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Seizure prediction algorithm based on simulated annealing and machine learning

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Abstract

Epilepsy is one of the widespread diseases of the central nervous system around the world, which is characterized by seizures with different periods and symptoms among people. Expecting incoming seizures is important and necessary to organize the patient's life and take the necessary precautions to preserve his life. Methods: We used a seizure prediction algorithm based on four stages. In the first round, one of the person's Electroencephalogram (EEG) channels is selected to be the input channel based on a statistical analysis of the person's EEG recordings. In the second round, the preictal period length (PIL) and the length of the sample segment (SEG) used are calculated. In the third round, several features from the selected channel's data are extracted, while in the fourth round, the simulated annealing method is used to find a set of features that achieve the best performance in differentiating between the Preictal and Interictal periods. Results: The results showed an average sensitivity of 77% and a low false prediction rate of 0.2 by testing the algorithm with the CHB-MIT scalp dataset. Conclusion and Significance: Comparing our results with the results of recent research showed the superiority of our results in terms of using one channel compared to multiple channels in other research.

Keywords: Biomedical and Health Informatics, Feature Extraction, Machine Learning, Seizure prediction, Simulated Annealing
2020 MSC: Primary 90C33; Secondary 26B25

1 Introduction

Epilepsy is a widespread prolonged brain disease with nearly 50 million patients worldwide, the early death rate of whom is 2 to 3 times that of disease-free persons, and it presents a heavy problem for the patients, their families, and society [14][30]. The electroencephalogram (EEG) signal is commonly utilized in epileptic seizure detection and prediction, as epilepsy diagnosis can be performed by identifying the abnormalities of EEG signals [25].

Major physiognomies of epilepsy are repetitive seizures. During a seizure cycle, four stages can be recognized. The interictal, is the time interval that lies relatively far from seizure onset, the preictal stage, is the time before the seizure commencement, the ictal stage, is the time when the seizure occurs, the postictal stage, which is the period immediately succeeds the end of a seizure [32]. Nevertheless, evolutions from the interictal stage to the ictal stage turn

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out to be gradual changes, and this is known as the pre-ictal state [17]. The existence of precautionary symptoms for a large group of epilepsy patients is also indicated in modern studies [24]. The researchers suggested many algorithms for seizure prediction, but obtaining a general and accurate algorithm to predict seizures is very difficult due to the following reasons:

1. EEG signal is extremely complex and varies unevenly over time [12].
2. The pre-ictal and interictal states across individuals are highly variable.
3. The distinction between pre-ictal and interictal states in an individual is vague and unclear.

There are no fixed rules used in the seizure prediction algorithms, so it is not fair to compare the performance of these algorithms as the conditions are different, but it is possible to summarize the common points and the sites of difference in the following:

1- The majority of researchers have used EEG signals as a source of information.

2- Different numbers of EEG channels have been employed.

3- Different values of the pre-ictal period have been utilized.

4- Different features are extracted and utilized.

5- Different types of feature learners and feature classifiers have been utilized.

As mentioned in point 4 in the previous paragraph, many linear and non-linear features are extracted from EEG signals. The main feature extraction methods are established on the time-domain, frequency-domain, time-frequency domain, and nonlinear analysis [2]. Examples of these features are correlation dimension, correlation entropy, noise level, Lempel-Ziv complexity, largest Lyapunov exponent [1], Wavelet energy and entropy [11], Zero-crossing rate [18], Energy, entropy, standard deviation [20], Spectral power estimation [19].

However, these features combined with machine learning cannot achieve high sensitivity and low false prediction rate (FPR) simultaneously, therefore, in this paper, a multi-stage seizure prediction algorithm is presented utilizing many of these mentioned features in a feature selection fashion by simulating annealing method [6]. Based on the fact that the EEG signals are varying from person to person; we conclude that there are no common features among individuals that will give discrimination between inter-ictal and pre-ictal intervals. So, a feature selection is substantial for a good seizure prediction algorithm [8].

The proposed multi-stage seizure prediction algorithm consists of 4 stages. The first stage is the EEG channel selection stage. The second stage is the stage of finding the optimum pre-ictal period and segment length. The third stage is the stage of extracting features from the EEG channels. Finally, the last stage is the stage of finding the set of features that gives the best prediction accuracy utilizing the simulated annealing method.

The rest of the paper is presented as follows. Section 2 provides a brief list of recent related works. Section 3 presents a pithy description of the feature extraction methods and the datasets employed throughout the research. The proposed algorithm is presented in section 4 and a summary of the results is presented in section 5. Finally, a comparison with other works and the concluding remarks are reported in sections 6 and 7 respectively.

2 Related Works

In this section, a brief review of some recent related works is presented. Given the research use of various databases in the seizure prediction field; our focus is on the research that utilizes the CHB-MIT database for comparison purposes.

A method based on time-frequency analysis EEG and unsupervised feature representation learning was used by Agboola et al. [3]. They extracted features named Normalized Logarithmic Wavelet Packet Coefficient Energy Ratios (NLWPCER) to be feature space of the classifier. Their prediction algorithm achieved a sensitivity of 87.26% and a false prediction rate of 0.08/h with the SVM classifier, an average sensitivity of 75.49%, and the false prediction rate of 0.13/h with the ANN classifier.

Alotaiby et al. [5] used Multichannel EEG signals and extracted common spatial pattern (CSP) based features from EEG signals. They trained a linear discriminant analysis classifier, with leave-one-out cross-validation strategy. Their prediction obtained method achieves an average sensitivity, and false prediction rate, of 0.89, and 0.39, respectively. They used a 60, 90, and 120-minute prediction horizon.

Elgohary et al. [10] introduced a method that depends on the counting of zero-crossings of wavelet coefficients of EEG signals. They used this number as an input feature to a binary classifier that discriminates between preictal and interictal states. They used an adaptive algorithm for channel choice to identify the optimum number of needed channels. Their method achieved an average accuracy of 94% and an average sensitivity of 96% with only 10 minutes of training data.

Chu et al. [7] (19) developed a seizure prediction method based on attractor state analysis. Their method depends on the power spectral density of low-frequency bands in the EEG which shows a comparative increase near a bifurcation point making a critical transition from the normal state to the seizure attractor state. Their method showed a sensitivity of 86.67% with a false prediction rate of 0.367 /h and an average prediction time of 45.3 min.

The wavelet transformation of the EEG signal and Convolutional filters are used by Khan et al. [16] to learn quantitative signs of seizure. They also calculated the optimal seizure prediction horizon from the data and found it to be 10 minutes. They achieved a sensitivity of 87.8% and a low false prediction rate of 0.142 FP/h.

Short-time Fourier transform of 30-s EEG windows used by Truong et al. [27] (21) to extract the frequency domain and the time domain information so that the algorithm automatically generates features for each patient. A convolutional neural network is used to classify these features as preictal and interictal states. Their approach achieves a sensitivity of 81.2% and a false prediction rate of 0.16/h, on the CHB–MIT scalp EEG dataset.

Long Short-Term Memory (LSTM) networks are introduced in epileptic seizure prediction by Tsiouris et al. [28] using EEG signals. They used a two-layer LSTM network with four different lengths of the preictal period, ranging from 15 min to 2 h. By evaluating the method with the CHB-MIT Scalp EEG database, they achieved false prediction rates (FPR) of 0.11–0.02 false alarms per hour, depending on the duration of the preictal window.

Al-Bakri et al [4] used several electrophysiological features like signal power in the delta, theta, alpha, beta, and gamma bands; and the mean, standard deviation, skewness, kurtosis, etc., in addition to measurements like blood volume pulse, heart rate, and skin temperature; a Naive Bayes classifier were trained with these features. The classifier achieved 69% sensitivity, 64% specificity, and 33% kappa for preictal sleep epochs; and 15%, 93%, and 10% respectively for wake epochs.

Usman et al. [29] applied empirical mode decomposition (EMD) to EEG signals before extracting time and frequency domain features. They assumed that the preictal period is a few minutes before the seizure onset, and they achieved true positive rate of 92.23% on the scalp EEG CHB-MIT dataset of 22 subjects.

Dissanayake et al. [9] used a convolutional neural network to automatically learn features of preictal and interictal segments, they achieved a sensitivity of 93.45% and Specificity of 81.64% with 1-hour preictal period.

Based on the foregoing, we see that the preictal period used by researchers varies, and then used features also vary. Therefore, we see that it is necessary to calculate the preictal period for each person separately. Also, the distinguishing features set are different between people, so the distinguishing features should also be found for each person separately. So we introduce a seizure prediction algorithm that takes these two points into account.

3 Methods for feature Extraction

The data used for this study is the CHB-MIT database which consists of multichannel long-term EEG recordings obtained from 21 epilepsy patients. The patients were monitored for several days using scalp electrodes placed according to the 10-20 system [26].

The data was divided into two parts, the training part, and the test part, and in each part, the pre-ictal and interictal intervals were taken equally to maintain the training unbiased. Because the interictal period is large compared to the preictal period, and to maintain the comprehensiveness of the data used in the training, samples were taken from different times during the interictal period, as clear from Fig. 1. The interval will be equal to the variable PIL, which is calculated through the algorithm for each patient individually, depending on the principle of the different nature of the EEG signals between people, and therefore the preictal period will also differ. The interval has also been divided into segments; the length of each segment is equal to the SEG variable, which is also calculated for each patient separately.

In this research, a large set of features were extracted and their usefulness was evaluated in differentiating between preictal and interictal status. It appeared when the algorithm was applied to patients' data that the differentiating

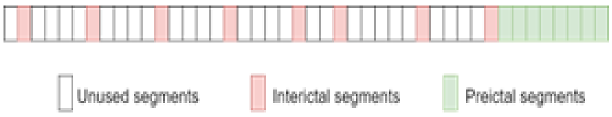

Figure 1: EEG segments used in training.

features differed from one patient to another. Among the features that appeared and gave a good performance in differentiating between the case of preictal and interictal are the following: Approximate entropy [21], Empirical mode decomposition (EMD) [13][31][22][23], Amplitude of power spectrum for delta, alpha, and beta bands [15], residual and mean envelope energy of Intrinsic Mode Function (IMF) No. 6, Number of sifting iterations used to extract IMFs, the standard deviation of IMF No. 1 and IMF No. 2, the relative tolerance of IMF No. 3, many linear and non-linear well-known features were extracted from the EEG signal, such as Lyapunov Exponent, Skewness, Correlation Dimension, Kurtosis, and Variance, to be added to the list of input features to the seizure prediction algorithm.

A. Simulated Annealing

Simulated annealing (SA) is a probabilistic method offered by Kirkpatrick, Vecchi and Gelett, and Cerny for locating the global minimum of a function that has several local minima points. “It emulates the physical process whereby a metal is gradually cooled so that when sooner or later its structure is ”frozen,” this takes place at a minimum energy configuration” [14].

4 The Proposed Algorithm

The proposed algorithm is a multi-round algorithm, at the first round, the channel selection round, the EEG channel that has the most relevant features is selected. The channel of choice is the channel or EEG electrode placed near the source area of epilepsy in the brain. Fig.2 shows the flowchart of the first round. The round starts with the reading of recorded EEG signals to convert them into segments of length SEG=10 seconds, the PIL is assumed to be 10 minutes. Then the features were extracted from the preictal and interictal periods. The statistical t-test was applied to feature data and the ratio of discriminating features that have p-value ¡ 0.05 to the total number of features stored for each EEG channel. The channel that has the maximum ratio will be the output of the first round. Table 1 shows the results of the round with 10 patients, the selected channel for each patient is well-matched with the seizure type for each patient.

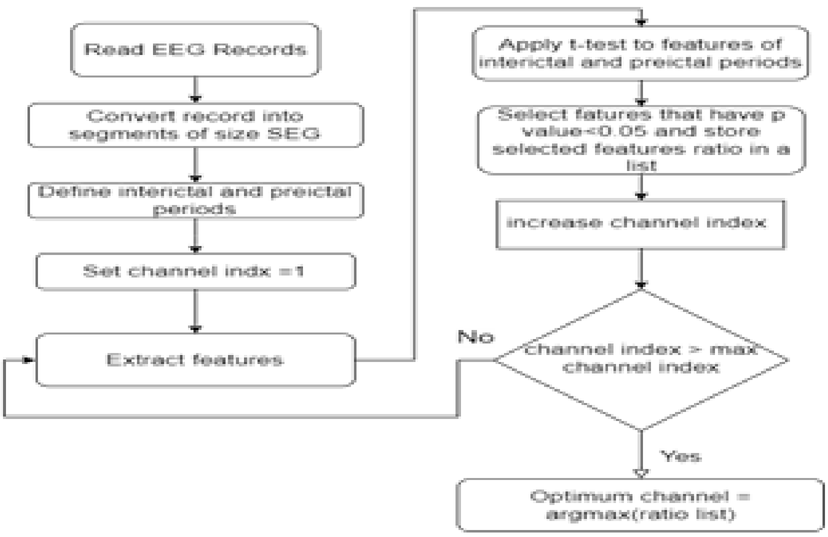

Figure 2: The flow chart for the first round.

The second round is for optimum PIL and SEG calculation, based on the fact that the EEG signals are patient-specific; we conclude that PIL also is patient-specific. However, in this round, only EEG data of the selected channel from the first round is used for further computations. Fig. 3 shows the flowchart of the second round. The round starts to iterate for values of PIL (10-30) minutes and SEG (10-30) seconds and for each value the features were

Table 1: The results of channel selection round with seizure type.

Patient ID	Gender	Age	Seizure type	Brain location	Selected channel
1	F	11	SP, CP	Frontal	FP2-F8
2	M	11	SP, CP, GTC	Temporal	T8-P8
3	F	14	SP, CP	Frontal	FP1-F7
4	M	22	SP, CP, GTC	Temporal	T7-FT9
5	F	7	CP, GTC	Frontal	FP2-F8
6	F	1.5	CP, GTC	Temporal/Occipital	FP1-F3
7	F	14.5	SP, CP, GTC	Temporal	FP1-F7
8	M	3.5	SP, CP, GTC	Frontal	T7-FT9
9	F	10	CP, GTC	Temporal/Occipital	C4-P4
10	M	3	SP, CP, GTC	Temporal	T7-P7
23	F	6	-	Temporal	FT9-FT11
24	-	-	-	-	C3-P3

extracted and t-tests were applied. The ratio of discriminating features that have a p-value ¡ 0.05 to the total number of features is stored for each PIL-SEG pair. Finally, the PIL-SEG pair that gives the maximum ratio is chosen.

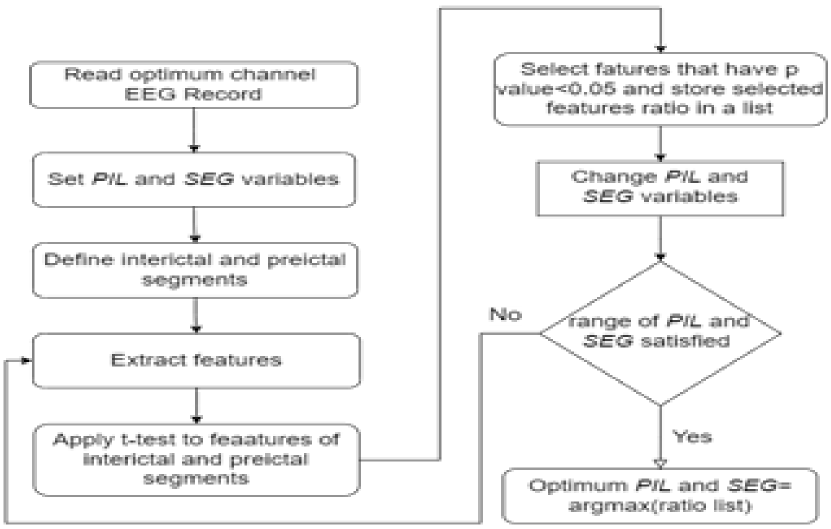

Figure 3: The flowchart of the second round.

In the third round (Fig. 4) the optimum channel and optimum PIL and SEG were used to form interictal and preictal data sets, and then extract 65 features from EEG data to form solution space for the simulated annealing (SA) algorithm. In the fourth round (Fig. 4) an initial subset x0 of 10 -features is selected randomly from the solution space. Table 2 shows the chosen parameters for the SA algorithm. SA algorithm is an optimization algorithm that finds the optimum solution iteratively. In each iteration a new solution is chosen randomly from solution space, the available data is split into a 70% training set and 30% testing set, and then an SVM model were trained and tested for the given solution. To make sure that the trained model with the current solution is neither over-fitted nor underfitted both resubstitution loss and test loss are used in cost function calculation. The cost function will be given as in (4.1):

$$\text{cost function } = \frac{\text{resubstitution loss+test loss}}{2} \tag{4.1}$$

After the cost function calculation of the current solution, it will be compared with the cost function of its preceding one, if there is any improvement the solution is accepted, else it will be accepted according to the Metropolis rule where the probability of accepting the solution is decreased with temperature decrease. Finally, if the maximum number of iterations is reached for the current temperature, the temperature will be decreased according to the cooling schedule and a new solution will be generated.

Table 2: Parameters for SA algorithm

Minimum temperature	1E-8
Annealing schedule or cooling function	@(T) (.95*T)
Maximum consequence rejections	1000
Maximum number of success	20
Boltzmann constant (k)	1
Maximum number of iterations	300

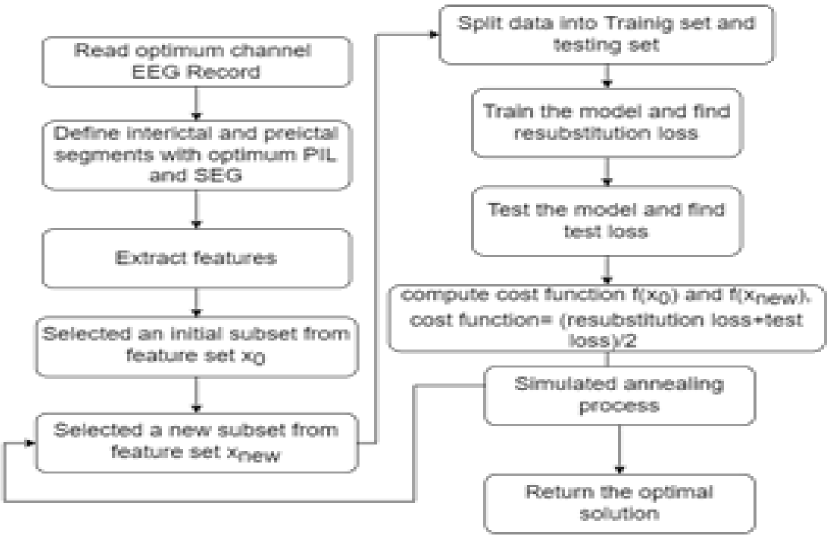

Figure 4: The flowchart of the third and fourth rounds.

5 Results and Discussion

In this section, the performance of the algorithm and obtained results are presented. The performance of the proposed seizure prediction algorithm was measured in terms of sensitivity and specificity. In each test, the sensitivity is evaluated as the percentage of successfully predicted seizures, whereas the specificity refers to the total false predictions that occurred per hour. In a seizure prediction test that screens EEG segments for a preictal, each tested segment either is a preictal segment or not. The test result could be positive or negative, which indicates that the segment is preictal or interictal, respectively. The test outcomes for each EEG segment in this scenery can be as follows (4):

- True positive (TP): Preictal segments correctly identified as preictal
- False positive/ False alarm (FP/FA): Interictal segments incorrectly identified as preictal
- True negative (TN): Interictal segments correctly identified as interictal
- False negative (FN): Preictal segments incorrectly identified as interictal

The sensitivity, specificity, and accuracy are computed as in (5.1):

$$\text{sensitivity} = \frac{\sum \mathrm{TP}}{\sum \mathrm{TP} + \Sigma \mathrm{FN}}$$

$$\text{specificity} = \frac{\sum \mathrm{TN}}{\sum \mathrm{FA} + \Sigma \mathrm{TN}}$$

$$\text{accuracy} = \frac{\sum \mathrm{TP} + \sum \mathrm{TN}}{\sum \mathrm{TP} + \sum \mathrm{FA} + \sum \mathrm{FN} + \sum \mathrm{TN}} \tag{5.1}$$

Table 3 represents the output of the last three rounds of the algorithm. The results showed a difference in the preictal period between patients (PIL), ranging from 20-30 minutes on the CHB-MIT scalp database. Also, the length of the EEG segment (SEG) used in the training process differed between patients, ranging from 20 seconds to 30 seconds. These values of PIL and SEG gave the highest percentage of discrimination between the preictal and interictal traits in patients, which would increase the accuracy and specificity in predicting a seizure.

The in-sample loss and test loss data give evidence of the generality of the algorithm and it's devoid of over-fitting.

We also note that the distinguishing features are different between patients with common features among several patients, for example, feature No. 59, which represents the standard deviation of the intrinsic mode function No.3. Other common features among patients are feature No. 1 and No. 33, which represent the largest Lyapunov exponent of EEG segment and the signal power in alpha band respectively.

Other important features in distinguishing between the interictal and the preictal periods are the following: standard deviation, skewness, and kurtosis of the EEG signal in the time domain, the power of the EEG signal in the theta, alpha, beta, and gamma bands in the frequency domain, the number of extreme points, sifting, and zero crossing in empirical mode decomposition, mean and standard deviation of intrinsic mode functions.

Table 3: PIL, SEG, and optimal features for each patient obtained from algorithm

Patient ID	PIL min	SEG sec	Optimum Channel	In sample loss	Test loss	Optimum feature indexes returned by the algorithm
Chb01	20	25	13	0	0.0347	59 57 19 12 16 25 65 3 8 62
Chb02	20	20	15	0.2024	0.1780	42 4 59 54 33 55 28 53 34 48
Chb03	20	25	1	0.3309	0.3221	56 4 59 34 62 33 29 21 30 9
Chb04	20	25	1	0.3941	0.4839	18 12 17 47 21 20 5 29 28 60
Chb05	10	30	13	0.2054	0.2194	21 11 16 65 61 9 59 18 53 39
Chb06	30	30	4	0.2534	0.2572	55 43 39 42 28 53 51 56 33 27
Chb07	20	30	1	0.2768	0.4444	4 52 24 19 11 58 8 53 64 3
Chb08	10	20	20	0.0476	0.0610	46 19 54 33 36 57 18 51 55 5
Chb09	10	30	11	0	0.3281	42 57 61 4 51 1 63 21 20 59
Chb10	10	20	3	0.2381	0.3100	12 21 6 54 11 25 59 33 1 16
Chb23				0	0.196	52 42 58 34 10 51 25 43 3 1

Table 4 summarizes the overall performance of the algorithm. The sensitivity, specificity, accuracy, and false alarm are listed for each patient. High accuracy with a very low false alarm rate was gained for patients 1, 8, and 9. While for other patients good accuracy with relatively low false alarms is obtained.

short PIL period, reduces stress and anxiety in the patient, compared to long periods in other research. As for the extracted features, the algorithm suggests different features for each patient, which will be important in reducing the

Table 4: Seizure prediction results obtained with the CHB–MIT scalp EEG database.

Patient ID	TN samples	FP samples	FN samples	TP samples	Sensitivity	specificity	accuracy	FA/h
1	239	1	4	236	0.983	0.996	0.999	0
2	105	15	32	88	0.733	0.875	0.804	0.125
3	136	56	70	122	0.635	0.708	0.672	0.29
4	119	77	87	105	0.547	0.607	0.577	0.39
5	72	8	27	53	0.663	0.9	0.781	0.1
6	315	78	136	284	0.676	0.802	0.737	0.19
7	48	32	20	60	0.75	0.6	0.675	0.4
8	133	17	0	150	1	0.887	0.943	0.1
9	75	5	10	70	0.875	0.938	0.906	0.06
10	136	74	36	174	0.829	0.648	0.738	0.35

arithmetic operations required to extract these features.

As indicated in Table 5 this work succeeded with all patients while other studies fail in prediction with patients Chb02 and Chb09 [27] [5]. The average sensitivity is 77% and the average FPR is 0.2.

Table 5: Benchmarking of recent seizure prediction approaches and this work

Patient ID	[21]		[22]		[20]		[16]		[17]		[19]		[25]		This work.	
	Sensitivity	FPR/h	Sensitivity	FPR/h	Sensitivity	FPR/h	Sensitivity	FPR/h	Sensitivity	FPR/h	Sensitivity	FPR/h	Sensitivity	FPR/h	Sensitivity	FPR/h
Chb01	85.7	0.24	100	0	-	-	100	0.03	100	0.33	100	0.06	-	-	98.3	0.004
Chb02	33.3	0	100	0	-	-	100	0.04	67	0.42	-	-	-	-	73.3	0.125
Chb03	100	0.18	100	0.26	-	-	100	0.06	50	0.13	66	0	-	-	63.5	0.29
Chb04	-	-	100	0.15	-	-	100	0.04	100	0.85	-	-	-	-	54.6	0.39
Chb05	80	0.19	100	0.31	-	-	66.7	0.11	80	0.56	66	0.612	-	-	66.2	0.1
Chb06	-	-	100	0.37	-	-	100	0.17	10	0.11	66	0.52	-	-	67.6	0.19
Chb07	-	-	100	0	-	-	100	.03	100	0.45	-	-	-	-	75	0.4
Chb08	-	-	100	0	-	-	-	-	100	0.46	100	0.88	-	-	100	0.1
Chb09	50	0.12	100	0.13	-	-	50	0.06	100	0.6	-	-	-	-	87.5	0.06
Chb10	33.3	0	100	0	-	-	100	0.18	100	0.47	100	1.59	-	-	82.5	0.35
23	100	0.33	100	0	-	-	-	-	100	0.67	100	0.52	-	-		
24	-	-	100	0.28	-	-	66.7	0.08	50	0.37	-	-	-	-		
Average	81.2	0.16	99.3	0.11	87.8	0.14	87.3	0.08	0.81	0.47	86.67	0.367	93.45	0.18	77	0.2
Number of channels	23		23		23		23		23		1		23		1	
PIL	5 min		>15 min		10 min		60 min		60 min		86 min		1 hour		>10 min specific for each patient	
Features	STFT spectral images		Statistical moments, zero crossings, Wavelet Transform coefficients, PSD, cross-correlation, graph theory		Wavelet Transform coefficients		Normalized Logarithmic Wavelet Packet Coefficient Energy Ratios		Common spatial pattern		Fourier coefficients of six EEG frequency bands, attractor state analysis		-		Patient-specific	

6 Conclusion

The ability to predict seizures has been studied and enriched over the last four decades. A flawless prediction is not yet obtainable, but with current prediction capabilities, it seems possible to warn patients so they can take some insurance for their safety. In this research, we presented a seizure prediction algorithm that depends on a short PIL period and only one EEG channel, which gives the patient a smooth workflow and is not restricted to wearing a full EEG helmet, as well as a short PIL period that allows the patient to take the necessary precautions without feeling anxious for long periods. Extracting different features for each patient means different required computational capabilities between patients, this means that the required computational capacities for some patients will be few depending on the required features. Using the proposed method, we obtained satisfactory results using only one EEG. A comparison with other research showed that our results are better in terms of the ratio of sensitivity to the number of used EEG channels.

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