World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Research Article)

A comprehensive study of machine learning-based methods to predict epileptic seizures

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World Journal of Advanced Engineering Technology and Sciences, 2024, 12(01), 065–072

Publication history: Received on 31 March 2024; revised on 09 May 2024; accepted on 11 May 2024

Article DOI: https://doi.org/10.30574/wjaets.2024.12.1.0187

Abstract

People with epilepsy have many difficulties as a result of this complicated brain condition, which is typified by frequent convulsions. Symptoms of these seizures include bizarre behaviors, odd sensations, and in extreme cases, loss of awareness. These seizures appear as episodes of aberrant electrical impulses in the central nervous system. Successful epilepsy management depends on early seizure detection and identification, which allows for appropriate intervention to minimize risks and improve patient outcomes. Two major reasons have contributed to the extraordinary advancements in the area of epilepsy investigations in the last few years: the explosive development of machine learning techniques and the decreasing cost of non-invasive electroencephalography (EEG) apparatus. The availability of low-cost EEG equipment has made it easier to gather information on brain activity, which has opened up new avenues for monitoring and analyzing episodes of epileptic seizures away from conventional medical settings. The abundance of data and the advancement of machine learning methods have created new opportunities for the early identification and forecasting of seizures. Machine learning algorithms can predict seizures based on EEG data, providing patients with epilepsy with more control and informed decision-making. This paper offers a current review of current methods for treating epileptic seizures. The feature extraction techniques and classification algorithms receive particular focus. The most popular EEG datasets and their accessibility are listed. The approaches that are examined range from those that use more established machine learning techniques, such as naive Bayes models, Support Vector Machines (SVM), and Linear Discriminant Analysis (LDA), to those that take advantage of more recent deep learning techniques, like (Long-Short Term Memory, or LSTM), and deep Convolutional-Neural-Networks (CNN).

Keywords: EEG Signal; Epilepsy; Machine Learning; Support Vector Machine; Linear Discriminant Analysis.

1. Introduction

Seizures are a symptom of epilepsy, a neurological condition. A significant number of brief electrical discharges from many nerve cells are the primary cause of epilepsy, Fisher et al. [1]. The patient's attitude and level of awareness are altered as a result of epileptic seizures, which can occasionally result in catastrophic mishaps, Litt, B., and Echauz [2]. Although the epileptic illness is not age-specific, 80% of individuals have epileptic symptoms before the actual age of 20 particularly throughout early childhood and teenage years, Macleod, S. and Appleton, R.E [3]. Around 50 million people worldwide are roughly affected by Epilepsy. Almost 30% of the patient population does not agree with clinical intervention or surgery, Fisher et al. [1].

Due to their abrupt onset, these forms of epilepsies pose a serious risk to the patients' lives. Additionally, they are the primary source of discomfort in the patient's social and private life. These factors led to the development of novel

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methods for epilepsy prediction. These techniques might enable the patient to anticipate the seizure before it occurs, Gajic et al. [4].

There are four different brain states for an epileptic patient: interictal, pre-ictal, ictal, and post-ictal. The three other phases are those of the actual seizure, whereas the inter-ictal phases are those of the normal brain. Before having a seizure, a patient or patients may experience a few Changes to the body, such as muscular twitches, gastrointestinal disturbances, etc. This period is known as the pre-ictal state, Mula, M. and Monaco, F [5]. These alterations are referred to as the epileptic aura. The length of the seizure is the ictal stage. The brief period following the seizure is known as the post-ictal state. It might be thought of as a transitional-state that exists between the inter-ictal state and the ictal state, Chiang et al. [6]. Figure 1 represents various seizure states or phases.

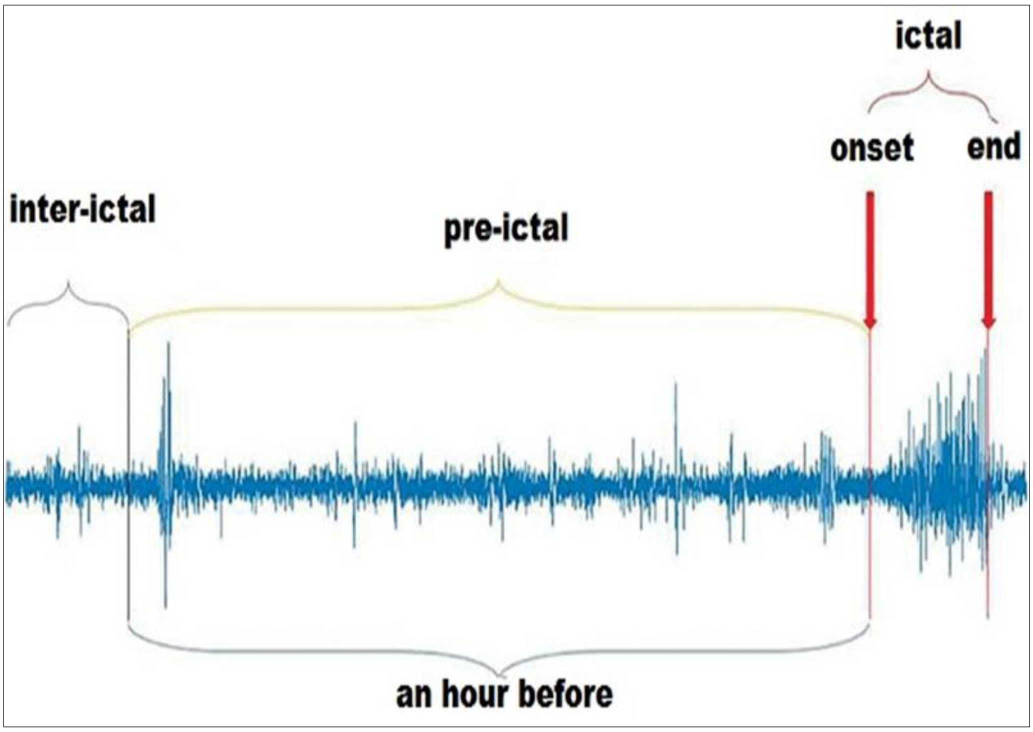

Figure 1 Different phases of epileptic seizure, Wei et al. [7].

Depending on the type of condition that is observed, many seizure detection and prediction methods exist. The ictal and interictal characteristics are retrieved during detection, whereas pre-ictal features are discovered during prediction. Compared to detection, epileptic seizure prediction requires greater knowledge. The patient's safety is greatly benefited by the seizure prediction, though. As a result, the primary focus of this work is seizure prediction, which requires identifying the pre-ictal state.

In this study, several strategies created to improve epilepsy prediction are discussed. It provides an explanation of those methods using feature extraction and classification approach. Based on the mix of information sets, the preprocessing phase, feature-extraction, and classification approaches employed, the review also offers a classification table of the aforementioned epilepsy prediction methods.

2. Model for predicting seizures

Figure 2 shows the overall process of a seizure diagnosis model. Preprocessing is required to remove unnecessary and unused data from the collected signal. After that, the signal undergoes filtering to eliminate distortion. The filtered signal contains the most distinguishing characteristics. The processed signal is then categorized as either a normal state or one of the seizure states using a classifier. The following sections provide visuals of these stages.

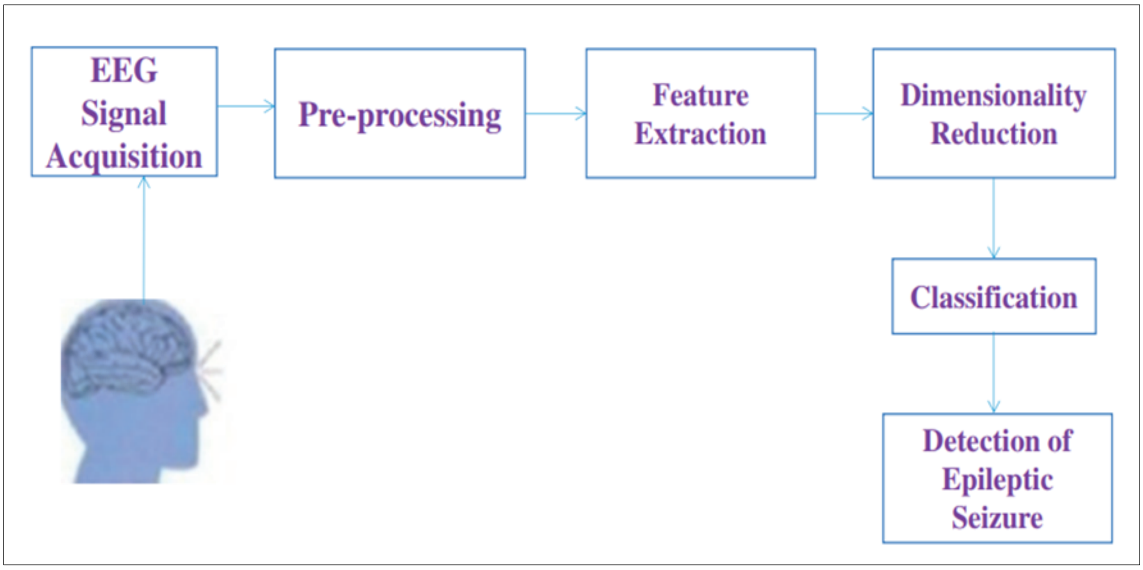

Figure 2 System for detecting epilepsy using identification of patterns, Sharmila, A [8].

2.1. EEG signal-acquisition

According to how they are captured, epileptic EEG signals can be classified as either within the skull or scalp electroencephalogram. Invasive electrodes are used to record the iEEG because they produce fewer artefacts and a higher-quality signal. According to how they are captured, epileptic EEG signals can be classified as either within the skull or scalp electroencephalogram. Because they provide fewer artefacts and a greater (signal-to-noise ratio) than scalp EEG data, intrusive electrodes are used to capture the iEEG. Electrodes that are not intrusive are used to record the sEEG. Because of the existence of body motion, activation of muscles, and electrode action, these signals are very prone to artefacts. They have a lower (signal-to-noise ratio) and more artefacts, making them more difficult to examine, Tsiouris, K.M., [9]. EEG recordings made over the scalp are safer, more useful, and simpler to utilize for daily monitoring than those made using cranial electrodes.

To assess novel approaches, researchers need trustworthy epileptic records. Many data records are freely obtainable, saving examiners the time-consuming task of signal gathering. Due to its accessibility to the public, CHB-MIT information is perhaps the most used dataset for epileptic-seizures. Through the scalp, it has been documented from 23 pediatric individuals, Shoeb and A.H., [10]. The cranial Freiburg dataset, which is a prominent information set as well, records data from a larger spectrum of individuals using harmful electrodes, Zhou et al. [11]. The information contained within it is no longer publicly accessible since it was combined with other epilepsy information sets stepping into data the European Epilepsy Database, Ihle, M., et al. [12], which is only accessible for a fee. Some researchers utilize separate private databases from others.

2.2. Pre-processing

After signal capture, preparation is a crucial step. Nearly all scalp EEG signals that have been recorded have noise and artefacts from various sources. The three basic categories of artefacts are experimental physiological, and environmental. As a result, filtering is crucial before continuing with the seizure prediction model's next step, Tavildar, S. and Ashrafi, A., [13]. Depending on the kind of artefacts or noise, different filtering techniques are used, Radüntz, T., et al. [14]. One technique used is the step-by-step elimination of artefacts, in which the noise is visually inspected and rejected by choosing the intervals for the artefacts. By choosing a certain frequency range being dismissed, filters including (bandpass, high-pass, and low-pass filters) are also employed to eliminate artefacts. Artefact elimination frequently makes use of mathematical procedures like [Independent Component Analysis (ICA), Principal Component Analysis (PCA), and EOG subtraction, Tandle, A., et al. [15]. The pre-processing of the prediction model of seizure was covered in further depth in Usman, S.M., et al. [16].

2.3. Extraction of features

A classifier's output quality could be adversely impacted by being given a vector with a large dimensionality. To extract the most crucial characteristics concerning the input signal and improve identification accuracy, feature extraction techniques are needed. A single channel, two channels, or many channels simultaneously, Rasekhi, J., et al., Mormann, F., et al. [17,18] can all provide these characteristics. Researchers looked at several extractions of features methods, according to the wavelet-based, time field domain, frequency field domain, and other categories, these approaches may be grouped, Fujiwara, K., et al. [19]. The EEG waveforms in the time field vary from patient to patient and are condition-dependent. This means that a patient-specific seizure identification system is preferred, Alotaiby, T.N., et al. [20].

The zero-crossing method or algorithm interprets EEG dynamics based on the repeated change of the waveform from an adverse to a favorable state. It is renowned for its resistance to noise and artifacts because it filters out some of the unimportant components. As a result, it has been effective in earlier epilepsy research, Tsiouris, K.M., Zandi, A.S., et al. [9, 21]. Common Spatial Filters (CSP for short) are among the most used statistical approaches in EEG-based healthcare applications. To make a distinction between pre-ictal and inter-ictal activity in prediction models, a matrix of covariance that enhances the variance of the other class and reduces the difference for the pre-ictal pulse or waveform must be created, Usman, S.M., et al., Alotaiby, T.N., et al. [16, 22].

Some mathematical models have difficulty detecting EEG activity in the time field because of non-stationary behavior and the non-linear of the EEG waveforms or signals. This issue can be solved using frequency domain methods, such as the Fast Fourier Transform, also known as the FFT, Fujiwara, K., et al. [19]. In order to forecast the pre-ictal state from EEG activity, the phase as well as the amplitude of the Fourier analysis are employed, Agarwal, P., et al., Chu, H., et al. [23, 24]. When the EEG signal is substantially unpredictable, it might be challenging to depend only on characteristics taken from the frequency domain or the temporal domain. The wavelet transform is seen to be an excellent option in this situation since it can localize and represent the properties associated with time-varying-frequency, Ocak, H., [25].

Wavelet representations are thought of as down-sampling sub-band reduction. Variable bursting levels make up the epileptic seizure signal. The wavelet sub-bands such can be used to distinguish between different levels Fujiwara, K., et al. [19]. To identify the pre-ictal state, wavelets are therefore widely employed in different studies Tsiouris, K.M., Elgohary, S. et al., Aribike, D.S. et al., Khan, H. et al. [9, 26, 27, 28]. Other methodologies for deep learning, such as Stacked autonomous encoders, Khan, H. et al. [28], or Convolutional neural networks, commonly referred to as CNN, Agarwal, P., et al., Wei et al. [23, 7] and Long Short-Term Memory which is LSTM, Tăuţan, A.M., et al., Daoud, H. and Bayoumi, M.A., [29, 30], have lately been applied in the extraction of features.

2.4. Classification

There is a wide range of learning algorithms, from relatively easy to extremely intricate and computationally demanding methods, for the binary classification problem. Some of these methods use linear classification techniques, which can produce accurate results with little data and with little analyzing effort and without a lengthy training procedure.

SVM is one of the well-liked methods for categorizing the seizure diagnosis issue. To distinguish between the two classes, it frequently seeks out the optimum hyperplane that increases the distance between them, Vapnik, V.N., [31]. Fisher's generalized variant is known as the linear discriminant assessment (LDA), Bashashati, A., et al. [32]. Although it works well for classifying more than two types of data, complicated data structures with non-Gaussian proportions cause it to fall short. It was effectively employed in Alotaiby, T.N., et al. [22]. SVM, the k-nearest-neighbor method (KNN), and the Nave Bayes algorithm were three linear classifiers that Usman et al. [16] examined.

On the other end of the spectrum, deep learning techniques may be preferable in cases when the set of data is expanding, particularly with more and more reasonably priced technology. A variety of deep network types, including as Convolutional neural network, commonly referred to as CNN, have been widely employed in the categorization of pre-ictal state, Tsiouris, K.M., et al. [9]. Large dimensional patterns and multivariate time series are classified using CNN, LeCun, Y., et al. [33]. It is a sigmoid function followed by a nonlinear propagation of the back neural network with several layers. Several researchers used CNN to identify the pre-ictal stage, Truong, N.D., et al. [34].

Recently, LSTM has been used to predict seizures Daoud, H. and Bayoumi, M.A., [30]. IHochreiter, S. and Schmidhuber, J., [35] indicate that LSTM is an improved version of the neural networks with recurrent connections that were previously applied in this sector. Petrosian, A., et al. [36] Large datasets allow the LSTM algorithm deep network model will perform better than alternative deep neural network strategies.

2.5. Key studies

The several relevant studies in the subject of epilepsy prediction are included in this section. The outcomes of these current methods are compared in Graphical Representation based on their degree of Sensitivity, average time for prediction, and rate of false alarms.

Elgohary et al. [26] created a unique strategy based on channel reduction and zero crossings for anticipating epileptic episodes. Combining filter and wrapper feature selection methods, they employed a hybrid channel selection strategy. The method provided the optimal channels after optimization by choosing channels for each iteration and evaluating them according to SVM accuracy. For eight CHB-MIT patients, the technique had a 96% sensitivity.

Usman et al. [16] investigated seizure prediction using feature extraction and noise removal to locate pre-ictal phases. To improve Signal to signal-to-noise ratio, they preprocessed data using CSP and Empirical Mode Decomposition. The classifier was fed with the retrieved characteristics, with SVM displaying the maximum sensitivity. The experiment used 22 participants from the CHB-MIT dataset and achieved a sensitivity of 92.23% with an average forecast period of 23.6 minutes.

F. M. Alotaibi [22] distinguished between pre-ictal and inter-ictal phases using CSP for reducing dimensions and extraction of features. They used the suggested method on all patients in the CHB-MIT information set, reaching an average sensitivity level of 89% and a false prediction rate of 0.39 per hour. The study did have several drawbacks, though, such as the inability to detect pre-ictal states right before a seizure starts and the need to assess data while it was being trained. The Empirical Mode Decomposition was also employed in the study to improve the signal-to-noise ratio. Three classifiers—Naive Bayes, SVM, and KNN—were given the collected features, with SVM displaying the greatest sensitivity. The method had a sensitivity level of 92.23% and a time average for prediction of 23.6 minutes prior to the commencement of the seizure.

Zandi et al. [37] developed a method to predict seizures using EEG data's probability distribution of positive zero-crossing intervals. The updated strategy uses variational Gaussian Mixture Models to represent these intervals. Data is separated into 15-second epochs, and a histogram is created from bins. Inter-ictal and pre-ictal stages are separated, and the patient-specific threshold is compared in the final phases.

Tsiouris et al. [9] coupled CNN and LSTM networks to predict seizures, extracting characteristics such as wavelet transform coefficients, zero-crossings, cross-correlation, PSD, graph theory, and statistical moments (Mean value, kurtosis, skewness, variance). On the CHB-MIT dataset, they applied this strategy and achieved sensitivity levels exceeding 99% and minimal false alarm rates. To overcome overfitting issues and determine the average forecast time, segment shuffling was performed.

To predict seizures, a hybrid approach combining CNN and SVM was suggested. Two-dimensional electroencephalogram pictures are fed into CNN which is referred as a (convolutional Neural Network), which creates high-level features and uses a Support-Vector Machines (SVM) classifier to differentiate between pre-ictal and non-ictal images.

Table 1 Literary results of seizure-prediction methods.

Author and References	**Feature Extraction**	**Sensitivity (%)**	**APT (min)**
F. M. Alotaibi [22]	Automatic diagnosis system, CSP	89	68.71
W. Jeong [24]	Attractor-based analysis, Fourier Transform (FT)	86	45.3
L. Marcuse [28]	Stacked autoencoders, Wavelet Transform	87.8	5.832
M. Bayoumi [30]	Deep convolutional Autoencoder (AEs)	99.72	60
M. Javidan [21]	Variational Mixture of Gaussians, Zero-Crossing Interval Histogram	88.34	22.5

3. Discussion

Usman et al. [16] specifically mentioned the initial processing of the model for prediction among the articles that were analyzed. There are several techniques for obtaining features that may be divided into classes based on the application domain. Since the wavelet transform is a technique that can handle both frequency and temporal domain capability, it is obvious that it is widely employed. SVM is the most well-liked linear classifier when it comes to classification. The feature extraction and classification steps may both be achieved using a deep neural network for this purpose. The ability of CNN to extract key features and differentiate between inter-ictal and pre-ictal phases was demonstrated. Following are a few of the issues that need more study and must be taken into account by examiners.

3.1. Comparison of skull and scalp electroencephalogram (EEG) datasets

The reliability of suggested methodologies must be thoroughly evaluated on several information sets. Some scalp-based information sets, such as the CHBMIT database, which was compiled from childhood patients, are recorded. Others offer data from intracranial EEG (iEEG) recordings made using damaging electrodes. There are differences between these two EEG kinds. A future trend may be to develop generalized methodologies that can apply to both (sEEG and Ieeg) signals after several researchers assessed their methods for the two different forms of recorded EEG.

3.2. pre-ictal as opposed to inter-ictal recordings

The imbalance of classes in the supplied information set, where one class has more occurrences than the other, is one of the primary problems with the classification issue, Zandi, A.S., et al., [37]. This issue also arises in epileptic seizure datasets, where there are many fewer pre-ictal data recordings than inter-ictal data, LeCun, Y., et al. [33]. Some classifiers may experience an overfitting issue as a result of this. They need to thoroughly explore how to balance the amount of data from the two classifications.

3.3. False-alarm rate versus prediction-rate compromise

A technique used to predict seizures caused by epilepsy could have grating erroneous alerts. It's critical to reduce the typical false alarm rate. A missed seizure might jeopardize the patient's safety; hence it is more important to identify a pre-ictal condition as soon as possible before the seizure starts.

3.4. Sensitivity versus extensive processing and long run times

While some approaches offer excellent sensitivity, they also need a lot of calculation and time. As the amount of data grows, deep learning systems demonstrate their ability to analyze biological signals like EEG signals, Sharmila, A., [8]. Although using sophisticated machine learning techniques raises system performance, they are time-sensitive and complexity-intensive. A compromise between these two mindsets is required for a good prediction system.

3.5. Predictive period

For caretakers to continue their meditations or for the patient to take protective measures to avoid harm, the seizure must be anticipated before it starts. This issue affects many of the current seizure prediction studies. Despite its significance, this is regrettably not directly stated in the majority of the research studies we have covered.

3.6. Literature Results of Seizure Prediction Approaches

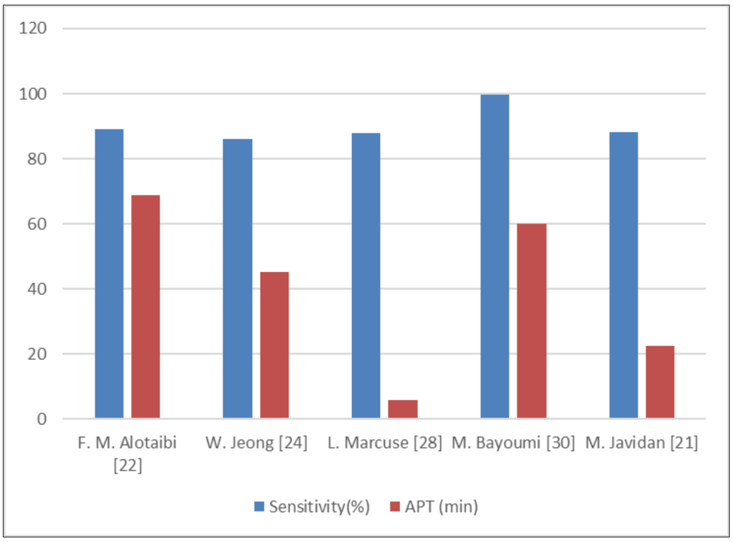

Figure 3 Graphical Representation of Sensitivity and APT (min)

4. Conclusion

The ability to predict when seizures will occur is essential for patients and those who take care of them to avoid injury and untimely death brought on by seizures. To successfully determine the pre-ictal condition of the seizure with a sufficient amount of time before the seizure commences, calls for a successful evaluation of EEG data. The multiple algorithmic learning techniques utilized along with the various seizure prediction model stages were reviewed in this study. Furthermore, it contrasts the research outcomes of the seizure prediction techniques depicted in Figure 3.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest is to be disclosed.

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