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Optimization of Pre-Ictal Interval Time Period for Epileptic Seizure Prediction Using Temporal and Frequency Features

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Abstract. Epilepsy is a neurological disorder characterized by recurrent seizures. Automated prediction of epileptic seizures is essential in monitoring the health of an epileptic individual to avoid cognitive problems, accidental injuries, and even fatality. In this study, scalp electroencephalogram (EEG) recordings of epileptic individuals were used to predict seizures using a configurable Extreme Gradient Boosting (XGBoost) machine learning algorithm. Initially, the EEG data was preprocessed using a standard pipeline. We investigated 36 minutes before the onset of the seizure to classify between the pre-ictal and inter-ictal states. Further, temporal and frequency domain features were extracted from the different intervals of the pre-ictal and inter-ictal periods. Then, the XGBoost classification model was utilized to optimize the best interval for the pre-ictal state to predict the seizure by applying Leave one patient out cross-validation. Our results suggest that the proposed model could predict seizures 10.17 minutes before the onset. The highest classification accuracy achieved was 83.33 %. Thus, the suggested framework can be optimized further to select the best features and prediction interval for more accurate seizure forecasting.

Keywords. Epilepsy, Seizure Prediction, Electroencephalogram, Machine Learning, Automated Detection.

1. Introduction

Epilepsy is a neurological disorder that causes sudden, recurring electrical disruptions in the brain. It affects approximately 50 million people of all ages [1], which makes it the second most common neurological disease. Epilepsy may be caused due to head

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trauma, stroke, brain tumors, infections, neurodevelopmental disorders like autism, and genetic factors. Epilepsy leads to episodes of seizures, brief changes in behavior, sensations, and sometimes loss of consciousness. Seizures can also cause changes in behavior, mood, and emotions. Seizure prediction is the process of predicting epileptic seizures and providing advance warning of an impending seizure so that clinicians can take preventative measures [2] to reduce the severity of the seizure or avoid it altogether. It also helps improve seizure control and quality of life, decreases the risk of injury, improves overall health, and improves daily functioning. Seizures can be predicted by detecting the beginning of the pre-ictal state, which denotes the onset of the seizure [3]. Electroencephalogram (EEG), which records abnormal electrical activity in the brain, can capture the different stages of seizure inter-ictal, pre-ictal, ictal, and post-ictal. However, seizure prediction has challenges such as variability of patient data, high false-positive rate, computing resources, limited data availability, and imbalanced classes of pre-ictal and inter-ictal states. Optimizing the pre-ictal interval will better classify the pre-ictal state and provide the prediction horizon for forecasting a seizure as different EEG features perform better at different lengths of interval [4]. In this study, we propose a machine-learning model for predicting epileptic seizures by optimizing the pre-ictal interval time. We have used Extreme Gradient Boosting (XGBoost) machine learning algorithm to classify pre-ictal and interictal states as it has shown better performance for diagnosis of epilepsy in the literature [4,5].

2. Methods

The process pipeline adapted in this study is shown in Figure 1.

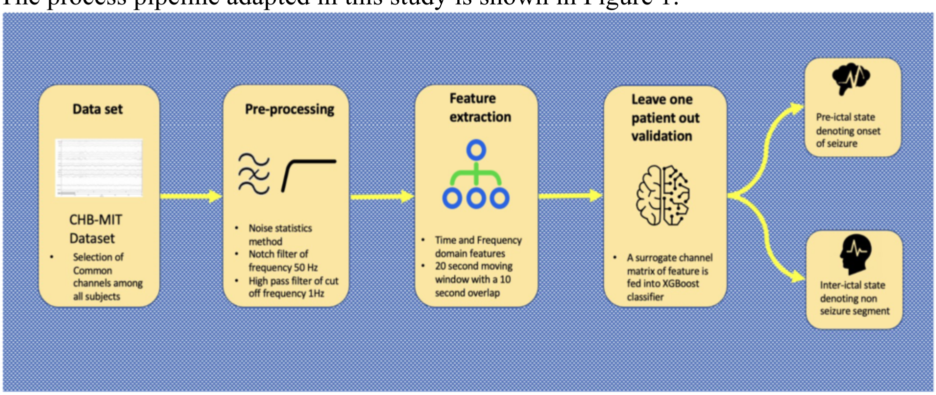

Figure 1. Process pipeline of pre-ictal EEG classification.

In this study, we utilized the CHB-MIT scalp EEG dataset, which is publicly avail-able online. It consists of scalp EEG data of 24 epileptic patients recorded for multiple hours using the conventional 10-20 electrode placement system and split into one hour recordings each. Each file that contained seizure data was annotated at the beginning and end of the seizure. The data was sampled at a frequency of 256 Hz. We found that the number of channels was different between the subjects and varied from 23-40 channels. The 14 channels common among all the subjects were chosen for further analysis. We pre-processed the EEG using a notch filter at 50 Hz and a high-pass filter at 1 Hz to improve the signal-to-noise ratio. The artifact removal was performed using the noise statistics method [5], in which the signal segments with higher RMS value than a threshold (mean±5*standard deviation) were first eliminated. We extracted an interval of 36 minutes before the onset of the seizure to classify between the pre-ictal and inter-ictal states (figure 2). A moving 20-second window with an overlapping of 10 seconds was chosen for feature extraction. Seizures with a minimum duration of 20 seconds were selected for the study in correspondence to the moving window duration.

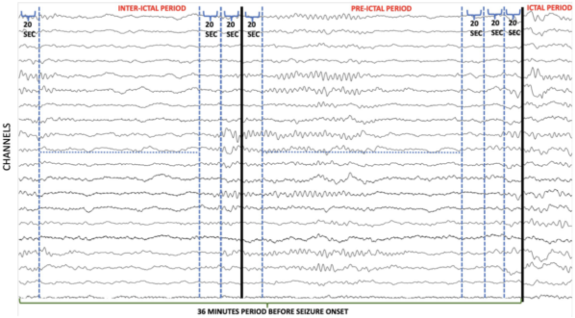

Figure 2. Pre-ictal period optimization process.

We excluded the EEG data of 2 out of 24 subjects as it failed to fit the seizure selection criteria. Time and frequency domain features extracted from the signals are provided in Table 1 [6]. The extracted features were then surrogated into a single channel by averaging the features obtained over all the channels to produce a single-channel feature matrix. These feature matrices obtained were then fed as inputs to the XGBoost classifier [5] as a leave one patient out process in which the classifier was trained, with all the remaining subjects leaving one out for testing. This was repeated for all the possible equal time intervals for the pre-ictal and inter-ictal within 36 minutes of the period before the seizure onset. The final accuracy for an interval was chosen by averaging all the validation accuracies obtained in the leave one patient out method for that particular interval.

Table 1. List of features

Feature type	Features
Time Domain (22)	Absolute Energy, Approximate Entropy, Average Power, Coefficient of Variance, Detrended Fluctuation Analysis (DFA), Higuchi Fractal Dimension, Hjorth Activity, Hjorth Complexity, Hjorth Mobility, Kurtosis, Lempelziv Complexity, Mean, Median, Peak to Peak, Root Mean Square (RMS), Sample Entropy, Skewness, Standard Deviation, Singular Value Decomposition (SVD), Total Signal Range, Variance, Zero Crossing Rate.
Frequency Band Power (3)	Delta Band Power, Beta Band Power, Gamma Band Power.

3. Results

Figure 3 shows the classification accuracy of the XGBoost classifier for the different pre-ictal period intervals. It can be noted that the classification accuracy is minimum at the lower and higher intervals. The classification performance was higher between 6-12 minutes compared to other time periods. We achieved a maximum classification accuracy of 83.33 % for an epileptic patient. However, the average leave one patient out classification accuracy, recall score, specificity, and F-measure were 61.22 %, 66.92 %, 63.15 %, and 58.85 %, respectively, for a pre-ictal interval having a duration of 10.17 minutes before the seizure onset.

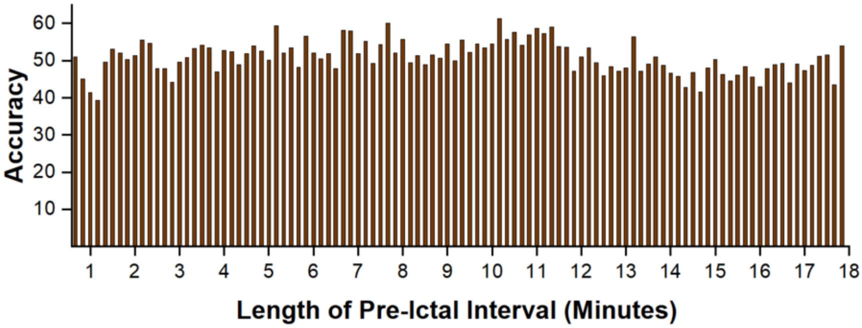

Figure 3. Classification accuracy for different intervals of pre-ictal period.

Figure 4 shows the top 10 features involved in classifying inter-ictal and pre-ictal EEG signals for the interval of 10.17 minutes. We can observe from the figure that the peak to peak and Hjorth complexity were the best features for classifying the pre-ictal and inter-ictal states using EEG signals. This is followed by sample entropy and theta band having influential contributions to classification. Out of the top 10 features, 9 were time domain features.

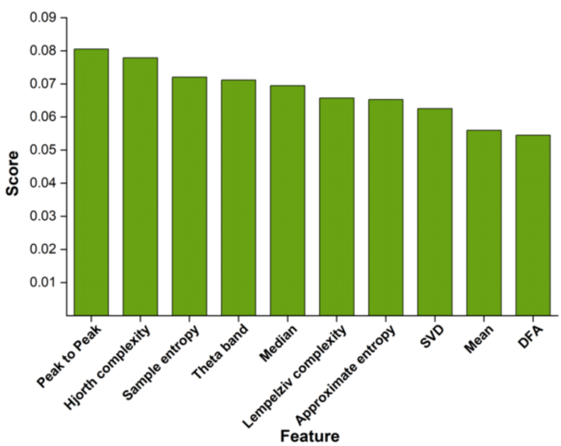

Figure 4. Feature importance based on XGBoost classification.

4. Discussions

We achieved reasonable results in the seizure classification using the CHB-MIT. However, we need to explore our classification model with more data available in other data sets to improve the performance and validate the model's generalizability. Only the time and frequency features were considered for pre-ictal classification and seizure prediction. We have never employed time-frequency domain features. However, they might provide complex information that might help with better classification. We have only employed the XGBoost model to improve classification performance, but more sophisticated machine learning and deep learning models can be explored. We plan to optimize the model to be able to forecast seizures in real time. In the future, we can expand the research to examine the effects of seizure forecasting on various physiological signals, like ECG and GSR, to study the utility of other biopotential signals on seizure prediction.

5. Conclusions

In this study, a process pipeline was proposed for classifying pre-ictal and inter-ictal states and identifying the pre-ictal period to mark the onset of the seizure. We used the time and frequency domain features to extract the patterns of seizure before onset and XGBoost to build the classification model. The highest classification accuracy achieved was 83.33 % for a pre-ictal duration of 10.17 minutes before the seizure onset. This model in future, has the ability to be deployed as a wearable device for continuous monitoring of epileptic patients.

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