Epilepsy Detection Based on Riemann Potato in Noisy Environment

Yandong Ru,1,2 Jinbai Li,3 and Zheng Wei1

1College of Electronic and Information Engineering, Heilongjiang University of Science and Technology, Haerbin 150027, China
2College of Electronic Engineering, Heilongjiang University, Haerbin 150006, China
3Shandong Artificial Intelligence Institute, Qilu University of Technology (Shandong Academy of Science), Jinan 250013, China

Correspondence should be addressed to Yandong Ru; 10564006@qq.com

Received 3 January 2022; Revised 23 April 2022; Accepted 20 May 2022; Published 6 June 2022

Academic Editor: Takashi Morishita

Copyright © 2022 Yandong Ru et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Epilepsy detection based on electroencephalogram (EEG) is important for the diagnosis and treatment of epilepsy. The existing feature extraction method not only consumes a lot of time but also leads to epilepsy information loss because of nonideal denoising. Therefore, the paper proposes to use noisy EEG signals to detect epilepsy. The original EEG signal is divided into normal signal and abnormal signal by Riemann potato, and the epilepsy detection model is established based on the normal signal and abnormal signal, respectively. Finally, the 2 detection results are combined as a final result. The detection performance of 94.84%, 83.03% sensitivity, and 97.67% specificity is achieved. The experimental results show that the original noisy signal which is separated by the Riemann potato can have high epilepsy detection performance.

1. Introduction

Epilepsy is one of the most common nervous diseases, which affects about 1.5% of the population. It will affect the life quality of patients and even pose a great threat to their lives [1]. Using EEG to detect epilepsy is widely used for epilepsy diagnosis [2]. The detection results are one of the important references for doctors to treat epilepsy. Traditional epilepsy detection is completed by doctors according to their own clinical experience. This method is not only time-consuming and inefficient but also depends on the subjective judgment of doctors [3]. Therefore, the realization of automatic epilepsy detection has been of great significance to clinical application.

Epilepsy detection methods are commonly divided into the statistical methods, machine learning methods, and deep learning methods. The statistical method is to use a certain feature of signal to distinguish between epileptic signal and nonepileptic signal and complete epilepsy detection according to the statistical results. The machine learning method is mainly to extract some features of the signal and use a machine learning model to complete epilepsy detection. The deep learning method is to establish a deep learning model and complete feature extraction to realize epilepsy detection. The performance of the statistical method is poor. The performance of the deep learning method is better but takes a lot of training time. The extracted features are fuzzy and cannot be understood by doctors. It is difficult to apply it to clinical epilepsy detection, which requires a certain detection speed. The machine learning method is the only method that can be used in practice with high detection performance.

The traditional machine learning methods include three steps: preprocessing, feature extraction, and classification. EEG is not only complex and weak but also mixed with eye electrical signal, electromyography signal, and other kinds of noise. Preprocessing is mainly to remove the noise from EEG signals [4]. However, in practice, there is a certain gap between extracted features and the real features due to the unsatisfactory denoising effect which will lead to poor detection performance. Therefore, scholars tried a variety of noise removal methods, in which filter denoising and independent component analysis (ICA) denoising are in common use. Filtering denoising is based on the characteristics of the spectrum of noise and pure signal distribute in different frequency bands [5]. However, filtering denoising has a boundary effect, which leads to a poor
denoising effect at the cut-off frequency boundary. At the same
time, a small part of the spectrum of noise and pure signal coin-
cides, and part of the EEG signal is filtered out when the noise is
filtered out. ICA is a noise removal method that assumes that
the components of EEG signals are independent of each other
and uses the least square method to estimate the model param-
eters after selecting the principal components [6]. The method
is based on multichannel, and the denoising ability will
decrease with the decrease of the number of channels. More-
over, the method consumes a lot of calculation time to remove
noise, and it is difficult to realize the task requires detection
speed. Therefore, the existing noise filtering methods are diffi-
cult to achieve high-performance epilepsy detection.

The paper uses a machine learning model to detect
epilepsy based on noisy EEG. The overall structure is
shown in Figure 1. The EEG signal was separated into
normal signals and abnormal signals by Riemann potato
method. The detection models for normal signal and
abnormal signal were established, respectively, and the 2
results from 2 models are combined as the final epilepsy
detection model.

The paper mainly has the following contributions: (1) It
is the first time to realize epilepsy detection in noisy environ-
ment, which proves that denoising is not a necessary step of
epilepsy detection. (2) Riemann potato is used to divide EEG
into two parts, which proves that the performance of epi-
lepsy detection can be improved through data division.

2. Related Methods

2.1. Region Division. In the paper, the experiment database is
provided by the Massachusetts Institute of Technology
(MIT), which is obtained by using a 10-20 system. Through
observing the database, the fact is that some patients lacked
some channel information. All patients shared 18 channels
including FP1F7, F7T7, T7P7, P7O1, FP1F3, F3C3, C3P3,
P3O1, FP2F4, F4C4, C4P4, P4O2, FP2F8, F8T8, T8P8, P8O2,
FZCZ, and CZPZ [7]. According to the channel location,
Figure 3: Continued.

(a) Nonepileptic signal
EEG regions are divided into region 1, region 2, region 3, region 4, region 5, region 6, region 7, region 8, and the central region. The region division is shown in Figure 2. It can be seen from Figure 2 that 18 channels cover different regions of the scalp. The region division can ensure that there is at least one channel in each region. In the paper, the epilepsy detection method based on multichannel is used to complete epilepsy detection which can ensure that there is at least one channel in each EEG region for feature extraction. The method can ensure the overall detection performance will not be greatly reduced due to individual channel loss.

2.2. Correlation Analysis of Channels. EEG is nonlinear, random, low-energy biological which is generated by the neurons in the brain. It is the comprehensive reflection of the group activity of neurons on the scalp surface [8]. During the process of signal transmission, it will be affected by many kinds of noise. Due to the close distance between channels in the same region, the influence of noise on adjacent 2 channels is similar. Hence, the EEG signals from adjacent channels have a certain similarities. In the paper, 6 of the 18 channels are selected as examples which is shown in Figure 3.

It can be seen from Figure 3 that the EEG signals from adjacent channels are similar to each other in both epileptic signals and nonepileptic signals. Therefore, according to the channel similarity, choosing the most suitable channel for epilepsy detection in the same region is meaningful. It can not only reduce the number of channels but also ensure that the selected channel has the advantage of multiple regional EEG signals. In the paper, the Pearson correlation coefficient is used to represent the similarity of channels.

Pearson correlation coefficient of $X$ and $Y$ is defined as follows:

$$
\rho_{X,Y} = \frac{\text{COV}(X,Y)}{\sigma_X \sigma_Y} = \frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - E^2(X)} \sqrt{E(Y^2) - E^2(Y)}},
$$

where $E(X)$ is the mathematical expectation of the $X$. 

Figure 3: Similarity of signals from different channels.
The paper analyzes the similarity of signals from 2 different channels. For the channels with large similarities, selecting the channel with strong epilepsy detection ability is used for feature extraction and at the same time abandoning the channel with weak epilepsy detection ability to reduce the number of channels. The method can improve the epilepsy detection speed.

2.3. Feature Extraction. The feature directly determines the performance of epilepsy detection. Williamson et al. found that the EEG signal with higher a power spectral density (PSD) has stronger ability to detect epilepsy [9]. Bai et al. found that the sample entropy has a strong anti-interference performance for EEG signals [10]. The paper selects the PSD and sample entropy as features.

(1) PSD

In the paper, the Welch method is used to calculate the PSD. The method divides data into L segments (allowing overlap), improving the signal variance characteristics and reducing the uncorrelation of each segment of data. The window is used to complete the data interception, and the PSD of each segment is denoted as \( P(\omega) \). The expression is shown in equation (2).

\[
P(\omega) = \frac{1}{MUL} \sum_{l=1}^{L} \sum_{n=0}^{M-1} x_l(n)d(n)e^{-j\omega n} \tag{2}
\]
where \( d(n) \) is the window. In the paper, the rectangular window is selected as the window. \( M \) represents the number of data in each segment. \( U \) is the normalization factor. The expression is shown in equation (3).

\[
U = \frac{1}{M} \sum_{n=1}^{M} d^2(n). \tag{3}
\]

(2) Sample entropy

In the paper, sample entropy is chosen as the feature. The sample entropy is a measure of complexity proposed by Richman and Randall [11]. They measure the complexity of time series by measuring the probability of generating new signal patterns. The greater the probability of new patterns, the greater the complexity of the time series is. The calculation of sample entropy does not depend on the data and has a good consistency. Sample entropy is widely used in the evaluation of the complexity of biological signals and the diagnosis of pathological state [10]. The sample entropy can reflect the small transformation of EEG signal during epileptic seizures [12], which can be used as a feature in the epilepsy detection model.

2.4. Significance Analysis. EEG signals will inevitably be mixed with noise. ICA is widely used in EEG acquisition equipment. It is officially declared that 95% of the noise can be removed [13]. It is recognized as the best denoising method for EEG signals so far. The feature obtained after denoising by ICA is also the closest to the real feature [10]. In the paper, all channels in the database are used for denoising by ICA. It is through the significance analysis of the features obtained before and after the denoising to determine whether the features of noisy signals can be used in the detection model.

In the paper, the significance test method is used to study the feature difference before and after denoising. The significance test is to make a hypothesis on the parameters or distribution on the form of population (random variable) and then use the sample information to judge whether the hypothesis (alternative hypothesis) is reasonable, that is, to judge whether the real situation of the population is significantly different from the original hypothesis. The significance test is used to judge whether there is a difference between different data groups and whether the difference is significant.

In the paper, one-way analysis of variance (ANOVA) is used to study the significance of features. The purpose of one-way ANOVA is to determine whether the same variable from different groups has different effects on the corresponding variable \( Y \). The expression of one way ANOVA was as follows:

\[
y_{ij} = a_j + \epsilon_{ij}, \tag{4}
\]

The hypothesis is as follows: \( y_{ij} \) is an observation value that represents the observation number and represents different groups of predicted variables. \( y_{ij} \) are independent of each other. \( \epsilon_{ij} \) is random error, independent, and normally distributed.
Figure 5: Continued.
distributed, with zero mean value and constant variance, that is, \( \varepsilon_{ij} \sim N(0, \sigma^2) \). \( a_j \) represents the overall average of group \( J \).

The ANOVA tests the hypothesis of \( H_0 \) which is different from the other group.

\[
H_0 : a_1 = a_2 = \cdots = a_k, \tag{5}
\]

\( H_1 \) means not all groups have the same mean.

In practical application, the threshold (e.g., 0.05) will be set to calculate the \( p \) value of the two groups of data. When the \( p \) value is greater than the threshold value, the same factors in different groups will have the same effect on the prediction variables, that is, the feature plays the same role in the detection model.

2.5. Riemann Potato. In the paper, the original signal (EEG with noise) is divided into normal signal and abnormal signal by Riemann potato. The Riemann potato is a mathematical method to detect outliers by covariance matrix based on Riemann geometry [14]. The distance distribution of the signal covariance matrix is calculated by setting the threshold artificially. When the distance between covariance matrices is beyond the threshold, it is considered an outlier. Riemann potato method was used to process each record. Each record was divided into two parts: normal signal and abnormal signal. Then, the normal signals are combined to form the normal data set, and the abnormal signals are combined to form the abnormal data set. Riemann potato schematic diagram is shown in Figure 4. For more details, refer to the literature [15].

3. Experiments and Results

3.1. Database. The database is provided by the Massachusetts Institute of Technology (MIT). The database contains 23 EEG records from 22 epileptic patients (one of them has two EEG records), containing the patient’s age, gender, and other information. The EEG signal is sampled by 256 Hz, and the information is stored with 16 binary values. The frequency range of the EEG signals is (0-100 Hz) [16]. The database contains a variety of epilepsy types, which is large and representative [7].

3.2. Channel Selection

3.2.1. Correlation Coefficient of Channels. Pearson correlation coefficient was used to analyze the correlation of 18 channels. The correlation coefficients between any two channels of epileptic signals and nonepileptic signals were calculated. The channel with a correlation coefficient of more than 0.5 is given in Table 1.

The 9 regions are divided according to the location including a central region which includes channel FZCZ and channel CZPZ. The correlation coefficient of channel FZCZ and channel CZPZ in epileptic signal is 0.5, and that of channel FZCZ and channel CZPZ in nonepileptic signal is 0.01. It can be seen that channel FZCZ and channel CZPZ are closely related, but the correlation is poor. The two channels are very close to the hippocampus area of an epileptic seizure, and the distance between the epileptic signal and the scalp is the smallest having the least noise. Therefore, channel FZCZ and channel CZPZ are selected for feature extraction in the central region. In other regions, only one channel is selected for extracting features to save time.

3.2.2. PSD Analysis. The greater the PSD, the stronger the ability to detect epilepsy is. In the paper, the average PSD of epilepsy signal and nonepilepsy signal in 3 patients is calculated which is shown in Table 2. The record number 0103 in the table represents the 3th EEG record from patient 01 in the database.

It can be seen from Table 2 that differences in the PSD live in different patients. The PSD of EEG signals obtained.
Figure 6: Continued.
from the same patients at different times is also different. On
the whole, the PSD of epileptic signals is greater than that of
nonepileptic signals. Thus, the PSD can be used as a feature
to distinguish epileptic signals from nonepileptic signals.

3.2.3. Channel Selection. The principle of channel selection in
the paper is as follows: in the 9 regions, one channel is selected
from each region (two channels are selected in the central
region). In the same region (excluding the central region), if
the difference between the average PSD is large, the channel
with a larger average PSD is selected for feature extraction. Otherwise,
select the channel farthest from the identified channel to ensure
that the channel used covers the scalp as much as possible. The
specific selection process is as follows: for channels T8P8 and
C4P4, the channel T8P8 with the largest PSD is selected. For
channels FP2F4 and FP2F8, the channel FP2F4 with the largest
PSD is selected. For channels FP1F7 and FP1F3, channel FP1F3
with the largest PSD is selected. For channels P4O2 and P8O2,
P4O2 with the largest PSD is selected. For channels T7P7 and
C3P3, the channel T7P7 with the largest PSD is selected. The
relationship between the PSD of channel F7T7 and channel
F3C3 is uncertain. To ensure that the selected channel contains
EEG information of different regions as much as possible, the
channel FP1F3 has been selected. In the paper, channel F7T7
which is far away from channel FP1F3 is selected. Similarly,
the relationship between the PSD of channel P7O1 and P3O1
is uncertain. Similarly, the relationship between the PSD of chan-
nel F4C4 and F8T8 is uncertain, and channel F8T8 is chosen. In
this paper, 10 channels including channels FP1F3, F7T7, T7P7,
P3O1, FP2F4, F8T8, T8P8, P4O2, CZPZ, and CZPZ are selected
for feature extraction.

3.3. Signal Processing by Riemann Potato. In the paper, the
13th record from patient 01 was analyzed as an example. The
98-second epileptic signal and 2000-second nonepileptic
signal were processed by Riemann potato. The epileptic signal
was composed of 72-second normal signal and 26-second
abnormal signal, and the nonepileptic signal was composed
of 152-second normal signal and 1848-second abnormal sig-
inal. In this paper, 2 of the 10 channels are selected as examples.
Figure 5 shows the time domain signal of the normal signal
and the abnormal signal from the epileptic signal. Figure 6
shows the time domain signal of the normal signal and abnor-
mal signal from the nonepileptic signal.

![Figure 5: Normal signal and abnormal signal from epileptic signal.](image1)

![Figure 6: Normal signal and abnormal signal from nonepileptic signal.](image2)

Table 3: Significance analysis of normal signal and abnormal signal.

| Type                  | FP1F3 | F7T7 | T7P7 | P3O1 | F8T8 | T8P8 | FP2F4 | P4O2 | FZCZ | CZPZ |
|-----------------------|-------|------|------|------|------|------|-------|------|------|------|
| PSD of nonepilepsy    | 9.3E-12 | 4.8E-10 | 2.5E-11 | 3.2E-08 | 2.3E-16 | 2.9E-18 | 3.4E-14 | 3.4E-15 | 1.6E-13 | 5.0E-15 |
| Sample entropy of nonepilepsy | 5.3E-06 | 0.046 | 0.055 | 0.004 | 2.0E-06 | 0.013 | 0.062 | 0.055 | 0.031 | 0.029 |
| PSD of epilepsy       | 2.0E-04 | 4.4E-06 | 7.2E-3 | 6.4E-4 | 3.7E-09 | 7.6E-06 | 6.9E-09 | 1.0E-10 | 2.3E-09 | 2.4E-08 |
| Sample entropy of epilepsy | 0.045  | 0.038 | 0.055 | 0.023 | 0.0056 | 0.0044 | 0.057 | 0.0002 | 0.063 | 0.056 |
signals from 10 channels is analyzed. The results are shown in Table 3.

It can be seen from Table 3 that there is significant difference in sample entropy and PSD obtained from normal signal and abnormal signal about the epileptic signal. Similarly, the sample entropy and PSD obtained from abnormal signals from nonepileptic signals are significantly different from those obtained from the normal signals. It can be seen that the PSD and sample entropy can be used as the distinguishing characteristics of the normal signal and abnormal signal.

Table 4: Significance analysis of sample entropy before and after denoising.

|       | FP1F3 | F7T7 | T7P7 | P3O1 | F8T8 | T8P8 | FP2F4 | P4O2 | FZCZ | CZPZ |
|-------|-------|------|------|------|------|------|-------|------|------|------|
| Epilepsy | 0.61  | 0.54 | 0.60 | 0.65 | 0.75 | 0.43 | 0.83  | 0.53 | 0.94 | 0.94 |
| Nonepilepsy | 0.54  | 0.62 | 0.72 | 0.81 | 0.72 | 0.78 | 0.63  | 0.69 | 0.80 | 0.68 |

Figure 7: Trend of mean PSD.
3.4. **Features Analysis in Noisy Environment**

3.4.1. **Analysis of Sample Entropy**

(1) **Significance Analysis of Sample Entropy**. In the paper, feature extraction needs to be completed in a noisy environment, so the selected features must perform well. The sample entropy is selected as the feature, the signal obtained by ICA denoising is regarded as the reference (so far, ICA is recognized as the best denoising performance), and 2 seconds is taken as the analysis period. The paper studied the sample entropy from patient 13 of 10 channels of EEG signals.

![Trend of mean PSD](image)

**Figure 8: Trend of mean PSD.**

|                | FP1F3 | F7T7 | T7P7 | P3O1 | F8T8 | T8P8 | FP2F4 | P4O2 | FZCZ | CZPZ |
|----------------|-------|------|------|------|------|------|-------|------|------|------|
| Epilepsy       | 0.98  | 0.19 | 0.74 | 0.77 | 0.63 | 0.78 | 0.66  | 0.98 | 0.86 | 0.98 |
| Nonepileptic signal | 0.20  | 0.96 | 0.72 | 0.94 | 0.37 | 0.95 | 0.30  | 0.80 | 0.61 | 0.97 |

**Table 5: Significance analysis of sample entropy before and after denoising.**
which were used to analyze the significance of sample entropy of epileptic signals and nonepileptic signals before and after denoising. The experiment results are shown in Table 4. It can be seen from Table 4 that the sample entropy of epileptic signal and nonepileptic signal is not significant. The difference of sample entropy as a feature in the classification model is very small, which proves that sample entropy can still be used as classification feature for noisy signal.

(2) Trend of Sample Entropy. Taking the EEG signal from patient 13 as an example, the average power spectrum density trend of epileptic signal and nonepileptic signal before and after denoising is given in Figure 7. It can be seen that although there are differences in the sample entropy values between epileptic and nonepileptic signals before and after denoising, the trend is consistent. The graph proves that the role of sample entropy as a feature in detection before and after denoising has not changed, and sample entropy can still be used as a feature for noisy signals.

3.4.2. PSD Analysis

(1) Significance Analysis of PSD. The PSD is selected as the classification feature, the signal obtained after denoising by ICA is used as the reference, and 2 seconds is used as the analysis period to study the PSD of 21 channels of EEG signals from patient 01. The significance of the PSD of epileptic signal and nonepileptic signal before and after denoising is analyzed, respectively. The experiment results are shown in Table 5.

It can be seen from Table 5 that the PSD of both epileptic signal and nonepileptic signal is not significant before and after denoising. The difference in the role of PSD as a feature in the classification model is very small, which proves that the PSD can still be used as a classification feature even in a noisy environment.

(2) The Trend of PSD. Taking the EEG signal of patient 13 as an example, Figure 8 shows the trend of PSD of epileptic signal and nonepileptic signal before and after denoising. It can be seen that although there are differences in PSD between epileptic signals and nonepileptic signals before and after denoising, the trend is consistent. Figure 8 proves that the role of PSD as a feature in detection has not changed before and after denoising, and the PSD can still be used as a feature for noisy signals.

3.5. Experiment Results. The random forest model is used for the detection of epilepsy. Random forest is an efficient integrated detection method composed of a large number of decision trees. The constructed decision trees have little correlation [17]. In the paper, random forest models are established for normal, abnormal, and original signals (data without denoising and Riemann potato processing). The parameters of the model are optimized by using the grid search method. The number of variables randomly selected in the normal signal classification model is 2. The optimal number of decisions is 500. The threshold for nonepilepsy and epilepsy is 0.5 and 0.55, respectively. In the abnormal signal classification model, the number of randomly selected variables is 1, the optimal decision number is 500, and the judgment threshold of nonepilepsy and epilepsy is 0.4 and 0.6, respectively. In the original signal classification model, the number of randomly selected variables is 2, the optimal decision number is 500, and the threshold of nonepilepsy and epilepsy is 0.5 and 0.5, respectively. Using R language to implement the model, the detection results are shown in Table 6.
It can be seen from Table 6 that the accuracy of the model used for the classification of abnormal signals is 93.91% correctly, and there are only a few nonepileptic classification errors for the normal signals. The main reason is that abnormal signals are separated by the Riemann potato, and the center of the Riemann potato is decided by average value. There is individual instantaneous noise in the noisy signal, resulting in a slight deviation of the average value of the signal, resulting in very few nonepileptic classification errors. In practice, if there is no instantaneous noise, the accuracy will be better in principle.

The comparison of detection performance between the proposed method and some existing methods is shown in Table 7. It can be seen from Table 7 that the performance of the proposed method is the best in terms of accuracy, sensitivity, and specificity, especially in terms of sensitivity, and it can achieve 94.84% correct classification of epileptic signals, which has important practical application value.

4. Conclusion

In the paper, the original EEG signal containing noise is selected as the research object, and 10 representative EEG channels are selected for feature extraction. The original signal is divided into normal signal and abnormal signal by Riemann potato. The epilepsy detection models of normal signal and abnormal signal are established, respectively, and the overall detection model is obtained by integrating the epilepsy detection model of normal and abnormal signal. The experiment results show that the accuracy is 94.84%, the sensitivity is 83.03%, and the specificity is 97.67%. Although the paper realized epilepsy detection in noisy environment, it has the following two limitations: (1) The research is based on the database provided by MIT and does not consider the generalization ability. (2) Although epilepsy detection is realized in noisy environment, there is still space for improvement. Aiming at the two limitations mentioned above, the following research needs to be done in the future: (1) It is necessary to establish an epilepsy detection model based on the characteristics of different data sets and individuals. (2) Although epilepsy detection can be realized in noisy environment, the detection performance is still far from practical application. It is of great significance to improve epilepsy detection performance.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors’ Contributions

Yandong Ru contributed the central idea, analyzed most of the data, and wrote the initial draft of the paper. Jinbai Li analyzed some data, proofread the paper, and revised the manuscript. Zheng Wei drew the figures and interpreted the experimental results.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (61370222), National Key R&D Program of China under grant 2020YFB1710200, and State Key Laboratory for Novel Software Technology (2020YFB1710200).

References

[1] A. Gupta, P. Singh, and M. Karlekar, “A novel signal modeling approach for classification of seizure and seizure-free EEG signals,” IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 26, no. 5, pp. 925–935, 2018.
[2] A. R. Hassan, A. Subasi, and Y. Zhang, “Epilepsy seizure detection using complete ensemble empirical mode decomposition with adaptive noise,” Knowledge-Based Systems, vol. 12, no. 191, pp. 2–12, 2019.
[3] M. Li, W. Chen, and T. Chen, “Automatic recognition of epileptic EEG based on DD-DWT and logistic regression,” Chinese Journal of Scientific Instruments, vol. 40, no. 6, pp. 1368–1377, 2017.
[4] P. Singh, S. D. Joshi, R. K. Patney, and K. Saha, “Fourier-based feature extraction for classification of EEG signals using EEG rhythms,” Circuits, Systems, and Signal Processing, vol. 35, no. 10, pp. 3700–3715, 2016.
[5] N. Ille, P. Berg, and M. Scherg, “Artifact correction of the ongoing EEG using spatial filters based on artifact and brain signal topographies,” Journal of Clinical Neuropsychology, vol. 19, no. 2, pp. 113–124, 2002.
[6] A. Delorme, T. Sejnowski, and S. Makeig, “Enhanced detection of artifacts in EEG data using high-order statistics and independent component analysis,” NeuroImage, vol. 34, no. 4, pp. 1443–1449, 2007.
[7] T. Zhu and L. Huang, “Epileptic seizure prediction from single-channel scalp EEG using support vector machine based on fuzzy feature extracted with empirical mode decomposition,” Journal of Instrumentation, vol. 31, no. 11, pp. 2434–2439, 2010.
[8] V. K. Mehla, A. Singhal, P. Singh, and R. B. Pachori, “An efficient method for identification of epileptic seizures from EEG signals using Fourier analysis,” Physical and Engineering Sciences in Medicine, vol. 44, no. 2, pp. 443–456, 2021.
[9] J. R. Williamson, D. W. Bliss, D. W. Browne, and J. T. Narayanan, “Seizure prediction using EEG spatial temporal correlation structure,” Epilepsy & Behavior, vol. 25, no. 2, pp. 230–238, 2012.
[10] B. Dongmei, Q. Tianshuang, and L. Xiaobing, “Sample entropy and its application in EEG epilepsy detection,” Journal of Biomedical Engineering, vol. 24, no. 1, pp. 200–205, 2007.
[11] J. S. Richman and M. J. Randall, “Physiological time-series analysis using approximate entropy and sample entropy,” American Journal of Physiology. Heart and Circulatory Physiology, vol. 278, no. 6, pp. H2039–H2049, 2000.
[12] Z. Jianzhao, J. Wei, and B. Maye, “EEG automatic detection in normal period, epileptic interval and seizure period based on sample entropy and wavelet packet energy feature extraction and real AdaBoost algorithm,” Journal of Biomedical Engineering, vol. 33, no. 6, pp. 1031–1038, 2016.
[13] Y. Shan and L. Yingjie, “A review of off-line removal of scalp EEG artifacts by transcranial magnetic stimulation,” *Journal of Biomedical Engineering*, vol. 36, no. 1, pp. 146–150, 2019.

[14] M. Congedo, A. Barachant, and R. Bhatia, “Riemannian geometry for EEG-based brain-computer interfaces; a primer and a review,” *Brain Computer Interfaces*, vol. 4, no. 3, pp. 155–174, 2017.

[15] Q. Barthélemy, L. Mayaud, D. Ojeda, and M. Congedo, “The Riemannian potato field: a tool for online signal quality index of EEG,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 2, pp. 244–255, 2019.

[16] A. Shoeb, *Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment*, [Ph.D. thesis], Massachusetts Institute of Technology, 2009.

[17] K. Q. Shen, C. J. Ong, X. P. Li, and Z. Hui, “A feature selection method for multi-level mental fatigue EEG classification,” *IEEE Transactions on Biomedical Engineering*, vol. 54, no. 7, pp. 1231–1237, 2007.

[18] Y. Yuan, G. Xun, K. Jia, and A. Zhang, “A novel wavelet-based model for EEG epileptic seizure detection using multi-context learning,” in *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pp. 694–699, Kansas City, MO, USA, 2017.

[19] T. Das, A. Ghosh, S. Guha, and P. Basak, “Classification of EEG signals for prediction of seizure using multi-feature extraction,” in *2017 1st International Conference on Electronics, Materials Engineering and Nano-Technology*, pp. 1–4, Kolkata, India, 2017.

[20] D. Jacobs, T. Hilton, M. Del Campo, P. L. Carlen, and B. L. Bardakjian, “Classification of pre-clinical seizure states using scalp EEG cross-frequency coupling features,” *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 11, pp. 2440–2449, 2018.

[21] C. Park, G. Choi, J. Kim, and J. Chong, “Epileptic seizure detection for multi-channel EEG with deep convolutional neural network,” in *2018 International Conference on Electronics, Information and Communication*, pp. 1–5, Honolulu, HI, USA, 2018.

[22] T. Zhang, W. Chen, and M. Li, “AR based quadratic feature extraction in the VMD domain for the automated seizure detection of EEG using random forest classifier,” *Biomedical Signal Processing and Control*, vol. 31, pp. 550–559, 2017.

[23] K. A. Khan, P. P. Shanir, Y. U. Khan, and O. Farooq, “A hybrid local binary pattern and wavelets based approach for EEG classification for diagnosing epilepsy,” *Expert Systems with Applications*, vol. 140, no. 3, pp. 1–9, 2020.

[24] L. Mingyang, C. Wanzhong, and Z. Tao, “FuzzyEn-based features in FrFT-WPT domain for epileptic seizure detection,” *Neural Computing and Applications*, vol. 12, pp. 9335–9348, 2019.

[25] H. Daoud and M. Bayoumi, “Efficient epileptic seizure prediction based on deep learning,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 7, pp. 10–20, 2019.