

# Epilepsy Detection using EEG signals in machine learning paradigm: Review and Challenges

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**Abstract**— *Epilepsy is the most prevalent neurological disorder in humans. Epilepsy is characterized by recurrent seizures. This happens due to an abnormality in brain wiring, an imbalance of nerve signaling chemicals called neurotransmitters, or some combination of these factors. Normally, neurons generate electrochemical impulses, act on other neurons, glands, and muscles to generate human thoughts, feelings and actions. Epilepsy is determined by EEG signal recording, which contain valuable information for understanding epilepsy. Epilepsy can create clear disturbance and leaves its signature on standard EEG signals. The detection of seizures occurring in the EEGs is an important component for the diagnosis and treatment of epilepsy. In recent years soft computing based techniques are attracting much attention from the scientific communities as an alternative tool. This technique for detection and classification of epilepsy has been reported by number of researchers. It is an important part of EEG based computer aided diagnosis (CAD) systems. This review investigates the application of different machine learning approaches for classification of EEG signals to detect epileptic and non epileptic seizures. Different components of machine learning such as feature extraction, feature selection and classification are explored and evaluated using CAD system.*

**IndexTerms**— EEG, Epilepsy, Computer aided diagnosis (CAD)

## I. INTRODUCTION

Epilepsy defines as most common brain disorder [1] which affects almost 50 million people around the world estimated by World Health Organization. More or less one person in out of every 100 persons experienced a seizure at some time in their life [2]. Most of the epilepsy cases starts at early stage or teenage and some cases starts at old age. Seizure is not the same disorder like epilepsy or can say that all the seizures are not belonging to epilepsy fits. The epilepsy is the kind of unprovoked seizure, which is occurred due to the involvement of the central nervous system. It happens when normal neuronal network abruptly turns into a hyper-excitabile network. This process is called epileptogenesis, which affect mostly the cerebral cortex. That's why it is random seizure and the risk is much inestimable. However, the non-epileptic seizure disorders are occurred due to several measurable causes, such as stroke, dementia, head injury, brain infections, congenital birth defects, birth-related brain injuries, tumours and other space occupying lesions. This type of epilepsy is called as secondary or symptomatic epilepsy. For secondary epilepsy, preventive measures can be adopted according to the various causes. The idiopathic or primary epilepsy is the broader type of epilepsy and it is therefore not preventable, but can be cured with antiepileptic medications. It is state that for more than 60% cases, exact cause cannot be ascertained [3]. This paper presents a review of different classifier for computer aided seizure detection and epilepsy diagnosis with an emphasis on research reported during the past decade.

### Computer aided epilepsy detection

A CAD system for detection, analysis and classification of EEG signal has been the area of interest of researchers since long time. It is clinically proven tool that increases the accuracy of detection and diagnosis of Epileptic seizure by assisting the physicians in decreasing observational oversights, in detecting/grading seizure in early stages. A CAD system can help neurologists make the diagnosis more efficiently and accurately. The signal-processing-based methods for automated diagnosis of epilepsy that work in time and frequency domains have been proposed in the literature.

## II. MATERIAL AND METHODS

### A. DATA ACQUISITION

In this section we explain only a short description of data set and refer to Andrzejak et al (2001) for further details [15]. The complete data consists of five sets (denoted A–E) each containing 100 single channel EEG segments. These segments were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements.

Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme (Fig4.2). Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from EEG archive of pre surgical diagnosis. EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Each file is recording of brain activity for 23.6 seconds. This time series is sampled into 4097 data points. Each data points are the value of the EEG recording at a different point in the time.

This dataset were providing  $y$  as a response variable.  $y$  contains the category of the 178 dimensional input vector in which  $y$  in  $\{1, 2, 3, 4, 5\}$ .

### B. Epilepsy analysis method

There are various methods have been used to analyze several slight changes in the EEG signal. This section gives a brief overview of various techniques reported in literature for classification of Epilepsy in EEG signal.

Initially Gotman proposed a computerized system for detecting a variety of seizures; he has developed a computer system which allows for the selective recording of interictal and ictal epileptic activity [4, 5]. In this method Gotman proposed an automatic detection in the EEG of

certain types of seizure: the seizures which include paroxysmal rhythmic bursts. Although this does not represent all the epileptic seizures, it represents an important proportion of them. Qu and Gotman extracted the EEG features in both time and frequency domain to detect the onset of epileptic seizures with the use of the nearest-neighbor classifier [6]. In this report features were evaluated from the time and frequency domain and the classifier used is a modified nearest classifier with onset detection rate was 100%.

Kemal Polat et al Proposed a hybrid system based on Fast Fourier Transform and decision tree classifier [7]. In this study same dataset is used for classify the epilepsy. In this study, he obtained 98.68% and 98.72% classification accuracies using 5 and 10-fold cross-validation. The same group proposed AR for feature extraction and C4.5 decision tree classifier for classification and reported an accuracy of 99.32% which is better than their previous work.

Srinivasan et al. proposed an automated epileptic EEG detection system using approximate entropy as the feature in Elman and probabilistic neural networks. Elman network yielded an overall accuracy of 100%

Ocak performed a method for automated seizure detection based on ApEn and DWT. The accuracy of seizure detection is more than 96% [8].

Acharya et al proposed four nonlinear parameters namely CD, FD, H and ApEn in SVM and GMM classifiers in the three class epilepsy detection [9]. It is found that, GMM classifier showed better performance with an average classification accuracy of 95%, sensitivity of 92.22%, and specificity of 100%. The Same group obtained 98.5% accuracy, 100% sensitivity, and specificity of 100% with SVM classifier using WPD coefficients [10]. Again, the same group obtained the 95.6% accuracy, sensitivity of 98.9%, and specificity of 97.8% using RQA parameters in an SVM classifier [11].

Hadi Ratham Al Ghayab et al has proposed a method using multi channel EEG signal for feature selection [12]. The classifier used to classify the features is least square support vector machine and it is reported that accuracy was 99.9%, sensitivity is 99.80% and specificity is 100%.

Ashwani et al proposed a method based on key point LBP for automated diagnosis of epilepsy from EEG signals [13].

Lasitha and Khan have used scalp and intracranial electroencephalogram (EEG) for patient specific novel real time automatic epileptic seizure onset detection [14]. The classifier used in present studies is relevance vector machine, because its efficiency in classifying sparse, yet high dimensional data sets. Author reported 99.8% classification accuracy using short term dataset B and 96% sensitivity 0.1 per hour median false detection rate and 1.89s average detection latency respectively.

### III. DISCUSSION

This chapter summarized the findings of many automated epilepsy activity classification techniques that use EEG as the base signal. Table 3.1 shows summary of the few studies for automated classification of normal and epileptic classes. It is found that a variety of methods like FFT, time frequency, DWT, statistical measures, nonlinear, chaotic and entropy measures, dimension reduction methods like PCA, ICA and LDA are used to analyze EEG to detect epilepsy from normal EEG data .Table 3.1 shows the performance comparison of classifiers of some previous studies uses Andrzejak [15] database.

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AUTHORS	CLASSIFIER	ACCURACY (%)
GÜLER AND ÜBEYLI (2005)	ANN (ARTIFICIAL NEURAL NETWORK)	98.68
KANNATHAL ET AL. (2005)	ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)	92.2
SUBASI (2007)	MIXTURE EXPERT MODEL (A MODULAR NEURAL NETWORK)	95
TZALLAS ET AL. (2007)	ARTIFICIAL NEURAL NETWORK	100
CHUA ET AL. (2008)	GMM	100
ÜBEYLI (2009)	ANN	99.6
GUO ET AL. (2010)	KNN	88.78
ORHAN ET AL. (2011)	ANN	96.67
YUAN ET AL. (2011)	ANN/SVM	96.5
ACHARYA ET AL. (2012)	VARIOUS CLASSIFIER	95.6
XIE AND KRISHNAN (2013)	SVM,K-NN FLD	96.7

#### IV. CONCLUSION

The automated detection of epileptic seizures has improved with technology. In the reviewed works for this survey, most researchers used classifier either ANN or SVM. ANN classifier is most commonly used classifier for patterns described by extracted features. It is efficiently distinguish the Epileptic seizure for EEG signal pattern. In this manner, a similar method with the same objective is SVM classifier. SVM classifier has been demonstrated to be faster and easier to implement than ANN. Thus, it is slowly replacing the ANN for classifying the EEG signals. In spite of several works as discussed in this section, there are some limitations and challenges identified from existing approaches:

- It is necessary to validate the developed technique using several large clinical databases collected using multicenter clinical trials. There is no way to compare new methodologies due to lack of open access to the reported datasets or benchmark.
- Combination of different feature selection techniques with different classifiers or combining supervised with unsupervised learning techniques can offer more possibilities to the experts. However, in order to utilize the reported CAD systems in clinical practice, their performance should be tested on large test data size.

#### REFERENCES

- [1] W. Blume, H. Lüders, E. Mizrahi, C. Tassinari, W. van Emde Boas, and J. Engel, "Glossary of descriptive terminology for ictal semiology: report of the ILAE task force on classification and terminology", *Epilepsia*. Vol.42 (9), 2001, pp. 1212-1218.
- [2] H. Qu, Self-adapting algorithms for seizure detection during EEG monitoring. PhD thesis, Department of Biomedical Engineering, McGill University, 1994.
- [3] D. J. Cross, and J. E. Cavazos, "The role of sprouting and plasticity in epileptogenesis and behavior, in: Schachter, S., Holmes, G. L. and Trenite, D. G. (Eds.), *Behavioural Aspects of Epilepsy*". Demos Medical Publishing, pp. 51-57.
- [4] J. Gotman, A few thoughts on "What is a seizure?" *Epilepsy Behavior*. Vol 22, 2011, pp. S2-S3.
- [5] J. Gotman, "Automatic recognition of epileptic seizures in the EEG", *Electroen. Clin. Neuro.* Vol 54:1982, pp.530.
- [6] H. Qu, and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: Possible use as a warning device". *IEEE Trans. Biomed. Eng.* Vol44 (2), 1997, pp. 115-122.
- [7] K. Polat, and S. Günes, "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform". *Appl. Math. Compu.*, vol 187, 2007, pp.1017-1026.
- [8] H. Ocak, "Automatic detection of epileptic seizures in EEG using discrete wavelet transforms and approximates entropy" *Expert Syst. Appl.* Vol.36 (2), 2009, pp. 2027-2036.
- [9] U. R. Acharya, K. Chua, C. Lim, T.C., Dorothy, J.S. Suri, "Automatic identification of epileptic EEG signals using nonlinear parameters" *J. Mech. Med. Biol.* Vol 9(4), 2009, pp.539-553.
- [10] U.R. Acharya, S. Vinitha Sree. And J. S Suri "Automatic detection of epileptic EEG signals using higher order cumulant features", *Int. J. Neural Syst.* 21(5), 2011, 1-12.
- [11] U. R., Acharya, S. Vinitha Sree, S. Chattopadhyay, Y. U. Wenwei, and A. P. C. Alvin, "Application of recurrence quantification analysis for the automated identification of epileptic EEG signals". *Int. J. Neural Syst.* Vol. 21(3), 2011.199-211.
- [12] H. R. Al-Ghayab, Li Y., S. Abdulla, M. Diykh, and X.-K Wan, 2016. "Classification of epileptic EEG signals based on simple random sampling and sequential feature selection". *Brain Informatics* Vol.3:85-91.
- [13] A. K. Tiwari, R. B. Pachori, V. Kanhangad, and B. K. Panigrahi, "Automated Diagnosis of Epilepsy Using Key-Point-Based Local Binary Pattern of EEG Signals". *IEEE Journal of Biomedical and Health Informatics*. Vol. 21(4), 2017.
- [14] L. S. Vidyaratne and K. M. Iftekharruddin. "Real-Time Epileptic Seizure Detection Using EEG, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*", Vol. 25(11), 2017.
- [15] RG Andrzejak, K Lehnertz, F Mormann, C Rieke, P David, CE Elger, "Indications of non linear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state", *Phys. Rev., E*, vol.,64, 2001, pp.061907.