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Detection of epilepsy with Electroencephalogram using rule-based classifiers

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A R T I C L E I N F O

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A B S T R A C T

Epilepsy is a common neurological disorder, characterized by recurrent seizures. Electroencephalogram (EEG), a useful measure for analysing the brain's electrical activity, has been widely used for the detection of epileptic seizures. Most existing classification techniques are primarily aimed at increasing detection accuracy, while the interpretability of the methods have received relatively little attention. In this work, we concentrate on the epileptic classification of EEG signals with interpretability. We propose an epilepsy detection framework, 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 of all–five-group classifications of EEG signals. The experimental results showed that RF outperformed the other three rule-based classifiers, achieving average accuracies of 0.9896, 0.9600, and 0.8260 for the two-group, three-group, and five-group seizure classifications respectively, and exhibiting higher interpretability.

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 per cent of them are in developing countries. Every year, more than two million new cases of epilepsy are diagnosed worldwide [2]. Electroencephalogram (EEG) signals are widely used to detect epilepsy by directly recording the brain's electrical activity [3]. As seizures generally happen infrequently and unpredictably, an automated detection system that is able to classify epileptic EEG signals from normal ones is very helpful in making diagnoses. In such a system, the recorded EEG signals are the input, while the classification of EEG signals is the output. Generally, two steps are involved in an automated detection system: (i) the extraction of features from the EEG input signals and (ii) the classification of the extracted features for seizure detection [4]. In this study, we concentrate particularly on the latter step by investigating the effectiveness of rule-based classifiers in detecting epileptic seizures using EEG signals acquired under five different conditions (see Table 1, to be discussed later). Investigations are conducted to detect epilepsy by classifying the signals into two, three, and five groups using rule-based classification techniques. A standard feature extraction method, i.e. the short time Fourier transform (STFT) [5], is employed in the study.

Many classification techniques have been applied to the automated detection of seizures. In general, the experimental results show that EEG signals contain informative features for the detection of seizure events, and that most automated seizure detection systems are effective [6,7]. For two-class classifications of epilepsy activities, the following have been applied: distinguishing EEG signals collected in the normal and ictal stages, a neural network based model [6], an adaptive neuro-fuzzy inference system [8], the Elman network [9], a mixture of experts model [10,11], a decision tree [12,13], a support vector machine (SVM) [13], and a least squares support vector machine (LS-SVM) [14]. For three-class classifications of epilepsy activities, the following have been explored: distinguishing EEG signals collected in the normal, interictal, and ictal stages, a recurrent neural network [15], a spiking neural network [16,17], a back propagation neural network [18–20], a radial basis function neural network [21], SVM [22], the k-nearest neighbour (KNN) [23], the Fuzzy classifier [24], and the C4.5 algorithm for the decision tree [25]. Although variations in the dynamic properties of brain electrical activities have been shown clearly at different extracranial and intracranial recording regions and at different physiological

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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
	C	100	EEG signals obtained from the hippocampal formation of the opposite hemisphere of the brain during seizure-free intervals
Subjects with epilepsy	D	100	EEG signals recorded from the epileptogenic zone during seizure-free intervals
	E	100	EEG signals captured during seizure activity

and pathological brain states [26], almost all existing studies on EEG signal analysis and classifications focus on the two-group classification and the three-group classification, with little attention paid to the most challenging five-group classification.

In addition, the EEG signal classification techniques that are frequently used, such as SVM have a major shortcoming: they are "black-box" models where the actual meanings of the learned rules are not available. Therefore, it is important to improve the interpretability of the classification methods, in order to make the automated seizure detection system more practical and useful in clinical diagnoses.

In order to avoid the abovementioned shortcoming, rule extraction approaches for SVM have been proposed in the last few years. They can be summarized into three categories: (i) the learning-based approach, where the SVM model is treated as a closed box, (ii) the eclectic approach, where rules are extracted from the support vectors (SVs), and (iii) the decompositional approach, where use is made of the SVs and of the decision function of the training data. In this study, the eclectic approach is used, as it has already resulted in good performances in different medical domains, such as diabetes, heart disease, breast cancer, and hepatitis. Barakat et al. proposed a method to extract rules from a subset of the SVs of an SVM model using a modified sequential covering algorithm, which involved an ordered search of the most discriminative features as determined by the inter-class separation [27]. Chaves et al. extracted fuzzy rules from SVM by projecting the coordinate axes of each feature onto the SVs to formulate the fuzzy sets [28]. The fuzzy membership degrees were then calculated so that each of the SVs was assigned to the fuzzy set with the highest membership degree. Finally, fuzzy rules were extracted from each SV. Another rule extraction method was also developed using the SV of the SVM by applying the decision tree classifier [29]. The method generated an artificial dataset, and the actual class labels were replaced with the predicted class labels. A decision tree was then applied to the artificial dataset to determine 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 the random forest algorithm (RF) are applied to classify the artificial datasets of SVs [30].

In this study, we focus on investigating rule-based classifiers for seizure detection by analysing EEG signals in an attempt to achieve both high accuracy and high interpretability. Four classifiers 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 SVM-based decision tree algorithm (SVM+C4.5) and the SVM-based RF algorithm (SVM+RF). The performance of the four classifiers 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 seizure detection is outstanding in both interpretability and classification accuracy in two, three, and five group classifications compared with the other three classifiers.

This paper is structured as follows. Section 2 describes the proposed detection framework used to evaluate the EEG signal classification methods. Section 3 discusses the EEG datasets adopted in the study and the STFT algorithm used for feature extraction, followed by a review of the SVM and rule-based classifiers 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 seizure detection. It is used to assess the performance of the algorithms in classifying EEG signals into two, three, and five separate groups.

Three stages are involved in the proposed detection framework. The first stage is feature extraction, where STFT is applied to the EEG signals to extract features. In the second stage, the four rule-based classifiers are applied to the training dataset, 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 classifying 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 to 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 classifications of EEG signals. Although SVM+RF has been shown to be superior to other rule-based classifiers for the diagnosis of diabetes [30], evidence is needed to support whether it will also outperform other methods in the detection of epileptic seizures. In addition, C4.5 has also been used for two-group and three-group classifications of epileptic EEG signals, but its performance on the five-group classification has yet to be evaluated. As a conventional rule-based algorithm, RF has not been applied to the classification of epileptic EEG signals. Hence, these algorithms have been selected for the detection of epileptic seizures in this study.

3. Datasets and feature extraction

3.1. Datasets

The EEG dataset provided by the University of Bonn, Germany, is adopted in this study [26]. The dataset has five groups of data, labelled A, B, C, D, and E. Each group contains 100 single-channel EEG segments captured in 23.6 s. The sampling rate of all of the data is 173.6 Hz. Groups A and B consist of EEG segments taken from five normal volunteers using the standardized electrode placement scheme. The volunteers were relaxed in an awake state with their eyes open (Group A) and eyes closed (Group B), respectively. Groups C, D, and E consist of EEG segments 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 were measured during seizure-free intervals (interictal state), while group E was measured during seizure activity (ictal state). Fig. 2 shows the typical EEG signal traces in the five groups of data. The