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EPILEPTIC SEIZURE DETECTION USING A NON-INVASIVE BRAIN-MACHINE INTERFACING SYSTEM

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ABSTRACT

This paper proposes a Brain-Machine Interface (BMI) for aiding epileptic seizure patients by monitoring their brain waves through electroencephalogram (EEG) recordings. EEG signals are highly prone to artifacts and noise from blinking eyes, muscle movements, and glossokinetic artifacts. Hence filtering must be done for the EEG brain wave obtained. The EEG signal received can be classified as a normal person's or an epileptic patient's based on the features extracted from these two categories. If an epileptic seizure will be predicted, then a distress signal is sent automatically to a centralized monitoring system through a GSM module. The patient's current location is acquired using a GPS module and transmitted along with the message to get immediate attention. From experimentation, it is found that the proposed methodology provides a highly accurate detection capability with high sensitivity, which is superior to other methods. The implementation has been carried out on the Spartan6 FPGA kit, using Xilinx ISE Design Suite 14.2, programmed in Verilog HDL. The GPS used is Neo-6M, and GSM is SIM900A. The embedded board STM32F0 discovery kit has also been used.

Keywords: brain-machine interface, epilepsy, feature classification, feature extraction.

INTRODUCTION

A Brain-Computer Interface (BCI) is an example of a Brain-Machine Interaction, wherein a machine interfaces with a human brain. The machine could be a mechanical or electrical device that modifies or transmits information to assist in human tasks' performance. Human-Machine Interface HMI and BMI devices aim to combine functionality, thereby creating new levels of sensor fusions to bring intelligent machines and robots closer to humans. A BMI system is implemented by extracting the brain waves through the EEG technique, which is highly prone to artifacts and noise from eye movements and blinking, muscle movements, etc. Using EEG brain waves obtained, we can predict the action intended by the subject. A non-invasive BMI system is a less intrusive form of BMI that involves simply placing electrodes onto the head's surface at specific points along the scalp [1, 2].

Seizure detection refers to recognizing a seizure using an automated algorithm by analyzing biological signals obtained from an epileptic seizure patient. Epilepsy is a neurological disorder that manifests several nerve cells or neurons firing simultaneously, associated with the brain's abnormal electrical activity. It leads to strange sensations and emotions (such as hallucinations, nausea, etc.), severe muscle spasms, convulsions, and even loss of consciousness. Epilepsy can arise due to other severe neurological disorders, including Alzheimer's disease, strokes, and heart attack.

There are several problems with existing systems- most works done in the field involve a fixed number of database items. Hence the overall flexibility of existing systems is poor. Furthermore, there is still the problem of artifacts that reduces the accuracy of the results. Even a 10% error in the detection of the EEG signals can lead to entirely wrong actions. So, the main challenge in EEG-based systems is to identify the particular EEG signal components or features [2], [3]. This requires a highly accurate filter system. There is also a great demand for the miniaturization of systems to increase portability. Besides, in real-time applications, the requirement for instant response is very crucial. Hence, area and delay are essential parametric considerations. Power reduction is another critical parameter.

This work's main objective is to aid epileptic patients on the advent of a seizure through remote monitoring using a Brain-Machine Interface (BMI). The accuracy of the BMI device is governed by predicting and analyzing the acquired EEG brain waves. The objective here is to design a near real-time BMI system that can monitor an epileptic patient's brain waves and send a warning to a remote system on the advent of a seizure, including the patient's accurate location to provide medical services. This demands the use of an exact and efficient filter, feature extraction, and classification techniques to minimize the artifacts in the detected EEG brain waves to increase accuracy.

LITERATURE REVIEW

Epilepsy affects almost 1 to 2 % of the population - approximately 50 million people. The sudden and unpredictable nature of epileptic seizures makes it very complicated. The most traditional and standard method of epileptic seizure detection is human visual analysis. However, this manual signal analysis of the data can lead to less accurate predictions and even missing out on seizures. Hence there is a need for computer-aided or machine-aided systems to detect epileptic seizures. Several authors have proposed such applications but not yet familiar due to technological barriers and practicality systems.

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Non-EEG and EEG Based Seizure Detection

Various literature is available for seizure detection, and they are either based on the Non-EEG method or based on EEG. Non-EEG based methods include measurement of hormone levels, non-formed vocalizations, and extraocular movements. Using cardiac cues to detect epileptic seizures is a common technique used in the case of new borne. The use of accelerometers for seizure detection is another technique. The Emfit movement monitor is another type of quasi-piezoelectric seizure detector which is fixed under the mattress system that can alert caregivers to unexpected motor activity. This system was able to detect 80% of seizures [4]. Researches are being carried out to invent invasive techniques for epileptic seizure detection as well as for suppression. Tariqus Salam et al. discussed such an invasive procedure experimented on a rodent. Deep Brain Stimulation (DBS) methods based on closed-loop paradigms may target various brain activity pathological aspects to treat various neurological disorders [5].

There are several methods available that are based on the classification of EEG into two distinct classes, epileptic or non-epileptic. Methods based on Short Time Fourier Transform (STFT), Fourier Transform (FT), and Discrete Wavelet Transform (DWT) are better options [6-13]. There are several methods available for classification in literature as well [14-16]. When EEG signals are obtained as waveforms from the database, image processing techniques such as Local Binary Pattern (LBP) and histogram based feature extraction methods are suggested in the literature as a technique for epileptic seizure detection [15]. Histogram of oriented Gradients is a global descriptor. Although a global descriptor, it can also be extended for use as a local descriptor. It has been proved experimentally in [16].

Database

For this work, a digital database has been used. The epileptic patients' data was obtained from Karunya University, whereas the normal individuals' data from NeuroWorks. Karunya University's database includes 108 subjects and NeuroWorks' database has 6 subjects. The database consists of patients with different types of seizures - generalized as well as focal. Sixteen electrodes have been used here so as to be able to generalize the system. The readings from sixteen electrodes namely Fp2, F4, C4, P4, F8, T4, T8, O2, Fp1, F3, C3, P3, F7, T3, T5, O1 have been used. The digital data involves 2560 sample data points for each of the electrodes for each patient. Sixteen electrodes have been used here so as to be able to generalize the system. The readings from sixteen electrodes namely Fp2, F4, C4, P4, F8, T4, T8, O2, Fp1, F3, C3, P3, F7, T3, T5, O1 have been used. The digital data involves 2560 sample data points for each of the electrodes for each patient. The data points have minimal values with negative amplitudes. So, to make the processing of data easier for analysis and parameter calculation, an offset value of 100 is added to each data point in the database to remove all negative values. This procedure is done for both epileptic as well as normal individuals' database obtained.

PROPOSED METHOD

The block diagram of the proposed system is shown in Figure-1.

Artifact Removal

The electrical signals obtained along the brain's scalp using EEG are always contaminated by artifacts - mostly biological artifacts; and other external artifacts such as electrode line noise, etc. [18]. The EEG signal has a sampling frequency of fs = 173.61 Hz. So, as per the Nyquist' criterion, the maximum frequency component would be $fm=fs/2$ = 86.805 Hz ≈ 86.81 Hz [19], [20]. Through several researches it has been found that neuron spike activity is closely related to the gamma and delta waves. In the methodology employed here, the delta waves have been used for analysis [18]. It falls within the frequency range of 0.1 Hz to 3 Hz or 4 Hz.

To eliminate the artifacts and filter out only the delta waves, a band-pass filter with 0.1 Hz settings to 5Hz is used. Its sampling frequency is set to 173.61 Hz [21]. By using the Filter Design and Analysis Tool in MATLAB, we can obtain the filter coefficients. An FIR Band-pass filter of order 268 is used. The filter coefficients obtained thus are used to program the FIR filter in Verilog HDL. Discrete-Time FIR Filter details obtained is depicted in Figure-2.

The block diagram of a 268th order FIR filter is shown in Figure-3. It consists of 269 multipliers, 268 adders and 268 delay blocks. 'D' represents the D flip-flop; 'cx' represents the coefficients where 'x' represents the stage; x(n) is the input signal to the filter block and y(n) is the final output.

Once the FIR filter filters out the delta wave, it is passed through the DWT block. EEG signals are non-stationary and using DWT the EEG signal can be used to quantify their spectral content as a function of time [22]. The Daubechies wavelet is used here. The signals are decomposed into four stages in this work, with four detail signals D1-D4 and one final approximation signal A4. In Figure-4, X[n] is the output from the FIR band-pass filter; g(n) represents a high pass filter, and h(n) represents a low pass filter. Delta wave being the lowest frequency band, the approximation signal A4 as output. The reason for the selection of the approximation signal is because of the energy compaction property of DWT

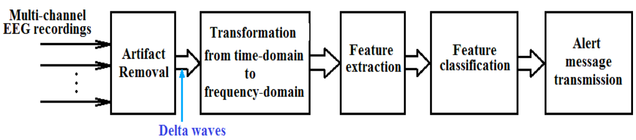

Figure-1. Block diagram of proposes system.

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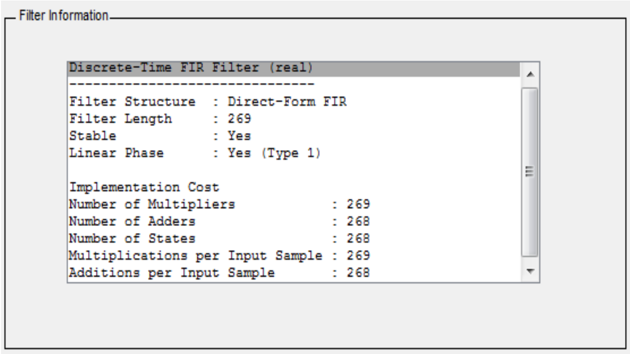
Filter Information

```
Discrete-Time FIR Filter (real)
-------------------------------
Filter Structure  : Direct-Form FIR
Filter Length     : 269
Stable            : Yes
Linear Phase      : Yes (Type 1)

Implementation Cost
Number of Multipliers            : 269
Number of Adders                 : 268
Number of States                 : 268
Multiplications per Input Sample : 269
Additions per Input Sample       : 268
```

Figure-2. Discrete-time FIR filter details from MATLAB.

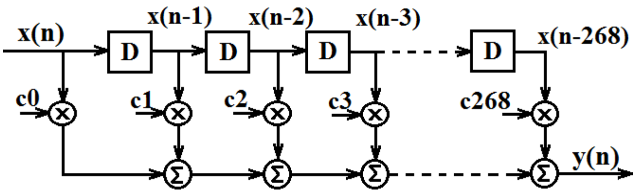

Figure-3. 268th order FIR band-pass filter block diagram.

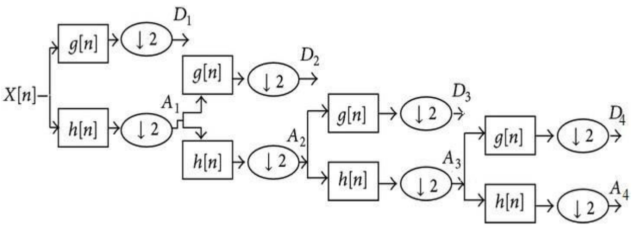

Figure-4. Four-stage DWT module.

Feature Extraction

The approximation signal is passed as input to the next stage, which is feature extraction. The feature extraction block uses statistical parameters such as mean, variance, standard deviation, energy, amplitude, etc. The database variance analysis, amplitude (maximum), minimum mean energy, and maximum mean energy are used. Equations for mean (m), variance (v) and mean energy (me) are given below:

$$m = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

$$v = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - m)^2 \tag{2}$$

$$m_e = \frac{1}{n}\sum_{i=1}^{n}(x_i)^2 \tag{3}$$

Where n is the number of samples and xi is the ith value of signal x.

The digital database selected for the work consists of 16 electrodes, each containing 2560 samples in it. For the study, the mean and variance values of all 16 electrodes for each subject is calculated and then compared to obtain the maximum and minimum values calculated to get the line of control (LOC) values to be used for the classifier. This is done because epilepsy could be focal or generalized. If focal, the EEG signal's erratic variation may be noticeable only in the electrodes in or near the brain region undergoing seizure.

So, it is necessary to compare all the 16 electrodes for the extracted parameters. Mean energy (m_e) parameters are calculated by dividing the 2560 samples into 8 sections of 320 samples and calculating the mean energy for each section, as shown in figure. 5. This is done to be able to detect any abrupt variation in amplitude of the EEG signal which occurs during seizure - the energy will be concentrated in regions where the seizure is occurring

So, for each electrode, there will be 8 mean energy values. Hence, there will be (8* 16) = 128 mean energy values for a single subject. The maximum and minimum of these values will be used as LOCs.

Feature Classifiaction

The parameters mentioned above are extracted from 10 epileptic patients and 3 normal individuals for the feature classification training phase. The values are extracted from the database to which the offset (of 100) has been added and is depicted in Table 1. For the prediction phase, 83 test inputs are applied, of which 80 were that of epileptic patients and 3 of normal specimens. The study attempts to detect the seizure activity as a two group classification problem: one with a healthy subject or normal EEG and the other with epileptic subjects during the seizure or ictal EEG. So, a binary SVM classifier is used for the purpose. The SVM classifier has been selected due to its advantages of being trained on small data size; the training and testing are easy, and any dimensional data can be used.

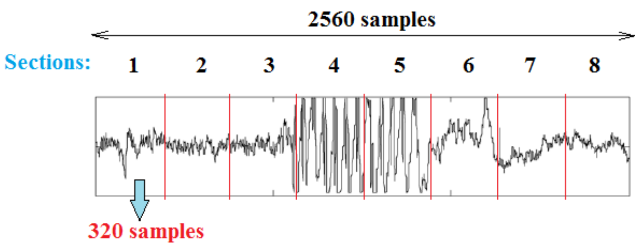

Figure-5. Mean energy calculation.

The SVM block has a single bit output that indicates whether the input signal indicates a seizure or not. The 'type' signal determines whether the classifier is operating in the training or prediction phase. If it indicates the training phase, then the 'load' signal is considered; otherwise, it is neglected and has no consequence. The 'load' signal denotes whether the inputs are an epileptic patient or a normal subject. In that case, the input signal will be used for obtaining the LOC values. Also, there will be a learning phase for the classifier - depending on the final output. The input data will be used to update the LOC values. This makes the classifier more flexible.

Transmission of Alert Message

Furthermore, the message transmission procedure is carried out using an embedded board - STM32F0 Discovery board. It houses an ARM Cortex M0 processor.

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The SVM output will be input to the embedded board in one of the I/O pins. It can be polled to detect when a seizure is detected. Once the seizure is detected, the current location of the patient can be obtained using the GPS module (Neo-6M) and given to the embedded board, which then appends the information (in the desired format) with the message and can be then sent to a pre-determined number via the GSM (SIM900A) module. This can be done by using the UART1 on the STM32F0 kit. The receiver pin and transmission pins are PA10 and PA9, respectively. The SIM900A module by SIMCom is an ultra-compact and reliable wireless module, controlled using SIMCom enhanced AT commands. The Neo-6M module is based on the NMEA commands. There are several NMEA commands used for interfacing. For the proposed work, to obtain the position information, the RMC output command has been used.

Table-1. Statistical parameters obtained from the database for 47 normal individuals and epileptic patients.

Test Parameters	Normal Individual		Epileptic Patient	
	Upper Limit	Lower Limit	Upper Limit	Lower Limit
Variance	8.35	2.10	281.27	21.16
Maximum Amplitude	93.66	84.86	163.00	126.00
Mean Energy (Minimum)	4624.0	2692.8	9809.25	9797.78
Mean Energy (Maximum)	5022.4	3179.4	10826.7	10234.5

RESULTS AND DISCUSSIONS

The proposed system is implemented in FPGA and Embedded environments, using Xilinx ISE Design Suite (14.2 version) platform and IAR Embedded Workbench IDE, respectively. Verilog Hardware Description Language (HDL) and Embedded C language have been used. GSM module SIM900A and GPS module NEO-6M were used for message delivery and location acquisition. The system mainly consists of a ROM (memory) block and the other main processing modules such as FIR filter, DWT module, feature extraction, and classification modules. The system inputs are ‘clk’ (clock) and ‘rst’ (reset) and output is ‘test’. The output will turn high when epilepsy is detected. Otherwise, if no epilepsy is detected, it will remain low.

Single and Sixteen Electrode Systems

The system has been simulated for a single electrode for each of the subjects – this is merely for implementation purposes. Besides the inputs and outputs, the internal registers are also shown. For the patient and normal individuals, both the maximum and minimum LOC values for each of the statistical parameters calculated are shown. For example, ‘NtempVarLow’ is the lower limit of the variance for normal individuals (obtained during the training phase) and ‘NtempVarHigh’ is the higher limit. Similarly, ‘PtempVarLow’ and ‘PtempVarHigh’ are the lower and higher limits of patients' variance. The test signal parameters are preceded by ‘Test’; for example, ‘TestVariance’. Next, the test parameters are compared to the LOC values, and the classification is correspondingly carried out. The test variance falls within the limits of that of a patient, and hence the output ‘test’ turns high. Simulation is also carried out for all the 16 electrodes of all of the subjects.

Imolimentation Results

The project settings are selected for Spartan6 kit with device specification as XC6SLX45 with CSG324 package. Verilog HDL is used for programming. The device utilization statistics are shown in Table 2. The report is obtained for the implementation of the single electrode system on Spartan6 FPGA board. The overall slices register utilization is 2%. The delay values and memory usage are as follows:

- Minimum period: 105.006ns
- Maximum Frequency: 9.523MHz
- Minimum input arrival time before clock: 106.913ns
- Maximum output required time after clock: 3.634ns
- Maximum combinational path delay: No path found
- Total memory usage is 416288 kilobytes

Alert Message Transmission

The ‘test’ signal from the output of the FPGA is used to trigger the transmission of alert message, i.e. whenever the ‘test’ signal becomes high. It means an epilepsy event is occurring, and the GSM module must then transmit the message to a predetermined centralized number for monitoring. It should also include in the message, the location information of the subject. This section of the processing is done on the ARM Cortex M0 processor. For that, the STM32F0 discovery kit has been used. Figure.6 shows the apparatus used for the purpose.

The ‘test’ signal is given as a polling input to the ARM Cortex M0 module on the STM32F051R8T6 Discovery Board. Whenever the signal goes high, the GPS data will be acquired using the UART1 receiver pin at PA10. After the latitude and longitude information is obtained and converted to the required format, this data and the message are transmitted to the predetermined number using the GSM module through the UART1 transmitter pin, PA9. The baud rate is set to 9600.

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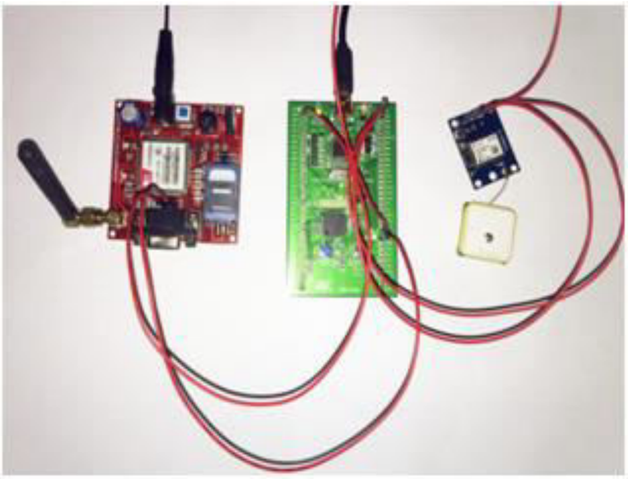

Figure-6. Apparatus set-up for alert message transmission.

Evaluation of Results

Eighty-three test inputs are applied to the system, of which 80 were epileptic subjects and three non-epileptic subjects. The training phase used 13 inputs, of which 10 were epileptic subjects and three non-epileptic subjects. The system provided accurate detection for each, and every subject applied - all epilepsy inputs were correctly recognized as epilepsy and non-epileptic signals as belonging to normal people. Also, the timing parameters show very low delay values. So, the system is very fast in operation. Some other evaluation parameters, such as the system's sensitivity and accuracy, can also validate the system. A value of 1 for sensitivity means that the sensitivity is very high and hence the performance is excellent. Specificity is also often calculated to estimate the performance of the system. Accuracy is the proportion of correctly classifies instances. Specificity is the capacity of the system to identify the negative cases correctly. Sensitivity is defined as the capacity to identify positive cases accurately.

The equation 4, 5, and 6 represents sensitivity, specificity and accuracy.

$$\text{Semsitivity} = \frac{N\mathrm{P}_j^j}{N\mathrm{P}_j} \quad (4)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (5)$$

$$\text{Accuracy} = \frac{N\mathrm{P}_c}{N\mathrm{P}} \quad (6)$$

Where $N\mathrm{P}_j^j$ is the number of patterns of class 'j' classified correctly as class 'j', $N\mathrm{P}_j$ is the total number of patterns in class 'j', TN is true negative, an outcome where the model correctly predicts the negative class, FP is false positive, an outcome where the model incorrectly predicts the positive class, $N\mathrm{P}_c$ is the number of correctly classified patterns, and $N\mathrm{P}$ is the total number of patterns.

In this work, out of 80 epileptic samples, all 80 are correctly classified. Therefore the sensitivity to epileptic patients test inputs is 1. Suppose we consider the positive output to be epilepsy patient detection and negative to be normal specimen detection. Then specificity is the same as the sensitivity of the system to the detection of normal individuals. In our method out of 3 normal samples, all three were correctly classified as normal. Therefore specificity calculated as 1. Since all the samples classified correctly the accuracy of our method is 100%

So, it can be said that the developed system provides very high sensitivity, specificity, and performance by providing 100% accuracy for the applied test signals.

CONCLUSIONS AND FUTURE SCOPE

An epileptic seizure detection system's primary goal is to predict an upcoming seizure based on the biomedical signals recorded from patients. Here, the EEG signal is acquired using 10/ 20 system using 16 electrodes placed over the patients' scalp at specific points, during the ictal stage. EEG signal is always contaminated by noise or artifacts due to blurring the signal by diffusion in the skull or skin, muscle activities, blinking of the eye, power line interface, etc. From research, neuron spiking characteristic during a seizure is very closely linked with mainly two bands – delta and gamma [18]. In the proposed work, only the delta waves are extracted for analysis. To remove the noise and extract only the delta wave, a 268th order bandpass FIR filter has been employed. EEG signals are non-stationary and the frequency analysis not being very successful for diagnostic classification, DWT has been used. DWT has space frequency localization property, acting as a mathematical microscope for observing different parts of the signal by just adjusting the focus [24]. A four-stage DWT has been employed. For feature extraction, we resort to use of statistical parameters such as variance, energy, amplitude, etc. Using SVM's machine learning technique, we then classify the data as either from a normal individual or an epileptic patient. Since there are only two classes, a binary SVM is sufficient.

The proposed methodology for epileptic seizure detection was tested on 83 individuals, of whom 80 were epileptic and three normal. For the training process, 13 individuals (10 epileptic and 3 normal) were used. The result provided 100% accuracy for the applied test signals with very high sensitivity and specificity and very low delay parameters.

Epileptic seizure is a mechanism which is still not understood in its entirety and therefore the duration of each seizure stage is determined purely through human speculation. Most of the literature papers use a single electrode for seizure detection. However, optimal electrodeposition selection is a significant concern in such works and cannot be used as a universal model [25]. Seizures can be generalized or focal. In focal, the seizure is confined to specific location whereas in generalized it is spread over the entire brain. So, EEG signal is a function of time and the sensor or electrodeposition on the scalp. Using a 16- electrode system here, is superior to several other systems already suggested in literature that use single electrode. Seizure prediction can be analyzed in different stages - ictal, inter-ictal or pre-ictal stages. The proposed study here uses the ictal data for classification. However, inter-ictal data can also be used to study the patterns for detecting seizure ahead of time, instead of at the onset of seizure. Another scope for study is to analyze other frequency bands or other brain waves for analysis (only delta wave has been studied in the proposed system). The problem of data contamination will always be a major concern. Therefore, enhancing the filter section for data acquisition remains a major concern and provides much scope for further improvement. Other transformation techniques can be used to test the performance; other wavelets can also be incorporated. The present work can be enhanced to detect what type of seizure (i.e., Petit Mal, Grand Mal, atonic, etc.) the patient is having. Also, this can be extended to study and detect other neurological disorders such as Alzheimer's disease, Hopkins's disease, etc. Furthermore, in the areas of BMBI and other HMI technologies, the proposed concept can be extended for extracting the human intention from brain waves; this is then used to carry out automated functionalities of the system without any physical interaction between human and machine. Yet another area of development is in invasive techniques - the proposed is a non-invasive technique. Invasive techniques are being developed for testing in rats but still a completely comprehensive human model has not been developed yet.

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