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SMART SENSOR FOR EEG ACQUISITION AND EPILEPTIC SEIZURE

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Abstract— This research paper proposes a novel and hybrid system for seizure detection and prediction using a real time EEG analyzer that strives to detect and predict seizures based on the EEG waveforms. The system offers an environment where users can test this model with minimal effort while allowing them to alter any parameters deemed fit. We evaluated the proposed technique using the CHB-MIT scalp EEG database. We also used the simulated data simulating real live patients. The results of the proposed system shows that analysis of EEG signals can be useful in detecting and predicting epileptic seizures in real time. Our proposed epileptic seizure detection gives an average sensitivity of 100% and an average specificity of 73.65%. The seizure prediction technique achieved an average sensitivity of 72.4% and an average specificity of 52.3% with an average warning window of 74.5s. Even though the seizure prediction study is still in its infancy, the results obtained in this paper are promising.

Keywords—Epilepsy,Seizure, EEG, waveform, Signal Processing, Machine Learning, Prediction

1. INTRODUCTION

EPILEPSY

Epilepsy, defined as a brain disorder characterized by mail. Comrepetitive seizures, is a chronic neurological disorder which affects various people, independent of age. In 2005, epilepsy was denominated as a brain disorder where two unprovoked seizures occurred in a time period greater than 24 hours[2]. To expand this definition to cater for more uncommon cases as well as clinical diagnoses, the International League Against Epilepsy (ILAE) formulated a more encompassing working definition, which now states that in addition to the pre-existing condition, epilepsy would also be determined by a probability of over 60% of further seizures, after the first unprovoked seizure, over a period of 10 years. Considering that seizures are unpredictable and unforeseen, epilepsy patients have no control on the seizure and this is the most threatening aspect of epilepsy. Symptoms include changes in movement, behavior, sensation, or awareness and these can lead to dangerous falls. In some cases, epilepsy could lead to sudden unexpected death. According to various studies, compared to the general population, the risk of sudden death in patients suffering from epilepsy is increased by 24 times[3]. Early diagnosis of epileptic seizures is essential to the development of effective prevention treatments so the patient can undergo treatments which can delay or prevent disease progression.

OBJECTIVES

Our objective in this paper is to investigate a feasible solution not only for effective seizure detection but also for prediction. The main objective is to design, implement and test such a model. By predicting an oncoming seizure within a given time frame, epileptic patients can prepare for the seizure and therefore remove themselves from any harm. This study summarizes the efforts undertaken to implement an effective seizure prediction system. Previous research at the University of Malta came up with a system that eases the testing of multiple models for seizure prediction involved processing using Matrix Laboratory (MATLAB) and a super computer [4][5]. While building on the achievements of this previous research, our investigation aims to achieve better seizure prediction accuracy without having the need of a supercomputer, using high-level language which is more powerful and that can be used on normal work stations.

Thus the overarching objectives include reviewing and evaluating previous seizure prediction research, designing and implementing a real-time electroencephalography(EEG) analyzer that attempts to detect and predict seizures using signal processing techniques on features of the EEG waveforms such as amplitude and frequency, designing and implementing a real-time EEG analyzer that attempts to detect and predict seizures based on classification of linear features of the EEG waveforms such as skewness and variance and testing such a model across a set of EEG seizure files. In order to give a perceptive and correct indication of performance of the model being tested, it was deemed necessary that the system is built on sound principles. For this reason, the system is designed in such a way that minimum effort is required for the user to adapt the system for his/hers purposes. Furthermore, the system is thoroughly tested by carrying out numerous runs using a set of known seizure prediction models with varying parameters, after which the results are analyzed and reported.

3. DESIGN APPROACH

In this paper we described an effective software seizure detection and prediction algorithm using the CHB-MIT database to simulate patients. This database contains over 1000 hours of recorded scalp EEG signals with over 190 seizure events of 23 distinct patients suffering from epilepsy.

As a result, based on the provided parameters, the system would read and prepare the raw data in the form of European Data Format (EDF) files and sample them accordingly for accurate final results. Therefore, modularity was retained as an integral concept when designing such a system. The system's procedure is to be divided into frames, each responsible for a specific task within a single execution run of the system.In order to increase accuracy, irrelevant or distorted channels shall be removed from the EEG signals and the most important features and channels of the signals that distinguish between seizures and non-seizures states are to be extracted and utilized. Amongst these features, the frequencies of these EEG signals together with the variation in amplitude are considered for better discrimination between abnormal and normal EEG signals. Another approach taken into consideration is classification, where a novel machine learning algorithm shall be considered for classification using other linear features of seizure and non-seizure states of the EEG signals.

This method aspires to devise a real time processor where the seizure probability level can be determined in real time. Although no previous work that implemented it was encountered in the literature review, this concept is frequently mentioned as future work. Since brain waves are unique for every patient [6], the processor would need to be retrained for every patient. This suggests that a multi-patient implementation would be beneficial and result in higher accuracy per patient. Moreover, flexibility between training and user modes could also help make the system more usable in practice since this would allow full flexibility when training the system.

In order to guarantee that the real time results are accurate and not biased or compromised in any way, careful measures must be implemented in every stage of the system's design. Moreover, this system guarantees user flexibility by the use of parameters. Finally, these results must be efficiently organized and properly formulated for ease of analysis and interpretation.

2. SPECIFICATIONS AND DESIGN

In this paper we have investigated the effective algorithm that detects and predicts seizure using the CHB-MIT database and simulates the patients in real time. Based on the provided parameters, the system would read and frames the raw data in the form of EDF files and sample them accordingly for accurate final results. Previous research done at the University of Malta [4][5] merged all the chosen EDF files into a single file requiring a substantial amount of memory and thus compelling the use of a supercomputer. However as stated in [8],choosing only relevant files decreases computation complexity saving time and power. Figure 1describes the design scheme of the proposed seizure prediction system. The design of the proposed system is essentially divided into two sections; the signal processing stage where all the pertinent features are extracted and the classification stage which is the machine learning stage.

Initially process starts with the EEG recordings acquired from the CHB-MIT database[10], which were then processed and prepared for the subsequent processing. The process includes the channels visualization, extraction and calculation

of features. In order to increase the accuracy, distorted channels are removed from the EEG signals and only the features of the signals such as variations of the amplitude (spikes), frequency, skewness and standard deviation that distinguish between seizure and non-seizure states are extracted, and probability of a seizure is obtained.

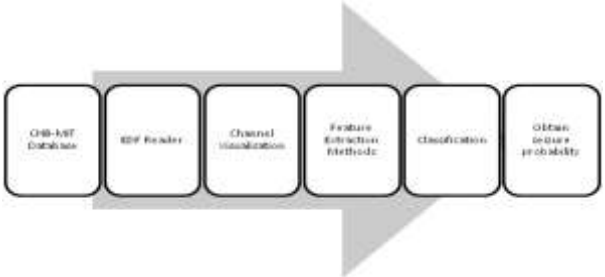

Fig. 1: The design flow showing the steps involved in outlining the proposed system

Ultimately, the classifier is executed to classify signals received based on the learnt parameters. These learnt parameters are compared with the new parameters and are analyzed using the nearest neighbor algorithm and classified accordingly. However, at any point in time, without having to stop the processing, users can train the classifier. An important design concept for the proposed system is the use of object oriented programming for a coherent structure and better design. Additionally, object oriented programming provides a convenient framework, where application functionality can be plugged in. Framework also allows for extensibility, where code can be added for a specific component and modularity. This framework structure is achieved by implementing interfaces for every feature extraction method.

CHB-MIT DATABASE

One of the essential parameters for the designed system is the dataset for the testing and is taken from CHB-MIT Scalp EEG Database as shown in figure 2, openly available for download through the PhysioNet website [10]. This database consists of scalp EEG recordings of 23 pediatric patients suffering from intractable seizures, assembled at the Children's Hospital of Boston. In total, this data is divided in 24 cases and EEG recordings are stored in European Data Format (EDF) files and each test case spans between 9 and 42 recordings resulting in an overall number of 664 EDF files of which 198 are seizure files. Moreover, these recordings were sampled at a frequency of 256Hz with a 16-bit resolution.The database is described in [19] and shown in fig 2.

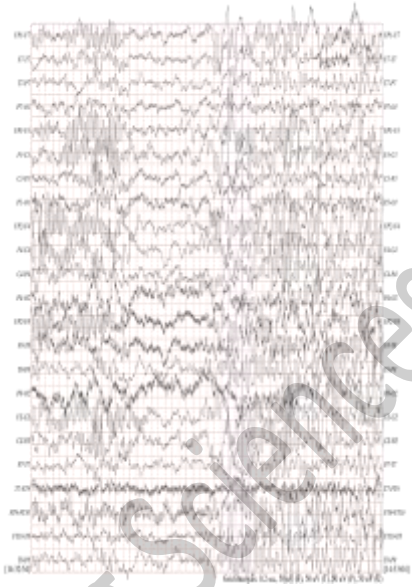

Fig. 2: EEG Recordings with grid intervals

EDF READER

We have saved the EEG recordings in EDF format thus, an EDF reader is used to convert these recordings. The EDF reader used in the proposed system was adapted from an application programming interface (API)[20] , the API adapted is implemented in C#. When C# is compared with MATLAB where it needs the code has to be analyzed and interpreted before execution while C# is compiled to byte code which executes faster and has a more direct access to machine resources hence increases the overall efficiency of the system.

An EDF data file comprises a header record that describes the patient together with technical aspects of the recordings. The fields that make up the first 256 bytes of the header record include the EDF version number, the patient and the recording identification, date and time of the recording the number of data records together with the total number of signals of each data record.

The code and the record header saved in the EDF format is shown below in table 1 and fig 3 shows a sample.

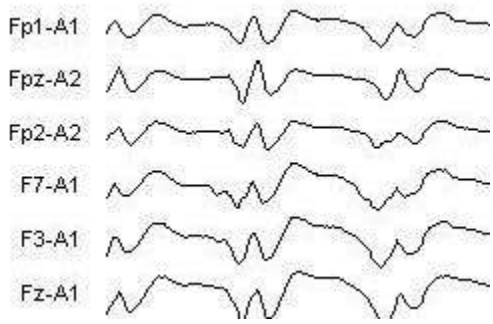

Fig. 3 A Sample of EDF data

Patient information consists of the hospital code for the patient, their sex, birth date, name and other information that can be available regarding that patient. Furthermore, the recording identification is made up of the start date of the recording together with the codes of the EEG recording, technician and the equipment used, and any other information regarding the recoding may also be added.

Table 1.Reading And Saving Of EEG Data in EDF

No	Function	Interpretation
1	function [data, header] = readEDF(filename)	To read in EDF format
2	function SaveEDF(filename, data, header)	To save in EDF format

We have used here object oriented programming design concepts in the proposed system. We further made it easier and structured by adding input classes with the modularity of an interface to handle the input class. As a result, a real time data capture device is implemented. This device is a proof of concept which needs further analysis, work and approvals to be used on patients.

4. DESIGN METHODS

When loading an EDF file in the EDF reader, the user can choose any channel from the list of channels used in the EEG's recording and perform our proposed three processing tools. These tools consist of; graphically visualizing the EEG recording, classification entirely based using signal processing techniques and using a hybrid machine learning technique on processed signal file.

GRAPHICAL VISUALIZATION

In order to obtain additional information and be able to acquire further analysis of the EEG recordings, a tool is developed to plot the data graphically. Moreover, this process also allows to plot a section from the recording by defining the range. This analysis will help in the design of the two previously mentioned tools which are the classification mechanism based on signal processing and the hybrid classifier combining machine learning techniques with signal processing.

SIGNAL PROCESSING

We have used signal processing techniques to evaluate properties of the signal during seizures phases. This process involves processing the signal sample by sample and extracting the required feature. Among these, the envelope of the raw signal is calculated using an envelope detector[11]. From the envelope, the rate of change in time domain of the signal envelope is determined which results in the calculation of the seizure likelihood. Another feature extracted is frequency, where using a band-pass Butterworth filter the signal is filtered from any noise and converted to frequency domain. An investigation carried out in order to identify the predominant frequencies during a seizure showed that the same frequency peaks present in seizures were also observed in non-seizure epochs and these would lead to false positives.

Furthermore, this frequency output is also passed through the envelope detector to calculate the frequency related seizure likelihood. In addition, linear features such as skewness, kurtosis and standard deviation are extracted by processing block after block of the signal and displayed for information purposes.

From these features extracted, their relevance is calculated and compared against defined threshold values to predict the seizure state. This was achieved by lightning a button following the traffic lights concept, where green suggests the inter-ictal state, yellow the pre-ictal state and red being the ictal state.

MACHINELEARNING TECHNIQUES

Another tool employed in this paper for seizure detection and prediction is the use of a hybrid classifier that combines various signal processing techniques with a machine learning technique. These techniques (skewness, kurtosis, standard deviation, variance, minima, maxima and mean) have been successfully utilized in [9].The signal processing techniques adopted in this process are the linear features as they are block based and hence more suitable for real time data processing. The system processes the incoming stream by organizing it into blocks which can then be used for feature extraction. The features can then be fed to the machine learning algorithm. The training and classification is achieved using colour coded buttons that determine the seizure state. When a user knows the occurrence of a seizure, he/she presses the appropriate buttons in order to delimit the various states which enable the parameters relevant to each state to be learnt. Otherwise, the system will proceed in classifying the unknown parameters by comparing them with the learnt parameters using a machine learning algorithm. Consequently, for the training of the classifier, four states are defined. These are the values that specify the pre-ictal, ictal, post-ictal and inter-ictal stages of the seizure file. The pre-ictal state denotes the amount of time prior to an ictal event, while the ictal state establishes the time where the seizure occurs. Similarly, the post-ictal state indicates a period of time after an ictal event. The states defining the inter-ictal stage are those states that indicate periods between seizures.

5. IMPLEMENTATION

In this section we have described the complex tasks involved in the implementation of the system as described in the previous section. Furthermore, we presented the back-end logic applied together with any design adjustments adapted in order to improve the system's performance to reach its goal. In this section we have implemented all the methods that we have described in previous section.

CHANNEL VISUALIZATION

The CHB-MIT database is used throughout this paper and all information about each recording is displayed on an interface as created from EDF File Form. cs as shown in Fig 4 below. On loading the EDF file, channels indicate the change between the two adjacent electrodes placed on the scalp. For instance, the difference in voltage between the FP2 electrode and F4 electrode is conveyed by the channel FP2-F4. Although the majority of data records listed a total of 23 channels, this could not be said to data record CHB15 as 8 extra channels were present. Moreover, CHB04, CHB09 and CHB12 contained secondary signals such as ECG, VNS and LOC-ROC present in enough files in order to perform useful comparisons used for evaluation.

Fig. 4: Interface that shows the specifications of the EDF recordings

Considering the significant number of channels present, in order to improve the system's performance, the relevant channels that show the major features are extracted. This was achieved by displaying the raw EEG signal as illustrated in Fig 5. This process was repeated for each channel as each channel is giving a separate EEG signal. By visually analyzing these raw signals, those channels that appear to shift in amplitude/frequency at a time frame before the seizure are noted in an excel file and shown fig 6.After loading the EEG file, the user must then choose the channels and adds them either to the scope where the system proceeds with feature extraction and processing or adds them to the classifier for training and testing.

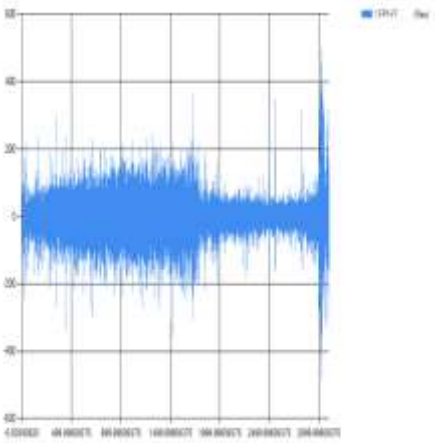

Fig.7: Raw signal of channel FP1-F7 of the data record CHB01_03

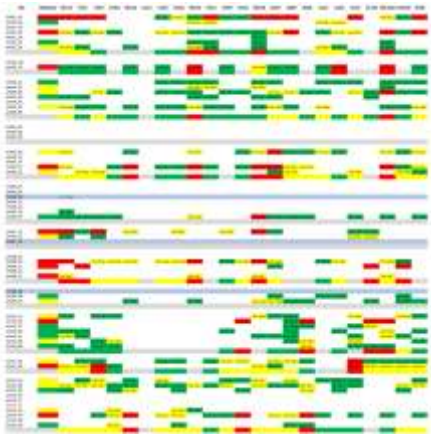

Fig. 6: Raw signal visualization

REAL TIME PROCESSING

After the signal is added to the scope, the system starts a number of threads to allow for simultaneously processing the multiple signals. Each thread processes its signal in a sample by sample manner. In the case of real time sampled signals, samples are processed as they arrive since the sampling rate mechanism is implemented in the sampling device. In order to depict the signal in real time sample by sample, the invokemethod is implemented in the windows form to ensure that the GUI thread updates the graphical user interface and the code snippet is shown below

```
this.Invoke((Method Invoker)delegate
{
Series.Points.Addxy(time,sample);
This.light.BackColor = Lightclor;
});
```

FEATURE EXTRACTION

One of the main stages of the proposed system is the process of feature extraction. This process works by loading the signal samples and executing the appropriate function as specified by the user from the drop down menu. Various features from the time and frequency domain are extracted in order to exploit any characteristics of an EEG signal pattern.

Envelope Detection

We have designed a function to obtain the envelope of the original signal. The envelope of a signal is the boundary marking the peaks of the signal in the time domain which can be obtained by an envelope detector. The envelope detector [11] as shown in Fig 7 takes as input the absolute magnitude value of the EEG signal which is then passed to a low pass filter.

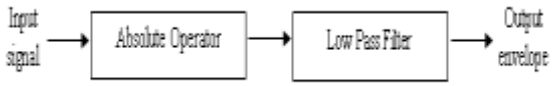

Fig. 8: The setup for envelope detection

A low pass filter is used in order to discriminate from any unwanted elements in the signal. This filter employed to adopt two distinct coefficients to represent attack and release. While the attack is the fade-in duration, the release is the fade-out duration. These factors control how fast or slow the signal reacts. Figure 8 illustrates the envelope of the EEG signal after envelope detection. As clearly displayed below in figure 8, the peaks are preserved thus implying that the attack factor is somewhat a low value. None the less, the signal goes down gradually as the release factor is a high value, resulting in a smoothing affect.

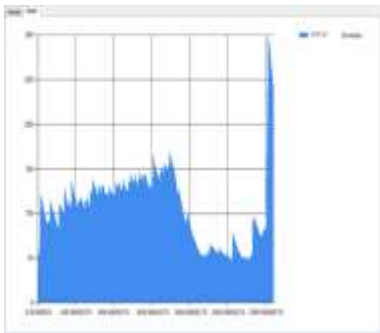

Fig. 9: The signal envelope of channel FP1-F7 of the data record CHB01-03

From the envelope detection, two other prediction and detection methods were observed, consisting of delta envelope and envelope likelihood. The delta envelope is calculated by finding the rate of change of the envelope. In order to clearly delineate this measure, the delta value is amplified by an adjustable value. This value is then compared to an adjustable threshold value in order to determine whether it is probable that a seizure will occur, determining the envelope likelihood and thus raising an alarm.

FREQUENCY DETECTION

Another feature analyzed is the frequency. The extraction of the frequency was built using a bandpass filter, which passes signals within a certain range while precluding any signals at unwanted frequencies. This range is defined as the bandwidth indicating the difference between a higher cut-off frequency (f_{CH}) and a lower cut-off frequency (f_{CL}). Thus the bandwidth is expressed as [12]:

$$bw = fc_V - fc_L \qquad (1)$$

These cut-off frequencies are computed as follows [62]:

$$f_c = \frac{1}{2\pi RC} \qquad (2)$$

Where R is the resistance and C is the capacitance. The bandpass filter employed is Butterworth filter [13], a filter that maintains maximally flat response due to the fact that the bandpass is devised in a way to have the frequency response as flat as possible [16] and is shown in figure 9.

In order to establish the cut-off frequencies, spectrograms of a sample of the EEG data records are computed using SigView. The figure below shows the spectrogram analysis of 7 seizure file data records.

The seizure files of 7 data records were chosen to carry out the spectrogram analysis and their respective range of frequencies during seizure can be found attached in figure 11 below. Due to the fact that all the channels of these EEG recordings vary, the cut-off frequencies chosen are a high pass frequency of 0.5Hz and a low pass of 30Hz as this is the frequency band mostly used[9][15].

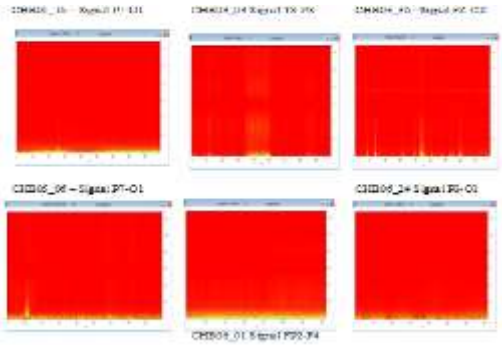

Fig. 10 Spectrograms

The seizure files of 7 data records were chosen to carry out the spectrogram analysis and their respective range of frequencies during seizure can be found attached in figure 11 below. Due to the fact that all the channels of these EEG recordings vary, the cut-off frequencies chosen are a high pass frequency of 0.5Hz and a low pass of 30Hz as this is the frequency band mostly used[9][15].

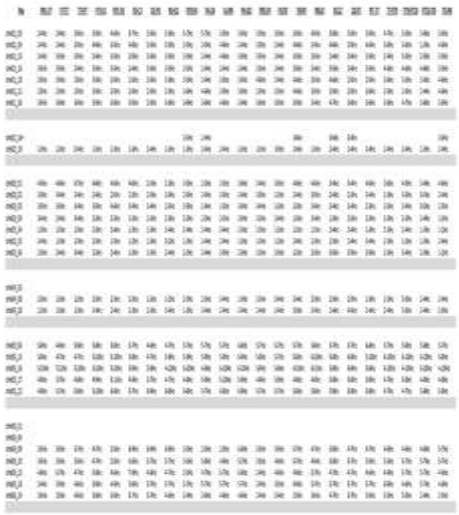

Fig. 11: Frequency Analysis

This frequency output was then passed as a parameter in the envelope detection function to evaluate the envelope frequency for any patterns. The rate of change of the frequency envelope together with its likelihood was computed. We also extracted the features which are statistical moments that grant information on the distribution of the amplitude of the signal across time, that include the moments such as skewness, variance, kurtosis, standard deviation, mean and number of maxima and minima.

AMPLITUDE DETECTION

We have also extracted other time domain features from the EEG recordings to acquire more insight on the patterns pertaining to the signals and is depicted in fig 12. Such features are statistical moments that grant information on the distribution of the amplitude of the signal across time. These moments include skewness, variance, kurtosis, standard deviation, mean and number of maxima and minima.

Variance is the sum of squares of the difference between the observed value and the average value, thus calculating how distant the values are from their mean value [21]. The square root of the variance value is the standard deviation that determines the distribution of the values. Kurtosis measure if the values are peaked or flat respective to a normal distribution. Hence, high kurtosis indicate that the values are distant from the mean value. On the other hand, skewness is a measure of symmetry of the values distribution [21].

These features were implemented [22]in the class Block Features Detector. cs, which according to a pre-set adjustable block size, feeds in a buffer with samples as they arrive. Every time the buffer is full, it is passed to the feature extraction mechanism and processed accordingly, buffer is then cleared and the cycle repeats indefinitely.

WARNING SIGNAL

In this paper we have raised an alarm using signal processing, to determine seizure probability level based on features extracted from the time domain and frequency domain. This approach involves the concept of traffic lights, where a light box was implemented that lit in green, yellow and red accordingly as shown in fig 13.Two threshold values that serve as a boundary are confirmed and contrasted against the likelihood values calculated from the envelope and frequency detection. Based on these calculations, if the likelihood value is greater than the lower threshold, the light changes from green to yellow indicating that a seizure may be oncoming. Furthermore, if the likelihood value is greater that the upper threshold, the light changes to red which means that a seizure is occurring.

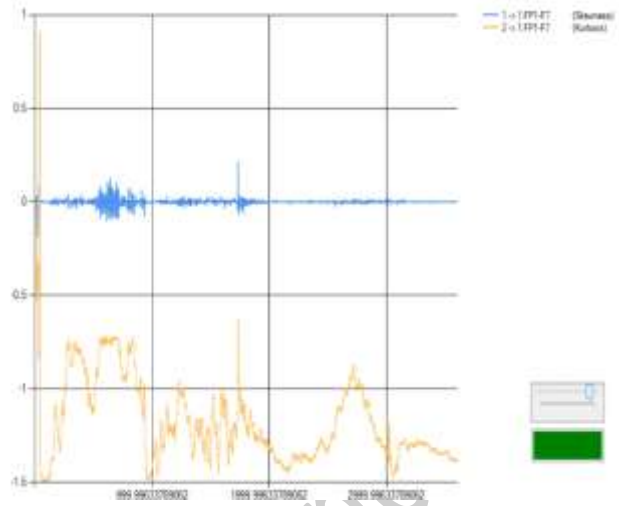

Fig. 12: linear features plot of channel FP1-F7 of the data record CHB01_03.

Classification

The machine learning classification approach adapted here to implement the classifier is quite different from any off the self classifiers such as SVMs and ANNs. This is due to a hybrid and a novel classification algorithm which can result in one of several states. This classification algorithm permits the users to train the classifier at any given point with no stops in the processing. Initially the data used for training and testing of this classifiers the linear feature extracted blocks. These blocks are to be classified in four states that are pre-ictal, ictal, inter-ictal and post-ictal. As the channel is added to the classifier, a thread starts processing the blocks. The values of the features which are skewness, kurtosis, standard deviation, variance, minima, maxima and mean are shown on the windows form ClassifierForm.cs.For the training of the classifier, as the time progresses, the user shall click on the colored buttons to save the values of the features at that time which will represent that particular seizure state shown in figure 13. The colour coding of the buttons indicates black for the unknown state, green for inter-ictal, yellow for pre-ictal, red for ictal and blue for post-ictal. When the signal file is processed, the value of the features pertaining to a particular state is saved in an appropriate data structure which is then used to generate the training data. The user can save and load the data as deemed fit.

Fig. 13: classifiers with the list of features and the color coded buttons

Due to the fact that an EEG recording varies with the person [6], a clear function is implemented that resets all the saved values pertaining to a particular state. Another revert function is implemented to load the trained data. The classifier is tested by loading the EEG file and if the black button is clicked, the system will display the light of the state nearest to the values pertaining to the features which is the nearest neighbor approach. This is done by calculating the percentage difference of each parameter. Each of these is assigned a weighting value due to the fact that these features enclose different properties of the signal whose relevance varies from patient to patient. Due to the fact that EEG signals are different for every person [6], conjointly the weighting of the features varies according to the properties of the particular signal. During the testing process, the following values were observed:

1. True Positives: The amount of correctly identified pre-ictal epochs

2. False Positive: The amount of inter-ictal epochs classified as pre-ictal

3. True Negatives: The amount of correctly identified inter-ictal epochs

4. False Negatives: The amount of pre-ictal epochs classified as inter-ictal

This was done in order to extract and calculate the performance metrics which are further discussed in the forthcoming chapter.

Real Time Device

In order to prove that the proposed system is applicable in real time, a proof of concept device was developed. This was achieved using an Arduino microcontroller board that reads values from scalp electrodes and transfers them to the software via universal serial bus(USB). The same processes apply for the seizure prediction and detection system however the only difference is that a serial port number is passed as a parameter for communication between the Arduino controller and the computer. Due to the fact that the Arduino reads up to 5V, amplification was required in order to increase the voltage. This is because the EEG signals recorded from electrodes range from 10 to 20 mV[14].The figure below shows the artefacts used in order to develop this proof of concept.

6. RESULTS

This section illustrates the optimal performance metrics obtained from the system tested, based on both signal processing techniques and the novel classification method. Similar to previous research[4][18], due to the limited time-constraint and computing resources that are available, tests were carried on 4randomly selected cases from the 24 cases available in the CHB-MIT database. The cases selected were: ‘CHB01’, ‘CHB03’, ‘CHB08’,‘CHB12’.

Throughout the testing, four values were observed consisting of; true positives, false positives, true negatives and true positives. In order to evaluate the performance of the system, these values are considered to calculate the following performance metrics [7]:

1. Sensitivity is defined as a measure of the correctly identified pre-ictal epochs, which is described in equation (3) as:

$$\frac{True\ Positives}{True\ Positives + False\ Negatives} \quad (3)$$

2. Specificity is the percentage of non-test seizures which where correctly identified as non-seizures as defined in equation (4):

$$\frac{True\ Negatives}{True\ Negatives + False\ Positives} \quad (4)$$

The research emphasizes the use of real time processing in order to develop a remarkable seizure prediction and detection algorithm. Having less data available and therefore no look ahead values is more challenging and must be kept in consideration when comparing results to other research that does not support real time processing.

EVALUATION OF SIGNAL PROCESSING TECHNIQUES

Seizure detection and prediction using signal processing techniques was achieved by calculating seizure likelihood in the time domain using the envelope detector and in the frequency domain using the bandpass Butterworth filter. Tests were carried out using six randomly selected seizure files, three for amplitude related seizure likelihood and another three for frequency related seizure likelihood. The seizure files selected were 'CHB01_03', 'CHB01_21', 'CHB08_21', 'CHB03_03', 'CHB03_34' and 'CHB01_26' tested accordingly and EEG files and prediction results are shown table 2.

The observations from the table 2 reveals the fact that amplitude related seizure likelihood obtained a sensitivity of 100% and a specificity of 75% while the frequency related seizure likelihood achieved a sensitivity rate of 100% and a specificity of 72.3%. Thus, on average, the signal processing techniques employed in the developed system attained an average sensitivity rate of 100% and an average specificity rate of 73.65%.Table 1 shows the results of the prediction evaluation. The average sensitivity rate was 100% with an average warning window of74s.It can be noted from the results obtained from this method identified all ictal states while having a small number of false positives.

It can be noted from the results obtained that this method identified all ictal states while having a small number of false positives.

Table **Error! No text of specified style in document.**II. Seizure Prediction Evaluation

Spectrograms	**Seizure Start**	**Average Warning Window**
CHB01_03	2996	2975
CHB01_21	327	285
CHB08_21	2083	1995
CHB03_03	432	385
CHB03_34	1982	1900
CHB01_26	1862	1700

EVALUATION OF MACHINE LEARNING TECHNIQUE

The second test done on the developed system is the testing of the novel and hybrid classifier. The machine learning mechanism is trained using the four previously mentioned test cases. This mechanism uses linear features that are weighted according to their relevance. Moreover, since different patients have different EEG signals [6], all the four test cases have their set of feature weighting values.

From the results shown in the table 3 above, the novel classifier attained an average sensitivity rate of 72.4% and an average specificity rate 52.3%. The average warning window was visually observed to be about 75s.Although the results presented leave ample room for improvement, it can be observed that the method is very patient specific further confirming that different patients have different EEG waveforms as explained by [6].

Table III. Average Sensitivity and Specificity rate

Spectrograms	**Seizure Start**	**Average Warning Window**
CHB01_03	2996	2975
CHB01_21	327	285
CHB08_21	2083	1995

CHB03_03	432	385
CHB03_34	1982	1900
CHB01_26	1862	1700

OVERALL EVALUATION

The results obtained from the two mechanisms employed, indicate that EEG signals can be used to detect and predict seizures. This has been proven since both novel techniques described above have resulted in a good level of accuracy.

Keeping in mind that only the ictal phases were professionally defined by neurologists while the other phases had to be reasonably assumed, the levels of accuracy achieved are deemed to be quite good. From initial tests included in this research, signal processing is very useful and can give usable results even on its own. Although the novel machine learning mechanism coupled with signal processing did not achieve a tangible improvement when compared to signal processing alone, the large number of configurable parameters it supports hints that further work is likely to improve its effectiveness by fine tuning their values. Overall, the two mechanisms employed in the development of the proposed system seem to be promising. Nonetheless, with further research, one might be proven more effective than the other.

Here, the possibility of analyzing EEG signals using the proposed novel techniques in order to detect and predict epileptic seizures was elaborated. This system entails a real time processor of the EEG signals used to simulate patients and the two approaches adopted consisting of the signal processing technique and the signal processing technique combined with a novel machine learning technique. The mechanisms presented herein are demonstrated to be effective and a considerable potential for a practical application which justifies further research in order to optimize these techniques. This would result in a novel and hybrid system that would be propitious especially to epileptic patients. While all of the aims and objectives of the system were achieved, one can observe that various improvements can be considered in order to enhance the proposed system for a real time EEG analyzer that aims to detect and predict seizures.

As presented in this paper, the system is currently processing each signal individually. We would like to expand the system to process two or more signals jointly, which can lead to more accurate results for seizure detection and prediction. Moreover, the system is limited to process a file at a time. Such functionality can be extended to process a batch of seizure files, one after the other.

While the novel machine learning technique of the system did indeed prove effective, the results of this mechanism could be improved by further tweaking the weightings of the features used.

Finally, to test the practicability of such a system, ethics approval would be acquired for the real time data capture device developed as proof of concept. Furthermore, the data read from this real time device can be saved in an EDF file format

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