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EEG Signal Classification for Epileptic Seizure Detection: A Review of Machine Learning Approaches

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Abstract

Purpose: Epilepsy is a severe, long-term neurological condition that can be identified by examining the signals that brain neurons produce. Complex connections between neurons allow them to generate impulses and communicate with human organs. Electrocorticography (ECoG) and electroencephalogram (EEG) modalities are frequently used to detect these brain impulses. These signals generate a lot of data and are complicated, noisy, non-linear, and non-stationary. As a result, identifying seizures and learning about the brain are difficult tasks. **Methods:** EEG data can be classified by machine learning classifiers, which can also identify seizures and provide pertinent, logical patterns without diminishing efficiency. **Results:** The classification algorithms utilized for epilepsy detection are thoroughly described in this work. The authors also go over the current challenges confronting the field of automatic epilepsy detection and offer possible avenues of study. **Conclusion:** The authors anticipate that the data collected will help apply appropriate machine learning techniques and give BCI researchers a starting point for improving future BCI systems.

Keywords: Epilepsy, Seizure, machine learning, Deep learning, classification

1 Introduction

Epilepsy is a neurological illness that impacts around 50 million individuals across the globe[1]. As indicated by International League against Epilepsy (ILAE)[2], the neurological community receives a standard topology for epilepsy identification. The clinicians rely on machine learning methods for diagnosis of epilepsy, as visual inspection is a tedious task. For the analysis of neurological disorder, for example, epileptic seizures[3] clinicians use brain signals. Among several brain signals, electroencephalogram (EEG) signals have been effectively utilized in identifying epileptogenic zones.Epilepsy is diagnosed by distinguishing between focal and non-focal EEG patterns. The areas affected by epilepsy are where focal EEG signals are found, whereas non-focal EEG data are obtained from areas where seizures are not occurring[4]. Different signal processing procedures have been utilized for programmed segregation of focal EEG signals. Several feature extraction methods have been

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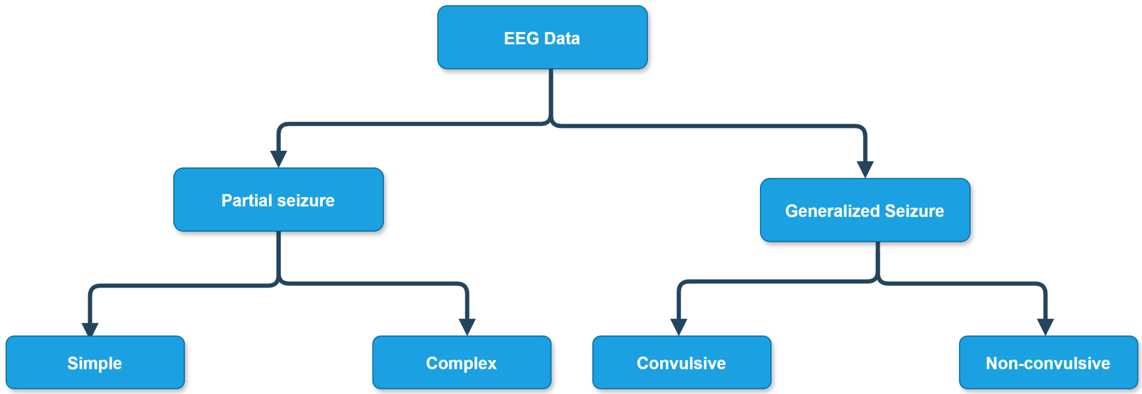

Fig. 1 Categories of Seizure

proposed for analyzing signals and extracting features like entropy[5, 6], mean[7] and standard deviation [8]. These features are then classified using various classification algorithms like Support Vector Machine (SVM) [5, 6], K-Nearest Neighbor (KNN) [9, 10], Neural Networks (NN) [8, 11, 12] and Deep Neural Networks (DNN) [13, 14].

1.1 Seizure Type

Experts in neurology divide seizures into two primary groups based on symptoms: partial and generalized [15, 16]; In Fig. 1, this distinction is shown. When a partial seizure, sometimes called a focal seizure, occurs, only a region of the cerebral hemisphere becomes infected.Partial seizures can be classified as either simple-partial or complex-partial. A patient does not lose consciousness in the simple-partial, but they are unable to speak effectively. When someone is in the complex-partial, they experience a ”focal impaired awareness seizure,” which is characterized by disorientation regarding their environment and aberrant behavior such as chewing and mumbling. Conversely, all brain regions are affected and whole brain networks rapidly become infected during generalized seizures . Although there are many different kinds of generalized seizures, they can be generically classified as either convulsive or non-convulsive.

1.2 Contribution

This study discusses an overview of machine learning for EEG-based epilepsy detection. The authors have thoroughly discussed the deep neural networks and techniques for machine learning that have been proposed by different researchers for the diagnosis of epilepsy. The study also covered a variety of machine learning-related research problems. Additionally, the authors noted the challenges that are present in this field. The format for the remainder of the paper is as follows: In Sect. 2, the research approach is discussed. This section outlines the procedures for choosing literature. Section 3 provides a thorough explanation of how machine learning techniques are applied in epilepsy detection. Section 4 describes the deep learning techniques used in epilepsy detection. section 5 addresses the challenges in epilepsy detection and section 6 concludes the study.

2 Review Planning

An outline of the approach used by the authors to carry out a thorough survey is provided in this section.

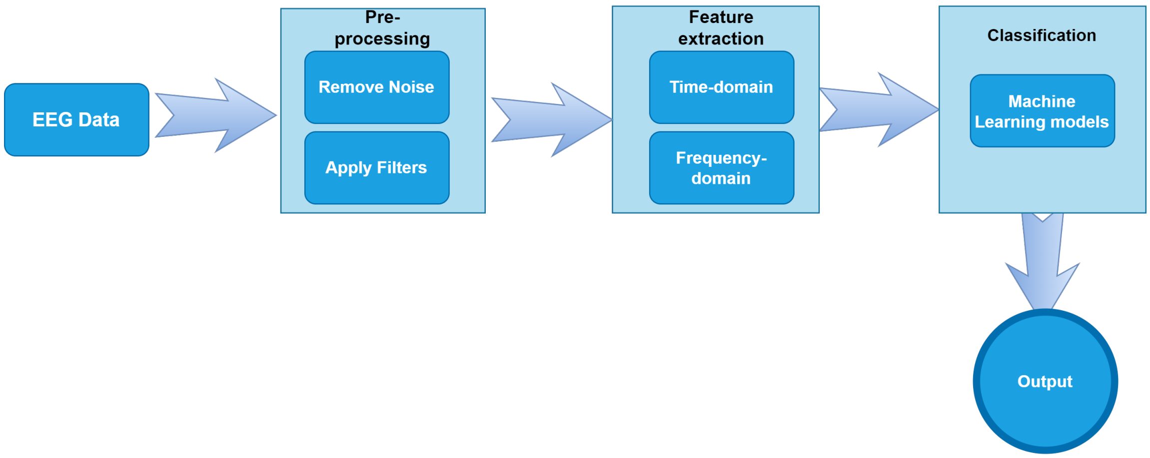

Fig. 2 Epilepsy Detection Process using Machine Learning

2.1 Research Questions

The primary goal of this study's analysis is to support emerging researchers in the field. This analysis provides solutions to multiple research questions. Through this investigation, they will be able to identify the primary research questions in this area and determine the underlying corpus of machine learning approaches utilized for epileptic seizure detection. These research questions are covered in Table 1.

Table 1 Research Questions addressed in this study

S.No.	Research Question
RQ1	Which machine learning techniques are used for epilepsy detection?
RQ2	Which deep learning models are used for epilepsy detection?
RQ3	What are the challenges for epilepsy detection ?
RQ4	What are the limitations in machine learning techniques used for epilepsy detection?
RQ5	What is the future direction in epilepsy detection using EEG ?

2.2 Exclusion Criteria

The authors analyzed the collected articles for inclusion and exclusion from the review. The exclusion criteria used are as follows: EC1: Paper not related to epilepsy detection and machine Learning and EEG EC2: Paper that does not provide any experimental results. EC3: Paper that talks about theoretical considerations. EC4: Publication before 2009.

2.3 Article Acquisition

The papers were found through a keyword search focused on EEG-based epilepsy identification. To find relevant publications, the search terms "EEG-based epilepsy detection," "epilepsy detection using machine learning," and "seizure detection using machine learning" are used. The authors looked through IEEE Explore and Science Direct. Initially, the authors picked 95 papers based on the keywords and importance of this analysis. Subsequently, additional filtering was done in order to extract insights from the most relevant publications, and 40 papers were excluded based on the previously specified exclusion criteria. Consequently, our study had a total of 55 publications from respectable journals and conferences.

3 Machine Learning for Epilepsy Detection

Researchers have been attempting to surmount the obstacles associated with the identification and prognosis of epilepsy since the turn of the century. Since EEG data are a vital source for tracking brain activity prior to, during, and following ES, the analysis of EEG recordings was the primary focus of ES prediction research initially. Muscle noise, blinks, eye movements, and heart impulses all contaminate EEG signals. Various techniques for filtering and noise reduction are employed to mitigate the impact of diverse sources of noise and artifacts [17]. Significant features are required for the development of machine learning techniques for the identification and categorization of pre-ictal and interictal stages after artifacts have been removed. Figure 3 shows the classical ML methodology for the epilepsy prediction.

Support Vector Machine (SVM) is utilized to separate a pair of classes with a hyperplane of the most extreme edge [18, 19]. Vapnik [20]developed an SVM that is based on the principle of structural risk minimization. SVM is named Linear SVM that creates decision boundaries by the linear function and nonlinear SVM that uses the kernel function to delineate information into higher dimensional space[21]. In most of the studies, the Least Square Support Vector Machine (LS-SVM) has been used for classifying focal and non-focal EEG. Manish Sharma et al.[5] and Pushpendra Singh et al.[22] proposed a method that explored LSSVM with polynomial and radial basis function. Rajeev Sharma et al.[23] used radial basis function (RBF), linear kernel and polynomial kernel of order2, order 3 and order 4. Abhijit Bhattacharyya et al. [24] also explored LSSVM with RBF and kernel function of the Morlet wavelet. Swastik Gupta et al.[18] also features the utilization of LS-SVM classifiers with various kernel functions for the identification of focal EEG signals. The linear and non linear SVM gives reasonable classification accuracy. to further improve the accuracy of the classifier. N. Sriraam [6] investigated optimized SVM with 10 fold cross validation and acquired the exactness of 92.15

K-Nearest Neigbor (KNN) is a non-parametric methodology where it predicts items, esteems or class participations dependent on the k-nearest preparing models in the element space. KNN is an administered non-parametric classifier that need not bother with earlier suppositions about the insights of the preparation tests. The separation parameter and K are the two parameters that are required to tune for the KNN classifier. Anindya Das et al. [25] used Euclidean distance as a parameter. Vipin Gupta et al. [26] proposed a method in which the author varied the value of K between 1 and 5 and used Euclidean, cosine, correlation and city-block distances for the optimization of classifier performance. Soumya Chatterjee et al.[19] choose Euclidean distance as separation parameter and the k is varied from 2 to 10. The author discovered that K = 5 and K = 7 gives better classification performance than other values of K . Artificial Neural Network (ANN) is non-direct classifiers made out of an enormous number of interconnected components named as neurons. Every neuron in ANN mirrors the biological neuron and plays out some computational tasks. NN is suitable for fast classification and gives better performance accuracy as compared to KNN and SVM classifiers. S. Deivasigamani et al. [8] proposed the Adaptive Neuro Fuzzy Inference System (ANFIS) classifier that contains the input layer, three hidden layers and the output layer. The amount of neurons required for input layer and hidden layer is reliant on extracted features and feature set respectively. The output layer has a single neuron that produces the result in a binary pattern. Sachin Taran et al.[11] used ELM classifier which is a single layer neural framework and works in feed forward style. The author used this classifier for clustering VMD based features. The individual NN falls into local minimum when using backward propagation. To overcome this limitation Mingyang Li et al [12] proposed a neural network ensemble composed of three independent network groups and a back propagation neural network as subnet. This neural system group is utilized for 3-class characterization of epilepsy.

4 Deep Learning for Epilepsy Detection

Convolutional Neural Network (CNN) has the capability to learn new features automatically. Moreover CNN can handle huge amounts of data and provides better results as compared to hand crafted features [27, 28].Arwa M. Taqi et al. [29] proposed a methodology in which the author used Caffe framework with LeNet, AlexNet, and GoogLeNet models. The author proposed convolution layer, pooling layer for feature extraction whereas fully connected, and soft-max classifier for classification. The hand crafted feature extraction to extract relevant features is too complex a process. Diyuan Lu et al. [30] address this issue and propose convolutional neural network architecture that includes residual blocks for automated feature extraction. Each residual block consisted of two convolution layers, one max pooling layer and one dropout layer. Furthermore, Zuochen Wei et al.[31] proposed another CNN architecture with MIDS and augmentation in which 12 layer CNN is structured with a merger of expanding and diminishing groupings to feature qualities of waveforms. At that point, data augmentation technique, Wasserstein Generative Adversarial Nets (WGANs) is applied. The proposed architecture has achieved better performance over basic CNN.

Table 2 State-of-art for epilepsy detection using machine learning

Author	Year	Classifier	Accuracy
Manish Sharma et al.	2016	Least Squares-Support Vector Machine	94.25
S. Deivasigamani et al.	2016	Adaptive Neuro Fuzzy Inference System	99
Anindya Das et al.	2016	K-nearest neighbor	89.40
Arwa M. Taqi et al.	2017	Deep Neural Network	100
N Arunkumar	2017	Non-Nested Generalized Exemplars classifier	98
Mingyang Li et al.	2017	Neural Network Ensemble	98.78
Abhijit et al.	2018	Least Squares-Support Vector Machine	85
M. Dalal et al.	2019	Robust energy-based least square twin support vector machine	90.20
Mehmet et.al.,	2021	CNN	97.92
Chen W et.al.,	2023	CNN	100

5 Challenges

Numerous classification algorithms have been applied successfully for classifying focal and non-focal EEG signals, still there are some challenges that affect the accuracy of the epilepsy detection and prediction systems. The challenges have been divided into categories as depicted in table 3. Several studies have used wavelet transforms for extracting features[26, 32]. The author in [26] explored Flexible wavelet analytic transforms that utilize Hilbert transform and provides flexibility in controlling quality factor and dilation factor. This approach allows flexible portioning of time-frequency covering. The significant hindrance in extraction of wavelet-based features is the assurance of proper decomposition level and determination of features. The classifiers available for detecting epilepsy are tested and validated in laboratories. However, to use in real time there is a need for robust classifiers that can be easily used online and works efficiently with EEG signals. The characteristics of non focal eeg signals vary across patients due to which classifiers have long delays in epilepsy detection, whereas patient specific classifiers obtain reasonable accuracy but have issues with new patients[33]. The challenges related to hardware are discussed in three studies. Turkey N Alotaiby et al [34] describes that designing implantable devices used for alerting a patient is a challenging task and suggest that Deep Neural Network can be used for this task. Most of the epilepsy detection systems were not able to balance accuracy with universality. To deal with this issue, Mingyang Li [32]proposed a method that consisted of wavelet-based non-linear analysis and a genetic algorithm optimized support vector machine (GA-SVM). This method is simple to compute and has obtained the accuracy of 99The studies [35, 36] from the literature revealed the requirement for a comprehensive dataset. The other challenges related to dataset and data collection is the presence of artifacts in EEG signals [36]and advancement in preprocessing of the signals [34] The modality challenges are cross patient variability, overlap in signal pattern and non stationary nature of EEG signals[37]. Depending on the needs and characteristics of the dataset, each classifier has advantages and disadvantages of its own . It is generally quite hard to determine which classifier performed best with brain datasets. A number of classifiers have been tested on EEG datasets in order to determine which one is the most capable; the classifier with the best performance is then taken into consideration for solving seizure detection and facilitating knowledge discovery. According to the literature, earlier researchers used a variety of techniques, the majority of which came from "black-box" models including ANN, KNN, and SVM. Their inability to offer suitable explanations for the patterns and logic rules concealed within the models is their greatest flaw. They are therefore not recommended for an exceptional process of information discovery. The internal processing of patterns may not be investigated by data scientists. All of these seizure detection findings raise a few intriguing research questions, such as choosing appropriate statistical features and machine learning classifiers to reduce computation time due to the large volume and high dimension of the dataset. The most important piece of missing data from machine learning classifiers is determining the precise location of the seizure at the brain lobe(s).

Table 3 Reported Challenges for Epilepsy Detection

Tier	Challenges	Articles
Feature Extraction	Selection of features from certain sub bands	[32]
Classification	Robust classifiers [RC]	[33]
	Rigrous evaluation of performance	
	Accuracy of patient non-specific classifiers	
Hardware	Realization of implantable devices used for alerting the patient	[32]
	Balance of accuracy with universality	[30]
	Most of the existing systems are trained on small scale datasets	[35]
Dataset and Data Collection	Need for comprehensive dataset	[33]
	EEG data acquisition system are susceptible to diverse range of artifacts	[35]
	Advanced pre-processing of EEG signals	[33]
Modality	Cross patient variability	[36]
	Overlap in Signal pattern	
	Non-stationary nature	

6 Conclusion

In this paper, authors have explored the different classification algorithms available for classification of focal and non-focal EEG signals. It has been found that Least Square Support Vector Machine (LS-SVM) has been commonly and successfully used. Much of the research has been shifting towards the Deep Neural Network to have a robust classifier that can be used online and for practical systems. Furthermore, the authors have discussed the existing challenges in this domain. With the increase of epilepsy, its accurate detection becomes increasingly important. A major challenge is to detect seizures correctly from a large volume of data. Due to the complexity of EEG signals in such datasets, machine learning classifiers are suitable for accurate seizure detection. Selecting suitable classifiers and features are, however, crucial. Further, The cross patient variability of the signals affects the accuracy of the patient specific classifier. Therefore, future work should focus on developing robust patient specific classifiers that would be able to handle data of new patients efficiently and might be used for real and practical systems.

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