J. Electrical Systems 20-5s (2024): 1033-1040

[1]Abhishek Parikh,

[2]Anilkumar Suthar,

[3]Manvitha Gali,

[4]Aditya Mahamkali

EEG Sensor-Based Frequency Domain Analysis for Epileptic Seizure Detection

Journal of Electrical Systems

Abstract: - FMRI cannot apply to patients with implants and it has several limitations like temporal resolution, hence the EEG based detection of abnormal activities for epileptic patients is very important as if correct treatment and medication given to patient on correct time it can make the patient seizure free. In this paper we have proposed technique and it's outcomes for the detection of epileptic seizure by using frequency domain analysis technique of EEG sensor array. And comparing it we've achieved classification accuracy is less 59% which is as compared to our previous study using time domain features which was 96.5%. We conclude that frequency domain features like Power spectral density, Kurtosis shall not be the selection but time domain features such as standard deviation and quartile ranges shall be considered.

Keywords: EEG, Epilepsy Seizure, Machine Learning, Patient classification, Real time diagnosis.

I. INTRODUCTION

As per the National brain survey of India in 2016 by the Government of India NIMHANS 14% of the youth has been affected by brain disorders like Schizophrenia, Parkinson's disease as well as mental illnesses like depression and Alzheimer [National mental health survey of India 2016 by Ministry of Health and Family welfare]. The same survey also shows that more than 5% of Indians have suicidal tendencies and 18% are consuming tobacco products. With expanding numbers of mental illnesses and brain disorders on daily basis it is mandatory to effectively diagnose and treat people. There are many ways including Ascertain functional connectivity of brain areas to determine mental health. The statistic functional connectivity determined different mental diseases such as Depression, Epilepsy, Schizophrenia, and Alzheimer. From the mentioned diseases, Epileptic seizures are a global problem from which nearly 1% of the population is suffering in some or other ways. One of the features to consider while categorizing the patients can be the country's income. For instance, the people of countries with lower-income populations suffer from Epilepsy due to malaria or neurocysticercosis while in higher-income countries, the reason for Epilepsy is found to be road accidents or birth injuries [1]. Epilepsy is a type of neurological disorder that arises with unusual signal discharge by a group of neurons in the brain [2]. Epilepsy can be detected by medical tests like an electroencephalogram (EEG), the EEG test is based on the brain's electrical signals/waves. By monitoring these waves, one can know whether there are abnormalities in the signals or not, and if abnormalities are seen in the signals then there is a high chance of Epilepsy. These changes in brain activities are often seen at times during seizures or at times of seizure [3]. Epileptic seizures are mainly classified in two ways, one is partial seizures which can be in the local brain area and they are seen in very few of the channels in the EEG signal and the other involves the whole brain which is known as generalized seizures. The latter is seen in every channel of the EEG signal [4]. Patients often experience diverse symptoms depending on the location and type of seizure as mentioned above. The biggest advantage of EEG over fMRI is that is it faster and has no side effects as the waves are monitored using the brain signals and no external forces or factors and yet the results and accuracy are surprisingly well. The setting time of the EEG signal is approximately 5 minutes which is very less as compared to setting an MRI machine. One of the disadvantages of EEG is that

[1] GTU and Innvonix Tech Solutions Pvt Ltd,

[2]New LJIET,

[3]Verizon

[4]Goldman Sachs

[1] parikh5555@gmail.com,[2] sutharac@gmail.com, [3]manvithagalicloud@gmail.com, [4]maditya6181@gmail.com

sometimes a change in a single neuron can activate an electrode along with the one it should, which at times can possibly show a wrong conclusion. Aim of the study is to detect epileptic seizures in the early stage can be a game-changer in the health sector. As we already have a huge amount of electroencephalogram (EEG) data, it becomes possible for researchers to detect epilepsy using advanced machine learning and deep learning techniques which are shown earlier by researchers focusing on the same domain. But there is a drawback in these methods and the main drawbacks are that these methods are very time-consuming and compute-heavy. To address the problem with a simpler and compute-efficient method, we used simple Gaussian filtering and raw conditional classification in our experiment. These methods are not just lightweight when it comes to computing but are very powerful and effective at the same time. Hare, we are detecting Epilepsy by classifying the EEG signals of patients as Epileptic seizure-containing or not. To add on top of it we are using time as one of the features which contributes to detecting the seizure in advance. By far we have achieved an accuracy of 96.5% and 95% on two different public datasets. Both the datasets contain EEG signal containing Epileptic seizure, EEG signal of normal patients, and EEG signal of patients who shows sign of seizure along with time as a feature. The proposed method showed the results in as little as 1.7 seconds.

II. Literature Survey

The 2 states which are found to be promising in detecting seizures are ictal state and preictal state. The ictal state is the state that begins at the time of onset of the seizure and ends with an attack. Whereas, the preictal state is the state before the seizure beings. So, the preictal state ends where the ictal state starts. Both of these have been very useful when it comes to classifying EEG signals as seizure and non-seizures [5]. Many researchers [6-10] have tried to predict the preictal state but only some have achieved satisfying results. One of the key areas to focus on to improve the detecting technique is preprocessing of EEG signals, here in preprocessing we want to increase the signal-to-noise ratio. Promising results were shown by the research conducted by [5] where they used Machine Learning techniques to detect seizures. The data used in this research was a public dataset CHB-MIT [11]. The dataset is created by collecting EEG signals from 23 electrodes which were placed on the scalps of 22 subjects. Here they performed the process in 2 stages, the first one of which is to convert the 23 channels EEG signals into a surrogate channel which is a single channel to improve the signal-to-noise (SNR) ratio. And the second stage is empirical model decomposition on the surrogate channels to improve the SNR. Here, Common Average Filtering, Large Laplacian Spatial Filter, and Common Spatial pattern Filters were used to convert the multi-channel signal to a single surrogate channel The empirical model decomposition decomposed the signal to the Intrinsic Model Functions (IMFs). These IMFs were the main features of the classification algorithm. The features extracted here are time ad frequency sensitive. The authors [5] compared three classification algorithms and the best results were achieved by the Support Vector Machine to classify preictal and ictal states.

Linear methods have also been used widely due to their simplicity and versatility in the detection of seizures. One of the simplest metrics when it comes to statistical analysis is the variance of the signal which is calculated in consecutive windows to provide underlying dynamics of EEG signals. A research was conducted by [12] using the same linear methods. The technique used there was Scored Autocorrelation Moment (SAM) analysis. The accuracy they received using this method was 91.4% even when the signals did not present differences in spectral properties. Another research was performed by [13, 14] using the Time-Frequency method. In a Research performed by [15-17], the authors used the features extracted from the Power Spectral Density (PSD) which was then fed to Artificial Neural Network for classification. With this approach, the accuracy they observed was from 89%-100% on three different datasets.

Another approach often seen is Information Theory-Based Analysis and Entropy which contains 3 main methods. Firstly, Kullback-Leibler Entropy, which is used to measure the similarity between two probability distributions. Secondly, Lempel-Ziv Complexity, which is used to measure the rate of recurrence of patterns with respect to time series. Thirdly, Permutation Entropy. Bandt [18], in his paper, has used it to measure complexity. It showed great potential as compared to sample entropy [19] when used in an application to predict Epileptic seizures and identification of preictal periods in rats.

In a Research by [20], the authors have used Functional MRI to detect seizures, it has been proven as one of the most widely used techniques to analyze brain activity. AS fMRI provides an insight into the metabolic consumption of oxygen of brain areas which is directly linked to region utilization of the brain [20][21]. fMRI uses Blood Oxygen level-dependent (BOLD) signals.

III. MATERIALS AND METHODS

The proposed method is divided into 4 sections namely Raw Data gathering, Data cleaning and preprocessing, Feature extraction, and lastly Features selection and classification. The process follows the same order as mentioned above. A total of 2 datasets are involved in the proposed solution.

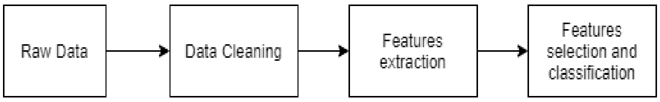

Fig. 1 Flow diagram of method

The first dataset is Bonn University EEG Dataset [22]. The sampling rate of the same is 173.61Hz. The Spectral bandwidth of the acquisition system is 0.5Hz to 85Hz. The Low pass filter is 40Hz. The dataset contains the data with open and closed Eyes which is categorized as Normal and Seizure and Seizure free zone which is categorized as Epileptic Patient's data. The recording interval for the dataset was 23.6 Seconds and in total there were 10-20 Electrodes involved in gathering the data.

The second dataset is Bern Barcelona EEG Dataset [23]. Here the sampling frequency was 512Hz. The recording interval for the EEG signal was 20 seconds. The data points involved in the gathering of data were 10240 which were divided into 3750 segments. The dataset unlike the first one has just two simple classes namely Patients with Seizures and Patients without Seizure zones. Study have been done on 5 epileptic patients having pharmacoresistant temporal lobe epilepsy and before epilepsy operation the data was collected, AD-Tech manufactured invasive electrode placed on 10-20 placement system, Signals were digitally band pass filtered with 0.5Hz and 150Hz 4th order butter worth filter.

Both the above-mentioned datasets are raw datasets and are needed to be processed and filtered before they can be used. The first step in data filtering is the removal of noise from EEG signals which is a very important task because without it the process could lead to wrong conclusions. Here there are several ways to filter the data.

Firstly, the Power line frequency and its harmonic noise. The main frequency is 50Hz/60Hz and its 2nd, 3rd, and 4th harmonics are at 100Hz, 150Hz, and 200Hz.

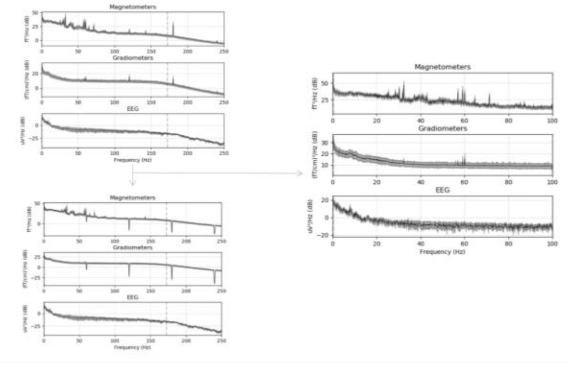

Fig. 2 Power line frequency removal with low pass filter frequency plot

Secondly, Eyeblink and eye movement-related artifacts. Here we have 4 ways to filter the data based on eye movement and blinks. Firstly, manually record eye blinks and remove them from the EEG signal. Secondly, Use adaptive filtering. Thirdly, Use a Regression-based approach. Lastly, Blind source separation.

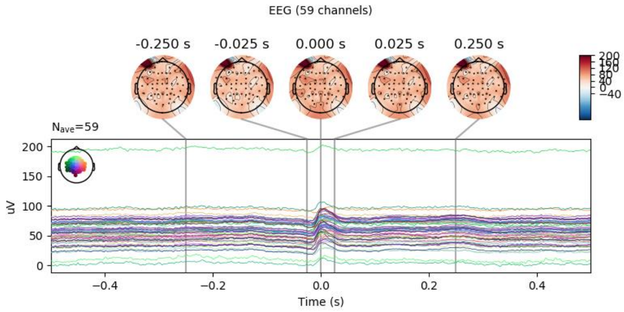

Fig. 3 Eye blink movement in EEG signals detection

As shown in figure 1, we have an EEG reading of brain movements when eye blinking occurs. Here at 0.000s, the blink occurs. Apart from the blink instance, we have the signal readings of 4 stages, two of which are pre-blink instances and two of which are post-blink instances of 0.250s and 0.025s respectively.

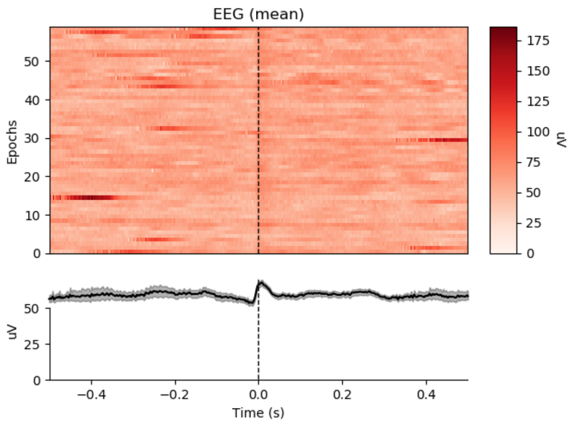

Fig. 4 EEG Signals for all epochs with mean epoch presentation in graph format with time and amplitude uV as the axis

As shown in fig. 4 all epochs have been shown along with the mean epoch hence the similar feature can be observed to all channel and in phase as well same as displayed in fig 5 as well.

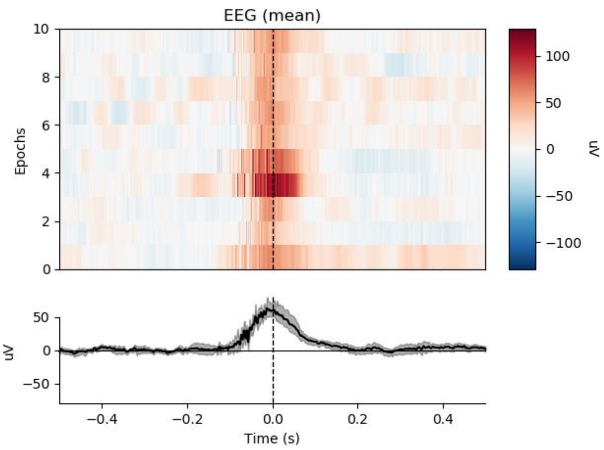

Fig. 5 EEG remove mean epoch

As described earlier Figure 4 has dc bias of 50uV which is removed to get the eye blink effect more precisely, which can be seen in fig. 5. After removing the bias voltage, the eye blink effect can be observed on all the electrodes with phase. To, have better visualization figure 6 we have assigned each electrode a color and shown in the sensor space. All electrode time series representation clearly shows that eye blink artifact can be removed once correctly detected the event.

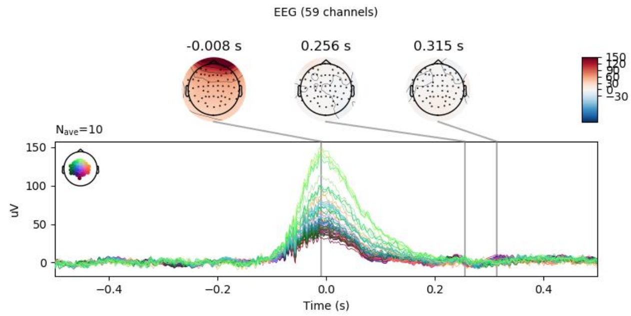

Fig. 6 EEG Individual all independent channel epoch

IV. RESULTS

For the classification of the epileptical seizure after the epoch and other filtering the analysis is followed. We have taken Kurtosis as a measurement parameter here for the observation. Kurtosis in probability theory represent measure of tailedness of probability distribution real valued random variable. As described earlie rall results are shown below.

$$\textbf{Kurtosis} = \mathbf{n} * \sum_{i}^{n}(\mathbf{Yi} - \mathbf{Y})^{4} / \sum_{i}^{n}((\mathbf{Yi} - \mathbf{Y})^{2})^{2} \qquad (1)$$

Kurtosis can be calculated using Eq. 1, where Yi represents ith variable of the distribution and Y describes mean of the Distribution and n is number of variables in the Distribution.

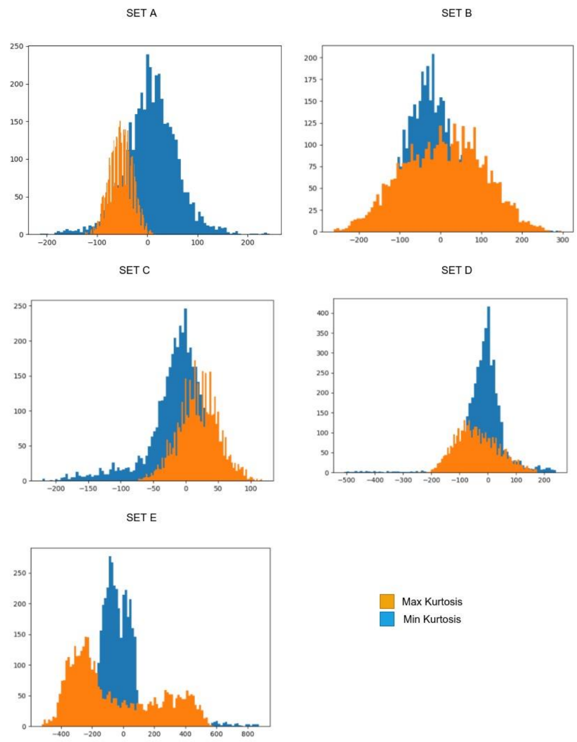

Fig. 7 Maximum and Minimum Kurtosis comparison

Table.1 Comparison of kurtosis for all five patients type

SET of Patients	Max Kurtosis	Min Kurtosis	Difference of Kurtosis
A - Normal	1.31308374488651	-0.253076442833439	1.566160188
B - Normal with closed eyes	0.840466807785508	-0.540304975577669	1.566160188
C - Early epileptic	2.83995921146648	-0.0894711856316212	2.929430397
D - Epileptic	11.5229269853694	-0.37674025084941	11.89966724
E - Epileptic while having seizures	6.79825661698114	-1.04253735678703	7.840793974

CONCLUSION

Applying the simple multiple classifiers with the selecting parameter as difference of kurtosis and compared the results, Approx 69% accuracy is obtained. 28% Patients with epilepsy are false negative and 4% normal subjects are identified as epileptic seizure patients which states that frequency domain features don't give accurate results which we had already received in past with time domain analysis in earlier research [33].

There's enormous research already done and yet going on these datasets still there is scope of new methods and techniques which can improve the accuracy of the classification which reduces the false outcomes. Artificial Neural Network [24][30] and Deep Neural Network [26] are widely used in this subject which is giving good accuracy 91% but consumes more time and resources of the system. 95% of Accuracy achieve by recent research work in [32] Machine learning and Wavelet [29][31][35] transform technique. Spike detection and classifier algorithm has also provided competitive accuracy as described in [27][28][34]. A real time detection method was developed with similar higher accuracy [33] using time domain features which is giving accuracy 96.5%.

REFERENCES

[1] World Health Organization article on Epilepsy patient spread on Earth available on:

https://www.who.int/news-room/fact-sheets/detail/epilepsy

[2] Mormann F, Andrzejak RG, Elger CE, Lehnertz K, Seizure prediction: the long and winding road. Brain 2007 Feb;130(Pt 2):314-33

[3] Exarchos, T., Tzallas, A., Fotiadis, D., Konitsiotis, S., & Giannopoulos, S. AL. EEG Transient Event Detection and Classification Using Association Rules. IEEE Transactions on Information Technology in Biomedicine 2006 10, 451-457.

[4] Gotman J. Automatic detection of seizures and spikes. J Clin Neurophysiol. 1999 Mar;16(2):130-40.

[5] [5] Syed Muhammad Usman, Muhammad Usman, Simon Fong Epileptic Seizures Prediction Using Machine Learning Methods. Computational and Mathematical Methods in Medicine 2017

[6] J. Rasekhi, M. R. K. Mollaei, M. Bandarabadi, C. A. Teixeira, and A. Dourado,:Preprocessing effects of 22 linear univariate features on the performance of seizure prediction methods, Journal of Neuroscience Methods, vol. 217, no. 1-2, pp. 9–16, 2013.

[7] C. A. Teixeira, B. Direito, M. Bandarabadi et al., Epileptic seizure predictors based on computational intelligence techniques: A comparative study with 278 patients, Computer Methods and Programs in Biomedicine, vol. 114, no. 3, pp. 324–336, 2014.

[8] M. Bandarabadi, C. A. Teixeira, J. Rasekhi, and A. Dourado,:Epileptic seizure prediction using relative spectral

power features, Clinical Neurophysiology, vol. 126, no. 2, pp. 237–248, 2015.

[9] K. Gadhoumi, J. Lina, and J. Gotman, : Discriminating preictal and interictal states in patients with temporal lobe epilepsy using wavelet analysis of intracerebral EEG, Clinical Neurophysiology, vol. 123, no. 10, pp. 1906–1916, 2012.

[10] A. S. Zandi, R. Tafreshi, M. Javidan, and G. A. Dumont, Predicting epileptic seizures in scalp EEG based on a variational Bayesian Gaussian mixture model of zero-crossing intervals, IEEE Transactions on Biomedical Engineering, vol. 60, no. 5, pp. 1401–1413, 2013.

[11] G. B. Moody, R. G. Mark, and A. L. Goldberger, PhysioNet: Physiologic signals, time series, and related open-source software for basic, clinical, and applied research, in Proceedings of the 33rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2011, pp. 8327–8330, USA, September 2011.

[12] Liu A, Hahn JS, Heldt GP, Coen RW (1992) Detection of neonatal seizures through computerized EEG analysis. Electroencephalogr Clin Neurophysiol 82(1):30–37

[13] Musselman M, Djurdjanovic D (2012) Time-frequency distributions in the classification of epilepsy from EEG signals. Expert Syst Appl 39(13):11413–11422

[14] Hassanpour H, Mesbah M, Boashash B (2004) Time-frequency based newborn EEG seizure detection using low and high frequency signatures. Physiol Meas 25(4):935–944

[15] Tzallas AT, Tsipouras MG, Fotiadis DI (2007) Automatic seizure detection based on time-frequency analysis and artificial neural networks. Comput Intell Neurosci 2007:80510

[16] Tzallas AT, Tsipouras MG, Fotiadis DI (2007) The use of time-frequency distributions for epileptic seizure detection in EEG recordings. 29th annual international conference of the IEEE engineering in medicine and biology society, 23–26 Aug 2007, pp 3–6

[17] Tzallas AT, Tsipouras MG, Fotiadis DI (2009) Epileptic seizure detection in EEGs using time-frequency analysis. IEEE Trans Inf Technol Biomed 13(5):703–710

[18] Bandt C, Pompe B (2002) Permutation entropy: a natural complexity measure for time series. Phys Rev Lett 88(17):174102

[19] Li XL, Ouyang GX, Richards DA (2007) Predictability analysis of absence seizures with permutation entropy. Epilepsy Res 77 (1):70–74

[20] Dr.Takuto Hayashi Ph. D., Yuko Mizuno-Matsumoto, M.D., Ph.D., Eika Okamoto, Ph.D., Tsutomu Murata, Ph.D., Makoto Kato, Ph.D.An fMRI study of brain processing related to stress states, IEEE World Automation congress 28 June 2012

[21] Martijn P. van den Heuvel ⁎, Hilleke E. Hulshoff Pol Exploring the brain network: A review on resting-state fMRI functional connectivity Elsevier European Neuropsychopharmacology (2010) 20, 519–534

[22] Bonn University EEG Dataset - https://www.upf.edu/documents/229517819/234490509/Z.zip/9c4a0084-c0d6-3cf6-fe48-8a8767713e67

[23] Bern Barcelona EEG Dataset - https://repositori.upf.edu/bitstream/handle/10230/42829/Data_F_Ind_1_750.zip?sequence=2&isAllowed=y

[24] Afshin Shoeibi, Navid Ghassemi, Roohallah Alizadehsani, Modjtaba Rouhani, Hossein Hosseini-Nejad, Abbas Khosravi, A comprehensive comparison of handcrafted features and convolutional auto encoders for epileptic seizures detection in EEG signals. Expert Systems with Applications. 2020,113788

[25] Diyuan Lu, Sebastian Bauer, Valentin Neubert, Lara Sophie Costard, Felix Rosenow, JochenTriesch: Staging Epileptogenesis with Deep Neural Networks, Center for personalized translational epilepsy research, 2020

[26] R. Mouleeshuwarapprabu, N. Kasthuri, Nonlinear vector decomposed neural network based EEG signal feature extraction and detection of seizure, Microprocessors and Microsystems, 2020.

[27] Feucht M, Hoffmann K, Steinberger K, Simultaneous spike detection and topographic classification in pediatric surface EEGs, Neuroreport. 1997;8(9-10):2193-2197.15.

[28] Adjouadi M, Sanchez D, Cabrerizo M, Interictal spike detection using the Walsh transform. IEEE Trans Biomed Eng. 2004;51(5):868-87216.

[29] Tzallas AT, Tsipouras MG, Fotiadis DI,: Epileptic seizure detection in EEGs using time-frequency analysis, IEEE Trans Inf Technol Biomed. 2009;13(5):703-710.17.

[30] Guo L, Rivero D, Pazos A.: Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks, J Neurosci Methods. 2010;193(1):156-16318.

[31] Übeyli, Elif Derya.: Combined neural network model employing wavelet coefficients for EEG signals classification, Digit. Signal Process. 19 (2009): 297-308.19.

[32] Jaiswal AK, Banka H.: Epileptic seizure detection in EEG signal using machine learning techniques, Australas Phys Eng Sci Med. 2018;41(1):81-94

[33] Abhishek Parikh, Anil Suthar, Sandeep Shah: Realtime Diagnosis of Epilepsy Using Time Domain Analysis and Conditional Classification Technique on EEG Data, Proteus Journal Vol 11 Issue 12 2020

[34] Ghosh-Dastidar S, Adeli et al. H.: A new supervised learning algorithm for multiple spiking neural networks with application in epilepsy and seizure detection. Neural Netw. 2009 Dec;22(10):1419-31.7.

[35] Acharya UR, Sree SV, Alvin AP, Yanti R, Suri JS, Application of non-linear and wavelet-based features for the automated identification of epileptic EEG signals. Int J Neural Syst.2012;22(2):1250002.