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Analysis of Techniques and Methods for Automated EEG signal for Epilepsy Diagnosis: A Review

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Abstract- Most of the recent research has explored the possibility of predicting & analyzing epileptic seizures by using different techniques & methods. Epilepsy is the second most common neurological disorder which affects people of all ages i.e. about 1-2% of the world's population affected by this major chronic disorder. The Electroencephalogram (EEG) signal is used as a useful tool for the early detection of epileptic seizures in several applications of epilepsy diagnosis. Many techniques have been developed for differentiate the features of seizures present in EEGs. This article reviews the seizure detection techniques & methods reported in last decade/years.

However, there are various techniques like Empirical mode decomposition (EMD), wavelet transform, tensors, entropy, chaos theory, and dynamic analysis which are used in the area of epilepsy diagnosis. For better treatment of the patients it is important that the seizures are detected correctly in time. Although efforts have been made for better prediction of the seizures, the translation of current analysis & results to clinical applications is still not possible. We have reviewed a framework of reliable algorithmic seizure prediction studies, discussing each component of the whole block diagram. We have also explored all the processes, from signal acquisition to adequate performance evaluation that should be opted in the designing of an efficient seizure advisory/intervention system. The present review has established that there is a potential for improvement and optimization in the seizure prediction framework.

***Keywords* -** Epilepsy; Seizure detection algorithm; Signal processing; Feature Extraction; Classification; Performance

1. INTRODUCTION

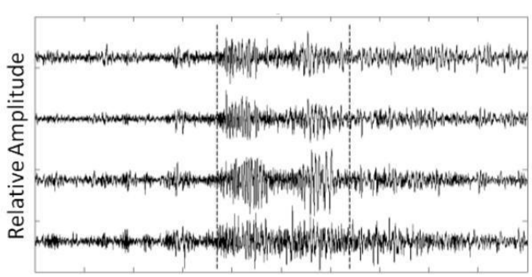
Epilepsy is most common chronic neurological disorder of the human brain that impacts on approx 60 million people of all age groups in every country in the world. As per WHO, epilepsy is distinguished by the release of excessive electrical charge in a group of brain cells which leads to sudden recurrent and transient disturbances in the brain [1]. During the seizure, the patient is unknown of their physical as well as mental condition and hence physical injury may occur. In case of monitoring epilepsy, we often encountered two types of seizure, namely behavioral and electrographic. A seizure which is sensed by the patient, seen by an observer, or recorded on video is termed as behavioral seizure. An electrographic seizure is defined as an abnormal sudden recurrence in EEG pattern. In many cases, there is dissociation between the both i.e. behavior and EEG signals [2]. The occurrence of seizure is unpredictable and the process is very random in nature, so it is very difficult to predict the seizure proactively.

Electroencephalogram (EEG) is a tool which is used to measure and record the electrical activity of the brain leads to detection and analysis of epileptic seizures [3]. Some examples are discussed here for better understanding of the seizure detection problem. A 4 channels scalp EEG, with the pre-ictal, ictal and post-ictal states figures 1(a) and (b) with 100- second records. In Fig. 1(a), these three states are easy to distinguish by visual inspection whereas in Fig. 1(b), the epileptic seizure can go unnoticed in a first or quick examination by a neurologist. Thus there is a need to find some important features such as amplitude, duration, and frequency that help to distinguish an epileptic seizure. However Visual analysis of EEG is, however, very time consuming process, so the automated detection of epileptic seizure is very useful as it helps the specialist to analyze the

EEG to make a better decision & prediction about epilepsy and the type of epilepsy. This can also helpful in drug delivery system of epilepsy [4].

Recent research has been mainly focused only to predict the epileptic seizure well in advance. There are various interesting reviews of seizure prediction have been published, but rarely someone describes the framework that classify the epileptic signal. We start by presenting basic model/framework for reliable and efficient seizure prediction. There are various methods/models used by researchers but we are paying special attention to algorithmic framework because this model is accepted in seizure advisory/intervention implantable devices. The basics, history, and advancements in algorithmic studies are detailed in a block-by-block fashion. This paper outlines the processing techniques and classifiers used for epilepsy detection. We have discussed various methods involving in signal processing, several acquisition modalities and feature extraction approaches linear and nonlinear with both univariate and multivariate methods [5]. Important feature selection techniques, classifiers as well as regularization functions are compared. We review algorithm-based studies in a methodological manner, discussing each component of the whole block diagram.

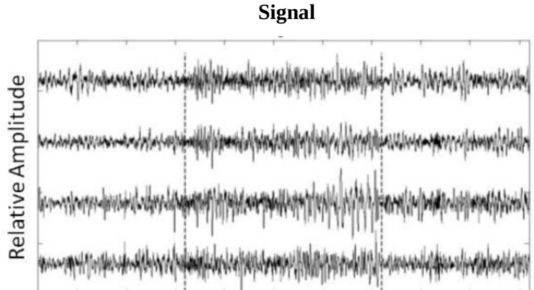
Signal



Time(s)

Figure 1(a)

Signal



Time(s)

Figure1 (b)

Figure 1[13] : Examples of two epileptic seizures from CHB-MIT Scalp EEG database [92]. Four channels of EEG record of epileptic seizure of Patient. In 1(a), preictal, ictal, and postictal states are easy to distinguish by visual inspection, whereas in 1(b), visual differences between these three states are difficult to discern. Black lines indicate the time boundaries of a seizure annotated by an expert

In this review paper, we explored all the processes, from signal acquisition to adequate performance evaluation that should be opted in the designing of an efficient seizure advisory/intervention system. This paper explores the functions & working of any seizure detection system in three sections.

Section 2.1 presents the techniques & methods for signal acquisition and after that preprocessing the acquired signal.

In section 2.2, we review various processing & feature extraction techniques/models.

Section 2.3 presents the methods for feature selection & classification.

In section 2.4, we conclude the review paper by explaining the regularization methods & comparing the performance of various seizure detection system proposed by other authors.

2. DETECTION SYSTEM

The Seizure detection Algorithm based study broadly categorized into three stages namely: Signal Acquisition and preprocessing, processing and feature extraction, and Decision making with help of classification. It can be better understand by following block diagram:

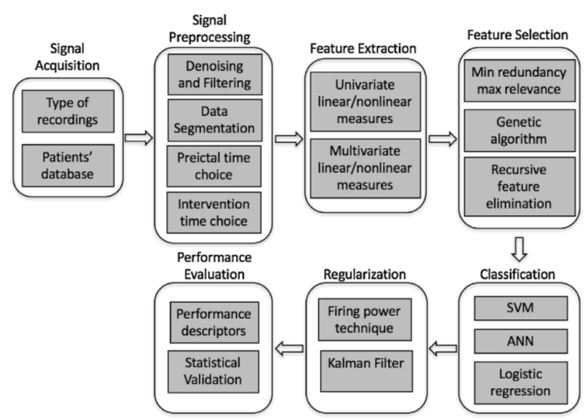


Figure 2[5]: Seizure Detection System

This algorithm based study can determine pre-ictal state based on EEG recordings, starting by enhancing the quality of signal by preprocessing EEG signal, extracting various features present in the signal and selecting the most distinct feature as input to the classifier. Most of the algorithm based seizure detection system has a regularization function as a post processing step to smooth classifier output. Then performance of the seizure detection system is evaluated.

2.1. SIGNAL ACQUASITION & PREPROCESSING

This section is broadly categorized into two parts: i) Signal Acquisition ii) Signal Preprocessing

2.1.1 Signal Acquisition: The review study in this category can be done in the dimension of types of recordings. There are two types of recordings namely iEEG and scalp EEG considered in seizure prediction studies. Scalp EEG captures brain activity with equally-spaced surface electrodes glued to the skin while iEEG involves intracranial electrodes positioned in areas of suspected epileptogenicity identified from available clinical, structural and functional data collected prior to implantation [6]. Several studies have explored the utility of scalp recordings for seizure prediction. Teixeira et al. [7] gives the comparison between iEEG & scalp EEG based on the two parameters sensitivity and false pre-diction rate (FPR). As a result values of scalp EEG were slightly better than iEEG. If we are comparing the statistical significance of result with the Kruskal-Wallis (K-W) test (p = 0.01), these differences have no significant in the calculations. There are some other studies also from which we can say that the performance of seizure prediction algorithms on scalp EEG is good as compare to iEEG. However, it must be remembered, that practically iEEG recordings are more suitable for chronic intervention devices. We summarize the performance evaluation of recent seizure-prediction studies comparing scalp and iEEG performances in table 1.

Table 1: comparison of iEEG & scalp EEG

Authors	**Recording type**	**No.of patients**	**Sensitivity (%)**	**FPR (h−1)**	**Statistical testing**
Bandarabadi et al [10]	Scalp iEEG	16 8	73.98 78.36	.06 .15	None None
Teixeira et al.[7]	Scalp iEEG	227 42	73.5± 24.83 67.66 ± 21.83	0.28 ± 0.28 0.39 ± 0.37	K-W K-W
Rasekhi et al.[11]	Scalp iEEG	8 2	76.67 68.7	.08 .33	None None

2.1.2 Signal Preprocessing: In biomedical signal processing, it is very important that the raw signal should be analyzed with the presence of noise and artifacts leading to minimized effect in feature extraction [8]. This step is usually employed in any EEG analysis and attempts to remove artifacts, increase signal-to-noise ratio and prepare signals for adequate feature extraction. The preprocessing of acquired signal can be done in following step:

a) Denoising and filtering: Most of the signal preprocessing approaches are using conventional filtering of recorded signals [8]. This conventional filtering use band pass filter to filter on the basis of frequency range of their interest as well as extracting artifacts from the EEG signal identified by visual inspection [9].

Some techniques, such as independent component analysis, are specifically designed to remove the artifact present in the EEG signal. It identifies the sources of artifacts based on blind source separation. Further it separates them on the basis of their statistical independence from the EEG. For artifact cancellation a technique named as adaptive filtering is used. In this technique, the transfer function is self adjusted according to an optimization algorithm driven by an error signal by a filter. The correctness of the method has been assessed using simulated data [10]. The method has been used to discard the ocular artifacts from EEG [11].

There is another approach to remove artifacts from EEG signal in which EEG data decomposes into space-time-frequency components, is known as multi-way analysis. Multi-channel EEG data has been constructed as a third-order tensor, an epilepsy feature tensor, with modes: time samples×frequency×electrodes [12]. This allows the spectral, spatial, and temporal signatures of an artifact to be found to define it using parallel factor (PARAFAC) analysis. Then artifact such as eye movements are removed through multilinear subspace analysis, so that the rest data does not accommodate any activity correlated with the artifact [13].

b) Data segmentation: Before feature extraction, Data should be segmented into smaller windows having data of similar characteristics meaningful to EEG analysis. In case of epilepsy the duration of these windows varied from 5 to 60 seconds. Park et al. [13] and some authors adopted moving window analysis which has a size of 20 seconds with half overlap. Others decided on a 5-s window with no overlap [15–16, 21]. Such a relatively short window is considered to be a compromise between the ability to capture specific patterns and stationary assumptions.

c) Preictal time choice: In early investigations, no standard or optimal preictal time slot has yet been defined. The American Epilepsy Society's seizure prediction challenge adopted a preictal time of 1 h prior to seizures, with a fixed intervention time of 5 min. Some studies have chosen fixed preictal times, such as 2 min, 20 min, 30 min, and 90 min, while others have considered several different preictal times. In an extensive study, Teixeira et al. [7] tested 4 different pre-ictal times (10, 20, 30, and 40 min)and observed no significant differences in terms of sensitivity, but longer pre-ictal time was found to significantly reduce FPR. These authors concluded that preictal time of 30.47 min was the most appropriate average value, leading to a patient-specific best predictor.

Considering that each study uses a different algorithmic strategy, performance comparison is not reliable at this stage. However, it is clear that no preictal time can be considered optimal or standard.

d) Intervention time choice. The study suggests that the longer intervention time gives the optimistic results with higher sensitivity. In contrast, using an Ngram-derived seizure prediction method Eftekhar et al. [15] found that shorter Intervention Time (10 min) resulted in increased sensitivity when analyzed three Intervention times (10, 20, and 30 min) with a seizure occurrence period of 10 min. Schelter et al. [16] reported sensitivity as function of IT. To use a uniform set of parameters across all patients of the same group [17], adopted a fixed IT of 2 min and achieved an average sensitivities of 82% and 89% using the dynamic similarity index and the mean phase coherence, respectively. Similarly, recent seizure prediction studies adopting a fixed intervention time of 5 min have reported promising performances [18]. Such classification strategies would allow more intervention time with chronic implantable devices.

2.2. PROCESSING & FEATURE EXTRACTION

In an automated seizure detection system, we have to find out the distinctiveness of the pre-ictal, ictal and post-ictal EEG signals and then evaluated. There are various features which have been identified for better description of the seizures. The features that are used for the identification of the seizure can better explained by the static behavior of the signals itself such as chaoticity and non-linearity [9].

The terms processing technique and feature extraction can be used for same purpose due to their close behavior for example, wavelet features make reference to the wavelet transform of the signal. Since the EEG signals are very random in nature, we require segmented EEG signals for applying linear processing techniques. The windowing technique is always used for this type of signal because we have to detect the transitions between non-seizure, pre-seizure, and seizure states [19].

The performance of algorithm based automatic seizure detection is based on the process of selecting features which explain the behavior of EEG signals. There are many types of features extraction and processing techniques, in which some are based on frequency-domain [20,21,22,23,24,25] time-domain [26,27] or time-frequency analysis [19], chaotic features such us entropy [28,29], energy distribution in the time-frequency plane [30,31], and wavelet features [21,22,32]. Another technique is multi-way analysis, which uses feature tensors to recognize seizures. Most detectors use a combination of two or more techniques and test a given set of features using more than one classifier [33-35].

2.2.1 Time Domain Analysis: The analyses in which EEG signals are estimated by time function are called time domain analysis. There are certain other features also which are often used such as amplitude, regularity, and synchronicity, which increase during epileptic events.
Instantaneous energy of a signal refers to amplitude. Signal power, which is the square of amplitude, focuses on variations more than energy but is thus more affected by noise [36]. Figure 2 demonstrate a case of EEG signal instantaneous energy. Notice that the exceptional increment of energy during the epileptic seizure (bounded by black lines).

Regularity is the measure of similarity of a signal with itself which is acquired by an auto-correlation function while Synchronicity gives a thought of how comparative signs are to each other or what events happened at the same time [37].

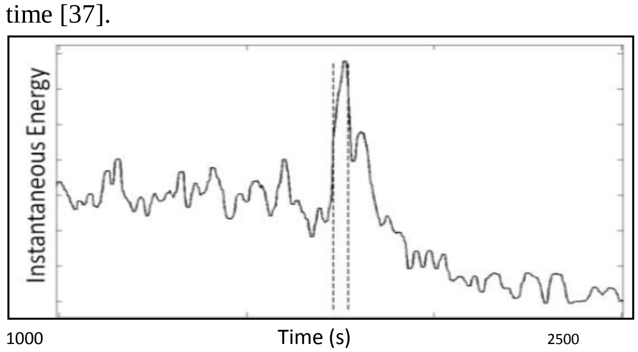


Figure 2[13]: Signal instantaneous energy, showing an increase during a seizure. Black lines indicate the time boundaries of a seizure annotated by an expert.

Usually, in most of the seizure detection algorithm, various time features are used like relative average duration, relative average amplitude, and the coefficient of variation of amplitude. Such features are implemented in the commercial seizure detection algorithm Monitor [38, 39] but its detection accuracy is under 80%. Acharya *et al*. proposed higher order spectra features (specifically cumulants) from normal, inter-ictal, and epileptic EEG segments for time series analysis, obtaining a high detection accuracy of 98.5% [28]. Other researchers reported achieving 93.11% classification accuracy with HOS-based features [41, 42]. Other works combined HOS with principal component analysis, achieving detection accuracies of over 95% [31].

2.2.2 Frequency Domain Analysis: The change in frequency component of EEG signals during epileptic seizure needs to quantify for useful information as shown in Fig.1 (a). Fourier transform method is used to extract the frequency features from the EEG signal described in terms of frequency component. Frequency features can be used to separate the human brain activity at different frequencies. In general, power spectral density is deliberated and then pertinent features are extracted [19]. There are some other common spectral features like central, mean, and peak frequencies [45], average band frequency, dominant frequency [25] and maximum power [44]. However, for more accurate detection due to the complexity of detecting seizures, new methods combine frequency analysis with time and other features.

2.2.3 Time-frequency Analysis: Time domain and frequency domain analysis have well known disadvantage while applied to EEG signal. By the Time-domain analysis, we can trace the exact location of events but it cannot determine which frequencies are involved in seizure. While in frequency-domain analysis we can determine the different frequencies present in a signal but not the time moment of their occurrence. So time frequency analysis technique is widely used because of these limitations. A classical method, such as spectrography, was used by Gabor *et al*. [30] and Gabor [46] to implement their commercial detector CNet. Other approaches include Wigner-Ville distribution [47], wavelet analysis, and Empirical mode decomposition which are the most widely used for EEG.

(a) Wigner-Ville distribution: The Wigner-Ville distribution is one of the most studied and best understood time-frequency distributions [47]. Its importance can be judged in both the areas i.e. time and frequency domains, having support for time and frequency properties [18]. Tzallas *et al*. [31] applied the WVD to selected segments of EEG signals and extracted several features for each segment that represent the energy distribution in the time-frequency plane.

(b) Wavelet transform: The Wavelet transform is a multi resolution decomposition of a signal into sub-band signals containing activity at different time scales achieved by passing the signal through an iterated filter bank structure [47]. The wavelet transform is a versatile signal processing tool and helps in capturing transient features which are localized in time and frequency domain. The preprocessed signal is analyzed post decomposition process (coarse approximation and detailed information) at different frequency bands with varying resolutions [48-50].

The commercial seizure detection algorithm Saab is based on the computation of the relative amplitude and the coefficient of variation of wavelet coefficients and a pure probabilistic classification with Bayesian formulation [51].

(c) Empirical mode decomposition: Epileptic seizure can be detected by empirical mode decomposition. EMD [52] is an adaptive method used to analyze non-linear and non-stationary signals. It divides the signal into fast and slow oscillations, which is local and fully data-driven. The main purpose of the EMD is to crumble the signal into a sum of intrinsic mode functions. An IMF is a function which satisfies following two conditions: (1) There should be equality or at most unit difference between the number of zero crossing and the extrema in the entire signal (2) at any point, the mean value of the envelope defined by the local maxima and local minima must be zero (or close to zero).

2.2.4 Chaos and dynamic analysis: EEG signals are very random in nature, so they can be considered as chaotic. Thus to characterize these signals, we require a tool that evaluate the state of chaos of a dynamic system. Entropies and Lyapunov exponents are effective tools for such evaluation.

(a) Entropy: In general, entropies are measures of uncertainty in the system. From the information theory perspective, entropy is the amount of information stored in a general probability distribution. Higher entropy means higher uncertainty in the system and thus a more chaotic system. Recently, various entropy estimators have been applied to quantify the complexity of signals [53]. Shannon spectral entropy, Renyi's entropy, Kolmogorov-Sinai entropy, and approximate entropy (ApEn) [54] are the most commonly used entropies.

(b) Lyapunov exponents: Opposite to concept of entropy, Lyapunov exponents mathematically describe the deterministic structure of a system. These exponents are statistics that quantify how much a system is deterministic when a small disturbance is introduced. Smaller Lyapunov exponents indicate a more deterministic system.

A chaos analysis based on the wavelet decomposition of EEG signals of healthy patient during a seizure-free interval and epileptic patient during a seizure, is conducted by Adeli *et al*. [55]. The randomness of EEG signal is measured in terms of the largest Lyapunov exponent and correlation dimension, of the different sub-bands of the EEGs for the detection of epileptic seizures. The effectiveness of these parameters was examined based on statistical importance of their differences between the EEG sub-bands. It was found that the LLE differentiates between the three groups in the lower frequency alpha sub-band [55]. Moreover, for the detection of seizures and epilepsy, Adeli et al.[35] presented a wavelet-chaos methodology for analysis of EEGs and EEG sub-bands. The wavelet-chaos method consists of three stages: I) wavelet analysis, II) preliminary chaos analysis and III) final chaos analysis. They use, as before, the estimators of CD and LLE. They also evaluated 4 types of classifier. The method was applied to EEG signals from (a) healthy or normal patients, (b) Affected or epileptic patients during a seizure-free interval (interictal EEG), and (c) epileptic subjects during a seizure (ictal EEG). The classification accuracy was higher than 95% [35].

2.3. FEATURE SELECTION & CLASSIFICATION

2.3.1 Feature Selection: Generally, Feature selection is the important & critical part for algorithm based seizure prediction system since transition from the interictal to the ictal state consists of complex mechanisms, so the prediction algorithms usually combine several features in an attempt to cover brain dynamics. It affects the classifier performance for example, if correlated features are selected; they represent redundant information leading to confuse the classifier. Several feature selection methods have been used in seizure prediction studies, such as ReliefF [56], minimum normalized difference of percentiles [57], mDAD [57], forward selection, minimum redundancy maximum relevance (mRMR) [58], and genetic algorithm (GA) [59]. We will discuss the latter 2 methods in this review because of their extensive citation.

In mRMR algorithm, we rank the features on the basis of maximum relevance and minimum redundancy, defined in terms of cost function. While mutual information is one of the most common cost functions [58], several metrics have been proposed, all having the same principle and relying on criteria of similarity. In [59], F-testing which is measure of relevance and Pearson's correlation as a measure of redundancy, is used as a basis for cost function in the mRMR and used to reduce feature dimensions from 4410 to the first 132 ranked features. Bandarabadi et al. [10] employed the mRMR method based on a mutual information criterion to decrease feature dimensions from 435 to an average of 9.1 features.

The genetic algorithm is a method which is used for solving both constrained and unconstrained optimization problem. These problems are solved using the method of natural selection, the process that drives biological evolution. Starting from an initial, random population, the powerful reproduction to survive and adapt to their external environment. Inspired by natural evolution, GAs generate solutions to optimization problems based on mutation, crossover, inheritance and selection. There are several types of GA based on selection method, genetic structure, and fitness function, which have been tested in seizure-prediction studies. In [59], genetic structure is a binary string that includes features as well as classifier hyper-parameters. An Elitist Non-dominated Sorting-based GA was included for the selection stage. Ataee et al. [60] proposed a GA-based method that optimizes selection of the best feature vector as well as its optimal window length. GA fitness function was based on Fisher Discriminant Ratio. These authors stated that window length and feature vector should be chosen simultaneously. However, it is not clear if out-of-sample testing was performed in this study. In [21], genetic structure was a binary string in which each feature was a binary number. The fitness function was classification loss according to a K-Nearest-Neighbor classifier. It is important to mention that since GA is an iterative procedure that aims to find an optimal combination of features, the size of the selected subset is not fixed and may vary.

2.3.2 Classification Algorithms: A prediction mechanism should be implemented based on the features selection which can detect the pre-ictal state. Two main approaches one is threshold based and other one is machine learning technique have been proposed to detect the pre-ictal state and they form the core of algorithmic seizure prediction studies [61].

The decision boundary between classes is drawn based on classification and is tagged using measured features. The classifier can be as simple as fixing a threshold for features or more sophisticated, such as machine learning algorithms. The obtained decision boundary is transformed into hyper planes in multidimensional feature space having maximum distance from all classes. The techniques which had played significant role in detecting epileptic seizures are ANNs, LDA, Hidden, Markov modeling, K-means clustering, fuzzy logic, and SVMs.

Various clustering and classification techniques have been developed, out of which association rules, ANNs, LDA, hidden Markov modeling (HMM), *k*-means clustering, fuzzy logic, and SVMs have mainly been used to detect epileptic seizure. Some of the important classifiers are explained below.

2.3.2.1. Support vector machines: The most popular approach in supervised machine-learning which have been adopted in a large number of seizure-prediction methods is the support vector machine (SVM) [10,23]. SVMs have been used to find the hyper plane for multidimensional data. The basic idea behind the SVM is to find a hyper plane in a feature space that optimally separates two classes. In other words a SVM is a margin classifier that implements a separating hyper-plane that maximizes distance between the nearest training points. This separation can be done by a decision boundary: cost and cost factor. Optimal pairing of these parameters can be achieved with cross validation [13] or grid search [7, 10, 46]. The most facing problem with the SVM is the imbalance between the number of samples of preictal and ictal state of the seizure. The accuracy of classifier depends on the dominating type of signals in the samples. Thereby, in most of the cases results in prediction of non-preictal samples[62].Several approaches like re-sampling have been taken to address this issue resulting in a balanced number of samples between the 2 classes [7,10]. Park et al. [13] deployed cost-sensitive support vector machines which are implemented by setting higher misclassification penalties on preictal data than on non-preictal data to handle imbalances in sample numbers. This type of SVM has proved to outperform comparison to other types of classifiers in terms of sensitivity and specificity. In Teixeira et al. [7] , a study of 278 patients from the European Epilepsy Database, compared the performance of 3 classifier types: an SVM, an artificial neural network with a multilayer perceptron structure and an ANN with a RBF structure. Interestingly, considering different processing possibilities, this comparison included 224,928 different classifier structures. The performance of the prediction algorithm significantly depended on classifier type (K-W test, $p < 0.01$) with better SVM performance in terms of FPR. Assi et al. [21] find out performance superiority with a SVM compared to an Adaptive Neuro-Fuzzy Inference System in terms of sensitivity and specificity but without any statistical testing or validation because of the small population size [7,10,13].

2.3.2.2. Artificial neural network : Artificial neural networks are a mathematical analogy of the low-level functions of biological neurons. ANNs is able to produce nonlinear decision boundaries while assembling several artificial neurons. The general structure consists of an input layer, a hidden layer, and an output layer. In this, knowledge about the problem is distributed in each functional unit (neuron) and connection weights of links between neurons.

The neural network is trained taking feature vectors as inputs to produce the desired mapping. The relationship is established between the input pattern and output by adjusting variables parameters, weights and biases. Costa et al.[63] compared the performance of 6 different ANN architectures for predicting epileptic seizures: RBF, Feed-Forward Back Propagation, Layer-Recurrent, Feed-Forward Input Time-Delay Back Propagation, Elman, and Distributed Time Delay. While they reported optimistic results, the lack of statistical validation and adequate performance evaluation limited the significance and reproducibility of their findings.

2.3.2.3. Logistic regression: Logistic regression is a linear classifier having two parameters weights and biases. This classifier has been successful in seizure prediction as it separates two classes by linear decision boundary. We have to find the adequate weights optimized by minimizing a predefined loss function while training the classifier. In a recent study that investigated the feasibility of seizure forecasting in canine epilepsy, Howbert et al. [24] used this classifier on 3 dogs to detect the preictal state based on spectral power features and found that this predictor were able to beat a random predictor with acceptable FPR and sensitivities. Mirowski et al. [64] evaluated the performance of bivariate synchronization features with 3 different classifiers: SVM, Logistic Regression, CNNs.

2.4. REGULARIZATION & PERFORMANCE EVALUATION

2.4.1 Regularization: To reduce the number of false alarm, a regularization function should be added after classification. The method temporal signal dynamics, such as Kalman filtering [65] or the firing power technique [61], have been employed for the regularization. The main goal of regularization is to improve the correctness of the classifier in alarm generation. Firing power is a measure that quantifies the number of predictions classified as preictal during the SOP. An alarm is generated if this measure exceeds a normalized threshold. The firing power technique gives good result while used by several studies [15,16]. Teixeira et al.[7] and Bandarabadi et al. [10] adopted a fixed threshold of 0.5.C. Teixeira et al. [66] showed that low threshold value gives lower FPR while comparing different thresholds (0.10, 0.15,. . .,0.85). Chisci et al. [65] were used the Kalman filtering approach as a regularization method to smooth SVM classifier out-put. This statistical paradigm that produces estimates tending close to true measurements. These authors compared the performance of the proposed method with that of a non-regularized classifier on iEEG in 9 patients from the University of Freiburg database. There was a significant improvement in performance but there is no statistical testing was done.

2.4.2. Performance Evaluation: Various methods and algorithms have been proposed to automatically detect epileptic seizures. However, there is no framework to assess the performance of seizure detection algorithms. It should be compared using the same dataset. The metrics employed to compare seizure detection systems vary from publication to publication, with different terms sometimes used to name a given measure. The performance descriptors are generally not sufficient alone but it should be validated statistically due to the complexity and proof of principle status of the seizure prediction field. Performance descriptors evaluate the performance of prediction algorithms, in which sensitivity and specificity are being analyzed. Testing the system performance on data used for training has previously led to overoptimistic results, as discussed in [67]. Several other measures have been adopted to evaluate system performance in terms of specificity, such as FPR and Time under False Warning. FPR is the number of false predictions per hour means an alarm is raised during any period other than preictal. FPR has been adopted as a measure of specificity in a large number of seizure prediction studies [7,10,13,57,68,69,70,71]. However, no minimum FPR value has been adopted as standard.

2.4.3. Comparison of Seizure detector performance: As mentioned previously, it is very difficult to compare seizure detection algorithms. To compare published algorithms, works using the same dataset are grouped and their performance in terms of accuracy (ACC), average detection rate (ADR), false detection rate (FDR), sensitivity (SEN), selectivity (SEL), and specificity (SPE) are summarized in Tables 2 and 3 based on the two validated EEG databases most used by researchers are briefly given below.

Table 2: Performance of detectors that use FSPEEG database

Reference	Number of patients	Metrics
Schad et al. (2008)	FSPEEG-IEEG (6 patients)	SEN = range between 38% and 77% with FDRmax
Aarabi et al. (2009)	FSPEEG-IEEG	SEN = 68.9% SPE = 97.8% SEL = 58.9% ADR = 82.8%
Raghunathan et al. (2011)	FSPEEG-IEEG (5 patients)	SEN = 87.5% SPE = 99.82% ADR = 93.66%
Orosco *et al*. (2011)	FSPEEG-IEEG	SEN = 41.4% SPE = 79.3% SEN = 69.4% SPE = 69.2%

Table 3: Performance of detectors that use Andrzejak database

Reference	Database	Metrics
Güler and Ü beyli (2005)	Andrzejak-IEEG/SEEG	ACC = 98.68%
Kannathal *et al*. (2005)	Andrzejak-IEEG/SEEG	ACC = 90%
Adeli (2007)	Andrzejak-IEEG/SEEG	Not comparable with others
Polat and Günes (2007)	Andrzejak-IEEG/SEEG	ACC = 98.72%
Subasi (2007)	Andrzejak-IEEG/SEEG	ACC = 95%
Tzallas *et al*. (2007)	Andrzejak-IEEG/SEEG	ACC = 100%
Chua et al. (2008)	Andrzejak-IEEG/SEEG	ACC = 88.78%
Guo et al. (2010)	Andrzejak-IEEG/SEEG	ACC = 99.6%
Ü beyli (2009)	Andrzejak-IEEG/SEEG	ACCRNN =98.15% ACCMLPNN= 92.9%
Yuan *et al*. (2011)	Andrzejak-IEEG/SEEG	ACC = 96.5 %
Oweis and Abdulhay (2011)	Andrzejak-IEEG/SEEG	ACCEMD = 94% ACCMEMD = 80%
Orhan *et al*. (2011)	Andrzejak-IEEG/SEEG	ACC = 96.67%

3. Conclusion: The Technology has improved the automated detection of epileptic seizures from EEG. There is a potential for improvement and optimization in the framework of seizure prediction. Each block can be used for future scope of seizure prediction algorithms for the improvement of the outcome of proposed methodologies.

Wavelet Transformation and entropy is most used methods by researchers. The WT can be combined with other techniques, such as chaos, which decompose the signal in different scales according to the sampling rate of the signal, and the objective is to differentiate the normal EEG rhythms from epileptic ones. Entropy is used to quantify the level of order/disorder of EEG signal during the seizure. Furthermore the acceptance of EMD method has been increasing as an alternative to classical time-frequency techniques.

Artificial Neural Network (ANN) classifiers are used to predict the seizure on the basis of patterns described by extracted features. They are expected to learn about EEG seizures in order to differentiate normal EEG from the affected one. A similar method named Support vector machine (SVM) which has been demonstrated to be faster and easier to implement than ANN with comparable performance results. Thus SVM is slowly replacing ANNs in detection.

There must be some standards in the field of epileptic seizure detection. First, same metrics should be used for evaluating the seizure detector performance so that we can able for homogeneous comparisons. Second, there should be some rules & guidelines for the determination of EEG record type (scalp or intracranial) and as well as the duration of these records However, a good epilepsy detector should have at least 80% sensitivity and specificity but in the case of drug delivery systems, the performance must be 100%, whereas for alarm systems, it could be lower.

Therefore, the standardization of the evaluation metrics used for detectors is important. Some researchers have begun to establish guidelines and to look for consensus in the scientific community to achieve these objectives.

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