CHAPTER 3

SEIZURE DETECTION AND PREDICTION ALGORITHMS

Research in automatic analysis of EEG for supporting the diagnosis of epileptic seizures took pace in the 1970s. Prior et al [45] suggested the use of a device called cerebral function monitor to demarcate generalized tonic-clonic seizures. These could be identified as a large increase in EEG amplitude followed by an observable decrease and by large EMG activity. Method described by Ives et al [46] involved filtering of 16 channel EEG and amplitude discrimination. Though, it could detect large seizure discharge it was not sensitive to smaller discharges. Babb et al [47] introduced an electronic circuit that could recognize a seizure through a rapid succession of large amplitude spikes.

From these beginnings, the analysis of EEG has developed in two main directions:

- Seizure Detection
- Seizure Prediction

3.1 SEIZURE DETECTION

3.1.1 BACKGROUND

To accurately characterize a complex seizure problem that can involve multiple seizure types, or to analyze the impact of antiepileptic medication, it is sometimes necessary to continuously monitor a patient up to 1 to 3 weeks. Continuous monitoring of EEG for several days or weeks is enormous and expensive task requiring considerable personnel for observation and equipment for recording [48]. Automatic seizure detection was developed to make the review of the huge continuous EEG recording less tedious and less expensive. It can also assists in the localization of epileptic foci for surgical removal.

Active worldwide research is going on to develop clinically usable automatic seizure detection methods. Various techniques have been proposed to meet this end. However, the general block diagram of a seizure detection system can be depicted as shown in Fig. 3.1. The major components of the system are preprocessing, feature extraction and classification.
In order to clean the EEG data from various internal and external interferences, it is necessary to preprocess the data. Physiological and technical artifacts are to be removed or reduced for automatic EEG analysis [49]. Muscle potentials, eye blinks and eye movements are the important causes for physiological artifacts. Fig. 3.2 shows EEG waveforms in which eye blinks produce large amplitude variations. These artifacts can create transient nonstationarities that are similar to epileptiform events. Technical artifacts include the interference from line frequency and ECG. The EEG data used for analysis should be cleansed from the contamination of various artifacts prior to feature extraction. Fig. 3.3 shows the spectrum of an EEG before and after removing the line frequency interference. Sometimes we may be interested in certain EEG frequency bands only. Then filtering out of unnecessary frequency bands also forms the part of

Fig. 3.1: Block diagram of a seizure detection system using EEG

Fig. 3.2: EEG waveform showing eye blink
Numerous methods are used for feature extraction so that several diverse features can be extracted from the same raw data. Such features are expected to distinguish between healthy and deviating cases. The performance of any automatic seizure detection method using EEG depends to a large extent on the extraction of the features that are being used to characterize the raw data.

As explained in Section 2.6, the extracted features of EEG signal are finally submitted to a classifier that will discriminate between normal and seizure EEG classes.

3.1.2 RELATED WORKS

Some of the earlier works attempted to detect epileptic seizures based on behavioural manifestations. For example, mechanical sensors were used to detect the strong rhythmic movement of tonic-clonic seizures [50]. But this method found to be less useful as many seizures do not include strong movements. So the attention was turned toward EEG analysis. There may be some seizures which do not have electrographic signatures. There are also seizures that have mild nonspecific EEG changes which make their differentiation from the normal EEG difficult. But these are not of grave concern because most of seizures have clear and relatively specific

![Power density Spectrum of EEG with and without 50Hz line frequency](image)

Fig. 3.3: Power density Spectrum of EEG with and without 50Hz line frequency
Besides the detection from simple calculations of amplitude, a significant method of seizure detection was proposed by Gotman [51] (1982) which was later modified in 1990 [52]. Observations of several seizures led to the conclusion that during their development most of the seizures include rhythmic paroxysmal activity compared to the background which sustained for several seconds. This method was subjected to independent evaluations which indicated the detection of 70% to 80% of seizures and the false detection rate was one to three per hour of monitoring.

Spiking was a common observable abnormality with epileptic patients. Fig. 3.4 depicts seizure EEG that shows the presence of high amplitude spikes in most of the channels except few like Fp2-F4, F4-C4, C4-P4 and P4-O2. Studies show that only 1% of non-epileptic EEG shows spikes, whereas 60-90% of patients with epilepsy show spiking tendencies [53]. Harding [54] presented an exclusive method for the detection of a recurring spiking pattern as well as of possible flattening at seizure onset based on intracerebral EEG. This has achieved a detection accuracy of 86%.

Qu and Gotman [55] presented a patient specific technique of seizure onset detection based
on template matching that could be used for designing a warning system. When first seizure happens with a patient, it will be stored as the template seizure. During EEG monitoring subsequent to the recording of the first seizure, the EEG is scanned for a good match with the stored one (template) and hence the name template matching. The method used time and frequency domain features like average wave amplitude and dominant frequency. When the method was evaluated with 12 patients using nearest-neighbor classifier, the system could detect the onset of all seizures with an average delay of 9.35 seconds after onset in patient specific case. The major limitation of this method was that it could detect only those seizures resemble with template seizures. Roessgen et al [56] proposed a detection technique which used a seizure EEG model (SEM). It was based on a previously developed local EEG model (LEM) with an added seizure waveform component. Though this method could detect 92.65% of seizure occurrences, the false detection was as high as 38.09%.

In the initial attempts of seizure detection described above, the accuracy was not as high as required for applications in real life situations. Though some methods exhibited high detection accuracies, their false detection was found to be high for practical applications.

Recent years have witnessed an active worldwide research for developing a sophisticated method of automatic seizure detection method that can be used in clinical settings or environment. Different methods based on time domain, frequency domain, time-frequency domain and nonlinear features have been introduced using different classifiers. A hybrid automated identification system that combined Welch (FFT) method for feature extraction, principal component analysis (PCA) for dimensionality reduction and artificial immune recognition system with fuzzy resource allocation for classification was introduced by Polat and Gunes [57]. Though this method achieved 100% accuracy in identifying normal and seizure EEGs, it had high computational cost. Ubeyli [58] proposed an algorithm in which three Eigen vector methods (Pisarenko, multiple signal classification and minimum-norm) were used to generate the power spectral density (PSD) estimates. Using multiclass support vector machine (SVM) with the error correcting output codes, it yielded an average accuracy of 99.3% when tested with EEG database provided by Andrzejak et al [23]. A feature set consisting of Shannon entropy, spectral entropy, spectral edge frequency, nonlinear energy, line length, wavelet energy and root mean square EEG amplitude were used to study the epilepsy detection with 411 neonatal seizures by Greene et al [59]. Linear, quadratic and regularized discriminant classifiers
models were used in the method. Among these, better performance was found with the one employing a regularized discriminant classifier model, which gave a correct detection of 81.03% with a false detection rate of 3.82%. Tzallas et al [60] described a time-frequency analysis method of seizure detection in which short-time Fourier transform (STFT) and 12 time-frequency distributions were used. The power spectral density obtained through this is used to extract features corresponding to the fractional energy of the windows defined on the time-frequency plane. When the method was applied to the EEG dataset described in [22], it yielded 100%, 100% and 89% respectively for 2 class, 3 class and 5 class problems.

The characteristic nonlinear and nonstationary behavior of biological signals paved way for analysis of EEG signals using nonlinear and wavelet domain features in recent times. One of the earlier studies on the feasibility of wavelet transform for classifying EEG signals were carried out by Hazarika et al [61]. When the wavelet coefficients obtained through sub-band coding were given to artificial neural network (ANN), it could successfully classify 66% normal and 71% abnormal EEGs in this work. Adeli et al [62] examined the utility of wavelet transform to detect absence seizures (petit mal) which is normally diagnosed by the presence of 3 Hz spike and wave complex. Harmonic and Daubechies order 4 wavelets were found to be more appropriate for wavelet analysis of spike and wave EEG signals. Khan and Gotman [63] developed a wavelet based method for seizure detection, examining how different frequency ranges fluctuate compared to the background. Detection sensitivity reported was close to 90% and the false detections were found to be 0.5 per hour. When STFT and wavelet transform methods were compared in their effectiveness to determine the epileptic seizure, the former was found to have lesser process time, whereas the latter was found to yield good resolution and high performance for the visualization of epileptic activity [64]. The wavelet decomposition was done using Daubechies order 2 wavelets in adaptive neuro-fuzzy inference system (ANFIS) model suggested in [65]. An accuracy of 98.68% has been reported in this method by combining the adaptive capabilities of neural networks and fuzzy logic approaches. The wavelet coefficients provide a compact representation of the energy distribution of the EEG signal in time and frequency. Therefore, certain statistical features based on the coefficients in each sub-bands were used as input to a modular neural network called mixture of experts [66]. It could achieve an accuracy of 94.5% in classifying normal and seizure EEGs. Wavelet coefficients of different
EEG sub-bands and their statistical properties were used in different seizure detection methodologies along with different types of classifiers in recent times [67, 68].

A generic, online and real-time automatic detection of multi-morphologic ictal patterns in the long term EEG was done by Meier et al [69]. The validation was done using continuous EEG recordings from 57 patients. 91 seizures representing six most common ictal morphologies (alpha, beta, theta and delta-rhythmic activity, amplitude depression and polyspikes) were analyzed during the course of work. It was observed that the seizure morphology plays a decisive role in making the detection performance of the system better and this work reported a detection rate of 96%. In a scheme based on discrete wavelet transform (DWT) followed by probabilistic neural network (PNN) [70], the detection accuracy was found to be 99.33%. There the EEG data were subjected to six level decomposition and energy values of the wavelet coefficients were used as the feature vector to characterize the epileptic activity. Four time-frequency and time-scale methods were studied by Nijsen et al [71] to know their usability in detecting myoclonic seizures. The methods used were: STFT, Wigner distribution, continuous wavelet transform (CWT) and matched wavelet transform (MOD) based on the accelerometry output measured on the arm of the patient during myoclonic seizures. Using data from 15 patients for training and 21 patients for testing, this work showed that both CWT and MOD are more powerful in detecting myoclonic seizures with an accuracy of 80% in both. Wang et al [72] proposed a hierarchical EEG classification system for seizure detection. The method used wavelet packet transform (WPT) coefficients and k-nearest neighbor classifier and achieved an accuracy of 99.45% in classifying normal and ictal EEGs.

As the complexity measures are important in quantifying brain wave dynamics [73], a number of studies have been carried out using these features. Srinivasan et al [74] proposed a method that uses approximate entropy (ApEn) which is a statistical parameter formulated to quantify the regularity of the time series of physiological signals. It could classify normal and seizure EEGs with 100% accuracy when used with Elman network classifier. The nonlinear dynamics of EEG were quantified in terms of correlation dimension (CD) and largest Lyapunov exponent (LLE) in a wavelet-chaos methodology of EEG analysis in [75]. In an attempt to differentiate between normal, interictal and ictal classes, CD was found to be a good discriminating feature in beta and gamma sub-bands. Also, LLE emerged as suitable for low frequency alpha sub-band. Guler and Ubeyli [76] demonstrated the efficacy of wavelet
coefficients and Lyapunov exponents as features to classify EEG signals. The multiclass SVM and PNN were used which gave accuracies of 99.28% and 98.05% respectively when fed with these features. Chua et al used higher order spectral parameters like bicoherence patterns and entropies to investigate normal, background and epileptic EEG signals. Analysis of variance (ANOVA) test is used to check if the mean values are different for the different classes. This test could distinguish epileptic EEG from normal and background EEG with high confidence level, p-value less than 0.05 [77].

Praveen Kumar et al [78] used wavelet, spectral and sample entropies along with two neural network models, namely recurrent Elman network (REN) and radial basis network (RBN) for seizure detection. Among the different entropy features used, they found the best performance with wavelet entropy features using REN. It showed a classification accuracy of 99.75% in normal vs. epileptic and 94.5% in normal vs. interictal cases. Liang et al [79] used a time frequency and approximate entropy analysis for feature extraction to yield an accuracy of 85.9%. This method used PCA for feature reduction and radial basis function SVM for classification.

The study of seizure detection using correlation sum [80], an important basis of chaotic dynamics of biological systems, gave an accuracy of 91.84%. The study presented a way for seizure detection based on aggregating the correlation sum of all electrodes into one single measure. Then this measure was projected into a two-dimensional plane where nonlinear decision functions segregate seizure EEG from non-seizure ones. When the ApEn values of wavelet coefficients were used as features, it could achieve an accuracy of 96% [81]. In a study that combined wavelet sub-band nonlinear parameters and genetic algorithm, Hsu and Yu [82] have obtained a sensitivity of 95.8%. The nonlinear features used in the work were time lag, embedding dimension, CD and LLE. The permutation entropy, a measure for time series based on comparing neighboring values, was used as a discriminating feature between seizure and nonseizure EEGs in [83]. The average sensitivity of 94.38% and average specificity of 93.23% is obtained in this case. An epileptic seizure detector based on a support vector machine assembly (SVMA) classifier was proposed by Tang and Durand [84]. The SVMA consisted of a group of SVMs each trained with a different set of weights between the ictal and non-ictal data. Median Teager energy, signal power and Lempel-Ziv complexity of the physiological sub-bands were the features used in the work. The proposed SVMA detector achieved the total accuracy of 98.72%.
Various methods proposed for the detection of epileptic seizure were being discussed in preceding paragraphs. These methods have used different combination of features belong to time, frequency and wavelet domains. Also they make use of different datasets whose lengths vary from few minutes to long hours. A number of different classifiers were also experimented with to yield good discrimination between different classes involved. But, majority of the methods discussed above fail to detect all the seizure instances under their test. The promising tendencies showed by some were marred by the computational complexities involved due to large number of features or classifiers requiring rigorous training. Hence there still exists a need for a simpler automatic seizure detection method that can detect all seizures with less complexity.

3.2 SEIZURE PREDICTION

One of the puzzling aspects of epilepsy is its seemingly unpredictable nature. The major motivation behind the works to develop seizure prediction algorithms was its usefulness in designing new therapeutic possibilities in preventing or at least controlling seizures. Analyses of scalp and intracranial EEG using linear and nonlinear methods have provided ample evidence to dynamical changes in EEG prior to the beginning of seizure. These changes have been observed minutes to several hours in advance of seizure onset [85-87].

3.2.1 INITIAL WORKS

Research on epileptic seizure prediction began in 1970s by Viglion and Walsh [88]. Investigations on predictability of seizures have developed from initial descriptions on seizure precursors to controlled studies applying prediction algorithms to day long EEG recordings in past 40 years [89]. Salant et al [90] reported preictal changes in the autoregressive modeling parameters within 6 s before seizure onset. Using the nonlinear approaches of analyzing systems, Lasemidis et al [91] estimated the LLE as an indicator for chaotic behavior of intracranial EEG. This work observed a decrease in chaotic behavior in the minutes before an epileptic seizure. Analyzing 3 to 14 day intracranial EEG recordings from 5 patients with mesial temporal lobe epilepsy, Litt et al [92] observed localized quantitative EEG changes well in advance. The changes identifying prolonged bursts of complex epileptiform discharges became more evident 7 hours before seizures and manifestations of highly localized subclinical seizure-like activity appeared 2 hours prior to seizure onset. Based on these observations, they concluded that
epileptic seizures may begin as a cascade of electrophysiological events that evolve over hours. Also the measures of preictal electrical activity could possibly be used to predict seizures far in advance of clinical onset. Le Van Quyen et al reported a preictal decrease in dynamic similarity index, a measure of spatiotemporal complexity, in both scalp [93] and interictal [94] EEGs.

One common drawback of all the methods described above is that their focus of interest was entirely limited to the preictal period. They did not include an evaluation of the seizure-free interval and thus neglected the issue of false prediction rate. This act as a constraint in telling conclusive remarks investigated measures' suitability for seizure prediction.

3.2.2 EMERGING SCENARIO

Optimism regarding seizure prediction algorithms that can be used in clinical settings was at its peak in the turn of millennium. Numerous algorithms based on EEG analysis of single or multiple electrodes to solve the problem of seizure prediction have been reviewed in [95]. With examples of five of their patients, Navarro et al [96] demonstrated that occurrence of drops in the similarity measure was more frequent during preictal period than the inter-ictal EEG. Chavez et al [97] used phase synchronization analysis after band pass filtering of the EEG and reported that preictal changes occur predominantly in the beta band.

Jerger et al [98] compared results of various linear and nonlinear methods in detecting the earliest dynamical changes preceding seizures. These methods include analysis of power spectra, cross-correlation, principal components, phase, wavelets and correlation integral. All the methods were successful in detecting the changes between one and two minutes before the first changes noted by the neurologist. An adaptive seizure prediction algorithm (ASPA) was developed by Lasemidis et al [86], based on the convergence and divergence of short-term maximum Lyapunov exponents (STLmax) among critical electrode sites selected adaptively. This system was designed to predict epileptic seizures only when the occurrence of the first seizure is known. The ASPA predicted 82% of seizures with a false prediction rate of 0.16/h. Seizure warnings were given an average of 71.7 min before ictal onset. For optimizing seizure prediction, D’ Alessandro et al proposed an algorithm [99] which made use of genetic based multi channel, multi feature univariate selection process. In order to predict seizures within 10 minute of its occurrence, a PNN was tuned. Initial interictal and seizure data used for training and the remaining EEG data for testing. Validation over 2 patients demonstrated a sensitivity of
100% and 1.1 false positives per hour for one patient and failure of the method for the other patient.

Developments in theory of nonlinear dynamical systems have introduced new analysis techniques to characterize the apparent irregular behavior of EEG. Univariate nonlinear measures like Lyapunov exponent, entropies, dimensions or bivariate approaches characterizing similarities, interdependencies, or synchronization were found to describe different states of normal and abnormal EEGs [100]. As the seizure generation is closely associated with an abnormal synchronization of neurons, phase synchronization between different parts of brain using intracranial EEG was investigated in [101]. Initial indications of preictal drop in synchronization led to exploring the usability of synchronization as a specific criterion to characterize the preictal state and to distinguish it from the interictal period. Experiments with 176 hours of epileptic EEG showed a decrease in synchronization prior to 26 out of 32 seizures involved. The duration of this preictal state is found to vary from several minutes to few hours. Based on the study that involved 30 different univariate and bivariate measures, F. Mormann et al [87] concluded that the most suitable approach for forthcoming seizure anticipation could be a combination of univariate and bivariate measures. Univariate measures that include CD and LLE showed statistically significant performance only in a channel wise seizure analysis using an adaptive baseline. The bivariate measures comprised of the mean phase coherence, the indices based on conditional probability and Shannon entropy etc. exhibited high performance values. Preictal changes for the former occurred 5-30 min before seizures, while it was at least 240 min before for latter case. Linear measures were found to perform similar to or better than non-linear measures.

The method proposed by Liu et al [102] was based on the initial assumption that the EEG measurements from epileptic patients can be described as a stochastic process and has a certain probability distribution. Calculating the energy of the frequency band of 4-12 Hz by wavelet transform, they developed a dynamic model where a hidden variable having the property of second order Markov chain was included. This method could predict 15 out of 16 seizures and the average prediction time was 38.5 minutes. The sensitivity reported was about 93.75% and specificity (false prediction rate) was approximately 0.09 FP/h. Two problems with this method were the requirement for a low noise EEG data and the need for an additional step to detect the channel in the brain regions where the seizure happens.
In order to detect and predict seizures, Schad et al [103] investigated two multivariate techniques based on simulated leaky integrate-and-fire neurons, which was introduced in [104]. While both algorithms have been applied to scalp recordings, this study investigated the feasibility of successfully using these with intracranial EEG and done a performance comparison between scalp and intracranial EEGs. Both methods were applied and assessed on 423 hours of recording and 26 seizures in total, recorded simultaneously from the scalp and intracranial EEG taken from six patients. The data comprised long interictal periods which were necessary for assessing a high specificity. This work predicted up to 59% of all seizures from scalp EEG and 50% of seizures from intracranial EEG, giving a maximum number of 0.15 false predictions per hour.

Ouyang et al [105] proposed a method of seizure prediction that combined wavelet techniques and nonlinear dynamics. Through the study based on 16 adult rats and four human subjects, they found that the method can obtain the best performance of seizure prediction at the beta frequency band. EEG signal was divided into segments of 10 seconds and the nonlinear similarity index was computed. The analysis was carried out for human EEG data at the B3 (16–32 Hz), B4 (8–16 Hz) and B5 (4–8 Hz) bands corresponding to wavelet resolution levels 3, 4 and 5, respectively. The similarity indices found to gradually decrease during the preictal phase. The results of seizure prediction for four patients showed that wavelet based nonlinear similarity index can successfully detect the preictal phase. Rajdev et al [106] suggested Wiener prediction algorithm which could predict seizures about 6.7 seconds before their clinical onset, when implemented on a real time digital signal processor. The sensitivity reported was 92% and FPR was 0.08 per minute. In a method that investigated the possible improvements in seizure prediction by combining the mean phase coherence and dynamic similarity index [107], the mean sensitivity improved from about 25% for the individual methods to 43.2%. Xu et al [108] proposed an algorithm based on morphological filter Kolmogorov complexity. A morphological filter with optimized structure elements was proposed to eliminate the ocular artifact. Results using scalp EEG recording of 5 epilepsy patients showed that Kolmogorov complexity of electrodes near the epileptogenic focus reduces significantly during preseizure period.

In recent years different prediction methods were proposed using the 21 patient Freiburg EEG dataset [21]. Aschenbrenner-Scheibe et al [109] investigated the sensitivity and specificity of the prediction method using dimension drops. It showed that for an FPR of less than 0.1/h the
sensitivity varied from 8.3% to 38.3% depending on the prediction window length. Maiwald et al [110] compared the performance of three nonlinear prediction methods viz effective correlation dimension, dynamic similarity index and increments of accumulated energy on the same dataset. With a rate of 1-3.6 false predictions per day the dynamic similarity index yielded the best result among the three: sensitivity between 21% and 42%. The major problem with dynamic similarity index discussed in [110] was to determine a radius value, which was applied for the normalized cross-correlation integral to calculate the dynamic similarity index, and the length of the windowed EEG recordings. In order to circumvent this, an improved dynamic similarity measure was proposed to predict seizures by Li and Ouyang [111]. The test results with the EEG recording of rats showed that the new dynamic similarity index was insensitive to the selection of radius value of the Gaussian function and the size of segmented EEG recordings. Also, comparing with the dynamic similarity index in [94], the improved dynamic similarity index is found better to predict epileptic seizures. The dynamic similarity index and mean phase coherence were assessed for seizure prediction by Schelter et al [112]. When the maximum FPR was fixed at 0.5/h, an average sensitivity of 82% and 89% were obtained for dynamic similarity index and mean phase coherence respectively.

Mirowski et al [113] applied 16 different seizure prediction methods on 21 patients. The feature extraction techniques adopted were based on maximal cross-correlation, nonlinear interdependence, difference of Lyapunov exponents and three measures of wavelet analysis based synchrony: phase-locking value, entropy of phase difference and coherence. The classifications were done using L1-regularized logistic regression, convolutional networks and SVM. In their work, at least one method predicted all seizures for each patient on average 60 minutes before the onset, with no false alarm. Chisci et al. [114] used auto regressive (AR) model based features along with SVM classifier. Trials done on the subset of Freiburg dataset by them predicted all seizures with 100% sensitivity and low FPR that ranges between 0 and 0.6 per hour. When the seizure prediction was done with spectral power of time/space-differential EEG signals [115], it yielded 86.25% average sensitivity and FPR of 0.1281. Williamson et al [116] proposed a prediction algorithm that used space-delay correlation and covariance matrices at several delay scales to extract the spatiotemporal correlation structure from multichannel ECoG signals. Evaluation of this method on Freiburg EEG database produced a sensitivity of 90.8% and FPR of 0.094.
Brown et al [117] suggested a method in which power spectral density measures were extracted using Welch's method. Feature reduction is achieved through the divergence measurement method proposed by Henze and Penrose [118]. For all 18 patients tested, the average sensitivity is 83% and false positive rate is 0.38/h. An adaptive seizure prediction algorithm put forwarded in [119] made use of 31 different features based on time, frequency and wavelet domains along with a multilayer perceptron (MLP) classifier. Average of sensitivity and FPR obtained for all patients were 99.52% and 0.1417 per hour, respectively.

Though there are some studies that analyzed scalp EEG, most of the prediction algorithms discussed above have been carried out using intracranial recordings. Intracranial EEG has the advantage of getting recording directly from ictal region. Also they have higher signal to noise ratio, better spatial resolution and the benefit of being mostly artifact free [120]. If seizure prediction algorithms proved to be successful, they would most likely be implemented in an implantable warning or intervention system. The technical feasibility of intracranial intervention systems has already been proven that are currently being tested in clinical trials for their ability to reduce seizure frequency [121]. Therefore researchers regard the usefulness of scalp EEG recordings for studies on seizure prediction as rather limited compared with intracranial recordings.

Many prediction algorithms listed above were based on shorter EEG recordings. Performance of a prediction algorithm should be tested on continuous long term recordings covering the full spectrum of physiological and pathophysiological states for individual patients [89]. Also the prediction time obtained in each case was not high enough to initiate some preventive measures against an oncoming seizure. Though, in most of the works reported so far, specificity was described in terms of false predictions per hour, some computed false prediction rates by dividing the number of all false positives by the total duration of the analyzed recording [86]. This definition ignores the existence of a preictal period associated with each seizure contained in the recording during which every alarm is counted as a true prediction. Therefore, if false prediction rates are reported, it is essential to report it only for the seizure-free inter-ictal period [89]. None of the methods of seizure predictions described above could yield 100% sensitivity by predicting all seizures tested using same set of features and classifiers. So there lies enough scope for exploring new set of features and classifiers which can provide a better prediction of epileptic seizures.
3.3 SUMMARY

The chapter discussed various methods proposed so far for the epileptic seizure detection and prediction. Though researches on seizure detection are underway for past 40 years, works on prediction got momentum only by late nineties of previous century. Different methods based on time-, frequency- and wavelet domain features were introduced for both prediction and detection. Many of the works exhibited improvements over the previous works in terms of detection accuracy, sensitivity and false prediction rate. But for clinical usability, the method should be able to detect all the seizures with no false detections. No method could classify different types of EEG classes involved in seizure detection problems to its respective classes with 100% accuracy in a computationally efficient way. Hence, the search for some efficient features that can discriminate between different EEG classes with maximum possible accuracy will contribute to the ongoing research for an efficient seizure detection mechanism that can be used in clinical settings. On the prediction front, the search should be aimed at developing new methods that provide better prediction time, sensitivity and FPR.