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Automated diagnosis of epileptic EEG using entropies

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ABSTRACT

Epilepsy is a neurological disorder characterized by the presence of recurring seizures. Like many other neurological disorders, epilepsy can be assessed by the electroencephalogram (EEG). The EEG signal is highly non-linear and non-stationary, and hence, it is difficult to characterize and interpret it. However, it is a well-established clinical technique with low associated costs. In this work, we propose a methodology for the automatic detection of *normal*, *pre-ictal*, and *ictal* conditions from recorded EEG signals. Four entropy features namely Approximate Entropy (*ApEn*), Sample Entropy (*SampEn*), Phase Entropy 1 (*S1*), and Phase Entropy 2 (*S2*) were extracted from the collected EEG signals. These features were fed to seven different classifiers: Fuzzy Sugeno Classifier (FSC), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Probabilistic Neural Network (PNN), Decision Tree (DT), Gaussian Mixture Model (GMM), and Naive Bayes Classifier (NBC). Our results show that the Fuzzy classifier was able to differentiate the three classes with a high accuracy of 98.1%. Overall, compared to previous techniques, our proposed strategy is more suitable for diagnosis of epilepsy with higher accuracy.

1. Introduction

Epilepsy is a physical condition that occurs in the brain and affects the nervous system. According to a 2009 report by the World Health Organization [58], around 50 million people worldwide have epilepsy. Around 90% of these people live in developing countries, and about three fourths of them do not have access to the necessary treatment. Epilepsy is also surrounded by a lot of social stigma. For example, in both China and India, epilepsy is generally seen as a reason for prohibiting marriages [58]. Thus, it is evident that the availability of affordable and reliable epilepsy detection techniques and anti-epileptic drugs would help patients in developing countries cope with the disease as well as face relatively less social discrimination.

In epileptic patients, the nerve cells in the brain send out excessive electrical impulses that cause episodes called seizures. An epileptic seizure is defined as "a transient symptom of excessive or synchronous neuronal activity in the brain" [1]. Epilepsy is defined by two or more such unprovoked seizures. Seizures can be focal or generalized. In the case of focal seizures, only a particular segment of the brain is affected, whereas the whole brain is affected in the case of generalized seizures. Epilepsy is generally evaluated using the Electroencephalogram (EEG) test in which electrodes are placed on the affected area on the brain (scalp region) and brain signals are recorded and analyzed [2–4]. Reviewing of the entire recorded EEG signals by a trained professional is time-consuming. Therefore, automated techniques look very appealing.

Due to the complex interconnections between billions of neurons, the recorded EEG signals are complex, non-linear, non-stationary, and random in nature. They consist of many sinusoidal components of distinct frequencies interacting non-linearly to produce one or more sinusoidal components at sum or difference frequencies [5]. Several studies have focused on the detection of epilepsy from EEG signals using non-linear methods that detect and quantify non-linear mechanisms and thereby better reflect the characteristics of the EEG signals. Non-linear features may be able to unearth the hidden complexities existing in the EEG time series. One of the earliest studies was by Babloyantz et al. [6] who used non-linear parameters like Correlation Dimension (CD) and Largest Lyapunov Exponents (LLE) to study the sleep wave signal. Such studies diversified the potential application areas of EEG non-linear analysis methodologies. Non-linear dynamical methods that

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are based on the concept of chaos have been applied to many areas including the areas of bio-signals [7,8]. Identification of epilepsy is one of the common application areas [9–11]. In 2001, Andrzejak et al. [12,13] presented a framework by introducing a new measure ξ, designed to discriminate between non-linear deterministic and linear stochastic dynamics. The ξ value was extracted from intracranial multi-channel EEG signals that were obtained during the inter-ictal state in 25 patients with unilateral mesial temporal lobe epilepsy. The results indicated that the signals from within the epileptogenic zone had strong indications of non-linear determinism, while those from other sites had linear stochastic dynamics. This indicates that non-linear time series analysis of EEG signals in patients with epilepsy is capable of providing potentially useful diagnostic information.

Entropy is a numerical measure of the randomness of a signal. Entropy as a parameter has been used to analyze psychological time series data such as Epilepsy EEG data [14]. In this paper, we present a methodology for the automatic detection of *normal*, *pre-ictal*, and *ictal* conditions from recorded EEG signals. Four entropy features namely Approximate Entropy (*ApEn*), Sample Entropy (*SampEn*), Phase Entropy (*S1*), and Phase Entropy 2 (*S2*) were extracted from the collected EEG signals. These features were fed to seven different classifiers: Fuzzy Sugeno Classifier (FSC), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Probabilistic Neural Network (PNN), Decision Tree (DT), Gaussian Mixture Model (GMM), and Naive Bayes Classifier (NBC).

The paper is organized as follows. Section 2 presents a description of the data used in this work, briefly describes the extracted features and classifiers that were used, and defines the performance measures used to evaluate the classifiers. Section 3 presents the results obtained. A detailed review of the literature related to the automatic detection of epilepsy from EEG signals is given in Section 4, which also discusses the results obtained in this work. Finally, conclusions are given in Section 5.

2. Materials and methods

2.1. Data

The EEG data used in this study was taken from the artifact free EEG time series data available at the Department of Epileptology, University of Bonn [40]. Three classes, namely, *normal*, epileptic background (*pre-ictal*), and epileptic seizure (*ictal*) of single channel EEG signals of 23.6 s duration were selected. The *normal* and *pre-ictal* datasets had 200 cases each, and the *ictal* class had 100 cases. The *normal* EEG data was obtained from five healthy volunteers using a standardized electrode placement scheme with the volunteers in a relaxed awake state with eyes-open (100 cases) and eyes-closed (100 cases). The *ictal* EEG data was recorded during the epileptic seizures that occurred in five epilepsy patients. The *pre-ictal* EEG data was recorded from the same five epilepsy patients when there was no seizure. All EEG signals were recorded by a 128 channel amplifier system, sampled at a rate of 173.61 Hz, and discretized with 12 bit A/D resolution. The data was filtered using a band pass filter with settings 0.5340 Hz ~12 dB/octave. Sample *normal*, *pre-ictal*, and *ictal* EEG signals are shown in Fig. 1. Epileptic EEGs were collected from intracranial electrodes that were placed on the correct epileptogenic zone [12,13].

2.2. Features

Five entropies have been extracted from each EEG signal. A brief description of these entropies is given in this section.

2.2.1. Approximate Entropy (ApEn)

Approximate Entropy is the logarithmic likelihood that the trends of the data patterns that are close to each other will remain close in the next comparison with next pattern. Thus, *ApEn* is a measure of data regularity. A greater likelihood of high regularity produces smaller *ApEn* values, and low regularity produces higher *ApEn* values. It represents an index that denotes the overall complexity and predictability of the time series. *ApEn*, proposed by Pincus [16], is scale invariant and model independent. It detects the changes in underlying episodic behaviour not reflected in peak occurrences or amplitudes [49]. In this work, the formula given by Pincus et al. has been used for the determination of *ApEn* from the EEG data. Accordingly, consider a time series $x(n)$, $n = 1,2\ldots,N$. A series of patterns of length e (called the embedding dimension which is the smallest integer for which the patterns do not intersect with each other) is derived from $x(n)$. *ApEn* is given by

$$ApEn\ (e.r, N) = \frac{1}{(N-e+1)}\sum_{i-1}^{N-e+1}\log\ \ C_i^e(r) - \frac{1}{(N-e)}\sum_{i-1}^{N-e}\log\ \ C_i^{e+1}(r) \quad (1)$$

where the index r is a fixed parameter which sets the *tolerance* of the comparison, $C_i^e(r)$ is the correlation integral.

Phase space is a point in the dynamical system depicting the instantaneous state. Sequence of such states over a period of time defines the phase space trajectory. The system will arrive at a permanent state, if it is governed by deterministic laws. Different physiological diseases have unique phase space plots [15]. The Correlation integral is plotted logarithmically against $\log(r)$ and depends on the given radii of the phase space neighbourhood and the embedding dimension. The Correlation integral given by Grassberger and Procaccia [43] reads as follows:

$$C_i^e(r) = \frac{1}{(N-m+1)}\sum_{j-1}^{N-e+1}\Theta\left(r - \left\|x_i - x_j\right\|\right) \quad (2)$$

where x_i, x_j are the points of the trajectory in the phase space, N is the number of data points in phase space, r is the radial distance around each reference point x_p and Θ is the Heaviside function.Correlation integral is the mean probability that, the states are close at two different times. r is the scale or tolerance parameter for accepting similar patterns between two segments, which should be equal to zero for the infinite amount of data. In order to avoid a significant contribution from noise in the EEG signals, we need to choose r larger than most of the noise. But for finite data (in our case), it was shown that the optimal r is to be 0.2 times the standard deviation of the data [16,17]. Embedding dimension (m) determines the length of the sequences to be compared, and is evaluated by calculating the false nearest neighbour (FNN) [18]. m is the value for which there will be no FNN or within the acceptable level and is found to be 2 in our work [56]. *ApEn* is mainly insensitive to low level noise, and hence, is very suitable for EEG signal analysis.

2.2.2. Sample Entropy (SampEn)

Sample Entropy, proposed by Richman and Moorman [52], is the negative natural logarithm of an estimate of the conditional probability that patterns of length e that match point-wise within a tolerance r also match at the next point [48]. It is also a measure of data regularity like *ApEn*. However, *SampEn* is largely independent of record length and displays relative consistencies under circumstances where *ApEn* does not [52]. Similar to *ApEn*, larger values of *SampEn* correspond to more irregularity in the data and vice versa.

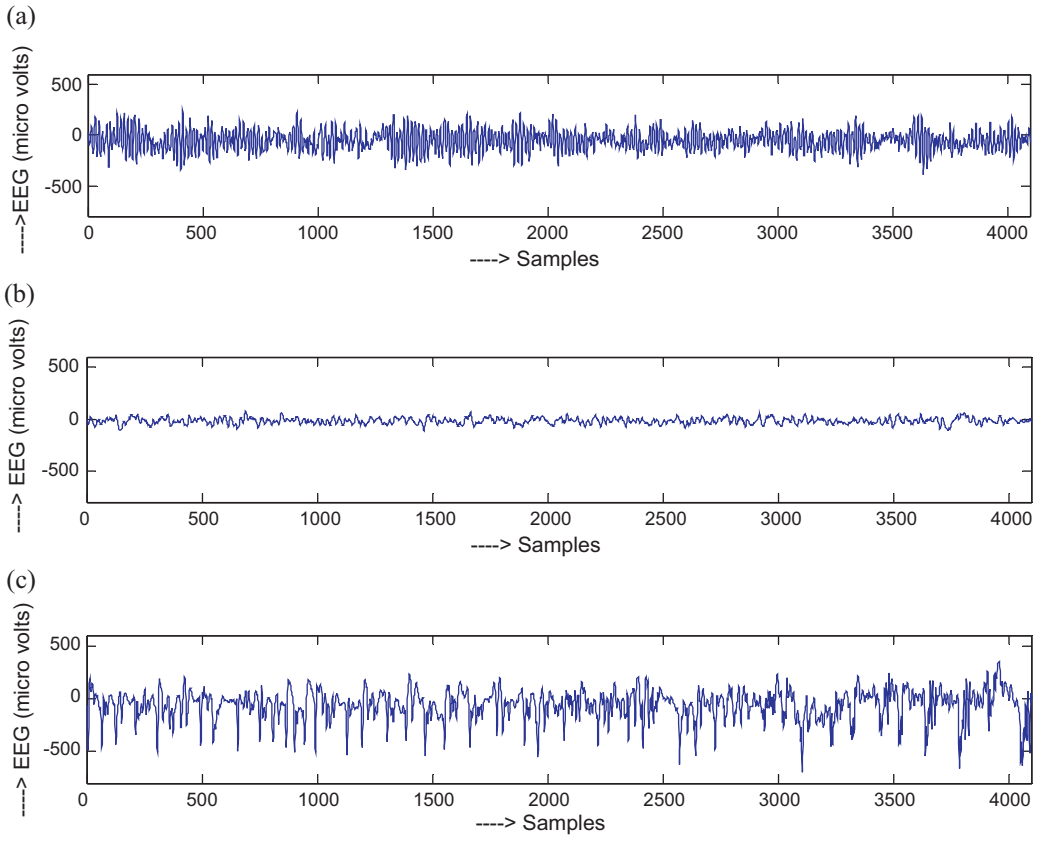

Fig. 1. Typical EEG signals (a) normal (b) pre-ictal (c) ictal.

To calculate the sample entropy, runs of points matching within the tolerance r are carried out until there is no match, while the count of template matches are stored in counters $A(k)$ and $B(k)$ for all lengths k up to e. *SampEn* is given by the formula

$$SampEn\ (k, r, N) = \ln\left(\frac{A(k)}{B(k-1)}\right) \tag{3}$$

where $B(0) = N$, the length of the input series. k is the embedding dimension. We have evaluated it using false nearest neighbour (FNN). The percentage of false neighbours should drop to zero when the appropriate k is reached. In our work, k value was found to be 2 [54].

2.2.3. Phase Entropies (S1 and S2)

Higher Order Spectra (HOS) are spectral representations of the higher order moments m^3, m^4... of a signal or the non-linear combinations of the higher order moments (also called the cumulants) c^1, c^2, etc. In other words, they are multidimensional Fourier transforms of the higher order moments or the cumulants. HOS can be defined for both deterministic signals and random processes [46]. In this work, the two phase entropies are derived from the bispectrum. The bispectrum, given by Eq. (4), is a complex-valued function of two frequencies.

$$B(f_1, f_1) = E\left[A(f_1)A(f_2)A^*(f_1 + f_2)\right] \tag{4}$$

where $A(f)$ is the Fourier transform of the signal a(nT).

The frequency f may be normalized by the Nyquist frequency to be between 0 and 1. The bispectrum, which is the product of three Fourier coefficients, exhibits symmetry, and is computed in the principal domain or the non-redundant region Ω (*i.e.* the triangle region in Fig. 2).

The two phase entropies are similar to spectral entropy. The equations for determining the entropies are given below [19].

$$\text{Phase Entropy 1} : S1 = -\sum_k p_k \log\ p_k \tag{5}$$

where $p_k = \frac{|B(f_1, f_2)|}{\sum_\Omega |B(f_1, f_2)|}$

$$\text{Phase Entropy 2} : S2 = -\sum_i q_i \log q_i \tag{6}$$

where $q_i = \frac{|B(f_1, f_2)|^2}{\sum_\Omega |B(f_1, f_2)|^2}$

The magnitude and the square of the magnitude are the L1 and L2 norms of the bispectrum. They were normalized by the sum of the norm over Ω such that each norm is now similar to a Probabil-

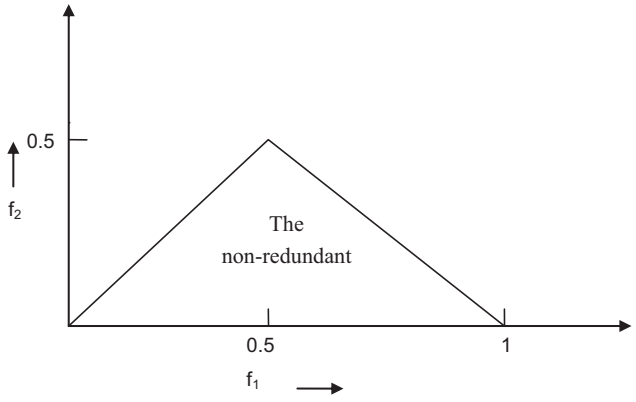

Fig. 2. Non-redundant region (Ω) of computation of the bispectrum for real signals. Parameters are calculated from this region Ω.

Table 1
Range of values of the entropies for the three EEG classes.

Class	Normal	Pre-ictal	Epileptic	*p*-Value
ApEn	2.2735 ± 3.320E−02	1.8650 ± 0.331	1.9325 ± 0.215	<0.0001
SampEn	1.3130 ± 0.120	0.99332 ± 0.189	0.92628 ± 0.139	<0.0001
S1	0.57012 ± 7.120E−02	0.47208 ± 6.149E−02	0.48325 ± 0.155	<0.0001
S2	0.76827 ± 3.125E−02	0.68072 ± 3.790E−02	0.73184 ± 4.555E−02	<0.0001

ity Distribution Function (PDF) with values estimated from the Ω region. The *normal*, *pre-ictal*, and *ictal* EEG are expected to have different PDF profiles of the bispectrum because of the different states of non-linear dynamics in them. Blocks of 512 samples of the EEG signal corresponding to 2.98 s at the given sampling rate were used for computing the bispectrum. These blocks were taken from each data record of 4096 points with an overlap of 256 points (*i.e.* 50%) [19,20]. The bispectrum was computed from an average taken over 15 blocks.

2.3. Classifiers

In this work, we have used seven classifiers namely FSC, SVM, KNN, PNN, DT, GMM, and NBC. They are briefly explained below.

2.3.1. Support Vector Machine (SVM)

An SVM classifier is a supervised classification technique [21]. It constructs a separating hyperplane that maximizes the margin between the input data classes that are viewed in an *n*-dimensional space (*n* is the number of features used as inputs). Essentially, this involves orienting the separating hyperplane to be perpendicular to the shortest line separating the convex hulls of the training data for each class, and locating it midway along this line. Two parallel hyperplanes, one on each side of the separating hyperplane, are constructed to calculate the margin from training data.

2.3.2. Gaussian Mixture Model (GMM)

GMM is a probabilistic model for density estimation using a mixture distribution. It is an unsupervised learning technique that uses expectation–maximization algorithms for classification [21].

2.3.3. Fuzzy Sugeno Classifier (FSC)

Fuzzy logic can be used to take fuzzy or imprecise observations for inputs and yet arrive at crisp and precise values for outputs. In this work, subtractive clustering technique was used to generate a Fuzzy Inference System (FIS) [53]. Clustering technique estimates the number of clusters and the cluster centres in the examined dataset. FIS comprises of inputs, outputs, and a set of rules that define the behaviour of the fuzzy system. Each input and output has as many membership functions as the number of clusters. Radius parameter is used to indicate a cluster centre's range of influence in each of the data dimensions. FIS structure containing set of fuzzy rules that cover the feature space is generated after the training. This is used to perform fuzzy inference calculations of the test data.

2.3.4. K-Nearest Neighbour (KNN)

KNN is a supervised learning technique where a new instance is classified based on the closest training samples present in the feature space [21]. It does not use any model to fit, and is only based on memory. When a test data is entered, it is assigned to the class that is most common amongst its *k* nearest neighbours.

2.3.5. Naive Bayes Classifier (NBC)

NBC is a probabilistic classifier based on Bayes theorem. It strongly assumes that the predictor variables are independent random variables [21]. This assumption helps it to compute probabilities required by the Bayes formula from even a small training data.

2.3.6. Decision Tree (DT)

In the case of decision trees, the input features are used to construct a tree. A set of rules representing the different classes is then derived from the tree [22]. These rules are used to predict the class of a new sample with an unknown class.

2.3.7. Probabilistic Neural Network (PNN)

Probabilistic neural networks are a kind of two-layer radial basis network suitable for classification problems [23]. The first layer is the radial basis layer that computes the distances from the input vector to the training input vectors and yields a distance vector. The second layer is the competitive layer that sums these contributions for each input classes and produces a vector of probabilities as its output. The 'compete' transfer function at the output of the second layer selects the maximum of these probabilities, and assigns a 1 for that selected class and a 0 for the other classes.

2.4. Performance measures

Performance of each classifier was assessed by measuring sensitivity, specificity, diagnostic accuracy, and positive predictive value. The contingency cross-table reported the classifier output against truth (*i.e.* nature of the EEG signal: *normal*, *epileptic*, or *pre-ictal*).

3. Results

The four entropy values were calculated from the EEG data. Table 1 presents the values (mean ± standard deviation) of these entropies for *normal*, *pre-ictal*, and *epileptic* EEG signals. A significant *p*-value of less than 0.0001 was obtained using ANOVA (Analysis Of Variance) test indicating that these features have good discriminating capability [24]. *Spectral entropy* quantifies the spectral complexity of the EEG signal. If the EEG signal consists of a wide range of dominant frequencies, the spectral entropy will be high, else it will be low. It is evident from Table 1 that the normal EEG segment has low spectral entropy than the other two classes, indicating a lesser number of dominant frequencies in the normal EEG segment. *ApEn* and *SampEn* quantify the regularity in a time-series data. Hence, both *ApEn* and *SampEn* are higher in the case of *normal* class, and lower for the other two classes, indicating more self-similarity of the *pre-ictal* and *ictal* segments. In the case of *bispectral phase entropies* (*S1 and S2*), which capture the Higher Order Spectra of the EEG signals, the *normal, pre-ictal*, and *ictal* EEG segments have different values due to their different PDF profiles of the bispectrum.

Fuzzy inference systems consist of if–then rules that specify a relationship between the input and output fuzzy sets. In Fig. 3, we have presented the fuzzy inference system containing the input membership functions (Fig. 3(a)), an example of mapping of input to output (Fig. 3(b)), and the five rules obtained during the first fold of training the fuzzy classifier (Fig. 3(c)). In the figure, out1 denotes the ictal state, out2 the pre-ictal state and out3 the normal state. in1, in2, in3, in4 denote ApEn, SampEn, S1, and S2, respectively. Each fuzzy rule yields a single number that represents the firing strength of that rule. This firing strength is obtained by combining the memberships of the inputs that are determined using the respective membership functions. The firing strength is then

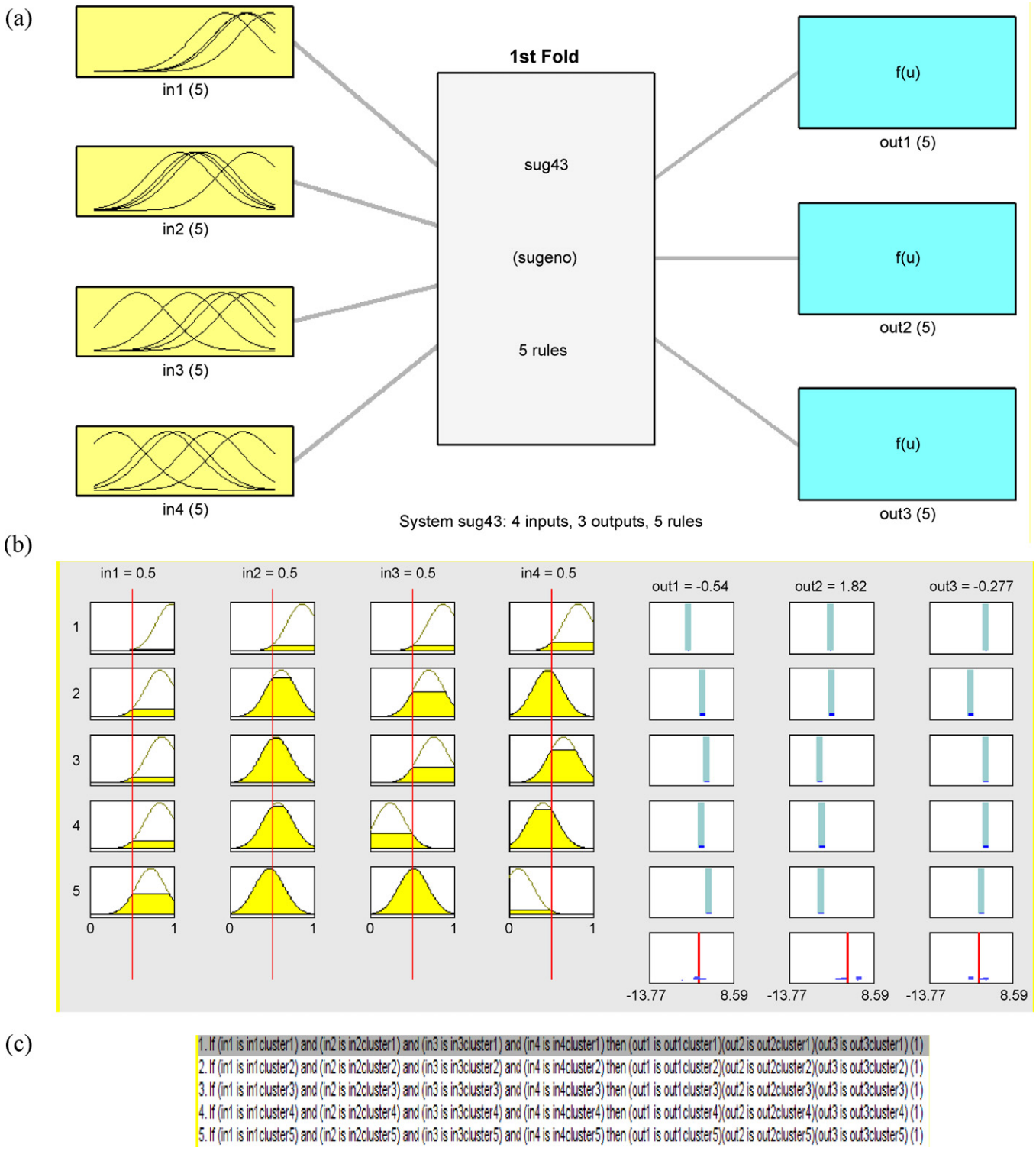

Fig. 3. (a) Fuzzy Inference System. (b) Example of input-to-output mapping. (c) The five fuzzy rules obtained during first fold of training.

used to shape the output fuzzy set that represents the consequent part of the rule. Subsequently, aggregation, which is a process whereby the outputs of each rule are unified, is carried out. Aggregation occurs only once for each output variable. The output of the aggregation process is the combined output fuzzy set. Finally, the aggregated output fuzzy set is defuzzified into a crisp single output value. Since we have used the Fuzzy Sugeno technique, the output membership function is a constant or a linear function as seen in Fig. 3(b).

These four entropy values were fed into the seven classifiers. Three-fold cross validation technique was used for evaluating the classifiers. In this technique, the entire dataset is divided into 3 sets each having similar proportion of samples from each class. Two sets are used for training the classifier, and the remaining one set is used for testing and to determine the performance measures. This procedure is repeated 3 times using a new test set each time. The average of all the 3 performance measures is taken as the final value. The number of True Positives (TP), False Negatives (FN), True Neg-

Table 2
Performance measures obtained using the seven classifiers.

Classifiers	TN	FN	TP	FP	Accuracy (%)	Positive predictive value (%)	Sensitivity (%)	Specificity (%)
Fuzzy	30	0	60	0	98.1	100	99.4	100
SVM	30	2	58	0	95.9	100	97.2	100
KNN	29	1	59	1	93	98.9	97.8	97.8
PNN	29	1	59	1	93	98.9	97.8	97.8
DT	27	1	59	3	88.5	95.7	98.3	91.1
GMM	29	1	59	1	95.9	97.9	98.3	95.6
NBC	29	3	57	1	88.1	98.9	94.4	97.8

TN (True Negative): Number of normal identified as normal; TP (True Positive): Number of abnormal identified as abnormal; FN (False Negative): Number of abnormal identified as normal; FP (False Positive): Number of normal identified as abnormal; Sensitivity = TP/(TP+FN); Specificity=TN/(TN+FP); Positive Predictive Accuracy (PPV)=TP/(TP+FP).

atives (TN), and False Positives (FP) obtained using each classifier is shown in Table 2. Table 2 also presents the classification accuracies, sensitivities, specificities, and positive predictive values for all the classifiers. It can be seen that the Fuzzy classifier presented the highest accuracy of 98.1%.

4. Discussion

All the entropies except the spectral entropy values indicate lower values for *pre-ictal* and *ictal* classes due to the periodicity or rhythmicity. The brain exhibits a change in chaotic electrophysiological behaviour from *normal* state to *pre-ictal* and *ictal* state. Hence, it agrees with the hypothesis that a loss of complexity appears when the biological systems become functionally impaired [51]. When the epileptic neurons at the epileptogenic zone get isolated, they may become idle and may result in seizure. During seizure, there is a decrease in the phase entropy (*S1* and *S2*) [25]. This decrease in entropy indicates reduction in information processing at the cerebral cortex [14,25,26,44]. During seizure, a massive group of neurons in the cerebral cortex suddenly begin to discharge in a highly organized rhythmic pattern. This pattern usually begins and terminates spontaneously, without external triggers. The initiation and termination of epileptic seizures reflect intrinsic, but poorly understood properties of the epileptic brain [27]. This rhythmic pattern causes decrease in the entropy.

Moreover, during epileptic seizure, a critical mass of neurons is continuously involved in synchronized high-frequency discharging [57]. There is a drop in phase synchronization (which is the degree of coupling between two EEG signals in the intracranial electrodes) during the pre-ictal state. This reduction is due to the decreased synchronization between the epileptogenic focus EEG signal and signals from surrounding region [9]. The epileptic neurons located in the epileptogenic zone become isolated due to a reduction in connections during the pre-ictal period [28]. This causes a reduction in the variability of the EEG signal, and therefore, results in lower entropy values (Table 1: normal vs. (pre-ictal and ictal)). When the epileptic neurons become isolated, epileptic seizure builds up. During seizure, there is a sudden increase in the neural discharge causing an increase in EEG signal variability, and hence, the entropy slightly increases in this state (Table 1: epileptic vs. pre-ictal). Also, the neurons in the cerebral hemispheres misfire and create abnormal electrical activity. Therefore, the number of neurons available for useful information processing reduces during seizures [29,30].

Table 3 shows a brief summary of studies that present various approaches to epilepsy detection using features extracted from EEG signals using the same dataset used in this study, and hence, the results are comparable.

Nigam and Graupe presented a technique that uses a multistage non-linear pre-processing filter in combination with an Artificial Neural Network (ANN) for the automated detection of epilepsy [45]. The proposed technique had a high accuracy of 97.2% in detecting epileptic signals. Another automated technique using Elman network, proposed by Srinivasan et al. [59], was evaluated using time-domain as well as frequency-domain EEG features. The network presented an accuracy of 99.6% on using single input features. The evaluation was performed using 100 normal and 100 epileptic EEG data.

Table 3
Summary of studies that present various approaches to epilepsy detection using features extracted from EEG signals using the same dataset used in this study.

Authors	Method	Accuracy (%)
Studies that dealt with a two-class (normal vs. epileptic) problem		
[45]	Non-linear preprocessing filter-diagnostic neural network	97.2
[59]	Time and frequency domain features – Recurrent neural network	99.6
[14]	Entropy Measures – ANFIS	92.2
[31]	Discrete wavelet transform – Adaptive neural fuzzy network	85.9
[32]	Discrete wavelet transform – Mixture expert model	95
[50]	Fast Fourier Transform – Decision tree	98.7
[33]	*ApEn*-Elman Network	100
[34]	Time-frequency methods – ANN	97.7
[47]	*ApEn* on DWT coefficients and classifier	96
[55]	DWT and PCA, ICA, LDA and SVM	98.75 (PCA), 99.5(ICA), 100 (LDA)
Studies that dealt with a three-class (normal vs. pre-ictal vs. epileptic) problem		
[35]	Lyapunov exponents – Recurrent neural networks	96.7
[36]	Mixed-band feature space – Backpropagation Network	96.7
[41]	Mixed-band feature space –Spiking Neural Networks	92.5
[60]	Mixed-band feature space –Principal component analysis-enhanced cosine radial basis function neural network classifier	96.6
[42]	Mixed-band feature space – Multi-Spiking Neural Network	90.7-94.8
[20]	Bispectrum entropies and bispectrum magnitude – Gaussian mixture model	93.1
[37]	Non-linear parameters – Gaussian mixture model	95
[38]	Four local maxima and four local minima values using Burg's method – SVM	93.3
[39]	Recurrence quantification analysis features – SVM	95.6
In this work	Entropies-Fuzzy Classifier	98.1

Kannathal et al. [8] used chaotic measures like Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Hurst exponent (H), and entropy to characterize the EEG signals (30 normal and 30 epileptic). It was shown that the chaotic measures had a good discriminatory power (accuracy of more than 90% in detecting epilepsy). In another study by the same group [14], different types of entropies were used to analyze the same dataset. Adaptive Neuro Fuzzy Inference System (ANFIS) was used for classification and an accuracy of more than 90% was achieved. Similar to the results of this work, they observed decreased entropy values for epileptic EEG signals compared to normal signals. Sadati et al. [31] used an Adaptive Neuro Fuzzy network (ANFN) to detect epileptic seizures. Classification accuracy of about 85.9% was achieved using ANFN.

Subasi [32] used the Discrete Wavelet Transform (DWT) coefficients of normal and epileptic EEG segments in a modular neural network called Mixture of Experts (ME). A classification accuracy of 94.5% was obtained that was higher than that obtained using standalone neural nets (93.2%). A hybrid framework that uses Fast Fourier transform based features in a DT classifier was presented by Polat and Guenes [50]. On evaluating the framework on normal and epileptic signal segments, they were able to obtain classification accuracies of 98.68% and 98.72% using 5- and 10-fold cross-validation, respectively.

A neural-network-based automated epileptic EEG detection system using *ApEn* as the input feature was studied [33]. Frames of 100 normal and 100 epileptic signals were used in the analysis. Elman and probabilistic neural networks were evaluated and an overall accuracy of 100% was obtained for the Elman network. Selected segments of the EEG signals were studied using time-frequency methods, and several features representing the energy distribution in the time-frequency plane were extracted for each segment [34]. Using these features in an ANN, a seizure detection accuracy of more than 97.7% was obtained.

A novel method for detecting epileptic seizures from EEG data by using *ApEn* and Discrete Wavelet Transform (DWT) was presented by Ocak [47]. When *ApEn* values were extracted from DWT transformed signals, the classification accuracy was 96%. This reduced to 73% when *ApEn* was calculated from raw EEG data. The dimensionality of the DWT features of the EEG signals were reduced using principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA) to classify into two classes normal and epilepsy EEG signals [55]. Then these features were fed to the SVM yielded 98.85% classification accuracy, sensitivity and specificity of 98.5% and 99.0% respectively using PCA method, 99.5% classification accuracy, sensitivity and specificity of 99% and 100% respectively using ICA method and 100% classification accuracy, sensitivity and specificity using LDA method.

Guler et al. [35] proposed the use of Recurrent Neural Networks (RNN) for the classification of the three types of EEG signals. The obtained results demonstrated that the proposed RNNs employing the Lyapunov exponents can be useful in analyzing long-term EEG signals for early detection of the electroencephalographic changes with an efficiency of more than 96%.

In another wavelet-based methodology [36], three features namely the standard deviation, CD, and LLE were extracted from sub-bands. They have shown that a particular mixed-band feature space consisting of nine parameters and back propagation neural network presented a high classification accuracy of 96.7%. The same group [36] evaluated three types of Spiking Neural Networks (SNN) training algorithms (SpikeProp, QuickProp, and RProp) to classify the three EEG classes. The model for EEG classification and epilepsy and seizure detection using RProp as training algorithm yielded a high classification accuracy of 92.5%.

In another research work by Ghosh-Dastidar and Adeli [41], a novel principal component analysis-enhanced cosine radial basis function neural network classifier was studied to detect epilepsy. Using 100 samples in each of the three EEG signal classes, their method yielded high classification accuracy (96.6%) and was robust to changes in training data with a low standard deviation of 1.4%. For epilepsy diagnosis, when only normal and inter-ictal EEGs were considered, the classification accuracy of the proposed model was 99.3%. The same group [42] developed a Multi-Spiking Neural Network (MuSpiNN) wherein information transfer between neurons happens via multiple synapses. Again using the mixed-band feature space, they obtained an improved accuracy range of 90.7–94.8% for the three classes.

Chua et al. [25] studied various HOS features to differentiate normal, pre-ictal, and epileptic EEG signals and demonstrated unique ranges for these features for the different classes with high confidence level (p-value of 0.002) [23]. In a subsequent study by them [20], these features were used in GMM and SVM classifiers. Their results show that the classifiers were able to achieve 93.11% and 92.67% classification accuracy, respectively. Recently, chaotic features like CD, Hurst exponent (H), LLE, Fractal Dimension, and ApEn in SVM and GMM classifiers were used for the classification of normal, pre-ictal, and epileptic EEG signals [37]. Their results show that the GMM classifier performed better with an average classification efficiency of 95%, sensitivity and specificity of 92.22% and 100% respectively.

Different modelling techniques and classifiers (ANN, GMM and SVM) were used to identify pre-ictal, ictal and normal EEG signals [38]. They showed that four local maxima and four local minima values that were extracted from the power density spectrum obtained using Burg's method in combination with SVM classifier provided the highest classification rate of 93.33%, sensitivity and specificity of 98.33% and 96.67% respectively. Recently Acharya et al., have automatically identified *normal, preictal* and *ictal* EEG signals using ten recurrence quantification analysis parameters and SVM classifier with an accuracy of 95.6%, sensitivity and specificity of 98.9% and 97.9% respectively [39].

Some of the above-presented studies demonstrated the utility of entropy as a feature for detecting epileptic signals. Most of the studies proposed automated techniques to classify normal from epileptic EEG signals. Moreover, most of the studies involving all three classes of EEG signals used segments and sub-bands of the EEG signals for extraction of features. This indicates an increased computational time requirement. Novelty of this contribution resides in using only entropy features and the classifier for the automated identification of three classes (normal, preictal and epileptic EEG signals). In fact, the work presented in this paper is the only study where in all three classes of EEG signals (*i.e.* the whole time series) have been classified using only entropy features. Relatively high significant classification accuracy of 98.1% has been obtained using Fuzzy classifier in classifying all three classes of EEG. Such an automated system can be used as an adjunct modality to cross check the diagnosis of the physicians. Complete automation and high accuracy make this technique a suitable candidate for extensive clinical validation. However, with more diverse training data and better features, the accuracy of classification and sensitivity can be further improved.

5. Conclusion

EEG signals can be used to discriminate *normal*, *pre-ictal* and *ictal* states. As indicated in many related works summarized in this paper, non-linear features have good discriminatory power for this purpose. In this work, we have extracted four entropy based non-linear features from full time series EEG data and trained seven classifiers. We have shown that the Fuzzy classifier could differentiate between the three classes with clinically significant classification accuracy of 98.1%. The proposed methodology offers suitable diagnostic accuracy and automation. Hence, it is a

suitable candidate for testing in clinical environment and in routine diagnostic protocols of epilepsy centres.

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