

From Electroencephalogram to Epileptic Seizures Detection by Using Artificial Neural Networks

Gaetano Zazzaro, Angelo Martone, Roberto V. Montaquila, Luigi Pavone

Abstract—Seizure is the main factor that affects the quality of life of epileptic patients. The diagnosis of epilepsy, and hence the identification of epileptogenic zone, is commonly made by using continuous Electroencephalogram (EEG) signal monitoring. Seizure identification on EEG signals is made manually by epileptologists and this process is usually very long and error prone. The aim of this paper is to describe an automated method able to detect seizures in EEG signals, using knowledge discovery in database process and data mining methods and algorithms, which can support physicians during the seizure detection process. Our detection method is based on Artificial Neural Network classifier, trained by applying the multilayer perceptron algorithm, and by using a software application, called Training Builder that has been developed for the massive extraction of features from EEG signals. This tool is able to cover all the data preparation steps ranging from signal processing to data analysis techniques, including the sliding window paradigm, the dimensionality reduction algorithms, information theory, and feature selection measures. The final model shows excellent performances, reaching an accuracy of over 99% during tests on data of a single patient retrieved from a publicly available EEG dataset.

Keywords—Artificial Neural Network, Data Mining, Electroencephalogram, Epilepsy, Feature Extraction, Seizure Detection, Signal Processing.

I. INTRODUCTION

EPILEPSY is a neurological disorder characterized by recurrent seizures caused by abnormal electrical discharges from the brain cells. Characteristics of seizures vary and depend on many factors, such as where they originate in the brain, the daily frequency and so on. Depending on the type of seizures, different kinds of side effects for the patients are possible, which severely impact their quality of life and their social, physiological and physical interactions. The ultimate goal of epilepsy treatment is to provide seizure control for all patients; however, only 70% of patients respond to medical treatments [1], while for the remaining 30% other approaches are needed to manage the disease. To accurately diagnose and treat epilepsy patients, precise seizure documentation by the patient himself or relatives is essential for good clinical and scientific practice, but information provided by patients or by their relatives is often incomplete and more than half of the seizures identified in long-term video EEG monitoring are not reported [2], so more precise measurements are needed.

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The most commonly used tool in the clinical practice to monitor and diagnose epilepsy is EEG signal, recorded either from the scalp (scalp-EEG) or intracranially (iEEG). The Scalp-EEG is recorded by placing the electrodes on the surface of scalp by using international standard 10–20 system [3], while the iEEG is caught by placing the electrodes directly on the surface of brain or in deep regions of the brain. For drug-resistant patients or for patients for which the diagnosis is not clear after the ambulatory screening, long-term EEG monitoring is needed, both for confirming the diagnosis of epilepsy, and for localizing the brain region producing the seizures [4]. Continuous EEG monitoring is often accompanied with video recording (video-EEG), synchronized with EEG, in order to detect behavioral phenomena that can help to classify the type of a seizure. In fact, long-term video-EEG monitoring provides information about seizure semiology, inter-ictal abnormalities, and ictal rhythms. It is a definitive method to differentiate between seizures and non-epileptic events, to classify seizures, and to localize the ictal onset zone.

Seizures are manifested in EEG as paroxysmal high-amplitude graphic elements, created by excessive neuronal synchronous discharges and their detection on EEG is commonly made manually, by visual inspection of epileptologists. The big amount of data generally available for each patient makes this work hard and long-lasting, so computerized and automated methods for seizure detection are needed in order to provide a valuable tool for clinicians to speed up the process of seizure detection and at the same time to provide precious and accurate data for epilepsy diagnosis and management. Almost all automated methods for seizure detection in EEG consist of extraction of features from the EEG signal and then the use of the Data Mining (DM) approach for feature selection and seizures classification.

In this paper, we present a seizure detection method based on the extraction of 26 features by means of an ad-hoc implemented software tool called Training Builder and seizures classification using DM techniques such as Artificial Neural Networks.

II. STATE OF THE ART

A. Most Recent Ideas and Methods for Seizure Detection

Until now, many studies had focused on developing automated seizure detection methods using EEG signals (both scalp or intracranial) not only for helping epileptologists in diagnose epilepsy and detect seizures from EEG but also for developing closed-loop therapies for epilepsy treatment. Closed-loop systems should be able to recognize seizures from

EEG and then try to abort seizures by, for example, sending an alarm to the patient or by stimulating electrically the site where the seizure started. Each of those seizure detection methods consist of a feature extraction step from brain signals and a feature classification and selection step. In the recent past, a considerable number of features have been used as markers for seizure detection, such as features based on time-frequency analysis [5]-[7], entropy-based approaches [8], [9], wavelet transform [10], [11], multivariate analysis [12] and recurrence plot based features [13]. Similarly, many types of classifier have been used, such as Convolutional Neural Net [14], [15], Bayesian classifier [16], Deep Neural Net [17], and fuzzy-rule based [18]. In the last years, DM approaches are becoming the gold standard approach in the field of seizure detection and many approaches have been proposed [19]-[21].

B. Data Mining Process for Seizure Detection

Fig. 1 shows the general process flow for seizure detection.

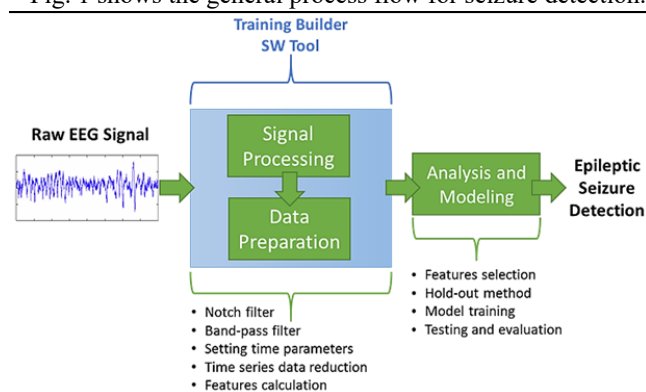


Fig. 1 Process flow for seizure detection

The process is a customization of the Knowledge Discovery in the Database Process (KDD), widely used for DM tasks [22]-[24]. The figure also displays, in the blue box, the functionalities of an implemented SW tool, called *Training Builder*, useful in the data preparation step: from signal processing to features calculation. In the next sections, all the steps of this process are described.

C. Data Mining Goal

This paper describes how to develop an algorithm able to detect seizures from EEG recordings of epileptic patients, using DM techniques, in order to automatically detect seizures. We approached the problem of seizure detection as a problem of binary classification, whose aim is to discriminate EEG signals containing seizures from EEG signals without seizures. Moreover, classification models are trained in order to detect the incipit of epileptic seizures.

III. DATA UNDERSTANDING AND PREPARATION

A. Freiburg Seizure EEG Database

In order to test our algorithm, we used data from the Freiburg Seizure Prediction EEG database (FSPEEG) [25], [26]. The database contains intracranial EEG recordings of 21 patients with drug-resistant epilepsy acquired during invasive

presurgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany. Recordings were at 256 Hz sampling rate with 16-bit A/D converter. Two expert epileptologists selected six EEG channels from the total number of available channels, three located near to the epileptogenic area started or where seizure activity had been detected (“InFokus” channels) and the remaining three located quite far from the seizure focus, where no seizure activity had been detected (“OutFokus” channels). For each patient, there are the “ictal” recordings, containing seizures, and “preictal” recordings, which are recordings acquired immediately before or after the ictal phase, but without seizures. For this study, we used only data from one representative patient (patient number 3), in order to evaluate the performance of our algorithm.

B. Signal Processing

Analog signals are quite often affected by different kind of noise, in particular by quantization noise, which is due to the process of Analog Digital Conversion (ADC). Hence, it is fundamental to filter EEG signals before any other processing [27], [28].

By using a band-pass filtering, the EEG signals (acquired from each InFokus/OutFokus electrode) was filtered through six different frequency bands (8-12 Hz, 13-20 Hz, 21-30 Hz, 30-45 Hz, 40-70 Hz, 70-120 Hz), obtaining six distinct signals. The upper limit of 120 Hz is constrained by the Nyquist-Shannon sampling theorem, considering that the sampling frequency at which the EEG signals was acquired is 256 Hz. These frequency bands correspond to well-known human brain oscillations. Then, almost the whole spectrum of available frequencies has been covered

C. Sliding Window and Training Builder Software

In order to train a classifier able to recognize specific fundamental fractions of the signal within time series, the sliding window (SIW) technique can be applied, which is a strategy widely used in Machine Learning and Stream Data Mining [29], [30].

SIW is a method to rearrange a time series dataset as a supervised learning problem. A class of algorithms for stream processing focuses on the recent past of time series by applying a SIW on the data. In this way, only the last values of each streaming time series are considered for the analysis. Given a continuous time series stream, the SIW technique (or paradigm) examines the most recent data points and moves S steps along the time axis as new measurements arrive, where s is the step size. In other words, every S points (or seconds) the analysis focuses on the last L points (or seconds) of the time series. S and L are the temporal shift and the length of the window, respectively. The SIW moves on the time axis identifying a group of k ordered data. If f is the data sampling rate, and L is the length of the window in seconds, $k=f*L$ is the number of the points in the window. While it is not easy to fix the length L of the SIW (or its k points), the value of L is related to both the historical series and the analysis technique to be used.

Each window may have elements in common with the

previous window, but if there are no elements in common between the two windows ($S > L$) the SIW is called “tumbling window”.

In most applications, each window is passed to a data processing unit, which performs some kind of time series classification, clustering, or anomaly detection.

TABLE I
WEB FORM FIELDS DESCRIPTION

Field Name	Meaning	Value
L Parameter	The length of the signal to be analyzed, expressed in seconds	[0, 3600]
S Parameter	The slippage of the signal to be analyzed, expressed in seconds	[0, 3600]
Patient	The patient number on which to perform the analysis	[1, 21]
Phase	The phase of a recording to analyze	PreIctal, Ictal
Registration file	The number of EEG recording to analyze	Number of recording (it depends on Patient)
Fokus	The electrodes to analyze	[IN, OUT]
Bandwidth	The frequency bandwidth to analyze (in Hertz)	B08=[8,12], B13=[13,20], B21=[21,30], B30=[30,45], B40=[40,70], B70=[70,120]
Univariate feature	The features of univariate type to be computed	See Table III
Bivariate feature	The features of bivariate type to be computed	See Table III
Bivariate calculation method	It indicates with respect to which reference signal to calculate the bivariate features	Wrt previous L, wrt zero, wrt outfokus electrodes

The Training Builder (TrB) [31] is a software application for the massive extraction of features from time series, by which the temporal analysis parameters can be chosen. The TrB creates the training sets that will be the input to Modeling next step, implementing the aforementioned SIW technique. In addition, because of time series are generally high-frequency data and a direct dealing with such data is very time and memory consuming, it is highly desirable to develop representation techniques that can reduce the number of points of time series.

Many techniques have been proposed for representing time series with reduced data points, among these, Piecewise Aggregate Approximation (PAA) [32], Symbolic Aggregate approximation (SAX) [33], Piecewise Linear Approximation (PLA) [34], etc. These time series representation algorithms have been implemented in TrB, as shown in the data preparation step of Fig. 1. So, output training set varies depending on:

- Time series (or better the recording of them).
- Temporal analysis parameters: L and S.
- Time Series Representation algorithm.
- Features to be computed.

The application was designed following the client/server architectural model, in which the server part is composed by the algorithms for features and representation computation and other support utilities, while the client part is composed by a responsive browser-based application, responsible for visualizing output results and submitting a form for temporal parameters selection. By using the responsive web-oriented graphical user interface of the TrB software application, all the

temporal analysis parameters, input sources, representation algorithms, and features can be selected by the user. Moreover, the user can select a subset of data points from a time series, specifying the time interval through a separate graphical window.

The output consists in a comma-separated values (csv) file format, where features are stored as column vectors. The output format can also be customized by using a set of options: e.g. the number of decimal digits, to include/exclude data source description, computation statistics, etc. Thanks to the implemented web application, we can easily fix all input parameters (e.g. temporal parameters, patient number, univariate/bivariate features, etc.) for the TrB.

Table I shows the description of the option fields.

For the training of the classifier, the temporal parameters of the TrB are fixed and are reported in Table II.

TABLE II
TEMPORAL PARAMETERS OF THE TRAINING BUILDER

L	S
The length of the signal to be analyzed, in seconds	The slippage of the signal to be analyzed, in seconds
5 s	1 s

D.Features Calculation and Selection

Following the SIW paradigm, every s seconds the previous L seconds of signal are analyzed and 26 features are calculated starting from L. Every second the analysis focuses on the last five seconds of the time series.

TABLE III
COMPUTED FEATURES

Id	Feature Name	Code	U/B	Selected	Count
1	Standard Deviation	SM1	U	X	4
2	Variance	SM2	U		
3	Skewness	SM3	U		
4	Kurtosis	SM4	U	X	10
5	Mean	SM5	U		
6	Hjorth Mobility	HP1	U		
7	Hjorth Complexity	HP2	U		
8	Shannon Entropy	EB1	U	X	16
9	Log-Energy Entropy	EB2	U	X	14
10	Kolmogorov Complexity	CB1	U	X	9
11	Upper Limit Lempel-Ziv Complexity	CB2	U		
12	Lower Limit Lempel-Ziv Complexity	CB3	U		
13	Peak Displacement	SE1	U		
14	Predominant Period	SE2	U		
15	Averaged Period	SE3	U		
16	Squared Grade	SE4	U	X	1
17	Squared Time to Peak	SE5	U		
18	Inverted Time to Peak	SE6	U	X	2
19	Conditional Entropy	MC1	B	X	16
20	Joint Entropy	MC2	B	X	22
21	Mutual Information	MC3	B	X	30
22	Cross Correlation Index	MC4	B		
23	Euclidean Distance	DB1	B	X	6
24	Dynamic Time Warping	DB2	B	X	13
25	Longest Common Sub-Sequence	DB3	B	X	31
26	Levenshtein Distance	DB4	B	X	28

Currently, the features have been divided into seven classes and can be Univariate (U) or Bivariate (B): 1) SM: Statistical Moments; 2) HP: Hjorth Parameters; 3) EB: Entropy Based; 4) CB: Complexity Based; 5) SE: Seismic Evaluators; 6) MC: Mutual Conditioned; 7) DB: Distance Based.

The seismic features have been calculated by considering [35], where the authors prove an analogy between earthquakes and epileptic seizures, and by considering [36] for their calculations. The calculation of these seismic variables has been adapted for the neurological field for the first time in this work.

Bivariate algorithms are used to compute similarity distance between the current running signal and a "reference" signal. This reference signal can be of three different types: 1) Previous L: the same signal taken at a previous L interval (s seconds backwards); 2) Zero: the constant signal equal to 0; 3) Different Synchronous Signal: the synchronous signal happening in the same instant but originated from different electrodes.

Table III shows the list of all implemented features. The final dataset has 2377 features (2376 features calculated by the Training builder tool + 1 target class), because $2376 = (a + b * c + b * d) * e * f$, where:

- $a = 18$ (univariate features).
- $b = 8$ (bivariate features).
- $c = 3$ (bivariate modality calculation).
- $d = 3$ (type of reference signal).
- $e = 6$ (number of the bandwidths).
- $f = 6$ (electrodes: 3 InFokus + 3 OutFokus).

We selected only the patient number 3 from the database because, thanks to a preliminary statistical analysis, it had a high number of seizures during its temporal monitoring and the seizures lasted longer than those of other patients. In particular, the patient had six epileptic seizures with an average duration of 92 s. The final dataset has 31270 cases, and each case refers to 5 seconds of signal.

The target class is instantiated with the value "NO" if the recording under investigation does not contain a seizure, with the value "YES" if it contains a seizure. Its distribution is [NO,YES]=[30665 (98%), 605 (2%)] and it is unbalanced, because the number of samples belonging to ictal recordings represent a small percentage of the final dataset. This condition is called the class imbalance problem. The number of input features has been reduced by applying a feature selection algorithm, based on the Information Gain (IG) formula [22]. We get that $IG \in [0, 0.313]$. We choice to remove all attributes that have a score of less than 0.2. Thus, the number of features decreases from 2376 to 202. Table III also shows the selected features. We can see how the bivariate features are very high in the ranking and much counted.

IV. MODELING, VALIDATION, AND TESTING

A. Hold-Out Method

In order to train a detection classifier, the hold-out method [22] is applied, in which the dataset with labeled examples is partitioned into two disjoint sets, called training and test sets,

respectively. A model is induced from the training set and its performances are evaluated on the test set. The algorithms parameters are fixed by applying the cross-validation method [22] with 10 folds. For the sake of clarity, the training and the test sets are formed by instances coming from different files of neurological recordings. In order to overcome the class imbalance problem, the subset of the records labeled with "NO" of the training set has been random undersampled, in order to be equal in number to the ones labeled with "YES". In particular, the training set has 508 records with target class label "NO" and 508 records with target class label "YES".

B. Training Neural Nets by Applying MLP Algorithm

In the modeling phase, models for epileptic detection are trained by using Artificial Neural Network (ANN) algorithms and finally they are tested. The name of the algorithm in Weka tool [23], [24] chosen for training Artificial Neural Networks is MultilayerPerceptron. ANN is the algorithmic technique chosen to realize the model for seizure detection. It is a widely used machine learning technique for supervised learning models. It is used for classification and regression analysis. An ANN training algorithm builds a model that assigns new examples into a class or another. ANN tries to simulate biological neuronal systems. In order to do this, an ANN consists of an interconnected assembly of nodes and directed links. One of the most used and studied model of artificial neural networks is the multilayer perceptron (MLP). MLP is widely used for both binary classification and regression. An MLP has three layers of nodes: an input layer, a hidden layer and an output layer, but its topology can be enriched with other intermediate layers. Except for the input nodes that are the features, each node is a neuron that uses an activation function [22]. The most widespread activation function is the well-known sigmoid function that is a nonlinear function and it is also incorporated in the MLP algorithm of Weka. MLP utilizes the backpropagation that is a supervised learning technique for the ANN training phase. By analyzing the fraction of the EEG signal immediately preceding the beginning of the epileptic seizure and the seizure itself, a classifier is trained on the selected features, in order to detect the signals with seizure by using the sliding window technique. The classifier based on MLP can be used to tag the time series of EEG signals. By using the training data, the MLP algorithm of Weka tool (v.3.8.3) is used to separate the two classes of signals, the EEG signal with seizure and EEG signal without seizure. The trained networks can be built by hand, created by an algorithm, or both. The networks can also be monitored and modified during training time. The nodes are all sigmoid (except for when the class is numeric, in which case the output nodes become unthresholded linear units).

In order to select the best classifier and to compare the results of the algorithms, many indicators and measures were calculated including Accuracy, Area Under the roc Curve (AUC), True Positive rate (TPR), False Positive rate (FPr) [22].

By changing the "hiddenLayers" and "trainingTime" parameters in Weka, many MLPs have been trained. HiddenLayers (H) defines the hidden layers of the neural

network, whilst trainingTime (T) defines the number of epochs to train through.

TABLE IV
SVMs DETAILED ACCURACY BY CLASS

N.	Confusion matrix	Accuracy	TPr	FPr	Precision	AUC	Class
F1	480 28	94.98	0.945	0.045	0.954	0.987	N
	23 485		0.955	0.055	0.945	0.987	Y
F2	461 47	90.65	0.907	0.094	0.906	0.933	N
	48 460		0.906	0.093	0.907	0.933	Y
F3	499 9	98.72	0.982	0.008	0.992	0.997	N
	4 504		0.992	0.018	0.982	0.997	Y

Table IV shows the performances of three MLP-based classifiers, trained by using the cross-validation method and the balanced training set and varying the parameters.

The **F1** model was obtained by fixing $H = t = \text{attrs} + \text{classes} = 202 + 2 = 204$ and $T = 500$ epochs. The **F2** model was obtained by fixing $H = a = (\text{attrs} \text{ classes}) / 2 = (202 + 2) / 2 = 102$ and $T = 700$ epochs. The **F3** model was obtained by fixing $H = 50$ and $T = 550$ epochs.

For the testing phase, we chose the F3 model, which showed the best performances, because it has the highest TPrate, the lowest FPrate, and the highest Accuracy.

C. Model Testing and Errors Analysis Evaluation

Table V shows the F3 detection model performances on the test set formed by recordings 135, belonging to the preictal phase and thus not containing a seizure, and 136, belonging to ictal phase and thus containing a seizure. These two sets are not included in the training set, obviously.

TABLE V
MLP DETAILED ACCURACY BY CLASS ON TEST SET

Confusion matrix	Accuracy	TPr	FPr	Precision	AUC	Class
4425 22	99.995	0.995	0	1	0.948	N
0 97		1	0.005	0.815	0.948	Y

The low number of false positives (22) and the very high accuracy (99.995) of the model demonstrate the high capacity of the binary classifier to discriminate between the elements coming from the preictal recordings and those coming from the ictal ones. ANNs, and therefore MLP, also have some general disadvantages. It is not always possible to have a simple analytical expression of the model, the process could be computationally time consuming, and the classifier is not easily explained by rules.

The two test files and the training set are disjoint sets, although the test sets belong to the same patient 3. This guarantees us a statistical reliability of the model; for the sake of clarity, thinking of using the same neural network to detect epileptic seizures for all patients is a thing that is hoped or wished for but in fact is illusory or impossible to achieve, because patients have different neurological damage, in different locations. Obtaining a personalized model for each patient, although expensive from the point of view of data mining, is certainly a way to reduce false alarms and classification errors. We underline, however, that the work described here is only a first research result and that we intend to deepen the analysis of data of other patients and train other detection models soon.

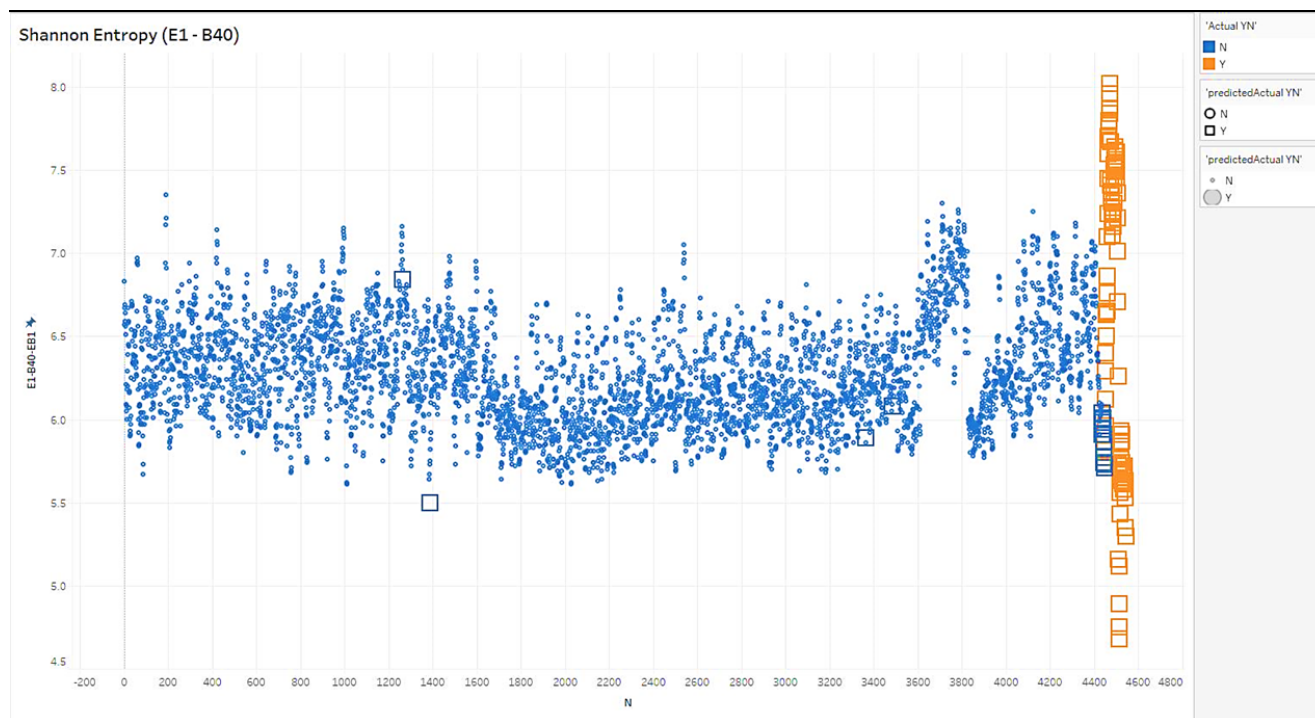


Fig. 3 Trend of the E1-B40-EB1 (Shannon Entropy) variable and classification errors

Fig. 3 shows the trend of the E1-B40-EB1 feature of the test set; “E1-B40-EB1” is a compact name which indicates that the variable refers to Shannon Entropy (EB1), of the signal recorded by the electrode number 1 (E1), computed in the frequency band 40-70 Hz (B40). The orange points indicate the “YES” records (that come from the ictal signal), while the blue points indicate the “NO” records (that come from the preictal signal). The blue boxes represent 22 false positives (false alarms), and they are very close and immediately before the true positives (hit rates).

Even before the real onset of the seizure, it seems that the model based on the MLP algorithm can detect changes in the electrical activity of the brain of patient number 3 a few seconds earlier, as if he were already in seizure phase. For this reason, these pre-ictal seconds belong to asymptomatic positive observations.

The F3 MLP classifier seems to have a predictive property that could be explored in future works.

V. CONCLUSION AND FUTURE WORKS

In this paper, an automated tool for seizure detection in EEG signals has been proposed in order to classify and detect epileptic seizures and seizure-free signals. The trained ANN-based model is able to classify with high accuracy the instances of the test file consisting of records from both seizure-free and epileptic EEG signals. The high performances achieved by the classifier are due to the ability of the extracted features to describe EEG signals, to the feature selection process, and certainly to the specificity of the model for the selected patient. The further step will be to test the model on the entire dataset in order to demonstrate the independence of the model from the specific patient and its feasibility for different patients and different epilepsy types. The goal will be to develop a unique model able to identify the onset of the seizures for all the patients and for all the different kinds of epilepsy. In fact, robustness of the model and its independence from the data will give it a high translational value, not only because it will be a valuable tool for epileptologists to speed up the process of seizure detection and improve epilepsy diagnosis, but, more important, because this method can be embedded in systems to develop closed-loop intervention therapies. For these kinds of applications, it is crucial that the whole algorithm has a low computational cost, in order to be feasible for real-time settings. Further improvements will be done to decrease this cost refining the performance of the classifier during the feature extraction and selection process, in order to be reusable for different patients and epilepsy types. Future studies should focus on testing online these algorithms on continuous unlabeled data. We plan to extend our framework by implementing other algorithms for the feature extraction and to move towards one of the new emerging massive data processing frameworks, e.g. Apache Spark [37].

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REFERENCES

- [1] World Health Organization, 2018, <http://www.who.int/news-room/fact-sheets/detail/epilepsy>.
- [2] C. E. Elger and C. Hoppe, “Diagnostic challenges in epilepsy: seizure under-reporting and seizure detection,” *Lancet Neurol*, 2018 Mar, 17(3), pp. 279-288.
- [3] American Clinical Neurophysiology Society. Guideline twelve: guidelines for long-term monitoring for epilepsy, *Journal of Clinical Neurophysiology*, Vol. 25, N. 3, June 2008.
- [4] R. K. Maganti and P. Rutecki, “EEG and epilepsy monitoring,” *Continuum (Minneapolis)*, 2013 Jun, 19 (3 Epilepsy), pp. 598-622.
- [5] Y. Li et al., “Epileptic Seizure Detection Based on Time-Frequency Images of EEG Signals Using Gaussian Mixture Model and Gray Level Co-Occurrence Matrix Features,” *Int J Neural Syst.*, 2018, 28(7).
- [6] A. Sengür, Y. Guo, and Y. Akbulut, “Time-frequency texture descriptors of EEG signals for efficient detection of epileptic seizure,” *Brain Inform* 3(2), 2016, pp. 101-108.
- [7] Y. Li et al., “Epileptic Seizure Classification of EEGs Using Time-Frequency Analysis Based Multiscale Radial Basis Functions,” *IEEE J Bio. Health Inf.* 22(2), 2017, pp. 386-397.
- [8] S. Raghu, N. Sriraam, G.P. Kumar, and A. S. Hegde, “A Novel Approach for Real-Time Recognition of Epileptic Seizures Using Minimum Variance Modified Fuzzy Entropy,” *IEEE Trans Biomed Eng* 65(11), 2018, pp. 2612-2621.
- [9] S. Raghu S, N. Sriraam N, and G. P. Kumar, “Classification of epileptic seizures using wavelet packet log energy and norm entropies with recurrent Elman neural network classifier,” *Cogn Neurodyn*, 11(1), 2017, pp. 51-66.
- [10] A. Sharmila, P. Mahalakshmi, “Wavelet-based feature extraction for classification of epileptic seizure EEG signal,” *J Med Eng Technol*. 41(8), 2017, pp. 670-680.
- [11] Q. Yuan et al., “Epileptic seizure detection based on imbalanced classification and wavelet packet transform,” *Seizure* 50, 2017, pp. 99-108.
- [12] N. Mahmoodian, A. Boese, M. Friebe, and J. Haddadnia, “Epileptic seizure detection using cross-bispectrum of electroencephalogram signal,” *Seizure* 66, 2019, pp. 4-11.
- [13] G. Ouyang, X. Li, C. Dang, and D. A. Richards, “Using recurrence plot for deterministic analysis of EEG recordings in genetic absence epilepsy rats,” *Clin Neurophys.* 119, 2008, pp. 1747-1755.
- [14] A. Emami et al., “Seizure detection by convolutional neural network-based analysis of scalp electroencephalography plot images,” *Neuroimage Clin.* 22, 101684, 2019.
- [15] A. H. Ansari et al., “Neonatal Seizure Detection Using Deep Convolutional Neural Networks,” *Int J Neural Syst.*, 1850011, 2018.
- [16] S. Kusmakar et al., “Improved Detection and Classification of Convulsive Epileptic and Psychogenic Non-epileptic Seizures Using FLDA and Bayesian Inference,” *Conf Proc IEEE Eng Med Biol Soc.*, 2018, pp. 3402-3405.
- [17] R. Hussein et al., “Optimized deep neural network architecture for robust detection of epileptic seizures using EEG signals,” *Clin Neurophysiol* 130(1), 2019, pp. 25-37.
- [18] A. Aarabi, R. Fazel-Rezaei, and Y. Aghakhani, “A fuzzy rule-based system for epileptic seizure detection in intracranial EEG,” *Clin Neurophysiol* 2009, 120, pp. 1648-57.
- [19] K. T. Tapani, S. Vanhatalo, and N. J. Stevenson, “Time-Varying EEG Correlations Improve Automated Neonatal Seizure Detection,” *Int. J. Neural Syst.*, 2018 Jun 24:1850030.
- [20] F. Manzouri et al., “A Comparison of Machine Learning Classifiers for Energy-Efficient Implementation of Seizure Detection,” *Front Syst Neurosci*, 2018 Sep 20; 12:43.
- [21] Y. Kassahun et al., “Automatic classification of epilepsy types using ontology-based and genetics-based machine learning,” *Artif Intell Med*, 2014 Jun, 61(2), pp. 79-88.
- [22] P. Tan, M. Steinbach, and V. Kumar, “Introduction to Data Mining”, Pearson Addison Wesley, 2005.
- [23] M. Hall, et al., “The WEKA Data Mining Software: An Update”, *SIGKDD Explorations*, Volume 11, Issue 1, 2009.
- [24] I. H. Witten and E. Frank, “Data Mining. Practical Machine Learning

- Tools and Techniques”, Morgan Kaufmann, 2005.
- [25] FSPEEG Website. Seizure prediction project Freiburg, University of Freiburg. <http://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database/> (accessed 8 May 2019).
 - [26] Freiburger Zentrum für Datenanalyse und Modellbildung: The Freiburg seizure prediction project. <https://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database> (accessed 8 May 2019).
 - [27] J. G. Proakis and D. G. Manolakis, “Digital Signal Processing,” Prentice Hall (4th Edition), 2006.
 - [28] M. Gentile and B. Straughan, “Bidispersive thermal convection,” International Journal of Heat and Mass Transfer Volume 114, November 2017, pages 837-840.
 - [29] J. Gama, “Knowledge Discovery from Data Streams,” Chapman & Hall/CRC, 2010.
 - [30] M. Last, A. Kandel, and H. Bunke, “Data Mining in Time Series Databases,” World Scientific Publishing Co. Pte. Ltd., 2004.
 - [31] A. Martone, G. Zazzaro, and L. Pavone, “A Feature Extraction Framework for Time Series Analysis. An Application for EEG Signal Processing for Epileptic Seizures Detection,” The 5th Int. Conf. on Big Data, Small Data, Linked Data and Open Data, March 2019, pp. 5-13.
 - [32] E. Keogh, K. Chakrabarti, M. J. Pazzani, and S. Mehrotra, “Dimensionality reduction for fast similarity search in large time series databases,” Knowledge and Info Sys 3(3), 2001, pp. 263–286.
 - [33] J. Lin, E. Keogh, S. Lonardi, and B. Chiu, “A symbolic representation of time series, with implications for streaming algorithms,” 8th ACM W on Research Issues in DM and KDD, 2003.
 - [34] G. Luo et al., “PLA - Piecewise Linear Approximation,” 31st Int Conf on Data Eng, 2015.
 - [35] I. Osorio, H. P. Zaveri, M. G. Frei, and S. Arthurs, “Epilepsy: The Intersection of Neurosciences, Biology, Mathematics, Engineering, and Physics,” in Rationales for Analogy between Earthquakes, Financial Crashes, and Epileptic Seizures, CRC Press, Taylor & Francis G, 2011.
 - [36] G. Zazzaro, F. M. Pisano, and G. Romano, “Bayesian Networks for Earthquake Magnitude Classification in a Early Warning System,” International Journal of Environmental, Chemical, Ecological, Geological and Geophysical Engineering, Vol:6 No:4, 2012.
 - [37] M. Zaharia, “An Architecture for Fast and General Data Processing on Large Clusters,” PhD Dissertation, 2013.