Epileptic Seizure Detection Using Topographic Maps and Deep Machine Learning

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ABSTRACT

One third of all epileptic patients is resistant to medical treatment. The construction of machines, that would detect an imminent epileptic attack based on EEG signals, represents an efficient alternative, that would help to increase their quality of life. In this article we described the implementation of an automatic detection method, based on the signal of different frequency sub-bands, using topographic maps and deep learning techniques. We constructed an ensemble of five convolutional neural networks, to classify samples of each sub-band and chose the final decision by a majority voting. The ensemble obtained 99.20% accuracy, 96.48% sensitivity and 99.27% specificity when detecting seizures of one patient. Moreover, when the networks were trained with samples taken randomly from the inter-ictal intervals, we identified on 18 of 21 seizures some false positive classifications close to the seizure onset, thus anticipating the detection of the seizure. Such misclassifications did not occur when training was performed with samples taken within five minutes of the seizure onset.

KEYWORDS

Epileptic Seizure Detection, Deep Learning, Topographic Maps, Electroencephalogram.

1 Introduction

Epilepsy is a neurological disorder characterized by sudden seizure attacks, that may cause in patients loss of consciousness and motor control. It is esteemed that epilepsy affects about 50 million people world-wide and represents up to 1% of the global burden of disease[6]. Although in the last decades many anti-epileptic drugs (AEDs) have been introduced[4], to more than 30% of the patients these treatments are ineffective. Therefore, their daily life activities are very restricted because of the unpredictability of the attacks. The development of different approaches, that could timely inform patients of an imminent epileptic attack is necessary to increase their quality of life.

The most used tool to monitor brain's electrical activity is the electroencephalogram (EEG). However, due to the complexity of the EEG signals, visual detection of epileptic seizures from the signal often results misinterpreted or mistaken. Therefore, in the last decades much research has been oriented towards finding automated detection procedures, that would efficiently analyze large chunks of signals, timely give out warnings and help the medical staff to deliver treatment on time[8].

Since the first studies of epilepsy seizures with EEG, it is known that an epileptic attack has a detectable electrical discharge in the brain (EEG onset), prior to the manifestation of convulsions, loss of consciousness and others symptoms (clinical onset)[7]. The time window between these events usually ranges between 0 to 30 seconds, sometimes reaching over 1 minute. Therefore, being able to detect early enough the EEG onset of the seizure could give enough time to the patient to get the treatment or at least to reach a safe environment.

Based on these motivations, we constructed the following model for epilepsy seizure detection, based on topographic maps generated from EEG signals and deep machine learning classifying techniques.

2 Experimental Setting

In this work we used data from the EPILEPSIAE database[5]. We selected a single patient, with a defined focal epilepsy in the temporal lobe. The recording of the patient of about 161.1 hours contained 22 seizures, averaging 3.28 seizures per day. However, one seizure was discarded from the study since it was described as not reliable. The sampling frequency of the machine was 256 Hz.

The work is composed by two studies, which follow the general processing pipeline: raw data is preprocessed and transformed from time to frequency domain, then the relative powers calculated from the signals of the frequency sub-bands are used to generate topographic maps, which are then fed to the classifier. After a regularization procedure, the performance of the model is evaluated. Figure 1 schematically describes the mentioned pipeline.

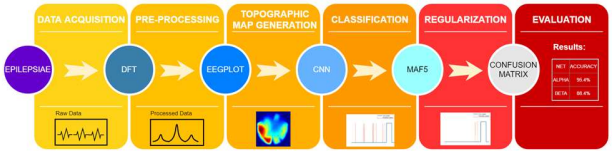

Figure 1: Processing pipeline of the DM process

2.1 Study 1: 80% overlap

2.1.1 Pre-Processing and Feature Extraction

Raw data needs to undergo few pre-processing steps, before it can be used to generate topographic maps. Here, we used functions

from the EPILAB® [3] package. Next, with a high-pass filter kept the frequencies between 0.1Hz and the Nyquist frequency, which in this case was 128 Hz, and then a 50 Hz notch filter was applied to remove possible power line artifacts.

EEG signals are non-stationary. Many mathematical tools for analysis assume the stationarity of the signal. One way to enforce an "artificial" stationarity is by segmenting the signal and making the analysis of the segments globally valid[11]. Initially, the chosen length of segments (sliding time windows) was 5 seconds, with an overlap of 80%. This allows to assume stationarity in these five second windows and preserve frequency resolution. Furthermore, by overlapping by 80% we obtain four time more samples than we would have obtained without it and we might detect additional information that could not be captured between the end of a window and the beginning of another. Five seconds window's length represent a good compromise to keep sufficient time and frequency resolutions and is often used in EEG analysis [2].

While pre-processing the data in time windows, 5 basic frequency features were extracted. Features corresponded to the relative powers of different frequency sub-bands obtained with the Discrete Fourier Transform (delta, theta, alpha, beta, gamma).

2.1.2 Topographic Map Generation

Topographic maps were generated using the *eegplot* function by I. Silva [9], publicly available on MATLAB Exchange. A map was generated for every seizure timepoint, for all five features, resulting in 929 samples for each feature (dataset A). To balance the datasets, the same number of non-seizure samples was generated with randomly selected timepoints. Both sets of samples were further on divided for training (80%), validation during training (10%) and testing (10%).

A second testing set was generated (dataset B), with non-seizure samples taken every second in series from the five-minute interval prior the seizure and half the number of seizure samples after the seizure. Unfortunately, due to limited data, the seizure samples were the same as the one used for training. The new testing set had 6775 non-seizure samples and 929 seizure samples. A clear representation of the datasets is shown in Table 1.

Table 1: Representation of the datasets

Dataset	Objective	Description
A	Training	- 929 ictal samples
	+ Testing	- 929 non-ictal samples taken randomly Separation of data: 80% train., 10% valid., 10% test
B	Testing	- 929 ictal samples (same as data set A) - 6775 non-ictal samples (5 min before the seizure + half the number of seizure samples, after the seizure)

2.1.3 Training and Classification

The classifier we used was an ensemble of five convolutional neural networks, one for each feature. All networks had the same topography, however they differed in the hyperparameters' value. The best hyperparameters for the networks were selected after a grid search on the initial training set. An example of the network structure is shown in Table 2.

Table 2: Example of a network structure

Layer:	Name	Output	Learnables
1	InputLayer	766x884x3	0
2	Conv1	383x442x16	448
3	BatchNorm1	383x442x16	32
4	ReLu1	383x442x16	0
5	MaxPool1	383x442x8	0
6	Conv2	383x442x8	520
7	BatchNorm2	192x221x4	8
8	ReLu2	383x442x8	0
9	DropOut1	383x442x8	0
10	MaxPool2	192x221x8	0
11	Conv3	192x221x4	132
12	BatchNorm3	192x221x4	8
13	ReLu3	192x221x4	0
14	DropOut2	192x221x4	0
15	FullCon1	1x1x32	5431328
16	ReLu4	1x1x32	0
17	FullCon2	1x1x2	66
18	SoftMax	1x1x2	0
19	ClassOutput		0

The networks were trained for 32 epochs, using the RMSprop optimizer, randomly shuffled minibatches of 16 samples and the training performance was validated every 30 iterations. The same networks were also used to test the second testing set.

2.2 Study 2: 98% overlap

2.2.1 Pre-Processing and Feature Extraction

Due to the limited ictal data in the first study, we decided to perform a second one with more samples. To augment the data, we increased the overlap to 98%, which produced ten times more samples. Besides the overlap, all the pre-processing steps were performed identically as in the first study.

2.2.2 Topographic Map Generation

In the second study the training samples were not selected randomly as in the first study, but they were picked from the intervals from five to one minute prior every seizure (dataset C). We intentionally kept the last minute out of training, with the intent of obtaining again the FP classifications close to the seizure onset. Furthermore, to balance the seizure and non-seizure datasets we added some more randomly picked non-seizure samples.

Next, similarly as in the first study, we generated another testing set with the samples taken in series, starting from one hour before the seizure (dataset D). However, in the second study the samples were taken every two seconds, due to the notorious computational overhead. Again, a better representation of the datasets is shown in Table 3.

Table 3: Description of used datasets

Dataset	Objective	Description
C	Training	- 8342 ictal samples - 5280 non-ictal samples (5-1 min before seizure) - 3062 non-ictal samples (taken randomly) 20% of the samples were used for validation
D	Testing	- 950 ictal samples - 37800 non-ictal samples (1 hour before seizure, samples taken every two seconds)

2.2.3 Training and Classification

In the second study we used the same topography of the classifier as in the first study, however the networks were trained with the new training set (dataset C). We opted to use the same hyperparameters as in the first study, since we used the same sub-bands and the same seizures of the same patient. We used the same training procedure, apart from the number of epochs and validation frequency, which were set to 16 and 500 respectively, due to the augmented data.

3 Results

3.1 Study 1: 80% overlap

The ensemble increased almost all the classification scores, comparing single individual networks, apart from the sensitivity in the theta sub-band network, which was originally higher than in the ensemble. The evaluation metrics are shown in Table 4.

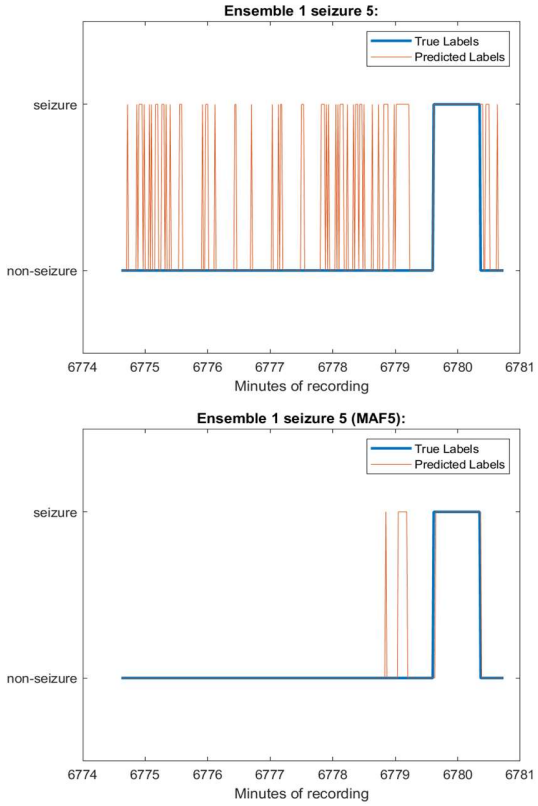

Figure 2: The effect of applying the MAF5 filter

Table 4: Evaluation metrics

	TP	TN	FP	FN	AC	SS	SP
Alpha	85	77	16	8	87.10%	91.40%	82.80%
Beta	86	79	14	7	88.71%	92.47%	84.95%
Gamma	80	86	7	13	89.25%	86.02%	92.47%
Delta	80	80	13	13	86.02%	86.02%	86.02%
Theta	89	88	5	4	95.16%	**95.70%**	94.62%
Ensemble 1	88	91	2	5	**96.24%**	94.62%	**97.85%**

When tested on the second set of samples, the specificity dropped to 89.88%, meaning that on this interval there was an increase of FPs. Since the samples were selected in series, we decided to apply a moving average filter (MAF5) to reduce FP predictions. Both AC and SP increased, while the SS dropped. These results are presented in Table 5. Furthermore, in Figure 2 is presented the effect of the MAF5 filter.

After applying the MAF5 filter, on 18 of 21 seizures we could identify FP classifications, within 1 minute before the seizure (see Figure 2). Such misclassifications are promising, since they suggest the model could even anticipate the seizure onset. This was also a reason, that led us perform a second test.

Table 5: Results of first study

	AC	SS	SP
Normal	90.99%	99.65%	89.88%
MAF5	**96.68%**	**92.56%**	**97.23%**

3.2 Study 2: 98% overlap

In the second study we tested the networks directly on the dataset D. After applying the MAF5 filter, the ensemble obtained 99.20% accuracy, 96.48% sensitivity and 99.27% specificity, as shown in Table 6.

Table 6: Results of second study

	AC	SS	SP
Normal	85.34%	98.96%	84.99%
MAF5	**99.20%**	**96.48%**	**99.27%**

We also noticed that the FP classifications close to the seizure onset did not occur in the second study. Moreover, they appeared further away from the seizure, mostly from 40 minutes to 10 minutes before (see).

4 Discussion

The first ensemble increased almost all the classification scores compared to individual networks. However, when tested with a series of samples taken close from the seizure onset, the number of false positives increased, while the seizures remained correctly classified. We believe that this high classification score of the

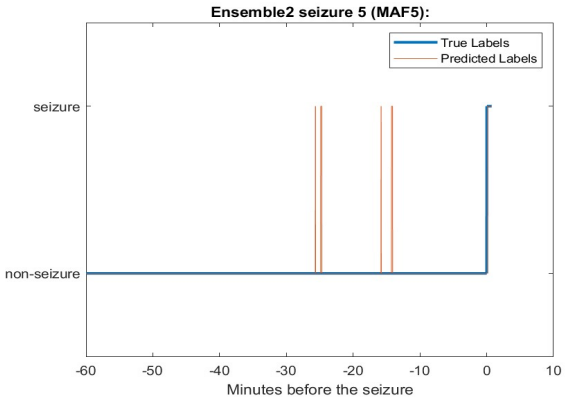

Figure 3: FPs appearing far from the seizure onset

seizure set was due the fact that 80% of the seizure samples used for this testing, were also the same used for training the network. Therefore, it is believed, that the network "remembered" those samples and classified them correctly.

The high increase of false positive classifications with the new test set are believed to be due the fact that the samples used for training, which are taken randomly from all the non-ictal intervals, were distinct from the ones really close the seizure onset. This leads to believe, that there is a noticeable change in the signal while approaching the transition from the non-ictal to the ictal phase. However, by applying the MAF5 filter, the score increased. The MAF5 filter could potentially suit the real-time detection, since it only requires a delay of few samples. In the case of 5 second sliding windows, with 80% overlap, this delay would be of 2 seconds with the filter size 5, which fits early detection necessities.

After applying a moving average filter, with a stride of five, to reduce the number of false positive classifications, we noticed that for 18 out of all 22 seizures, within a range of 1 minute, some false positive classifications persisted (as seen in Figure 2). This is curious, since these false predictions could anticipate the occurrence of an imminent attack. Thus, we retrained the networks with augmented data, to see if these false predictions persist.

After testing the second ensemble on the dataset D, we could not identify the false alarms close to the seizure onset as in the previous testing. Moreover, only four seizures had a false alarm within five minutes before the seizure. We believe that this is a consequence of the training set C. Although samples from one minute before the onset were left out of training, with the intention of producing some false alarms, they were classified correctly in the test. Another evidence supporting our claim are the false predictions far from the seizure, that appear in most of the seizures. Hence, to get rid of them and produce the false predictions close to the seizure onset, the training set should include more samples that are far away from the seizure. However, these results show that there is a difference within non-ictal samples far from the seizures and non-ictal samples close to them.

5 Conclusions

As expected, the second study's classification scores outperformed the first one, since it was trained on a larger dataset. It obtained a 99.20% accuracy, 96.48% sensitivity and 99.27% specificity. However, it failed to replicate the FP predictions close to the seizure onset, as the first one did.

Overall, the model obtained scores that are comparable to the state-of-the-art results[1,8,10]. Although this model does not have an early prediction performance, it still yields good detection scores. Furthermore, both studies give some insights on the early detection, that might be possible to perform, due to the diversity of the non-ictal samples, located far and close to the seizure.

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