# Seizure Prediction & Segmentation Merge Yielding a Boosted Low Power Model

Ingy Alaa*, Nourhan Ahmed*, Mostafa Nader*, Abdelrahman Magdy*, Mohamed Ibrahim*, Michael Khalil*, Michael H. Zakhari*, Hassan Mostafa*!
* Electronics and Communications Department, Cairo University, Giza, 12613, Egypt.
! University of Science and technology, Nanotechnology and Nanoelectronics Program, Zewail City of Science and Technology, October Gardens, 6th of October, Giza 12578, Egypt

***Abstract* — Epilepsy, simply put, is an abnormality in the central nervous system that leads to unplanned-for seizures affecting millions of people worldwide. Medication is the most common treatment for all those suffering from epilepsy, however, this paper introduces the idea of designing an implantable/embedded chip that is to be fed with a machine learning algorithm, specifically Support Vector Machine (SVM) to predict seizure periods prior to their occurrence to be able to notify the patient or suppress the seizure from happening. Since the system's problem is binary classification between pre-ictal and normal periods, determining the right set of features along with the SVM kernel function is the first step in designing the chip. This paper proposes two tracks, a Linear Features-Linear Kernel combination with a set of time-domain hardware-inexpensive features namely; Coastline, Absolute Mean, Root Mean Square, and Standard Deviation. In addition to the Non-Linear Feature-RBF Kernel combination with another time-domain feature namely; Hurst Exponent. This paper also introduces the concept of segmenting the testing data which showed extremely promising results in the Non-Linear Feature-RBF Kernel combination.**

***Keywords* —Epilepsy, Seizure Prediction, SVM, SMO, Implantable Chip, EEG Signals, Pre-ictal Periods.**

## I. Introduction

### A. Epilepsy

Epilepsy is one of the most common neurological disorders, affecting millions of people worldwide, characterized by an abnormality in the brain activity, which leads to recurrent seizures. If two or more unprovoked seizures occur to a person over a time span of more than 24 hours, then that person is diagnosed as an epilepsy patient. [2] About 1% of the global population are epileptic patients with an estimate of their third not respondent to medicine. Even for those who take medication, their quality of life is affected tragically as the seizure occurs unexpectedly, potentially causing a life-threatening experience. Structural malfunctions of the brain cause the electrical surge that causes a seizure. [4] These malfunctions cause frequent spontaneous seizures and thus, epilepsy, a long-lasting neurological disorder. Epilepsy can refer to a broad variety of symptoms such as blank stares, uncontrollable movements, sudden jerks in the whole body, body stiffness, and loss of consciousness. It could be classified according to the cause of the seizure; whether it is genetic or a result of trauma, stroke, brain tumor or infection, or of an unknown cause.

Medication, surgery, and neuromodulation are forms of treatment, but none of them is considered 100% successful. Antiepileptic drugs, AEDs, are successful in about 66% of the cases, but unfortunately, with side effects such as depression and rash. [5]. A patient who is not respondent to AED would be suffering from refractory epilepsy and thus would typically be subjected to pre-surgical evaluation.

Surgery would be possible in the case that the epileptogenic zone is localized. However, epilepsy is not usually confined to a single area of the brain, but rather it is an epileptic network where different areas of the brain interact synchronously causing these pathological spikes or seizures. Thus, surgery is only of a 60% success rate for an epileptogenic zone at the temporal lobe, and a mere 35% success rate in case it was at the extratemporal lobe. [6] In case that surgery was not a viable option, neuromodulation could be the last resort.

Neuromodulation methods such as Deep Brain Stimulation, DBS, or Vagus Nerve Stimulation, VNS, could relatively be successful options. However, all mentioned devices lack accuracy, are very expensive to afford, hard to implement and they are power-hungry meaning that the patient having these devices in his brain must undergo a complex expensive surgery every two years to only change their batteries.

During a seizure cycle, stage transitions take place. The main stages are pre-ictal – the period of time before the seizure onset, ictal – the interval during which the seizure occurs, post-ictal – the period immediately succeeding the end of a seizure, and inter-ictal – the time between two consecutive seizures. These stage transitions are conveyed by EEG signals.

Electroencephalography, EEG, is a monitoring method used to record electrical brain activity. Thus, one can forecast upcoming seizures by inspecting changes in EEG recordings.

### B. Seizure Prediction

Epileptic seizure detection is concerned more with how to accurately detect seizure occurrence. Many reasarchers have worked to accelerate seizure detection systems as in [6,10,11] achivieng high detection rates but epileptic seizure detection is only concerned with how to accurately detect a seizure's occurrence, without considering how late it was reported for medical treatment, while seizure prediction is quite useful as it is expected to make the earliest possible alarm once a seizure takes place and might as well be able to suppress its occurrence without any medical interference.

The seizure detection is considered a classification problem between two classes, the first class is the ictal period where a true seizure happens and the second class is the non-ictal period including post-ictal, pre-ictal and inter-ictal periods. On the other hand, the seizure prediction is also a classification problem between two classes, but the first class is the pre-ictal period and the second class is the non-pre-ictal period including inter-ictal, ictal and post-ictal periods.

Although, seizure prediction is more complex than detection and more prone to error, yet, the paper's main focus is "Seizure Prediction" as it is believed to cause a leap in the field. Not only was the novelty of the paper the main concern, but it is also known for sure that prediction of seizures will protect many innocent souls from going through this harsh, painful and unforgettable experience as they will actually be able to stop it before it even starts.

## II. DataSet

Data and algorithms are the most important basis of any machine learning project. Data must be analyzed and well organized to feed the algorithm to obtain precise results. A simple algorithm with good data will outperform a complex one; on the other hand, a complex and powerful algorithm with bad data will cost time and consume power. That is why choosing the dataset became one of the most critical concerns. After plenty of researching, the CHB-MIT dataset was found to be very promising due to the length of the recordings.

Not only was the number of patients huge, but also, there were many recordings for each patient. Yielding the data was never an issue since it was available online with a very detailed description. The problem was that some of the patients' recordings were missing, so they had to be excluded. Eventually, the 23 patients ended up being 6 for the training, testing, and optimization of the system. The chosen patients were patients 7, 8, 11, 19, 20, and 23.



978-1-7281-4058-2/19/$31.00 ©2019 IEEE

## A. Data Labeling

Unfortunately, although the data was very compatible with the project, it was not labeled for prediction; meaning that, the data could not be used for neither the training nor testing of the system. The pre-ictal period was not highlighted in a way or another. However, it was argued that the pre-ictal period varies between 5 minutes to 60 minutes prior to the seizure in many research papers. Therefore, in order to know which of those is the correct pre-ictal period, tests had to be conducted. Not only optimization was done, but also, many examinations and analysis with a variety of features had to be conducted on all patients.

The following table shows a sample of what was obtained:

TABLE I: Pre-ictal periods performance results

| | 15-minute | 20-minute | 30-minute |
|---|---|---|---|
| **Accuracy** | 74.9% | 69.9% | 68.9% |
| **Specificity** | 77.4% | 71.9% | 73.0% |
| **Sensitivity** | 41.7% | 47.8% | 50.6% |

The 30-minute interval showed the best results as all three performance metrics were above 50%. Thus, labeling of the pre-ictal period using the 30-minute interval became the new concern. A function was implemented on MATLAB called "Get Preictal", with a main role of labeling the pre-ictal period in order to help continue the seizure prediction project.

# III. MACHINE LEARNING

A Classification Machine Learning problem is a supervised learning type of problem that is mainly based on a proper separator between multi-classed data. There are many techniques used to solve such problems, but, support vector machine (SVM) achieved the best results concerning the accuracy, time and power consumption

## A. Support Vector Machine

SVM is a discriminative classifier that takes the input data to create a model that can classify any other test input into different classes with the help of a separating hyperplane. There are two versions of SVM: Hard Margin and Soft Margin, knowing that one can be extended from the other. [8]

### 1. Hard Margin

The Hard Margin version of SVM separates the feature extracted data linearly by creating two parallel hyperplanes that separate the two classes (pre-ictal and non-pre-ictal) so that it maximizes the distance to the optimal. It can be expressed as follows:

$$\max \frac{2}{\|w\|} \quad (1)$$

Subject to

$$y_i * (\vec{w} \cdot \vec{x}_i + b) \geq 1 \quad (2)$$

where $x_i$ is the i-th training vector (sample), and $y_i$ is the output class of this training sample. The value $y_i$ is +1 for one class (pre-ictal) and –1 for the other. [1]

### 3. Soft Margin

The Soft Margin version of the SVM model gives a certain penalty to those data points which are violating the hard constraint. To overcome the overlapping of these two classes; the kernel trick was used which is hardware implementable and more efficient than increasing the dimensionality, and the optimization problem is reduced to the following Lagrange function:

$$\min_\alpha \sum_{i=1}^{N} \alpha_i - 0.5 \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_j \mathrm{k}(x_i, x_j) \alpha_i \alpha_j \quad (3)$$

Finding $\alpha_{min}$ is a Quadratic Programming Problem,QP, which can be efficiently solved by Sequential Minimal Optimization. [1]

# IV. FEATURES EXTRACTION

The approach of the features extraction stage was to characterize various differences from the EEG raw input signal; as this work's scope is predicting the epileptic seizures. It is facilitating for the SVM to differentiate between the pre-ictal and the non-pre-ictal periods through extracting certain features. In this case, optimization between 14 different linear and non-linear features was implemented as in [12], and settling on two different tracks at the end, applying four linear features (Absolute Mean, Root Mean Square, Standard Deviation and Coastline) on the linear kernel or applying the Hurst Exponent non-linear feature on the RBF kernel for yielding the best results.

TABLE II: Extracted features from raw EEG

| Feature | Illustration |
|---|---|
| **Absolute Mean** | The central value of a set of positive values $\mu = \frac{\sum_{i=0}^{n} \lvert x_i \rvert}{n}$ |
| **Root Mean Square** | The square root of the mean of the sum of values squared $X_{rms} = \sqrt{\frac{1}{n}({X_1}^2 + {X_2}^2 + \cdots + {X_n}^2)}$ |
| **Standard Deviation** | The deviation of a group's value from the same group's mean $S = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (X_i - \mu)^2}$ |
| **Coastline** | The absolute distance between each two successive datapoints $CL = X(i) - X(i-1)$ |
| **Hurst Exponent** | The measure of long-term memory of time series $HE = \frac{MAX(X_i - \mu) - MIN(X_i - \mu)}{S}$ |

# V. Segmentation

Data segmentation is the process in which the data is being divided into equal parts which make dealing with it more effective. It was believed that this process could boost the results and performance of the system if it was applied to the testing data in the testing block, as more detailed characteristics and properties of the data will be captured. In other words, if it is decided to divide the data into 5 segments, instead of providing the testing block with a huge chunk of data, the testing block will be given 5 small chunks instead, taken one after the other and then the decision would be made on those chunks concatenated. Although this process increased the complexity of the code, the results were worth it.

## *A. Segmentation Approaches*

There were two approaches for the decision making and the classification, making the decision either based on the **segment** or based on the **30-minute period**. However, the **30-minute based** decision yielded better performance results.

For the **30 minute-based** decision, if there exist 5 segments, the true test labels vector of each segment is analyzed to check if it has more ones than zeros and vice versa. Then, records of all 5 true test labels are kept, and in the end, if more than half of the total number of segments have more ones than zeros, then it is safe to assume a final true test label vector of all ones. The final true test label vector enters the SVM classifier with the SVM trained data, which will result in a single final classification in the end.
The following figures show sensitivity, which is the line with higher values, and specificity

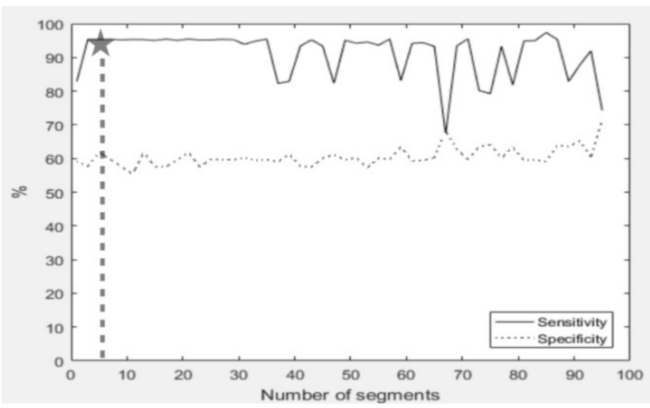


Fig. 1: Linear Feature-Kernel Combination

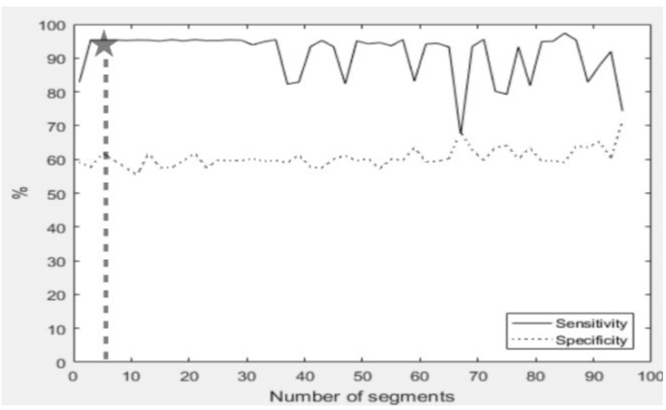


Fig. 2: Non-linear Feature-Kernel Combination

# VI. Hardware Flow

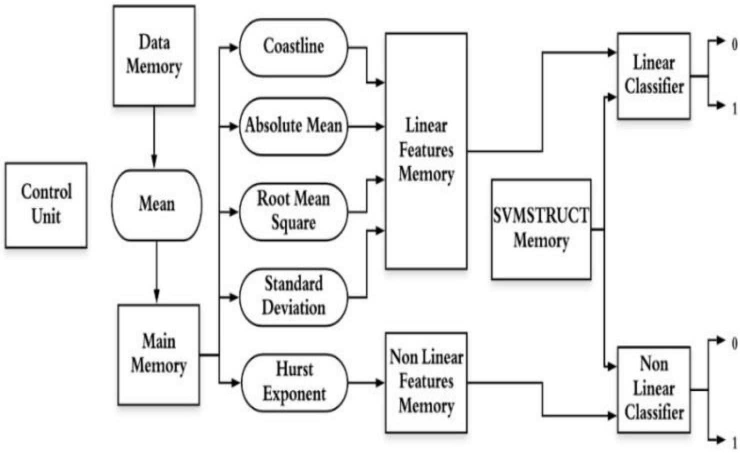


Fig. 3: System Block Diagram

# VII. Results

TABLE III: Software Results

| | Accuracy | Specificity | Sensitivity |
|---|---|---|---|
| **Linear Features-Linear Kernel combination** | | | |
| No segmentation | 65.4% | 62.1% | 79.1% |
| Segmentation (89 segments) | 64.6% | 64.7% | **81.1%** |
| **Non-Linear Feature-RBF Kernel combination** | | | |
| No segmentation | 61.7% | 61.1% | 68.2% |
| Segmentation (5 segments) | 64.9% | 61.4% | **95.3%** |

TABLE IV: Hardware Results

| POC | LF | LK | NLF | NLK |
|---|---|---|---|---|
| **Total power (mW)** | 6 | <1 | 6 | 3 |
| **Area**<br>**A- LUTs**<br>**B- Registers** | <br>4606<br>2941 | <br>567<br>959 | <br>1745<br>1917 | <br>1323<br>1293 |
| **Delay (ns)** | 6.762 | 5.459 | 4.620 | 5.405 |

By comparing the two aforementioned feature-kernel combinations in terms of hardware applicability, a trade-off was clearly presented. The power in the linear feature-kernel combination is 27.78% lower than that of the non-linear feature-kernel combination. On the other hand, the linear feature-kernel combination has a greater area of 68.6% more LUTs and 21.49% more registers. Moreover, the delay of the nonlinear feature-kernel combination is 17.96% lower than the linear feature-kernel combination.

TABLE V: Comparison of all models

| Model | Zewail | CUFE | Teixeira et al. | Macau | Zandi et al. | Linear Proposed Model | Non-linear Proposed Model |
|---|---|---|---|---|---|---|---|
| **Data set** | CHB-MIT | CHB-MIT | VGH | CHB-MIT | CHB-MIT | CHB-MIT | CHB-MIT |
| **Detection/Prediction** | Detection | Detection | **Prediction** | **Prediction** | **Prediction** | **Prediction** | **Prediction** |
| **Sensitivity** | 62.1% | 88.0% | 73.5% | 92.2% | 83.8% | 81.1% | **95.3%** |
| **Specificity** | 99.9% | 87.0% | - | - | - | 64.7% | 61.4% |
| **Accuracy** | 99.8 % | 89.3% | - | - | - | 64.6% | 64.9% |
| **Power** | 90 mW | 156.13 mW | - | - | - | **7 mW** | **9 mW** |
| **Number of registers** | - | 1183 | - | - | - | 3900 | 3210 |

## VIII. CONCLUSION

Since seizure prediction is a binary classification problem between pre-ictal and non-preictal periods, SVM was ideally used in this system. The simulation was dependent on the CHB-MIT Scalp EEG Database offered by PhysioNet. [9] However, and for the sake of having continuous preictal recordings, only 6 patients were chosen. After multiple simulations, the pre-ictal period was set as a 30-minute window before the start of the ictal period. Taking accuracy, specificity, and sensitivity into consideration, only two combinations of 14 features and 2 SVM kernels showed promising results: Four linear features (Standard Deviation, Root Mean Square, Absolute Mean, Coastline) along with the linear SVM kernel and the other combination was one non-linear feature (Hurst Exponent) along with the non-linear SVM kernel (RBF). Segmenting the EEG data was found to be very effective in improving the overall performance of seizure prediction, yielding 40% improvement in the sensitivity in the case of the non-linear feature- kernel combination (5 segments).

Regarding hardware specifications, the chip area, power, and delay are the main evaluation criteria. In the case of the linear feature-kernel combination, the power is minimized (7mW), butthe area is much bigger since there are 68.6% more LUTs and 21.49% more registers than the second option. On the other hand, the non-linear feature-kernel combination presented a smaller, more compact area but with a 38.46% higher power consumption than the first option.

Finally, the proposed project had four main strength points; a seizure prediction model with high performance results, introduction of the segmentation concept in the seizure prediction field helped boost the results maximally, moreover, very low power was achieved using FPGA which means that, in the production phase when the use of ASIC is needed; the power will be reduced to the minimum, and finally, two tracks were yielded so that adaptive mode could be introduced.

When a fully charged battery is available; the non-linear feature- kernel combination could be used. However, as the battery starts to drain, the linear feature-kernel combination would be more suitable.

## ACKNOWLEDGEMENT

This work was partially funded by ONE Lab at Zewail City of Science and Technology and at Cairo University, NTRA, ITIDA, and ASRT.

## REFERENCES

[1] https://www.cs.cmu.edu/~tom/10701_sp11/recitations/rec12.pdf
[2] National Academy of Neuropsychology Foundation, "What is Epilepsy?,"[Online].
[3] J. Platt, "Sequential minimal optimization: A fast training of support vector machines.," Technical Report, Microsoft Research, no. 14, p. 98, 1998.
[4] S. Sanei and J. A. Chambers, EEG Signal Processing, Hoboken: John Wiley & Sons Ltd,2 007.
[5] M. Brodie, S. Barry, G. Bamgaous, J. Norrie and P. Kwan, "Patterns of treatment response in newly diagnosed epilepsy," *Neurology,* no. 78, p. 1548, 2012.
[6] K. Helal, A. Y. Aboelmakarem, A. – M. B. R. Fouad, T. S. Kamel, K. A. M. Nageeb, M. M. K. Mohamed, M. M. Abdelrhman, Y. Ismail, and H. Mostafa, "Low-Power High-Accuracy Seizure Detection Algorithms for Neural Implantable Platforms", IEEE International Conference on Microelectronics (ICM 2017), Beirut, Lebanon, pp. 231-234, 2017.
[7] P. Boon, T. Vandekerckhove, E. Achten, E. Thiery, L. Goossens, V. K, D. M, G. Van Hoey, B. Vanrumste, B. Legrosand e. al., "Epilepsy surgery in Belgium, the experience in gent," Acta Neurologica Belgica, no. 99, p. 256, 1999.
[8] "Understanding Support Vector Machine algorithm from examples (along with code)," 13 9 2017.[Online]
[9] "Physionet,"Physionet, Available: https://physionet.org/cgi-bin/atm/ATM.
[10]H. Elhosary, M. H. Zakhari, M. A. ElGammal, M. Abd Elghany, K. Salama and H. Mostafa, "Low-Power Hardware Implementation of a Support Vector Machine Training and Classification for Neural Seizure Detection," in *IEEE Transactions on Biomedical Circuits and Systems*. doi: 10.1109/TBCAS.2019.2947044M.
[11]M. A. Elgammal, H. Mostafa, K. N. Salama and A. Nader Mohieldin, "A Comparison of Artificial Neural Network(ANN) and Support Vector Machine(SVM) Classifiers for Neural Seizure Detection," *2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS)*, Dallas, TX, USA, 2019, pp. 646-649.
doi: 10.1109/MWSCAS.2019.8884989
[12] M. Elgammal, O. A. Elkhouly, H. Elhosary, M. E. Sayed, A. Mohieldin, K. N. Salama, and H. Mostafa, "Linear and Nonlinear Feature Extraction for Neural Seizure Detection", IEEE International Midwest Symposium on Circuits and Systems (MWSCAS 2018), Windsor, Ontario, Canada, pp. 795-798, 2018