Continuous ambulatory epilepsy detection system incorporating feature engineering

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Abstract. Epilepsy is a prevailing disease that affects people from different age brackets and demographic backgrounds. It leads to uncontrollable onset of seizures and can result in severe neurological injuries. In this paper, we devised a novel seizure prediction system as a real-time early warning system for patients. By using real-time transmissible, portable, and wireless devices, we can acquire raw data from scalp electroencephalogram (EEG) without any pre-processing for the input. After pre-processing, the data is fed into selected prediction algorithms based on literature review and a combination of methodologies. After times of iteration, our result shows a promising performance, with an accuracy rate of 100% Bonn dataset. We further designed a hardware data acquisition apparatus (with our program built-in) to smooth and ameliorate the data acquisition process when eliminating overmuch electrodes, which may serve as a promising seizure onset detecting device in the new era.

Keywords: brain-machine interface, epilepsy, scalp EEG, ambulatory seizure detection

1. Introduction

According to the latest update from the International League Against Epilepsy (ILAE) [1], epilepsy is identified by recurrent epileptic seizure symptoms due to abnormal brain activities. Epilepsy affects more than 50 million patients worldwide; patients may lose consciousness and go into convulsion[2]. More than a quarter of Grand mal seizure patients have seizure-related severe injuries that demand hospitalization or surgical intervention, and 30% of epilepsy patients' seizures are uncontrollable with anti-epileptic drugs [3, 4]. Unpredictable seizure onset may result in social isolation and poor quality of life.[4]

There are several characteristics of seizure signals: electrocerebral inactivity, spike and sharp wave complexes, rhythmic hypersynchrony, and a continuous discharge of polymorphic waveforms with variable amplitude and frequency[5]. During a seizure event, the delta (0–4Hz) and theta (4–8Hz) subwaves in an EEG signal exhibit high magnitude and low frequency[5].

The video-electroencephalography (vEEG) and epilepsy monitor unit are the golden standard of seizure diagnosis [6]. Self-report of symptoms is not always possible because patients can only recognize half of their seizure onsets[7, 8]; idiopathic epilepsy involves absence seizures in which patients pause their tasks and lose awareness. This method requires manual monitoring from human experts, which makes the process unaffordable and impractical for common households, and it makes the situation worsen that patients have to do the seizure monitoring test under hospitalization conditions. Consequently, ambulatory seizure monitoring systems with high accuracy and portability are in high demand.

Currently, most ambulatory seizure monitoring systems are based on intracranial electroencephalography (iEEG), which requires long-term electrode implantation under the scalp that has many drawbacks: in the study, one-third of iEEG patients exhibited signs of procedural headaches, and some even suffered from device-related postoperative nausea, seroma, and device migration within months after implantation [9].

Due to the inconvenience associated with vEEG and the high inflammatory responses induced by iEEG, there is a growing trend towards using non-invasive methods for predicting seizures, such as real-time physiological signal monitoring wristbands and scalp EEG. These methods are safer compared to iEEG since it involves no surgery on patients' skulls and patients can wear the prediction system for extended time periods. These methods could adapt to the high demand for wearable devices in domestic environments [10–13], especially for parents to monitor their children with epilepsy [14]. The wristband that achieved state-of-art performance is *"Empatica,"* which is commercially available. By monitoring accelerometers and electrodermal activity data, the sensitivity of correct seizure warnings can reach about 93% among thirty patients [15, 16]. However, non-EEG-based equipment like "*Empatica"* has reached a plateau in terms of potential enhancements and lacks the sensitivity to detect minor voltage fluctuations in patients with epilepsy; consequently, ambulatory scalp EEG detection system is favored in the literature since it includes more psychological information and make more accurate prediction.

Though there is extensive research on using scalp EEG to conduct seizure warnings, there is still a bottleneck in the cost-effective and efficient EEG hardware implementation[17]. Scalp EEG is multi-dimensioned, non-linear, and non-stationary[18], classifying them requires extraction of complicated information from seizure systems. Currently, deep learning models and traditional feature engineering are the two main genres for seizure prediction tasks[19, 20]. For deep learning models [9, 21–27], the advantage is that deep neural networks can automatically extract the features needed and be transferred to other tasks with ease. However, deep learning models need to have large datasets and human-selected hyperparameters[28, 29]. Even worse, the deep learning methods can be easily disturbed by unexpected noise, which causes the model to give wrong answers with high confidence [30]. The users of the deep learning algorithms, who are EEG analysts or patients, lack computer science knowledge, so they cannot trust the algorithms no matter how high the accuracy is. The deep learning algorithms cannot be interpreted by humans, which limits its usage [31]. Traditional feature engineering could also achieve accurate warnings. The widely used mathematically designed features in the literature include empirical model decomposition [32], Fourier Transform [33], wavelet transform [34–36], etc. These features are manually devised based on the characteristics of the task. For the long-investigated epilepsy classification task, there are already numerous proposed features that can separate seizure and non-seizure data. So that the time cost for manual feature selection is decreased. Further, the change in feature value is meaningful and can be interpreted, because of its mathematical nature. Another benefit is that the dimension of the data can have a significant reduction, reducing the computational costs of seizure warning, and making it more suitable to be implemented in ambulatory seizure warning systems.

As a result, this paper proposed a continuous ambulatory seizure detection system for grand mal seizure, incorporating previously defined mathematical features for seizure detection. The validation of this seizure warning algorithm proposed in this paper was conducted on public datasets.

DOI: 10.54254/2753-8818/32/20240806

2. Methods

2.1. Hardware Systems

Many hardware systems are used in the neurological data acquisition system [13, 19, 37]. In the paper, the wireless data acquisition apparatus is used in figure 1(c). The change of electric potential in the brain is gathered through a 3.5 mm signal acquisition cable *(Shenzhen Setolink Electronics Co, LTD ST-EC11-C5I)*. The signal is then transferred to the wireless receptor board using the convertor in figure 1(b). After amplification, analog input is converted to digital signals. The data is transmitted by Wi-Fi through a Serial Peripheral Interface[38]. The computer receptor software is used to present all the data. After receiving the data, the prediction application will analyze the acquired data and give users feedback on whether there are oncoming seizures. The flowchart of the processing model is illustrated in figure 1(a). The forehead electrodes will be used at the FP1 and FP2 locations, as defined in the international 10-20 system [39]. The position of electrodes is further explained in figure 1(d).

In the EEG signals there are artifacts, which are not generated by the brain are called *artifacts*. There are two main groups of artifacts: 1) physiology artifacts and 2) technical artifacts. The most significant impact on the data is the ocular signal, which has a wide frequency range, high amplitude, and significant impact on forebrain signal-gathering processes [40]. Besides, various muscle activity, cardiac activity, respiration, and metabolisms including sweating may all affect the precision of the data being gathered. Another potential source of error is the non-physiological artifacts, such as mechanical movements of cables [41], 50Hz AC electromagnetic interferences, and the distortion of data within the device.

To remove artifacts, the data gathered from the electrodes will go through pre-processing before they are used as the input for the algorithms. Butterworth bandpass filters [42] are used for extracting the valid signals. Since the characteristic seizure waves dominantly at frequencies between 1Hz~30Hz[43], we set the filter range between 0.2Hz and 30Hz to remove environmental artifacts, including those occurring at low frequencies, such as breathing, eye movements, and arbitrary direct current offset and slow drifts, and at high frequencies, such as muscle contractions, stimulators, and the powerline interference.

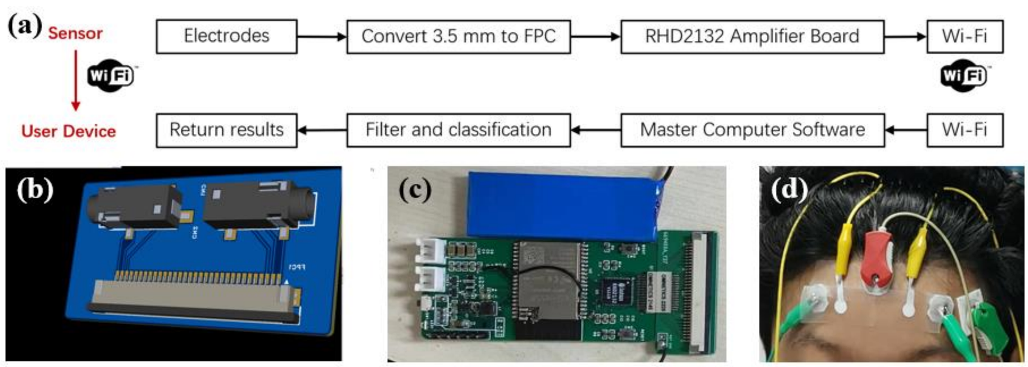

Figure 1. (a) The flowchart of the epilepsy prediction system. **(b)** The conversion board was used to convert the data gathered from the 3.5 mm cables to the amplifier board. **(c)** Picture of the amplifier board. **(d)** The location of each electrode. The two green electrodes are **FP1** and **FP2**; the red electrode is the reference electrode; the large green electrodes are the ground electrodes.

2.2. Datasets

In this paper, we trained the proposed model and evaluated it on the Bonn EEG time series dataset [44] published and publicly available on Bonn University's Epileptology Department website [45]. The dataset was from surface EEG recordings from healthy volunteers and intracranial EEG recordings from epilepsy patients when they are having seizures or in the interictal phase. All channels are separated and in a random series. Each piece of recording has a duration of 23.5 seconds with a frequency of 173.61

DOI: 10.54254/2753-8818/32/20240806

Hz. All artifacts are removed by selected human experts. The pre-processing code for this research paper was gathered from Professor Manoosh Samiei and his lab [46].

2.3. Feature Extraction

This paper uses six features that were proposed in the literature to classify seizure and non-seizure EEG signals. The features included have been used in various biomedical areas, such as genetic sequence analysis and recognition of heart failure[47, 48], as well as epilepsy detection [49, 50]. The detailed definitions of these features are listed in [51].

- Detrended Fluctuation Analysis (DFA)
- Petrosian Fractal Dimension (PFD)
- Fisher Information (Fisher Info)
- Spectral Entropy (Spectral En)
- Hjorth Fractal Dimension (HFD)
- Singular Value Decomposition Entropy (SVD En)

2.4. Seizure Importance Ranking

A Random Forest Classifier [52] is used to compare different features' importance scores for further feature selection. The importance scores are calculated from the Gini Impurity in the models. The detailed methods are defined in [53]

2.5. Model: Feature Classifications

After the extraction of six chosen features, the data is fed into various machine learning classification models, such as AdaBoost, Naive Bayes, Quadratic Discriminant Analysis, Nearest Neighbours, Linear SVM, Radial Basis Function SVM, Gaussian Process, Decision Tree, Random Forest, and Neural Network. The best-performing models are decision trees, random forests, and AdaBoost.

2.6. Model Evaluation

Models are evaluated based on accuracy and sensitivity [17].

$$\text{Accuracy} = \frac{\text{True positive} + \text{True negative}}{\text{True positive} + \text{False Negative} + \text{True negative} + \text{False Negative}}$$

The confusion matrices were also included to demonstrate the performances of the model.

3. Results

3.1. Feature extraction

The average feature values are shown in figure 2(a). There are significant differences for the features extracted in each group ($p<.0001$) tested using an independent t-test. The importance scores were calculated, and the Fisher Information is the most significant feature for classifications (figure 2(b))

3.2. Classification and seizure warning

The results for seizure prediction are shown in **Figure 2(c).** The best-performed model (AdaBoost, Random Forests, Decision Tree, Gaussian Process) reached an accuracy of 100% on the Bonn dataset, showing their capability to classify the seizure and non-seizure data. The results are higher than the other models using this dataset.

We chose the AdaBoost [54] algorithm in the system because it can find flexible margins between margins through different classes and, thus, has a higher generalization ability. Although Decision Tree Classifier (DTC) [55] and Random Forest Classifiers [56] (Random Forest Classifier is an optimization of the Decision Tree algorithms) are among the 100% accuracy models, they are not used in the epilepsy warning systems because there are a few disadvantages when using a decision tree. For example, they are not as accurate as the other classifiers when doing other tasks. Furthermore, the success of the specific DTC implementation has a significant impact on DTC performance. Since a tiny alteration to the training datasets may have a significant impact on the output prediction, they are typically less robust than other approaches. [57].

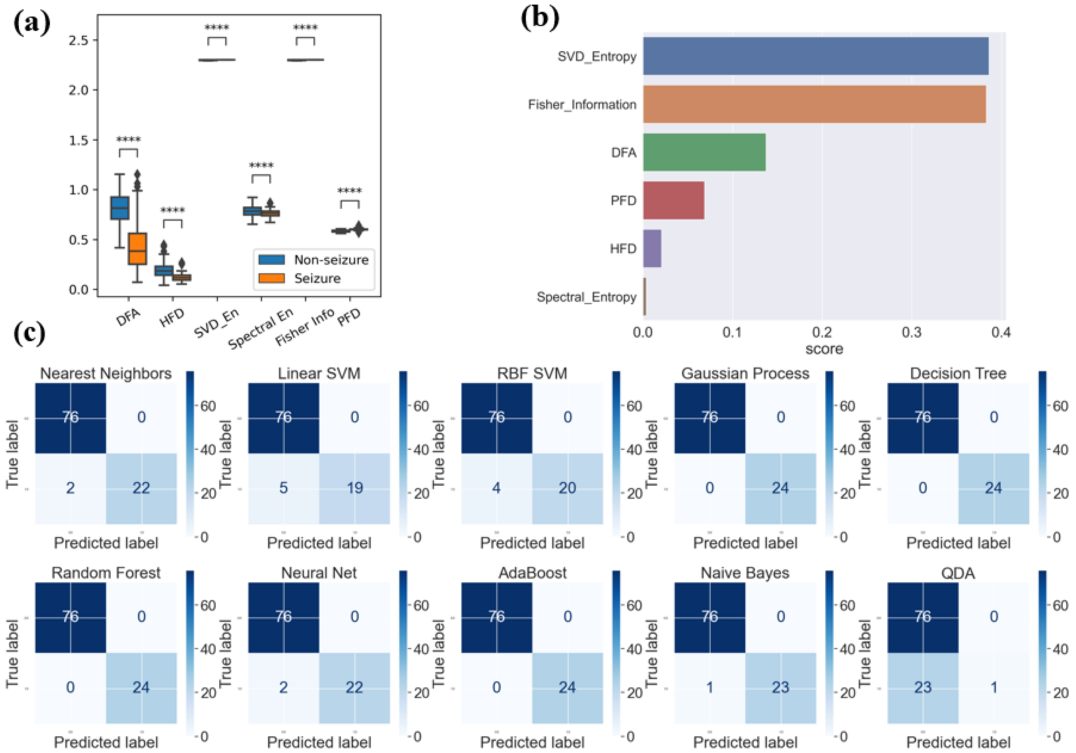

Figure 2. (a) Six features extracted for the two groups of seizure patients and the comparison of the mean of features from seizure and non-seizure groups. **(b)** The importance scores were calculated from random forests classifiers. **(c)** Confusion Matrix for different classification models. AdaBoost and Decision Tree perfectly qualified this task with an accuracy of 100%.

3.3. Ambulatory seizure detection system

The trained model is incorporated into the seizure warning application in the computer. Once a seizure is detected, the computer application would update the warning status as “seizure onset,” and the clients and their caregivers would receive notification about the seizure onset.

4. Discussion

As mentioned in the literature review, there are many approaches to providing accurate seizure warning to patients. This study set out to address the need for ambulatory seizure warning systems and utilized selected algorithms to give correct predictions.

The analysis of extracted features demonstrated that the feature extracted is significantly different, leading to possibilities of accurate prediction. These feature values are in line with the assumption that the brain exhibits randomness during normal stages and shows deterministic chaos when neurons have synchronized discharge [58].

The algorithms utilized in this study offer certain benefits over other models that use the same dataset. While models employing wavelet decomposition have achieved accuracy rates of up to 99.1%[59], and those using principal component analysis have reached 98.75% accuracy[60], another model that applies a random forest after empirical mode decomposition has attained 99.4% accuracy[61]. Remarkably, Sharma’s group achieved a perfect accuracy rate of 100% using LS-SVM and fractional dimension[62]. However, the model presented in this study is advantageous as it requires fewer computational resources

DOI: 10.54254/2753-8818/32/20240806

than deep learning models, resulting in faster prediction speeds. The algorithm presented in this study is already incorporated in the continuous ambulatory seizure detection system, capable of 24-hour detection and processing of the data on computer-based software.

The seizure warning system proposed in this study can increase the convenience of seizure detection systems because only electrodes on the forebrain (FP1 and FP2) were used to gather data. The proposed algorithm is computationally easier and reliable enough that could be implemented in computer applications.

While our study provides promising results for the development of a new seizure prediction system, it is important to acknowledge its limitations. Firstly, our study was the Bonn dataset used in this study is relatively small (with a sample size of 500 EEG segments). Moreover, the manually-extracted features may not scale well for the entire epilepsy patient population [63]. Besides, the algorithms are patient-dependent studies because of the high variability of EEG data [21]. This limits the generalizability of our findings and may not fully represent the diverse range of seizure patients. Future studies with larger and more diverse samples are needed to validate our findings and ensure the effectiveness of our algorithm across different populations. Secondly, our study is recruiting real patients to test the algorithms, and currently, the findings are not validated on human patients. The use of real patient data could provide a more accurate and realistic evaluation of the performance of our seizure prediction system. It's crucial to note that individual differences among patients, such as variations in seizure types and frequencies, can significantly impact the effectiveness of seizure prediction algorithms. Therefore, future research should aim to test these algorithms in real-world clinical settings with actual patients.

In the future, the system can be improved in the following aspects. Change the configuration of the electrode acquiring system: Gather information for the primary motor cortex, having more precise monitoring of the tonic chronic seizure onset. What's more, larger datasets can be used in the future model, and the classification can include the pre-ictal stages.

5. Conclusion

Epilepsy patients currently have a high demand for convenient devices that could notify their care-giver to preclude further injury and seizure-related death. This paper devised a new scalp EEE gathering hardware system, capable of filtering irrelevant distortion of data. Using the light-weighted design, this equipment would monitor seizure onset for patients with minimum burden to life, with the cost and easiness to use that incomparably outperform the traditional i-EEG or vEEG based seizure warning system. We found that using **FP1** and **FP2** electrode positions, scalp EEG signals could be received without the need for conducting resin, supporting continuous data acquisition. Secondly, to complete the seizure system, we combined feature extraction techniques reported in the literature, which when combined, could result in distinguishable classification of seemingly arduous seizure onset EEG classification issues. The extracted features later were inputted for several machine learning classification models, and the model with the highest accuracy and generalizability (AdaBoost) was selected for the final seizure prediction model, with an extraordinary accuracy rate of 100%, fully capable clinical application. The entire seizure warning and prediction systems are incorporated into the computer application.

The present study highlights the need for more clinical data to validate the effectiveness of the research design. It is essential to gather data from FP1 and FP2 positions to improve the accuracy of seizure warning systems. Moreover, the availability of more data is likely to lead to new discoveries and improvements in seizure warning systems.

6. Data and code availability

Python programming language was used to process the data. The data and code supporting this study's findings are available upon reasonable request.

DOI: 10.54254/2753-8818/32/20240806

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