possible states that the amplitude of wavelet decomposed EEG are quantized into and  $p_i$  the probability of each state is  $p = \{p_i\}$ ,  $0 \leq p_i \leq 1$  and

<sup>1</sup> [http://epileptologie-bonn.de/cms/front\\_content.php?idcat=193&lang=3&changelang=3](http://epileptologie-bonn.de/cms/front_content.php?idcat=193&lang=3&changelang=3).

<sup>2</sup> <http://www.physionet.org/pn6/chbmit>.

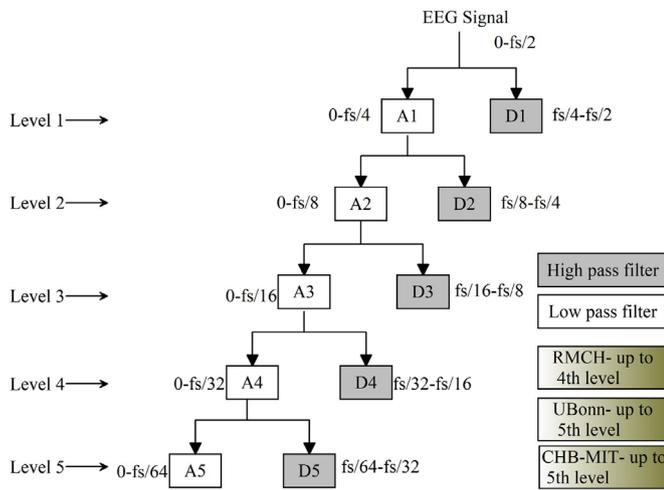


Fig. 2. Structure of wavelet decomposition of EEG up to the fifth level.

**Table 1**  
Information about EEG sub-bands and frequency range of wavelet decomposition of EEG signal for RMCH ( $f_s = 128$  Hz), UBonn ( $f_s = 173.71$  Hz) and CHB-MIT ( $f_s = 256$  Hz).

Decomposition level	Sub-bands	Frequency range of sub-bands	Frequency range (Hz)		
			RMCH	UBonn	CHB-MIT
1	A1	0-fs/4	0–32	0–43.4	0–64
	D1	fs/4-fs/2	32–64	43.4–86.8	64–128
2	A2	0-fs/8	0–16	0–21.7	0–32
	D2	fs/8-fs/4	16–32	21.7–43.4	32–64
3	A3	0-fs/16	0–8	0–10.85	0–16
	D3	fs/16-fs/8	8–16	10.85–21.7	16–32
4	A4	0-fs/32	0–4	0–5.43	0–8
	D4	fs/32-fs/16	4–8	5.42–10.85	8–16
5	A5	0-fs/64	–	0–2.70	0–4
	D5	fs/64-fs/32	–	2.70–5.43	4–8

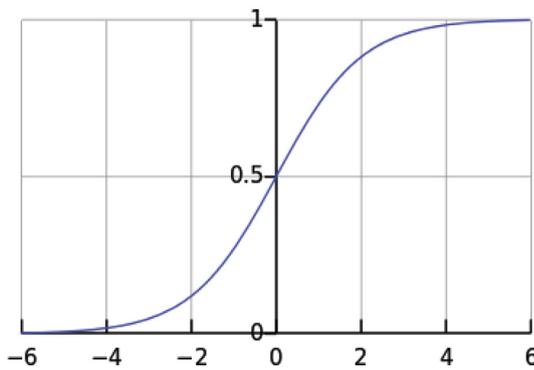


Fig. 3. Sigmoid function with the output between 0 and 1.

$\sum_{i=1}^n p_i = 1$ . In this study probability of the occurrence of EEG signal is calculated using the histogram method by specifying bin ranges. The bin range of 0.05  $\mu v$  was considered for all the three databases.

Now by replacing  $t$  with  $p$  in (4), where  $p = \{p_1, p_2, p_3, \dots, p_n\}$ , (4) becomes

$$\sigma(p) = \frac{1}{1 + e^{-p}} \quad (5)$$

Expanding (5) becomes

$$\sigma(p) = \frac{1}{1 + e^{-p_1} + e^{-p_2} + e^{-p_3} + \dots + e^{-p_n}} \quad (6)$$

The amount of information captured by (6) is referred to as sigmoid

entropy ( $H_s$ ) for time domain and (6) can be written as

$$H_s = \frac{1}{1 + \sum_{i=1}^n e^{-p_i}} \quad (7)$$

Similarly, sigmoid entropy for the frequency domain is calculated using

$$H_s = \frac{1}{1 + \sum_{i=1}^n e^{-p_{f_i}}} \quad (8)$$

where  $p_f$  is probability values derived from power spectral density (PSD) of the wavelet decomposed EEG signal that was calculated using the periodogram method.

The dynamic range of the sigmoid entropy lies between 0 and 1. According to the characteristics of the sigmoid function, maximum entropy of ‘1’ infers less variation of the signal and more variation or fluctuation of the signal indicated to low entropy.

### 2.5.3. Property of sigmoid entropy

The property of sigmoid function is defined as [55], If  $\sigma(t) = \frac{1}{1 + e^{-t}}$ , then differential equation is  $\sigma'(t) = \sigma(t)(1 - \sigma(t))$ . Similarly, the property of sigmoid entropy can be written as, if  $H(p) = \frac{1}{1 + \sum_{i=1}^n e^{-p_i}}$ , then.  $H'(p) = H(p)(1 - H(p))$

### 2.5.4. Additivity property

Shannon entropy [56] and Tsallis entropy [57] are well known extensive and non-extensive entropy measures respectively. Given two independent systems  $A$  and  $B$ , where  $H_A$  and  $H_B$  are their entropy values, respectively, for which the joint probability density must satisfy the following properties.

1. **Shannon entropy:**  $H(A \cup B) = H(A) + H(B)$  that meets the additive property for  $H = -\sum_{i=1}^n p_i \log_2(p_i)$  [56].

2. **Tsallis entropy:** Tsallis brings out the non-extensive entropy equation as follows [57].

$$S_q = \frac{1 - \sum_{i=1}^n (p_i)^q}{q - 1} \quad (9)$$

where,  $n$  is the number of possible states of the system, and  $q$  is the entropy index, and it defines the degree of non-extensive. The pseudo additivity property of the Tsallis entropy is given as [57].

$$H(A \cup B) = H(A) + H(B) + (q - 1)H(A)H(B) \quad (10)$$

3. **Sigmoid entropy:** As similar to the Shannon and Tsallis entropy, additivity property for sigmoid entropy can be written as:

$$H_s(A \cup B) = H_s(A) + H_s(B) - \delta(H_s(A)H_s(B)) \quad (11)$$

where  $\delta = (n - 1) + (1 - \text{erf}(\text{erf}(\sum_{i=1}^n p_i) = 1))$ . We consider the  $\text{erf}$  function because sigmoid function resembles Gaussian error function shape [58]. The  $\text{erf}$  function is calculated for  $\text{erf}(1)$  since  $\sum_{i=1}^n p_i = 1$ .

Thus,  $\delta$  can be rewritten as  $\delta = (n - 0.7750)$ .

Hence, (11) can be rewritten as follows:

$$H_s(A \cup B) = H_s(A) + H_s(B) - (n - 0.7750)(H_s(A)H_s(B)) \quad (12)$$

## 2.6. Classification

The classification of epileptic seizures was performed using the SVM classifier as the good performance was reported in previous studies [12,24,25,34,48,59,60]. SVM uses kernel method to transform the feature set that draws an optimal boundary between possible outputs [61]. The preliminary study reveals better performance using radial basis function kernel and the same was implemented for further analysis.

In order to find the best wavelet and a decomposition level for seizure detection on the RMCH database, a segment-based and event-based classification approach was employed as reported in Ref. [17].

The optimal decomposition level and wavelet were identified from a segment-based approach employed for event-based classification approach. The SVM classifier was implemented with leave-one-subject-out cross-validation method for the RMCH database.

To evaluate the segment-based approach, we have used performance measures, namely sensitivity, specificity, accuracy, and F measure [5,12,20]. F-measure is the harmonic mean of precision and recall. The recall is the same as sensitivity and precision is the positive predictive value (PPV).

$$Sensitivity = \frac{TP}{TP + FN} \tag{13}$$

$$Specificity = \frac{TN}{TN + FP} \tag{14}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{15}$$

$$Fmeasure = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{16}$$

$$PPV = \frac{TP}{TP + FP} \tag{17}$$

$$NPV = \frac{TN}{TN + FN} \tag{18}$$

where, *TP* is true positive, *FN* false negative, *TN* is true negative and *FP* is false positive.

Further, the performance of the event-based seizure detection on the RMCH database was evaluated using seizure detection rate (SDR), false detection rate (FDR) and mean detection delay (MDD) [50].

- *SDR*: Number of correctly detected epileptic seizure events
- *FDR*: Percentage of false seizure detections per hour
- *MDD*: Mean time difference between seizure occurrence and algorithm detection

Similarly, UBonn database was evaluated using a segment-based approach with 10-fold cross-validation and the performance was assessed in terms of sensitivity, specificity, accuracy and F measure. Further, PPV and negative predictive value (NPV) were used to compare the results with existing methods (See Table 6) obtained using UBonn database.

Cohen's Kappa coefficient is a statistical method that measures between two raters [62]. In our study, two raters were an epileptic seizure and normal EEG. Kappa determines if there is an agreement between two raters by chance with a percentage. Table 2 shows cell probabilities for two raters. The predictions A and B represent the epileptic seizure and normal EEG respectively. In other words, these predictions can be obtained from the confusion matrix.

To compute Kappa, first, we need to calculate the observed level of agreement ( $P_o$ ) and expected agreement ( $P_e$ ), which is given by Ref. [62].

$$P_o = \frac{P_{AA} + P_{BB}}{P_T} \tag{19}$$

$$P_e = \left( \frac{P_{AA} + P_{AB}}{P_T} * \frac{P_{AA} + P_{BA}}{P_T} \right) + \left( \frac{P_{AB} + P_{BB}}{P_T} * \frac{P_{BA} + P_{BB}}{P_T} \right) \tag{20}$$

**Table 2**  
Calculation of Kappa values.

Rater #2		
Rater #1	Prediction of A Value	Prediction of B Value
	Prediction of A Value	$P_{AA}$
	Prediction of B Value	$P_{BA}$
		$P_{AB}$
		$P_{BB}$

where,

$$P_T = P_{AA} + P_{AB} + P_{BA} + P_{BB} \tag{21}$$

Finally, the Kappa coefficient is calculated as [62].

$$K = \frac{P_o - P_e}{1 - P_e} \tag{22}$$

The Kappa is always less than or equal to 1. The Kappa coefficient with a value of 1 implies perfect agreement and any value less than 1 can be interpreted as follows: Poor agreement (<0.2), Fair agreement (0.2–0.4), Moderate agreement (0.4–0.6), Good agreement (0.6–0.8), and Very good agreement (0.8–1).

### 2.7. Alarm for seizure detection

Tawfik et al. [17] have proposed channel fusion based seizure detection by combining the results obtained from different channels to determine the seizure onset. Similarly, Zandi et al. [46] have proposed seizure alarm method, when at least three different channel alarms occur within a duration of 5 s. Bogaarts et al. [6] have applied both epochs based and event-based seizure classification. Their mechanism helped to reduce the false alarm and improve the sensitivity.

In our study, to improve the performance of the algorithm, post-processing of the SVM classifier in the event-based approach was employed as reported in Refs. [6,17,46]. Fig. 4 depicts the procedure of alarm for seizure detection. The channels were marked as seizure if at least three channels classifier output was 1; otherwise, those channels were marked as non-seizure. The reason behind choosing three channels for the decision making was that a minimum of three channels was associated with seizures in case of focal seizures.

## 3. Results

### 3.1. Spectrogram analysis

Fig. 5 shows the EEG (channel T5) from the RMCH database and its spectrogram analysis before and after pre-processing. Fig. 5a and c shows raw EEG and filtered EEG signal respectively. The line noise at 50 Hz can be observed in Fig. 5b and spectrogram of filtered EEG are shown in Fig. 5d. Spectrogram analysis revealed that PSD during epileptic activity was found to be higher resulting in better discrimination as compared to the normal activity. Therefore, good discrimination in terms of amplitude and PSD for epileptic activity was achieved. These influenced to derive the DWT based sigmoid entropy both in time and frequency domains.

### 3.2. Analysis of sigmoid entropy using synthetic signal

We explore the sigmoid entropy to observe the changes in EEG signal under different conditions. A synthetic signal was created which comprises of three parts of 5 s duration each with different probability density functions [63]: (A) Gaussian distribution with zero mean and standard deviation of 1, (B) normal EEG signal from channel T5, (C) epileptic EEG from channel T5. Fig. 6 shows the analysis of sigmoid entropy for the synthetic signal. The following were the facts derived from the synthetic signal analysis:

- 1 Entropy was less for Gaussian distribution and further less for epileptic EEG.
- 2 Entropy was maximum for normal EEG.
- 3 The transition from one distribution to another was clearly seen.

### 3.3. Segment-based approach classification results

The segmentation length of 1 s was applied for feature extraction and seizure detection. The EEG signal was decomposed up to the fourth

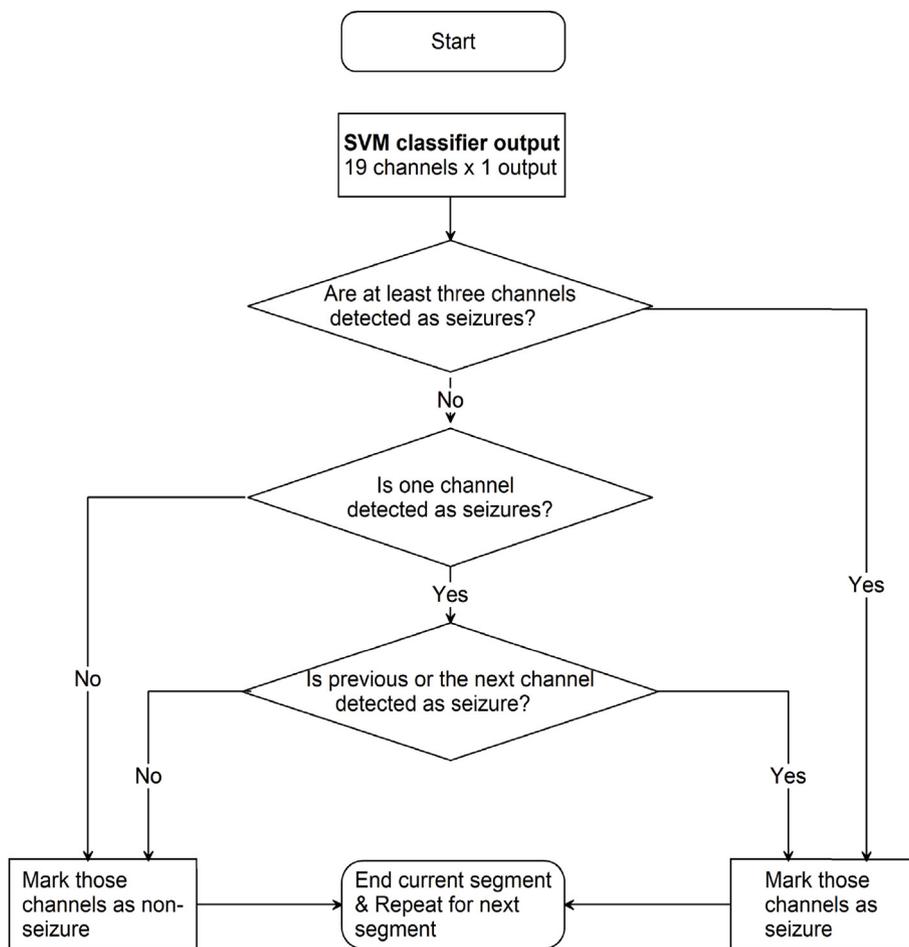


Fig. 4. The flow chart of alarm for seizure detection. During the preliminary visual marking and training phase of SVM, it was seen that the minimum duration of seizure activities was found 6 s. Therefore, when the consecutive segments are marked as seizures for a minimum of 6 s, then it is considered as one seizure event. This mechanism helped us to reduce the false detections that arise due to artifacts and non-epileptic activities.

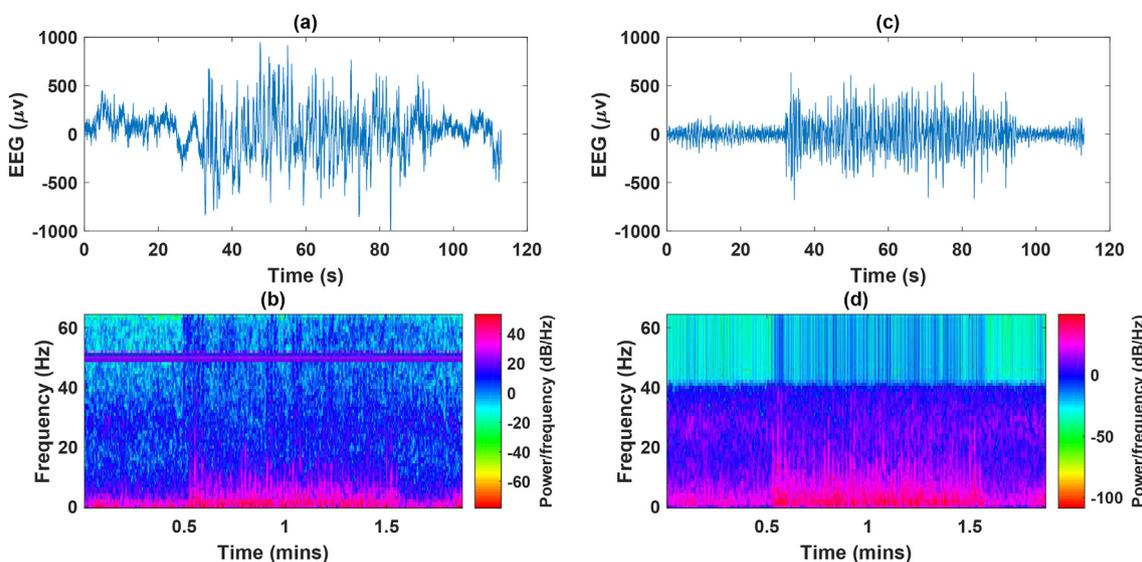


Fig. 5. An example of EEG (channel T5) from the RMCH database and its analysis. (a) Raw EEG with 50 Hz line noise. (b) The spectrogram showing the presence of line noise at 50 Hz and an increase in power value during seizure activity. (c) EEG after applying a notch filter and bandpass filter (refer 2.2 for filter specifications). (d) The spectrogram showing line noise is removed at 50 Hz and bandpass filtered between 0.5 and 40 Hz. The spectrogram was plotted with the following specifications: Window = Hamming, Window length = 128, Number of overlap samples = 120, Number of DFT points = 128, and Sampling rate = 128 Hz.

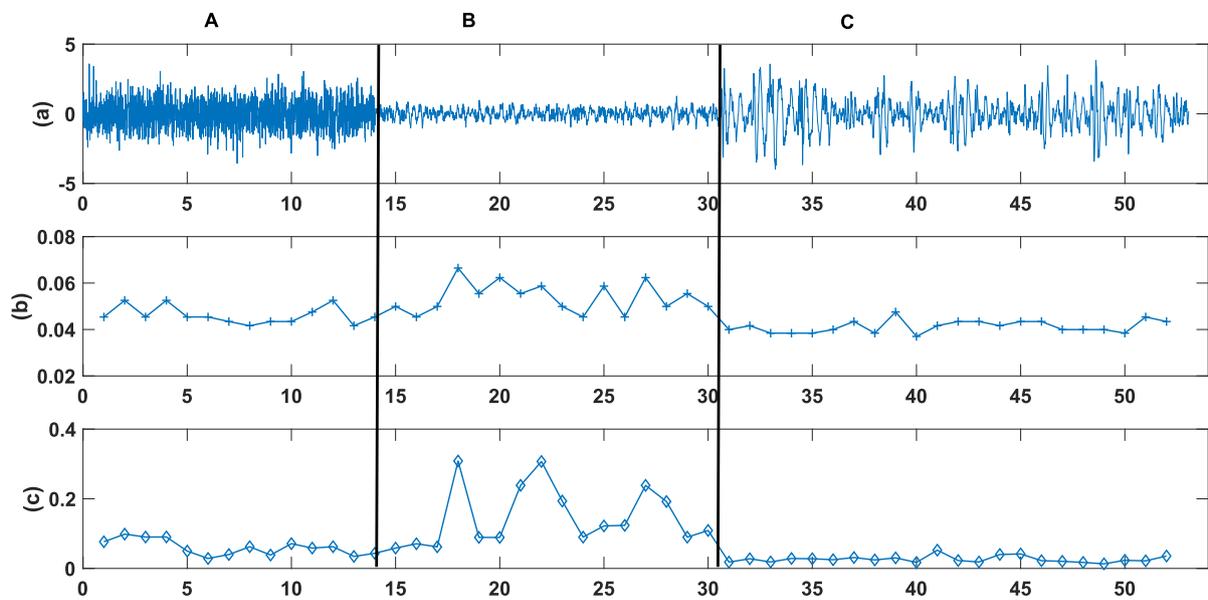


Fig. 6. (a) A synthetic signal. (b) Sigmoid entropy in the time domain. (c) Sigmoid entropy in the frequency domain.

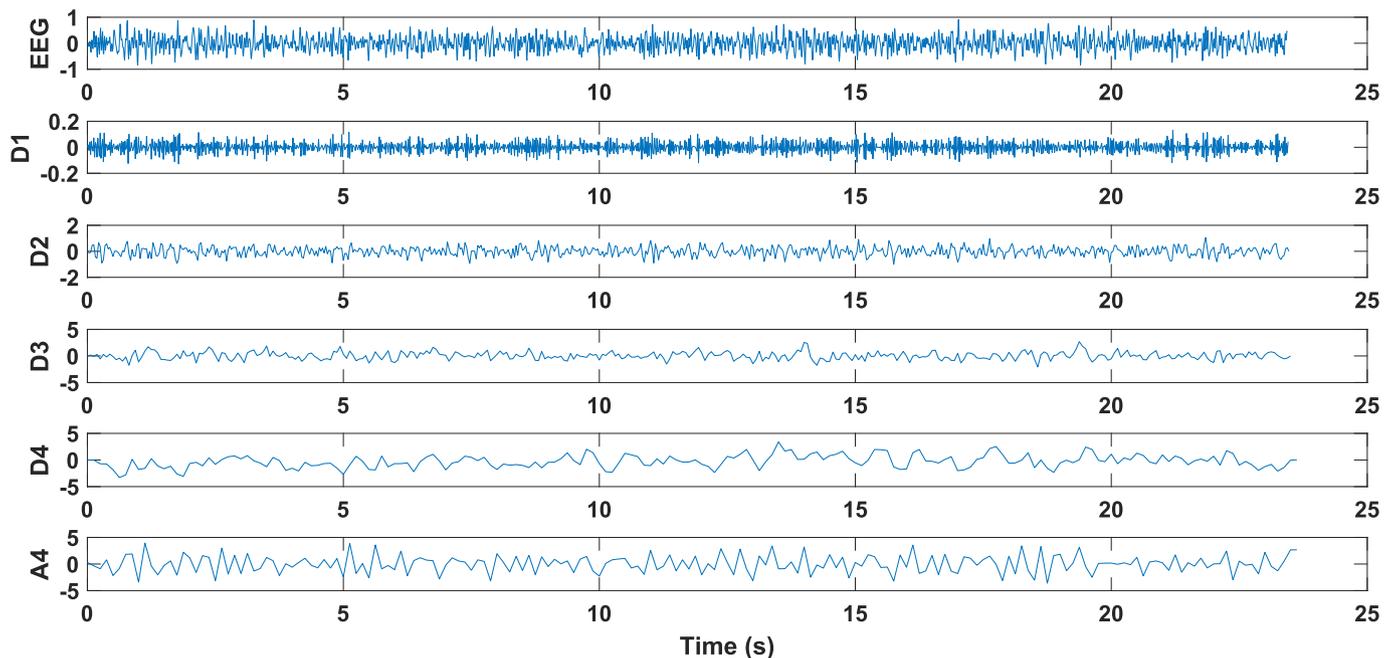


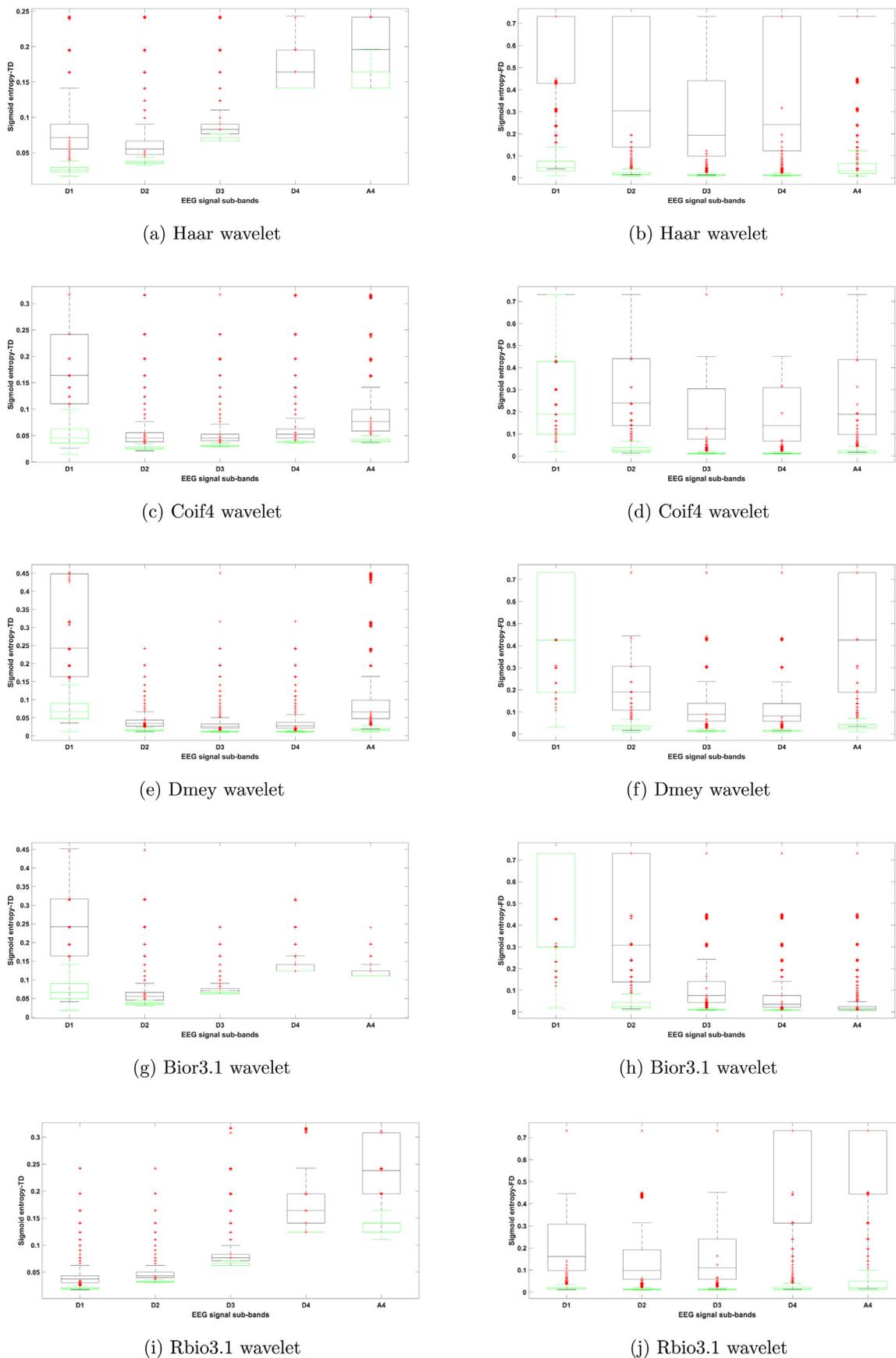
Fig. 7. Wavelet decomposition of a sample EEG up to the fourth level using Bior3.1 wavelet. The EEG displayed in the following order from top to bottom: EEG, D1, D2, D3, D4, and A4 sub-bands.

level using Haar, Coif4, Dmey, Bior3.1, and Rbio3.1 mother wavelets for RMCH database. An example of decomposed EEG in D1, D2, D3, D4, and A4 sub-bands are shown in Fig. 7. Fig. 8 shows the Boxplot of sigmoid entropy in time and frequency domains derived from DWT. In Fig. 8 the black and green boxes indicate the distribution of the sigmoid entropy values of normal and epileptic EEG respectively. Boxplot analysis showed good discrimination in terms of median, quartile, upper quartile and interquartile range for all the wavelets.

In order to find the best decomposition level and wavelet, we employed the segment-based classification approach [6,17,46]. The optimal decomposition level and wavelet obtained in segment-based approaches were employed for event-based classification approach. Fig. 9 shows the classification results achieved using the segment-based approach. The sensitivity of 100% was seen in the D1 sub-band using Coif 4, Dmey, Bior3.1, and Rbio3.1 wavelets. However, sensitivity obtained

in the D1 sub-band using Haar wavelet was very close to other wavelets. Further, again sensitivity of 100% was seen in the D2 sub-band using Haar, Coif 4, Dmey, and Bior3.1 wavelets. The highest sensitivity of 99.72% was achieved in the D3 sub-band using Dmey, Bio3.1 and Rbio3.1 wavelets. Similarly, Dmey and Bio3.1 wavelets in D4 sub-bands showed 100% sensitivity. The maximum sensitivity of 99.97% seen in the A4 sub-band using Dmey wavelet. The results showed that all the wavelets were capable of producing good sensitivity (i.e., seizure detection) using sigmoid entropy. The specificity of 100% was obtained in D2 (Rbio3.1), D3 (Haar, Coif4, and Bior3.1, and Rbio3.1), and D4 (Haar, Coif4, and Bio3.1) sub-bands. The least sensitivity and specificity obtained was 92.28% in (Rbio3.1) and 86.34% in D1 (Dmey) respectively. The highest sensitivity, specificity, and accuracy of 100% was achieved using Bior3.1 wavelet in D4 sub-band.

In Fig. 9, the last bar shows the F-measure for the same. The least F-



**Fig. 8.** The boxplot of sigmoid entropy in the time domain (left column) and frequency domain (right column). The box displayed in Black boxes and Green boxes represents normal and epileptic EEG respectively. The data points displayed using + are whiskers. Wilcoxon rank sum test showed  $p < 0.05$  between normal and epileptic EEG sigmoid entropy for all the wavelets and decomposition level.

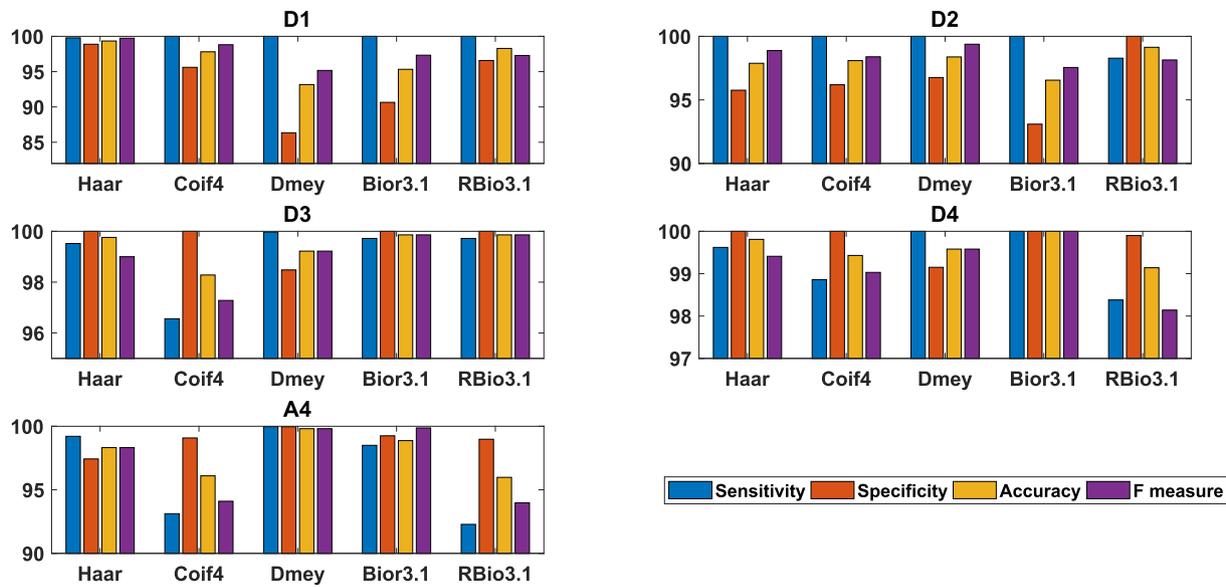


Fig. 9. Classification results using a segment-based approach on the RMCH database. The results are grouped wavelet wise for each sub-band.

measure were 93.05% (Dmey), 96.45% (Bior3.1), 98.10% (Coif4), 99.10% (Rbio3.1) and 95.80% (Rbio3.1) in EEG sub-bands D1, D2, D3, D4, and A4 respectively. Among all the sub-bands and wavelets, highest sensitivity, specificity, accuracy, and F-measure of 100% was achieved using Bior3.1 wavelet in D4 sub-band. Therefore, the segment-based approach showed that Bior3.1 wavelet in D4 sub-band is the optimal choice for the event-based approach.

### 3.4. Event-based approach classification results

For the event-based approach, Bior3.1 wavelet in D4 sub-band was employed as it showed superior performance (Section 3.3). Fig. 10 presents EEG, sigmoid entropy in time and frequency domains and

classifier output corresponding to different channels of an epileptic patient data obtained from RMCH database. According to the visual identification of the EEG by experts, the seizure starts at 32 s and ends at 93 s. As shown in the right panel of Fig. 10, the seizure was detected immediately after the onset at 32 s (in F4, T3, and T5) and with some delay in channels Cz and P3. On applying the proposed method to the complete epileptic data, which consist of 162 seizures, SDR of 96.34% along with the MDD of 1.2 s and FDR of 0.5/h was observed. Thus, the proposed method was capable of capturing the seizure onsets shortly after its occurrence reducing the detection delay. Nearly 60% of the seizure onsets across each channel were detected within 1 s, and remaining were identified within 2 s.

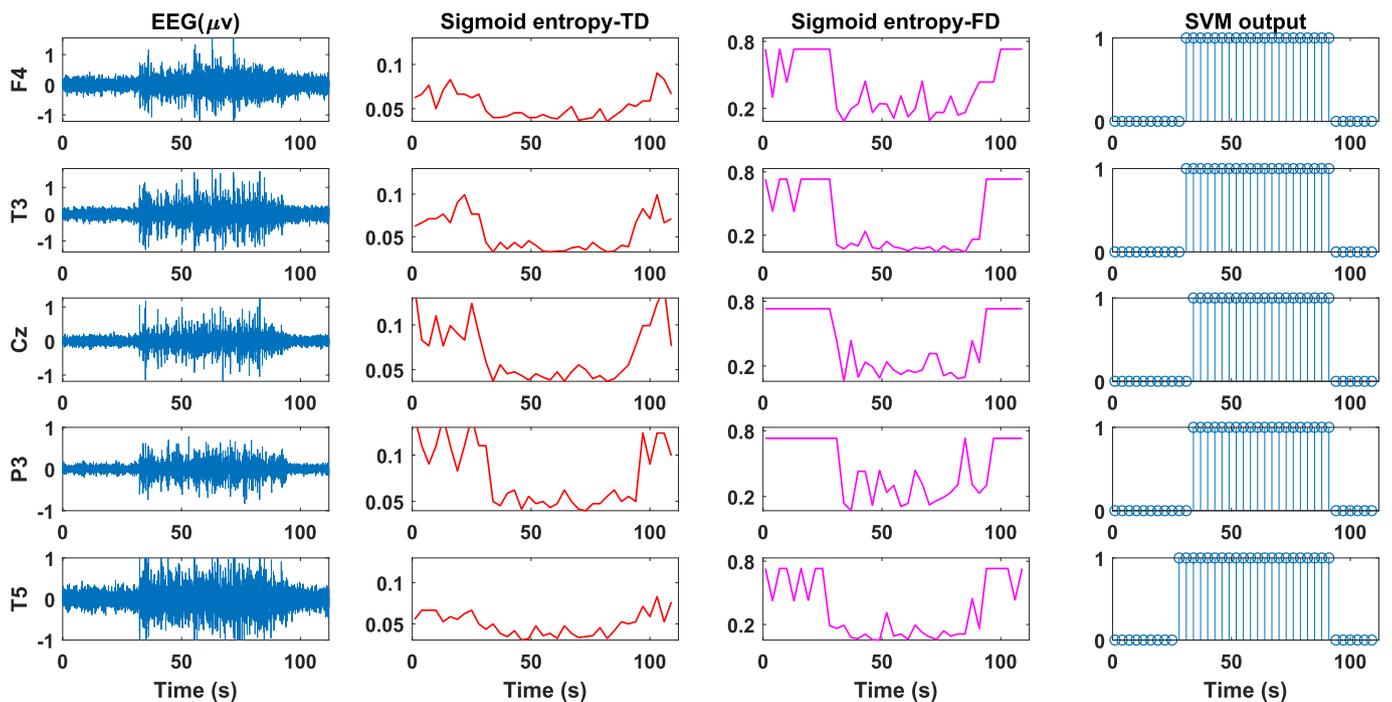
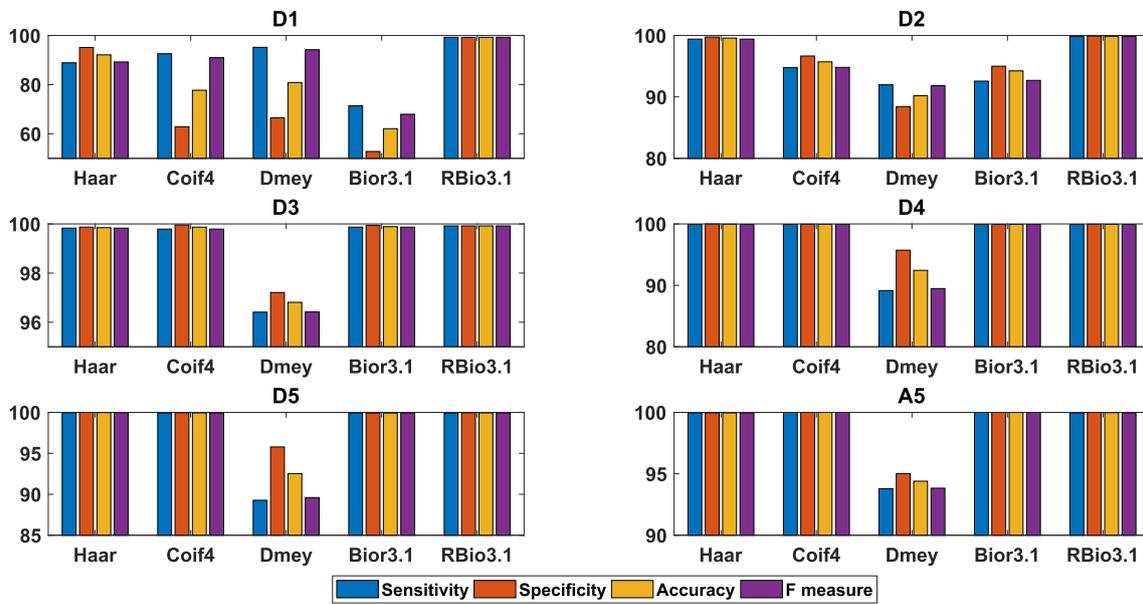
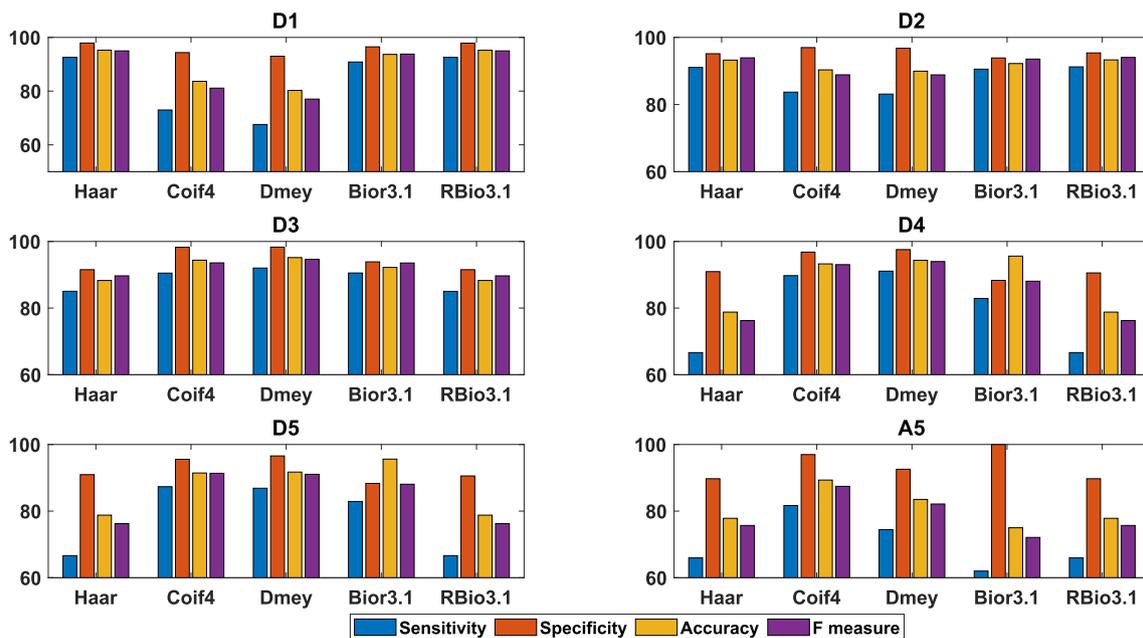


Fig. 10. The EEG, sigmoid entropy in time and frequency domain and classifier output corresponding to different channels of an epilepsy patient. The seizure starts at 32 s and ends at 93 s. The description of data showed in this figure as follows: **First column:** EEG of different channels, **Second column:** Sigmoid entropy in the time domain, **Third column:** Sigmoid entropy in the frequency domain, and **Fourth column:** SVM classifier output.



(a)



(b)

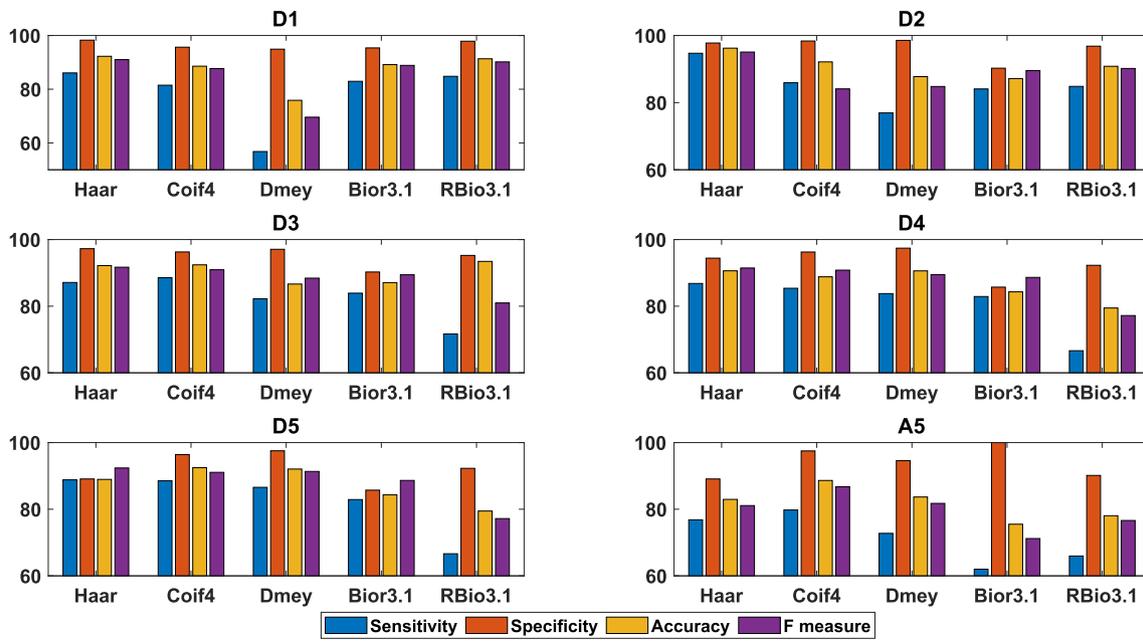
Fig. 11. Classification result using segment-based classification approach for UBonn database. (a) Classification problem {A}-{E}. (b) Classification problem {ACD}-{E}. (c) Classification problem {ABCD}-{E}. (d) Classification problem {AB}-{CD}-{E}. The results are grouped wavelet wise for each sub-band.

3.5. Results using UBonn database

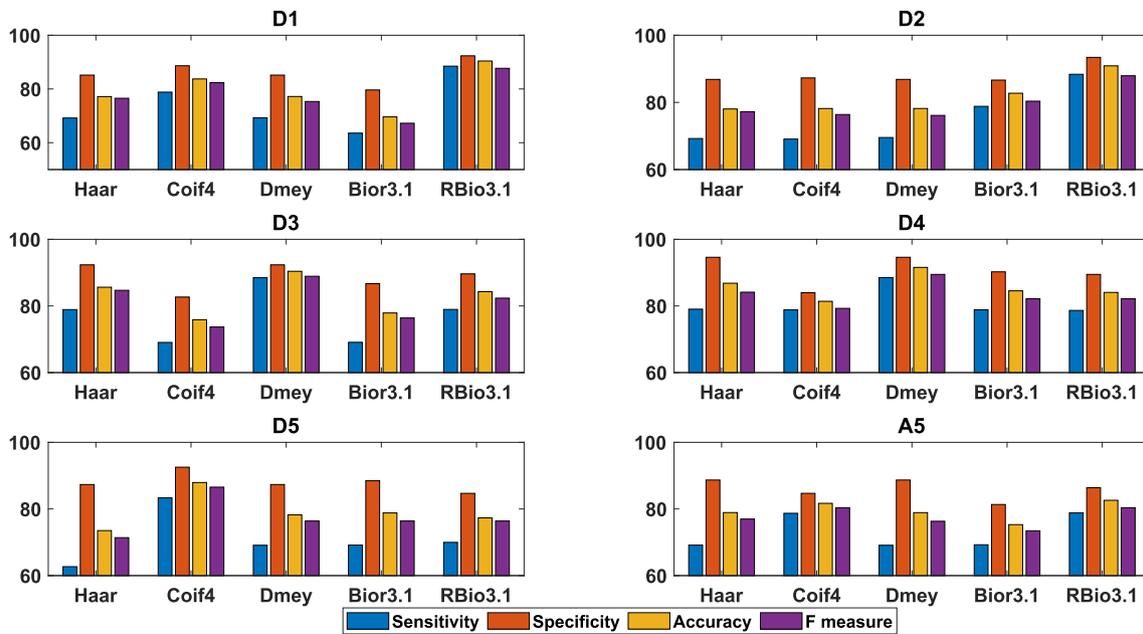
The proposed method was applied to one of the gold standard EEG database obtained from the UBonn [47] to evaluate the generalization and efficiency of the algorithm. The sigmoid entropy feature extracted from the UBonn database was classified using the segment-based approach with 10-fold cross-validation. Since the sampling frequency of UBonn database was 173.71 Hz, EEG was decomposed up to the fifth level. For UBonn database, the following sub-bands were considered: D1 (fs/4-fs/2), D2 (fs/8-fs/4), D3 (fs/16-fs/8), D4 (fs/32-fs/16), D5 (fs/64-fs/32) and A5 (0-fs/64). The frequency content within the sub-bands are as follows: 43.4–86.8 Hz, 21.7–43.4 Hz, 10.85–21.7, 5.42–10.85 Hz,

2.70–5.43 and 0–2.70 Hz for D1, D2, D3, D4, D5, and A5 respectively.

Fig. 11a shows the classification results obtained for the UBonn database for the case {A}- {E}. The highest sensitivity of 99.28% (Rbio3.1), 99.83% (Rbio3.1), 99.92% (Rbio3.1), 99.92% (all except for Dmey), 100% (Coif4 and Bior3.1) in D1, D2, D3, D4, and A4 sub-bands were obtained respectively. All the four performance measures showed 100% in sub-band A5 using Haar and Rbio3.1 wavelets. One can observe that results in D3, D4, and D5 sub-bands using all the wavelets were close to 100% except in Dmey wavelet. The results obtained in D1 sub-band was less as compared to other wavelets except for Rbio3.1 wavelet. Dmey wavelet in all the sub-bands except D1 showed poor performance against other wavelets. The interesting fact observed was



(c)



(d)

Fig. 11. (continued)

that the performance measures achieved using Rbio3.1 wavelet in all the bands were greater than 99.24%. Further, Bior3.1 wavelet showed similar results to Rbio3.1 wavelet in D3, D4, D5, and A5 sub-bands.

Fig. 11b shows the results obtained for classification problem {ACD}-E. The highest classification accuracy of 95.61% was achieved using Bio3.1 wavelet in sub-band D4. Further, Haar wavelet in sub-band D1, Coif4 in sub-band D3, Dmey in sub-band D3, and Rbio3.1 in sub-band D1 showed the highest accuracy of 95.24%, 94.38%, 95.16%, and 95.21% respectively. The highest classification accuracy of 96.23% was obtained using Haar wavelet in sub-band D2 for classification problem {ABCD}-E (refer Fig. 11c). The 3-class classification problem

{AB}-E showed the highest accuracy of 90.89% using Rbio3.1 wavelet in sub-band D2 (refer Fig. 11d).

### 3.6. Results using CHB-MIT database

The proposed method was tested on one of the largest EEG database CHB-MIT [49] available in the open source. The classification methodology adopted for the RMCH database was applied to this database also. Fig. 12 shows the classification results obtained for CHB-MIT database. Good results were obtained in D1 to D4 sub-bands using all the wavelets. The highest accuracy of 88.48% (D3), 90.65% (D1), 90.78%

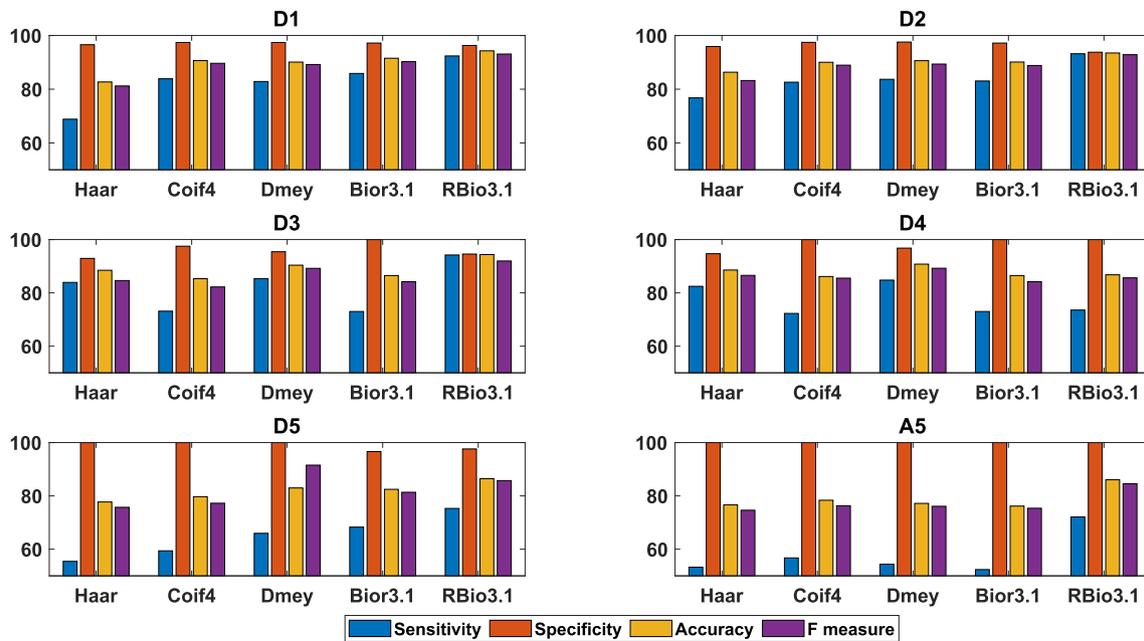


Fig. 12. Classification results using CHB-MIT database. The results are grouped wavelet wise for each sub-band.

(D4), 91.53% (D1), and 94.38% (D1) was obtained using Haar, Coif4, Dmey, Bio3.1, and Rbio3.1 wavelets respectively. Among all the wavelets, the highest sensitivity of 94.21% was obtained in sub-band D3 using Rbio3.1 wavelet. The highest sensitivity of 100% was seen in many sub-bands and wavelets. Notably, the classification results obtained using sub-bands D5 and A5 were less as compared to other sub-bands.

UBonn and CHB-MIT databases exhibited higher sigmoid entropy for normal EEG similar to the RMCH database. Hence, it shows that sigmoid entropy performs fairly better on different databases exhibiting good generalization for seizure detection.

### 3.7. Analysis of Cohen's Kappa coefficient

Table 3 shows the Kappa coefficient obtained from all the three databases. The highest Kappa of 1 (very good agreement) was obtained for Bio3.1 wavelet in sub-band D4 using the RMCH database. It was

**Table 3**  
Cohen's Kappa Coefficient obtained for all the three databases.

Database	Sub-band	Haar	Coif4	Dmey	Bior3.1	Rbio3.1
RMCH	D1	0.972	0.961	0.921	0.934	0.962
	D2	0.965	0.963	0.967	0.958	0.972
	D3	0.982	0.972	0.984	0.987	0.989
	D4	0.982	0.981	0.984	1.00	0.980
	A4	0.942	0.932	0.980	0.975	0.952
UBonn	D1	0.922	0.853	0.868	0.716	0.985
	D2	0.997	0.945	0.895	0.932	1.00
	D3	0.985	0.982	0.952	0.989	0.982
	D4	1.00	1.00	0.923	1.00	1.00
	D5	1.00	1.00	0.926	1.00	1.00
CHB-MIT	A5	1.00	1.00	0.948	1.00	1.00
	D1	0.812	0.892	0.884	0.903	0.932
	D2	0.843	0.894	0.891	0.890	0.923
	D3	0.869	0.842	0.884	0.843	0.940
	D4	0.857	0.789	0.883	0.843	0.836
D5	0.752	0.774	0.812	0.802	0.834	
A5	0.742	0.762	0.746	0.762	0.846	

Interpretation of Kappa values: Poor agreement (<0.2), Fair agreement (0.2–0.4), Moderate agreement (0.4–0.6), Good agreement (0.6–0.8), and Very good agreement (0.8–1).

observed that the Kappa coefficients obtained for the RMCH belonged to the very good agreement range of (0.8–1). Further, the Kappa coefficient of 1 was obtained for many sub-bands and wavelets for the UBonn database. The results obtained for class A-E are only reported in Table 3. Finally, the highest Kappa coefficient of 0.940 was achieved for Rbio3.1 wavelet in sub-band D4 for the CHB-MIT database. Notably, the least Kappa coefficients were obtained for CHB-MIT as compared to the RMCH and UBonn databases. Overall, the Kappa coefficients obtained from all the databases belong to either good or very good agreement category.

## 4. Discussion

The primary aim of the proposed method was to enhance the SDR, FDR, and MDD for real-time seizure detection. In that context, a novel feature referred to as sigmoid entropy using DWT in both time and frequency domains was proposed and evaluated on three EEG databases.

The seizure detection algorithm using weighted permutation entropy proposed in Ref. [17] reports a lower measure for epileptic seizure EEG as compared to normal EEG signal. Further, similar results were obtained in Ref. [18] using minimum variance modified fuzzy entropy. In resemblance to Refs. [17,18], sigmoid entropy measure also exhibited lesser entropy for epileptic EEG than normal EEG in our study.

### 4.1. Performance comparison with other entropy methods

Table 4 shows the performance comparison of the studies that use entropy methods for the classification of seizures. The studies [5,10,12,19,20] have used a single database to test their proposed algorithm. Whereas, in the proposed study, three different databases have been studied to test the algorithm. It can be seen from Table 4 that the results are shown by our study were better for the UBonn database.

In order to compare the performance of the sigmoid entropy with other entropy methods, the three most widely used Shannon, Renyi, and Tsallis entropy were tested on all the three databases. An entropy index of 2 was set for both Renyi entropy and Tsallis entropy [5]. Different entropy was estimated using Bior3.1 wavelet in D4, Rbio3.1 wavelet in A5, and Rbio3.1 in D3 sub-bands for the RMCH, UBonn, and

**Table 4**  
Performance comparison of the studies that are used entropy methods.

Authors	Feature extraction	Classifier	Database	Results
[5]	ApEn, Sample entropy, Phase Entropy 1 and 2	Fuzzy classifier	UBonn	Accuracy = 98.1%
[10]	Optimized sample entropy	Extreme learning machine	UBonn	Accuracy = 99.0%
[12]	DWT based ApEn	Artificial neural network	UBonn	Accuracy = 100%
[13]	Fuzzy entropy	SVM	UBonn	Accuracy = 100%
			CHB-MIT	Sensitivity = 98.27%
				Accuracy = 98.31%
[19]	Wavelet entropy	Recurrent Elman networks	UBonn	Accuracy = 99.75%
[20]	Wavelet packet based log energy entropy	Recurrent Elman networks	UBonn	Accuracy = 99.7%
			RMCH	Sensitivity = 96.34%
<b>Proposed</b>	<b>DWT based sigmoid entropy</b>	<b>SVM</b>	<b>UBonn</b>	<b>Sensitivity = 100%</b>
			<b>CHB-MIT</b>	<b>Sensitivity = 94.21%</b>

CHB-MIT databases respectively (These were concluded as superior in Section 3).

Fig. 13 shows the performance comparison of four entropy methods using the RMCH, UBonn, and CHB-MIT databases. On all the three databases, sigmoid entropy showed the highest classification results as compared to other entropy methods (refer Fig. 13). Further, for UBonn database, sensitivity for Shannon and Renyi entropy was the same as our method, but not for other measures. However, the classification results of other entropy methods were very much close to the results of sigmoid entropy.

The seizure detection algorithm must be computationally efficient for quick detection of seizure activity. Therefore, we ran the algorithm for ten trials and mean time (s) was calculated that includes pre-processing ( $T_p$ ), DWT ( $T_{DWT}$ ), feature extraction ( $T_{FE}$ ) and classification ( $T_{CL}$ ) using SVM. The total computation time (CT) required to execute a complete algorithm can be expressed as:

$$CT(s) = T_p + T_{DWT} + T_{FE} + T_{CL} \quad (23)$$

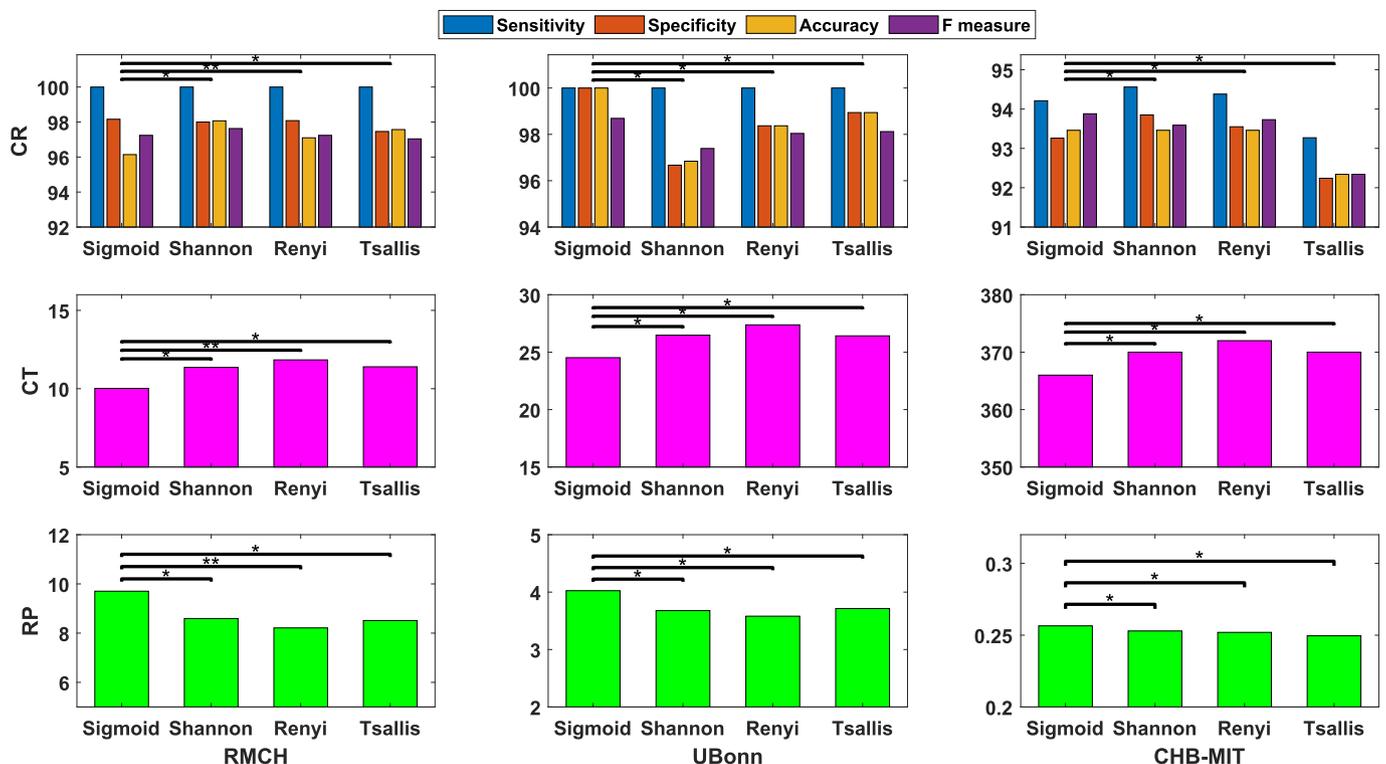
The complete experiment was implemented in MATLAB 2017b

using 8 GB RAM, CPU 2 GHz with an Intel I3 processor. The performance results may differ from machine to machine based on the system configuration.

Fig. 13 shows the computation time taken to execute the algorithm for each entropy. The proposed sigmoid entropy displayed lesser computation time than other existing entropy methods for the RMCH (10.02 s), UBonn (24.52 s), and CHB-MIT (366.05 s) databases. Relative performance (RP) was used to compare the efficiency of the sigmoid entropy against other entropy measures [20]. It is defined as the ratio of the F measure to the computation time (s), and it can be expressed as:

$$RP = \frac{Fmeasure}{CT} \quad (24)$$

The higher the RP better the performance of the algorithm. Fig. 13 shows the RP obtained for four entropy methods. Sigmoid entropy exhibits slightly better performance as compared to the other three entropy methods for all the three databases. Hence, it confirms that sigmoid entropy is better and computationally efficient as compare to other entropy methods.



**Fig. 13.** Performance comparison of sigmoid entropy results with other entropy methods. **First row:** Classification results (CR). **Second row:** Computation time (CT) in seconds. **Third row:** Relative performance (RP) of the algorithm. **Left column:** RMCH, **Middle column:** UBonn, and **Right column:** CHB-MIT.  $p < 0.05(*)$ ,  $p < 0.01(**)$ ,  $p < 0.001(***)$ .

**Table 5**  
Performance comparison of epileptic seizure detection methods.

Authors	Duration of EEG (h)	Number of subjects	Number of channels	Number of seizures	Feature extraction	Classifier	SDR (%)	FDR (/h)	MDD (s)
[64]	652	28	24	126	Wavelet transform, energy amplitude and variance	Bayes network	78	0.86	9.8
[65]	525	21	16	88	Wavelet transform, energy, amplitude, variance, cross-correlation, relative derivative	Bayes network	81	0.60	16.9
[67]	22,278	159	19	794	Moving window STFT, averaged and integrated power	Adaptive thresholding	87.3	0.22	-
[46]	76	14	15	63	Combined seizure index	Cumsum thresholding	90.5	0.51	8.02
[66]	236	26	28	79	Regularity index, combined seizure index	Cumsum thresholding	91	0.33	7
[34]	509	21	18	161	Wavelet transform, relative energy, fluctuation index, coefficient of variation	SVM	94.46	0.58	-
[49]	844	23	18	163	and relative amplitude	SVM	96	0.083	3
[7]	440	23	23	150	Spectral energy, spatial features, temporal features	RVM	96	0.1	1.34
<b>Proposed</b>	<b>58</b>	<b>115</b>	<b>19</b>	<b>162</b>	Harmonic wavelet packet transform fractal dimension, spatial and temporal features <b>Sigmoid entropy</b>	<b>SVM</b>	<b>96.34</b>	<b>0.5</b>	<b>1.2</b>

4.2. Performance comparison using long term EEG

Table 5 shows a comparison study with other existing methods. The studies considered for the comparison are based on the criteria that the algorithms have used long-term multichannel EEG and reported SDR, FDR, and MDD. The proposed algorithm attained a good sensitivity of 96.34%, which is comparable to Refs. [7,49] and higher than other studies reported in Table 5. Our method shows significant improvement in MDD (1.2s), which is better than the results reported in Refs. [46,64–66]. The FDR of 0.5/h was achieved that was almost similar to other studies.

4.3. Performance comparison using UBonn database

We have evaluated the generalization of our algorithm on UBonn database. Table 6 shows the performance comparison of the studies conducted using UBonn database. The studies considered for the comparison that have reported the performance measures, namely sensitivity, specificity, accuracy, PPV, and NPV. Few studies have attained lesser performance measures despite employing DWT with more number of features. Noticeably, the proposed method showed better results on all measures using DWT.

Fig. 14 shows the performance comparison using radar chart for the studies conducted using UBonn database that was reported in Table 6. In the radar chart, the best method spans a larger Pentagon. Our seizure detection method exhibited the largest area (red pentagon in Fig. 14) as compared to other studies.

4.4. Significant findings of the study

The significant findings of the study are listed below:

- 1 This study introduced DWT based sigmoid entropy in time and frequency domains that were derived from the sigmoid function for the detection of epileptic seizures.
- 2 The proposed algorithm was tested on three databases, namely RMCH, UBonn, and CHB-MIT for its generalization and robustness.
- 3 Five commonly used wavelets, namely Haar, Coif4, Dmey, Bior3.1, and Rbio3.1, were examined and compared with different decomposition levels. Among five different wavelets, Bio3.1 in D4 sub-band, Rbio3.1, and Haar in A5 sub-band, Rbio3.1 in D3 sub-band was found to be the best choice for RMCH, UBonn, and CHB-MIT databases respectively. Further, Dmey wavelet showed the least performance for UBonn database.
- 4 The classification results obtained in D5 and A5 sub-bands using CHB-MIT database was less as compared to other sub-bands.

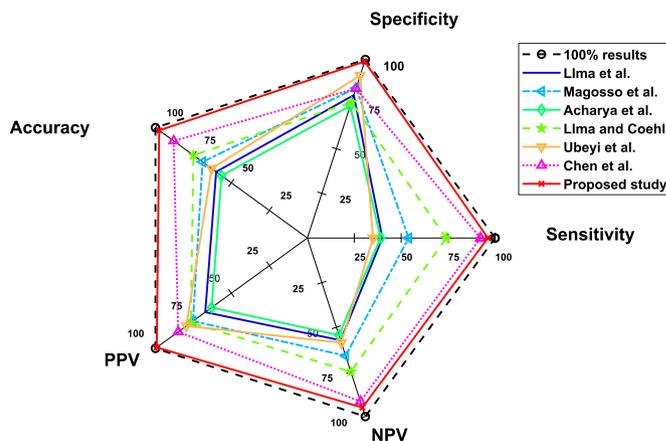


Fig. 14. The performance comparison using radar chart for the UBonn database. The outermost dotted black line indicates the 100% performance. The Pentagon represents the performance of each method in a different color.

**Table 6**  
Performance comparison of the studies conducted using UBonn database.

Authors	Method	Sensitivity (%)	Specificity (%)	Accuracy (%)	PPV (%)	NPV (%)
[25]	DWT + Statistical features and RVM	40	80	60	67.19	57.28
[28]	DWT + Signal energy	54	84	69	75.28	65.95
[29]	Wavelet packet decomposition + Eigenvalues and Gaussian mixture model	39	74	56.5	62.97	54.38
[30]	Wavelets + 21 features and SVM	74	76	75	76.71	74.91
[26]	Wavelet + Statistical features and Combined neural network	35	91	63	79.67	58.6
[24]	DWT + 9 features and SVM	92.24	83.76	88	85.03	91.52
<b>Proposed</b>	<b>DWT + Sigmoid entropy and SVM</b>	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>	<b>100</b>

5 The results reveal that the transition from normal to epileptic activity in the brain can be better described using sigmoid entropy.

6 Sigmoid entropy measure for epileptic EEG was found to be lower than normal EEG, which is similar to the methods proposed in Refs. [17,18].

7 It has been proven that non-extensive Tsallis entropy is better than Shannon entropy only when proper entropy index  $q$  was chosen. However, no such selection is required for the estimation of sigmoid entropy.

#### 4.5. Limitations and future directions

During the simulation, it was observed that the bin ranges should be set properly during the probability estimation of the signal. Improper selection of such parameter leads to *not a number* or *infinity* in a MATLAB platform. As a future direction, the proposed algorithm will be tested on more number of EEG recordings. Further, sigmoid entropy will be explored on EEG signals obtained for different conditions such as detection of the level of alcohol, drowsiness detection, and anesthesia depth level detection. In addition, a deep learning based approach will be introduced to all the three databases.

#### 5. Conclusion

In this paper, a novel feature referred to as sigmoid entropy was proposed for the detection of epileptic seizures in the EEG signals. Sigmoid entropy was estimated by decomposing the EEG signal using DWT. Experimental results showed that sigmoid entropy was capable of capturing the transitions in the EEG that reflected the abnormal activity in the brain. The results showed that the sigmoid entropy value was lower for epileptic activity as compared to normal EEG. The best wavelet and decomposition level (sub-band) was identified using five wavelets. Among five different wavelets, Bio3.1 (sub-band D4), Rbio3.1 and Haar (sub-band A5), and Rbio3.1 (sub-band) D3 was found to be the best choice for the RMCH, UBonn, and CHB-MIT databases respectively. The classification results showed an SDR of 96.34%, MDD of 1.2 s and FDR of 0.5/h for the RMCH database. Further, the highest sensitivity of 100% and 94.21% were obtained using UBonn and CHB-MIT databases respectively. Our experimental results conclude that sigmoid entropy can be used to analyze the brain dynamics to understand the epileptic seizures behavior with less computational complexity.

#### Conflicts of interest

None declared.

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