Majority Vote of Ensemble Machine Learning Methods for Real-Time Epilepsy Prediction Applied on EEG Pediatric Data

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***Abstract* – The main aim of the study is to develop a real-time epilepsy prediction approach by using the ensemble machine learning techniques that might predict offline seizure paradigms. The proposed seizure prediction algorithm is patient-specific since generalization showed no satisfactory results in our previous studies. The algorithm is tested on CHB-MIT database comprised of EEG data from pediatric epileptic patients. Based on relations to number of seizures and number of files, gender and age, three patients have been chosen for this study. The special majority voting algorithm is proposed and used for raising an alarm of upcoming seizure. EEG signals are denoised using MSPCA (Multiscale PCA), the features were extracted by WPD (wavelet packet decomposition), and EEG signals were classified using Rotation Forest. The significance of the study lies in the fact that the proposed seizure prediction algorithm could be used in novel diagnostic and therapeutic applications for pediatric patients.**

***Keywords* – Majority Vote, Rotation Forest, Real-Time Prediction, Epilepsy.**

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1. Introduction

Epilepsy is neurological disorder that has characteristics of the brain recurring tendency to make unexpected burst of atypical electrical activity that disturbs other functions of the brain [1]. These kinds of activities are known as seizures; they happen randomly and can happen many times in one day. Loss of awareness or consciousness, and movement disturbances and sensation are included in clinical manifestations. According to the World Health Organization estimations, epilepsy is extremely prevalent; at least 8.2 per 1,000 of the overall population labor from the condition, and may have reflective social, physical and psychological effects [2, 3].

In order to diagnose and identify epileptic seizure, it is necessary to monitor the EEG of the patient for several days. This monitoring is time-consuming, tedious and expensive. Therefore, a reliable real-time seizure-detection system can make easier long-term monitoring and seizures treatment. Furthermore, if partial seizure is detected at the first step of its development; its main emphasis might be localized according to the clinical symptoms and the EEG patterns, which is helpful in presurgical evaluations [4, 5].

Electroencephalogram (EEG) has been used for many decades in order to diagnose clinical epilepsy. If we compare other techniques like Electrocorticogram (ECoG) with EEG, the EEG seems to be more appropriate way for detecting the brain activity. It is well established clinical analysis of EEG traces for seizure identification. Nevertheless, the features analyzed types and how they are applied to classify the signal depend from the automated EEG based techniques performance.

Shoeb & Guttag [6] report the first approach of machine learning applying CHB-MIT database (CHB-MIT Scalp EEG Database). The patient-oriented method achieves the accuracy of 96% of 173 seizures for test, with 3s of latency and false detection rate (FDR) of 2 per hour. Khan et al. [7, 8] completed another study and they improve detection accuracy which is presented in [6]. There are also studies where authors focus on separation of seizure-free and seizure period using CHB-MIT database. Rafiuddin et al. [9] achieve accuracy of 96.5% for epileptic seizure detection applying wavelet-based feature extraction method on 23 patients with 195 seizures. In [10] is presented a supervised machine learning technique for detection of seizure applying records from multiple records. In [11] is proposed a new model based on electroencephalography (EEG) measurements, that is completely in charge of automated seizure onset detection and seizure onset prediction. The accuracy of this model generally achieved 100% in ictal vs. inter-ictal EEG. Prediction of season onset could differentiate between inter-ictal, pre-ictal, and ictal EEG with the accuracy of 99.77%, and between inter-ictal and pre-ictal EEG states with the accuracy of 99.70%.

2. Methodology

CHB-MIT Dataset is freely available from psihonet.org and consists of 23 different subsets containing EEG records from 22 different pediatric patients including 17 females and 5 males. This dataset contains 686 scalp EEG recording and 182 seizures. Generally, each of these digitized records is one-hour long. Sampling frequency is 256 Hz with 16-bit resolution. All seizure starts, and ends were confirmed by board-certified electroencephalographer who analyzed all EEG records manually [12, 13, 11]. From this database, based on the proportion between the number of seizures and the number of files, gender and age we pick three patients which will be processed in this study. Information about selected patients is showed in Table 1.

Table 1. Analyzed EEG data

Patient	**Gender**	**Age**	**Number of files**	**Number of files with seizures**	**Hours of recording per file**
CHB03	F	14	38	7	1
CHB08	M	3.5	20	5	1
CHB16	F	7	19	6	1

MSPCA

Principal Component Analysis is the combination of the variables as a linear weighted sum transforms an $n \times p$ data matrix, *X* as

$$X = TP^T \qquad (1)$$

where, n and p are the estimations and the primary segment loadings recorded as P and the principal segment scores are characterized as T. A huge choice in PCA is to pick the proper important parts that include the basic relationship. Some methods are available for this task and are studied by Jackson [14] and Malinowski [15]. A cross-validation can be used, if an approximation of the error is not available [16]. Multiscale PCA (MSPCA) is blend of the PCA capacity to evacuate the cross-relationship between the factors. The perceptions are decayed utilizing wavelet change for every factor to join the PCA and the advantages of the wavelets. This outcomes in information framework change, X into a matrix, WX, where W is an orthonormal matrix exhibiting the orthonormal wavelet change. The amount of vital parts to be saved at each scale isn't changed by the wavelet decay since it doesn't change the main connection between the factors at any scale [16, 17, 17].

DWT - WPD

One of the powerful time-recurrence procedures for investigation of different non-stationary signals, for example, EEG, has a place in a gathering of wavelets-based strategies. Discrete Wavelet Transform breaks down a flag into an arrangement of capacities (wavelet coefficients) by scaling and moving of mother wavelet work. The signal can be modified as direct mix of wavelets and weighting wavelet coefficients.

The procedure for DWT disintegration starts with the choice of the quantity of wavelet decomposition levels indicated as *j_max*. For the principal disintegration level *j* = 1, discrete-time EEG signal, $x[k]$, went through the high-pass channel, $h[\cdot]$, and the low-pass channel, $l[\cdot]$, and after that down sampled by 2. The corresponding outputs are Detail, D_j, and Approximation, A_j, respectively:

$$D_j[i] = w_{high}[i] = \sum_k x[k] \cdot h[2 \cdot i - k] \quad (2)$$

$$A_j[i] = w_{low}[i] = \sum_k x[k] \cdot l[2 \cdot i - k] \quad (3)$$

After D_j and A_j have been obtained, the approximation A_j is set as $x[k]$ and j is set as 2 (increased by 1), and the aforementioned procedure is repeated until j exceeds j_max [18].

Wavelet Packet Decomposition (WPD) is equal to DWT except that the detail coefficients D_j are further disintegrated as well. For a k-level wavelet decomposition, WPD will produce 2^k diverse sets of wavelet coefficients (each level has its own approximation and detail record), whereas DWT generates $k+1$ sets of wavelet coefficients (each level has its own detail coefficient plus one final approximation).

Rotation Forest

Rotation Forest is another recently represented compelling classifier generation technique [19], where the preparation set for each base classifier is made by utilizing PCA to turn the underlying characteristic axes. Accurately, to produce the preparation information for a base classifier, the property set F is arbitrarily separated into K subsets and PCA is utilized to each subset.

All principal components are kept because of preserving the variability data information [20].

3. Proposed Method

The plan is as follows: firstly, we will check the relation between the number of files we have for a patient and the number of seizures, based on the data we have, we are going to choose three patients with the highest number of seizures in combination with the least number of EEG recording files. Then we divided the seizures into two groups according to their length. So, longer seizures will be trained, and the rest are going to test. The whole sample of 23 channels has been used for every signal, ictal and preictal signals. Those signals have been taken and the new one was generated with 48 minutes of preictal signal plus the length of the ictal. We have checked the interictal signals for chosen patients and divided them into train and test. 23 channels of each signal were loaded, and the structure was created from them. After that we separated motions on 2048 pieces and produced new one with those parts. 23 channels of interictal and preictal information from the preparation dataset will be isolated into smaller portions (8 seconds – 2048 examples). The matrix will be made at regular intervals of these sections (the matrix size will be 2048 x 1380). The matrix will be denoised utilizing MSPCA. Wavelet packet decomposition highlights will be removed from each denoised 8-seconds in length section and put into preparing database. 10-overlap cross validation will be performed on the preparation database to tune the machine learning algorithm parameters. The window time of 8 minutes has been taken since we have 48 minutes of preictal time (contains 6 of these time windows). Five of these time windows (40 minutes) will be utilized for making any expectation of future possible seizure. We will find it alarming if 3 continuous chunks were predicted as seizure from 5 chunks.

4. Results

Figure 1 presents seizure prediction of the first seizure for Patient 3. As we can see, we have perfect prediction where we captured the incoming seizure approximately 50 minutes before it happened. It gives enough time for the patient to take some measures in order to make the seizure easier for him. We used 12 hours of interictal signals combined with 1h of preictal and 1h of ictal signal. This patient has 7 seizures, and we used 3 of them for training, and 3 for testing, because the first seizure happened within the first recording signal, so we don't have preseizure time in order to predict the seizure.

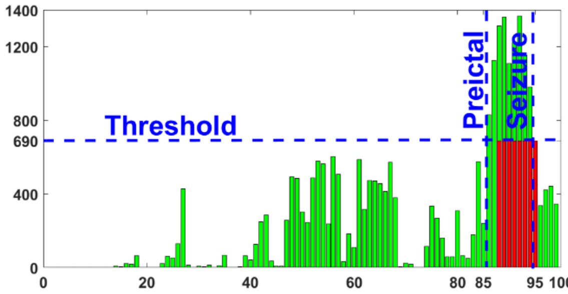

Figure 1. Epilepsy prediction for first seizure of patient 3

Figure 2 represents seizure prediction of the second seizure for patient 3. We used 12 hours of interictal signals in combination of preictal and ictal signal. We predicted seizure for significant time before it starts, and it is around 45 minutes.

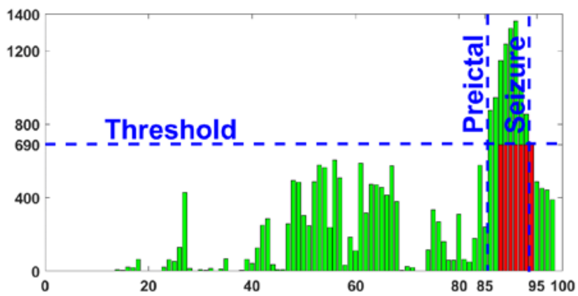

Figure 2. Epilepsy prediction for second seizure of patient 3

Figure 3 represents seizure prediction of the third seizure for patient 3. We again used 12 hours of interictal signals in combination of preictal and ictal signal. We predicted the seizure for significant time before it starts, and it is around 65 minutes.

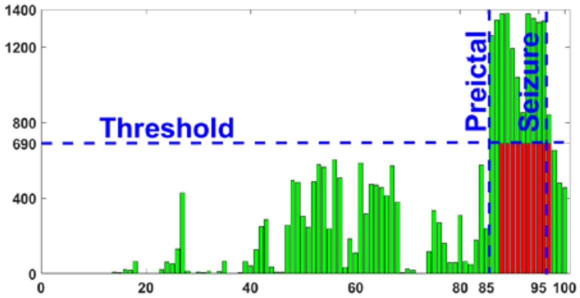

Figure 3. Epilepsy prediction for third seizure of patient 3

Experiment has been made on patient 8 as well. This patient has 2 seizures for testing so Figure 4 presents prediction time of the first seizure. We used 7 hours of interictal signals, 1 hour of preictal and ictal signal. We predict seizure and turn on alarm around 25 minutes before the seizure starts.

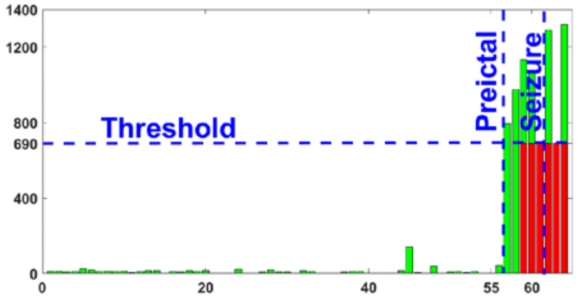

Figure 4. Epilepsy prediction for first seizure of patient 8

For the second seizure prediction of Patient 8 we used the same interictal signals, and we combined them
with 1 hour of preictal and 1 hour of combination of preictal and ictal signal. As you can see in Figure 5, we again predict the seizure the very first time and give around 70 minutes to the patient to take some actions in order to make the seizure attack easier for him.

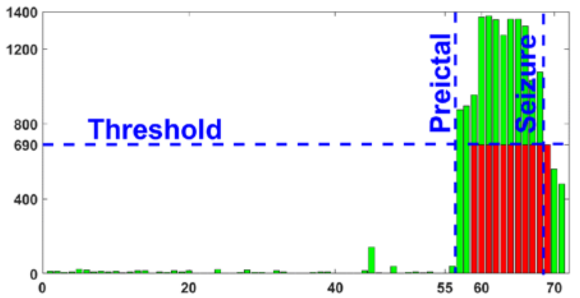

Figure 5. Epilepsy prediction for second seizure of patient 8

Patient 16 has 3 test seizures and prediction results of the first one is presented in Figure 6. For this patient, we used 6 hours of interictal signal, 1 hour of preictal and 1 hour of combination of preictal and ictal. As you can see in the following figure, we predict beginning of seizure around 70 minutes before it starts, and it is one of the earliest seizures predicted for the processed patients. In two chunks, we predict seizure in the interictal period, but because of our majority system for alarm, we did not mark that as seizure period.

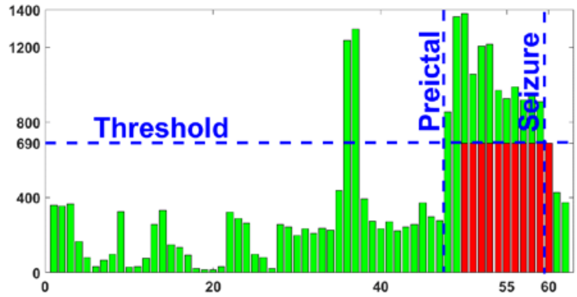

Figure 6. Epilepsy prediction for first seizure of patient 16

Figure 7 presents second seizure prediction for patient 16. We used the same interictal signals and got the same result in interictal period where we predicted two chunks as a seizure, but we did not rise alarm, because it should be 3 seizure predictions in a row in order to mark that period as preseizure period. We used 6 hours of interictal signals in combination with preictal and ictal signal and we predicted seizure about 30 minutes before it starts.

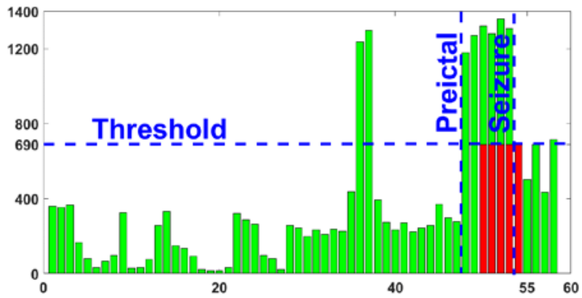

Figure 7. Epilepsy prediction for second seizure of patient 16

Our last figure 8 represents the third seizure prediction for patient 16. We used the same number of interictal signals, but this patient has two seizures in one file. For the first seizure in this file we did not have enough preictal time, so we predict seizure around 3 minutes before it starts, and for the second seizure in this file, we had enough preictal time, so we predict that seizure around 25 minutes before it starts.

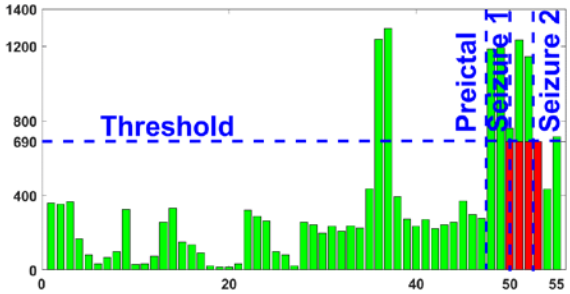

Figure 8. Epilepsy prediction for third and fourth seizure of patient 16

5. Discussion

In terms of our proposed method can say that it is in the frame of real-time, since datasets that we have used for training and testing are entirely separated. Therefore, for the training phase we used 15 hours from interictal and 2 or 3 preictal and ictal phases, so we used all of those signals to create training dataset. On the other hand, in order to test the purpose, we used completely unknown signals, we managed them like we managed training signals, and send to trained model for evaluation. We sent chunk of 8 minutes signal and made decision after every chunk. If 3 chunks out of 5 were categorized as seizure, then we defined alarm state, and the patient got notification about that. Not only that we had predicted all of the upcoming seizures for all three patients, but they were also informed about the attack at least half an hour before it actually happened.

In our experiment, we used threshold which is half of the total value for preictal signal, and we compared our predicted value with the threshold as well.

The threshold which have been used for the experiment showed good accuracy therefore it was not necessary to change the method. However, the use of dynamic threshold would be better since it would include half of middle value for preictal predicted values.

If we check our results, you might see that we predict all seizures, so we can say that prediction for these 3 patients achieved 100% accuracy.

The patients that were included in the experiment showed excellent results, however, the third seizure of the patient number 16 was not provided with enough preictal signal, which produce very late seizure prediction, but again we predicted the seizure before it started. Overall, for all the patients, we managed to predict the seizure 30 minutes before it started, which is enough time for the patient to take some action in order to make the seizure easier or to take some medicament which will stop the seizure.

All the patients have different prediction value for interictal signals. Patient 16 has two chunks which are predicted as preictal period, but because of the majority of the system which is implemented in our experiment, we did not mark that as alarm.

For patient 8 we had perfect prediction for the interictal period, where we can decrease threshold, and again to obtain 100% accuracy.

Table 2. Comparison table for seizure prediction on CHB-MIT database

Author	**Accuracy (%)**
Khan et al. [7]	91.8
Nasehi et al. [8]	98
Shoeb [12]	96
Ferguson et al. [21]	98
Qidwai et al. [22]	90
Alickovic et al. [11]	99.7
This work	**100**

As we can see from Table 2 our proposed method provides better accuracy than all other related experiments. The reason for that we can find in a patient-oriented way of doing our experiment where for each patient we defined different model based on it own train data.

6. Conclusion

This research shows satisfactory and successful result based on achieved accuracy for epilepsy prediction that we achieved as well as huge reduction in time execution. The limitation of this experiment is testing data which were recorded before it is used for online (real-time) epilepsy prediction. This research applied completely new way of epilepsy prediction method where we focus on majority, which is developed based on machine learning technique. With better budget, this research could be implemented for real life usage and with device which will include the proposed method we can make big positive influence on the life of the patients which have epilepsy diseases. We proved that segmentation and majority voting for epilepsy prediction could be sufficient method and future research in this area go in the direction of recording EEG signal from the patient and try to do prediction with the incoming data.

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