Patient Specific Epileptic Seizures Prediction based on Support Vector Machine

Abdalla Gabara[1,*], Retaj Yousri[2, 3*], Darine Hamdy[4,*], Michael H. Zakhari[5,*], and Hassan Mostafa[5, 6]
[1]*Electronics and Communication Department, the American University in Cairo, New Cairo, Egypt*
[2]*Biomedical Engineering Department, Faculty of Engineering, Helwan University, Cairo, Egypt*
[3]*Wireless Intelligent Networks Center (WINC), Nile University, Giza 12677, Egypt*
[4]*Electronics and Communication Department, Faculty of Engineering, Alexandria University, Egypt*
[5]*Electronics and Communication Department, Faculty of Engineering, Cairo University, Giza 12613, Egypt*
[6]*University of Science and technology, Nanotechnology Department Zewail, October Gardens, 6th of October, Giza 12578, Egypt City*

***Abstract*— Throughout the last decades there has been an increasing interest in analyzing the EEG signals of epilepsy patients in order to relate it to epilepsy seizure onsets. Previous research papers were published exploring the possible techniques to utilize the EEG signals for detecting and predicting seizure onsets through Machine Learning and Deep Learning models, such as Support Vector Machines and Convolutional Neural Networks. The aim of this work is to build practical hardware-implementable Machine Learning classifiers capable of predicting the seizure onsets prior to their occurrences with high sensitivity and accuracy. The classification method proposed involves removing certain channels for each patient, extracting the features from the EEG signal, selecting the best feature combination for each patient, and finally training the selected SVM classifier accordingly. Evaluating the performance of the proposed classification technique yields promising results for the selected patients with accuracies exceeding 95%.**

***Keywords*: EEG, Seizure prediction, SVM, Machine Learning.**

I. INTRODUCTION

Epilepsy is a common neurological disorder characterized by abnormal brain cells activity, which triggers recurrent and unprovoked seizures. An epileptic seizure can cause a wide range of symptoms, depending on whether it is focal or generalized. Symptoms include shaking, jerking of different body parts, uncontrollable twitching, momentarily staring blankly, and even losing consciousness. Due to the random and unpredictable nature of seizure occurrences, they can be life-threatening especially if they occur while the patient is driving or exercising. Thus, predicting the occurrence of these seizures guarantees sufficient time before their occurrence avoiding potential dangers by taking proper medications or by staying away from hazards.

The electroencephalogram (EEG) is widely used in epilepsy diagnosis as the EEG signals measured from a healthy person is vastly different from that of an epileptic patient. There are four major distinct states of brain activity in an epilepsy patient: ictal, pre-ictal, post-ictal and inter-ictal. The pre-ictal state precedes the seizure onset, the ictal state is the state that coincide with seizures, the post-ictal state starts after the ictal state, and the inter-ictal state starts after the post-ictal state. The aim of this paper is to predict seizures before their occurrence by detecting the pre-ictal state and consequently raising an alarm for the patient before the seizure occurs.

In previous publications, the problems of seizure predication and detection were addressed using different approaches such as Machine Learning (ML) models [1], Deep Learning models [2-3], statistical models [4-5], and other approaches [6-7]. One of the most commonly utilized machine learning methods is Support Vector Machines classifiers which demonstrated effectiveness in previous works. In this work, predictive patient-specific SVM models that has achieved high sensitivity in comparison to previously published models [8] with relatively low computational cost, are introduced. In order to maximize the performance and lower the computation intensity, experimentations with different channels were conducted in order to exclude some channels from the classification models for each patient and consequently lower the dimensionality of the classifier input vector. Further experimentation was conducted with different features that have been shown to be highly effective in seizure detection in [9], in order to determine the best combination of features for each patient in the context of predicting seizures.

The rest of the paper is organized as follows. Section II illustrates the details of the training procedure. Section III discusses the analysis conducted on the EEG channels. Section IV illustrates the feature extraction process and the superior features selected for each patient. Section V gives a brief overview of the Support Vector Machine algorithm. Section VI shows the performance of the built classifiers before concluding the paper in Section VII.

II. DATASET TRAINING

A. Dataset processing

The training and testing of the proposed ML classifiers is based on the publicly available CHB-MIT database, consisting of the EEG records of 24 patients sampled at a frequency of 256 Hz from 23 electrodes placed on the scalp of each patient [8]. Out of the 24 patients, 6 were selected for experimentation. Next, the data of each patient were divided into epochs. The length of each epoch was set to be 4 seconds in order to guarantee both the stationarity and continuity of the signal contained in each epoch [10]. Binary labels for each epoch were set manually by 3 experts to differentiate between ictal and non-ictal epochs [1]. Based on these labels, epochs preceding the ictal epochs were labeled pre-ictal which are the ones to be classified positively by the classifier. Experimentations show notable similarities between ictal epochs and pre-ictal epochs [1]. These similarities are highly likely to cause poor performance by the classifier in some patients. Therefore, before commencing the training process, seizure labeling used in previous work was used to eliminate the ictal-epochs which empirically improves the classifier performance [1]. 70% of the data were used for training, while the other 30% were used for testing. Due to the tremendous imbalance of the data as a result of having far more non-pre-ictal epochs than pre-ictal epochs, the training data had to be artificially balanced in order to minimize the bias of the trained classifier. Balancing the training data resulted in classifiers with higher performance.

B. Performance Metrics

The problem in hand is of a binary nature where the classifier is to determine whether the epoch processed is pre-ictal or not. Therefore, the relevant performance metrics are True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) which are represented in a Confusion Matrix. These numbers are used to calculate the sensitivity and the specificity. Sensitivity is the ability of the classifier to classify the positive epochs (pre-ictal) correctly, while the specificity is the ability of the classifier to classify the negative samples (non pre-ictal) correctly. However, given that the data used for training is highly imbalanced as the number of positive samples is far less than the negative samples, a higher priority is given to the sensitivity compared to the specificity in the used metric system.

III. CHANNELS SELECTION

Before commencing the training process, the EEG channels were studied in order to explore the potentials of removing channels. One of the challenges faced when handling the EEGs signal is its noisy nature [11]. Such noise might be a result of eye movements, eye blinks, improper electrode positioning on the scalp, or poor skin-electrode contact [12-14]. More rarely, electrodes may also have mechanical faults, for example frayed wiring, which can partially or entirely degrade the signal received. The movement of electrodes on the scalp results in a change in impedance between the scalp and the electrodes, which consequently affects the electrode voltage offsets [14]. Figure 1 illustrates the placement of the electrodes corresponding to the channels of the CHB-MIT dataset [8].

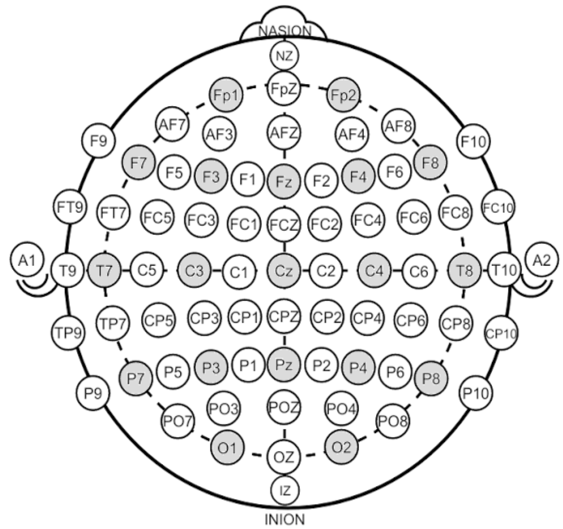

Fig. 1: The grey spots show the common electrodes in all the patients' records of CHB-MIT database.

Seizures occur in different parts of the brain depending on the type of the seizure, which clearly differs from one patient to another. It is, therefore, expected that certain channels are superior to others in predicting seizures as not all patients suffer from the same type of seizures. Therefore, experiments were conducted for each patient such that the classifiers are fed the features extracted from only one channel at a time to determine whether certain channels are superior to others at all. The results show significantly low performance of certain channels compared to others. For example, channels C4-P4, P8-O2 (near the neck), and FT9-FT10 (near the ears) performed significantly worse than other channels in all selected patients. However, other channels such as CZ-PZ and F7-T7 achieved high performance in some patients while achieving low performance in other patients. The low performance of some channels might be due to the noise generated in the signal as a result of reasons mentioned before or due to the nature of the seizures experienced.

For each patient, the performance of the classifier with each channel was recorded and channels that performed significantly lower than others were excluded in the final models, which enhanced the performance of the classifiers.

IV. FEATURE EXTRACTION

In order to classify different epochs of EEG time series, a set of features that yielded promising performance in detecting seizure onsets in previous work were selected for experimentation [1]. Feature extraction involves processing the signals of the selected channels in order to extract crucial characteristics of the time series, based on which the classification is carried out. For each patient, the features are extracted from each selected channel and averaged across all channels. The results suggest the superiority of certain features including Fractal Dimension, Fluctuation Index, Variation Coefficient, and Kurtosis. Table 1 illustrates the equations of the superior features, where x_i is the i^{th} sample in the epoch, N is the number of samples in each epoch (1024 samples), σ is the standard deviation of the epoch, μ is the average of the epoch, k is an integer set to be equal 5, $L_i(k)$ is the length of the curve as defined in [15], SC is the spectral centroid of epoch x, and PSD(w) is the power spectral density of the epoch x.

Feature number	Feature Name	Equation
1	Standard Deviation	$\sqrt{\frac{\sum_{i=1}^{N}(x_i-\mu)}{N-1}}$
2	Fractal Dimension	$\frac{1}{k}\sum_{i=1}^{k}\frac{log(\,L_i(k))}{log(1/k)}$
3	Hurst Exponent	$E[\frac{\sum_{i=1}^{N}(x_i-\mu)}{SD}]$
4	Kurtosis	$\frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4$
5	Fluctuation Index	$\sum_{i=1}^{N}\lvert x_{i+1}-x_i\rvert$
6	Variation Coefficient	$\frac{\sum_{w=-N+1}^{N-1}(w-SC)^2.PSD(w)}{\sum_{w=-N+1}^{N-1}PSD\,(w)}$

Table 1: Equations of extracted features

V. SUPPORT VECTOR MACHINE

To successfully predict the epileptic seizure, pre-ictal epochs has to be detected correctly by the classifier. The authors of [16] employed several classifiers to build iEEG-based patient-specific models for predicting seizures. Their work demonstrates the superiority of SVM classifiers over logistic regression, Naïve Bayes, decision tree and discriminant analysis. Therefore, in this work, SVM is employed to successfully detect the pre-ictal epochs, as it yields models with high sensitivity and relatively low computational power.

A Support Vector Machine (SVM) classifier is a discriminative classifier fundamentally defined by a separating hyperplane for binary classification. The SVMs tend to find an optimal hyper-plane in high dimensional feature space in order to maximize the distance between this hyper-plane and the nearest data point of each class. Support Vector Machine classifiers use a kernel function to project the input vectors from their original space into a new space. This space transformation is typically done by selecting a number of points with which the similarity is estimated using a kernel function for each input vector.

There is a number of kernels that can be used in Support Vector Machines models, some of which are shown in Table 2, where d is a polynomial degree set manually, and X_i *and* X_j are vectors in the input space, [17].

$K(X_i,X_j)$=	$(X_i * X_j)$	*Linear*
	$(X_i * X_j + 1)^d$	*Polynomial*
	$exp(-\gamma * \lvert X_i - X_j\rvert^2)$ $for\,\gamma > 0$	*RBF*

Table 2: Equations of Different kernels used

Experiments conducted demonstrated the superiority of RBF kernels in all patients.

VI. RESULTS

For each patient, the best set of features were determined by experimenting with all possible features combinations and different SVM kernels. Table 3 shows the performance of the final SVM classifiers trained on each patient at a time and the best set of features for each patient. All the results shown in the table are obtained from SVM classifiers with an RBF kernel which is SMO (Sequential Minimal Optimization) trained using MATLAB 2016b. The training phase is conducted on the features extracted from the selected channels after balancing the training set. Table 4 compares the results of the trained models with the reported results of other works, demonstrating higher performance in comparison.

Patient	Features	Sensitivity	Accuracy
1	3,5,6	98%	96%
3	2,5,6	92%	95%
18	1,2,3,5,6	88%	96%
19	2,5,6	99%	97%
20	1,4,5	100%	100%
22	5	97%	93%

Table 3: Final Results of the classifiers

Model	Number of patients	Sensitivity	Accuracy
[1]	6	95.3%	64.9%
[2]	15	83.33%	_
[3]	13	81.2%	_
[4]	10	77%	_
[5]	10	88.89%	_
[6]	3	83.81%	_
[7]	13	83.33%	_
This work	6	95.7%	96.2%

Table 4: Comparison of result with preexisting works using open CHB-MIT EEG database

The RBF-SVM classifiers were Hardware implemented on Virtex-7 as reported in [1] with all of its hardware related details reported in Table 5. The RBF classifiers were developed with its hyper-parameters trained and selected to be as low as possible in order to avoid overfitting [18].

POC	RBF Classifier	F1	F2	F3	F5
Power (mW)	3	2	15	5	2
LUTs	1323	173	713	343	68
Registers	1293	2	250	8	2

Table 5: Hardware implementation details

VII.CONCLUSION AND FUTURE WORK

Simple SVM Classifiers demonstrate promising potential for classifying EEG epochs to predict seizure onsets in epilepsy patients. In this work, each patient of interest was approached as a distinct problem such that the complexity of the predictive SVM models were reduced by eliminating certain channels from the feature extraction process and limiting the feature extraction phase to a low number of features for each patient while maintaining a high performance. However, developing general classifiers for more than one patient is more challenging due to the patient-specific nature of epilepsy.

As Table 1 shows, features 4 and 6 are hardware exhaustive features, which is why their results are obtained from a software implementation as a start. Hardware implementing all the features is set as a future goal to complete a fully accelerated system.

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