Statistical Techniques for Epileptic Seizure Detection

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Abstract

Epilepsy, a neurological disorder affecting over 50 million individuals globally, is characterized by seizures due to abnormal brain activity. Despite recent advancements, the optimal diagnosis and treatment of this disorder remain primitive due to its multifactorial and heterogeneous nature of seizures. This project delves into the development of advanced statistical techniques for accurately detecting the onset of epileptic seizures. This project uses Electroencephalogram (EEG) data, a critical tool for recording brain activity without invasive procedures. The algorithms work by utilizing the distinction between normal and epileptic neural activities. Potential future research will focus on the enhancement of these algorithms to incorporate additional biomarkers, including electrocorticogram (ECoG) and stereo electroencephalogram (sEEG). Such multi-modal input could broaden the algorithm's capabilities, enabling detection of not only seizure onset timing but also different seizure types.

1 Introduction

Epilepsy is a prevalent chronic neurological disorder characterized by abnormal brain activity, leading to seizures or periods of unusual behavior and sensation. The World Health Organization reports that over 50 million people globally suffer from epilepsy [1]. In the United States, an estimated 1 in 26 people will develop epilepsy during their lifetime [2]. In some cases, the cause of epilepsy is apparent, such as strokes, tumors, trauma, genetic, etc. However, the exact cause often remains unclear. There are two types of seizures: focal and generalized. Focal seizures affect a specific part of the brain, while generalized seizures can impact the entire brain. Epilepsy can often be managed with medications, typically involving single or combination anti-seizure treatments. However, some epilepsy are drug-resistant, requiring surgical removal of the brain region responsible for seizure initiation [3]. However, epilepsy surgery, involving craniotomy, carries high risks. Furthermore, despite careful pre-surgical analysis, brain function may be compromised due to the removal of brain tissue.

An alternative strategy involves the application of electrical stimulation to the brain with the intention of suppressing seizure activity. Currently, there are two FDA-approved devices available for this purpose: the Percept PC Neurostimulator developed by Medtronic [4] and NeuroPace's RNS [5]. These devices consistently monitor brain activity by employing depth electrodes, such as sEEG, or ECoG-like 2D electrodes. On the detection of the onset of epileptic seizures, the devices promptly administer electric currents via the electrodes to terminate the abnormal neuronal activity.

Although this direct interaction with the neural circuitry offers a compelling alternative for patients suffering from drug-resistant epilepsy or those who are not candidates for surgery, the effectiveness of these devices is somewhat constrained. The conclusive results from the pivotal trial of the RNS system indicate that patients experienced a reduction in seizure frequency of 44% at one year and a 53% reduction at two years following implantation [6].

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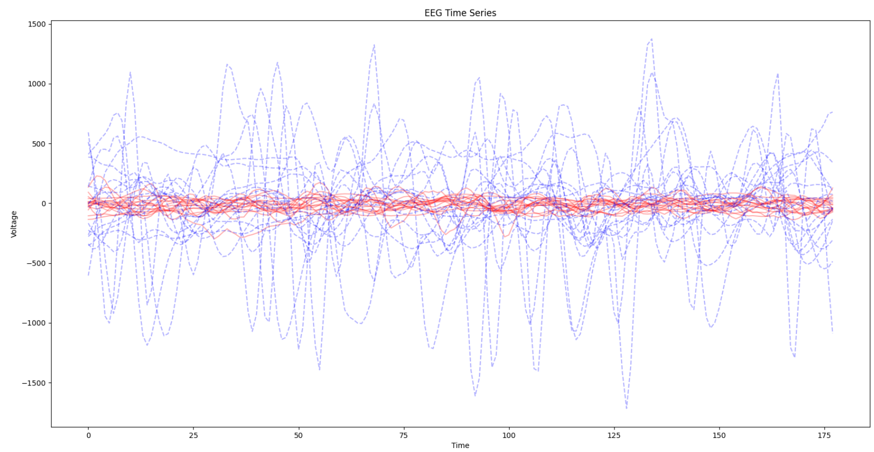

Figure 1: Plot of EEG Time Series. Red solid line represents the normal brain activity. Blue dotted line represents the brain activity during epileptic seizures.

A promising strategy to enhance the efficacy of brain stimulation involves improving the precision of seizure onset detection, thereby enabling the more timely application of electrical stimulation. To this end, this project investigates various statistical methods and applies them to an epileptic seizure dataset for seizure detection tasks.

2 Dataset

The dataset used for this project is from the Epileptic Seizure Recognition Kaggle competition [7], with the original data having been collected and published via the UCI Machine Learning Repository [8]. The dataset comprises EEG recordings, originally categorized into five folders, each encompassing 100 files. Each of these files corresponds to an individual subject, offering a 23.6-second record of brain activity, subsequently sampled into 4097 data points. The dataset has been restructured into 23 chunks, each containing 178 data points per second, resulting in a total of 11,500 rows of information. The final column, labeled 'y', contains the classification of the 178-dimensional input vector. The 'y' column values range from 1 to 5, each representing a different class:

Label 1 corresponds to the EEG recording of seizure activity.

Label 2 corresponds to the EEG recording from the brain region where a tumor is located.

Label 3 corresponds to the EEG recording from a healthy brain region.

Label 4 corresponds to the EEG recording while the patient had their eyes closed.

Label 5 corresponds to the EEG recording while the patient had their eyes open.

However, because the primary focus of this project is to detect the occurrence of seizures, the dataset only need two classes (i.e., whether an EEG recording was taken during a seizure event or not). As such, the dataset has been pre-processed to ensure that the 'y' column displays binary values. In this context, '0' signifies an EEG recording taken from patients who were not experiencing a seizure, while '1' denotes an EEG recording from patients undergoing seizure activity.

Figure 1 illustrates 15 randomly selected EEG recording samples from each class to contrast normal activity (depicted by red solid lines) and seizure activity (depicted by blue dotted lines). Upon visual inspection, it is clear that EEG recordings during seizure events exhibit higher fluctuations compared to recordings of standard brain activity. This observation is in alignment with the known characteristics of epileptic seizures.

Statistical technique	Accuracy on Test Set
Logistic Regression	81.30%
Decision Tree	93.96%
XGBoost	97.17%
Random Forest	**97.26%**
SVMs	97.04%
FC Neural Net	95.74%

Table 1: Accuracy of each statistical techniques.

3 Methodology

Given that raw EEG signals contain large amounts of noise from a variety of sources, it is crucial to apply artifact removal algorithms before feeding these signals into classification algorithms [9]. However, the dataset used in this project has already undergone a pre-processing phase, thereby eliminating the necessity of a noise removal stage. Accordingly, the emphasis of this project is primarily placed on investigating numerous statistical methodologies and evaluating their efficiency in identifying seizure occurrences. In particular, the subsequent techniques are implemented to the dataset:

- Logistic Regression [10]
- Decision Tree Classifier [11]
- XGBoost [12]
- Random Forest [13]
- Support Vector Machines (SVMs) [14]
- Neural Network (NN) [15, 16]

The Logistic Regression, Decision Tree, Random Forest, and SVM algorithms were implemented using the scikit-learn package [17], a toolset readily available in Python. The XGBoost algorithm was employed via the official dmlc XGBoost implementation [18]. The Neural Networks were implemented using the Pytorch library [19].

4 Result

The following results are from preliminary experiments. As described in the dataset section previously, the original dataset has the shape of (11500, 178). In other words, there are 11500 data samples, with each sample comprising a one-dimensional vector that contains 178 elements. The dataset is split into a training set (80%) and a testing (20%) set, resulting shapes of (9200, 178) for training and (2300, 178) for testing. All models are trained on the training set and then tested on the testing set.

Table 1 shows the binary classification accuracy of each statistical techniques on the dataset. From this preliminary result, I can see that the Random Forest approach outperforms others with respect to this particular training-testing split. XGBoost and SVMs are demonstrating comparable proficiency, while Logistic Regression lags somewhat in performance compared to the other techniques.

For the final report and poster, I will conduct more thorough analysis by performing K-Fold Cross Validation. Due to constraints on the length of this report, some figures, such as the ROC curve and the train-test error plot, have been omitted. However, these will be included in the final report.

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