Fundamenta Informaticae 176 (2020) 141–166
DOI 10.3233/FI-2020-1968
IOS Press

Pattern and Rule Mining for Identifying Signatures of Epileptic Patients from Clinical EEG Data

Abhijit Dasgupta, Losiana Nayak, Ritankar Das
Machine Intelligence Unit
203 Barrackpore Trunk Road, Kolkata 700108, India
{*abhijitju06, losiananayak, ritankar07*}*@gmail.com*

Debasis Basu, Preetam Chandra
Department of Neuro-Medicine
Medical College and Hospital, Kolkata, India
{*neurodebasis, chandra07preetam*}*@gmail.com*

Rajat K. De*
Machine Intelligence Unit
203 Barrackpore Trunk Road, Kolkata 700108, India
rajat@isical.ac.in

Abstract. Epilepsy is a neurological condition of human being, mostly treated based on the patients' seizure symptoms, often recorded over multiple visits to a health-care facility. The lengthy time-consuming process of obtaining multiple recordings creates an obstacle in detecting epileptic patients in real time. An epileptic signature validated over EEG data of multiple similar kinds of epilepsy cases will haste the decision-making process of clinicians. In this paper, we have identified EEG data derived signatures for differentiating epileptic patients from normal individuals. Here we define the signatures with the help of various machine learning techniques, *viz.*, feature selection and classification, pattern mining, and fuzzy rule mining. These signatures will add confidence to the decision-making process for detecting epileptic patients. Moreover, we define separate signatures by incorporating few demographic features like gender and age. Such signatures may aid the clinicians with the generalized epileptic signature in case of complex decisions.

*Address for correspondence: Machine Intelligence Unit, 203 Barrackpore Trunk Road, Kolkata 700108, India

Keywords: Epileptic signature; Epileptic Network; Feature Selection; Fuzzy Logic; EEGLAB

1. Introduction

Epilepsy is one of the most frequently occurring neuropathological conditions affecting around fifty million people globally[1]. Epileptic seizures can be lethal [1]. Epileptogenesis is a long-term dynamic progressing process of hyperexcitability and abnormal synchronization of brain neurons until the manifestation of a seizure. Available drugs treat epileptogenesis indirectly by suppressing ictogenesis (the expression of seizures) [2]. Aetiologically and pathophysiologically, epilepsy is a heterogeneous disease [3]. This neurological disorder affects humans of all age groups [4]. Treatment of epileptic patients is mostly symptomatic, based on clinical features.

An "epileptic network", can be defined as a distributed network of distinct and distant brain regions causing hyperexcitability and hypersynchrony in a case of epilepsy [5]. Analysis of the epileptic networks may help in localization of a brain-region based signature in epileptic patients [6]. Till date, we have a limited idea of epileptogenesis. Epilepsy does not have a cure yet. Moreover, there does not exist any signature pattern of brain region based connections that can successfully categorize epileptic patients from normal human beings in real time. The case becomes more complex, when we try to incorporate demographic features like gender or age to EEG data of epileptic patients.

Seizure detection and classification from EEG data have been done earlier using artificial neural networks and time-frequency analysis [7], fast Fourier transform and decision tree classifier [8], discrete wavelet transform (DWT) and probabilistic neural network (PNN) [9], statistical features [10], adapted wavelet packets [11], and deep convolutional neural networks [12] among others. However, computational analysis of EEG data for detection of epileptic signatures in brain region based connections is a relatively new concept.

In this paper, we differentiate epileptic patients from normal individuals based on brain-region connection based signatures derived from EEG data. Moreover, we try to answer a few questions. How different is male epilepsy from female epilepsy? Do they over-represent different connections in various brain regions? How does child epilepsy differ from teenage and adult epilepsy? Do we find different patterns of over/under-representation of connections among various brain regions for different demographic categories? Can they be used as signature patterns clinically? In addition, we have aided our results with findings from pattern mining and fuzzy rule mining based approaches. Each discovered pattern is a collection of different functional connections, while a discovered rule is a combination of presence/absence of brain region based connections.

The paper is organized as follows. Section 2 provides information regarding demography, mode of collection, and preprocessing. The methodology involved in the generation of brain connectivity network, classification and feature selection, pattern mining, and fuzzy rule mining is discussed in Section 3. This is followed by Section 4, where we report the results on computational predictions obtained by feature selection, pattern mining, and fuzzy rule mining. In Section 5, we discuss the salient features signifying the overall, gender-based and age-based epileptic signatures. We conclude the paper with limitations and future prospects of this work in Section 6.

[1]http://www.who.int/mediacentre/factsheets/fs999/en/ visited on 24th August 2018 01:55 PM Indian Standard Time

2. Data

The dataset consists of electroencephalograms (EEGs) collected from 60 healthy individuals and 80 patients suffering from epilepsy. The data have also been grouped and studied according to gender and age. We have used data from 31 normal males and 29 normal females. Likewise, we have 43 epileptic male and 37 epileptic female data. Patients with less than 13 years of age have been defined as children. Teenagers have an age range of 13-19 years, whereas patients with more than 19 years of age have been defined as adult epileptic patients. Out of 60 healthy individuals, we have 23 children, 14 teenagers and 23 adults. Likewise, we have data of 41 children, 22 teenagers and 17 adults to make a total of 80 epileptic patients.

2.1. Data acquisition and filtering

Data collection has been done with a computerized EEG machine (16 channels Recorders & Medicare Systems Pvt. Ltd. (RMS)). It has been used to record EEGs for an interval of 20-30 minutes. The data of each epileptic patient have been split into epochs of 10 seconds interval. The internationally accepted Modified Combinatorial Nomenclature (MCN) system accepted scheme, as depicted in Figure 1, for the location of electrodes has been followed. According to this scheme, each location is denoted by a combination of letter(s) and number. The letter(s) are used to identify the position of the electrodes on the brain lobes, whereas the numbers denote the hemispherical regions on the brain. The frontal polar, frontal, temporal, parietal, central and occipital lobes are represented by the letters 'FP', 'F', 'T', 'P', 'C' and 'O' respectively, whereas odd and even numbers stand for electrode positions on the left and right hemisphere respectively. The name and location of each electrode have been described in Table 1. During the collection of data, it has been asked to all the participants to stay awake and motionless with wide open eyes. Subsequently, they have been requested to attain a no-thinking

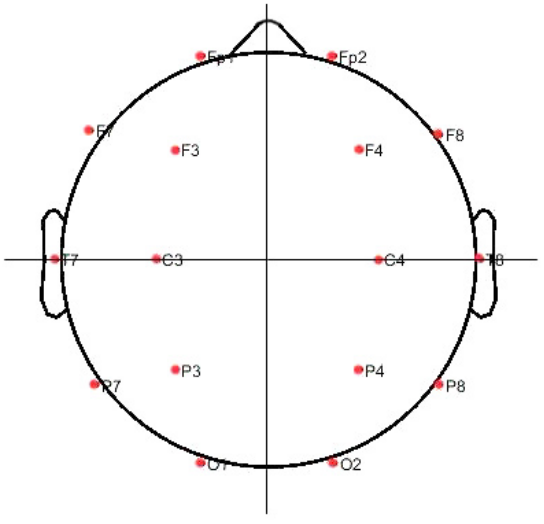


Figure 1: A typical head map showing the position of sixteen electrodes (marked as red dots).

state as far as possible. Each data has been recorded using a series of activation procedures, *i.e.*, eye blinking, photic stimulation, and hyperventilation among others.

Table 1: List of names and locations of EEG electrodes placed on scalp.

Electrode name	Lobe on which placed	Brodmann area	Anatomical gyrus
FP1	Left frontal polar	ba10L	Frontopolar
Fp2	Right frontal polar	ba10R	Frontopolar
F7	Left frontal	ba47L	Orbital part of inferior frontal
F3	Left frontal	ba08L	Intermediate frontal
F4	Right frontal	ba08R	Intermediate frontal
F8	Right frontal	ba45R	Triangular
T7	Left temporal	ba42L	Anterior transversal temporal
C3	Left central	ba02L	Caudal postcentral
C4	Right central	ba01R	Intermediate postcentral
T8	Right temporal	ba21R	Middle temporal
P7	Left parietal	ba37L	Occipitotemporal
P3	Left parietal	ba39L	Angular
P4	Right parietal	ba39R	Angular
P8	Right parietal	ba37R	Occipitotemporal
O1	Left occipital	ba18L	Parastriate
O2	Right occipital	ba18R	Parastriate

Table 2: List of symbols and their description.

	Symbols	Description
Mathematical symbol	x	A connection between two electrodes, considered as a feature
	y	A connection between two electrodes, apart from x, also considered as a feature
	F	A feature matrix
	m	Number of individuals/samples in **F**
	n	Number of features (*i.e.*, 120) in **F**
Membership functions for FCR algorithm	SA	A feature that is strongly absent in an individual
	A	Absence of a feature
	P	Presence of a feature
	SP	A feature that is observed to be present strongly

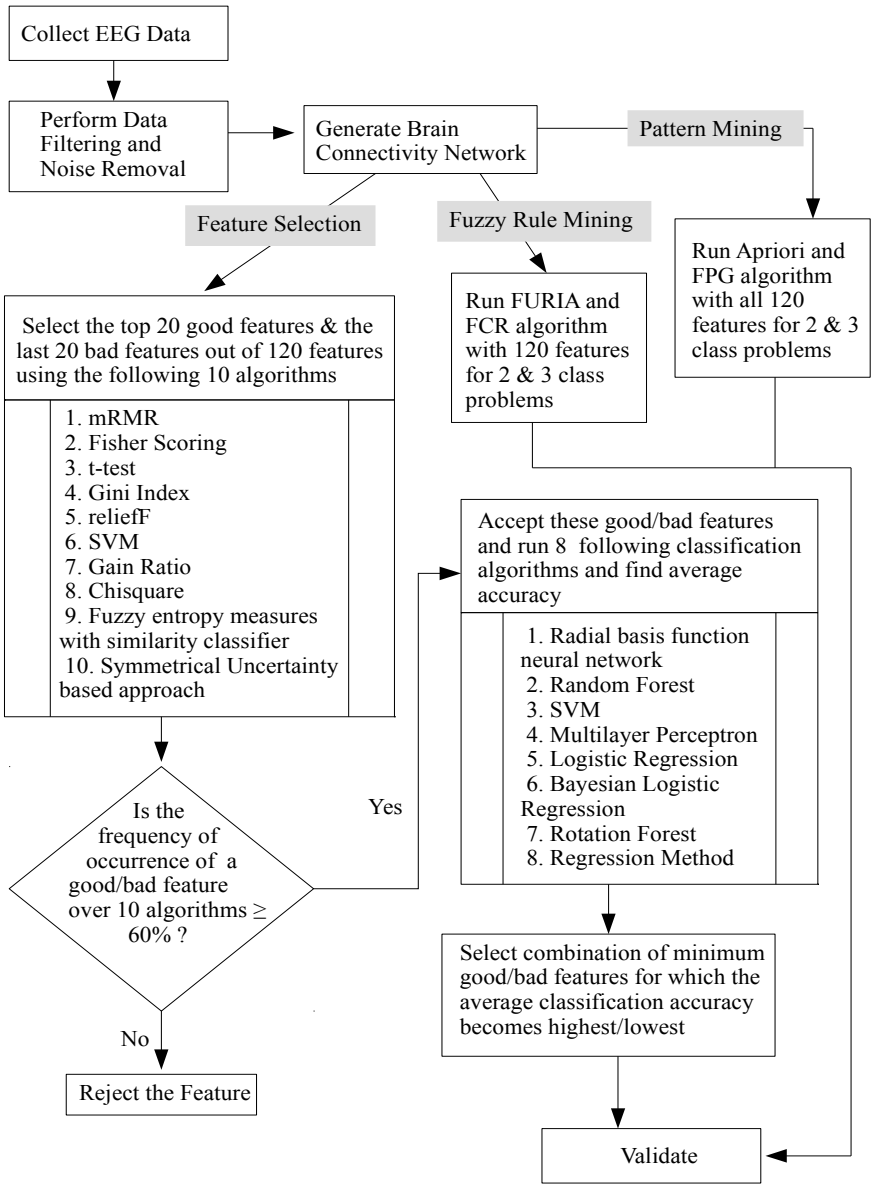


Figure 2: Flow chart of the methodology.

After recording of EEG data, firstly, the noise has been removed manually by experienced neurotechnologists. Then we have used EEGLAB toolbox version 13 [13], implemented in MATLAB R2015a, for further data filtering purpose. The EEGLAB plugin, called CleanLine, has been used to remove sinusoidal noise from raw EEG data. The resultant data have been filtered again using Finite Impulse Response (FIR) filter within the range of 4-60 Hz to remove sleep waves and noise due to electrical circuits. Here, we have used Independent Component Analysis (ICA) by applying the Runica

algorithm [14]. Thus, a multivariate signal is decomposed into its additive independent non-Gaussian components to separate the maximum likely components from a number of noisy components using neural network. Lastly, a final manual check has been done to assure that artefacts from the data have been removed. These steps have been shown as "Collect EEG Data" and "Perform Data Filtering and Noise Removal" in Figure 2.

3. Methodology

We have divided the methodology into a few significant steps which are individually described in the following sub-sections. They have helped in selecting significant features, and in finding important patterns and rules for epileptic patients in general, and for different demographic categories in particular. Figure 2 depicts the flowchart of the methodology pipeline. In this context, it may be mentioned that the necessary and sufficient conditions for identifying signatures of epileptic patients from clinical EEG data involve the following steps.

- The individuals should lie down motionless. Besides, they need to be in a no thinking state with eyes wide open to reduce artifacts.
- Removal of electrical and line noise is important in every case.
- Sleep wave should be removed using finite impulse response filter.
- Presence of noise and artifacts should be removed manually from the raw data by experienced neurologists.
- Independent component analysis should be performed to remove noisy components from maximum likely components.
- Finally, EEG data of sufficient normal individuals should be collected to differentiate signatures that are unique in epileptic patients.

3.1. Brain connectivity network generation

We have calculated the correlation coefficient between every pair of electrode positions using Pearson's correlation coefficient [15]. The sixteen electrode positions have been considered as vertices. If two vertices are found to be correlated (positively or negatively), we have created an edge between them. Thus, we have developed the brain connectivity network of normal individuals and epileptic patients, depicted as "Generate Brain Connectivity Network" in Figure 2. The detailed explanation of this procedure can be found in one of our previous investigations [16].

3.2. Determination of feature values

As there are 16 electrodes, we have developed a 16×16 adjacency matrix for each brain connectivity network representing either a healthy volunteer or an epileptic patient. This adjacency matrix is symmetric with '0's in its diagonal elements. Thus, maximum $(\frac{16\times15}{2}) = 120$ unique undirected connections are possible from such a matrix. The parameter values associated with these 120 connections have been considered as feature values.

3.3. Feature selection and classification

In "Feature Selection" step of Figure 2, we have identified the key features distinguishing normal individuals from epileptic patients (a two-class problem), male epileptic patients from female epileptic patients (another two-class problem) and child epileptic patients from teenage as well as adult epileptic patients (a three-class problem). For this purpose, we have tried to use a number of algorithms, ranging from univariate filtering methods to embedded and fuzzy systems, so that the selected features are generalized and not biased to any specific algorithm. Moreover, selected algorithms are easy to use and implement. Here, we have considered ten well-established methods, *viz.*, mRMR [17], Fisher scoring [18], t-test [19], Gini index [20], reliefF [21], Support Vector Machine (SVM) [22], gain Ratio [23], Chi-square [24], fuzzy entropy measures with similarity classifier [25], and symmetrical uncertainty based approaches [26, 27, 28] to identify top twenty most significant features and last twenty least significant features for the above mentioned classification problems.

We have selected the most/least significant features whose frequency of occurrence over these ten algorithms is more than 60%. For the task of classification, we have used eight well-known algorithms, *viz.*, radial basis function neural network [29], random forest [30], SVM [22], multilayer perceptron [31], logistic regression [32], Bayesian logistic regression [33], rotation forest [34], and regression method [35], to classify the combination of the minimum number of most and least significant features, as depicted in Figure 2. In comparison with the aforesaid algorithms, random tree [36], linear discriminant analysis [37], k-nearest neighbour [38] and a few others have shown comparatively inefficient performance as depicted in Kukreja et. al. [39]. However, although Naïve Bayes algorithm [40] has been reported to be superior on biological data compared to some others [39], we have purposely excluded it because the features are not independent here. It has been done to maximize the average classification accuracy based on the most significant features and minimize the same using the least significant features. Thus, a combination of features has been selected for each of the classification problems mentioned earlier.

3.4. Pattern mining

In the step of "Pattern Mining" in Figure 2, we have selected apriori [41] and Frequent Pattern Growth (FPG) algorithms [42] to scan over the whole feature set in order to find out a set of frequent features highlighting a general trend in the dataset under consideration. In comparison with the selected apriori and FPG algorithms, Transcription Mapping (TM) [43] and Can-Mining [44] show poor performance when the Minimum Support Threshold (MST) value is low. In addition, Equivalence Class Transformation (EClaT) [45] and TreeProjection [46] consume a lot of memory space and time for the datasets containing a lot of distinct patterns. Moreover, previous studies [47, 48] have demonstrated that FPG performs better than EClaT and Relim [49]. A comparative study [50] on different FPM algorithms depicts that both apriori and FPG algorithms are more efficient than the others in terms of execution time.

Apriori is one of the most influential and widely used algorithms, which is used to mine frequent patterns based on boolean association rules. However, as the dimensionality of the dataset increases, the computational cost of this algorithm increases. On the other hand, FPG is an effective pattern growth algorithm that mines frequent itemsets for large datasets.

Here we present a comparative study of these two algorithms and try to infer rules that are common to both. We have set the MST at 60% for both the FPM algorithms. Support is calculated as the ratio between the number of occurrences of a pattern (described by features) and the total number of features in terms of percentage. It is an indication of how frequently the pattern appears in the dataset. Besides, we have also calculated the confidence of each pattern found to be present. The minimum confidence threshold (MCT) for both the algorithms has been set at 80%.

3.4.1. Apriori algorithm

It is an association rule learning algorithm [41] that finds frequent patterns from the dataset. The algorithm is based on the idea that a subset of a frequent pattern (of features) must also be a frequent pattern. Here, we have considered the presence/absence of electrode-electrode connections as features and tried to find out these patterns that are frequent for the classes under consideration. Here, the order of the features across a pattern is not important.

3.4.2. Frequent Pattern Growth (FPG) algorithm

While using FPG algorithm [42], we have considered all 120 features for each individual belonging to their respective classes and performed similar operations as in apriori algorithm [41]. FPG algorithm implements a divide and conquer technique to mine frequent patterns without the costly candidate generation process as in apriori. In order to make the search quick and consume less memory space, it applies data compression by employing a special data structure called frequent pattern tree. Finally, frequent item sets are extracted by searching through these trees repeatedly. It leads to significant cost reduction in terms of algorithmic complexity.

We have calculated confidence and lift values for each frequent pattern thus obtained. It may be mentioned that support of one or more features taken together can be treated as a ratio of number of individuals having those features and the total number of individuals. On the other hand, confidence of a rule $x \Rightarrow y$ (x and y are two features) can be defined as

$$confidence(x \Rightarrow y) = \frac{support(x, y)}{support(x)} \tag{1}$$

where $support(x, y)$ and $support(x)$ can be written as

$$support(x, y) = \frac{Number\ of\ individuals\ with\ both\ x\ and\ y}{Total\ number\ of\ individuals} \tag{2}$$

$$support(x) = \frac{Number\ of\ individuals\ with\ x}{Total\ number\ of\ individuals} \tag{3}$$

The higher the confidence value, the more likely is the rule found to be more significant. Here, we have considered frequent item sets satisfying user specified minimum support threshold. Among such frequent item sets, we have treated the item sets having minimum confidence threshold (user specified) as strong association rules. In this context, it may be mentioned that support and confidence are two unique quality measurements for association rule mining [51]. Besides, user specified

minimum support and confidence threshold values should be high enough to guarantee stable general rules differentiating between epileptic and normal individuals from any given datasets.

The other quality measurement lift determines the importance of a rule. It is the ratio of the random confidence of a particular rule and its expected confidence. It can be expressed as

$$lift(x \Rightarrow y) = \frac{support(x, y)}{support(x).support(y)} \tag{4}$$

A lift value > 1 indicates that the antecedent and the consequent appear more often than expected, thus the antecedent has a positive effect on the consequent. Whereas, a lift value close to 1 indicates that the antecedent and consequent appear almost as expected. Naturally, we have considered the rules with lift value > 1 to be more significant ones.

3.5. Fuzzy rule mining

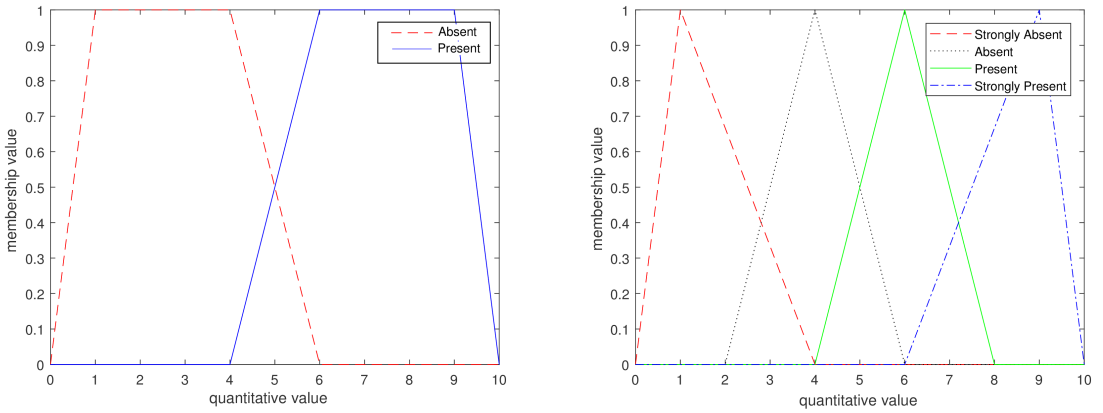
The notion of fuzzy sets and fuzzy logic is used to develop powerful mathematical tools to deal with uncertainty. They facilitate approximate reasoning for decision making in the absence of complete and precise information. Hence, they are applied to a wide variety of applications, *viz.*, traffic monitoring systems [52], weather forecasting [53] and gene expression data analysis [54] among others. In addition, researchers employ fuzzy logic to solve various complex mathematical problems like FredholmVolterra integro-differential equations [55], fuzzy differential equations [56] and second order two point fuzzy boundary value problems [57].

Here, in "Fuzzy Rule Mining" step of Figure 2, we try to employ fuzzy logic to dilute the crisp boundary among features with an objective to identify rules to differentiate epileptic patients from normal individuals. Two rule mining algorithms, such as Fuzzy Unordered Rule Induction Algorithm (FURIA) [58] and Fuzzy Coherent Rule Mining (FCR) [59], have been implemented to identify rules for differentiating epilepsy patients from normal individuals, and similarly for the different gender-specific and age-specific categories present in them. In this context, it should be mentioned that association rule mining algorithms suffer from some unwanted bias as the classes are not treated in a symmetric way. Moreover, they compromise comprehensibility due to priority based rule sorting. In order to overcome this problem, an unordered set has been used for learning in FURIA. Here FURIA has used a rule stretching method based on a previous investigation [60]. Besides, FCR employs the properties of propositional logic to overcome the problem of predefined minimum support threshold required in all association rule mining algorithms.

In our previous investigation [61], we have used FURIA with two fuzzy sets (Figure 3(a)), *viz.*, present or absent. For a more precise solution to the problem in hand, we have introduced four classes, *i.e.*, strongly present (SP), present (P), absent (A) and strongly absent (SA) using FCR (Figure 3(b)).

3.5.1. FURIA

It is a novel classification algorithm which learns fuzzy unordered rules based on rule stretching method. Here, we have used trapezoidal membership function to divide the universe of discourse into two fuzzy sets *viz.*, present or absent (Figure 3(a)). Here, we have considered all 120 features



(a) (b)

Figure 3: Graphical representation of fuzzy membership functions for (a) FURIA and (b) FCR.

of an epileptic/normal network as input to FURIA. Besides, we have calculated the Certainty Factor (CF) which is a numerical value quantifying the reliability of a rule. CF lies in an interval of [-1, 1]. If the antecedent and consequent clauses are related, the value of CF becomes positive. A higher value of CF represents a more significant rule.

3.5.2. Fuzzy Coherent Rule mining (FCR) algorithm

FCR algorithm [59] employs fuzzy triangular membership functions on the sample-wise feature matrix with class levels to derive rules differentiating classes under consideration. We have used a triangular membership function owing to its simplicity and smoothness to span the whole range of membership values.

Let us consider a feature matrix $(\boldsymbol{F})$ of dimensions $(m \times n)$, where m and n represent the number of individuals and the number of features respectively. We then randomly select 10 individuals. From the remaining $(m - 10)$ individuals again 10 individuals are selected randomly and the process continues until $\boldsymbol{F}$ has been divided into $(\approx m/10)$ smaller submatrices. Thereafter, for every submatrix, we find the sum of each of n $(= 120)$ columns to form a feature vector of dimension $(1 \times n)$. This is done for all $(\approx m/10)$ submatrices to form a new feature matrix of dimension $((m/10) \times n)$, the value of which varies from 0 to 10. Here, a quantitative value of 10 implies that the feature is present in all the randomly chosen individuals and thus has the highest electrode-electrode connectivity, while 0 represents absence in all individuals.

Based on the strength of electrode-electrode connection present, we have developed four membership functions, *viz.*, SP (quantitative value 6-10), P (quantitative value 4-8), A (quantitative value 2-6), and SA (quantitative value 0-4). The membership values and the corresponding electrode-electrode connections are depicted in Figure 3(b). Here, we have considered all the 120 features as input. Besides, we have calculated the prediction accuracy to identify certain class types using the rules extracted by FCR.

Table 3: List of significant features differentiating epileptic patients from normal individuals; male from female epilepsy; and child from teenage and adult epilepsy. Odd numbers following node names indicate left hemisphere of the brain, and similarly, even numbers indicate right hemisphere of the brain. The frequency of occurrence is given in percentage.

Normal Individuals vs Epileptic Patients				
Connection between lobes (Features)	Nodes	Epileptic	Normal	In epilepsy
Left central lobe & left frontal lobe	C3-F3	40	16.66	More
Left frontal lobe & left occipital lobe	F7-O1	57.50	23.33	More
Left frontal lobe & right occipital lobe	F7-O2	52.50	0.10	More
Left temporal lobe & left frontal lobe	T7-F7	35	0.12	More
Left parietal lobe & right parietal lobe	P7-P4	45	88.33	Less
Right frontal lobe & left frontal polar lobe	F8-FP1	42.50	0.13	More
Right temporal lobe & left frontal lobe	T8-F3	0.15	38.33	Less
Right parietal lobe & right parietal lobe	P8-P4	33.75	0.10	More
Right parietal lobe & left parietal lobe	P8-P7	35	0.07	More
Male vs Female Epileptic Patients				
Connection between lobes (Features)	Nodes	Male	Female	In female
Right parietal lobe & right frontal lobe	P4-F4	0.06	35.13	More
Right occipital lobe & left central lobe	O2-C3	44.18	27.02	Less
Right parietal lobe & right central lobe	P8-C4	60.46	83.78	More
Right occipital lobe & left parietal lobe	O2-P3	32.55	18.91	Less
Left parietal lobe & right occipital lobe	P7-O2	48.83	29.72	Less
Right frontal lobe & left frontal lobe	F8-F7	48.83	29.72	Less
Child vs Teenage & Adult Epileptic Patients				
Connection between lobes (Features)	Nodes	Child	Teenage	Adult
Right frontal lobe & left frontal lobe	F8-F3	49	13.63	11.76
Right parietal lobe & left frontal polar lobe	P8-FP1	0.07	40.90	35.29
Right parietal lobe & right temporal lobe	P8-T8	29.26	40.90	64.70
Right occipital lobe & right frontal lobe	O2-F4	12	9.09	35.29
Right occipital lobe & left occipital lobe	O2-O1	68	86.36	47.05
Left occipital lobe & left frontal polar lobe	O1-FP1	34.14	18.18	11.76
Right occipital lobe & left frontal lobe	O2-F3	48.78	54.54	23.52
Left frontal lobe & right parietal lobe	F7-P4	19.51	9.09	17.64

4. Results

Here we discuss the results obtained from feature selection, pattern mining [41, 42] and fuzzy rule mining [58, 59] methods. Feature selection and pattern mining algorithms have highlighted the class-specific presence or absence of some features. The fuzzy rule mining algorithms have reported some unique rules involving the features (present/absent) to further define the classes. In the following subsections, we discuss the salient features obtained from the results that can be later combined and considered as a normal/epileptic, male/female epileptic and child/teenage/adult epileptic signatures. It is to be mentioned here that some of the features have been found in more than one competing classes, and have been termed as global features. We have ignored them, as considering them would beat the basic purpose of finding class specific epileptic signatures.

4.1. Results on feature selection

We have found certain brain-region based connections (features) over-represented and a few under-represented, while comparing epileptic patients with normal volunteers. C3-F3, F7-O1, F7-O2, T7-F7, F8-FP1, P8-P4 and P8-P7 features have been found to be over-represented in epilepsy. On the other hand, P7-P4 and T8-F3 features have been found to be under-represented. The combination of these nine significant features (Table 3) has shown 82.59% average classification accuracy with 20 fold cross-validation. On the other hand, the least significant features have shown an average accuracy of 54.11% to separate normal individuals from epileptic patients in general.

In a similar way, we have found a few over-represented and under-represented features while comparing male and female epileptic patients. P4-F4 and P8-C4 features have been found to be over-represented along with under-representation of O2-C3, O2-P3, P7-O2 and F8-F7 features in case of female epileptic patients. Here, we have found 70.94% average classification accuracy with 20 fold cross validation for a combination of these six significant features (Table 3) for identifying male and female epileptic patients separately. However, a combination of six bad features yields an accuracy of 58.91% in this case.

On the other hand, the combination of eight good features (Table 3) has shown 62.14% average classification accuracy to discriminate child epileptic patients from teenage along with adult epileptic patients, while the least significant features have shown an accuracy of 45.54% for the same. F8-F3 feature has been found to be over-represented along with two under-represented P8-FP1 and P8-T8 features in case of child epilepsy. In the cases of teenage epilepsy, we have found an over-represented O2-F3 feature and under-represented F7-P4 feature. P8-T8 and O2-F4 features have been found to be over-represented in the case of adult epilepsy.

4.2. Results using apriori algorithm

Using all the available 120 features as input to the apriori algorithm [41], certain representative patterns have been identified with 60% minimum support threshold and 80% minimum confidence threshold. Global features, which are common to all classes, have been ignored.

Table 4: Features (by using apriori algorithm) with 60% minimum support threshold (MST) and 80% minimum confidence threshold (MCT) for differentiating epilepsy from normal individuals; male from female patients; and child from teenage and adult epilepsy. Odd numbers following node names indicate left hemisphere of the brain and even numbers indicate right hemisphere of the brain.

Normal Individuals vs Epileptic Patients										
Class	Features Present					Features Absent				
Epilepsy	(FP2-F3)	(T8-F7)				(F4-O1)	(C4-O1)	(P4-C3)		
Epilepsy	(C4-C3)	(T7-F4)				(F4-O1)	(C4-O1)	(T8-P7)		
Epilepsy	(O2-O1)	(F8-P4)				(C4-O1)	(P4-C3)	(T8-P7)		
Epilepsy	(T7-F4)	(T8-F7)				(C4-O1)	(P4-C3)	(P8-O1)		
Epilepsy	(F8-O2)	(T8-F7)				(C4-O1)	(T8-P7)	(P8-O1)		
Normal	(O1-FP1)	(FP2-F3)	(C4-P3)	(P7-P4)	(P8-T7)	(FP2-O1)	(C4-O1)	(P4-C4)	(T7-P4)	(P8-P7)
Normal	(O1-FP1)	(F4-C3)	(C4-P3)	(P7-P4)	(P8-T7)	(FP2-O1)	(C4-O1)	(T7-FP1)	(T7-P4)	(P8-P7)
Normal	(O1-FP1)	(C4-P3)	(P4-FP1)	(P7-P4)	(P8-T7)	(FP2-O1)	(C4-O1)	(T7-P4)	(P7-C4)	(P8-P7)
Normal	(O1-FP1)	(C4-P3)	(P7-O1)	(P7-P4)	(P8-T7)	(FP2-O1)	(C4-O1)	(T7-P4)	(F8-P7)	(P8-P7)
Normal	(O1-FP1)	(C4-P3)	(P7-P4)	(F8-O2)	(P8-T7)	(FP2-O1)	(C4-O1)	(T7-P4)	(P8-O1)	(P8-P7)
Normal	(O1-FP1)	(C4-P3)	(P7-P4)	(T8-F4)	(P8-T7)	(FP2-O1)	(C4-O1)	(T7-P4)	(P8-P4)	(P8-P7)
Normal	(O1-FP1)	(C4-P3)	(P7-P4)	(T8-F7)	(P8-T7)					
Normal	(O1-FP1)	(C4-P3)	(P7-P4)	(T8-T7)	(P8-T7)					
Male vs Female Epileptic Patients										
Class	Features Present					Features Absent				
Male	(FP2-F3)	(T7-F4)	(T8-F7)			(P3-F3)	(C4-O1)			
Male						(P3-F3)	(P4-C3)			
Male						(P3-F3)	(P4-F4)			
Male						(C4-O1)	(P4-C3)			
Male						(C4-O1)	(P4-F4)			
Male						(C4-O1)	(F7-FP1)			
Male						(C4-O1)	(T7-P4)			
Male						(C4-O1)	(P8-O1)			
Male						(P4-C3)	(P4-F4)			
Male						(P4-C3)	(F7-FP1)			
Male						(P4-C3)	(T7-P4)			
Male						(P4-F4)	(T7-P4)			
Female	(FP2-F3)	(P8-C4)				(F4-P3)	(C4-O1)	(F8-T7)		
Female	(C4-C3)	(T7-F4)								
Female	(C4-C3)	(F8-P4)								
Female	(C4-C3)	(P8-C4)								
Female	(P4-FP1)	(T7-F4)								
Female	(P4-FP1)	(F8-P4)								
Female	(P4-FP1)	(P8-C4)								
Female	(O2-O1)	(T7-F4)								
Female	(O2-O1)	(F8-P4)								
Female	(O2-O1)	(P8-C4)								
Female	(T7-F4)	(F8-P4)								
Female	(T7-F4)	(P8-C4)								
Female	(F8-P4)	(P8-C4)								
Female	(T8-F7)	(P8-C4)								
Child vs Teenage & Adult Epileptic Patients										
Class	Features Present					Features Absent				
Child	(FP2-F3)	(T7-FP2)	(F8-P4)			(C4-O1)	(P4-C3)	(O2-F4)		
Child						(C4-O1)	(P4-C3)	(T7-O2)		
Child						(C4-O1)	(P4-C3)	(T8-F3)		
Child						(C4-O1)	(P4-C3)	(P8-FP1)		
Child						(C4-O1)	(T7-O2)	(P8-FP1)		
Child						(C4-O1)	(T8-F3)	(P8-FP1)		
Teenage	(O2-O1)	(T7-F4)	(T8-F7)			(FP2-P3)	(F4-O1)	(C4-O1)	(F8-P7)	
Teenage	(O2-O1)	(T7-F4)	(P8-C4)			(FP2-P3)	(C4-O1)	(O2-F4)	(F8-P7)	
Teenage	(O2-O1)	(T8-F7)	(P8-C4)			(F4-O1)	(C4-O1)	(P4-F3)	(F8-P7)	
Teenage						(F4-O1)	(C4-O1)	(O2-F4)	(F8-P7)	
Teenage						(F4-O1)	(C4-O1)	(O2-F4)	(F7-P4)	
Adult	(FP2-F3)	(T7-F4)	(T8-F7)			(F4-FP1)	(P4-C3)	(T7-P4)	(T8-FP1)	
Adult						(F4-FP1)	(O2-C4)	(T7-P4)	(T8-FP1)	
Adult						(F4-FP1)	(F7-FP1)	(T8-FP1)	(T7-P4)	
Adult						(F4-FP1)	(T7-P4)	(T8-FP1)	(T8-F7)	

Presence of the features C4-C3, O2-O1, T7-F4 and F8-P4 along with absence of F4-O1, T8-P7 and P4-C3 features have been found to be associated with epilepsy patients. On the other hand, presence of the features O1-FP1, F4-C3, C4-P3, P4-FP1, P7-O1, P7-P4, T8-F4 and P8-T7 along with absence of FP2-O1, P4-C4, T7-FP, T7-P4, P7-C4, F8-P7 and P8-P7 features have been found to be associated with normal individuals (Table 4).

With the similar cut-off criteria, we have noticed absence of the features P3-F3, C4-O1, P4-C3, P4-F4, F4-P3, F7-FP1, T7-P4, P8-O1 and F8-T7 in case of male epileptic patients. Presence of the features C4-C3, P4-FP1, O2-O1, F8-P4, P8-C4 and F8-P4 have been noticed in female epileptic patients as reported in Table 4.

While comparing epileptic patients according to their age, presence of the features T7-FP2 and F8-P4 along with absence of P4-C3, T7-O2, T8-F3 and P8-FP1 features have been associated with child epileptic patients ($<$ 13 years of age). On the other hand, presence of the features O2-O1, and P8-C4 along with absence of FP2-P3, F4-O1, P4-F3, F8-P7 and F7-P4 features have been associated with teenage epileptic patients (13-19 years of age). Moreover, absence of the features F4-FP1, P4-C3, O2-C4, F7-FP1, T7-P4 and T8-FP1 have been associated with adult epileptic patients ($>$ 19 years of age). The detailed results are given in Table 4.

4.3. Results using FPG algorithm

We have used FPG algorithm with the cut-off values [60% minimum support threshold (MST) and 80% minimum confidence threshold (MCT)] to support/refute the results previously obtained by the apriori algorithm. In addition, the presence or absence of features have been supported by their respective confidence and lift values as reported in Table 5.

After ignoring the global features, presence of the feature F8-O2 and absence of the features P8-P3, F4-O1, F7-C4 and T8-P7 have been found to be associated with epilepsy patients. On the other hand, presence of the features P8-C4 and absence of the features P8-P4, P8-O1, F8-P7, P4-C4, FP2-O1, F7-O2 and T7-P4 have been found to be associated with normal individuals.

While comparing male and female epileptic patients, we have identified some following patterns (Table 5). Presence of the features T8-P3, C4-C3, F7-O2, F8-T7, F4-C3 and O2-O1 along with absence of O2-FP2, P4-F4, P4-C3 and T8-F8 features have been found to be associated with male epileptic patients. On the other hand, presence of the features T8-F4, P8-C4, F8-O2, F4-F3, P7-O1, F8-P4 and T7-P3 along with absence of F4-P3, F7-C4, F7-O2, P3-FP1, P8-P3, F8-T7 and C4-P3 features have been found to be associated with female epileptic patients.

Age-specific comparison of features also have revealed some interesting results (Table 5). Presence of the features T8-P4, F4-FP1, F8-P4, C4-F3, F4-P4 and T8-O2 along with absence of T7-C4, P3-FP1, P4-C3 and C4-P3 features have been reported in the case of child epilepsy. On the contrary, teenage epilepsy has been found to be associated with presence of P8-C4, P4-O1, O2-O1, O2-P3, F8-C4, T8-C3 and C4-F3 features along with absence of F4-C3, F7-P4, F8-P7 and P8-P3 features. Adult epilepsy patients have been found to be associated with presence of P7-C4, T7-P3, P8-P4 and T8-O2 features along with absence of the features P4-C4, T8-P7, T8-FP1, T7-P4 and F4-FP1.

Table 5: Features (used by FPG algorithm) with 60% minimum support threshold (MST) and 80% minimum confidence threshold (MCT) for differentiating epilepsy from normal individuals; male from female patients; and child from teenage and adult epilepsy with their respective confidence and lift values. Odd numbers following node names indicate left hemisphere of the brain and even numbers indicate right hemisphere of the brain.

Normal Individuals vs Epileptic Patients										
Class	Features Present			Confidence	Lift	Features Absent			Confidence	Lift
Epilepsy	(FP2-F3)	(T8-F7)		0.84	1.06	(P8-P3)	(C4-O1)		1	1.02
Epilepsy	(T7-F4)	(T8-F7)		0.84	1.06	(F4-O1)	(C4-O1)		0.96	1.03
Epilepsy	(C4-C3)	(T7-F4)		0.86	1.12	(F7-C4)	(C4-O1)		0.96	1.03
Epilepsy	(O2-O1)	(F8-P4)		0.87	1.15	(T8-P7)	(C4-O1)		0.94	1.02
Epilepsy	(F8-O2)	(T8-F7)		0.84	1.1	(F8-T7)	(C4-O1)		0.94	1.03
Normal	(FP2-F3)	(F8-P4)		0.81	1.01	(P8-P4)	(T7-P4)		1	1.02
Normal	(C4-C3)	(FP2-F3)		0.9	1.16	(P8-O1)	(T7-P4)		1	1.02
Normal	(P8-C4)	(F8-P4)		0.8	1	(C4-O1)	(F7-O2)	(T7-P4)	1	1.02
Normal	(P8-C4)	(T7-F4)		0.84	1.03	(C4-O1)	(P8-T7)	(T7-P4)	1	1.02
Normal	(FP2-F3)	(T7 - F4)		0.91	1.12	(F8-P7)	(T7-P4)		0.98	1
Normal	(C4-C3)	(T7-F4)		0.93	1.14	(P4-C4)	(T7-P4)		0.98	1
Normal	(FP2-F3)	(T7-F4)		0.85	1.04	(FP2-O1)	(T7-P4)		0.98	1
Normal	(T8-F7)	(FP2-F3)		0.8	1.03					
Normal	(O2-O1)	(T7-F4)		0.8	1.03					
Normal	(O2-O1)	(F8-P4)		0.86	1.08					
Normal	(O2-O1)	(T8-F7)		0.81	1.07					
Normal	(T7-F4)	(FP2-F3)	(C4-C3)	0.9	1.28					
Normal	(FP2-F3)	(C4-C3)	(T7-F4)	0.95	1.16					
Male vs Female Epileptic Patients										
Class	Features Present			Confidence	Lift	Features Absent			Confidence	Lift
Male	(T8-P3)	(F4-C3)		0.91	1.18	(O2-FP2)	(T8-F8)		0.97	1.06
Male	(C4-C3)	(T7-F4)	(FP2-F3)	1	1.17	(P4-F4)	(P4-C3)		0.94	1
Male	(C4-C3)	(T8-F7)	(FP2-F3)	1	1.17	(P4-F4)	(C4-O1)		0.94	1
Male	(F7-O2)	(FP2-F3)		1	1.17	(P4-C3)	(C4-O1)		0.94	1
Male	(T8-P3)	(T7-F4)		0.95	1.24	(T8-F8)	(C4-O1)		0.94	0.99
Male	(F8-T7)	(FP2-F3)		0.92	1.07	(T8-F8)	(P4-C3)		0.94	0.99
Male	(FP2-F3)	(O2-O1)	(T8-F7)	0.91	1.14					
Female	(FP2-F3)	(F8-O2)	(T8-F7)	0.92	1.18	(F4-P3)	(C4-P3)		1	1.07
Female	(T7-F4)	(F4-F3)	(F8-P4)	0.96	1.3	(F7-C4)	(C4-O1)		0.97	1.04
Female	(T8-F4)	(P7-O1)		0.92	1.53	(F7-O2)	(C4-O1)		0.97	1.04
Female	(P8-C4)	(P7-O1)	(T7-P3)	0.92	1.59	(P3-FP1)	(C4-O1)		0.97	1.04
Female						(P8-P3)	(C4-O1)		0.97	1.04
Female						(F8-T7)	(C4-O1)		0.93	0.99
Child vs Teenage & Adult Epileptic Patients										
Class	Features Present			Confidence	Lift	Features Absent			Confidence	Lift
Child	(T8-P4)	(F8-P4)		0.97	1.13	(T7-C4)	(C4-O1)		0.97	1.02
Child	(F4-F3)	(FP2-F3)		0.96	1.13	(O2-F4)	(C4-O1)		0.97	1.02
Child	(F4-FP1)	(F8-P4)		0.96	1.13	(P3-FP1)	(C4-O1)		0.97	1.02
Child	(F8-P4)	(F4-F3)	(FP2-F3)	0.96	1.12	(O2-F4)	(P4-C3)		0.97	1.05
Child	(C4-F3)	(FP2-F3)		0.93	1.09	(P4-C3)	(P8-FP1)	(C4-P3)	0.97	1.02
Child	(F8-P4)	(T8-O2)	(FP2-F3)	0.92	1.08	(C4-O1)	(P4-C3)		0.95	1.02
Teenage	(P8-C4)	(O2-P3)		1	1.16	(F4-C3)	(C4-O1)		1	1
Teenage	(P4-O1)	(T8-F7)		1	1.16	(F7-P4)	(C4-O1)		1	1
Teenage	(T7-F4)	(P8-C4)	(O2-O1)	1	1.16	(O2-F4)	(C4-O1)		1	1
Teenage	(O2-O1)	(F8-C4)	(T7-F4)	1	1.22	(F8-P7)	(C4-O1)		1	1
Teenage	(P8-C4)	(T8-C3)	(O2-O1)	1	1.16	(P8-P3)	(C4-O1)		1	1
Teenage	(T7-F4)	(C4-F3)	(T8-F7)	1	1.16					
Adult	(P7-C4)	(FP2-F3)		1	1.21	(P4-C4)	(T7-P4)		1	1
Adult	(T7-P3)	(P8-P4)		1	1.31	(T8-P7)	(T7-P4)		1	1
Adult	(F4-F3)	(T8-F7)		1	1.31	(T8-FP1)	(F4-FP1)		1	1.06
Adult	(T8-F7)	(T8-O2)	(T7-F4)	1	1.42	(T7-P4)	(F4-FP1)		1	1.06
Adult	(FP2-F3)	(T7-F4)	(T8-F7)	1	1.31	(F8-FP1)	(T7-P4)		1	1

4.4. Results using FURIA

In support of the aforementioned results, a fuzzy rule-based association mining study using FURIA has been done with all possible 120 features for finding some unique rules. We have performed this study to generate support for our earlier findings. We have found 6 unique rules for epileptic patients while 5 other rules have been found to be associated with normal individuals. Some features, *viz.*, T7-F7 and P8-P7 have been found to be associated with epilepsy as described earlier in Table 3. Presence of the feature T7-F7 has been found coupled with presence of two other features P7-F3 and P3-FP1.

Table 6: Fuzzy rules (obtained by FURIA) along with their certainty factors (CF) for differentiating epilepsy from normal individuals; male from female epilepsy; and child from teenage and adult epilepsy. Features are either present (P) or absent (A). Range of CF is [-1,1]. Odd numbers succeeding node names indicate left hemisphere of the brain and similarly, even numbers indicate right hemisphere of the brain.

Normal Individuals vs Epileptic Patients		
IF condition	Then	CF
(P7-P4) A & (P8-F7) A & (O2-C4) A	Epilepsy	0.97
(P4-FP2) P & (O2-FP2) P & (C3-FP1) A	Epilepsy	0.96
(F7-O2) P & (O2-FP2) A & (O2-F4) A	Epilepsy	0.96
(T7-F7) P & (P7-F3) P & (P3-FP1) A	Epilepsy	0.95
(P8-P7) P & (C4-FP1) P	Epilepsy	0.93
(P3-C3) P & (F8-FP2) A & (O2-FP1) A	Epilepsy	0.92
(P7-P4) P & (P4-FP2) A & (T7-F7) A & (F8-P3) A	Normal	0.96
(F7-O2) A & (T7-P3) A & (P7-F7) A	Normal	0.92
(P7-C3) A & (P4-FP2) A & (F7-C4) P & (P3-F3) A	Normal	0.94
(P8-O1) P & (F8-O1) P & (O1-C3) A	Normal	0.84
(P7-P4) P & (O2-FP2) A & (T7-F7) A & (P3-C3) A	Normal	0.96
Male vs Female Epileptic Patients		
IF condition	Then	CF
(F8-T7) P & (O1-FP1) P	Male epilepsy	0.92
(O2-P3) P & (O1-FP1) A	Male epilepsy	0.91
(P7-O2) P & (F7-F3) A & (T8-F8) A	Male epilepsy	0.93
(P4-F4) P & (P8-P3) P	Female epilepsy	0.89
(C3-FP1) P & (T7-C4) A & (F8-T7) A	Female epilepsy	0.91
(P8-F7) P & (F8-F7) A & (P3-C3) P	Female epilepsy	0.88
(F8-O1) P & (F4-P3) A & (C3-FP1) A	Female epilepsy	0.86
Child vs Teenage & Adult Epileptic Patients		
IF condition	Then	CF
(F8-F3) P & (T7-FP2) A	Child epilepsy	0.94
(O1-C3) P & (C4-C3) P	Child epilepsy	0.89
(F8-P4) P & (P8-FP1) A & (C4-F3) P	Child epilepsy	0.92
(P8-F4) P & (T7-C4) A & (FP2-O1) At	Child epilepsy	0.89
(P7-P4) A & (P8-FP1) P & (F7-P4) A	Teenage epilepsy	0.86
(P7-P3) P & (C3-FP1) A & (O1-C3) A	Teenage epilepsy	0.82
(P8-T8) P & (F8-P4) A & (T8-FP1) A	Adult epilepsy	0.8
(F4-C3) A & (T7-F7) P & (F7-O1) P	Adult epilepsy	0.74
(T8-FP2) P & (P8-P4) P & (F3-FP1) A	Adult epilepsy	0.74

The rule indicates epilepsy with a certainty factor of 0.95. Presence of P8-P7 feature has been found associated with the presence of a new feature C4-FP1 with a certainty factor of 0.93.

Moreover, multiple rules have been found for P7-P4 feature. Absence of the feature along with absence of two other features P8-F7 and O2-C4 have been found to be associated with epilepsy with a certainty factor of 0.97. On contrary, presence of P7-P4 feature along with absence of three other features P4-FP2, T7-F7 and F8-P3 has been found in normal individuals with a certainty factor of 0.96. Also, presence of the same factor along with absence of three other features O2-FP2, T7-F7, and P3-C3 has been found in normal individuals with a certainty factor of 0.96. In both the cases, the feature T7-F7 and its absence is a common factor. Such findings reflect the variable states of brain regions even for a very specific disease state.

Presence of feature F7-O2 along with absence of two other features O2-FP2 and O2-F4 has been associated with epilepsy with a certainty factor of 0.96. On the contrary, absence of the same feature along with absence of T7-P3 and P7-F7 features has been seen in normal individuals with a certainty factor of 0.92.

In the case of male versus female epileptic patients, presence of O2-P3 feature along with absence of the feature O1-FP1 has been found to be associated with male epilepsy with a certainty factor of 0.91. Similarly, presence of feature F8-T7 along with presence of another feature O1-FP1 has been found to be associated with male epilepsy with a certainty factor of 0.92. In contrast, presence of P4-F4 feature along with presence of the feature P8-P3 has been found to be associated with female epilepsy with a certainty factor of 0.89. Absence of the feature F8-F7 along with presence of features P8-F7 and P3-C3 have been found to be associated with female epilepsy. Such results support our earlier finding of regarding presence/absence of the features in male and female epilepsy as given in Table 3.

We have also performed an age-specific fuzzy rule mining study as given in Table 6. Here presence of F8-F3 and absence of P8-FP1 features have been found in two separate rules. They have been found to be associated with child epilepsy with certainty factors of 0.94 and 0.92 respectively. Absence of P8-FP1 feature along with presence of the features P7-P4 and F7-P4 with a certainty factor of 0.86 has been found to be associated with teenage epilepsy. In the case of adult epilepsy, presence of feature P8-T8 along with absence of two additional features F8-P4 and T8-FP1 has been found to be associated with a certainty factor of 0.8.

4.5. Results using FCR algorithm

Fuzzy rule mining study employing FURIA has determined some unique rules for each class, based on the presence or absence of features. Further categorization of the same features has been done by fuzzy coherent rule mining (FCR) algorithm, where four membership functions have been designed based on the strength of electrode-electrode connectivity. The rules that have been discovered using the algorithm are reported in Table 7.

The feature P7-P4 has been found to be absent in epilepsy patients. Absence of this feature coupled with strong presence of the feature FP2-F3, along with presence of features P8-T7 and C4-C3, with an accuracy of 69.29% can be considered as a unique rule for distinguishing epilepsy patients from normal individuals. Similarly, two more rules have been found for classifying epileptic patients with

Table 7: Fuzzy rules (obtained by FCR) along with their accuracy percentage (AP) for differentiating epilepsy from normal individuals; male from female epilepsy; and child from teenage and adult epilepsy. Features are termed as strongly present (SP), present (P), absent (A) or strongly absent (SA). Odd numbers following node names indicate left hemisphere of the brain and even numbers indicate right hemisphere of the brain.

Normal Individuals vs Epileptic Patients		
IF condition	Then	AP
(P4-FP1) SP & (O1-FP1) P & (T8-F7) SP & (F8-O2) SP	Epilepsy	74.64
(P7-P4) A & (FP2-F3) SP & (C4-C3) P & (P8-T7) P	Epilepsy	69.29
(F8-P4) SP & (P7-P4) A & (FP2-F3) SP & (P8-T7) P	Epilepsy	69.11
(T8-F7) SP & (P4-FP1) SP & (FP2-F3) P & (P8-T7) SP & (C4-C3) A	Normal	73.57
(P4-FP1) SP & (T8-F7) SP & (FP2-F3) P & (O1-FP1) P & (C4-C3) A	Normal	73.14
Male vs Female Epileptic Patients		
IF condition	Then	AP
(T7-F4) P & (FP2-F3) SP & (F4-C3) P & (P4-FP1) SP & (F8-O2) SP	Male epilepsy	75.35
(T7-F4) SP & (F4-C3) SP & (T8-F7) SP & (P4-FP1) P & (F8-O2) P	Male epilepsy	75.35
(T8-F7) SP & (P4-FP1) SP & (FP2-F3) P & (P8-T7) SP & (C4-C3) A	Female epilepsy	73.57
(P4-FP1) SP & (T8-F7) SP & (FP2-F3) P & (O1-FP1) P & (C4-C3) A	Female epilepsy	73.14
Child vs Teenage & Adult Epileptic Patients		
IF condition	Then	AP
(T7-P3) P & (C4-C3) SP & (P8-C4) P & (P7-O1) P & (F8-P4) SP & (T7-F4) SP	Child epilepsy	73.17
(T7-C3) A & (C4-C3) P & (T7-F4) P & (T8-P3) P	Teenage epilepsy	72.73
(P4-FP1) P & (C4-C3) SP & (T8-O2) SP & (T7-C3) SP	Teenage epilepsy	68.18

an accuracy of 74.64% and 69.11% as reported in Table 7. For normal individuals, presence of FP2-F3 feature along with absence of C4-C3 feature has been reported.

In association with the above features, P4-FP1 and T8-F7 have been found to be strongly present in the case of normal individuals. Further, feature P8-T7 and O1-FP1 have been found to be strongly present with an accuracy of 73.57% and 73.14% respectively, for two rules as given in Table 7.

Similarly, two unique rules have been reported - each for male and female epileptic patients. One rule has been found for child epileptic patients, while two other rules have been found to be associated with teenage epilepsy patients (Table 7). No unique rule has been discovered for adult epileptic patients by FCR algorithm.

5. Discussion of class-specific signatures

The features obtained from feature selection, apriori and FPG algorithms, along with the rules generated by FURIA and FCR algorithms have been combined and considered for generating the overall (epilepsy/normal individuals), gender-specific (male/female epilepsy) and age-specific (child or teenage or adult epilepsy) signatures (Table 8).

In order to generate such signatures, features that are more dominant for a particular class (as observed in Table 3) have been considered to be present in that class. On the other hand, non-dominant

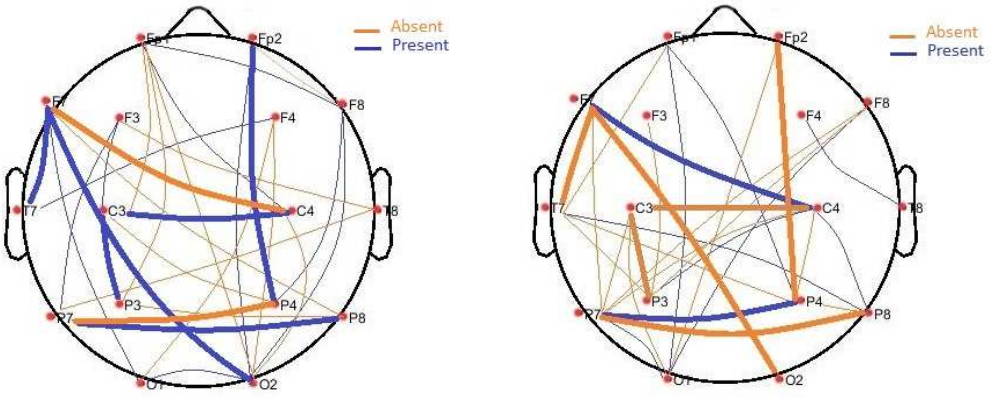
Table 8: Feature-based signatures found by combining results obtained from feature selection (S), apriori (A), FPG (F), FURIA (R) and FCR (C) algorithms for differentiating epilepsy from normal individuals; male from female patients; and child from teenage and adult epilepsy patients. Particular features present in one class and absent in the other class are similarly color coded. For example, presence of feature F7-O2 in epilepsy and absence of feature F7-O2 in normal individuals are color-coded similarly in blue. Color coding of features for overall, gender-based and age-based signatures have been done separately.

	Overall signatures		Gender-based signatures		Age-based signatures		
Features	Epilepsy	Normal	Male Epilepsy	Female Epilepsy	Child Epilepsy	Teenage Epilepsy	Adult Epilepsy
Present	F8-P4(S,A,C)	O1-FP1(A)	T8-P3(F)	P8-C4(S,A,F)	F8-F3(S,R)	O2-O1(S,A,F)	P8-T8(S,R)
	C3-F3(S)	C4-P3(A)	F7-O2(F)	P4-F4(S,R)	O1-FP1(S)	P8-FP1(S,R)	O2-F4(S)
	F7-O1(S)	P7-P4(A,R)	F4-C3(F,C)	P4-FP1(A)	F7-P4(S)	O2-F3(S)	P7-C4(F)
	F7-O2(S,R)	P8-T7(A)	O2-P3(R)	F8-P4(A,F)	F8-P4(A,F,R,C)	P4-O1(F)	P8-P4(F,R)
	T7-F7(S,R)	P4-FP1(A)	P7-O2(R)	T8-F4(F)	T8-P4(F)	O2-P3(F)	T7-F7(R)
	F8-FP1(S)	P7-O1(A)	T7-F4(C)	F4-F3(F)	F4-FP1(F)	F8-C4(F)	F7-O1(R)
	P8-P7(S,R)	T8-F4(A)		T7-P3(F)	C4-F3(F,R)	T8-C3(F)	T8-FP2(R)
	C4-C3(A,C)	P8-C4(F)		P8-F7(R)	O1-C3(R)	P7-P3(R)	
	O2-O1(A)	F7-C4(R)		P3-C3(R)	C4-C3(R)	T8-P3(C)	
	T7-F4(A)	F8-O1(R)		F8-O1(R)	P8-F4(R)	P4-FP1(C)	
	F8-O2(F,C)			P8-T7(C)	P7-O1(C)		
	P4-FP2(R)			O1-FP1(C)			
	O2-FP2(R)						
	P7-F3(R)						
	C4-FP1(R)						
	P3-C3(R)						
Absent	P7-P4(S,R,C)	FP2-O1(A,F)	P3-F3(A)	O2-C3(S)	T7-O2(A)	FP2-P3(A)	F4-FP1(A,F)
	T8-F3(S)	T7-P4(A)	C4-O1(A)	O2-P3(S)	T8-F3(A)	F4-O1(A)	T7-P4(A,F)
	F4-O1(A,F)	P8-P7(A)	P4-C3(A,F)	P7-O2(S)	P8-FP1(A,R)	F8-P7(A,F)	T8-FP1(A,F)
	P4-C3(A)	P4-C4(A,F)	P4-F4(A,F)	F8-F7(S,R)	T7-C4(F,R)	P4-F3(A)	O2-C4(A)
	T8-P7(A,F)	T7-FP1(A)	T7-P4(A)	F7-C4(F)	P3-FP1(F)	F7-P4(F,R)	F7-FP1(A)
	P8-P3(F)	P7-C4(A)	F7-FP1(A)	F7-O2(F)	C4-P3(F)	P8-P3(F)	P4-C4(F)
	F7-C4(F)	F8-P7(A,F)	P8-O1(A)	P3-FP1(F)	FP2-O1(R)	P7-P4(R)	T8-P7(F)
	P8-F7(R)	P8-P4(A,F)	O2-FP2(F)	C4-P3(F)		C3-FP1(R)	F8-P4(R)
	O2-C4(R)	F7-O2(F,R)	T8-F8(F,R)	T7-C4(R)		O1-C3(R)	F3-FP1(R)
	C3-FP1(R)	T7-P4(F)	F7-F3(R)	F4-P3(R)			
	O2-F4(R)	P4-FP2(R)		C4-C3(R)			
	P3-FP1(R)	T7-F7(R)					
	F8-FP2(R)	F8-P3(R)					
	O2-FP1(R)	T7-P3(R)					
		P7-F7(R)					
		P7-C3(R)					
		P3-F3(R)					
		O1-C3(R)					
		P3-C3(R)					
		C4-C3(C)					

features for a particular class (as depicted in Table 3) have been considered to be absent in that class. For the rules obtained from FCR algorithm, both present and strongly present features (as shown in Table 7) have been considered with equal weightage. Similarly, both absent and strongly absent features (as depicted in Table 7) have been given equal weightage. The combined signatures obtained from all algorithms under consideration have been reported in Table 8. Moreover, competing features have been avoided as they create confusion while defining a class-specific signature.

The signature for epileptic patients has been found to be a combination of sixteen present and fourteen absent features. Presence of ten features and absence of twenty features have together consti-

tuted the signature for the normal individuals (Table 8). Interestingly, six of present features (F7-02, T7-F7, P8-P7, C4-C3, P4-FP2 and P3-C3) of epileptic patients have been found to be absent in the opposite class, *i.e.*, in the normal individuals. In a similar manner, two of absent features (P7-P4 and F7-C4) of epileptic patients have been supported by their presence in normal individuals. The features have been accordingly color coded in Table 8. Such kind of clear distinction in the pattern of a feature (present/absent) in opposite classes generates confidence for the overall signatures (Figure 4).

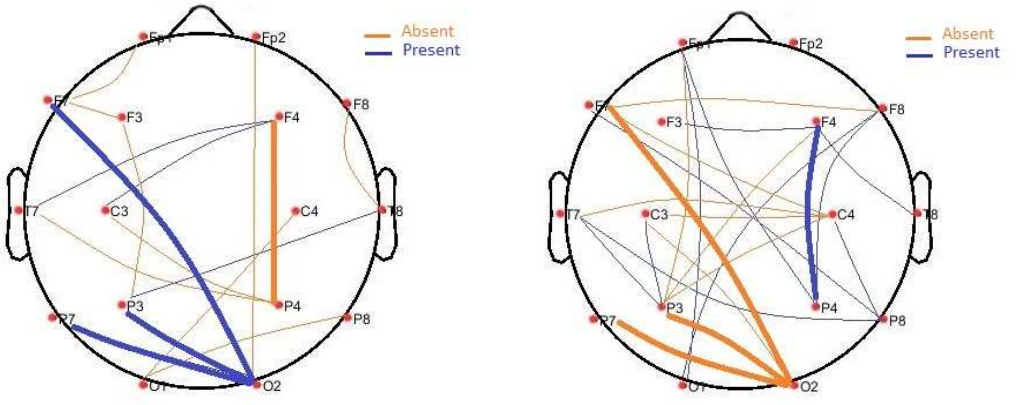


(a) (b)

Figure 4: Contrast expression patterns of features of overall signatures representing (a) epilepsy patients and (b) normal individuals respectively. The patterns are color-coded and bold-marked accordingly.

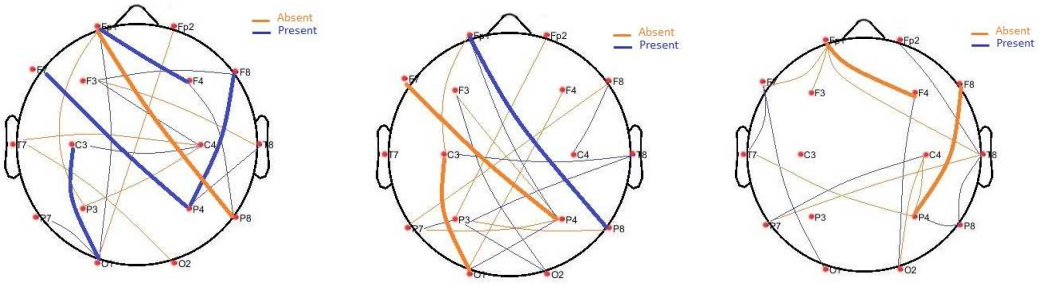
The male epilepsy-related signature has been found to be a combination of six present and ten absent features as reported in Table 8. Similarly, female epileptic patients have been found to be associated with a signature of twelve present and eleven absent features. The features F7-O2, O2-P3 and P7-O2 have been found to be present in male epileptic patients and absent in female epileptic patients. Similarly, the feature P4-F4 has been found to be absent in male epileptic patients but present in female epileptic patients (Figure 5). These present and absent features together with other features as given in Table 8 can be used to distinguish male and female epileptic patients.

Child epilepsy specific signature is a combination of eleven present and seven absent features (Table 8). Teenage epileptic patients have been found to be associated with a signature comprising ten present and nine absent features as reported in Table 8. Adult epilepsy specific signature is a combination of seven present and nine absent features (refer Table 8). The features F7-P4 and O1-C3 have been found to be present in child epileptic patients while the same features have been found to be absent in teenage epileptic patients. F4-FP1 and F8-P4 features have also been found to be present in child epileptic patients while they have been found to be absent in adult epileptic patients. The feature P8-FP1 has been found to be absent in child epileptic patients, but it has been found to be present in teenage epileptic patients as given in Figure 6. The contrasting pattern of features, *i.e.*, either present or absent in opposite classes, strengthens the age-specific signatures.



(a) (b)

Figure 5: Contrast expression patterns of features of gender-based signatures representing (a) male and (b) female epilepsy patients respectively. The patterns are color-coded and bold-marked accordingly.



(a) (b) (c)

Figure 6: Contrast expression patterns of features of age-based signatures representing (a) child, (b) teenage and (c) adult epilepsy patients respectively. The patterns are color-coded and bold-marked accordingly.

We have also discovered some new rules based on the fuzzy rule mining studies (FURIA and FCR). These rules could not be established earlier only from the feature selection and pattern mining studies. These new rules have contributed to creating well-defined signatures for future machine learning based detection of epilepsy.

6. Conclusions

In this paper, we have found generalized epileptic signatures from EEG data. Besides, we have also shown some gender and age specific epileptic signatures. In general, the epileptic signature has shown strong correlation between two brain regions, such as right frontopolar-right angular (FP2 - P4), left

caudal postcentral-right intermediate postcentral (C3 - C4), left anterior transversal temporal-left orbital part of inferior frontal (T7 - F7), left caudal postcentral-left angular (C3 - P3), left orbital part of inferior frontal-right parastriate (F7 - O2) and left occipitotemporal-right occipitotemporal (P7 - P8), in terms of EEG signals compared to healthy individuals. It is not always easy for medical practitioners to rightly identify an epileptic patient without multiple EEG recording sessions. The discovered epileptic signatures may help them in overcoming the lengthy existing procedure involved in epilepsy detection. Moreover, this kind of predictions can come in handy with minimal human intervention in peripheral and rural areas where proper medical facility is not available as of yet. The signatures can quickly be employed to detect probable epilepsy, after which the patient can be referred for proper medical care. Here, we have also discovered epilepsy signatures for different gender and age groups. Female epileptic signature has shown a strong correlation between right intermediate frontal and right angular (F4 -P4) in terms of EEG signals compared to male epileptic signature. Moreover, child epileptic signature has depicted strong correlation between two brain regions, such as left caudal postcentral-left parastriate (C3 - O1), left orbital part of inferior frontal-right angular (F7 - P4), right triangular-right angular (F8 - P4) and left frontopolar-right intermediate frontal (FP1 - F4), in terms of EEG signals compared to teenage and adult epileptic signatures. According to clinicians, identifying the gender-specific epileptic signatures is an interesting concept and may be helpful in future.

Acknowledgements

Abhijit Dasgupta acknowledges Digital India Corporation (formerly Media Lab Asia), Ministry of Electronics and Information Technology, Government of India, for providing him a Senior Research Fellowship under the Visvesvaraya Ph.D. scheme for Electronics and IT. Losiana Nayak acknowledges University Grants Commission, India for a UGC Post-Doctoral Fellowship (No. F.15-1/2013-14/PDFWM-2013-14-GE-ORI-19068(SA-II)). Ritankar Das acknowledges Council for Scientific and Industrial Research (CSIR), India for providing him a Senior Research Fellowship (09/093(0182)/2018 EMR-I).

References

[1] Devinsky O. Sudden, unexpected death in epilepsy. New England Journal of Medicine. 2011 Nov 10; 365(19):1801–1811. DOI: 10.1056/NEJMra1010481.

[2] Giourou E, Stavropoulou-Deli A, Giannakopoulou A, Kostopoulos GK, Koutroumanidis M. Introduction to Epilepsy and Related Brain Disorders. In: Cyberphysical Systems for Epilepsy and Related Brain Disorders 2015 (pp. 11–38). Springer, Cham. DOI: 10.1007/978-3-319-20049-1_2.

[3] Donders J, Hunter SJ. Neuropsychological Conditions Across the Lifespan. Cambridge University Press. 2018 Aug 2016. ISBN: 9781316996751.

[4] Devinsky O, Vezzani A, O'Brien TJ, Jette N, Scheffer IE, de Curtis M, Perucca P. Epilepsy. Nature Reviews Disease Primers, 2018. 4(18024). URL `https://doi.org/10.1038/nrdp.2018.24`.

[5] Wendling F, Chauvel P, Biraben A, Bartolomei F. From intracerebral EEG signals to brain connectivity: identification of epileptogenic networks in partial epilepsy. Frontiers in Systems Neuroscience, 2010 Nov 25; 4:154. URL `https://doi.org/10.3389/fnsys.2010.00154`.

[6] Dixit AB, Banerjee J, Tripathi M, Chandra PS. Presurgical epileptogenic network analysis: A way to enhance epilepsy surgery outcome. Neurology India, 2015 Sep 1;. 63(5):743. DOI:10.4103/0028-3886.166546.

[7] Tzallas AT, Tsipouras MG, Fotiadis DI. Automatic seizure detection based on time-frequency analysis and artificial neural networks. Computational Intelligence and Neuroscience, 2007. URL `http://dx.doi.org/10.1155/2007/80510`.

[8] Polat K, Güneş S. Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform. Applied Mathematics and Computation, 2007 Apr 15; 187(2):1017–1026. URL `https://doi.org/10.1016/j.amc.2006.09.022`.

[9] Gandhi T, Panigrahi BK, Bhatia M, Anand S. Expert model for detection of epileptic activity in EEG signature. Expert Systems with Applications, 2010 Apr 1; 37(4):3513–3520. URL `https://doi.org/10.1016/j.eswa.2009.10.036`.

[10] Gopan G, Sinha N, Babu D. Statistical features based epileptic seizure EEG detection-an efficacy evaluation. In: 2015 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE, 2015 Aug 10 (pp. 1394–1398). DOI: 10.1109/ICACCI.2015.7275808.

[11] Ahmadi A, Shalchyan V, Daliri MR. A new method for epileptic seizure classification in EEG using adapted wavelet packets. In: Electric Electronics, Computer Science, Biomedical Engineerings' Meeting (EBBT). IEEE, 2017 Apr 20 (pp. 1–4). DOI: 10.1109/EBBT.2017.7956756.

[12] Park C, Choi G, Kim J, Kim S, Kim TJ, Min K, Jung KY, Chong J. Epileptic seizure detection for multi-channel EEG with deep convolutional neural network. In: International Conference on Electronics, Information, and Communication (ICEIC). IEEE, 2018 Jan 24 (pp. 1–5). DOI: 10.23919/ELINFOCOM.2018.8330671.

[13] Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of Neuroscience Methods. 2004 Mar 15; 134(1):9–21. URL `https://doi.org/10.1016/j.jneumeth.2003.10.009`.

[14] Naik GR, Kumar DK, Palaniswami M. Multi run ICA and surface EMG based signal processing system for recognising hand gestures. In: 2008 8th International Conference on Computer and Information Technology. IEEE, 2008 Jul 8 (pp. 700–705). DOI: 10.1109/CIT.2008.4594760.

[15] Sedgwick P. Pearsons correlation coefficient. BMJ. 2012 Jul 4; 345:e4483. URL `https://doi.org/10.1136/bmj.e4483`.

[16] Dasgupta A, Das R, Nayak L, De RK. Analyzing epileptogenic brain connectivity networks using clinical EEG data. In: 2015 International Conference on Bioinformatics and Biomedicine (BIBM). IEEE, 2015 Nov 9 (pp. 815–821). DOI: 10.1109/BIBM.2015.7359791.

[17] Peng H, Long F, Ding C. Feature selection based on mutual information: criteria of max-dependency, max-relevance, and min-redundancy. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2005 Aug 1; (8):1226–1238. DOI: 10.1109/TPAMI.2005.159.

[18] Mika S, Ratsch G, Weston J, Scholkopf B, Mullers KR. Fisher discriminant analysis with kernels. In: Neural Networks for Signal Processing IX: Proceedings of the 1999 IEEE Signal Processing Society Workshop (cat. no. 98th8468). IEEE, 1999 Aug 25 (pp. 41–48). DOI: 10.1109/NNSP.1999.788116.

[19] Zhou N, Wang L. A modified T-test feature selection method and its application on the HapMap genotype data. Genomics, Proteomics & Bioinformatics. 2007 Jan 1; 5(3–4):242–249. URL `https://doi.org/10.1016/S1672-0229(08)60011-X`.

[20] Park H, Kwon S, Kwon HC. editor. Complete gini-index text (git) feature-selection algorithm for text classification. In: The 2nd International Conference on Software Engineering and Data Mining (SEDM). IEEE 2010 Jun 23 (pp. 366–371). ISBN: 978-1-4244-7324-3.

[21] Urbanowicz RJ, Meeker M, La Cava W, Olson RS, Moore JH. Relief-based feature selection: introduction and review. Journal of Biomedical Informatics. 2018 Sep 1; 85:189–203. URL https://doi.org/10.1016/j.jbi.2018.07.014.

[22] Wang L, Zhang Z, Design CX. Theory and applications. Support Vector Machines, volume 177. Springer Science & Business Media, 2005. ISBN 978-3-540-24388-5.

[23] Priyadarsini RP, Valarmathi M, Sivakumari S. Gain ratio based feature selection method for privacy preservation. ICTACT Journal on soft computing. 2011 Apr; 1(4):201–205. DOI: 10.21917/ijsc.2011.0031.

[24] Chen YT, Chen MC. Using chi-square statistics to measure similarities for text categorization. Expert Systems with Applications. 2011 Apr 1; 38(4):3085–3090. URL https://doi.org/10.1016/j.eswa.2010.08.100.

[25] Luukka P. Feature selection using fuzzy entropy measures with similarity classifier. Expert Systems with Applications. 2011 Apr 1; 38(4):4600–4607. URL https://doi.org/10.1016/j.eswa.2010.09.133.

[26] Saeys Y, Inza I, Larrañaga P. A review of feature selection techniques in bioinformatics. Bioinformatics. 2007 Oct 1; 23(19):2507–2517. URL https://doi.org/10.1093/bioinformatics/btm344.

[27] Shang W, Huang H, Zhu H, Lin Y, Qu Y, Wang Z. A novel feature selection algorithm for text categorization. Expert Systems with Applications. 2007 Jul 1; 33(1):1–5. URL https://doi.org/10.1016/j.eswa.2006.04.001.

[28] Liu H, Motoda H., editors. Computational methods of feature selection. CRC Press; 2007 Oct 29. ISBN: 13:978-1-58488-879-6.

[29] Yingwei L, Sundararajan N, Saratchandran P. Performance evaluation of a sequential minimal radial basis function (RBF) neural network learning algorithm. IEEE Transactions on Neural Networks. 1998 Mar; 9(2):308–318. DOI: 10.1109/72.661125.

[30] Liaw A, Wiener M. Classification and regression by random Forest. R News, 2002. 2(3):18–22.

[31] Orhan U, Hekim M, Ozer M. EEG signals classification using the K-means clustering and a multilayer perceptron neural network model. Expert Systems with Applications. 2011 Sep 15; 38(10):13475–13481. URL https://doi.org/10.1016/j.eswa.2011.04.149.

[32] Schuster I, Jähnichen P. Classification using Logistic Regression. Universität Lepzig, 2012. URL http://asv.informatik.uni-leipzig.de/uploads/document/file_link/530/TMI05.2_logistic_regression.pdf.

[33] Genkin A, Lewis DD, Madigan D. Large-scale Bayesian logistic regression for text categorization. Technometrics. 2007 Aug 1; 49(3):291–304. DOI: 10.1198/004017007000000245.

[34] Rodriguez JJ, Kuncheva LI, Alonso CJ. Rotation forest: A new classifier ensemble method. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2006 Aug 21; 28(10):1619–1630. DOI: 10.1109/TPAMI.2006.211.

[35] Bernardo J, Berger J, Dawid A, Smith A, et al. Regression and classification using Gaussian process priors. Bayesian Statistics. 1998 Jun 6; 6:475. ISBN: 0198504853, 9780198504856.

[36] Witten IH, Frank E, Hall MA, Pal CJ. Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann; 2016 Oct 1. ISBN: 0128043571, 9780128043578.

[37] Mika S, Ratsch G, Weston J, Scholkopf B, Mullers KR. Fisher discriminant analysis with kernels. In: Neural networks for signal processing IX: Proceedings of the 1999 IEEE signal processing society workshop (cat. no. 98th8468). IEEE 1999 Aug 25 (pp. 41–48). ISBN: 0-7803-5673-X.

[38] Weinberger KQ, Saul LK. Distance metric learning for large margin nearest neighbor classification. Journal of Machine Learning Research. 2009; 10(Feb):207–244. URL http://www.jmlr.org/papers/volume10/weinberger09a/weinberger09a.pdf.

[39] Kukreja M, Johnston SA, Stafford P. Comparative study of classification algorithms for immunosignaturing data. BMC bioinformatics. 2012 Dec; 13(1):139. URL https://doi.org/10.1186/1471-2105-13-139.

[40] McCallum A, Nigam K. A comparison of event models for naive bayes text classification. In: AAAI-98 workshop on learning for text categorization. 1998 Jul 26; (vol. 752, No. 1, pp. 41–48). URL http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.65.9324&rep=rep1&type=pdf.

[41] Agarwal R, Srikant R. Fast algorithms for mining association rules. In: Proceedings of the 20th VLDB Conference. 1994 (Vol, 1215, pp. 487–499). ISBN: 1-55860-238-0.

[42] Han J, Pei J, Yin Y. Mining frequent patterns without candidate generation. In: ACM Sigmod Record 2000 May 16 (vol. 29, No. 2, pp. 1–12). ISBN: 1-58113-217-4.

[43] Song M, Rajasekaran S. A transaction mapping algorithm for frequent itemsets mining. IEEE transactions on knowledge and data engineering. 2006 Feb 27; 18(4):472–481. DOI: 10.1109/TKDE.2006.1599386.

[44] Hoseini MS, Shahraki MN, Neysiani BS. A new algorithm for mining frequent patterns in Can Tree. In: 2015 2nd International Conference on Knowledge-Based Engineering and Innovation (KBEI). IEEE, 2015 Nov 5 (pp. 843–846).

[45] Zaki MJ. Scalable algorithms for association mining. IEEE transactions on knowledge and data engineering. 2000 May;. 12(3):372–390. DOI: 10.1109/69.846291.

[46] Agarwal RC, Aggarwal CC, Prasad VVV. A tree projection algorithm for generation of frequent item sets. Journal of parallel and Distributed Computing. 2001 Mar 1; 61(3):350–371. URL https://doi.org/10.1006/jpdc.2000.1693.

[47] Győrödi C, Győrödi R, Holban S. A comparative study of association rules mining algorithms. In: SACI 2004, 1st Romanian-Hungarian Joint Symposium on Applied Computational Intelligence. 2004 (pp. 213–222). URL http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.123.2771&rep=rep1&type=pdf.

[48] Bonchi F, Goethals B. FP-Bonsai: the art of growing and pruning small fp-trees. In: Pacific-Asia Conference on Knowledge Discovery and Data Mining. Springer, 2004 May 26 (pp. 155–160). URL https://doi.org/10.1007/978-3-540-24775-3_19.

[49] Borgelt C. Keeping things simple: finding frequent item sets by recursive elimination. In: Proceedings of the 1st international workshop on open source data mining: frequent pattern mining implementations. ACM, 2005 Aug 21 (pp. 66–70).

[50] Chee CH, Jaafar J, Aziz IA, Hasan MH, Yeoh W. Algorithms for frequent itemset mining: a literature review. Artificial Intelligence Review. 2019 Dec 1; 52(4):2603–2621. URL https://doi.org/10.1007/s10462-018-9629-z.

[51] Qodmanan HR, Nasiri M, Minaei-Bidgoli B. Multi objective association rule mining with genetic algorithm without specifying minimum support and minimum confidence. Expert Systems with Applications. 2011 Jan 1; 38(1):288–298. URL https://doi.org/10.1016/j.eswa.2010.06.060.

[52] Khalid M. Intelligent traffic lights control by fuzzy logic. Malaysian Journal of Computer Science. 1996 Dec 1; 9(2):29–35. URL https://ejournal.um.edu.my/index.php/MJCS/article/view/2995.

[53] Riordan D, Hansen BK. A fuzzy case-based system for weather prediction. Engineering Intelligent Systems for Electrical Engineering and Communications. 2002 Sep 1; 10(3):139–146. URL https://pdfs.semanticscholar.org/0719/a63450701017c89bfe3d60800485ae72c76b.pdf.

[54] Woolf PJ, Wang Y. A fuzzy logic approach to analyzing gene expression data. Physiological Genomics. 2000 Jun 29; 3(1):9–15.URL https://doi.org/10.1152/physiolgenomics.2000.3.1.9.

[55] Arqub OA. Adaptation of reproducing kernel algorithm for solving fuzzy Fredholm–Volterra integrodifferential equations. Neural Computing and Applications. 2017 Jun 1; 28(7):1591–1610. URL https://doi.org/10.1007/s00521-015-2110-x.

[56] Arqub OA, Mohammed AS, Momani S, Hayat T. Numerical solutions of fuzzy differential equations using reproducing kernel Hilbert space method. Soft Computing. 2016 Aug 1; 20(8):3283–3302. URL https://doi.org/10.1007/s00500-015-1707-4.

[57] Arqub OA, Al-Smadi M, Momani S, Hayat T. Application of reproducing kernel algorithm for solving second-order, two-point fuzzy boundary value problems. Soft Computing. 2017 Dec 1; 21(23):7191–7206. URL https://doi.org/10.1007/s00500-016-2262-3.

[58] Hühn J, Hüllermeier E. FURIA: an algorithm for unordered fuzzy rule induction. Data Mining and Knowledge Discovery. 2009 Dec 1; 19(3):293–319. URL https://doi.org/10.1007/s10618-009-0131-8.

[59] Chen CH, Li AF, Lee YC. A fuzzy coherent rule mining algorithm. Applied Soft Computing. 2013 JUl 1; 13(7):3422–3428. URL https://doi.org/10.1016/j.asoc.2012.12.031.

[60] Eineborg M, Boström H. Classifying uncovered examples by rule stretching. In: International Conference on Inductive Logic Programming. Springer, 2001 Sep 9 (pp. 41–50). URL https://doi.org/10.1007/3-540-44797-0_4.

[61] Dasgupta A, Nayak L, Das R, Basu D, Chandra P, De RK. Feature Selection and Fuzzy Rule Mining for Epileptic Patients from Clinical EEG Data. In: International Conference on Pattern Recognition and Machine Intelligence, Kolkata. Springer, 2017 Dec 5 (pp. 87–95). URL https://doi.org/10.1007/978-3-319-69900-4_11.

[62] Hühn JC, Hüllermeier E. An analysis of the FURIA algorithm for fuzzy rule induction. In: Advances in machine learning I. Springer 2010 (pp. 321–344). URL https://doi.org/10.1007/978-3-642-05177-7_16.