An Extensive Review of Significant Researches on Epileptic Seizure Detection and Prediction using Electroencephalographic Signals

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Abstract: Epileptic seizure is a brain disorder caused by large number of small electrical discharges of nerve cells. Electroencephalographic (EEG) signals are the most commonly used source for Epileptic seizure prediction. A variety of temporal changes in perception and behavior may be caused by Epileptic seizures. In the human EEG, they are depicted by multiple ictal patterns, where epileptic seizures typically become perceptible as characteristic, usually rhythmic signals, often concurring with or even preceding the earliest observable changes in behavior. Earliest possible detection of observable onset of ictal patterns in the EEG can, thus, serve to initiate more-detailed diagnostic procedures during seizures and to distinguish epileptic seizures from other stipulations with seizure-like symptoms. Lately, warning and intervention systems triggered by the detection of ictal EEG patterns have fascinated escalating interest. As the workload implicated in the detection and prediction of seizures by human experts is quite formidable, a number of attempts have been made to devise automatic seizure detection and prediction systems. So far, none of these have found extensive application. There have been an increased number of researches carried out with the purpose of devising an automatic seizure detection and prediction system.
In this paper, we present an extensive review of the significant researches associated with the detection and prediction of Epileptic Seizures using EEG signals. In addition, we have presented an in depth description of Electroencephalogram, Epileptic Seizure and its types along with Epilepsy.

**Keywords:** Brain, Electroencephalogram (EEG), Epilepsy, Seizures, Epileptic Seizures, Partial seizures, Generalized seizure, Electrooculogram (EOG), Epileptic Seizure prediction, Artificial Neural Networks (ANN), Correlation, Similarity Measure, Synchronization, Statistical analysis.

1. **Introduction**

Epilepsy is an important medical issue that stands for the disorder of cortical excitability. The right diagnosis of a patient’s epilepsy syndrome enables the choice of appropriate drug treatment and also assists an accurate assessment of prognosis in most cases. Human epilepsy is the intrinsic brain pathology in most of the cases [1]. Epilepsy is identified as the world’s second most common brain disorder after stroke with nearly 3 million people in the U.S. and over 40 million people worldwide (1% of the population) at present suffering from epilepsy. Uncontrolled epilepsy poses a significant burden to modern population owing to the associated health care costs. The diagnosis and treatment of epilepsy is convoluted by the disabling feature that seizures come about spontaneously and unpredictably because of the nature of the chaotic disorder [2]. Excessive, synchronized activity of large groups of neurons is the cause for Epileptic seizures. Based on the localization and degree of ictal epileptic activity, epileptic seizures can cause a variety of momentary variations in perception and behavior [3]. One aspect of understanding the mechanism of epilepsy and seizure development is to know how seizures evolve and progress [2].

The EEG is an important clinical tool for diagnosing, monitoring and managing neurological disorder associated with epilepsy [4]. In EEG, the epileptic seizures become lucid as characteristic, typically denoted by rhythmic signals, frequently correspond with or even preceding the earliest discernible changes in behavior. EEG’s chief manifestation is the epileptic seizure, which can encompass a discrete part of the brain partial or the complete cerebral mass generalized [5]. Some significant parameters are extracted from EEG signals, which are greatly beneficial for the diagnosis of epileptic seizure. Regardless of over 40 years of analysis into the physiology of epilepsy, it is still impossible to elucidate how and over what time period spontaneous clinical seizures materialize from the relatively normal brain state observed between them [6]. As seizures are concise and comparatively unpredictable, continuous EEG/ECoG (Electrocorticogram) monitoring is required to implement new therapies, such as contingent electrical stimulation for seizure blockage, via implantable devices, in subjects with pharmaco-resistant epilepsies [7].

Seizures are manifested in the EEG as paroxysmal events characterized by stereotyped repetitive waveforms that advance in amplitude and frequency before decaying ultimately [8]. There are many anomalies that occur naturally in EEG signals that declare an occurrence of seizure by causing detectors to fire when actually it is not. Nevertheless, seizures should be detected as early as possible so that the medication can be provided right away to control the seizure without further consequences [9]. Researchers have now agreed that the EEG signal of an epileptic patient depicts a more complex behavior that includes a ‘preictal’ stage in addition to ‘seizure’ and ‘interictal’ states [10]. Owing to the increasing number of patients with epilepsy and the substantial workload involved in the detection of seizures by human experts, several attempts have been taken to devise automated seizure detection systems [3]. Copious number of researches has been performed to improve the detection, prediction and understanding of epilepsy. Current researches are carried out to perk up the methods in existence. Up gradations and implications on the existing methods owing to arguments are yet in discussion term. Existing works in literature performed by other researchers on EEG...
detection was algorithm development that is based on pattern recognition of spike and sharp wave detection [11].

Modern research also has focused on physiological and biochemical mechanisms that are triggered during seizures. On the other hand, a seizure encompasses large portions of the cerebral cortex, hence, ten to hundreds of thousands of interacting neurons. So, it is probable that analysis into the epileptic brain as a system will reveal important mechanisms from underlying seizures [12]. Significant restraints of formerly published energy based methods for seizure prediction are that they are reliant upon selection of randomly chosen baseline data segments, and that they are by definition retrospective, and cannot be directly applied in a causal, real-time system [13]. Digitization of the EEG data allows the application of computerized algorithms that automate the seizure detection process; this is a considerable enhancement over visual analysis of thousands of hours of video or EEG data [14]. The long EEG recordings are made feasible by the rapid improvement in the performance ratio of computers and storage devices, but experts with the ability of investigating these recordings spanning possibly over twelve hours are in great demand, hence a system capable of performing automatic EEG evaluation to alleviate the work load of the examining physician is a lucrative prospect [5].

The development of a fully automated seizure detection system may be challenged by insurmountable factors namely, the possible inter-subject differences and the presence of artifacts that may lead to false positive detections. Nonetheless, even a semi-automated system with high sensitivity and specificity would be a valuable assist to physicians [8]. Numerous researches are available in the literature for automated detection and prediction of Epileptic seizures using EEG signals [28, 30, 31, 35 – 37, 50, 52 -54, 57]. One of the most exciting methods in epileptic seizures prediction and detection is the process of developing computational methods termed as classifiers (e.g. neural networks). The primary objective of these studies is to precisely determine the epileptic EEG states by the processing of extracted EEG features. Other computational tools such as neuro-fuzzy computing techniques were lately manifested as extremely promising in the identification of seizure patterns [16]. In this article, we have presented an extensive review of the noteworthy researches related with the detection and prediction of Epileptic Seizures using EEG signals. Along with this, a detailed description about Electroencephalographic signals, Epileptic seizures, types of epileptic seizures and epilepsy is provided.

The rest of the paper is organized as follows: In Section 2, an in depth description about Electroencephalographic signals is presented. A concise description of epileptic seizure and its types is provided in Section 3. The extensive reviews on the study of research techniques for Epileptic seizure detection and prediction using EEG signals are presented in Section 4. The conclusions are summed up in Section 5.

2. Electroencephalographic(eeg) signals

In 1923, Hans Berger discovered electrical activity from the cerebrum and termed them as Electroencephalographic (EEG) signals. These signals encompass of several distinct waves of different amplitudes and frequencies that characterize various processes, for instance sleep, rest, wakefulness, pathologies, etc. In general, Specific EEG patterns express a standard of normality; while abnormality is illustrated by the deviations from this standard [17]. The unavailability of an adequate model of the central nervous system that is consistent with the EEG observations severely hinders the interpretation of time-serial EEG data. Hjorth, in 1970, established three parameters (activity, mobility, and completeness) to illustrate and quantify the EEG signal in the spatio-temporal domain [18]. Ever since its introduction by Hans Berger in 1929, Electroencephalography (EEG) has been widely used as a clinical diagnostic tool for more than 70 years.
The EEG signal signifies the superposition of brain activities which are recorded as electrical potential variations at multiple spots over the scalp. The EEG signals absorb a significant amount of information concerned with the function of the brain. EEG obtained from scalp electrodes, is a superposition of a huge amount of electrical potentials arising from a number of sources (including brain cells i.e. neurons and artifacts) [21]. The electrooculogram (EOG) signal is the principal and most common artifact in EEG analysis caused by eye movements and/or blinks [19]. Repressing eye-blink over a sustained recording course is largely difficult due to its amplitude that is more than ten times the order of average cortical signals. Provided the blinking artifacts magnitude and the high resistance of the skull and scalp tissues, EOG might affect the superior part of the electrode signals including those recorded over occipital areas. Recently, it has become exceedingly simple to efficiently remove the eye-blink artifacts without any distortions to the underlying brain activity [20].

The potentials originating from independent neurons within the brain, not their superposition, are of chief importance to the physicians and researchers to demonstrate the cerebral activity. Direct measurements from the diverse centers in the brain necessitate the placement of electrodes inside the head, which in turn needs surgery. This was not suitable since it would cause pain and risk for the subject. An improved solution would be to determine the signals of interest from the EEG obtained on the scalp [22]. Signal processing is utilized to handle diverse issues in EEG analysis including data compression, detection and classification, noise reduction, signal separation, and feature extraction. The study of these signals is significant both for research and for medical diagnosis and treatment. Figure 1: illustrates a four second sample of an EEG data.

Figure 1: A four second sample of an EEG data

![EEG data](image)

EEG, a representative signal containing information of the electrical activity measured from the cerebral cortex nerve cells, has been the extensively used signal for the clinical assessment of brain activities, and the identification of epileptiform discharges. The pattern of electrical activity is chiefly advantageous for epileptic seizure detection and also to investigate other conditions that might affect brain function, like head injuries, brain tumors or bleeding on the brain (hemorrhage) [17].

3. Epileptic seizure and its types

Epileptic seizures signify one of the most frequent manifestations of neurological impairment in the pediatric population. Epileptic seizures can manifest themselves as either of the specified phenomena namely, positive or negative motor, sensorial, psychic and autonomic. Several definitions for epileptic seizures have been postulated. Epileptic seizures are characterized by the existence of synchronous, abnormal, sporadic and generally self-limited brain activity [23]. Epileptic seizures are caused by excessive, synchronized activity of large groups of neurons. Among the broad spectrum of mechanisms that are likely to cause pathologic activation include, structural malformations of the cerebral cortex, brain injuries of various types, and physiological
conditions leading to changes in network excitability. Based on the localization and extent of ictal epileptic activity, epileptic seizures can exhibit a variety of temporary changes in perception and behavior [3]. The most significant tool for the epilepsy diagnosis is the EEG, in which epileptic seizures become evident as characteristic, usually rhythmic signals, often coinciding with or even preceding the most primitive observable changes in behavior. Their detection can, thus, be used to counter to an impending or ongoing seizure, or to differentiate epileptic seizures from other conditions with paroxysmal, seizure-like symptoms. Epileptic seizures result from a temporary electrical disturbance of the brain. Sometimes seizures may go unnoticed, based on their presentation, and sometimes may be perplexed with other events, such as a stroke, which can also cause falls or migraines [24].

Seizures can be categorized as partial or generalized [25] (Table 1). Partial seizures usually originate from a discrete or localized area of the brain, and may or may not spread to other areas. If a patient sustains responsiveness during a partial seizure he/she is diagnosed with simple partial seizures. If non-responsive, the event is classified as a complex partial seizure. A simple partial seizure may develop into a complex partial and/or secondary generalized seizure. A generalized seizure does not have a regular onset, and an immediate loss of awareness is detected. There are numerous kinds of generalized seizures that are recognized namely: absence (brief lapse of awareness); the petit mal; grand mal (tonic then clonic activity); the convulsive; myoclonic (sudden massive jerk, usually of upper body); atonic (sudden loss of tone); and tonic (brief generalized stiffening) [25].

4. Extensive review of significant researches on epileptic seizure prediction and detection

Epileptic seizures are caused by the transient and unexpected electrical disturbances of the brain. Roughly stated, one in every 100 persons is likely to experience a seizure at some time in their life. The recording of seizures is of prime importance in the assessment of epileptic patients. Seizures can be defined as the phenomenon of rhythmicity discharge from either a specific area or the whole brain and the individual behavior generally lasts from seconds to minutes [23]. In general, as seizures are observed occasionally and unpredictably, automatic detection of seizures during long-term electroencephalograph (EEG) recordings is greatly recommended. Since EEG signals are non-stationary, the general methods of frequency analysis are not satisfactory for diagnostic purposes. A plentiful of researches is available in the literature concerned with automated detection and prediction of epileptic seizures using EEG signals. Here, we have conducted an extensive review of some of those noteworthy researches. The significant researches reviewed are classified based on the approaches utilized for detection and prediction,

<table>
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<tr>
<th>Table 1. Classification of Seizures</th>
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<td><strong>Partial (seizures with a focal or localized onset)</strong></td>
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<tr>
<td>- Simple partial (awareness* is not lost)</td>
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<td>- Complex partial (loss of awareness)</td>
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<tr>
<td><strong>Generalized (Generalized seizures affect both hemispheres simultaneously, without a focal onset.)</strong></td>
</tr>
<tr>
<td>- Absence seizures</td>
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<tr>
<td>- Myoclonic seizures</td>
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<td>- Tonic seizures</td>
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<td>- Clonic seizures</td>
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<tr>
<td>- Atonic seizures</td>
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<td>- Tonic-clonic seizures</td>
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like neural networks, similarity measurement, correlation and more.

4.1. Review of similarity measure based approaches

Lee M. Hively and Vladimir A. Protopopescu [17] have provided a solution for the blind application of Phase-space dissimilarity measures (PSDM) that might produce a problem of channel discrepancy, whereby several datasets from the identical patients give way to contradictory forewarning indications in the same channel. When compared to the intracranial data, the use of scalp EEG was much less invasive. Channel-consistent total trues are a much more stringent measure of forewarning performance, which was addressed by: 1) formulating a quantitative measure of channel consistency in both true positives (TPs) and true negatives (TNs) for multiple datasets from several patients; 2) measuring forewarning performance in terms of channel-consistent total trues; 3) developing a methodology to make the most of this performance measure; and 4) showing that these improvements raise the channel-consistent total trues considerably.

Thomas Maiwald et al. [29] have suggested a method for determining the performance of a seizure prediction method based on the application of the seizure prediction characteristic as a function of sensitivity and the maximum false prediction rate (FPRmax), the seizure prediction horizon (SPH), and seizure occurrence period (SOP). Three nonlinear seizure prediction methods were evaluated and those methods were compared to select an appropriate method for a particular patient and type of intervention. For a range of FPRmax between 1 and 3.6 per day, SPH shorter than 2 min and SOP up to 30 min, the dynamical similarity index is considered to be the best result among the three evaluated prediction methods, as it attained sensitivity between 21 and 42%. In the accumulated energy, the sensitivity of increments lie between 18 and 31%, and for the dimension drops of the effective correlation dimension, between 13 and 30%. The higher values of FPRmax are questionable when dealt with clinical applications. Even with a sensitivity of 100%, at least 50% of all alarms would be false alarms, while monitoring patients. When compared to the performance of the unspecific methods like the random or periodical prediction, the outcomes of the investigated nonlinear prediction methods were considerably better. Even then, for clinical applications the resultant seizure prediction characteristics were not adequate.

To study the problem of seizure prediction, Wanpracha Chaowlitwongse et al. [30] have offered the dynamical approaches and multi-quadratic integer programming techniques. The data utilized in their study comprises of continuous intracranial electroencephalograms (EEGs) from patients with temporal lobe epilepsy. The attained results verified their hypothesis that the set of most converged cortical sites in the current seizure and the reset after seizure onset was more likely to be converged again during the next seizure than other converged cortical sites. Based on the optimization and nonlinear dynamics of multichannel intracranial EEG recordings, it was likely to guess an impending seizure. To guess epileptic seizures, the outcome of their study can be utilized as a criterion in order to pre-select the critical electrode sites. Since the cortical sites taking part in the preictal transition varied from seizure to seizure, development of a seizure prediction algorithm was complex. The above problem was solved by the use of their proposed approaches to solve multi-quadratic 0 - 1 problem, as the algorithm chooses the candidate electrode sites and by analyzing continuous EEG recordings of numerous days of duration, the computational approach was used to resolve the optimization problem capably.

In order to find out epileptic seizures in electroencephalograms (EEG), an enhanced dynamic similarity measure has been developed by Xiaoli Li and Ouyang [31]. They have employed three methods to predict epileptic seizures. Initially, mutual information measure [26] and Cao’s method [27] were employed to reconstruct a phase space of preprocessed EEG recordings by using the positive zero crossing method. Later on, a Gaussian function was used...
to replace the Heavy side function within
correlation integral at calculating a similarity
index. The crisp boundary of Heavy side
function was eliminated because of the Gaussian
function’s smooth boundary. Finally, an
adaptive detection method based on the
similarity index was proposed to predict the
epileptic seizures. They carried out tests on
twelve rats to illustrate that their dynamical
similarity index was good to predict the epileptic
seizures. From the test results of the EEG
recordings of the rats, it has been revealed that
the new dynamical similarity index was
insensitive to the choice of the radius value of
Gaussian function and the size of segmented
EEG recordings. With the dynamical similarity
index -linear developed by Le Van Quyen et al.
[28] they then compared their method and
summarized that their similarity index was
insensitive to the choice of the radius value and
the EEG signal length, it was more robust during
the interictal state than dynamical similarity
index, and the false positive rate was minimized
and also it has gained a longer anticipation time.
At last, they have concluded that their similarity
index is very much robust than dynamical
similarity index during the interictal state.

4.2. Review of Synchronization based
approaches

The process of seizure generation is strongly
related with an abnormal synchronization of
neurons. With the intention of examining the
process, Florian Mormann et al. [34] have
measured phase synchronization between
diverse regions of the brain by means of
intracranial EEG recordings. On the basis of
their preliminary finding of a preictal drop in
synchronization, they examined whether the
planned phenomenon can be utilized as a
sensitive and particular criterion to characterize
a pre-seizure state and to differentiate the state
from the interictal interval. The examination of
the spatial distribution of preictal
desynchronization specified that the process of
seizure generation in focal epilepsy was not
essentially confined to the focus itself, but may
as an alternative involve more distant, even
contra-lateral areas of the brain. At the same
time, their work illustrated an intra-hemispheric
asymmetry in the spatial dynamics of preictal
desynchronization that is found in most of the
seizures and appears to be an imminent part of
the mechanisms underlying the initiation of
seizures in humans.

Thomas Kreuz et al. [35] have developed a
methodology to verify the performance of
measures used to predict epileptic seizures
statistically. Firstly they have produced an
ensemble of surrogates by a constrained
randomization by means of simulated annealing
from the measure profiles rendered by applying
a moving-window technique to the
electroencephalogram. The seizure prediction
algorithm was then applied to the original
measure profile and to the surrogates. If there
are any noticeable changes prior to seizure onset
exist, highest performance values were to be
attained for the original measure profiles along
with the null hypothesis. By applying two
measures of synchronization namely, mean
phase coherence and event synchronization to a
quasi-continuous EEG recording and by
assessing their predictive performance by means
of a straightforward seizure prediction statistics
they have demonstrated their method. Two
diverse evaluation schemes are utilized to
investigate the predictive performance of two
bivariate measures of synchronization, the mean
phase coherence as a measure for phase
synchronization [32] and the newly proposed
event synchronization [33]. It is recommended
that their proposed method was moderately
universal and has been applied to a lot of other
prediction and detection problems.

To a selected subset of multi-contact intracranial
EEG recordings, Matthias Winterhalder et al.
[36] have applied a phase and a lag
synchronization measure and evaluated changes
in synchronization with respect to seizure
prediction. From the results, they had
demonstrated that synchronization changes in
the EEG dynamics preceding seizures were used
for seizure prediction. They have investigated
the results of individual patient, groups, spatial
aspects using focal and extra-focal electrode
contacts and two evaluation schemes examining
decreased and increased synchronization.
Averaged sensitivity values of 60% were
observed for a false prediction rate of 0.15 false predictions per hour, a seizure occurrence period of half an hour, and a prediction horizon of 10 minutes. Approximately, from half of all the 21 patients, a statistically significant prediction performance was obtained for one synchronization measure and evaluation scheme.

Numerous efficient procedures were developed with the purpose of predicting the occurrence of epileptic seizures. Till now, all proposed algorithms are far from being adequate for a clinical application. This is usually not obvious when results of seizure prediction performance are reported. Schelter et al. [37] have stated the impacts of long prediction horizons for clinical needs and the strain on patients by examining long-term continuous intracranial electroencephalography data. On the basis of the synchronization theory, they have presented the assessment of a prediction method and also investigated the trade-off between intervention times and occurrence periods based on the long-term continuous intracranial EEG data sets of four patients extending over a number of days. On considering a therapy based on a prediction algorithm, the fraction of false alarms as well as the "false warning time" were estimated, i.e., the ratio of time the patient is awaiting for a non-occurring seizure. They have applied a statistical test so as to check whether the achieved performance is certainly better than that of a random predictor for calculating the performance of the prediction method.

4.3. Review of Correlation based approaches

For patients with medically intractable epilepsy, there have been very small numbers of efficient techniques that would substitute resective surgery, a destructive, irreversible treatment. A strategy is gaining improved attention which utilizes interictal spike patterns and continuous EEG measurements from epileptic patients to foresee and lastly control seizure activity by means of chemical or electrical control systems. Kristin K. Jerger et al. [30] have conducted a comparative study of their results of seven linear and nonlinear methods (analysis of power spectra, cross-correlation, principal components, phase, wavelets, correlation integral, and mutual prediction) in detecting the most primitive dynamical changes prior to 12 intracranially-recorded seizures from 4 patients. To compare the methods, they utilized a method of standard deviations, and the initial variations from thresholds identified from non-seizure EEG are compared to a neurologist's judgment. Even though, investigation of phase correlation proved to be the most robust, all the other methods explained were also successful in identifying deviations leading to a seizure between one and two minutes previous to the first changes noticed by the neurologist. The achievement of phase analysis can be owed to its complete insensitivity to amplitude, which has given a significant source of error.

From nonlinear analysis the performance of traditional linear (variance based) methods for the recognition and prediction of epileptic seizures are differentiated with "modern" methods. In demonstrations claiming to set up the efficiency of nonlinear techniques a number of flaws of design are noticed by Patrick E. McSharry et al. [40]. For precursor identification they have inspected the published evidence in specific. By means of relevant surrogate data they have performed null hypothesis tests to show that decreases in correlation density before and during seizure reflected increases in the variance. To find out the role of diverse linear correlation they have used Block Univariate surrogates and Block Multivariate surrogates. Window by window these surrogates are built as well as the variance in each window was also protected for correlation calculation. A simple linear statistic (variance) is compared with a nonlinear statistic (the correlation density [38]) which is used in [39].

The arbitrariness of the occurrence of epileptic seizures contributes to the burden of the disease to a major degree. In order to guess the onset of seizures on the basis of EEG recordings several methods have been proposed. An apparently challenging approach is a nonlinear feature motivated by the correlation dimension. Formerly the studies showed that this method is for recognizing 'preictal dimension drops' up to
19 min before seizure onset, more than the variability of interictal data sets of 30-50 min duration. The sensitivity and specificity of that method is examined by Aschenbrenner-Scheibe et al. [41] on the basis of invasive long-term recordings from 21 patients with medically intractable partial epilepsies, those who went through the invasive pre-surgical monitoring. Within time windows of up to 50 min before seizure onset and interictal periods was examined the relation between the dimension drops is later analyzed. Based on the prediction window length for false-prediction rates below 0.1/h, the sensitivity varied from 8.3 to 38.3%. On the whole, the mean length and amplitude of dimension drops demonstrated no noteworthy differences between interictal and preictal data sets. To predict seizures with enough specificity it is accomplished that, to recognize changes during interictal periods the sensitivity of the method may cause a fundamental limitation to its ability employed affect PPV and sensitivity.

To distinguish interictal spikes and seizures from normal brain activity, noise, and, artifact long-term EEG monitoring in chronically epileptic animals creates very big EEG data files which require efficient algorithms. On the basis of the below mentioned facts Andrew M. White et al. [14] have compared four methods for seizure detection 1) utilizing amplitude squared (the power method) the computed EEG power, 2) the sum of the distances between consecutive data points (the coastline method), 3) automated spike frequency and duration identification (the spike frequency method), and 4) data range autocorrelation combined with spike frequency (the autocorrelation method). The method was employed by them in order to examine a arbitrarily chosen test set of 13 days of continuous EEG data in which 75 seizures were imbedded which were taken from eight dissimilar rats representing two diverse models of chronic epilepsy (five kainate-treated and three hypoxic-ischemic). The EEG power method had a positive predictive value of 18% and a sensitivity of 95%, the coastline method had a PPV of 78% and sensitivity of 99.59, the spike frequency method had a PPV of 78% and a sensitivity of 95%, and the autocorrelation method yielded a PPV of 96% and a sensitivity of 100%. By means of computationally effective unsupervised algorithms they are likely to find out seizures automatically in prolonged EEG recording. PPV and sensitivity is affected by the quality of the EEG as well as the analysis method used.

Estimation of the Hurst parameter provides information Regarding the memory range or correlations (long vs. short) of processes (time-series). For the Hurst parameter an application is designed by Ivan Osorio and Mark G. Frei [7], real-time event detection, was recognized. By means of the following factors Hurst parameter is estimated, rescaled range (R/S), dispensual analysis (DA) and bridge detrended scaled windowed variance analyses (bdsWV) of seizure time-series recorded from human subjects reliably identify their onset, termination and intensity. Through the signal decimation detection the sensitivity was unaltered as well as the window size is increased. The high sensitivity to brain state changes, the capability to operate in real time and small computational requirements have done the Hurst parameter estimation the most suitable for implementation into miniature implantable devices for contingent delivery of anti-seizure therapies.

Owing to the detection of seizure and epilepsy Hojjat Adeli et al. [42] have offered a wavelet-chaos methodology for analysis of EEGs and delta, theta, alpha, beta, and gamma sub-bands of EEGs. In the form of the correlation dimension (CD, representing system complexity) and the largest Lyapunov exponent (LLE, representing system chaoticity) the non-linear dynamics of the original EEGs are quantified. The new wavelet-based methodology isolated the changes in CD and LLE in specific sub-bands of the EEG. The methodology was applied to three diverse groups of EEG signals: healthy subjects, epileptic subjects during a seizure-free interval (interictal EEG), and epileptic subjects during a seizure (ictal EEG). The effectiveness of CD and LLE in distinguishing between the three groups is examined based on statistical importance of the variations. It has been noted that in the values of the parameters acquired from the original EEG there may not be noteworthy differences,
differences may be recognized when the parameters were employed in conjunction with particular EEG sub-bands and concluded that for the higher frequency beta and gamma sub-bands, the CD distinguished between the three groups, in disagreement to that the lower frequency alpha sub-band, the LLE distinguished between the three groups.

4.4. Review of Neural Networks based approaches

The efficiency of utilizing an artificial neural network (ANN) is assessed by Steven Walczak and William J. Nowack [43] in order to determine epileptic seizure occurrences for patients with lateralized bursts of theta (LBT) EEGs. By means of the examination of records of 1,500 successive adult seizure patients training and test cases are obtained. Owing to the development of the ANN categorization models the small resulting pool of 92 patients with LBT EEGs requisite the usage of a jackknife procedure. Evaluations of the ANNs are for accuracy, specificity, and sensitivity on categorization of each patient into the correct two-group categorization: epileptic seizure or non-epileptic seizure. By means of eight variables the original ANN model generated a categorization accuracy of 62%. Consequently, a modified factor analysis, an ANN model using just four of the original variables attained a categorization accuracy of 68%.

One of the significant and difficult biometric problems is predicting the onset of epileptic seizure, which has gained increased attention of the intelligent computing community more than the past two decades. In order to extract the classifiable features from human electroencephalogram (EEG) by means of artificial neural networks (ANN) M. Kemal Kiymik et al. [44] have examined the performance of the periodogram and autoregressive (AR) power spectrum methods. Owing to the automatic comparison of epileptic seizures in EEG a method is offered by them, which allows the combining of seizures that have alike overall patterns. Every channel of the EEG was first broken down into segments having comparatively stationary characteristics. For each segment the features are calculated, and all segments of all channels of the seizures of a patient are combined into clusters of same morphology. With the examination of 5 patients with scalp electrodes that demonstrated the capability of the method to cluster seizures of alike morphology and observed that ANN categorization of EEG signals with AR preprocessing gave improved outcome, and those outcome could also used for the deduction of epileptic seizure.

The use of autoregressive (AR) model is examined by Abdulhamit Subasi et al. [45] by using utmost likelihood estimation (MLE) also interpretation together with the performance of this method to dig out classifiable features from human electroencephalogram (EEG) by means of Artificial Neural Networks (ANNs). It is noticed that; ANN classification of EEG signals with AR produced noteworthy results. Their approach is on the basis of the earlier where the EEG spectrum enclosed a few characteristic waveforms which fall primarily within four frequency bands-delta (< 4 Hz), theta (4–8 Hz), alpha (8–14 Hz), and beta (14–30 Hz). For the automatic classification of seizures a method is offered as well as attained a classification rate of 92.3% by means of a neural network with a single hidden unit as a classifier. The classification percentages of AR with MLE on test data are over 92%. As a result of employing FFT as preprocessing in the neural net an average of 91% classification is attained.

The application of quantum neural networks (QNNs) in finding out the epileptic seizure segments from neonatal EEG has been defined by Karayiannis et al. [46]. The ability of QNN is assessed in order to capture and quantify uncertainty in data and their performance is evaluated against that of conventional feed forward neural networks (FFNNs). In their examination the major problem which was taken into account is the classification of short sequences of neonatal EEG recordings. Owing to the classification of short segments of epileptic seizures in neonatal EEG QNNs and FFNNs are trained in their work. Both the FFNN and QNN comprise one sigmoid output unit.
necessary to respond with 1 (0) to input segments from the seizure (non-seizure) class. At the same time, they have assessed their ability to cope with ambiguity, their investigation first paid attention on the internal representation of sample training data by the two models. By demonstrating the ability of trained QNNs to put into practice a multi-level partition of the input space their experimental results are proved. To end with, on the capability of trained QNNs to capture the uncertainty linked with labeling input EEG segments as seizure or non-seizure segments is concentrated in their study. The uncertainty linked with labeling of input EEG segments is found from the responses of the trained QNN, specifically when the input EEG segments comprised few or no seizure segments in their next neighborhood. On the other hand, the uncertainty in the input data was not reproduced by the responses of the trained FFNN.

For optimizing seizure prediction a possible method is proposed by Maryann D’Alessandro et al. [10], offered with an array of implanted electrodes and a set of candidate quantitative features computed for every contact location. A genetic-based selection process is used by them, and then tuned a probabilistic neural network classifier in order to predict seizures within a 10 min prediction horizon. For training initial seizure and interictal data is utilized, as well as for testing the remaining intercranial electroencephalogram (IEEG) data is employed by them. It is illustrated from their work that a prospective, exploratory implementation of a seizure prediction method is designed to get used to each patients with a vast variety of preictal patterns, implanted electrodes and seizure types. More than two workshop patients they have validated and exposed their results as well as demonstrated a sensitivity of 100%, and 1.1 false positives per hour for Patient E, using a 2.4 s block predictor, and a failure of the method on Patient B.

For seizure activities of the brain a neural network model has been designed by Hiremath and Udayshankar [47]. The seizure types and electroencephalographic features of glucose transporter type-I deficiency syndrome is characterized as well as built biologically plausible neural network model that shows spontaneous, stochastic transitions between low activity state and high activity state by merging in vivo electrophysiology, data analysis by means of neural network modeling. It is accomplished that the neural network model replicates a copy of many of the noticed activities of epileptically seizure (Glut-1 Deficiency Syndrome). Glut-1 Deficiency Syndrome data was called again as well as its characterization was studied by utilizing Hopfield Net Model. The most generalized EEG finding in all ages is a normal interictal EEG. To conclude they have noticed the mentioned seizure types: absence, myoclonic, partial, and atonic.

A wavelet-chaos-neural network methodology for classification of electroencephalograms (EEGs) into healthy, ictal, and interictal EEGs has been offered by Samanwoy Ghosh-Dastidar et al. [48]. In order to decompose the EEG into delta, theta, alpha, beta, and gamma sub-bands the wavelet analysis is utilized. Three parameters are used for EEG representation: standard deviation (quantifying the signal variance), correlation dimension, and largest Lyapunov exponent (quantifying the non-linear chaotic dynamics of the signal). The classification accuracies of the following techniques are compared: 1) unsupervised - means clustering; 2) linear and quadratic discriminant analysis; 3) radial basis function neural network; 4) Levenberg–Marquardt back propagation neural network (LMBPNN). The research was carried out in two phases with the intention of minimizing the computing time and output analysis, band-specific analysis and mixed-band analysis. In the second phase, over 500 different combinations of mixed-band feature spaces comprising of promising parameters from phase one of the research were examined. It is decided that all the three key components the wavelet-chaos-neural network methodology are significant for enhancing the EEG classification accuracy. Judicious combinations of parameters and classifiers are required to perfectly discriminate between the three types of EEGs. The outcome of the methodology clearly let know that a specific
mixed-band feature space comprising of nine parameters and LMBPNN result in the highest classification accuracy, a high value of 96.7%.

To categorize the types of epileptic seizures a simple approach is offered by Najumnissa and Shenbaga Devi [49]. Their concentration is on the detection of epileptic seizures from scalp EEG recordings. On the basis of two stages seizures are categorized: Stage I was a set of neural network-based epileptic seizure detector and stage II was a neural network, which classifies the abnormal EEG from, stage I. From 34 patients 436 features have been chosen. In order to train the neural network out of 436 feature sets, 330 feature sets from 26 patients are utilized and the remaining 106 feature sets of eight patients were kept for testing. By means of the wavelet transform technique the features are pulled out. Two networks are used by them one is for detecting normal and abnormal conditions, the second one for classification. The onset of the seizure was continuously moving by the window and the time of onset was recognized. In the tests of the system on EEG denoted a success rate of 94.3% was obtained. The system was made as a real-time detector by their method and it enhanced the clinical service of Electroencephalographic recording.

An automated epileptic system, which uses interictal EEG data to categorize the epileptic patients, was developed by Forrest Sheng Bao et al. [50]. The diagnostic system was used to detect seizure activities for additional examination by doctors and impending patient monitoring. They have built a Probabilistic Neural Network (PNN) fed with four classes of features extracted from the EEG data. Their approach was more efficient when compared to the present conventional seizure detection algorithms because they are seizure independent i.e. doesn’t necessitate the seizure activity attained from the EEG recording. This feature shuns intricacy in the EEG collection as interictal data was much easier to be collected than ictal data. In their work, the PNN was employed to classify 38 extracted EEG features. During cross validation their interictal EEG based diagnostic approach achieved a 99.5% overall accuracy. The classification based on ictal data also showed a high (98.3%) degree of accuracy. Thereby, with both interictal and ictal data their algorithm worked well. The function of the classifier was further extended to achieve patient monitoring and focus localization. An accuracy of 77.5% stated impending focus localization. The speed of the classifier was good classifying an EEG segment of 23.6 seconds in just 0.01 seconds.

Kezban Aslan et al. [1] have conducted a study to examine epileptic patients and perform classification of epilepsy groups. The classification process groups into partial and primary generalized epilepsy by employing Radial Basis Function Neural Network (RBFNN) and Multilayer Perceptron Neural Network (MLPNNs). The parameters acquired from the EEG signals and clinic properties of the patients are used to train the neural networks. The experimental results obtained, depicted that the predictions corresponding to the learning data sets were convincing for both neural network models. It would be stated from the results that RBFNN (total classification accuracy = 95.2%) produced better classification than MLPNN (total classification accuracy = 89.2%). From the results, it is determined that the RBFNN model can be used as a decision support tool in clinical studies to validate the epilepsy group classification after the development of the model.

4.5. Review of Statistical Analysis Based Approaches

An adaptive procedure is described by Leon D. Iasemidis et al. [24] to prospectively analyze continuous, long-term EEG recordings when the occurring time of the first seizure was only known. Their algorithm was on the basis of the convergence and divergence of STLmax [51] amid critical electrode sites chosen adaptively, and then a warning of an impending seizure was given. Owing to the selection of the critical groups of electrode sites Global optimization techniques were used. From a group of five patients with
refractory temporal lobe epilepsy the adaptive seizure prediction algorithm (ASPA) was tested in continuous 0.76 to 5.84 days intracranial EEG recordings. The ASPA algorithm was on the basis of the multi-electrode nonlinear dynamical analysis of the EEG. To all the predicted cases a fixed parameter setting was applied, 82% of seizures with a false prediction rate of 0.16/h. Seizure warnings take place at an average of 71.7 min before ictal onset. Optimizing the parameters for individual patients enhanced sensitivity (84% overall) and minimized false prediction rate (0.12/h overall). It has been known from the outcome that ASPA could be applied to implantable devices for diagnostic and therapeutic purposes.

Andrew B. Gardner et al. [53] have demonstrated a one-class support vector machine (SVM) novelty detection application meant for the detection of seizures in humans. By categorizing short-time, energy-based statistics calculated from one-second windows of data, their technique mapped intracranial electroencephalogram (IEEG) time series into corresponding novelty sequences. They have trained a classifier on epochs of interictal (normal) EEG. The seizure activity causes induction of distributional changes in feature space during the ictal (seizure) epochs of EEG. The above process increases the empirical outlier fraction occurs. A hypothesis test conducted subsequent to the parameter change varied radically from its nominal value, indicating a seizure detection event. In order to reduce the false alarm rate of the system the outputs were gated in a “one-shot” manner using persistence. The obtained results were better than the novelty detection technique based on Mahalanobis distance outlier detection. Also, it was almost equivalent to the performance of a supervised learning technique used in experimental implantable devices of Echauz et al., [52]. On comparison with other challenging methods, this detection paradigm overcame three significant limitations: the necessity to collect the seizure data, mark the seizure onset and offset times precisely and achieved detector training by performing patient-specific parameter tuning.

A stochastic framework based on a three state hidden Markov model (HMM) (representing interictal, preictal, and seizure states) has been presented by Stephen Wong et al [54]. The feature of the stochastic framework is the periods of increased seizure probability can change back to the interictal state. The clinical experience and improved interpretation of published seizure prediction studies has been reflected by their proposed concept. Their model consists of clipped EEG segments and formalized instinctive notions about statistical validation. In their work, equations were derived for the false-positive error and false-negative errors which provided the validation thresholds, which were used as a function of the number of seizures, duration of interictal data, and prediction horizon length. In addition to this, they have also verified the utility of the model with the proposed seizure detection algorithm that appeared to have predicted seizure onset. They proposed framework was an imperative tool for designing and validating prediction algorithms and for facilitating collaborative research in that area. The seizure prediction algorithm’s performance is computed against a null hypothesis. This is done in such a way that the outputs of a seizure prediction algorithm could be examined in a transparent fashion. Also it has produced measures to facilitate the process of calculating data requirements in clinical trials involving seizure prediction algorithm, which is a very useful and practical application in the clinical setting.
At last, their model redefined the preictal period as a stochastic, probabilistic state out of which seizures may occur.

4.5. Review of Other Researches

In order to forecast a universal epileptic seizure Amir B. Geva et al. [58] have offered electroencephalogram (EEG)-based brain-state identification method. On the existence in the EEG of a pre-seizure state the method relied, with extractable exclusive features, a priori without definition. 25 rats are exposed to hyperbaric oxygen till the generalized EEG seizure appears. With the help of the fast wavelet transform EEG segmented from the pre-exposure, early exposure and the period up to and together with the seizures is processed. Features that are taken out from the wavelet coefficients are inputted to the unsupervised optimal fuzzy clustering (UOFC) algorithm. By assigning every temporal pattern to one or more fuzzy clusters the vague brain transitions are obviously treated on the whole. By means of the categorization it was accomplished in recognizing numerous, behavior-backed, EEG states such as sleep, resting, alert and active wakefulness, as well as the seizure. From 16 instances a pre-seizure state, durable between 0.7 and 4 min are described. Substantial individual variability in the number in addition to the characteristics of the clusters postponed the realization of universal epilepsy warning in the early hours.

Evelyne Peeters [59] have devised a comprehensive decision tree to direct non-medically trained caregivers in treating seizures. The development proved useful within nonhospital settings of patients with proven and well-assessed epilepsy. It was examined over 16 months for its efficiency. The duration and severity of the seizures logged were recorded. Type, dose, and time of antiepileptic treatment were also noted. Results were compared against a retrospective review done over 6-months. Once the seizure onset was indicated in the tree, the antiepileptic drug treatment was to be initiated within 5 or 7 minutes. The application of the decision tree to seizure treatments resulted in decreased duration of seizures, lasting only up to 37 minutes in the prospective study when compared to 18 hours in the retrospective review. The patient’s experiencing seizure can be treated properly by the nonmedical staffs with the use of this tree. It was showed that with every seizure treated as a medical emergency, its duration, severity, and frequency were decreased. Decision tree implementation was suggested for establishments with patients prone to seizures. The usage of decision trees were taught to caregivers and parents of patients with well-known epilepsy.

An adaptive method employing electric fields for controlling epileptic seizure-like events in hippocampal brain slices has been described by Bruce J. Gluckman et al. [60]. The method involved the continuous recording of the extracellular neuronal activity during field application through differential extra cellular recording techniques, followed by the regular updation of applied electric field strength using a computer-controlled proportional feedback algorithm. Their approach when used with negative feedback was efficient enough for sustaining amelioration of seizure events. It was discovered that the induction or enhancement of seizures could be achieved using fields of opposite polarity through positive feedback. The set of findings in negative feedback mode provided a technology for seizure control.

Brian Litt et al. [61] have incessantly investigated intracranial EEG recordings from five patients with mesial temporal lobe epilepsy obtained during evaluation for epilepsy surgery collected over 3-14 days. They have perceived the localized quantitative EEG changes for recognizing prolonged bursts of complex epileptiform discharges that turned out to be more prevalent, 7 hr before seizures and highly localized sub clinical seizure-like activity that became more frequent 2 hr prior to seizure onset. Analyzing from a few patients they recommended that epileptic seizures may commence as a cascade of electrophysiological events that evolve over hours and those quantitative measures of pre-seizure electrical activity could perhaps be used to predict seizures very much prior to the clinical onset. Their
results demonstrated that the variations in cellular and network function that lead to epileptic seizures were likely develop over hours, providing exhilarating clue potential mechanisms underlying seizure generation. Moreover, their study enabled an immediate opportunity to develop intelligent, implantable therapeutic devices as precursors to be better understood. It was feasible to trace the initial precursors of seizures back to their site(s) of origin, perhaps enabling ablation of critical regions of abnormal function by minimally invasive surgery or other techniques to replace large-scale brain resections.

The detection of epileptic seizures from scalp EEG recordings was the area of focus for McSharry et al. [64]. A synthetic signal was created by merging a linear random process and a non-linear deterministic process. They introduced a multidimensional probability evolution (MDPE) statistic capable of detecting faint variations in the underlying state space that were associated with modifications in the dynamical equations used in production of synthetic signal. F-tests were used to calculate the significance of the observed difference between the variances of the recording, all through the learning period and testing the window. Moreover, the significance of the observed difference between the multidimensional distributions observed in the state space all through those periods are attained using tests and also the linear statistics and the MDPE statistics were used by them to analyze the database of scalp EEG recordings. The MDPE and variance were utilized for seizure detection but the MDPE offered better accuracy for seizure onset detection in recordings E/1, E/2, and F/1. Nonlinear statistics largely augmented the scope of automatic detection, but its utilization has justified on a case-by-case basis.

The electrographic onset of seizures in human mesial temporal lobe epilepsy was witnessed by brief bursts of focal and low amplitude rhythmic activity that were observed just a few minutes in advance, using the EEG. Those periods that constitute of discrete, individualized synchronized activity in patient-specific frequency bands ranging from 20 to 40 Hz was identified by Joel J. Niederhauser et al. [66]. They have offered a method termed as joint sign periodogram event characterization transform (JSPECT) meant for detecting and representing those events by means of a periodogram which is a sign-limited temporal derivative of the EEG signal. Then on application of JSPECT to incessant 2-6 day depth-EEG recordings from ten temporal lobe epilepsy patients, it illustrated that these EEG events which are patient-specific happened consistently 5-80s prior to electrical onset of seizures in five patients noticed with focal, unilateral seizure onsets. The rest of the patients with bilateral, extra temporal or more diffuse seizure onsets on EEG were not revealed to have this type of activity prior to the seizures by JSPECT. Seizure generation in temporal lobe epilepsy has been greatly influenced by Patient-specific, localized rhythmic events. Thereby, JSPECT method was found to efficiently detect those events and was used as component of an automated system for predicting electrical seizure onset in appropriate patients.

A dependable clinical application controlling seizures, comprising of a seizure prediction method and an intervention system would enhance the quality of patient’s life. On the basis of the clinical, behavioral, and statistical considerations, M. Winterhalder et al. [67] have extended the approach of Osorio et al [57], [65] and recommended the "seizure prediction characteristic" to assess and compare against the performance of other seizure prediction methods. Their assessment was carried out on the basis of the clinical and statistical considerations and it mainly concentrated on the properties and basic requirements of a clinically applicable seizure prediction method, which decides on the assessment criterion in a straightforward way. Their approach was demonstrated by its application to the "dynamical similarity index," a seizure prediction method using intracranial EEG data from 21 patients with pharmaco-refractory focal epilepsy that contains 582 hours of EEG data and 88 seizures. Finally, it has been predicted and summarized that the values of the seizure prediction characteristic of the dynamical

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similarity index are considerably superior to those of the unspecific prediction methods.

Maryann D’Alessandro et al. [6] have developed an individualized seizure prediction method for deciding on the EEG features and electrode locations on the basis of the precursors that arise within ten minutes of electrographic seizure onset. An intelligent genetic search process was applied to EEG signals obtained from multiple intracranial electrode contacts and derived multiple quantitative features. The method’s performance was evaluated on multiday recordings acquired from four patients implanted with intracranial electrodes during evaluation for epilepsy surgery. From that group, an average probability of prediction (or block sensitivity) of 62.5% was attained. The acquired results from individual patients were given as an example of a method for training, testing and validating a seizure prediction system on data.

The first prospective analysis of the online automated algorithm for detection of the preictal transition in ongoing EEG signals was reported by Panos M. Pardalos et al. [69]. Their algorithm comprised of a seizure warning system and also the developed algorithm estimated term highest Lyapunov exponent (STLmax), a measure of the order or disorder of the EEG signals recorded from individual electrode sites. For the warning of epileptic seizures, the optimization techniques were employed to choose critical brain electrode sites that showed the preictal transition. Particularly, a quadratically constrained quadratic 0-1 programming problem was devised to identify the critical electrode sites. The automated seizure warning algorithm was tested in continuous, long-term EEG recordings acquired from 5 patients with temporal lobe epilepsy. For every patient, the parameter settings were trained with the first half of seizures, which was evaluated by Receiver Operating Characteristic ROC curve analysis. The algorithm was applied to all cases predicted an average of 91.7% of seizures with an average false prediction rate of 0.196 per hour with the best parameter setting. Their results indicated that it was possible to develop an automated seizure warning devices for diagnostic and therapeutic purposes. The electrode selection problems were solved capably and the solutions were optimally achieved with the help of their technique.

Diagnosis, classification of seizure and epilepsy types, selection of appropriate auxiliary studies, selection of anti-epileptic drugs, and formulation of a long-term management plan are greatly influenced by a carefully organized clinical history. Nizan Ahmed and Susan S. Spencer [25] have presented a number of directions and guidelines for both the family practice physician and the specialists for evaluating the patient population in the clinics. Some of their suggestions are, for patients presenting with the first seizure, the arrangement of auxiliary studies like EEG and MRI for localization-related epilepsy should be done. Before initiating the antiepileptic drug, a complete blood count, liver function tests, electrolytes and renal function tests should be conducted. For patients with newly diagnosed seizures, a neurologist consultation is a must to address the necessity for further examinations and for the choice of antiepileptic medications.

The concept of exponential sensitivity to initial conditions (ESIC) of deterministic chaos is generalized to power-law sensitivity to initial conditions (PSIC). Jianbo Gao et al. [70] have analyzed the long continuous EEG signals with epileptic seizures by applying PSIC. For computationally investigating PSIC from a time series, they have explained an easily implementable procedure. They established that when there was no noise, the PSIC attractor could not be observed from a scalar time series by studying noise-free and noisy logistic and Henon maps near the edge of chaos. While the dynamic noise was present, the motions in the region of the edge of chaos were simply regular with the presence of dynamic noise or truly asymmetrical when there was no noise, all collapse onto the PSIC attractor. Therefore, dynamic noise was of great importance for the observation of PSIC. In identifying epileptic seizures from EEG signals, the PSIC concept has revealed that it was very efficient when compared to the Lyapunov exponent based methods from the conventional ESIC framework.
On the basis of the chaos theory and global optimization techniques, Chaovalitwongse et al. [71] have evaluated a method for identifying pre-seizure states by monitoring the spatiotemporal changes in the dynamics of the EEG signal. To quantify the EEG dynamics per electrode site, their method employed the estimation of the STLmax, a measure of the order (chaoticity) of a dynamical system. They employed a global optimization technique to find out critical electrode sites that took part in the seizure development. The development of an automated seizure warning system (ASWS) is a vital practical result obtained from the work. Their algorithm was tested in continuous, long-term EEG recordings, 3–14 days in duration, obtained from 10 patients with refractory temporal lobe epilepsy. From the results of their study, it was noted that a seizure warning algorithm was formulated to identify dynamical patterns of critical electrode sites that were capable of giving a seizure warning 22.4–135.0 min prior to a seizure onset. Yet, the performance (sensitivity and false prediction rate) of the ASWS algorithm was still significantly lower to the results reported from their previous seizure predictability studies.

Iasemidis et al. [72] have assessed the performance of a prospective on-line real-time seizure prediction algorithm based on data of two patients obtained from a common database. A dynamical entrainment detection method was combined with their previous observations presented in [62], [63], [68] to efficiently predict epileptic seizures. Subsequently, the algorithm was tested in two patients with long-term (107.54 h) and multi-seizure EEG data B and C ([73]). Lastly they have accomplished that their algorithm has offered warning of impending seizures potentially and in real-time that it was encompassed of an on-line and real-time seizure prediction scheme. They have also suggested that the proposed seizure prediction algorithm could be used in the diagnostic and therapeutic applications in epileptic patients.

Rosana Estellera et al. [13] have made an attempt to eliminate the constraints of seizure prediction methods that necessitated a comparison to ‘baseline’ data, sleep staging, and selecting seizures, by the application of continuously adapting energy threshold, and to recognize stereotyped energy variations through the seizure cycle (inter-, pre-, post- and ictal periods). Accumulated energy approximation was done by utilizing an adaptive decision threshold and moving averages of signal energy calculated for windows of length of 1 and 20 min. Predictions arose as the energy within the shorter running window was beyond the decision threshold. The experimental results have confirmed that predictions for time horizons of less than 3 h did not achieve statistical significance in the data sets analyzed that had an average inter-seizure interval ranging from 2.9 to 8.6 h. 51.6% of seizures across all patients exhibiting stereotyped pre-ictal energy bursting and quiet periods. They have concluded that the accumulating energy alone was not sufficient for predicting seizures using a 20 min running baseline for comparison.

The performance of an adaptive threshold seizure warning algorithm (ATSWA), which identifies the convergence in STLmax values amid critical intracranial EEG electrode sites, as a function of diverse seizure warning horizons (SWHs) was assessed by Chris Sackellares et al. [74]. The ATSWA algorithm was evaluated against two statistical based prediction algorithms (periodic and random) those do not utilize EEG information. Three performance indices “area above ROC curve” (AAC), “predictability power” (PP) and “fraction of time under false warnings” (FTF) were compared and defined followed by the assessment of the effect of SWHs on those indices. It was found that EEG based seizure warning method provided significantly better (P < 0.05) results than both prediction schemes. It was recommended that the EEG based analysis is utilized for seizure warning and their results established that the performance indexes were dependent on the length of the SWH.

The objectives of Simone Carreiro Vieira et al. [23] were to define the main epidemiological aspects of pediatric patients that present with the first unprovoked epileptic seizure, considering clinical data, classification of the seizures, electroencephalographic and neuro image
findings. To accomplish the same, they conducted a study on a group of patients from a tertiary pediatric hospital in the South of Brazil. All subjects chosen for study were subjected to EEG and cranial Computed Tomography (CT) within 72 hours after the occurrence of the event. Seizures were categorized based on the International League against Epilepsy (ILAE) classification criteria of 1981. They have revealed that there were 387 patients, 214 (55.3%) male, average age 4.2 years and neuropsicomotor development was normal in 315 (81.4%) patients. Seizure classification: 167 (43.15%) generalized, tonic-clonic being the most common of these (105/62.85%), pursued by typical absence (22/13.17%), clonic (20/11.98%), tonic (13/7.78%) and atonic (7/4.19%). Focal seizures: 220 (56.85%), complex partial with secondary generalization as the most common of these (81/36.82%). From the test set, 208 (53.75%) cases generated normal EEG results.

Florian Mormann et al. [75] have analyzed the seizure predictability by comparing the predictive performance of a variety of univariate and bivariate measures constituting of both linear and non-linear approaches. They have evaluated 30 measures based on their capability to distinguish between the interictal period and the pre-seizure period. They have investigated on the continuous intracranial multi-channel recordings from five patients and employed ROC curves to discern between the amplitude distributions of interictal and preictal time profiles computed for the respective measures. Moreover, they have compared different evaluation schemes comprising channel wise and seizure wise analysis plus constant and adaptive reference levels. Univariate measures depicted a statistically noteworthy performance only in a channel wise, seizure wise analysis using an adaptive baseline. Preictal changes associated with these measures happened 5–30 min before seizures. Bivariate measures showed signs of high performance values attaining statistical significance for a channel wise analysis utilizing a constant baseline. Preictal changes were detected as a minimum 240 min before the occurrence of seizures. Linear measures were found to achieve similar or better performance in comparison to non-linear measures. Lastly, they have concluded that the results stated a statistically significant evidence for the prevalence of a preictal state. From their research, it was evident that the most promising approach for prospective seizure prediction was a combination of bivariate and univariate measures.

Leon D. Iasemidis et al. [12] have conducted an investigation on brain dynamics by analyzing the multichannel, multiday EEG recordings with multiple epileptic seizures. The research demonstrated that: 1) critical cortical sites become dynamically entrained long (approximately 30 min) prior to a seizure and were dynamically disentrained considerably faster (approximately 12 min) following epileptic seizures. 2) At any time point t, the criterion for brain resetting was that the dynamical entrainment period before t was larger than the corresponding disentrainment period after t. Based on the aforesaid criterion, three hypotheses can be derived namely, Hypothesis I: Resetting takes place at seizure points involving a critical subset of cortical sites Hypothesis II: Resetting occurs specific to seizure occurrences, and Hypothesis III: Resetting is time-irreversible , and all these hypotheses were established at the 95% confidence level. The methodology of combining optimization and nonlinear dynamic techniques enabled to obtain better results. The results obtained were utilized for understanding the epileptic seizures and epileptogenesis, and also for the treatment of epilepsy and the spatiotemporal transitions of dynamical systems (e.g., in coupled chaotic systems of spatial extent).

G.R. de Bruijne et al. [76] have proposed a patient monitoring system based on audio classification for detecting the epileptic seizures. The system facilitated an automated detection of the epileptic seizures which is likely to have a significant positive impact on the daily care of epilepsy patients. Their system comprised of three stages. First, the signal was improved by means of a microphone array, followed by a noise subtraction procedure. Secondly, the signal was evaluated by audio event detection and
audio classification. The characteristics were extracted from the signal on detection of an audio event. Bayesian decision theory was used to categorize the feature vector on the basis of discriminate analysis. At last, it decides whether to activate an alarm or not. With the help of the audio signals obtained from the measurements with the epileptic patients the performance of the system was tested. They have achieved better classification results with a limited set of features.

Epilepsy patients with burn injuries have been reported extensively. An epileptic attack occurs generally accompanied by a short period of unconsciousness in which patients are likely to be exposed to heat resulting in severe and deep burns. We should not underestimate the burn injury caused by seizures, which is of serious concern for epileptic patients. A surgical interference is required almost every time to heal such kind of deep injuries. I.A. Adigun et al. [77] have conducted a review over the last five years on the total number of burn patients managed in their unit. In that they observed 2 patients with burn injury because of epilepsy. Finally they have presented a prevention measure to avoid the burn injury in epileptic patients.

Sonia Rezk et al. [78] have offered a new mathematical tool of estimation to solve the problem of the physiological signals analysis, markers of unexpected changes such as an epileptic activity in EEG and QRS complex occurrence in ECG. The tool was built on the basis of a combination of differential algebra and operational calculus [55], [56]. They have advocated an estimator of the "instantaneous" angular frequency with the aid of a simple local model making certain a physiological signal representation during a short lapse of time. Their method was applied to the EEG recordings of patients recovering from an epileptic activity for seizure detection.

A method for generic, online, real-time and automated detection of multi-morphologic ictal-patterns in the long-term human EEG and its validation in continuous, routine clinical EEG recordings collected from 57 patients with duration of approximately 43 hours and additional 1,360 hours of seizure-free EEG data for the inference of the false alarm rates has been presented by Ralph Meier et al. [3]. They have deduced that the detection performance of the system was greatly improved by taking the seizure morphology into account. Moreover, it facilitates a reliable (mean false alarm rate < 0.5/h, for specific ictal morphologies < 0.25/h), premature and precise detection (average correct detection rate > 96%) within the first few seconds of ictal patterns in the EEG. Their system enabled the automated categorization of the common seizure morphologies without the need to adapt to specific patients.

Ariane Schad et al. [15] examined on two multivariate techniques based on simulated leaky integrate-and-fire neurons to detect and predict seizures. The application and assessment of both the techniques on EEG recordings of 423 h resulted in recordings of 26 seizures simultaneously from the scalp and intracranium continuously over a few days from six patients with pharmaco-refractory epilepsy. The examined methods were successfully applied to the intracranial EEG as it is with non-invasive EEG. Specifically, the method illustrated a promising performance for seizure detection which was suitable for practical applications in EEG monitoring. A similar dynamical performance was exhibited by the features produced from the simultaneous scalp and intracranial EEG data. The techniques predicted about 59%/50% of all seizures from a scalp/invasive EEG, with a maximum number of 0.15 false predictions per hour. The detection algorithm was offered a propensity to better performances for scalp EEG.

5. Conclusion

Transient and unexpected electrical disturbances of the brain are recognized as the possible causatives for Epileptic seizures. Ever since its establishment, the electroencephalographic (EEG) signal has been the most commonly utilized signal to clinically assess brain activities. The detection of epileptic seizures in the EEG signals is a significant process in the
diagnosis of epilepsy. More precisely, parameters extracted from EEG signals are greatly valuable for diagnostics. In this paper, we have presented a comprehensive survey of the significant and recent researches that are concerned with effective detection and prediction of Epileptic seizures using EEG signals. Along with this, an introduction to Epilepsy, EEG signals, and epileptic seizures with its types have been presented. The main goal behind this review is to assist the budding researchers in the field of epileptic seizure prediction and detection to understand the available methods and to aid their research further.

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