Scientific Journal Impact Factor (SJIF) : 3.518
International Journal of Modern Trends in Engineering and Research
ISSN (ONLINE) : 2349 - 9745
ISSN (PRINT) : 2393 - 8161

CRITICAL REVIEW OF EPILEPTIC PREDICTION MODEL USING EEG

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Abstract - Epilepsy is a condition that affects the brain and causes repeated seizures. Epilepsy is the second most common neurological disorder, affecting 0.6–0.8% of the world's population. In this neurological disorder, abnormal activity of the brain causes seizures, the nature of which tend to be sudden. The cells in the brain, known as neurons, conduct electrical signals and communicate with each other in the brain using chemical messengers. During a seizure, there are abnormal bursts of neurons firing off electrical impulses, which can cause the brain and body to behave strangely. The severity of seizures can differ from person to person. For most people with epilepsy, treatment with medications called anti-epileptic drugs (AEDs) is recommended. These medications cannot cure epilepsy, but they are often very effective in controlling seizures. The unpredictable nature of seizures poses risks for the individual with epilepsy. It is necessary to find more effective ways of preventing seizures for such patients. The early detection of oncoming seizures, before their actual onset, can facilitate timely intervention and hence minimize these risks. Before a seizure happens, a number of characteristic, clinical symptoms occur that is used to identify the pre-seizure state by monitoring brain activity through the electroencephalogram (EEG). In this paper, we present an extensive review of the significant researches associated with the prediction of Epileptic Seizures using EEG signals. In addition with different Seizure prediction method.

Keywords - Epileptic, Electroencephalogram (EEG), Seizures prediction method, Time-domain seizure Prediction, Wavelet-domain seizure prediction

I. INTRODUCTION

Epilepsy is a neurological disorder with prevalence of about 1-2% of the world's population(Mormann, Andrzejak, Elger & Lehnertz, 2007). It is characterized by sudden recurrent and transient disturbances of perception or behavior resulting from excessive synchronization of cortical neuronal networks; it is a neurological condition in which an individual experiences chronic abnormal bursts of electrical discharges in the brain. The hallmark of epilepsy is recurrent seizures termed "**epileptic seizures**". Epileptic seizures are divided by their clinical manifestation into partial or focal, generalized, unilateral and unclassified seizures (James, 1997; Tzallas, Tsipouras & Fotiadis, 2007a, 2009). Focal epileptic seizures involve only part of cerebral hemisphere and produce symptoms in corresponding parts of the body or in some related mental functions. Generalized epileptic seizures involve the entire brain and produce bilateral motor symptoms usually with loss of consciousness. Both types of epileptic seizures can occur at all ages. Generalized epileptic seizures can be subdivided into absence (petit mal) and tonic-clonic(grand mal) seizures (James, 1997). The unpredictable nature of seizures poses risks for the individual with epilepsy. It is necessary to find more effective ways of preventing seizures for such patients. The early detection of oncoming seizures, before their actual onset, can facilitate timely intervention and hence minimize these risks. Before a seizure happens, a number of characteristic, clinical symptoms occur that is used to identify the pre-seizure state by monitoring brain activity through the electroencephalogram (EEG). The electroencephalogram (EEG) has become an important tool in the diagnosis of epilepsy.

Seizure prediction research has evolved via diverse mathematical and engineering approaches, from its starting point in the 1970s. Viglione and Walsh[1] was implemented the first prediction model by using Linear approaches such as pattern detection and spectral analysis with the help of EEG signals which detected preictal changes up to 6 seconds before seizure onset.

In the 1980s, time series analysts became aware of seizure prediction as a potential field of application. These and later studies predominantly analyzed EEG signals from patients undergoing video-EEG monitoring, with chronic electrodes implanted directly inside or on the surface of the brain to localize the seizure focus for possible surgical resection.

During the 1990s several quantitative EEG studies reported *pre-ictal phenomena* using characterizing measures such as the largest Lyapunov exponent (Iasemidis et al. 1990)[2].
The correlation density (Martinerie et al. 1998) or a dynamical similarity index (Le Van Quyen et al. 1999, 2001)[3]. The common feature of these studies was that their focus of interest was entirely limited to the pre-ictal period and that they did not include an evaluation of control recordings from the seizure-free interval, so the specificity of the applied techniques was not assessed.

Another group of *proof-of-principle studies* addressed the issue of specificity by comparing pre-ictal changes in dynamics to inter-ictal control recordings, although the reported findings remained on an anecdotal level (Mormann et al. 2000, Navarro et al. 2002, Chávez et al. 2003).
Litt et al. [4] conducted a controlled experiment on continuous multi-day EEG recordings of a population of 5 patients evaluated for epilepsy surgery. This study reported that quantitative signal changes were detected 7 hours, 2 hours and 50 minutes prior to the seizure onset, with an increase in accumulated energy 50 minutes prior to the seizure onset, suggesting that the cascade of electrophysiological events, which have evolved from several hours before the onset, can be identified as a reliable and timely indication of seizures.

Xiaoli Li and Ouyang [5] developed an enhanced dynamic similarity measure method. In order to find out epileptic seizures in electroencephalograms (EEG) They have employed three methods to predict epileptic seizures. Initially, mutual information measure [6] and Cao's method [7] 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.
Hung et al.[8] developed a very large scale integration (VLSI) setup of wavelet-based seizure prediction algorithm using the correlation dimension (D_c) and its correlation coefficient .
Daou and Labeau[9] presented a wavelet-based approach for EEG signal compression and seizure detection, simultaneously .

Chiang et al. developed an online wavelet-domain retraining method to improve the seizure prediction by enlarging the training dataset gradually [10]. Their method is based on the method of Mirowski et al. [11] that uses non-linear interdependence, cross-correlation, difference of Lyapunov exponents, and phase locking.

Moghim N,Corn DW[12] develop ASPPR algorithm for epileptic prediction model. ASPPR facilitates the learning of predictive models targeted at recognizing patterns in EEG activity that are in a specific time window in advance of a seizure. It then exploits advanced machine learning coupled with the design and selection of appropriate features from EEG signals. Results, from evaluating ASPPR independently on 21 different patients, suggest that seizures for many patients can be predicted up to 20 minutes in advance of their onset. Compared to benchmark performance represented by a mean S1-Score (harmonic mean of Sensitivity and Specificity) of 90.6% for predicting seizure onset between 0 and 5 minutes in advance, ASPPR achieves mean S1-Scores of: 96.30% for prediction between 1 and 6 minutes in advance, 96.13% for prediction between 8 and 13 minutes in advance, 94.5% for prediction between 14 and 19 minutes in advance, and 94.2% for prediction between 20 and 25 minutes in advance.

II. ELECTROENCEPHALOGRAM (EEG)

Epileptic seizures are among the most observed abnormalities, the best tool for diagnosing the different abnormalities is the EEG which uses special sensors (electrodes) placed on the surface of the scalp to measure the electrical activity of the brain [13]. An illustration of EEG recording of abnormal brain signal using EEG Scalp electrodes is shown in Figure (a)

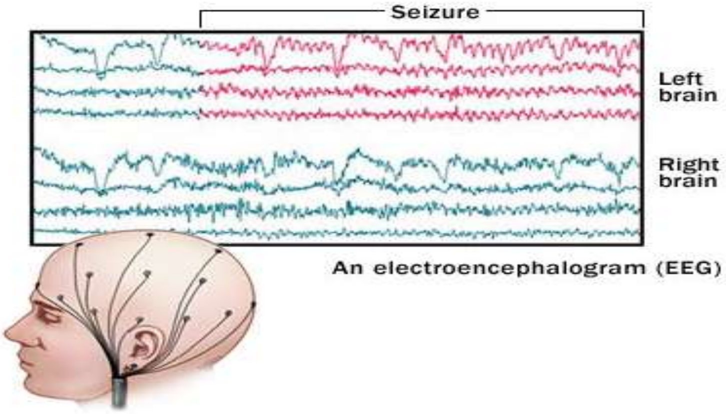

Figure: a) EEG recording of abnormal brain signal

Before a seizure happens, a number of characteristic, clinical symptoms occur such as lack of oxygen, haemorrhage, meningitis, infection and strokes [14]. This concept has allowed researchers to study EEGs in a different way, to find correlates of such processes and identify the pre-seizure state. The main question researchers have been addressing is whether characteristic features can be extracted from an EEG which correlate with the occurrence (and time of the occurrence) of seizures.In that case, treatments could move from therapeutic and long-term preventive plans to on-demand strategies (i.e. immediately before the seizure occurs), such as fast-acting anticonvulsant substances, or deep-brain stimulation technology in order to reset the brain as soon as seizure activity is detected, to prevent the seizure happening.

Measurements of brain electrical activity with EEG have long been one of the most valuable sources of information for epilepsy research and diagnosis, yet this rich resource may still be underutilized. Electroencephalography carries a large amount of complex information that is valuable in detecting ongoing seizures. Automated methods of EEG analysis are emerging from the concept that normal brain dynamics, which involve limited, transient synchronization of disorganized neural activity, evolve into a persistent, highly synchronized state that incorporates large regions of the brain during epileptic seizures. While EEG provides a great wealth of data that can be interpreted via automated methods.

III. SEIZURE PREDICTION METHOD

The seizure prediction models have certain common features. Most of them have two necessary steps. First; all of them try to detect and extract EEG-based measures over time characterizing different stages of the epilepsy cycle including interracial, predictable, octal, and postictal stages as shown in fig b. In this regard, they use a moving window analysis in which a linear or nonlinear characterizing measure is calculated from a window of EEG data with a predefined length [15], [16]. The second step is distinguishing and classifying the measures into predictable and octal state. The two other states are not important in seizure prediction

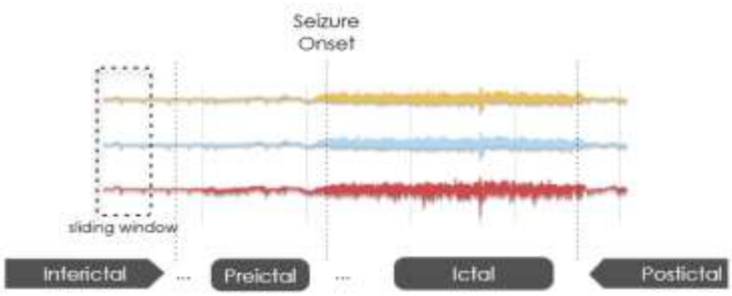

Figure: b) EEG Time series

Techniques used to predict seizures include Frequency domain method, Time domain methods, and Wavelet-domain method statistical analysis of EEG signals, non-linear dynamics (chaos), and Intelligent expert systems. Time domain method and wavelet domain method is very richer in the epileptic prediction. The review of some of the time domain and wavelet domain method of epileptic prediction is as follows.

3.1 Time-domain methods

The local activities of EEG waveforms vary from patient to patient; therefore, seizure prediction algorithms are preferred to be patient specific. It is clear that there is a difference between seizure and non-seizure intervals. As we are able to differentiate between these intervals visually, time-domain prediction methods attempt to differentiate between them automatically, and evaluate the performance using different metrics such as the sensitivity, specificity, accuracy, and false-positive value [17]. The research work on the issue of time-domain seizure prediction is richer in the seizure prediction problem. The seizure prediction problem as a detection problem of the pre-ictal state on seizure records. This requires a considerable long inter-ictal state for good prediction results. The statistics like the zero-crossing rate can be used for seizure prediction.

Li et al. presented a time-domain method for seizure prediction that is based on spike rate estimation [18]. Morphological operations and averaging filters are applied to transform each signal segment to a train of spikes in a way similar to the process of envelope detection. Based on the spike rate, ictal, inter-ictal, and pre-ictal states can be identified through comparison with a certain threshold. This method was applied on 21 patients from Freiburg database, and it achieved a sensitivity of 75.8% and an average false-alarm prediction rate of 0.09/h.

Another approach to process EEG signals in the time domain in order to predict seizure is to create models from the EEG signal segments corresponding to different activities. One of such models is the auto-regressive (AR) model, which can be thought of as a data reduction model that transforms the EEG signal segment into few coefficients. Chisci et al. studied the implantation of monitoring and control units on drug-resistant epilepsy patients with AR modeling [19]. They adopted AR modeling with a least-squares parameter estimator for EEG feature extraction in addition to a binary SVM classifier to distinguish between pre-ictal, ictal, and inter-ictal states. This algorithm is computationally simple enabling real-time implementation. Simulation results on the Freiburg database have shown 100% sensitivity with low false-alarm rate. This is attributed to the regularization strategy of the SVM classifier with Kalman post-processing.

Schelter et al. presented a new method to minimize the false alarms adopting circadian concepts [20]. A circadian rhythm is defined as any biological operation that reveals an endogenous, entrainable oscillation for 24 h. The authors used the output of the mean phase coherent algorithm, which measures the interaction between pairs of EEG signals, as a seizure predictor, which causes an alarm to be raised if it exceeds a certain threshold. It was assumed that the seizures occur while the patient is sleeping. The false alarms display a circadian dependency with most of the seizure prediction algorithms. The seizure predectability is increased during night due to the large number of seizures. Accordingly, threshold adaptation can be used in day and night to enhance predictability. The authors evaluated this method utilizing iEEG data from eight patients and a total of 1400 h, which include 172 seizures and reported a good prediction performance for 40% of the patients.

The realization of implantable seizure prediction devices that can be used for alerting the patient and taking an action is a very challenging task. Cellular non-linear networks (CNNs), which represent a paradigm for high-speed computations, can be used for this task. Tetzlaff and Senger presented four different CNN-based approaches for epileptic seizure prediction towards an implantable seizure warning device working on any type of simple time-domain features [21]. This method can be used with any of the abovementioned features. The CNNs have been used in these approaches because they consist of locally coupled dynamical systems that can simulate the non-linear phenomena encountered in physical communication.

Zandi et al. used the zero-crossing rate of EEG signal segments to develop a patient-specific seizure prediction method [22,23]. A moving window analysis is used in this method. The histograms of the different window intervals are estimated and selected histogram bins are used for classification into pre-ictal and inter-ictal states based on comparison with reference histograms. A variational Bayesian Gaussian mixture model has been used for classification. In this method, a combined index for the decisions taken on selected bins is computed and compared with a pre-defined patient-specific threshold to raise an alarm for coming seizures. This method has been tested on 561 h of scalp EEG containing 86 seizures for 20 patients. It achieved a sensitivity of 88.34%, a false prediction rate of 0.155 h^{-1}, and an average prediction time of 22.5 min.

Wang et al. proposed an adaptive learning system that interactively learns from the patient and improves its seizure predictability over time [24]. It is based on reinforcement learning and online monitoring, in addition to adaptive control theory. In this system, a sliding window size of 10 min is used to read continuous multi-channel EEG data with a 50% overlap at each move. Then, k-nearest neighbor (KNN) method is adopted for the classification of the windowed epochs to normal or pre-seizure states based on pre-constructed baselines for both states using pre-specified baseline for normal and pre-seizure states. Finally, according to the prediction feedbacks, the two baselines are updated. This method was evaluated using iEEG data for five patients having temporal lobe epilepsy. The EEG data consisted of 26 channels with a duration range from 3 to 13 h. This method achieved an accuracy of 70% compared to 50% for the Poisson random predictor with a mean interval of λ minutes.

Aarabi and He [25] developed a time-domain rule-based patient-specific seizure prediction method which consists of three stages: pre-processing, feature extraction, and rule-based decision making. In the pre-processing stage, the iEEG data is filtered using a 0.5- to 100-Hz band-pass filter in addition to a 50-Hz notch filter. Then, the filtered signal is segmented into non-overlapping 10-s segments. Five univariate features (correlation entropy, correlation dimension, Lempel-Ziv complexity, noise level, and largest Lyapunov exponent) and one bivariate feature (non-linear independence) were extracted from each segment in the second stage.
Based on the theory of chaos, the correlation dimension (denoted by v) represents a dimensionality measure of the space having a set of random points; in our case, EEG signals. For an m-dimensional space containing a set of N points, we have:

$$\vec{x}(i) = [x_1(i), x_2(i), ...x_m(i)], \quad i = 1, 2, ...N \qquad (1)$$

The correlation integral $C(\epsilon)$ can be estimated as [26]:

$$c(\in) = \lim_{N \to \infty} \frac{g}{N^{2'}} \qquad (2)$$

where g represents the total number of pairs of signals or points having a distance less than ϵ. As the number of points increases and tends to infinity and the distance tends to be shorter or close to zero, the correlation integral, in turn, for small values of ϵ becomes:

$$c(\in) \approx \in^{v} \qquad (3)$$

If a large number of evenly distributed points exists, a log-log graph of the correlation integral versus ϵ can be used to estimate v. For objects with higher dimensions, several ways exist for points to be close to each other, and hence, the number of pairs which are close to each other jumps rapidly for higher dimensions [26].

Correlation entropy is a Kolmogorov entropy variant, which is similar to the mutual information between two sequences of data. Large mutual information between an available data segment and stored segments with specific patterns is an indication that the segment at hand belongs to a dataset with similar characteristics to the stored pattern [27]. The Lempel-Ziv complexity is a measure of randomness of data sequences [28]. It counts the number of data patterns with certain characteristics in data segments. For example, if we find enough short patterns with specific mean, variance, or higher-order statistics in an EEG segment, we can classify this segment as a seizure segment.

The Lyapunov exponent of a dynamical system determines the separation rate of very closely related trajectories. Hence, two signal vectors in the phase space with an initial separation of $\delta\mathbf{Z}_0$ will eventually diverge at a rate given by:

$$|\delta z(t)| \approx e^{\lambda t} |\delta z_0|, \qquad (4)$$

where λ is the Lyapunov exponent. This can be achieved if the divergence can be dealt with within the linearized approximation.

The separation rate differs based on the initial separation vector orientation. The maximal Lyapunov exponent can be estimated as [29]:

$$\lambda = \lim_{t\to\infty} \lim_{\delta z_0 \to 0} \frac{1}{t} \ln \frac{|\delta z(t)|}{|\delta z_0|} \qquad (5)$$

The limit $\delta\mathbf{Z}_0 \to 0$ ensures the validity of the linear approximation at any time.

This method has been evaluated using iEEG data from two patients (frontal, temporal lobe origin) from Freiburg Seizure Prediction EEG (FSPEEG) database with a 256-Hz sampling rate and a total of 58 h, and 10 seizures with 50-min pre-ictal at least [30]. The results demonstrated average sensitivities of 90% and 96.5% for patient one and patient two, respectively. The average false prediction rates were 0.06/h and 0.055/h for both patients for prediction horizons of 30 and 60 min

Researchers have proved that symptoms like sleep problems or headaches are observable from the analysis of the iEEG. These symptoms can be utilized as a major tool for seizure prediction. Bedeeuzzaman et al. have presented a seizure prediction algorithm with a statistical feature set consisting of mean absolute deviation (MAD) and inter-quartile range (IQR) to predict epileptic seizures [31]. A linear classifier has been used to find the seizure prediction time in pre-ictal iEEGs. A sensitivity of 100% with zero false-positive rate (FPR) in 12 patients and low values of FPR for the rest were achieved using Freiburg iEEG dataset. Average prediction time varied between 51 and 96 min.

3.2 Wavelet-domain seizure prediction

The concepts of wavelet signal analysis used for seizure prediction with the target as the detection of the pre-ictal state. In general, EEG signals containing seizures are build up of constantly changing bursting levels. This signal nature enables discrimination between different signal activities from wavelet sub-bands. The residual sub-band wavelet entropy (RSWE) can be directly used to estimate the entropy of bursts from the sub-bands as proposed by Paul et al. [32]. The wavelet decomposition equation for an EEG signal using a sliding window of index *m* is given by

$$s(t) = \sum_{t=-\infty}^{\infty} a_L^m(\mathrm{T})\phi(2^{-L}t - T) + \sum_{l=1}^{L}\sum_{t=-\infty}^{\infty} C_l^m(t)\psi(2^{-l}t - T), \qquad (6)$$

where $Cm1(\tau),Cm2(\tau),\ldots,CmL(\tau)$C1mτ,C2mτ,…,CLmτ are the wavelet coefficients. The sequence $\{amL(\tau)\}$a Lmτ is the coarser-resolution signal for a high-level decomposition. The authors experimented lower and higher numbers of levels and found that the five levels are the optimum choice.

The relative wavelet energy (RWE) of the wavelet coefficients is used to derive a sub-band wavelet entropy (SWE) feature. For a sliding window with index *m*, the field potential (FP) is given by [33]:

$$E_l^m(T) = \left|C_l^m(T)\right|^2 \qquad (7)$$

The wavelet coefficients total energy is given by:

$$E_{rmtotal}^m = \sum_l \sum_t E_l^m(T) \qquad (8)$$

The RWE can be expressed with normalization as:

$$p_l^m(T) = \frac{E_l^m(T)}{E_{rmtotal}^m} \qquad (9)$$

The SWE at scale *l* can be defined with a probabilistic approach as:

$$H(C_l^m) = \sum_T p_l^m(T) \log_l^m(T) \qquad (10)$$

The *l*th level RSWE of the *n*th frame is given by:

$$J(C_l^{m,n}) = H(C_l^{m,n}) - \frac{1}{N_0} \sum_{n=1}^{N_0} H(C_l^{m,n}), \qquad (11)$$

Where *Cm*,*nl*Clm,n represents the wavelet coefficients of the *n*th frame in the *m*th window.

For the estimation of the RSWE, a sliding window of 1-min length has been used assuming that the FP is stationary during this window. It was also assumed that the background FP fluctuations stay statistically unchanged for frames of 5-s length during the main sliding window. On the other hand, the FP fluctuations have another component that is statistically variant over the 5-s frames. Hence, an averaging process is performed on the background entropy components estimated in the main window. Consequently, resulting residual entropy corresponds only to the bursting components. A key observation on this approach is that there is an increment in the mean cortical RSWE during the transition from the pre-ictal to inter-ictal period. This increment can be used with an efficient slope change detector and used for early seizure prediction.

Rojas et al. presented a seizure prediction method depending on brain excitability recognized with couplings between low-frequency phases (delta: 0.5 to 33 Hz, theta: 3 to 8 Hz) and high-frequency amplitudes (low gamma: 40 to 70 Hz, high gamma 70 to 140 Hz) of brain waves [34]. They evaluated this method on 20 patients from EPILEPSIAE scalp EEG database [35]. The EEG data was recorded using either depth or subdural stereotactic electrodes at a sampling rate 1,024 Hz with a total of 267 seizures and more than 3,400 h of inter-ictal activities. They found that in 50% of the cases, their predictor performed better than the random predictor, which is based on Poisson process, with an average sensitivity 98.9%, false rate of 1.84/h, and pre-ictal window length of 10 min.

Hung et al. developed a very large scale integration (VLSI) setup of wavelet-based seizure prediction algorithm using the correlation dimension (D_c) and its correlation coefficient [33]. Their system comprises arithmetic functional and control units. The arithmetic functional units are the DWT, correlation dimension, correlation coefficient, and seizure prediction. The DWT of the pre-processed signal is estimated to decompose it into four sub-bands (0 to 63 Hz, 64 to 128 Hz, 0 to 1 Hz, and 32 to 64 Hz). The higher-frequency sub-bands are then represented in the phase space. The correlation dimension and correlation coefficient are estimated in the phase space as seizure prediction features. The authors evaluated their method utilizing iEEG data from 11 patients of the Freiburg database with 256-Hz sampling rate. Their method achieved an average of 87% sensitivity, 0.24/h false prediction rate, and in average a 27-min warning time ahead the ictal.

Chiang et al. developed an online wavelet-domain retraining method to improve the seizure prediction by enlarging the training dataset gradually [36]. Their method is based on the method of Mirowski et al. [37] that uses non-linear interdependence, cross-correlation, difference of Lyapunov exponents, and phase locking. Post-processing is used in this method to reduce the false-alarm rate if two consecutive patterns are classified as pre-ictal. The authors evaluated their method using three datasets: Freiburg database, CHB-MIT database (eight patients), and National Taiwan University Hospital database for scalp EEG (one patient) [38]. This method achieved sensitivities of 74.2% and 52.2% on intracranial and scalp databases, respectively. It also achieved an improvement in the sensitivity of off-line training on both databases by 29.0% and 17.4%, respectively.

Wang et al. presented a wavelet-based online adaptive seizure prediction system [39]. This system adopts Lyapunov exponent, correlation dimension, Hurst exponent, and entropy features extracted from the wavelet transform of EEG recordings. It adopts also a KNN classifier. The adaptation is performed in this system with a reinforcement learning algorithm. A 150-min prediction horizon used on ten patients and the system achieved the best prediction results of 73% sensitivity and 67% specificity.

Soleimani et al. presented a simple and fast adaptive online method for the detection of pre-ictal patterns depending on multiple features [40]. These features are time domain and wavelet domain. The time-domain features are the curve length, the average energy, non-linear energy, six-order power at time *n*, kurtosis, skewness, and variance. The wavelet-domain feature include mean of absolute values, average power, standard deviation, absolute mean of sub-bands of a fifth level Daubechies wavelet transform. In this method, a neuro-fuzzy model is used for combined features learning in an adaptive manner. An adaptive tuning process is used in the classifier operation to build a personal seizure predictor. Freiburg database of intracranial recordings for 21 patients has been used with this classifier. Simulation results revealed that on-line adaptive seizure prediction achieves better results than off-line non-adaptive seizure prediction. The percentage of prediction was 99.52%, and the FPR was 0.1417/h. It is possible to use some time-domain features with wavelet-domain features to enhance the detectability of seizures. Costa et al. have selected 14 features for efficient seizure prediction from EEG recordings [41]. These features include energy estimated from time-domain signals, energy variation, energy level, non-linear statistics, and sub-band energies extracted from the wavelet sub-bands. They used a neural network classifier for signal classification into four states: pre-ictal, ictal, inter-ictal, and post-ictal. They achieved an average specificity of 99%, an average sensitivity of 83%, and an average accuracy of 96% on patient records from Freiburg database. Moghim and Corne compared the Costa et al. results with multi-class SVM and evolved neural network classifiers [42]. They carried out this comparative study on one patient (patient 2: 135 min, 3 seizures, 30 to 40 min before and 10 min after each seizure) from Freiburg database, and they reported that 8- to 10-min detection before the onset can be achieved with reasonable specificity and sensitivity.

IV. CONCLUSION

The unpredictable nature of seizures poses risks for the individual with epilepsy. It is necessary to find more effective ways of preventing seizures for such patients. The early detection of oncoming seizures, before their actual onset, can facilitate timely intervention and hence minimize these risks. A method reliably predicts the occurrence of seizures could significantly improve the quality of life for these patients Review of the early seizure predicting models showed that advances in seizure prediction have promised bright future in seizure control and management. Further studies are needed to increase the sensitivity of prediction model as well as developing best EEG based measures as precursor of impending seizures.

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