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Using Artificial Intelligence Techniques For Epilepsy Treatment

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Abstract: *Epilepsy is a combination of neurological disorders that causes people to have seizure. Immediate seizures occurring might cause injuries of the patients or other. Recent studies of epilepsy are based on two approaches. The first one is detecting and predicting epilepsy using algorithms based on EEG Analysis. The second approach is implanted devices for seizure. In this paper, we propose an algorithm for advanced seizure prediction. The approach can predict up to 5 minutes in advance. We combine the two approaches (Computer modeling and Advanced Prediction Algorithm) by proposing an algorithm that illuminates the need of a physician in implanted device RNS which is trained to continuously monitor brain signals and adjusting the parameters manually. The algorithm with which seizures can be predicted from EEG data is the main concern of this paper. The results reveal that the proposed algorithm is able to predict the seizure up to 5 minutes in advance with accuracy of 81.7%. Also, prediction accuracy ranges from 80.7% to 81.5% when considering the results for each individual channel.*
Keywords: *Computer Modeling, EEG, Implanted device, RNS, SVM*

I. Introduction

Epilepsy is a chronic disorder of the brain that affects people in every country of the world. Around 50 million people worldwide have epilepsy. Epilepsy can affect anyone, at any age [1]. Epilepsy responds to treatment about 70% of the time, yet about three fourths of affected people in developing countries do not get the treatment they need [2]. Epilepsy is caused by abnormal electrical activity in the brain. People with epilepsy have seizures that are a bit like an electrical brainstorm. Epilepsy is a condition, not an illness [1].
Methods to treat epilepsy include medication, brain stimulation, surgery, dietary therapy or various combinations of the above, directed toward the primary goal of eliminating or suppressing seizures. For many epileptic patients, seizures are well controlled with anti-epileptic drugs (AEDs). However, approximately 30% of epileptic patients suffer from medically refractory epilepsy. These patients continue to exhibit seizures despite treatment with a maximally tolerated dose of a AED, alone or in combination with at least one adjuvant medication [3]. This has motivated clinicians and researchers alike to investigate the mechanisms of seizures in refractory epilepsy using techniques from many scientific disciplines, including molecular biology, genetics, neurophysiology, neuroanatomy, brain imaging and computer modeling.

Electroencephalography (EEG) records electrical activity along the scalp, via the placement on the scalp of multiple electrodes; it measures voltage fluctuations resulting from ionic current flows within the brain. EEG measures the electrical activity of the brain and represents a summation of post-synaptic potentials from a large number of neurons. EEG has several advantages over the other methods; its temporal resolution is higher and it directly measures the electrical activity of the brain. Also EEG has been a very useful clinical tool not only in the field of epileptology, but also in other areas of neurology and psychiatry [1-5].Traditional method of analysis of the EEG is based on visually analyzing the EEG activity using strip charts. This is laborious and time consuming task which requires skilled interpreters, who by the nature of the task are prone to subjective judgment and error. Furthermore, manual analysis of the temporal EEG trace often fails to detect and uncover subtle features within the EEG which may contain significant information, Hence many researchers are working to develop an automated tool which easily analysis the EEG signal and reveal important information present in the signal [3].

II. Background and Related Work

In recent years, there has been growing research interest in two approaches, first approach is computer modeling and experimentation which is complementary in research and the development of therapeutics. The second one is seizure detection and prediction from EEG recordings.

2.1 In Computer Modeling Approach

Apart from traditional treatment such as drugs and surgery, different computer modeling approaches have been proposed such as using implanted devices or developing an individualized brain model [5]. Implanted devices could characterize electrical activity in real time; they are used for preventing the onset of seizures by the immediate detection of brain's pre-ictal state [6].

The individualized brain model is a biologically realistic computational model, designed using patient specific details such as genetic mutation or head trauma. This technique helps doctors determine the best treatment regimen for that patient [5].As an attempt to build a detailed biologically realistic model of human brain, IBM studied the concept of intelligence by using “Blue Gene”, which is a super computer used to represent the neuron software [4].IBM lunched the Blue Brain Project (BBP) using the enormous computing power of IBM’s prototype Blue Gene [5]. The goal of BBP was a simulation of rat’s neocortical column, which is responsible for brain’s higher function, the conscious thought. This neocortical column is a group of neurons in the brain cortex. A neuron plays a very important role in brain behavior. The neuron is considered a nerve cell or an electricity cell that processes and transmits information by electrical signals [4]. After getting a deeper understanding of the brain’s functional activities, several therapies were proposed to prevent seizures. Therapies can be divided into the following:

Static Therapies

Static therapies use devices that deliver scheduled pulses for reducing the frequency of seizures. These devices are independent of the occurrence of a seizure and their activity is defined by a present pattern. Since there is no need for seizure detection, no extended calibration period is needed [7].

Dynamic Therapies

Dynamic therapies are used for online analysis of epileptic patients, detection and response of the occurrence of seizures. EEG traces are used for monitoring to detect seizures [7].
Below are some of the approaches for correcting the abnormal activity after seizure detection.

2.1.1.1 Responsive Neurostimulator (RNS)

RNS device is a small computer implanted in the skull. With RNS model, it senses the electrical activity that may mean a seizure is about to start and delivers stimulation to in an effort to prevent the seizure [9].The RNS System is an investigational device made up of the responsive neurostimulator and leads (tiny wires with electrodes). The RNS System also includes a programmer for the study physician and a data transmitter for you to provide information from your neurostimulator to the study physician [8]. The RNS® System is manufactured by NeuroPace with the Joseph I. Sirven, MD | Patricia O. Shafer, RN, MN on 5/2014.

The device is powered by a battery and contains a computer chip that detects and stores a record of the brain’s electrical activity [9] When the device identifies seizure activity, it attempts to suppress the seizure by sending electrical stimulation through the leads to a small part of the brain. The stimulation settings are selected so that stimulation cannot be felt. This type of treatment is called responsive stimulation.The physician operated programmer communicates with the RNS neurostimulator via a hand-held wand. The study physician uses the programmer to look at information stored in the device about patients’ detections and stimulations. The study physician can also look at records of actual brain electrical activity. This information helps the study physician select the best detection and stimulation settings. The programmer is then used to program the detection and stimulation settings in the neurostimulator [10]. With Neuropace RNS System User Manual 2013, the data transmitter (or DTR) is used to provide information to the study physician. A wand is used to transfer information from the neurostimulator to the DTR. DTR is then connected to a phone line and information is provided to the study physician via a protected website. The study physician is then able to view the response to the stimulation and decide on the best seizure detection and stimulation settings.The system is implanted by a study physician during a two- to five-hour procedure that occurs while patients are asleep. Two to four leads are placed in the brain where the seizures start. Then the neurostimulator is placed in the skull. After the procedure, patients typically stay in the hospital one to three days [10]. The RNS System is currently being evaluated to determine how well it can reduce the frequency of uncontrolled seizures. It is approved by the FDA only for use in clinical research studies [9]. Fig.1 includes the latest release of RNS device.

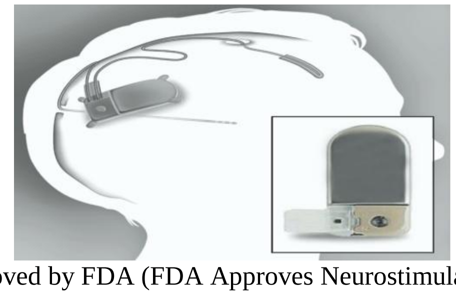

Figure 1. RNS System is approved by FDA (FDA Approves Neurostimulator Device to Treat Epilepsy added by Nancy Schimelpfening on November 16, 2013)

2.1.1.2 Vagus Nerve Stimulation (VNS)

VNS is a technique used to treat epilepsy. It involves implanting a pacemaker-like device that generates pulses of electricity to stimulate the vagus nerve. The vagus nerve is one of the 12 cranial nerves, which conduct impulses between the brain and other parts of the brain and various body structures, mostly in the head and neck. The vagus nerve - the longest of the cranial nerves - also extends to organs in the chest and abdomen [11]. (The word vagus comes from a Latin word for "wandering.') It serves many organs and structures, including the larynx (voice box), lungs, heart and gastrointestinal tract. The VNS implant devices are built by Cyberonics Steven[11].

While the patient is asleep (general anesthesia), the stimulator device - which is about the size of a silver dollar - is surgically placed under the skin in the upper part of the chest. A connecting wire is run under the skin from the stimulator to an electrode that is attached to the vagus nerve, which is accessible through a small incision (cut) in the neck [11].

After it is implanted, the stimulator is programmed using a computer to generate pulses of electricity at regular intervals, depending on the patient's tolerance. For example, the device may be programmed to stimulate the nerve for 30 seconds every five minutes. The settings on the device are adjustable, and the electrical current is gradually increased as the patient's tolerance increases. Re-programming the stimulator can be done in the doctor's office. The patient also is given a hand-held magnet, which when brought near the stimulator, can generate an immediate current of electricity to stop a seizure in progress or reduce the severity of the seizure [10].

VNS is an add-on therapy, which means it is used in addition to another type of treatment. Patients who undergo VNS continue to take their seizure medications. In some cases, however, it may be possible to reduce the dosage of medication. Fig.2 shows division of the autonomic nervous system.

Figure 2. VNS System is approved by FDA (The FDA approved the VNS on November 2013 (formerly known as the NCP® NeuroCybernetic Prosthesis System))

2.1.1.3 Deep Brain Stimulation (DBS)

DBS is a surgical treatment for people whose seizures are not controlled with medication. It involves implanting electrodes into specific areas of the brain. That used by Howard L. Weiner, MD | Joseph I. Sirven, MD There are several ways to treat epilepsy [11]. How well each treatment works varies from one person to another. Deep brain stimulation (DBS) therapy can be used for people who have epilepsy that is difficult to treat, or for people who cannot have epilepsy surgery to separate or remove the part of the brain that causes seizures to happen [12].

DBS therapy aims to control excess electrical activity in the brain using regular electrical impulses to reduce the frequency and severity of seizures. Trials show that for some people their seizures become much less frequent. For others DBS therapy may reduce their seizures a little, and for others it has no effect [12].

The effect of DBS therapy may not happen straight away, has been approved by(2002) by the Food and Drug Administration (FDA) It can take up to two years for it to have an effect on someone's seizures. It is used alongside anti-epileptic drugs (AEDs) not instead of them. If the treatment works, it may be possible to reduce a person's AEDs over time [10].

Other therapies that exert their effects independently of the patient's state include pharmacological treatments. These agents affect subcellular mechanisms, such as ion channels, transporters, pumps, and receptors. Fig.3 represents electrophysiological principles of deep brain stimulation.

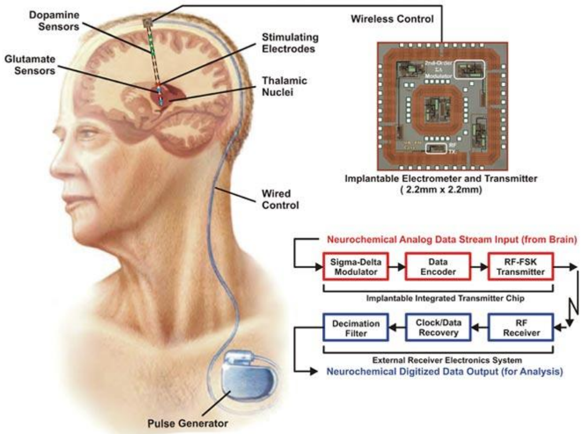

Figure 3. DBS System is approved by FDA (FDA Approves Deep Brain Stimulation system to Treat Epilepsy on February 19, 2009)

2.2 EEG Analysis Approach

In recent years, seizure detection and prediction from EEG recordings has increased in the research field and couple this information with advanced stage of a technology allowing early treatment, minimizing or even prevention of seizures in advance, the patient presents many signs or symptoms of seizure [13].
Symptoms may occur during unconsciousness or consciousness state; these include motor, sensory, psychic and enlarge in oxygen availability. In addition to these changes, it is believed that an increased number of critical interactions among the neurons in the focal region unfold over time. This concept has allowed researchers to study EEGs in an alternative way, in order to find correlates of such processes and identify the pre-ictal (pre-seizure) state [14].

A much higher incidence of symptoms commonly seen in complex partial seizures or episodic dyscontrol, and in addition had a much higher incidence of EEG abnormalities, particularly posterior sharp activity. Characteristics features can be extracted from EEG have been addressing on correlation with the occurrence of seizures and time of the occurrence. In that case therapies comprehensible could move from preventive strategies to on-demand therapy by proposing deep-brain stimulation technology to avoid seizures occurrence [14].

In this context, Stein et al. [15] have imagined the effect of anticonvulsant substances, while Fisher as we mentioned in the previous approach has proposed deep-brain stimulation technology to detect seizure and prevent seizures occurrence. The early work on predicting seizures dating back to the 1970s by by Viglione and Walsh [16] for seizure precursor's extraction of absence seizure EEGs were carried out by different groups using linear approaches [14] and later Salant et al, a French group of researchers reported seizure's changes at 6 seconds in pre-ictal files. Siegel et al. track EEG activities about 1-minute epochs prior to the seizure and analysis on the spike occurrence rates in the EEG. Le Van Quyen et al. [16] follow researches and compared pre-seizure dissimilarity between seizures and divulged a dynamical similarity index which decreasing seizure occurrence. Moreover there are some other studies used analytical methods and algorithms approaches to predict seizure automatically. Costa et al. [17] presented neural network for estimating features and classifying EEG files to main four classes related to seizure activities. This is reported sensitivity 98.5%, 98.5% for specificity and Accuracy. It seems a high value compared with previous work but this result was implemented on only two patients and it was a small, limited and insufficient instance. So we couldn't consider it as a generic performance.

In such studies, more attention is therefore paid to the use of features that can be quickly computed from streaming EEG data and to the design of predictive algorithms [18] [19]. The present study draws from analysis-oriented studies with regard to choosing features which are associated with good discrimination of the seizure state, and follows other prediction-oriented studies in terms of standards and protocols for method and evaluation. However, the present work goes beyond other prediction-oriented studies in terms of the coupling of a relatively long advance-prediction window (20 to 25 minutes) with validation of our approach over a relatively large sample (21 patients).

III. Proposed Method

In this study, an algorithm is proposed for seizure prediction in advance.
Seizure prediction characteristics features have been applied on correlation with the occurrence of seizures and occurrence time. In that case therapies comprehensible could move from preventive strategies to on-demand therapy by proposing deep-brain stimulation technology to avoid seizures occurrence.

Convulsions occur in a variety of epilepsy when abnormal signals from the dynamics of the brain change the way the body functions. This study used the prediction algorithm for specific patients, at least 24 h of continuous recordings for 21 patients.

This algorithm is employed to build predictive models from that data; depending on hardware processing, building the predictive models may take some time around 2 hours, but as a result can be operating immediately and can be used for real-time intervention on that patient who has RNS implanted device as a replacement to physician who continuously and manually monitor brain activates to prevent seizure occurrence. Time in advance is the most sufficient and associated factor using in distinct predictive models for this algorithm.

The proposed algorithm comprises three main components: i) Data preparation and Artifact Removal steps which generate a separate utilized dataset for training each specific 'time-in-advance' predictive model.
ii) The selection feature component, which extract 14 out of 204 features for each patient, according to the ReliefF criteria ranking [27] feature selection algorithm. iii) Support Vector Machine which train individual 'time-in-advance' predictive model [28]; in this study, this training utilize 10-fold cross validation on a randomly identified 70% of an individual patient's data; the observed results indicate performance on the remaining 30% not used in training.

IV. Materials and Methods

a. Source Dataset

The Freiburg Center is able to provide the full range of EEG database which is the one of widely used resources in recent researches [20]. The Freiburg Epilepsy Center serves as a reference center not only for German epileptologists but also for worldwide patients. The EEG database contains the most infest data for patients. These recordings for 21 Epilepsy patients who differ vastly in age, seizure focal point and seizure class in 24 hour-long as pre-surgical evaluation. EEG data were recorded from 128 EEG electrodes at 256 Hz sampling rate. From these electrodes, 6 channels were extracted by visual inspection of EEG experts. The first three channels were labelled from 1-3 corresponded to epilepsy focal area of the brain and 4 -6 included extra-focal recordings. Fig.4 describes an EEG signal from a patient showing the four stages of the signal including the seizure.

b. Data Preparation

The datasets represent both Ictal and Inter-Ictal files from the Freiburg EEG database. In this study only Ictal files data were used .The files that contain a corresponds to leading up to the occurrence of a seizure data are called Inter Ictal Files and hence may not contain traces of seizure activity. Using Ictal files reduces the computational costs of building the predictive models and gives best performance. Ictal files typically represent 3 hours of the total of 24 hours of data available per patient.

c. Artefact Removal

A pre-processing step is utilized in order to eliminate the forms of disordering signals are considered as disturbances in a measured EEG-signal. The artifact can be divided into parts: external and internal categories.
In this study EEG data was treated using eye artefact which is considered as visual detection. Several attempts where performed based on EEG experts using ICA method in the ERP or EPILAB or EEGLAB and TSTool Matlab software package. Best results were achieved using the EEGLAB [21] in Matlab software.

d. Feature Extraction

To build the predictive model and train the dataset we extracted Features from each patient's Ictal file of EEG data. In details there are 34 distinct features processed independently for each of the 6 EEG channels. In aggregate 204 extracted features. The first 14 features are extracted using signal energy, Wavelet transform and Non-Linear dynamics. These features are used only for research to build guideline results that are drawn from the feature extraction approach taken by EPILAB, EEGLAB and MATLAB [22, 23] and also by Costa et al. [24]. The Methods and its features extracted are listed in Table [1]. In [25] you can find detailed information about these features and their extraction. Additional features were then extracted (an additional 20 features per channel) to hold up the algorithm construction of building effective predictive models via feature selection from a richer feature set. As follows we present the details of the features.

Signal Energy

One of the concepts usually used in feature extraction. A signal energy feature is the average value of energy over analysis period. The mean energy values are determined through a sliding window. Energy diversity demonstrates windowed features. These are Short Term Energy (STE) where w=2304 (9 sec) and Long Term Energy (LTE) where w=46080 (180 sec) corresponding 265 HZ. The Signal Energy of patients from the Freiburg EEG database, captured from all 6 channels. From Table 1, it can be observed that the signal energy produced by each channel is particularly variable during the seizure. Accumulated Energy (AE) is powerful method of finding brain's disorder behavior, and usually employed in seizure prediction studies. AE is summation of successive values of signal energy from a series of moving windows where AE (q) indicates the accumulated energy at time-point q, calculated from successive values of signal energy [19]. Since AE values are not exactly known for the first seizure chronic of each patient in the Freiburg database (24% of the seizures in the database), it is sensible to avoid prejudice by adding a suitable random constant (a different constant per file) to the AE values in each Ictal file.

Table 1: Present the details of the 14 extracted features

Method	**Features**
Signal Energy	Accumulated Energy level (AE) Energy variation (short term energy STE) Energy variation (long term energy LTE)
Wavelet Transform	Energy STE 1 (0Hz − 12.5Hz) Energy STE 2 (12.5Hz − 25Hz) Energy STE 3 (25Hz − 50Hz) Energy STE 4 (50Hz − 100Hz) Energy LTE 1 (0Hz − 12.5Hz) Energy LTE 2 (12.5Hz − 25Hz) Energy LTE 3 (25Hz − 50Hz) Energy LTE 4 (50Hz − 100Hz)
Nonlinear system dynamics	Correlation dimension Max Lyapunov Exponent

Discrete Wavelet Transform (DWT)

DWT is a decomposition coefficients analysis. DWT decomposes a signal in different frequency bands, as a Fourier Transform, either way that reflects two properties of the signal frequency and temporal. Thereby acquiring and catching more characteristics that have been missed by other features. Costa et al. [24], eight features were extracted based on the DWT, corresponding to the signal energy for four frequency bands at each of two time windows. Once a factor was extracted for a specific frequency band and applied to this signal component for a fixed time window. The frequency bands extracted were 0Hz–12.5 Hz, 12.5 Hz–25 Hz, 25 Hz–50 Hz and 50 Hz–100 Hz, and the time windows were 'STE and 'LTE'. The Daubechies mother wavelet [26] was used, with decomposition level 4 using the EEGLAB tool [21].

Features Based On Non-Linear Dynamics

Non-linear features have had mixed review in the EEG signal- processing community. In some studies they have been suggested to be superior in performance in comparison to the linear features due to the aperiodic and unpredictable behavior of seizures, while other studies suggest that linear attributs perform as well, if not better than non-linear dynamics [27]. Non-linear features are drawn from the theory of dynamical systems [28] in contraste to the direct derivation of linear methods from the time-series signal. Non-linear dynamical systems can represent chaos, a perceivably unpredictable behavior that is fundamentally deterministic. Dynamical systems capture the behavior of a system in different states in time through fixed deterministic rules, and the states at any given time are derived from a state space. We used two features based on non-linear dynamics, namely the maximum Lyapunov exponent and the correlation dimension.

Lyapunov exponents [29] formally relate to the rate of separation of infinitesimally, close trajectories in the phase space (i.e. the space where all possible states of the system are represented). Essentially they characterize the chaotic dynamics of a system, and the 'maximal Lyapunov exponent' serves as a surrogate measure for the stability of the system.

The correlation dimension provides an alternative measure related to stability; it is an estimate of the number of active degrees of freedom of random points within a state space, and is calculated using the correlation integral [31]. Extraction of both the maximal Lyapunov exponent and the correlation dimension was done in this work by using the corresponding functionality in TSTOOL (a software package for analyzing time-series data) [30], parameterized to sample each of these in windows of length 1280 (5 seconds).

Additional 20 Features

For Purpose Additional Features like Spectral Moments, Band and Frequency, in the above section we extracted 14 features for oriented seizure prediction therefore that is a solid foundation for benchmark comparison.In addition to the 14 features above (used for recent prediction- oriented seizure studies and consequently underpinning our benchmark comparaison), a further 20 distinct features were extracted per EEG channel. The first 6 of these further 20 features comprised the standard statistical measures of mean, skewness, and kurtosis of the raw signal value, averaged over STE and LTE windows (9 seconds and 180 seconds respectively). These represent the first, third and fourth standard statistical moments; note that the existing 'signal energy' feature already captures variance, which is the second moment.

A further ten features were extracted based on Spectral Band Power (SBP). SBP is simply the signal energy in a specific frequency range, as calculated via a Fourier transform. The ten SBP features used in this study correspond to the ten combinations arising from five frequency bands and the familiar two windows, STE (9 seconds) and LTE (180 seconds). The five frequency bands are chosen according to their common usage in analysis of neuronal signals since they seem to capture useful information [32], and are 0.5 Hz–4 Hz, 4 Hz–8 Hz, 8 Hz–13 Hz, 13 Hz–30 Hz, and 30 Hz–48 Hz; these bands are respectively termed a, b, c, d, and e. SBP feature extraction was implemented using SBP functions In EEGLAB [21].

Finally, four features were extracted relating to Spectral Edge Frequency (SEF). SEF is a measure that characterizes the signal's energy distribution in terms of how signal power is concentrated in the frequency spectrum. The measure SEF-X measure indicates the lowest frequency F such that X% of the spectral power is contained within the frequency band 0.5 Hz–F Hz. In this paper we use four features that comprise SEF-90 and SEF-50 (also called the median frequency), each measured over both the 9-seconds STE and 180-seconds LTE windows, and implemented using SEF functions available in EEGLAB [21]

Labeling Of Data Instances

Following the feature extraction phase, each data instance was labeled as one of the following states: Ictal, this labels the seizure activity in the brain and is marked precisely by EEG experts. It is of varying length but is typically close to 3 minutes long. Pre-ictal is marked as the 5 minutes immediately prior to the seizure onset and is believed to hold predictive markers of seizure activity [35].

Post-ictal is marked as brain activity following the seizure offset for duration of 5 minutes. Abnormal exactement in the signals may be observed in this state, particularly as patients are recovering from the seizures. Inter-ictal is non-seizure data preceding the pre-ictal state and proceeding the post-ictal state are marked as inter-ictal, where studies have traced early predictors of future seizure activity [33].

Fig.4 further illustrates the signal divisions of the EEG signals of a patient from the Freiburg EEG database. These labels were manually set according to the seizure onset and end markers provided in the Freiburg EEG database notes. In training the predictive models, we use 4 states rather than 2 states as practiced, since intuition suggests that distinguishing the activity among the four states will benefit the learning process, and facilitate a more even balance that avoids dominance of the inter- ictal states over ictal activity. Finally, the data labeling step described here was used to produce the dataset for training the 't = 0' predictive models – in other words, models that attempt to distinguish pre-ictal instances from others, where a pre-ictal instance corresponds precisely to the expectation that seizure onset will occur between 0 and 5 minutes in the future. To produce training data for the 't = N' predictive models, where N ranged from 1 minute to 20 minutes in steps of 1minute, specific and simple manipulation was applied to the 't = 0' dataset, which is detailed later.

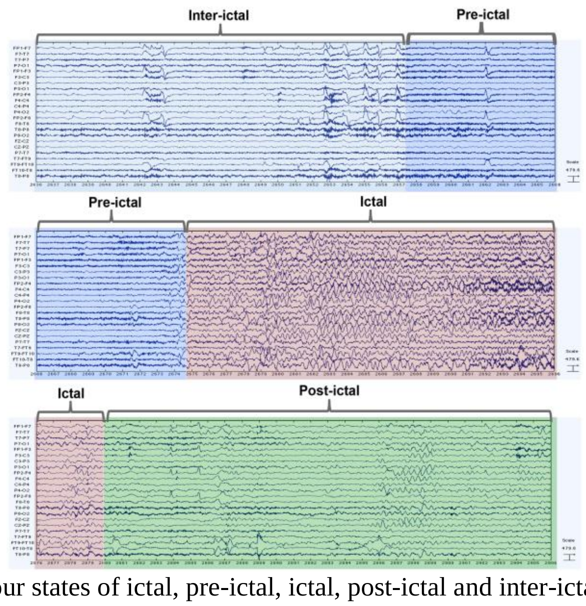

Figure 4. All four states of ictal, pre-ictal, ictal, post-ictal and inter-ictal are colour coded. [doi:10.1371/journal.pone.0099334.g004]

e. Learning Model

Kernel-based techniques demonstrate a major development in machine learning algorithms. Support Vector Machines (SVM) [34] are a set of observed learning methods that applied to classification or regression. Support vector machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships.The proposed algorithm uses SVM classifier, implemented here by using the SMO function from the WEKA [36] classifier to train inter-ictal EEG epochs and build a predictive model for multi class problem.

V. Experiments

The pre-ictal files are divided into four parts, each part denotes a specific stage of five minutes before epilepsy development. The first stage covers the first 6 seconds of the series. Stage two ends at minute one, followed by 2 minutes for stage three. Finally, stage four contains the last two minutes of the recording. The objective is to determine in advance in which of the four stages the seizure will occur. This changes our problem from a traditional regression prediction problem, into a more specific classification problem where the class is the onset of an epilepsy stage.

A set of experiments are performed to analyze recorded data from 21 patients, each containing 6 channels. In the first experiment, for each recording, 34 features are extracted from each channel and concatenated together to form a feature vector containing 204 features. The next experiment examines each channel individually, each using a 34 feature vector. Finally, we explore concatenating all channels vertically increasing the number of instances of training data. All experiments are evaluated using 10 fold cross validation, and using the open source machine learning tool WEKA [36] .The results for each experiment are shown in the next section.

VI. Results

Table 2 shows the results of training SVM using 34 features extracted for 6 channels. The percentage of accuracy, TP rate and total number of instances are demonstrated. As shown, the seizure is predicted with accuracy percentage of 81.7 % when all channel features are concatenated together for 53863 instances. Fig.5 shows the accuracy achieved for each channel individually. It is clear that channel 5 outperforms all other channels. The results range approximately from 80.7% to 81.5% across all channels. Finally, table 3 presents the results for the last experiment, 80.7% accuracy is reached when channel information is used as instances, and only 34 features are used. Similar to the first experiment, a true positive rate of 0.8 is achieved. The total number instances used are 323178.

The results denote that the features used in this study can predict the onset of the seizure in advance. It is shown from the results of experiments 1 and 3 that each channel's feature space alone does not provide sufficient information. Combining features simultaneously from each channel highly boosted the accuracy. After exploring each channel separately, the results from experiment 2 show that channel 5 yields the highest percentage of accuracy among the 6 channels although not very significant. This could help professionals at the stage of determining the most adequate location for the RNS device for patients suffering from epilepsy at the 6 focal channels similar to the 21 patients in the used data set. Support vector machine train each classifier to distinguish one class from another. SVM decision is biased towards the majority class which has a strong estimation prejudice to first class among 4 classes.

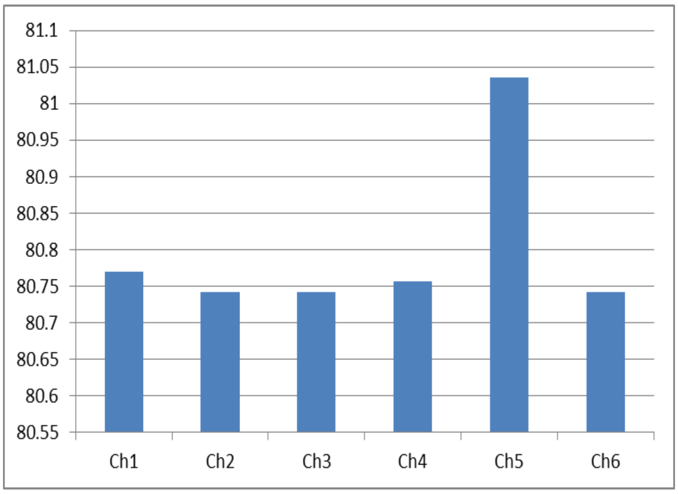

Figure 5. Percentage of accuracy for seizure onset prediction for each channel individually

Table 2: Percentage of accuracy, TP rate and Number of instances for seizure onset prediction using features extracted for each channel

Percentage of Accuracy	81.75%
TP rate	0.81
Total number of instances	53863

Table 3: Percentage of accuracy for seizure onset prediction using channels as instances

Percentage of Accuracy	80.74%
TP rate	0.8
Total number of instances	323178

VII. Conclusion

Epilepsy is a range condition with an extensive variety of seizure types. The proposed algorithm has three primary segments: i) Features selection and extraction. ii) Data preparation and Artifact Removal. iii) Support Vector Machine. This paper used a data set of recorded EEG data for 21 patients. Data was preprocessed and signal disturbances were removed. Various features were extracted for each of the 6 recorded channels. The results revealed that the proposed algorithm was able for predicting the seizure up to 5 minutes in advance with overall accuracy 81.7%. For future work, we will extend our studies to the theoretical and experimental work by incorporating more channels for deeper analytics of brain seizure.

Acknowledgment

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