Epileptic Seizure Detection Using EEG Signals: A Review

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Abstract:

Epilepsy is chronic neurological disorder of repeated seizures of very brief or large time periods. It has a considerably negative impact on both the quality and the expectancy of life of the patient. Electroencephalogram or EEG are test to evaluate the electrical signals of brain neurons and hence to detect epilepsy. The living standard of such patients can be improved drastically if occurrence of seizures can be predicted which is the main aim of EEG. Analysis of seizures from long-term EEG recordings for neurologists is complicated and time-consuming. The use of machine training algorithms for the recognition and classification of Epileptic EEG signal has led to the automated detection of epilepsy that has gained considerable popularity amongst scientists because it can prove very useful for treatment. Advanced EEG machines are now available which provides high quality signals but the main challenge in automated epilepsy detection is to collect precise data and to develop detection algorithm with minimum computation. Feature extraction and classification are the two key steps involved in machine learning. The extraction feature reduces the space of the input pattern by keeping information and assigns the classifier to a class label. We present various methods of extraction and grading algorithms to automatically detect epilepsy in this paper.

Keywords: Epilepsy, Feature extraction, Classification

Introduction:

Epilepsy is a neurological disorder caused by transient and unexpected disorder caused by excessive synchronized brain neurons. It may happen for anyone regardless of gender, age, region or race, but it is more vulnerable to children and adolescents. In some of the literature, seizure and epilepsy are sometimes referred to as the same, not all of these seizures are epileptic and seizures may also occur due to acute neurological annoyance (like brain trauma, stroke). In the electrical signals of brain neurons, the electroencephalogram or EEG is tested and, hence, epilepsy is detected. Worldwide, millions of people have this brain disease, which has a large impact on their normal lives as a result of an anomalous behaviour, which is also social stigma. If seizures can be predicted, the live standards of such patients can be drastically improved. This is EEG's main objective. Using machine learning algorithms for the signal and classification of epileptic EEG, epilepsy is automated and gained considerable popularity among researchers since it can be very helpful in treating it. Advanced EEG machines that provide high quality signals are now available but the main challenge in the field of automated epilepsy detection is precision data collection and the development and minimum calculation of detection algorithms [1-6].

The small variation in EEG voltage oscillations reveals the occurrence of neuronal activity. Generally, these abnormalities are identified using visual inspections and, in addition, long EEG recordings take much time and are subject to human error. The results may be imprecise because artifacts are present in the signals. By using computer-aided technologies, these signals are processed and analysed for fast and accurate results. EEG signalling plays a pivotal role in the diagnosis of different disorder of neurological and Neuropsychiatric signals, including epilepsia[7,8], MDD[9,10], ALS[11,12] and dementia[13,14], such as Brain Tumors, Alzheimer's, mild cognitive discomfort(MCI), Parkinson's, and Lewy's epilepsy . Low cost, high temporal resolution, non-invasive, user friendly, portable and harmless nature make EEG into a powerful tool in relation to other techniques such as PET, magneto-encephalogram (MEG), FMRI, Transcranial Magnetic Stimulation (TMS). High quality signals are available on advanced EEG, scalp or EEG intracranial machine to detect epilepsy with minimum computational requirements [15].

Based on the characteristics in EEG signals, they are helpful for determining several phases of an epileptic seizure before and during a seizure. The following are different stages [16]

a. **Pre-ictal State**: is a state before a seizure occurs. It must be used clinically in a warning system so that the duration of false warning is reduced at an early date.

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b. **Ictal State** : a condition occurring during a seizure.
c. **Post-Ictal State:** a condition, after seizure.
d. **Interictal State**: is a state beginning after the first seizure and ending before the beginning of the consecutive pre-ictal state of seizures.

The epileptic seizure identification mechanism is grouped into one or more networks. In one single channel the signal is selected with certain steps, such as local variation, which is high and near the source of the seizure [16, 17]. The combining of information from more than one source performs better by using data fusion techniques [18]. In [19–21], either linear or non-linear is defined in a single attempt. Epilepy detection methods were defined by Tzallas et al. as pattern detection, parametrical methods, methods of degradation, and data mining [22]. Alotaiby et al. [23] identify methods of seizure detection of time, frequency, wavelet domain. Moreover, when seizure from a certain EEG era is detected, another domain, known like a rational domain, is more successful than wavelet[24].

Several techniques were developed in previous research using EEG signals to detect epileptic seizure. The two steps to diagnose seizures include extraction and classification of characteristics. Improving classification output requires main EEG signals to be extracted. Features derived from EEG signaling are classified in the literature on the detection of epileptic seizure as duration, frequency, time-frequency and linear or non-linear methods [25]. The numerous extractor features include eliminating the occult pattern of EEG signals such as EMD, Discrete Transform Wavelet (DWT), DWT, Fourier Transform (FT), Discrete Transforming Fourier (DFT) and Inverted Discrete Transforming Fourier (IDFT), Short Time Transforming Fourier (STFT), Transforming Fourier Fourier (SFT) (FFT). For further study, signals can be broken down in various subbands using a band pass filter to extract features. From raw or pre-treated signals features may be derived. Some of the methods of extraction used to extract different detailed sub-bands from the different characteristics (Table – I, II, III) are given here [26]-[30].

Features are recognized in order to detect epileptic seizure with feature extraction methods by removing artifacts. Strength of features selected depends on a fine classifier. The classifiers such as supervised, unsupervised, deep learning neural architectures and ensemble learning models are used for classification. Some of them are SVM (Support Vector Machine), LDA (Linear Discriminant Analysis), KNN (k –Nearest Neighbour), naive bayes, MLP (Multi Layer Perceptron), RF (Random Forest), GRNN (General Regression Neural Network), Decision Trees, GBM (Gradient Boosting Machine), ANN (Artificial Neural Network), CNN, RNN etc., [31-34].

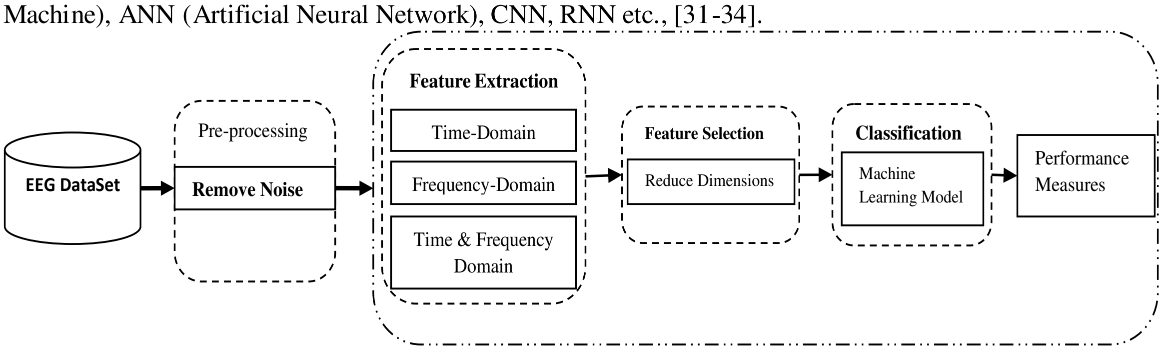

Fig.1 Various Stages in epilepsy detection using EEG dataset as input

2. EEG Dataset

For researchers the biggest challenge is EEG dataset. Dataset selection places a key role in evaluating the performance of proposed models. The below described are some of the popular datasets that are used in automated epileptic seizure detection.

University of Bonn database - It's a small database and easier to classify. It has five subsets each one denoted as (A-E), consists of hundred single channels recording which has 23.6 sec duration captured by 10-20 system. Signals are recorded with 128-channel amplifier.

ECoG Dataset - an open electrocorticogram signal dataset for epilepsy patients. 76 electrodes were collected by placing them on the scalp in non-invasive and invasive (64 electrodes) (12 electrodes). The recorded data is sampled at a frequency of 400 Hz and a duration of 10 sec.

Freiburg EEG - This dataset was registered at the Freiburg University hospital, Germany during invasive pre-chirurgical epilepsy monitoring. There are 21 patients recorded, 13 of which were 24 hours long, and 8 were recorded under 24 hours.

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TUH EEG DataSet - EEG corpus was released by Temple University hospital (TUH), it's huge in terms of patients, duration and seizures.
If Own hospital dataset, can also be used for research work.

3. Feature Extraction methods:

In this section, details are described on epileptic seizure detection capabilities that can be classified as time, frequency, time frequency, linear or non-linear. TDFs(Time-domain Features) are calculated using a raw EEG or pre-transformed signal such as EMD (empirical mode decomposition). FDFs(Frequency-domain features) are computed on the basis of a raw EEG-transform from discrete Fourier. Transformed EEG signals containing both time characteristics and frequency characteristics, such as STFT (short time Fourier transforming) spectrogram or DWT [25].

3.1. Time domain features

The signal value changes over time is referred as time domain i.e. time factor is the signal variable. These methods are generally specific to patient or problem and analyze the periods (epochs). This is thus an analysis of the value of a given signal x (t). Transformations are not required so they are usually quick. Smart watches, tablets, etc are used as seizure detectors.

Energy, average power, root mean squared value, curve length, amplitude-integrated EEG, nonlinear energy, Shannon entropy, approximate entropy, weighted-permutation entropy, a group of statistical parameters such as spike rhythmicity, relative spike amplitude, mean, variance, median, mode, kurtosis, maximum and minimum, coefficient of variation, standard deviation, activity, mobility, complexity, Mean Absolute Value, Zero Crossings, Slope Sign Changes (SSC) and Waveform Length (WL) etc., are some of the time domain features.
Small segments of 1 s EEG epoch are used in time domain for extracting the features. To identify the epileptic seizures the small sections of EEG provide the accuracy in time domain, as close to the clinical point of onset. In EEG signal analysis, TDFs are not major since the EEG signals are not periodic.

Type of feature extracted	Issues solved in EEG
Hjorth parameters(Mobility and complexity)	Emotion recognition, Sleep stage classification
Zero crossings	Sleep stage classification, Depression
Shannon entropy	Emotion recognition, Epilepsy and autism
Permutation entropy	Dementia
Approximate entropy	Drowsiness detection
Maximum and minimal singular value	Seizure/epilepsy
Energy	Sleep stage classification

Table-I Review of Time domain features

3.2 Frequency Domain Features

FDFs reports about [on Y-axis define magnitude and frequency on X-axis] the signal frequency spectrum. It highlights and indicates the significant propriety of the signals which cannot be visually viewed of the actual signal and unseen signals in the time domain. Signals with different frequencies are theoretically divided into absolute sinusoidal signals. The signal is distorted into a frequency domain, and the magnitude and phase of the Fourier transform can be exploited. This analysis of the signal is called an amplitude-frequency. Methods of FDFs are stronger compared to TDFs [24].

Frequency domain analysis is vital because the frequency of the EEG signal provides helpful information of signal patterns. In these feature computations, the input signal is supposed to be stationary and the small sections help in estimating the stationarity of the EEG signal. In an epileptic seizure detection, there is quick change in frequency, which is measured by this. Frequency domain features include power ratio, intensity weighted average frequency (IWMF), bandwidth-based intensity (IWBW), specimen-based entropy (SEF), mean power, minimum, maximum, variance, average power in the main energy zone and normalized spectral entropy. The high frequency is also referred to as a dominant frequency.

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Type of feature extracted	**Issues solved in EEG**
Mean frequency	Sleep stage classification
Median frequency	Dementia, Depression
Spectral entropy	Sleep stage classification, Dementia
Power ratios, product of powers	Sleep stage classification, Epilepsy

Table-II Review of Frequency domain features

3.3. Time-Frequency Domain Features:

In time-frequency, additional information is gathered by considering dynamic changes on non-stationary signals. Various transformation and decomposition techniques that provide information in terms of both time and frequency have been extensively considered for epileptic seizure detection. To extract frequencies at a specific time instant and the information of time moment, this the most suitable method, which a limitation in the above models. So, a time-frequency analysis is widely used to find multi-resolution decomposed sub-band signals by passing the EEG signal through filter banks.

In the time-frequency statistical features such as mean, skewness, maximum and minimum values etc., are common, energy, line length, entropies, auto regressive moving average, Root Mean Square (RMS) and Recursive Energy Efficiency (REE) etc., are some other.

Type of feature extracted	**Issues solved in EEG**
Mean Median standarddeviation Minimum Maximum	Epileptic Seizure Detection ,Sleep stage classification, Depression, Alcoholism
Gabor-based features	Emotion Recognition
Kurtosis	Epileptic Seizure Detection Sleep stage classification Depression, Alcoholism
RMS	Sleep stage classification Eyes state classification Depression
Skewness	Sleep stage classification Eyes state classification Depression Alcoholism

Table-III Review of Time-frequency domain features

4. Machine Learning Techniques:

4.1 Supervised Learning Methods

In Supervised Learning, machines learn by feeding them label data and explicitly specifying that this is the input, and this is exactly how the output must be. It takes training data that contains set of occurrences labelled by hand with right output.

In this Classification process, the data is grouped into two sets training and testing. Training set is used for constructing a classifier and by using testing set the classifier performance is assessed. This assessment at times repeated for various parameters of the classifier so the parameters are optimized. After the optimization, features with unknown class labels can be assigned a class label by classifier.

The algorithms in the supervised classification method predicting categorical labels are LDA, support vector machine, logistic regression, naïve Bayes classifier, decision trees, Kernel estimation Neural networks (NN), K-NN (K-nearest neighbour), Gaussian process Regression, etc.,

In most of the biomedical studies have a preference of supervised classification.

4.2 Unsupervised Learning Methods

In unsupervised Learning, based on some measure of inherent ability data clustered into classes. In this method, training data is not hand-labelled so for testing of new instances the right output

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value is predicted based on inherent patterns hidden in the data. In this, even for tiny set of data the class labels info is not available. The algorithms that are generally used in unsupervised classification are K-means Clustering, kernel PCA, PCA, categorical mixture model, hidden markov models, ICA.

4.3 Deep Learning Methods

Deep Learning models automatically extract the useful patterns of information needed to make future predictions or make a decision. These are implemented through neural networks and motivated behind neural networks is the biological neuron. They are widely considered because of better performance in most of the ML applications related to biomedical signals such as sleep stage classification, drowsiness detection, dementia etc... They are capable of handling raw data.

These consists of computational models with several layers that operate mutually for processing data and produce result. To extract relevant features these layers are helpful also in assessing to get the output. The central part of these models is, they have segmented layers which are aimed to learn data using general purpose algorithms. Usually used neural networks are CNN, RNN etc.

RNN is used in EEG signal analysis to detect temporal patterns for seizure detection. Latest researches for epileptic seizures prediction using EEG signals, LSTM has been used. Convolutional Neural Networks (CNNs) is extensively used in analysis of EEG signal because it is highly effective to reduce noise. CNNs can be applied to the raw data and wavelet space to get good performance in the epileptic EEG signals classification. It has the capability of learning new features automatically which gives better results compared to hand-crafted features.

Application	Time Domain features	Frequency domain features	Time-frequency domain features	Non-linear features	Classifier(s)	Number of classes
Motor Imagery tasks	Yes	No	No	No	LR	4
Epilepsy	No	No	Yes	No	SVM	4
Motor Imagery tasks	No	No	Yes	No	kNN	4
Epilepsy	Yes	No	No	No	SVM	2
Emotion recognition	Yes	No	Yes	Yes	SVM	4
Epilepsy	Yes	No	Yes	No	ANN	3
Mental disorder	No	Yes	Yes	Yes	ANN	4
Epilepsy	Yes	No	No	No	kNN	8
Epilepsy	Yes	No	No	No	kNN	8
Motor Imagery tasks	No	Yes	No	No	LDA	3
Apnea	No	No	No	Yes	kNN	2
Emotion recognition	No	No	Yes	Yes	SVM	4
Epilepsy	No	No	Yes	Yes	LDA, KNN, SVM and DT	3

Table - IV Applications related to EEG: a review

5. Performance Measures:

The outcome can be tested using different output measures for automatic detection of epilepsy. The 10-fold cross validation, a familiar training process, requires the use of nine segments as training datasets as well as the other one horizontal segment in the dataset. The most commonly used

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performance measures are recall, precision, f-measure, sensitivity, accuracy, specificity, negative predictive value and positive predictive value, false alarm rate, area under curve. The possible classification outcomes are True-Positive (TP), False-Positive (FP), False-Negative (FN) and True-Negative (TN).

Recall = TP / (TP+FN)

Precision = TP / (TP + FP)

F-measure = (β^2 + 1) (Precision * Recall) / (β^2 * Precision + Recall)

Accuracy = (TN+TP) / (TN+TP+FN+FP)

Specificity = TN / (FP+TN)

False alarm rate (FAR) per hour is the average no. of false alarms triggered per hour.

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Table V : A Review on Features and Classifiers used in various issues related to EEG signal

Authors/Year	Title	Features/Transforms used	Classifiers	Window Size	Dataset	Performance metrics
Alejandro et al. (T), 2017	Optimizing EEG Energy-based Seizure Detection using Genetic Algorithms	Energy/multichannel	Genetic algorithm/threshold	N/A	CHB MIT	0.39 False rate per 24 h in average
Mursalin et al. (T),2017	Automated Epileptic Seizure Detection Using Improved Correlation-based Feature Selection with Random Forest Classifier	mode, mean etc. / wavelets	Random forest	N/A	Bonn dataset	98.45 Average acc.
Guangyi Chen et al., 2017	Automatic Epileptic Seizure Detection in EEG Using Nonsubsampled Wavelet–Fourier Features	Amplitude of coefcients/wave-let/Fourier	KNN		Bonn database	Classifcation rates (100%)
Rezvan et al., 2017	Selecting Statistical Characteristics of Brain Signals to Detect Epileptic Seizures using Discrete Wavelet Transform and Perceptron Neural Network.	Maximum, minimum, average and standard deviation/sin- gle/wavelet	Multi Layer Perceptron Neural network	26.3s	Bonn database	confusion matrix: accuracy, 98.33
Sabrina et al., 2016	Whole brain epileptic seizure detection using unsupervised classification	Euclidian, IMFs	PHA(unsupervised)	2s	CHB-MIT	98.84% Accuracy
Cui et al,2018	Epileptic Seizure Detection Based on Time-Frequency Images of EEG Signals Using	Codebooks construction, Bag of waves segments	ELM	2s	Bonn database	70.5% Sensitivity 75% Specificity
Dattaprasad et al., 2017	EEG Signal Classification into Seizure and Non-Seizure Class using Empirical Mode Decomposition and Artificial Neural Network	Coefcients of Hilbert(IMF)/ EMD/Hilbert	Artificial Neural Network	23.6s	Bonn database	96% Accuracy

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