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Detection of Epilepsy with Electroencephalogram using Rule-based Classifiers

Guanjin Wang[1,2,*] , Zhaohong Deng[3], Kup-Sze Choi[1,2,4]

[1]School of Nursing, Hong Kong Polytechnic University, Hong Kong, China
[2]Centre for Smart Health, School of Nursing, Hong Kong Polytechnic University, Hong Kong, China
[3]School of Digital Media, Jiangnan University, Wuxi, Jiangsu, China
[4]Interdisciplinary Division of Biomedical Engineering, Hong Kong Polytechnic University, Hong Kong, China

Corresponding author. Tel.: +852-2766-3913; fax: +852-2364-9663.
E-mail address: guanjin.br.wang@connect.polyu.hk (G. Wang)

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Abstract

Epilepsy is a common neurological disorder and is characterized by recurrent seizures. Electroencephalography (EEG) signals, as a useful measure for analysing the brain's electrical activity, has been widely used for the detection of epilepsy. Most of current relevant researches primarily aim at increasing the detection accuracy, while the interpretability of the methods receives relatively little attention. In this work, we concentrate on the epileptic classification of EEG signals with interpretability. We first propose an epilepsy detection framework for EEG data, followed by a comparative study under this framework to evaluate the accuracy and interpretability of four rule-based classifiers, namely, the decision tree algorithm C4.5, the random forest algorithm (RF), the support vector machine (SVM) based decision tree algorithm (SVM+C4.5) and the SVM based RF algorithm (SVM+RF), in two-group, three-group, and the most challenging five-group classification of EEG signals. The experimental results show that RF outperforms the other three rule-based algorithms, achieving average accuracies of 0.9896, 0.9600 and 0.8260 for two-group, three-group and five-group seizure classification respectively, and exhibiting higher interpretability.

Keywords: seizure detection, EEG, random forest, SVM, ensemble learning approach

1. Introduction

Epilepsy is a common brain disorder, characterized by recurrent seizures [1]. Approximately fifty million people over the world suffer from epilepsy and eighty percent of them are in developing countries. More than two million new cases of epilepsy are diagnosed per year worldwide [2]. Electroencephalogram (EEG) signals are widely used to detect the existence of epilepsy by directly recording the brain's electrical activity [3]. However, EEG signal analysis is non-trivial, and given the spontaneity of epileptic seizures, the detection of an epileptic seizure remains a clinical issue, where the treatment relies on an accurate diagnosis. Hence, an automated detection system that is able to classify epileptic EEG signals from normal ones is helpful for making diagnosis. For such a system, the recorded EEG signals ~~recorded~~ are the input whereas the classification of EEG signals is the output. Generally, two steps are involved in the detection system: (i) extraction of features from the EEG input signals and (ii) classification of the extracted features to identify epileptic EEG signals [4]. In this study, we concentrate particularly on the latter, investigating the effectiveness of rule-based classification approaches in detecting epileptic seizures using EEG signals acquired under five different conditions (see Table 1, to be discussed later) [5]. Investigations are conducted to detect epilepsy by classifying the signals into two, three and five groups using machine learning techniques. A standard feature extraction method, i.e. short time Fourier transform (STFT) [6,8], is employed in the study.

Many machine learning methods have been applied to classify EEG signals. The experimental results show that EEG signals contain informative features for the detection of seizure events and automated diagnostic systems constructed by machine learning methods are effective [7] [8]. For two-class epilepsy classification, i.e. distinguishing EEG signals collected in normal and ictal stage, neural network based model [7,9-18], adaptive neuro-fuzzy inference system [19], Elman network [20], mixture expert model [21, 56], decision tree [22] [23], support vector machine (SVM) [24-26]and least square support vector machine (LS-SVM) [27] have been applied for diagnosis of epilepsy. For three-class epilepsy classification involving normal, interictal and ictal stages, recurrent neural network [12], spiking neural network [28, 29], back propagation neural network [30], radial basis function neural network [31], SVM [32-35], k-nearest neighbour (KNN) [15], Fuzzy classifier [36] and the C4.5 algorithm for decision tree [37] have been explored. Although variations in dynamical properties of brain electrical activities have been shown clearly at different extracranial and intracranial recording regions and at different physiological and pathological brain states [5], almost all the existing researches on EEG signal analysis and classifications focus on two-group classification and three-group classification, with little attention paid on the most challenging five-group classification.

Besides, a shortcoming with the frequently used EEG signal classification techniques, e.g. SVM and artificial neural network (ANN) [38] [39] , is that they suffer from the “black-box” problem where the actual meaning of the rules learned is not available even though a working model can be obtained. Therefore, it is important to improve the interpretability of the classification methods in order to make automated epilepsy detection system practically more useful for clinical diagnosis applications.

The SVM algorithm is a machine learning technique that can be integrated to extract the underlying rules from datasets obtained from a system, like the traditional approach of decision trees. It is a nonlinear predictive data mining technique and exhibits good generalization behaviour. The existing rule extraction approaches based on SVM can be summarized into three categories [36]: (i) learning based approach, treating SVM model as a closed box, (ii) eclectic approach, extracting rules from the support vectors (SVs), and (iii) decompositional approach, making use of the SVs and decision function of the training data. In this study, the eclectic approach is used which integrates both learning based and decompositional approaches by only using SVs or applying rule-based model to train the synthetic data based on the SVs [37, 38]. The approach can also extract the rules with high accuracy from datasets in different medical domains, e.g. diabetes, heart diseases, breast cancer, hepatitis and on the SVs [37, 38]. Barakat et al. proposed a method to extract rules from a subset of the SVs of a SVM model by a modified sequential covering algorithm which involved an ordered search of the most discriminative features as determined by the inter-class separation [40]. Chaves et al. extracted fuzzy rules from SVM by projecting the coordinate axes of each feature onto the SVs to formulate the fuzzy sets [41]. The fuzzy membership degrees were then calculated so that each of the SVs was assigned to the fuzzy set with the highest membership degree, and finally the fuzzy rules were extracted from each SV. A rule extraction method was also developed based on decision tree model using the SV of SVM [42]. The method generated an artificial dataset and replaced the actual class labels by the predicted class labels. A decision tree learner was then applied to the artificial dataset to learn what the SVM had learned to generate the rules. Similarly, a hybrid method was proposed for diabetes diagnosis using the *ensemble learning* approach where the C4.5 algorithm and random forest algorithm (RF) are applied to classify the artificial datasets of SVs [43].

In this study, we focus on the investigation of rule-based classification techniques for epilepsy detection with EEG data in an attempt to identify the ones with both high accuracy and high interpretability. Four approaches are studied, including the traditional decision tree algorithm C4.5, RF, and two SVM-based rule extraction algorithms developed using the ensemble learning approach, namely, the SMM-based decision tree algorithm (SVM+C4.5) and the SVM-based RF algorithm (SVM+RF). The performance of the four algorithms in detecting epileptic seizures is compared with reference to their ability to identify two, three and five groups of distinct EEG signals. The major findings of the study are as follows:

1. The ensemble learning approach is adopted to deal with the “black-box” issue with SVM by incorporating the RF and C4.5 algorithms respectively to improve the interpretability. The feasibility and performance are evaluated by comparing them with the results obtained using the traditional RF and C4.5 algorithms alone.

2. The results of the study indicate that the overall performance of RF in epileptic EEG signal detection is outstanding among the four approaches. In addition to the high interpretability it offers, RF demonstrates high classification accuracy in differentiating two,, three or five groups of EEG signals.

This paper is structured as follows. Section 2 describes the detection framework used to evaluate the epileptic EEG signal classification methods. Section 3 discusses the EEG datasets adopted in the study and the STFT algorithm used for feature ex-traction, followed by a review of the SVM and rule-based classifiers concerned in Section 4. The experimental results are discussed in Section 5, and conclusions are given in Section 6.

2. The Proposed Detection Framework

A framework is proposed to evaluate the EEG signal classification algorithms for epileptic seizure detection. It is used to assess the performance of the algorithms in classifying EEG signals into two, three and five separate groups. The five sets of EEG signals were acquired from healthy subjects with their eyes open (eye open) and their eyes closed (eye closed) respectively;

and from subjects with epilepsy at interictal (signals measured at two different locations of the brain) and ictal state [5].

Three stages are involved in the proposed detection framework. The first stage is feature extraction, where STFT is applied to the EEG signals to generate the training and testing dataset with the extracted features. In the second stage, the training dataset is used by the four rule-based classifiers, i.e. the decision tree algorithm C4.5, RF, and two ensemble learning approaches SVM+C4.5 and SVM+RF, to construct the rules for classification on the extracted features. In the third stage, the rule sets generated from the four classifiers are evaluated on the testing dataset and the corresponding results are compared. The proposed detection framework is shown in Fig. 1.

Note that while SVM has previously been applied for the analysis of EEG signals, the SVM-based ensemble learning approaches for rule extraction, SVM+C4.5 and SVM+RF, have never been used for multi-class classification of EEG signals. Although SVM+RF exhibits superiority over the other rule-based classifiers for diagnosis of diabetes [43], evidence is needed to support whether it would also outperform others in the detection of epileptic seizures in EEG signals. Besides, C4.5 has also been used for two-group and three-group classification of epileptic EEG signals, but its performance on five-group classification has yet to be evaluated. As a conventional rule-based algorithm, RF has not been applied used for the classification of epileptic EEG signals. Hence, these algorithms are of interest for the detection of epileptic seizures with EEG signals and are selected for evaluation in this study.

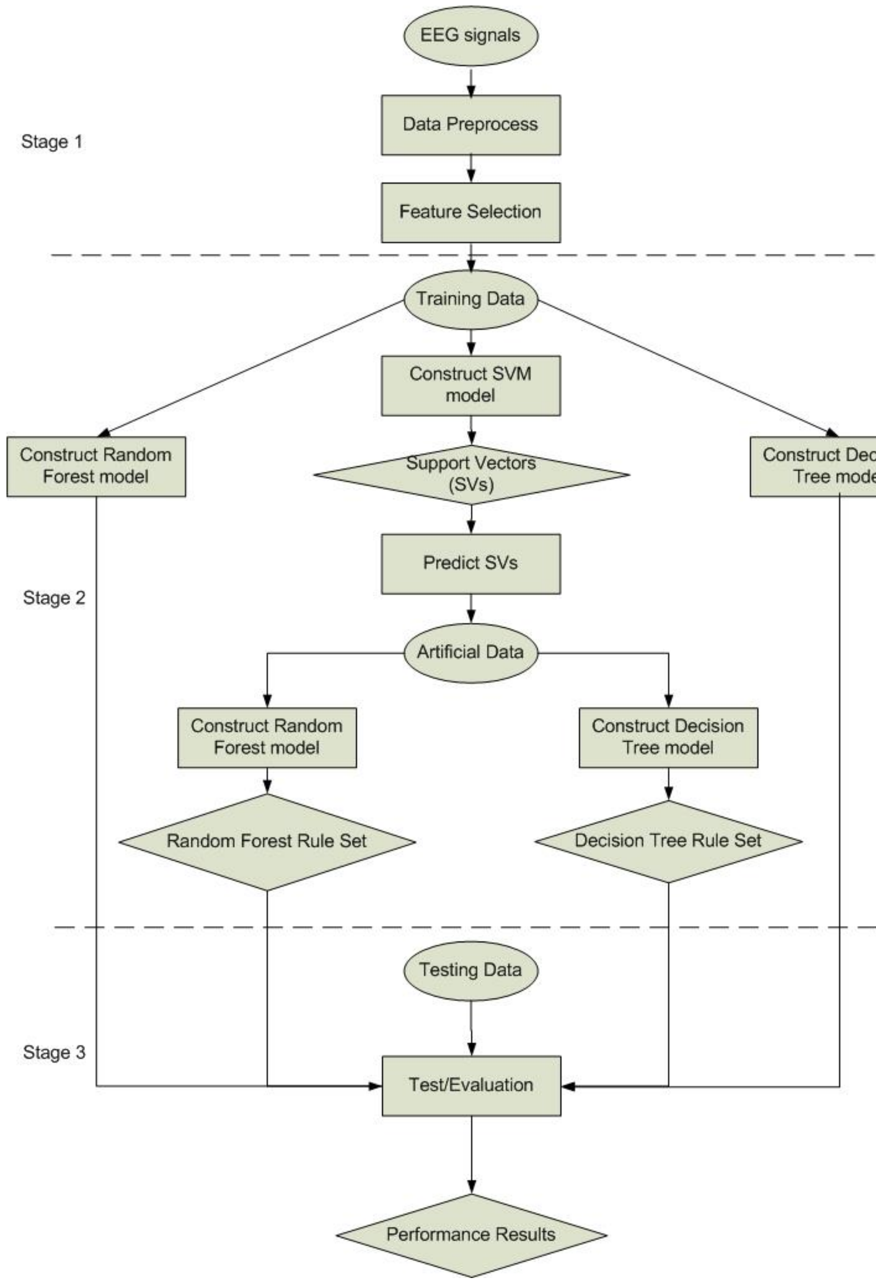

Fig. 1. Detection Framework for EEG signals

3. Datasets and Feature Extraction

3.1. Datasets

The EEG dataset provided by the University of Bonn, Germany, is adopted in this study [5]. The dataset has five groups of data, labelled as A, B, C, D and E. Each group contains 100 single-channel EEG segments captured in 23.6 seconds. The sampling rate of all the data is 173.6Hz. Groups A and B consist of EEG signals taken from five normal volunteers using the standardized electrode placement scheme. The volunteers were relaxed in an awake state with eyes open (Group A) and eyes closed (Group B) respectively. Groups C, D and E are groups with EEG signals collected from subjects with epilepsy during pre-surgical diagnosis. Segments in group C were recorded from the hippocampal formation of the opposite hemisphere of the brain and those in group D were recorded from the epileptogenic zone. Both groups C and D contain only signals measured during seizure free intervals (interictal state) while group E contains data recorded during seizure activity (ictal state). Fig. 2 shows the typical EEG signal traces in the five groups of data. The settings used for the data collection are described in Table 1.

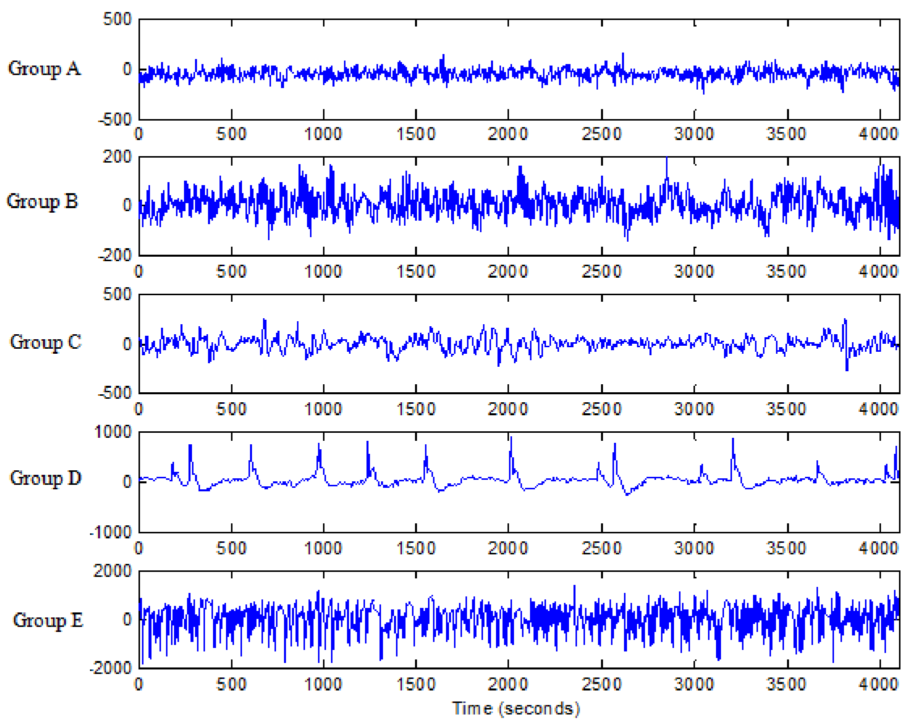

Fig. 2. Typical signal traces in the five groups of EEG data

Table 1. Descriptions of EEG segments in Group A to Group E

Subjects	Groups	EEG segments	Settings
Healthy subjects	A	100	EEG signals captured with eyes open
	B	100	EEG signals captured with eyes closed
Subjects with epilepsy	C	100	EEG signals obtained from the hippocampal formation of the opposite hemisphere of the brain during seizure free intervals
	D	100	EEG signals recorded from the epileptogenic zone during seizure free intervals
	E	100	EEG signals captured during seizure activity

Three experiments, denoted as Expt 1, Expt 2 and Expt 3, are carried out to evaluate the performance of the four rule-based algorithms in classifying the EEG signals into two, three and five distinct groups respectively. Details about the data used in the three experiments are described below and summarized in Table 2.

Expt 1: Two-group classification. The experiment is conducted to evaluate the performance of the algorithms in classifying EEG signals into two groups, i.e. EEG signals of (i) healthy subjects and (ii) subjects with epilepsy. The first group of data is composed of 200 EEG segments of healthy subjects in datasets A and B, whereas the second group contains the 100 EEG segments in dataset E of subjects with epilepsy during seizure. In the experiment, the distinctive features extracted from sub-band frequency analysis are identified and used to classify the data. Here the two-class SVM model is used for rule extraction.

Expt 2: Three-group classification. The experiment is conducted to classify the EEG signals into three groups, i.e. EEG signals of (i) healthy subjects, (ii) subjects with epilepsy during seizure-free intervals, and (iii) subjects with epilepsy during seizure. The corresponding groups of data used in the experiment are, respectively, composed of the 200 segments of healthy subjects in datasets A and B, the 200 EEG segments in datasets C and D of subjects with epilepsy during seizure free intervals; and the 100 segments in dataset E of subjects during epileptic seizures. The multi-class SVM model is used in the experiment for rule extraction.

Expt 3: Five-group classification. This experiment is further refined to evaluate the performance of the algorithms in classifying the five groups of subjects (A to E) in the original dataset of EEG signals. The multi-class SVM model is also used for rule extraction. The five-group classification experiment is of interest since algorithms with stronger classification ability can differentiate EGG signals recorded from different extracranial and intracranial regions, and during different physiological states and brain activities, which is helpful in the analysis of the dynamical properties of the brain's electrical activity [5]. This is advantageous in that the finer classification results can provide insights into the activities of the brain, or enable the determination of whether the EEG signals collected are able to provide enough information to reveal the underlying dynamical properties [44]. There is no previous research conducted for five-group classification by using the complete EEG dataset provided by the University of Bonn; And the five-group classification is still a challenging task.

Table 2. Data used in the three experiments

Experiments	No. of classes	Descriptions
Expt 1	2	(i) Healthy subjects – Groups A and B, 200 EEG segments in total; (ii) Subjects with epilepsy during seizure – Group E, 100 EEG segments.
Expt 2	3	(i) Healthy subjects – Groups A and B, 200 EEG segments in total; (ii) Subjects with epilepsy during seizure – Groups C and D, 200 EEG segments in total; (iii) Subjects with epilepsy during seizure – Group E, 100 EEG segments.
Expt 3	5	The five groups in the original dataset, i.e. Groups A to E, each with 100 EEG segments.

3.2. Feature Extraction

In this work, as a widely used approach for epilepsy detection, the standard feature extraction method STFT [8, 17, 20, 32] is utilized for the EEG signals before they are trained and tested by the classifiers.

To perform STFT, a small sliding window is used for the Fourier transform. STFT can be computed by

$$F_{STFT}(u, f) = \int_{-\infty}^{\infty} x(t) g(t-u) e^{-j2\pi ft} dt \tag{1}$$

where $x(t)$ is a given continuous EEG signal; $g(t)$ is a window function of limited width with the centre at u; F is a transformation function mapping $x(t)$ into the time-frequency plane. The process of performing STFT on the EEG signals for feature extraction can be stated as follows. Firstly, the EEG signals are distributed by STFT into different local stationary signal segments, and a group of spectra of local signals is obtained through Fourier transform. Then, the discrepancy in local spectrum of the signals at different times can be identified. Finally the energy of the EEG signals is separated into five standard frequency bands as listed in Table 3, and the energies of different bands can be taken as the new features for EEG analysis. An example of the features extracted from the EEG signals by STFT in Group A is illustrated in Fig. 3 [8].

Table 3. Five frequency bands in EEG analysis

Bands	Frequency range (Hz)
Delta	0-4
Theta	4-8
Alpha	8-15
Beta	15-30
Gamma	30-60

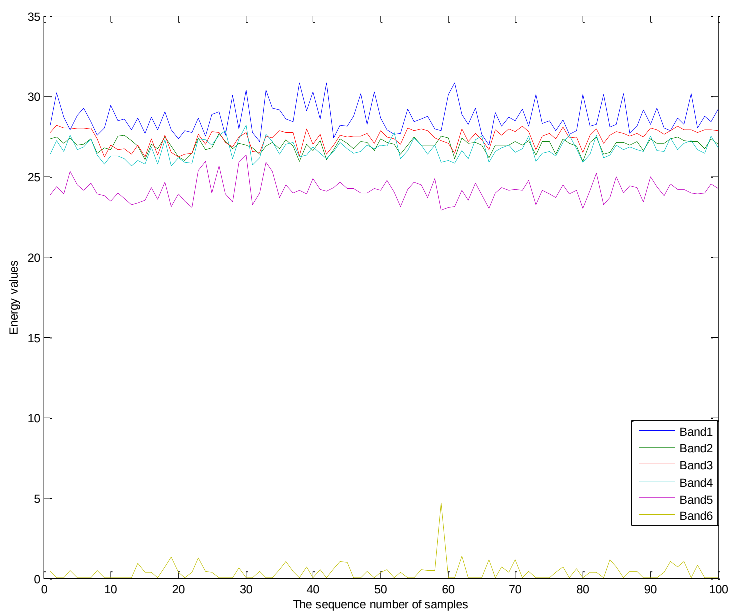

Fig. 3. Extracted features of EEG signal in group A by STFT

4. Rule-based Classifiers

The four rule-based classifiers, i.e., C4.5, RF, SVM+RF and SVM+C4.5, investigated in the study are discussed in this section.

4.1. Decision Tree

Decision tree algorithms learn rules by splitting the training dataset into subsets by testing attributes. In the form of a tree-like graph, where each non-leaf node of the tree denotes a test on an attribute whereas each leaf node holds a class label. Decision tree algorithms have high interpretability through the learned rules, and the obtained rules are also readily compressible with Boolean logic. The widely adopted C4.5 algorithm, which is practically feasible in many applications, is used as the decision tree classifier in this study [45].

4.2. Random Forest

RF algorithm is an ensemble learning method for classification. It makes use of many decision tree classifiers as a "forest", and aggregates the results for classification. Multiple models are used in the algorithm to achieve better learning performance, which is more complex yet flexible than using a single decision tree model [46]. Classification of a new input vector is performed by using each of the trees in the forest to classify the vector, followed by a vote from each classification tree based on the individual result. The algorithm then identifies the class that the input vector belongs to according to the one getting the highest vote among all the trees in the forest.

4.3. Support Vector machines

SVM is the most typical kernel-based technique in supervised learning. The basic principle of SVM is to create a classification hyperplane as a decision surface, where classification is achieved by maximizing the edge of the isolation between the categories with respect to the hyperplane. The SVM classification process consists of two stages. In the first stage, the input data vectors are mapped to a high-dimensional space. The dimension of the new space is effectively larger when compared that of the original input space [47]. In the new space, the algorithm will be executed to search for a hyperplane which is able to classify the data with the largest margin, so as to obtain the best generalization ability. For a given training dataset $\mathbf{T} = \{(\mathbf{x_1}, y_1), \ldots, (\mathbf{x}_N, y_N)\} \in (X \times Y)$, $\mathbf{x}_i \in X = \mathbf{R}^n$, $y_i \in Y = \{1, -1\} (i = 1, 2, \ldots, N)$, where the training data matrix X contains two separable classes with the class labels -1 and +1 stored in the set Y. Fig. 4 illustrates schematically a case where two linearly separable classes, denoted using the symbol circle (-1) and triangle (+1). The data points closest to the hyperplane are the SV, whereas the distance between SVs and hyperplane is the margin.

Applying Lagrangian multipliers with the appropriate kernel function $K(\mathbf{x}, \mathbf{x}')$ and the regularization parameter C, the SVM can be formulated as the dual optimization problem below

$$\min \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) - \sum_{j=1}^{N} \alpha_j \, , \tag{2}$$

$$\text{s.t.} \sum_{i=1}^{N} y_i \alpha_i = 0, 0 \le \alpha_i \le C, i = 1, \ldots, N$$

where the optimal solution is given by $\boldsymbol{\alpha}^* = (\alpha_1^*, \ldots, \alpha_N^*)^T$ and b^* is a threshold value. The decision function for classification is therefore given by

$$f(\mathbf{x}) = \mathrm{sgn}\left(\sum_{i=1}^{N} \alpha_i^{*} y_i K(\mathbf{x}, \mathbf{x}_i) + b^{*} \right), \tag{3}$$

The summation in Eq. (3) is performed only on a small group of SVs whose corresponding parameters α_i are not zero.

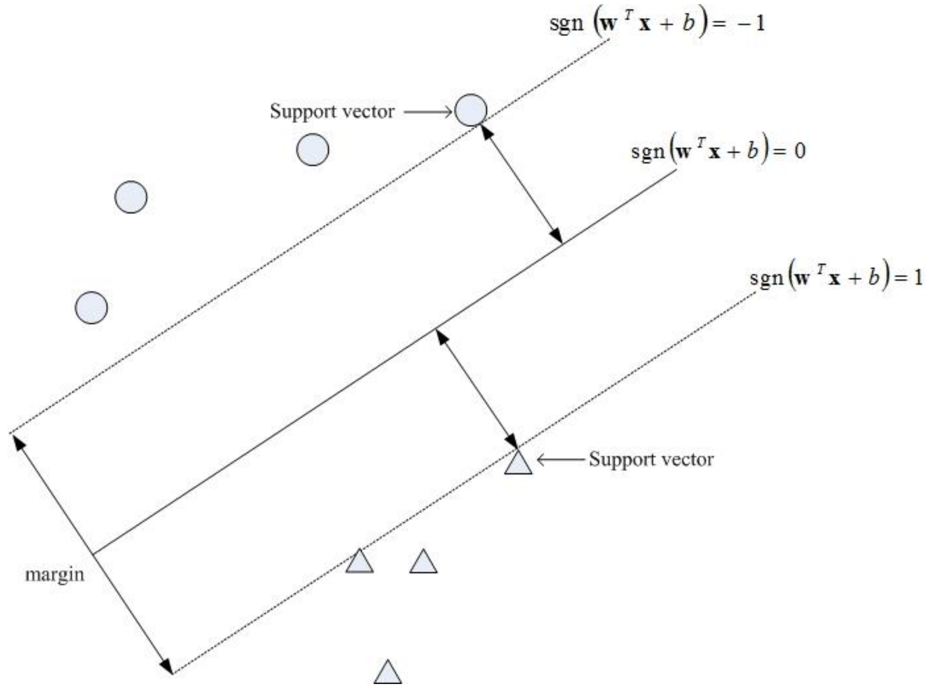

Fig. 4. SVM learns a hyperplane which best separates the two classes with circle and triangle representing class label of -1 and +1 respectively

In three-group and five-group classification, multiple one-against-all SVMs with continuous decision functions are utilized to determine multiple decision functions that separate one class from the other classes [48]. For the ith decision function, the maximum margin which splits the class i from the remaining classes is

$$f_i(\mathbf{x}) = \mathbf{w}_i^T \varphi(\mathbf{x}) + b_i, \tag{4}$$

where $\mathbf{w}_i$ is the decision vector, $\phi(\mathbf{x})$ is the mapping function that maps x into the feature space, and b_i is the bias term. Then continuous decision functions are applied for the classification. For the data sample $\mathbf{x}$, it is classified into the class with the maximal result:

$$\max_{i=1,\ldots,M} f_i(\mathbf{x}), \tag{5}$$

where M denotes the total number of classes.

In this study, the “black-box” issue of SVM is tackled by combining it with C4.5 and RF respectively. The resulting SVM+C4.5 and SVM+RF algorithms are ensemble learning approaches which begin by using the training dataset to construct the SVM model. The model parameters are tuned by the multi-fold cross validation (CV) strategy. The algorithms then extracts the SVs from the best model constructed in the CV process, which are plugged into the SVM model constructed to obtain the predicted labels. Finally, an artificial dataset is created by replacing the actual labels of the SVs with the predicted label. The purpose of the replacement is to maximize the simulation of the prediction made by the SVM model. By introducing the rule extraction techniques C4.5 and RF into SVM, an insight into the black-box model can be gained and the noise can be eliminated [49]. The SVs are used to construct two rule sets separately by C4.5 and RF, which are fixed by tuning the parameters through the CV strategy.

5. Results and Discussion

As discussed in previous sections, to evaluate the performance of the four rule-based classification algorithms RF, C4.5, SVM+RF and SVM+C4.5, the experiment is conducted by first applying the STFT technique to the original EEG signals to obtain the corresponding datasets with extracted features, which are then used to detect epilepsy with the classification algorithms respectively and the accuracies are recorded for comparison. In this study, the performance of the rule-based algorithms is also compared with that of three conventional black-box type classification methods – back-propagation neural network (BPNN) [50], radial-basis-function neural network (RBFN) [51] [52] and SVM.

The experimental settings for SVM+RF and SVM+C4.5 are as follows. The algorithms are run on the dataset for the 10-fold CV in which each run, the dataset is randomly divided into 10 equal parts with nine used as training dataset and the remaining one as testing dataset. In the first run of the 10-fold CV, 90% of the data are used for training the SVM, where common kernel functions are adopted and the grid-search strategy is used to obtain the optimal regularization parameter C and the kernel's parameter. Here, Gaussian kernel is selected in Expt 1 and Expt.2 while tanh kernel is selected in Expt 3 after comparing different kernels' performances in each experiment. A number of models are obtained in the process. The ultimate SVM model is the one which yields the best classification result on the testing dataset. Finally, the SVM model is tested on the remaining 10% of the dataset. For the remaining nine runs of the CV, in order to ensure fair performance comparison of the trained model, the nine shuffled datasets are trained using SVM parameterized with the same values as identified in the first round.

Similarly, RF, C4.5, BPNN and RBFN are executed on the same dataset for the 10-fold CV. The number of trees to grow (numTrees) in RF, the percentage of incorrectly assigned samples at a node (inc_code) in C4.5, the learning rate in BPNN and the spread in RBFN are determined by the grid search strategy in the first round of the CV process. The settings of the parameters in these algorithms are summarized in Table 4. The results of the three experiments, in terms of average classification accuracy, are shown in Table 5. In particular, the generated SVs for both SVM+RF and SVM+C4.5 are used in the SVM model as the training dataset to predict the labels. An artificial dataset is created by replacing the original labels in the dataset with the predicted labels. The artificial dataset is then used by the RF and C4.5 models to construct the rule sets and obtain the corresponding experimental results as illustrated in the last two rows of Table 5.

Table 4. Parameter settings in experiments

Classifiers	Parameters	Parameter settings		
		Expt 1	Expt 2	Expt 3
SVM	Kernel type	Gaussian	Gaussian	tanh
	Kernel's parameter	0.2	2e1	2e-3
	C	200	200	200
RF	numTrees	2000	1500	1000
C4.5	Inc_node	10	25	10
BPNN	Learning rate	0.05	0.1	0.05
RBFN	Spread	2e1	2e2	2e1
SVM+RF (i.e, RF on SVs)	numTrees	2000	1000	1000
SVM+C4.5 (i.e, C4.5 on SVs)	Inc_node	20	20	20

Table 5. Average accuracy results in experiments of 10-fold CV for 10 runs

Classifiers	Expt 1 (mean±SD)	Expt 2 (mean±SD)	Expt 3 (mean±SD)
SVM	**0.9963±0.0117**	**0.9660 ± 0.0325**	0.6704 ± 0.0601
RF	0.9930±0.0044	0.9569 ± 0.0369	**0.8311 ± 0.0515**
C4.5	0.9852±0.0259	0.9311 ± 0.0286	0.7178 ± 0.0555
BPNN	0.9852±0.0191	0.9222 ± 0.0424	0.6516 ± 0.0816

RBFN	0.9867 ± 0.0233	0.9000 ± 0.0301	0.6600 ± 0.0492
SVM+RF (i.e, RF on SVs)	0.9900 ± 0.0161	0.9432 ± 0.0467	0.9216 ± 0.0348
SVM+C4.5 (i.e, C4.5 on SVs)	0.9917 ± 0.0118	0.9218 ± 0.0708	0.9102 ± 0.0362

To compare the performance of the four rule-based algorithms involved ed in the study – SVM+RF, SVM+C4.5, RF, C4.5, they are tested on the corresponding testing datasets ten times, with the performance of SVM, BPNN and RBFN also evaluated in the same way to provide the results as a reference in the comparison. The results are show in Table 6. It can be seen that RF generally outperforms the other algorithms. Paired t-test is conducted between RF and other algorithms for the three experiments to evaluate whether the outstanding performance observed in RF is of statistical significance. The p-values of the t-tests are shown in the same table. As the performance of RF in five-group classification is particularly outstanding, further investigation is conducted by expressing the classification accuracy of the five distinct groups of EEG signals using a confusion matrix, as shown in Table 7.

Table 6. Classification performance on the testing datasets

Classifiers		Expt 1	Expt 2	Expt 3
SVM+RF	Mean	0.9967	0.9720	0.6980
	(std)	(0.0105)	(0.0253)	(0.0797)
	p-value[a]	0.3060	0.4342	0.0034[(+)]
SVM+C4.5	Mean	0.9933	0.9433	0.6820
	(std)	(0.0141)	(0.0312)	(0.0649)

	p-value	0.6036	0.2471	0.0012$^{(+)}$
RF	Mean	0.9896	0.9600	0.8260
	(std)	(0.0157)	(0.0311)	(0.0525)
	p-value	-	-	-
C4.5	Mean	0.9920	0.9367	0.7220
	(std)	(0.0144)	(0.0416)	(0.0537)
	p-value	0.5041	0.2339	0.0028$^{(+)}$
SVM	Mean	0.9940	0.9400	0.6600
	(std)	(0.0123)	(0.0351)	(0.0736)
	p-value	0.3988	0.1411	2.7105e-4$^{(+)}$
BPNN	Mean	0.9927	0.9472	0.6836
	(std)	(0.0139)	(0.0368)	(0.0539)
	p-value	0.5041	0.4679	1.9979e-4$^{(+)}$
RBFN	Mean	0.9900	0.9320	0.6580
	(std)	(0.0161)	(0.0368)	(0.0569)
	p-value	0.6036	0.0011$^{(+)}$	8.3565e-4$^{(+)}$

[a] The superscript (+) denotes that the RF method is better than the method under comparison based on t-test results. The smaller the p-value, the more significant the difference of the average values. A p-value of 0.05 is considered to be statistically significant.

Table 7. Confusion matrix presenting the classification performance of RF in Expt 3

	Predicted Groups				
Actual Groups	A	B	C	D	E
A	100%	0	0	0	0
B	0	100%	0	0	0

C	0	0	100%	0	0
D	25%	0	33.3%	41.7%	0
E	0	0	10%	0	90%

From the results of Expt 1 in Table 6, it can be seen that the two ensemble approaches SVM+RF and SVM+C4.5 give the best results in two-group classification, with average accuracies of 0.9967 and 0.9933 respectively, which the performance of RF is the worst yet still achieved an accuracy of 0.9896. However, the t-test results indicate the difference in performance is not statistically significant, and therefore the algorithms under comparison are considered to have comparable performance in two-group EEG signal classification. In Expt 2, SVM+RF and RF are the best two algorithms in the classification of the three groups of EEG signals, yielding the accuracies of 0.9720 and 0.9600 respectively. The classification accuracies of the other algorithms are all below 0.9500, where the accuracy attained by RFBN, i.e., 0.9320, is statistically worse than RF. In Expt 3, the performance of RF stands out in five-group classification of EEG signals, achieving the highest accuracy of 0.8260 among the algorithms under comparison. C4.5 gives the second highest accuracy of 0.7220, whereas the accuracy of the other algorithms is all below 0.7000.

Apart from the four rule-based algorithms, the three algorithms serving as references for comparison in the study, i.e. SVM, BPNN and RBFN, show moderate performance in two-group and three-group classification, with an accuracy above 0.9900. The accuracy in five-group EEG signal classification is relatively low, with BPNN yielding an accuracy of 0.6580 at best.

On the other hand, it can be seen from the diagonal of the confusion matrix in Table 7 that the average accuracy attained by RF is as high as 100% in classifying the EEG segments in

Group A (healthy subjects with eye open), Group B (healthy subjects with eye open) and Group C (subjects with epilepsy during seizure free interval). An accuracy of 90% is also achieved for classifying EEG segments in Group E (subjects with epilepsy during seizure). That is, the states of eye-open and eye-closed can be well distinguished using RF. The result is in line with a previous study where the two states were differentiated using frequency power levels [53]. However, it is also noted that the classification accuracy of EEG segments in Group D is very low, only 41.7%. This reveals a potential weakness of RF in distinguishing EEG signals recorded from different locations of the brain for subjects with epilepsy during seizure free intervals.

As shown in Table 5, SVM achieves high accuracies of 0.9963 and 0.9660 respectively in two-group and three-group EEG signal classification, which indicates the motivation of rule extraction from SVM. However, in five-group classification, due to the fact that SVM's already have a low accuracy of 0.6704, the rule extraction from SVM by the ensemble learning approaches may be to a certain extent directly affected by this pre-existing low accuracy.

Moreover, for the ensemble learning approaches SVM+RF and SVM+C4.5, their RF and C4.5 work respectively with the artificial datasets consisting of the SVs with the predicted labels. However, Table 5 demonstrates that at this moment RF and C4.5 are almost comparable in performance with each other in Expt 1, Expt 2 and Expt 3. In other words, SVM+RF does not provide any evidence to demonstrate its superiority over SVM+C4.5. Particularly, even though there are acceptable levels of accuracy in Expt 3 for RF and C4.5 on the artificial dataset consisting of the SVs, we should notice their poor performance in Expt 3, see Table 5.

In summary, among the four rule-based algorithms concerned in the study, RF shows the best overall performance in two-group, three-group and five-group classification of EEG signals, attributed to its strong ensemble learning capability with multiple decision trees. The performance of RF in five-group classification is particularly outstanding when compared to SVM and the SVM-based ensemble learning approach. This is potentially due to the poor performance of SVM which directly affects accuracy of rule extraction from the SVM model using the ensemble learning approaches. This finding is also in line with the claim in [54] that RF is most likely to be the best classifier after evaluating 179 classifiers covering all the relevant classifiers available today (SVM, decision trees, rule-based classifiers, etc) on 121 datasets representing the whole UCI database and other real problems. On the other hand, RF is also advantageous in that, when compared to SVM, parameter tuning is not necessary, which makes it easy to implement and scale up the computation for complicated analysis.

When compared with the three algorithms included in the experiments as reference, i.e., SVM, BPNN and RBFN, the performance of RF in two-group classification is slightly lower, whereas the performance in three-group classification is moderate and the performance in five-group classification is significantly better. The weakness of RF in two-group classification might be due to the small size of the dataset. Meanwhile, the experimental results also show that the SVM-based ensemble learning approaches can at least achieve a performance equivalent to that of using SVM alone, which is in line with the results in previous studies [55].

6. Conclusion

In this paper, we investigate the performance of the four rule-based classifiers – C4.5, RF, SVM+C4.5 and SVM+RF – in the detection of epilepsy with EEG, in terms of their ability in classifying two, three and five distinct groups of EEG signals acquired under different conditions. Three conventional black-box algorithms, SVM, BPNN and RBFN, are also involved in the experiments as references. After extracting the features in the EEG signals using STFT, the classification accuracies of the seven algorithms are evaluated for performance comparison. In particular, rule extraction from the SVM model is performed by using the ensemble learning approaches SVM+RF and SVM+C4.5, where the SVs are obtained by SVM, followed by the use of RF and C4.5 respectively to turn the "black box" of SVM decisions, represented by SVs, into interpretable rules for the classification of epileptic EEG signals.

The experimental results indicate that RF has the competitive advantage in two- and three-group classification of EEG signals. Its advantage is more noticeable in five-group classification where the accuracy of identifying EEG signals under five different conditions is the highest (0.8260) among the four rule-based algorithms investigated. In addition to classification accuracy, the rule sets generated by RF can serve as additional information that is more comprehensible by clinicians for the diagnosis of epilepsy with EEG signals.

A future work of the study is the pruning of the rule sets obtained by RF such that the size of the rule sets can be reduced to facilitate diagnosis but without significantly degrading the classification accuracy of EEG signals. Besides, even though the EEG dataset used here has been analyzed by many other research groups since 2003, we have to admit the size of the dataset is comparatively small. Further investigation will be conducted to improve the accuracy of RF in classifying more abundant EEG signals collected from subjects with epilepsy at different locations within the brain.

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