Implementation of Epileptic Seizure detection in FPGA Using ELM Classifier

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Abstract

Electroencephalography (EEG) Signals are widely used to determine the brain disorders. The Electrical activity of human brain is recorded in the form of EEG signal. The abnormal Electrical activity of the human brain is called as epileptic seizure. In epilepsy patients, the seizure occurs at unpredictable times and it causes sudden death. Detection and Prediction of Epileptic seizure is performed by analyzing the EEG signal. The EEG signal of human brain is random in nature, hence detection of seizure in EEG signal is challenging task. Hardware implementation of Epileptic seizure detection system is necessary for real time applications. In this paper an efficient method is used to detect the Epileptic seizure and which is implemented in FPGA (Field Programmable Gate Array).The hardware implementation of epileptic seizure detection algorithm is done using Xilinx System generator tool. In the first step the EEG signal is extracted from the human brain and it is filtered by using Finite Impulse response (FIR) band pass filter. The band pass filter separates the EEG signal into delta, theta, alpha, beta and gamma brain rhythms. The band separated brain signal is modeled by linear prediction theory. In the next step features are extracted from the modleled EEG signal and the classification of normal or seizure signal is done by using Extreme Learning Machine (ELM) classifier. The EEG signals used in this paper were obtained from Epilepsy Center at the University of Bonn, Germany. The hardware architecture, Look up tables, resource utilization, Accuracy and power consumption of the algorithm is analyzed using xilinx zynq-7000 all programmable soc.

Keywords : Electroencephalography EEG; Epileptic; Linear prediction; FPGA; ELM

1. INTRODUCTION

Brain is one of the most important organs of humans, for controlling the coordination of human muscles and nerves. The transient and unexpected electrical disturbances of the brain results in an acute disease called Epileptic seizures. Numbers of researchers have presented automated computational methods for detecting epileptic seizures from EEG signals. The word ‘epilepsy’ is derived from the Greek word epilambanein, which means ‘to seize or attack’. Seizures are the result of sudden brief, excessive electrical discharges in a group of brain cells called neurons. Transient symptoms can occur, such as loss of awareness or consciousness and disturbances of movement, sensation (including vision, hearing, and taste), mood, or mental function. The seizures occur at random to impair the normal function of the brain. [1].

Selvathi et al proposed a method for Epileptic Seizure detection using amplitude and frequency Analysis of EEG Signals and implemented in FPGA [2]. In this method 82% of LUTs and 14% registers were utilized to implement the algorithm. The time required to implement the algorithm is 13.568ns**.** The major drawback of this work is that the complexity of the algorithm is high in terms of LUTs used. Sreethu Raj et al proposed a system for FPGA Implementation of EEG Feature Extraction and Seizure Detection [3]. This approach uses FIR filtering method and wavelet based feature extraction technique. The classification of the signal is performed by using Support vector machines. Verilog hardware description language is used to implement the proposed system. John mosses et al [4] described the concept of interpolation algorithms and its hardware architecture. The performance of the algorithm is analyzed based on the gate count, frequency, and power and memory buffer.

In recent years, a few attempts have been reported on seizure detection and prediction from EEG analysis using two different approaches: 1) Examination of the waveforms in the preictal EEG to find events or changes in neuronal activity such as spikes [5], which may be precursors to seizures. 2) Analysis of nonlinear spatio-temporal evolution of the EEG signals to find a governing rule as the system moves from a seizure-free to seizure state [6].Some work has also been reported using artificial neural networks [7] for seizure prediction with wavelet pre-processing [8].

For seizure detection, t-f distributions are widely used. Markos G. Tsipouras, and Dimitrios have demonstrated various time frequency distributions for extracting the features of EEG signals and to classify the signals based on artificial neural network [9].This method offers the ultimate classification of EEG segments regarding the presence and absence of seizures. Lina Wang et al proposed a system which is based on multi-domain feature extraction and nonlinear analysis of EEG signals [10].The artifacts in the EEG signal is removed by using wavelet threshold method. Information theory techniques are used to extract the nonlinear features and time-frequency domain features. Principal Component analysis is used to select optimum features for the classifier. The classification of the features is performed by using support vector machine Classifier

2. METHODS USED

The schema of proposed method used in this paper is shown in Fig1. The input EEG signal is filtered by using band pass filter to remove the unwanted noise present in the signal. The band pass filter is used to separate the EEG signal into five EEG subbands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30Hz). The bandpass filter is designed by using Xilinx Sysgen block set. The segmented band signal is further modeled by using linear prediction theory which is used to estimate the random quantity from certain available data. The statistical features are extracted from each subband and form a feature vector. The ELM classifier is used to classify whether seizure is existing or not in the given signal. The feature extraction process and ELM classifier algorithm is designed by using Xilinx System block set.

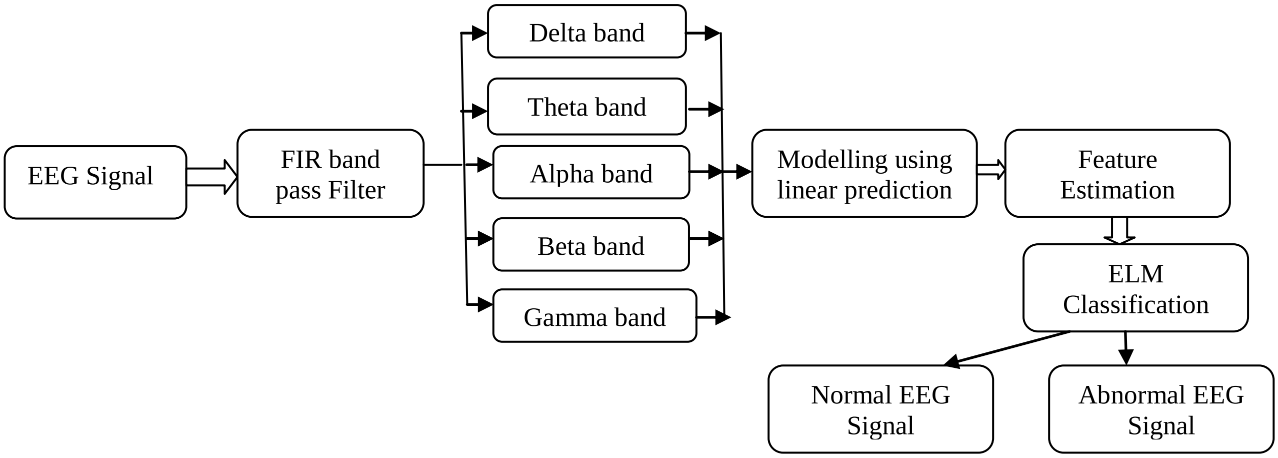

Fig1: Flow chart of the Proposed Approach

2.1 Dataset Used

The data set used in this work is obtained from University of Bonn, Germany .It includes both normal and abnormal EEG signal. The dataset contains 100 normal EEG signal (denoted as Z) and 100 Epileptic seizure EEG Signals (denoted as S). The duration of each signal is 23.6 seconds. The sample EEG signal available in the dataset is shown in the Fig2

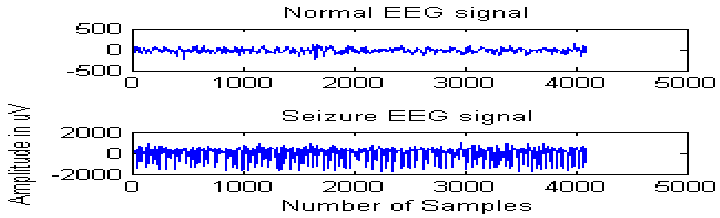

Fig 2 Sample EEG Signals

2.3 Filtering of EEG Signal

The individual EEG subband signals are obtained by using band pass FIR filter. The FIR filter has the advantages of linear phase, high stability and scale space analysis. The primary EEG signal contains five subbands: delta, theta, alpha, beta, and gamma. The sampling frequency of the EEG dataset obtained is 173.61 Hz. According to the Nyquist sampling theorem, the maximum useful frequency is half of the sampling frequency (ie 86.81 Hz). In the band pass filter, the pass band cut of frequency is based on different subband frequency. The filter coefficient for the required filter is designed using FDA tool which is available in the Xilinx System block set. The complete setup of the blocks used to implement the proposed work is shown in Fig3. The Verilog code for xilinx vivado zynq-7000 is developed from the block design using system generator module.

3. Modelling of sub band signal using Linear Prediction

The concept of Linear prediction approach is based on probabilistic theory .This modelling is used for the estimation of random brain signal parameters from the available brain waves. In this modelling the prediction of a sampled value is based on the past sample values. Consider the sample value x(n) has to be predicted from its past sample value x(n-1). The predicted sample value $\bar{x}(n)$ is given by first order predictor equation

$$\bar{x}(n) = ax(n-1) \text{ ---------------- } (1) \quad \text{where a is a real constant}$$

The prediction error is expressed as e(n) and is given by the equation

$$e(n)=x(n)-\bar{x}(n)$$

$$e(n)=x(n)-ax(n-1) \text{ -------------}(2)$$

the mean square error is given by the equation

$$\mathcal{E} = E[e^2(n)]=E[(x(n)-ax(n-1))^2] \; .$$

The condition for minimum error is given by $\frac{\partial}{\partial a}[E(e^2(n))]=0$

Substituting for e(n) from equation (2) yields the orthogonally relation equation and is given by

$$E[e(n)x(n-1)]=0$$

$$E[(x(n)-ax(n-1))x(n-1)]=0 \text{ ---------------}(3)$$

The autocorrelation $R_{xx}(.)$ expression based on equation (3) is given by

$$R_{xx}(1)=aR_{xx}(0)$$

The optimum value of a is given by

$$a=\frac{R_{xx}(1)}{R_{xx}(0)}$$

Based on the optimum value of ‘a’ the minimized error value is estimated and is given by

$$\xi_{\min} = (1-a^2)R_{xx}(0)$$

3.1. Feature Extraction

The main purpose of feature extraction is to reduce the original data by measuring certain features that distinguish one input pattern from another. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named feature vector). Transforming the input data into the set of features is called feature extraction.

3.1.1 Energy

The energy feature describes the strength of the signal. It is extracted by using sum of squared modulus value. The energy of the signal is expressed as

$$E = \sum_{n=0}^{N-1} |X_n|^2$$

Where X_n is the sample values in each subbands and *N* is the total number of samples

3.1.2 Spectral Entropies

The probability of variability within the signal is described by spectral entropies. The Entropy of different frequency band is estimated to reveal more information about the signal. The entropy feature is used to represent the dynamical characteristics of non linear signals. The entropy feature of the EEG signal is estimated using the following equation.

$$Entropy = -\sum_{n=0}^{N-1} P_n \log P_n \qquad (3)$$

P_n represent the relative power of the signal

3.1.3Power Spectral Density (PSD)

The Power Spectral Density (PSD) represents the distribution of the energy of the signal over the *t-f* plane. It refers to the amount of power per unit (density) frequency (spectral) as a function of frequency. The integral of the PSD over a given frequency band computes the average power of the signal over that frequency band. Different algorithms are used for the estimation of PSD. Periodogram is the most popular and simple method used for computing PSD. The steps involved for computing the PSD is given below.

1) Fast Fourier transform (FFT) is computed for each subband signal $X(\omega_i)$
2) PSD is calculated by using the equation

$$P(\omega_i) = \frac{1}{N} |X(\omega_i)|^2$$

Where N is the total number of samples present in the spectrum of the band.

3) The maximum value is estimated from the PSD of each subbands and is considered as third feature vector

4. Extreme Learning Machine classifier

Conventional gradient-based learning algorithms are widely used for training the multilayer feed forward neural networks. The learning speed of these algorithms is slower than required and it has been a major drawback in their applications. The two main reasons for this drawback are due to slow gradient learning algorithms which are used to train the neural networks and the parameters for the networks are needed to be tuned iteratively by using these algorithms. To overcome this problem an efficient learning algorithm for single-hidden-layer feed forward neural networks (SLFNs) called Extreme learning machine (ELM) was proposed by Huang, et al.. SLFNs consist of single layer of hidden nodes (neurons), input nodes and output nodes .The structure of SLFNs is shown in the Fig 3. In ELM algorithm the input weights (linking the input layer to the hidden layer) and hidden biases (for hidden layers) are randomly chosen, and the output weights (linking the hidden layer to the output layer) are analytically determined by using Moore–Penrose (MP) generalized inverse. The weights and biases are randomly generated and then fixed based on best performance. ELM classifier provides better generalization performance and the learning speed is thousand times than other neural network algorithms. (at higher learning speed).

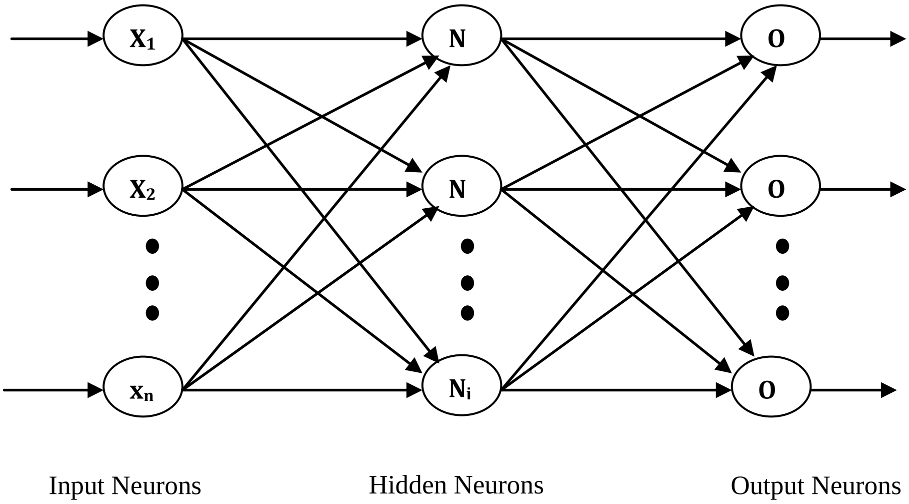

Fig. 3 Structure of SLFNs

Let us Consider the feature set as $\{x_i,t_i\}$, where $x_i = [x_{i1}, x_{i2}, \ldots x_{in}]^T$ be the feature values of the signals *and* $t_i = [t_{i1}, t_{i2}, \ldots t_{im}]^T$ be the class label values for target class. The Standard mathematical model for SLFNs with N hidden neurons (nodes) and activation function g(x) is modelled as

$$\sum_{j=1}^{N} \beta_j g(w_j . x_i + b_j) = O_i \ , \qquad i = 1, \ldots \ldots n \tag{4}$$

Where n is the total number of features and m is the total number of training signals where $w_j = [w_{j1}, wj2, \ldots Wjn]^T$ is the weight vector connecting the j^th hidden nodes (neurons) and their input neurons, $\beta_j = [\beta_{i1}, \beta_{i2}, \ldots \ldots \beta_{in}]^T$ is the weight vector connecting the j^th hidden neuron and the output neurons and b_i is the bias value for the j^th hidden neurons .In the equation $w_j . x_i$ is the inner product of the feature values and the input weight matrix .

The above equation (4) can be rewritten as

$$H\beta = O$$

Where H = $g(w_j . x_i + b_i)$ is the hidden layer output matrix which is given by

$$H = \begin{bmatrix} g(w_1 . x_1 + b_1) & \cdot \ \cdot \ \cdot & g(w_N . x_1 + b_N) \\ \vdots & \cdot \ \cdot \ \cdot & \vdots \\ g(w_1 . x_m + b_1) & \cdot \ \cdot \ \cdot & g(w_N . x_m + b_N) \end{bmatrix} \tag{5}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix} \quad \text{and} \quad O = \begin{bmatrix} t_1^T \\ \vdots \\ t_K^T \end{bmatrix}$$

4.1 ELM Algorithm

In machine learning classifier, the learning algorithms use a finite number of feature samples for training. For the given training feature set $\{x_i,t_i\}$,input parameters for the ELM algorithm is described below

(i) The number of input neurons (nodes) selected is equal to the total number of features used for an individual signal.
(ii) The number of hidden neurons N which is much less than the number of training samples m.
(iii) The activation function is g*(x)*. The various activation functions available are signmoidal function, polynomial function, hard-line function, etc... In this work the activation function used is Gaussian function.
(iv) The total number of output neurons (nodes) which is equal to the total number of output class required to classify.

5. Experimental Results and Discussion

The proposed method is implemented using Xilinx Vivado design suite and Matlab Sysgen tool box. The proposed method is synthesized using Xilinx Vivado synthesizer. In this paper 100 non-seizure and 100 seizures EEG signal is used to test the performance of the system. Each EEG signal is sampled at 173.6Hz. EEG signal is decomposed using FIR bandpass filter to form delta, theta, alpha, beta, gamma subbands. The Sysgen block contains Finite Impulse Response (FIR) band pass filter, Feature extraction block and ELM Classifier.The Simulink System Generator Model for Epileptic seizure detection is shown in Fig3. The device utilization summary of epileptic seizure detection system is shown in Table 1. The Verilog code for xilinx vivado zynq-7000 SOC is generated from the proposed model using system generator module. The generated verilog code is synthesized and implemented in xilinx vivado design suite. The device utilization summary of epileptic seizure detection is tabulated in table 1. The device utilization summary provides the information about number of registers, LUTs and IO required to implement the proposed model in FPGA.

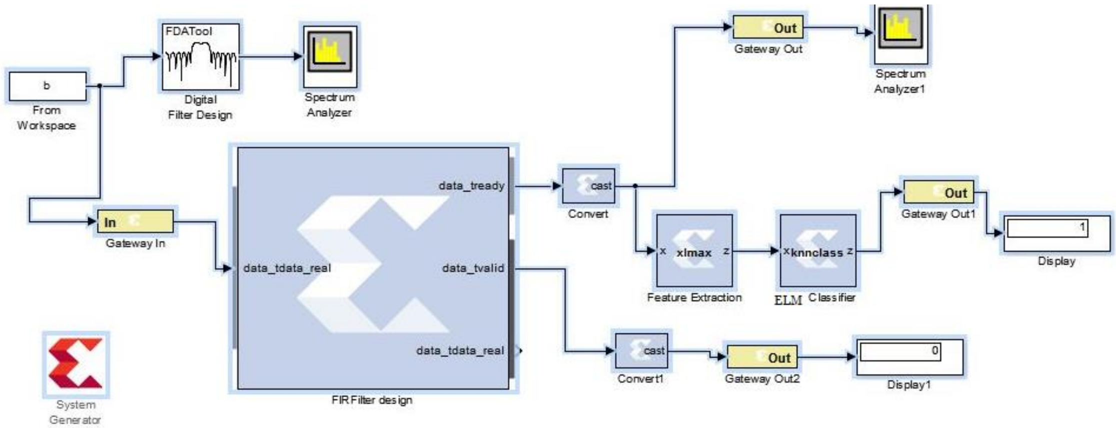

Fig3. Simulink System Generator Model for Epileptic seizure detection

Table1: Device utilization Summary

Resource	Utilization	Available	Utilization %
Slice LUTs	**243**	**203800**	**1**
Slice Registers	**1084**	**407600**	**1**
DSP	**16**	**840**	**2**
IO	**33**	**442**	**7**

The synthesized hardware architecture of the algorithm generated by using Xilinx vivado design suite is shown in the Fig4

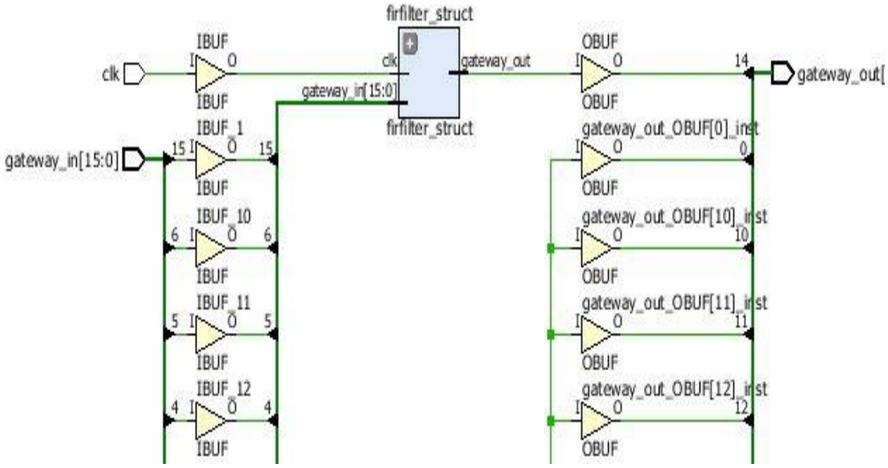

Fig4. Hardware Architecture of the System

The power analysis report of the proposed algorithm is mentioned in the below table2.

Table2.Power Analysis Report

SlNo	Parameter	Value(W)
1	Total On-Chip Power	0.16
2	Dynamic power	0.001
3	Device Static	0.158
4	Junction Temperature	25.3
5	Confidence Level	high

The summary of power analysis of the algorithm derived from constraints files, simulation files is shown in Fig 5

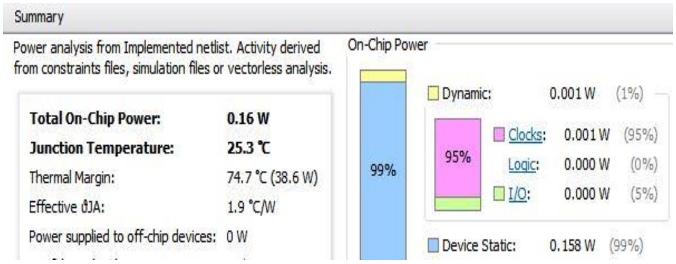

Fig5: Power Analysis summary

The table 2 explains the power analysis of total on chip power, dynamic power, device static, confidence level of the Algorithm. The power requirement of the proposed algorithm is very less when compared to other existing works in the literature The total On-Chip Power and Dynamic Power of the algorithm is very less when compared to the other works. The Confidence level of the work is high for real time implementation.

The performance of the system is measured in terms of accuracy. The accuracy is given by

$$Accuracy = \frac{correctly\ detected\ patterns/signals}{total\ number\ of\ patterns/signals}$$

In the classification problem 160 signals feature values are considered as training features and 40 signals features are used for testing the classifier. Out of 160 training signals 157 signals are correctly classified and the 40 testing signals used for testing are correctly classified without error .So the accuracy obtained by this method is 98.5%.

5.1. Comparison with others works

There are many other methods proposed for the epileptic seizure detection in Literature. The comparison accuracy of the results obtained by this method and other method in the described dataset is given in the Table 4. In the existing methods real time implementation of the system was not analyzed. This method analyzed the performance of the system with respect to hardware complexity of the algorithm. The Slice LUTs and registers used by this ELM classifier is less when compared to existing methods. The detailed comparison between the algorithms related to epileptic seizure detection is tabulated in Table 3.

Table 3 :Analysis of Algorithms

Algorithm used	Devices	Speed	Number of LUTs	Power
Amplitude and Frequency Analysis of EEG Signals	Virtex-5 kit	13.56ns	82%	0.58(w)
DFT based Search Algorithm v	Virtex-5kit	30.56ns	40%	0.48(w)
Mutual information based algorithm	Altera Stratix	20.32ns	30%	0.21(w)
Proposed method	Zynq-Soc	1ps	1%	0.16(w)

Table 3: The comparison of the classification accuracy

Researchers	Methods used	Accuracy
Nigam and Graupe	Nonlinear pre-processing filter-Diagnostic neural network	97.2
Srinivasan et al.	Time & frequency domain features-Recurrent neural network	99.6
Kannathal et al.	Entropy measures-Adaptive neuro-fuzzy inference system	92.22
Kannathal et al	Chaotic measures-Surrogate data analysis	90
Polat and Gunes¸	Fast Fourier transform-Decision tree	98.72
Alexandros T.Tzallas*	Time frequency analysis-Artificial neural network	100
This Work	**FPGA Implementation of Epileptic Seizure detection Using KNN Classifier**	**98.5**

6.Conclusion

The epileptic seizure detection was performed by analyzing the features of the signal and classification is performed by using ELM algorithm.. The EEG signal is filtered by using FIR band pass filter. The model of the system is synthesized implemented using Xilinx Vivado design suite. The resource utilization and power analysis report of the algorithms are analyzed. Accuracy of the classifier is computed. The accuracy obtained in this method is much better than other results available in the literature. The implementation results provided the timing summary of the method. And the timing resolution is 1ps .Autoregressive model and various time-frequency distributions can also be used to extract the features for comparing the performance and accuracy for detecting Epileptic Seizure in EEG signals.

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