A Review of Machine Learning Approaches for Epileptic Seizure Prediction

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***Abstract*— Epilepsy is a neurological disorder that causes unusual behavior, sensations, and, in some cases, loss of awareness. It is accompanied by seizures, which are periods of abnormal patterns of brain activities. Early detection and prediction of the Epileptic seizures are important for providing effective instantaneous treatment and reducing the risk of injury. This has been an active area of research, fueled by the increasing affordability of non-invasive EEG capturing devices and the fast evolvement of the machine learning algorithms. This study provides an up-to-date review of the recent approaches for the prediction of epileptic seizures. Special attention is directed towards the feature extraction methods and classification algorithms. The commonly-used EEG datasets and their availability are noted. The discussed approaches range from those which rely on the traditional machine learning such as Support Vector Machine (SVM), Naïve Bayes, and Linear Discriminant Analysis; to those that benefit from the recent deep learning approaches, such as Convolutional Neural Network (CNN) and Long Short Term Memory. It also includes the hybrid approaches that combine traditional and deep learning techniques, such as combining CNN with SVM. The study concludes the discussed approaches and their limitations by a comparative discussion based on the reported performance in terms of sensitivity, false alarm rate and prediction time.**

Keywords*— *Epilepsy, seizure prediction, feature extraction, classification, machine learning, electroencaphlography

I. INTRODUCTION

Epilepsy is a neurological disorder that is marked by the occurrence of seizures. The main cause of epilepsy is a large number of small electrical discharges of nerve cells [1]. The epileptic seizures cause different changes in the attitude and consciousness of the patient, sometimes leading to fatal accidents [2]. The epileptic disorder is not specific to a certain age group, however, 80% of the patients develop epileptic symptoms before the age of 20 specifically in the childhood and adolescence periods [3]. A population of 50 million people around the world is diagnosed with epilepsy. Almost 30% of patients do not respond to medical or surgical intervention [1].

These types of epilepsies are of great threat to the patients' lives due to their sudden occurrence. They are also the main cause of unease in the patients' social and personal lives. For these reasons, new techniques for epilepsy prediction were developed. Such methods would help the patient foresee the seizure before its occurrence [4].

For a patient of epilepsy, there are four states of the brain: inter-ictal, pre-ictal, ictal and post-ictal. The inter-ictal state is the normal brain state, the three remaining phases are those of the seizure itself. The pre-ictal state marks the moments prior to the seizure. During the pre-ictal state, the patient may feel few physiological changes such as muscle twitches, gastro-intestinal changes, etc. [5]. Such changes are called the aura of the seizure. The ictal state is the duration of the seizure itself. The post-ictal state is the few moments after the seizure ends. It can be considered as the transitional state between the ictal and the inter-ictal states [6]. Figure 1 illustrates the different seizure states

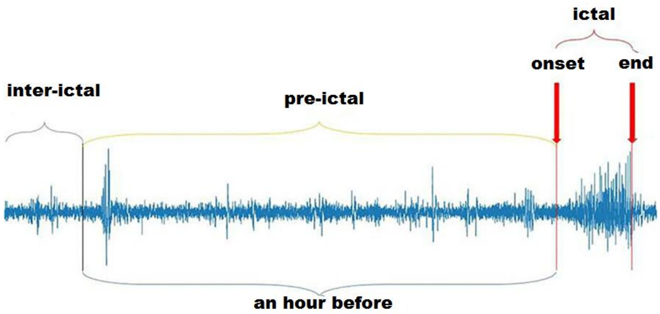

Fig. 1 The states of the epileptic seizure [7].

The detection and prediction of seizures differ according to the type of state detected. In detection, the features related to the ictal and inter-ictal states are extracted, while in prediction the pre-ictal features are detected. Prediction is epileptic seizure is hard to detect compared to detection. Meanwhile, prediction of seizure is of high benefit for patient's safety. Consequently, this study is mainly concerned with seizure prediction which involve the detection of the pre-ictal state.

In this paper, different approaches developed for the sake of enhancing epilepsy prediction are reviewed. It explains those techniques based on the feature extraction and the classification methodology. The review also provides a classification table of the aforementioned epilepsy prediction techniques based on the combination of datasets, the preprocessing, feature extraction, and classification techniques used.

II. Seizure Prediction Model

The general workflow of the seizure prediction model is shown in Figure 2. The acquired signal has to be pre-processed by removing redundant and irrelevant data. The signal is then filtered to remove noise. The most discriminant features are extracted from the filtered signal. Finally, a classifier is used to detect whether the processed signal is classified as one of the seizure states or a normal state. These phases are illustrated in the upcoming sections.

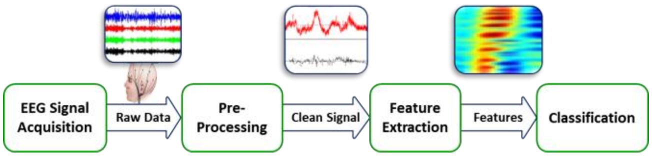

Fig. 2 Seizure prediction workflow.

A. *Signal Acquisition*

Recorded epileptic EEG signals can be categorized according to the way they are recorded either intracranial EEG (iEEG) or scalp EEG (sEEG). The iEEG is recorded through invasive electrodes, as they deliver a higher signal-to-noise ratio and less artifacts compared to scalp EEG data. The sEEG signals are obtained through non-invasive electrodes. They are highly susceptible to artifacts due to the presence of body motion, muscle activity, and electrodes movement. They are more challenging to analyze due to the low signal-to-noise ratio and the presence of artifacts [8]. However, for daily monitoring, the scalp EEG recordings have greater potential in terms of safety, applicability, and ease of use compared to intracranial electrodes.

Researchers require reliable epileptic datasets to benchmark new techniques. Several datasets are publicly available which saves researchers from having to perform the signal acquisition step. The CHB-MIT dataset is one of the most popular epileptic seizures datasets as it is publicly available. It is recorded from 23 pediatric patients through the scalp [9]. Another popular dataset is the intracranial Freiburg dataset which is recorded from a wider range of adults through invasive electrodes [10]. This dataset is not publically available anymore, as it was merged among other epileptic datasets into the European Epilepsy Database [11], which is available with charges. Other private datasets are used individually by some researchers.

B. *Pre-processing*

Preprocessing is a critical step after the signal acquisition. Almost all the scalp EEG signals recorded contain noise and artifacts arising from variant sources [12]. Such artifacts can be categorized into three main types: physiological, experimental and environmental. As a consequence, filtering is essential before moving to the next step in the seizure prediction model [13]. The filtering methodology is different depending on the type of artifacts or noise. One of the methods applied is the manual artifacts removal in which the noise is visually examined and rejected by selecting the artifacts intervals. Filters are also used in the removal of the artifacts such as bandpass, low pass, and high pass filters, by selecting a certain band frequency to be rejected. Mathematical algorithms such as Independent Component Analysis (ICA), Principle Component Analysis (PCA) and EOG subtraction are used in artifacts removal [14]. In [15], the preprocessing of the prediction model was discussed in more details.

C. *Feature Extraction*

Passing high dimensionality vector to a classifier may have adverse effects on output quality. Feature extraction techniques are required to extract the most important features from the input signal and thus, improving classification accuracy. The features can be extracted from: one single channel (univariate) [16], two channels (bivariate) [17] or from multiple of channels concurrently (multivariate) [18].

Various feature extraction techniques were examined by researchers. These techniques can be categorized according to time domain, frequency domains, wavelet based and others [19]. In the time domain, the EEG waveforms differ from one patient to another. Therefore, the seizure prediction algorithm is preferable to be patient-specific [19]. The Zero-crossing algorithm analyzes EEG dynamics based on the successive change of the waveform from negative to positive. It is known for its robustness against noise and artifacts where it removes some of the irrelevant components. Therefore, it was applied successfully in previous epilepsy studies [8] [20]. Common Spatial Filters (CSP) is one of the popular statistical methods in the time domain that is widely used in medical applications based on EEG. It is used in prediction models to discriminate between pre-ictal and inter-ictal activities by generating a covariance matrix that minimizes the variance for pre-ictal waveform and maximizes the variance of the other class [15] [21].

It is hard for some mathematical models to identify EEG activities in the time domain due to the non-stationarity and non-linearity of the EEG signals. The frequency domain techniques can be used to overcome this problem, such as the Fast Fourier Transform (FFT) [19]. Thus, the magnitude and phase of the Fourier transform are used in the prediction of the pre-ictal state from EEG activities [22] [23].

In some cases, the EEG signal becomes highly non-stationary such that it is difficult to rely on features extracted from the time domain or frequency domain only. In this case, the wavelet transform is considered a good choice, as it has the capability of reflecting and localizing the characteristics of time varying-frequency [24]. Wavelets are considered as sub-band decomposition with down-sampling. The epileptic seizure signal consists of varying bursting levels. The discrimination between these levels can be obtained from the wavelet sub-bands [19]. Therefore, wavelets are extensively used in many studies for detecting the pre-ictal state [8] [25] [26] [27]. Other techniques as deep learning techniques have been recently employed in feature extraction as Stacked autoencoders [28] and Convolutional Neural Network (CNN) [22] [7], Long Short-Term Memory [29].

D. *Classification*

The binary classification problem tends to differentiate between pre-ictal and non-pre-ictal states. The pre-ictal state can occur before the seizure from few seconds to several hours. The non-pre-ictal state encompasses three states; ictal, post-ictal, and inter-ictal states. There is a wide spectrum of machine learning techniques that ranges from simple to highly complicated and computationally challenging approaches. Some of these approaches are linear classifiers that do not require extensive training process. They can obtain reliable results with few data and low computational needs.

Support Vector Machine (SVM) is one of the most commonly used techniques in the classification of the binary seizure prediction problem [15] [22] [25] [26]. It tends to find the best hyperplane that can separate between the two classes. This hyperplane tries to maximize the distance between the two classes [30]. The Linear Discriminant Analysis (LDA) is considered Fisher's generalized form [31]. It is good in separating more than two classes yet it fails with complex data structure having non-Gaussian distribution. It was used successfully in [21]. Usman et al. [15] compared the results of three linear classifiers; SVM, K-Nearest Neighbor (KNN) and Naïve Bayes.

On the other hand, if the dataset is growing large, the deep learning approaches can be considered better alternatives especially, with increasingly affordable hardware. Different types of deep networks have been broadly used in the classification of pre-ictal state [8], e.g. the Convolutional Neural Network (CNN). CNN is used to classify high dimensional patterns and multi-variate time series [32]. It is a nonlinear multi-layer back propagation neural network followed by a sigmoid function. CNN was applied by several researchers for the detection of the pre-ictal state [33].

The Long Short-Term Memory (LSTM) is used in the analysis of EEG epileptic seizure prediction [29]. LSTM [34] is considered an evolution of the Recurrent Neural Networks (RNN) that has been used previously in EEG analysis [35]. LSTM deep network model can outperform other deep learning techniques with large datasets. It has an advantage over CNN which is having the capability of isolating the brain's temporal characteristics throughout different states.

E. Key Studies

This section discusses different notable researches in the epilepsy prediction field. Table I compares the results of these recent approaches in terms of sensitivity (True Positive; *number of correctly predicted seizures*), False Alarm Rate (FAR) and Average Prediction Time (APT).

Elgohary et al. [25] demonstrated a novel methodology for the prediction of epileptic seizures. The proposed approach used zero crossings calculated from wavelet transform detail coefficients. The zero crossings used the Haar function to count the detail coefficient of each channel. It corresponds to the variation of the direction of the input signal between the pre-ictal and the inter-ictal states. Then, channel reduction is applied to select the channels of significantly high performance and neglecting those of high redundancy or irrelevancy. A hybrid channel selection approach was used, which combines the characteristics of both the filter and the wrapper feature selection models. This approach starts with selecting a channel per iteration, then each channel is evaluated based on the accuracy obtained from SVM. When the optimization terminates, the best channels are produced. Finally, SVM is used in the classification phase. This approach achieved 96% sensitivity for eight patients of the CHB-MIT.

Usman et al. [15] tackled two main challenges in seizure prediction; noise removal and feature extraction. This study aimed to detect the pre-ictal of the seizure before the start of the onset with sufficient time. The preprocessing was performed on two main steps to enhance Signal to Noise Ratio (SNR). First, CSP was applied to the EEG signals of the 23 channels to acquire one surrogate channel. The Empirical Mode Decomposition (EMD) is applied to the surrogate channel for further increase of the signal-to-noise ratio. As it is well known for being effective in handling non-stationary and non-linear signals. The Statistical features were extracted in the time domain, whereas, spectral features are obtained from the frequency domain. The extracted features are then fed into a classifier to discriminate between pre-ictal and inter-ictal states. Three different classifiers were compared; K-Nearest Neighbor (KNN), Naïve Bayes, and SVM. The SVM classifier gave the highest sensitivity compared to others. The approach was applied on 22 subjects from the CHB-MIT dataset where it achieved 92.23% sensitivity with average prediction time 23.6 minutes before the seizure onset.

Alotaiby et al. [21] used CSP for feature extraction and dimension reduction. The extracted features were passed to Linear Discriminant Analysis (LDA) classifier, to differentiate between pre-ictal and inter-ictal stages. This study examined three prediction interval locations; 60, 90, and 120 minutes with interval lengths 3, 5, and 10 minutes. The best prediction performance was obtained with 3 minutes pre-ictal size. The proposed approach was applied on all patients of the CHB-MIT database. This approach achieved 89% average sensitivity, and 0.39/hour average false prediction rate, with 68.71 minutes average prediction time. One of the main challenges of seizure prediction is the ability to detect seizures prior to the onset with sufficient time. Though this study achieved good results yet, its main drawback is that it detects pre-ictal state just before the seizure begins. Another drawback is that it involved the testing data during the training process where CSP features are extracted from both training and test data.

Zandi et al. [36] proposed an approach that predicts seizures by roughly calculating the probability distribution of certain positive zero crossing intervals recorded from EEG. A new patient-tailored approach was discussed in the new version of the paper [20]. It depends on the usage of variational Gaussian Mixture Models of the zero-crossing intervals in the scalp EEG signals.

The workflow in [20] goes as follows: the data is divided into epochs of 15 seconds each with no overlapping. Each epoch constructs a histogram of a number of bins that contain the positive zero crossing intervals in such epoch. After that, bins differentiating between inter-ictal and pre-ictal states are chosen. The Bayesian Gaussian Mixture Model (GMM) was used for classification. Within the final steps, the patient-specific threshold was compared with a combined index that was calculated and compared based on a sequence of decisions taken on the selected bins.

The basic idea is to inspect the differences and similarities between the epochs of the EEG signals and pre-recorded references of inter-ictal and pre-ictal data. However, some limitations faced this approach, one of which was the short and discontinuous recordings of some of the patients. Another limitation was the low number of seizures for some of the patients.

This approach was tested on 20 patients of the Vancouver General Hospital dataset. It reached a sensitivity level of 88.34%, an average time of prediction of 22.5 minutes and a 0.155/hour false prediction rate.

In [8], Tsiouris et al. combined the Long Short-Term Memory (LSTM) networks with CNN for seizure prediction. They extracted a wide range of frequency and time domain features; statistical moments (mean value, variance, skewness, kurtosis), zero crossings, wavelet transform coefficients, PSD, cross-correlation, and graph theory. This approach was applied to the CHB-MIT dataset. The use of the deep learning LSTM achieved sensitivity higher than 99% with a very low false alarm rate of 0.11–0.02 per hour. This approach applied segment shuffling to overcome the overfitting problem which arose due to the few numbers of pre-ictal segments. This shuffling resulted in being unable to calculate the average prediction time which is the interval from the pre-ictal detection to the seizure onset.

In [22] a hybrid technique that combines CNN with SVM for prediction of seizures was proposed. The time-frequency features are extracted using the Fast Fourier transform. At the same time, more information was retrieved from pre-processing the alpha, beta, and theta frequency bands. This information is then used to generate two dimensional EEG images that are then fed into the CNN. The CNN (based on feed-forward neural networks) has the ability to produce high-level features. Both the high-level features and the frequency-time features are passed to the SVM classifier to discriminate between pre-ictal and non-pre-ictal images. This approach achieved (97.86±0.5) % accuracy, (96.47±0.5) % and (98.81±0.5) % specificity on the dataset of Mayo Clinic and University of Pennsylvania.

III. Discussion

Table II highlights the most commonly used techniques in each phase. As concluded, the majority of studies relied on the CHB-MIT scalp dataset which is publicly available. Among the reviewed studies, only Ref. [15] discussed explicitly the preprocessing of the prediction model. There is a wide range of feature extraction techniques that can be categorized according to the domain used. It is noticeable that the wavelet transform is used extensively since it can handle characteristics of frequency and time domain. As for classification, SVM is the most popular linear classifier. The deep neural network can be used in both feature extraction and classification phases. CNN proved its efficiency in the extraction of high-level features and also in discrimination between pre-ictal and inter-ictal states. Some of the challenges that are still open topics and must be taken into consideration by researchers are:

1) Scalp EEG versus intracranial EEG Datasets

To check the robustness of proposed approaches, they must be broadly examined on more than one dataset. Some datasets are recorded from the scalp (sEEG) as the CHB-MIT database, where it mainly consists of pediatric patients. Others provide intracranial EEG (iEEG) data that are recorded through invasive electrodes. These two types of EEG have different characteristics. Some researchers examined their approaches for the two different types of recorded EEG and this may be a trend in future for obtaining generalized approaches that can fit for both types of signals; sEEG and iEEG.

2) Pre-ictal versus inter-ictal recordings

One of the main challenges facing the classification problem is the imbalance between classes of the given dataset where one class has many instances compared to the other [37]. Epileptic seizure datasets also encounter this problem where the recordings of pre-ictal data are extremely few compared to inter-ictal data [33]. This may lead to an overfitting problem with some classifiers. Balancing the amount of data of the two classes must be investigated in depth by researchers.

3) Compromising false alarm versus prediction rate

A seizure prediction system may encounter annoying false prediction alarms. It is important to minimize the average false alarm rate. Meanwhile, it is more critical to detect a pre-ictal state within a suitable time before the seizure occurs as a missed seizure may affect the patient's safety.

4) Sensitivity versus high computation and time consumption

Some techniques provide high sensitivity, meanwhile, they suffer from high computation and time. As data increase, the deep learning algorithms reveal their power in analyzing biomedical signals as EEG signals [8]. Though using deep learning techniques help in improving system performance, yet they suffer from high complexity and huge time consumption. A reliable prediction system requires compromising these two paradigms.

5) Prediction time

The seizure must be predicted prior to onset with sufficient time, to allow caregivers to proceed with meditations or allow the patient to make his/her precautions so as not to get injured. Many existing seizure prediction studies face this problem. Unfortunately, this is not explicitly indicated in most of the research work we have discussed in spite of its importance.

IV. Conclusion

The prediction time of seizures is a crucial issue in helping patients and their caregivers to keep them safe from the sudden death caused by seizures and to protect them from being injured. This requires an efficient analysis of EEG signals to accurately detect the pre-ictal state of the seizure with a suitable time before the seizure starts.

This paper managed to review the different machine learning approaches that are used along with the different phases of the seizure prediction model. It also compares the results of different approaches as shown in Table I. The taxonomy of machine learning approaches that are reviewed in this paper is illustrated in Table II.

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TABLE I. RESULTS OF SEIZURE PREDICTION APPROACHS IN LITERATURE

Author	Feature Extraction	classifiers	dataset	Subjects	Sensitivity (%)	FAR (h-1)	APT (min)
Tsiouris et al. [8]	statistical moments, zero-crossings, Wavelet Transform, PSD, cross correlation, and graph theory	LSTM + CNN	CHB-MIT	24	99.00	0.11–0.02	-
Elgohary et al. [25]	Zero-crossing of wavelet	SVM	CHB-MIT	8	96.00	-	-
Agboola et al. [26]	Wavelet Transform	SVM	CHB-MIT	17	87.26	0.08	-
		ANN			75.49	0.13	
Usman et al. [15]	Entropy, approximate entropy, Hjorth parameters, spectral, and statistical moments.	SVM	CHB-MIT	22	92.23	-	23.6
		k-NN			-		-
		Naive Bayes			-		-
Alotaiby et al. [21]	CSP	LDA	CHB-MIT	24	89.00	0.39	68.71
Agarwal et al. [22]	Fourier Transofrm	CNN+SVM	Mayo Clinic and University of Pennsylvania	8	96.47	-	-
Chu et al. [23]	Fourier Transofrm	SVM	CHB-MIT	13	86.67	0.367	45.3
			Seoul National University	3			
Khan et al. [27]	Wavelet Transform	CNN	CHB-MIT	22	87.8	0.142	5.832
Daoud et al. [29]	Deep convolutional Autoencoder	Bidirectional LSTM	CHB-MIT	8	99.72	0.004	60.00
Zandi et al. [20]	Zero-Crossing Interval Histogram	Gaussian Mixture Model	Vancouver General Hospital (17) CHB-MIT (3)	20	88.34	0.155	22.5
Truong et al. [33]	Short-Time Fourier Transform	CNN	CHB-MIT	13	89.10	0.17	-
			Freiburg	13	89.80	0.09	-

TABLE II. TAXONOMY OF EPILEPTIC PREDICTION TECHNIQUES

System Components			**Studies**										
			[8]	[25]	[26]	[27]	[15]	[21]	[22]	[23]	[29]	[33]	[20]
Signal Acquisition	***Scalp EEG***	***CHB-MIT***	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
		Vancouver											✓
		other				✓				✓			
	Intracranial EEG	***Frieburg***										✓	
		Mayo clinic							✓				
Pre-processing	***Noise Removal***	***EMD***					✓						
	Filtering	***CSP***					✓						
Feature Extraction	***Frequency domain***	***Fourier***							✓	✓		✓	
		PSD	✓				✓						
	Time domain	***CSP***					✓	✓					
		Zero-crossing	✓	✓									✓
		Descriptive Statistics	✓										
		Inferential Statistics*	✓										
	Freq.-Time	***Wavelet***	✓	✓	✓	✓							
		Graph theory	✓										
	Deep Learning	***Autoencoders***									✓		
		CNN							✓				
Classification (Machine Learning)	***Traditional (Shallow) Learning***	***SVM***		✓	✓		✓		✓				
		LDA						✓					
		Naïve Bayes					✓						
		K-NN					✓						
		GMM											✓
		ANN			✓								
	Deep Learning	***CNN***	✓			✓						✓	
		LSTM	✓								✓		

* *Cross correlation*