ISSN: 2581-3404 (Online) IF: 5.68 (SJIF)
IJIRTM, Volume-8, Issue-6, December-2024.

Automated Epileptic Seizure Detection and Prediction Using EEG Signal Processing: Challenges and Advances

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Abstract. *The Epileptic seizures, caused by abnormal electrical activity in the brain, represent a significant challenge for diagnosis and treatment due to their unpredictability and the need for continuous monitoring. The manual observation and diagnosis of seizures, traditionally conducted by neurologists, are time-consuming and error-prone, highlighting the necessity for automated seizure detection systems. This paper provides a comprehensive overview of epileptic seizure detection, focusing on Electroencephalogram (EEG) signal analysis and the various techniques used for seizure detection, including time-domain, frequency-domain, and hybrid methods. The paper also discusses the intricacies of EEG signal processing, including preprocessing, feature extraction, classification techniques, and performance evaluation. Furthermore, seizure prediction methods, based on detecting preictal states, are explored in depth. The challenges encountered in developing reliable, real-time, and efficient seizure detection systems are also highlighted, such as dealing with noise, non-stationarity, and ensuring accurate classification in the presence of artifacts. The development of robust automated systems that integrate EEG signal processing with advanced machine learning models promises significant improvements in seizure detection, providing real-time monitoring and facilitating better therapeutic decisions for patients.*

***Keywords:* -** Epileptic Seizure Detection, EEG Signal Processing, Seizure Prediction, Automated Detection Systems, Feature Extraction, Machine Learning.

INTRODUCTION

Epilepsy is a momentary event of signs and symptoms due to abnormal synchronization and rapid neuronal activities in the brain [1, 2]. It is one of the brain neurological chronic disorders that affect around 50 million people worldwide due to the brain cells' excessive electrical activities, and it is characterized by epileptic seizures [3]. These epileptic seizures can result in neurological, physiological, social and cognitive consequences as a result of loss of consciousness and can even lead to death if proper monitoring and diagnosis have not been in place [4,5]. The loss of consciousness as a result of epileptic seizures has some common features with disorders of consciousness (DOCs), as established in the literature such as the work of [6–8]. In this condition, the eyes of the patient may be open, but even with external stimuli, their response might be meaningless. Moreover, a simple response/behavior may be observed even though the presence of sleep–wake cycles cannot be guaranteed due to a lack of sufficient time to determine its presence. Therefore, some of the types of disorders of consciousness exhibited during the occurrence of seizures are acute consciousness disorders (ACDs) that include coma, confusion, drowsiness and stupor, as well as delirium and chronic disorders of consciousness (CDOCs) that consist of minimally conscious and vegetative states (VS) [9]. One major difference between impaired consciousness during the seizure and these types of DOCs is in their duration, in which seizures only last for a short time, with the exception of status epileptics, while other DOCs last for days, months or years [6,10]. The convergence of some types of DOCs and epileptic seizures to a common structure such as in cortical and sub cortical regions helps researchers to develop models that improve epileptic seizure patients' lives and treatment methodologies by analyzing the behavioural and clinical features of these types of DOCs [11]. The detection, prediction and classification of epileptic seizures may shed more light on determining the path physiology and physiology of other types of DOCs. Two types of seizures have been considered from the monitoring aspect: electrographic and behavioural. An electrographic or electroencephalographic epileptic seizure is an irregular paroxysmal pattern of an electroencephalogram (EEG). Simultaneously, a behavioural epileptic seizure is the clinical signs of epilepsy that the patient or an observer can observe or that can be recorded on video [12].

The observation and diagnosis of epileptic seizures manually by a neurologist is tedious, time-consuming and easily prone to errors. The development of an automatic computer-aided system is therefore of paramount importance to help neurologists and patients identify and detect epileptic seizures by minimizing the long-term EEG recording to be analyzed by neurologists [13,14]. To develop an automatic CAD system, there are several steps for epileptic seizure detection from EEG analysis such as signal acquisition, data preprocessing, feature extraction, channel selection, classification and performance analysis/decision making. Due to the complex morphology of the EEG signal and visual similarity between epileptic and normal signals, suitable and meaningful features need to be extracted for classifiers to properly and correctly recognize and characterize different epileptic seizures [15–16]. The EEG signals can be used to acquire significant information to describe neurological conditions and need to be recorded to localize epileptic seizures. One of the most important scales in clinical EEGs for evaluating defects and cognition is frequency. A recorded EEG has a frequency somewhere within the 0.01 to 100 Hz range. The frequency content can be divided into five major bands known as delta, theta, alpha, beta and gamma.

II EPILEPTIC SEIZURE PROPERTIES

Epileptic seizures are abnormal electrical disturbances in the brain that present unique physical and behavioral symptoms, which vary depending on the type of seizure and the brain regions involved. These disturbances create specific patterns in electroencephalogram (EEG) signals, making EEG a crucial tool in seizure detection. Epileptic seizures are broadly classified into two main categories: generalized and focal. Generalized seizures affect both brain hemispheres simultaneously and often lead to a loss of consciousness or awareness. Common types include tonic-clonic seizures, marked by muscle stiffening and rhythmic jerking; absence seizures, characterized by brief periods of staring or blinking; and myoclonic seizures, which involve sudden muscle jerks. In contrast, focal seizures originate in a specific brain area and can either remain localized or spread. Simple focal seizures do not affect consciousness but may cause unusual sensations or muscle jerking, while complex focal seizures impact awareness, often leading to repetitive movements or sensory distortions.

In EEG signals, epileptic seizures produce characteristic patterns, typically displaying distinct frequency, amplitude, and waveform features. These changes often disrupt normal brainwave frequency bands, including delta (0.5 - 4 Hz), which is usually associated with deep sleep but appears in abnormal levels during seizures; theta (4 - 8 Hz), which is prominent in children but abnormal in adults with seizure activity; alpha (8 - 13 Hz), which is the normal background rhythm but often disrupted in seizures; and beta (13 - 30 Hz) and gamma (>30 Hz) bands, which can indicate hyperactivity in seizure-prone areas. Certain waveforms are also commonly associated with seizures, including spikes, sharp waves, and spike-and-wave complexes, which appear as high-amplitude oscillations often preceding or accompanying seizure events. These patterns vary, with spike-and-wave complexes commonly seen in absence seizures and polyspikes often observed in myoclonic seizures. Seizures typically progress through three main phases: onset, spread, and termination. In the onset phase, there are rhythmic, high-frequency oscillations as neurons begin to fire synchronously. During the spread phase, the seizure may propagate from the focal area to other regions of the brain, showing increased synchronization and higher amplitude. The termination phase is characterized by desynchronization, often followed by a "postictal" period of suppressed or irregular EEG activity with slow waves or irregular rhythms.

III EPILEPTIC SEIZURE DETECTION SYSTEMS

This section provides a general overview of an epileptic seizure detection system. A typical system consists of the following stages, as shown in Figure 1:

1. Data acquisition,
2. Preprocessing,
3. Feature extraction,
4. Classification and
5. Performance analysis and evaluation.

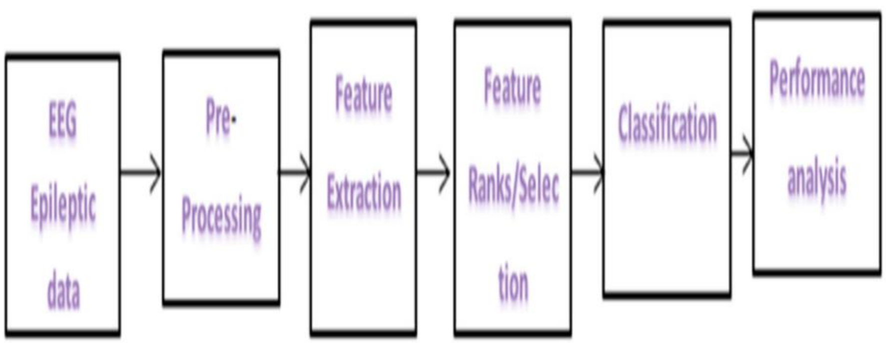

Figure 1: Block diagram of an epileptic seizure detection system.

Data Acquisition and EEG Database

The study of epileptic seizure detection and analysis has been carried out with both scalp EEG recordings (EEG) and intracranial EEG recordings (iEEG). Scalp EEG recordings use electrodes placed on the surface of the head at equal distance with the 10–20 system as the most commonly used configuration [20,33]. The iEEG signals use intracranial electrodes placed inside the skull when the clinical, structural and functional data are obtained before implantation to locate the epileptogenicity region in the brain [22]. Local databases that were used in previous studies were developed based on the information and data obtained and analyzed from epilepsy patients before epileptic surgeries. The small sample sizes, short time durations prior to seizures and small seizure actions hindered their applicability, limiting the specificity evaluation in the interictal signals. Therefore, recording of long-term signals from various seizures to properly and efficiently evaluate the sensitivity and specificity of algorithms is necessary [32]. Figure 2 shows University of Bonn data for class S for ictal conditions and class N for interictal conditions.

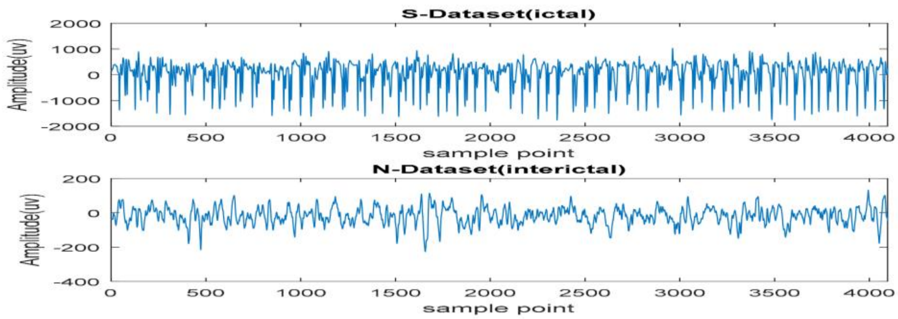

Figure 2: Example of epileptic seizure signals for ictal and interictal conditions.

Preprocessing

Biomedical signals are usually contaminated with various types of noise and artifacts during data acquisition and processing, which greatly influences the quality of feature extraction techniques. The artifacts' sources are generally categorized into technical, physiological and environmental sources [41–43]. Therefore, one of the aims of biomedical signal processing is to search for how to minimize or eliminate artifacts and still retain the most useful and relevant information in the raw EEG signal. Artifacts that are caused by technical issues or instruments used during EEG acquisition are related to the equipment's settings and the EEG type, that is, either an EEG recorded from the scalp or an intracranial EEG recording [17]. Some of these settings are gain, high-pass and low-pass filters' cut-off frequencies, sampling rate and electrode types. Artifacts due to physiological sources are electromyograms (EMGs), which are muscle activity, electrooculograms (EOGs) due to eye movement and electrocardiograms (ECG), which are due to the heart rate activity. In contrast, environmental interference depends on the environmental conditions and setting of EEG acquisition and recording [44–46].

Feature Extraction Techniques

To develop a robust automated scheme for epileptic seizure detection, categorizing EEG signals (epileptic seizures) into a pre-seizure, seizure and post-seizure occurrence must be identified and evaluated. Many features have been explored in the literature to describe seizure behavior properly. These features describe the EEG static behavior in time and space as well as dynamic properties. Feature extraction techniques commonly found in the literature include time domain, frequency domain and time–frequency analyses, wavelet analysis, energy distribution, entropy analysis and feature tensors [64]. However, recently, most CAD systems use two or more methods combined as a hybrid technique. A general feature selection process is depicted in figure 3.

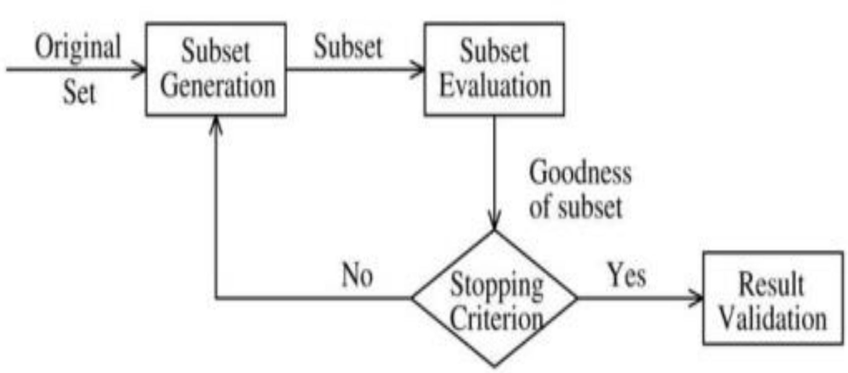

Figure 3: Feature selection flowchart.

Classification Techniques

The quality of classification algorithms is largely dependent on the feature extracted and fed to the classifier. The features are extracted with the assumption that they can be characterized between normal and different seizure categories. Classifiers are decision making systems in which the class data boundaries are defined and labelled based on their features. The classification method can be simple such as thresholding techniques, or complex such as machine learning algorithms. In the classification stage. There are generally two steps to be carried out, that is, training and testing phases. The extracted features are divided into those phases, and after training the classifier with training data, the new data can be classified with the trained network. Classifiers in epileptic seizure detection systems can be developed using statistical analysis such as clustering, machine learning or, recently, deep neural networks [89].

IV LITERATURE SURVEY

Epileptic seizure detection has been extensively researched, with numerous methodologies and techniques developed to enhance accuracy and reliability. Tanishk Thakur et al. [1] introduced an Internet of Health Things (IoHT) system for seizure detection. Their approach integrated multiple pre-processing techniques to extract features such as statistical measures, wavelets, and Hjorth parameters. These features were then classified using various machine learning methods, yielding notable results. Specifically, a combination of discrete wavelet transform (DWT), Hjorth parameters, and statistical features—utilizing the bior 1.5 wavelet—achieved high accuracy. For k=5, the k-nearest neighbors (kNN) algorithm obtained 86% accuracy, while a support vector machine (SVM) with a linear kernel reached 93% accuracy. Logistic regression and decision trees further improved the reliability to 95.5%.

M. Shamim Hossain et al. [2] leveraged an open-access EEG dataset from Boston Children's Hospital to train a convolutional neural network (CNN) for seizure detection. By extracting both spectral and spatial features from EEG data, the model demonstrated resilience to signal fluctuations. Their results included a median sensitivity of 90.00%, selectivity of 91.65%, and precision of 98.05% across 23 patients. Additionally, the cross-patient classification precision was 99.46%, surpassing previous methods and establishing their model's effectiveness. Min Wu, Hong et al. [3] proposed a novel seizure detection framework using DWT and a multi-channel long short-term memory-like spiking neuron model (LSTM-SNP). Features extracted through DWT were categorized into different frequency bands and used to train the LSTM-SNP model. On the CHB-MIT dataset, the model achieved 98.25% precision, 98.22% specificity, and 97.59% sensitivity, demonstrating its efficacy in early seizure detection. Noor Kamal et al. [4] investigated automated seizure classification in children using supervised and deep learning models. Initial experiments employed SVM, kNN, and decision trees on EEG datasets. Subsequently, recurrent neural network (RNN) architectures, including GRU, LSTM, and BiLSTM, were utilized for classification. By combining entropy-based features with temporal domain characteristics, the study achieved enhanced performance in seizure classification. R. Priyanka et al. [5] evaluated seizure recognition techniques using machine learning and deep learning models. Their study analyzed 11,500 EEG data points from the UCI repository and introduced an Enhanced Fitness Function Genetic Algorithm (IGA) for optimal feature selection. This method was integrated with CNN-RNN algorithms, improving seizure detection rates and overall classifier performance. Alshaya H. et al. [6] developed a deep learning framework combining LSTM and ResNet architectures for seizure classification. Using a 1D ResNet module, the framework addressed issues such as gradient vanishing and overfitting. The LSTM component encoded long-term dependencies, while the SMOTE technique balanced the data by increasing minority class samples. This approach was validated on the TUH database, showcasing its robustness. Ulvi Başpınar et al. [7] employed machine learning to classify seizures, utilizing statistical features derived from EEG signals processed through the Whole Harmonic Mode Segmentation methodology. The results highlighted the method's potential, outperforming traditional approaches. Saminu S., Xu et al. [8] conducted a comparative analysis of seizure detection algorithms developed over the past decade. Their study reviewed both traditional and modern deep learning methods, highlighting advancements in epileptiform identification and their implications for diagnosing disorders of consciousness (DOCs). The study emphasized the importance of precision in detection and classification methodologies. Ali Alqahtani et al. [9] introduced a binary classification approach for seizure diagnosis using EEG signals. After preprocessing the data, an optimal feature set was selected using a hierarchical biological algorithm. This method demonstrated excellent classification results, distinguishing between epileptic and febrile seizures. Jeppesen J. et al. [10] presented a patient-adaptive seizure detection algorithm based on LRML classifiers. The method achieved 78.2% accuracy and a false alarm rate (FAR) of 0.62 per 24 hours. By adapting to individual patient responses, the approach reduced FAR by 31% compared to prior methods, supporting its integration into wearable devices for real-time seizure monitoring. Tran LV et al. [11] proposed an ML-based method for seizure detection using EEG data. The technique utilized dynamical wavelet transform analysis for feature extraction and binary particle swarm optimization for feature selection, reducing data dimensionality by 75% and processing time by 47%. The resulting model was further optimized through hyperparameter tuning, achieving efficient classification. Subasi A. et al. [12] developed a flexible EEG analysis framework using DWT for feature extraction and dimensionality reduction via PCA, ICA, and LDA. These features were fed into an SVM classifier to detect epileptic seizures, achieving reliable results. Shaikh M. et al. [13] conducted a review of AI-based predictive diagnostics for neurological conditions, including epilepsy. The study discussed methodologies for feature extraction, selection, dimensionality reduction, and classification, offering insights into advancements in the field. Naser A. et al. [14] utilized the Andrzejak dataset to classify seizures using DWT for feature extraction and SVM with an RBF kernel for classification. This approach effectively differentiated between three seizure classes and normal EEG signals. Raluca M.A. et al. [15] combined Daubechies DWT with correlation analysis of EEG, EMG, and PPG signals for seizure prediction.

Artificial neural networks (ANNs) were employed for pre-ictal detection, enhancing diagnostic accuracy. Maryati Nita Dwi et al. [16] classified focal, generalized, and tonic-clonic seizures, along with normal EEG signals, using SVM. Feature extraction techniques such as ICA, Hjorth parameters, and MFCC were combined to improve classification performance.

V SEIZURE PREDICTION METHODS

The research work on the issue of time-domain seizure prediction is richer than time-domain seizure detection due to the importance of the seizure prediction problem. We can think of 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. Similar statistics to those used in seizure detection like the zero-crossing rate can be used for seizure prediction. Zandi et al. used the zerocrossing rate of EEG signal segments to develop a patient-specific seizure prediction method [17,18]. 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 as shown in Figure 4.

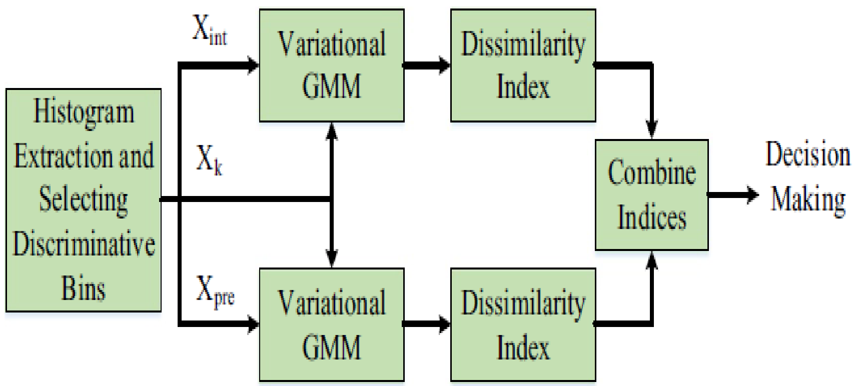

Figure 4: Seizure prediction method.

VI CHALLENGES IN EEG BASED SEIZURE DETECTION

Working on the EEG based Seizure detection poses several challenges as the following:

- The automated seizure registration techniques for improving the quality of seizure data.
- An accurate professional database, because seizure monitoring is crucial for therapeutic decisions for patients or caretakers. Inaccurate seizure documentation has a bad effect on the patient’s treatment.
- A real-time seizure detection system and subsequent evaluation by experts are still required.
- The issue of obtaining longer recordings is due to technical reasons.
- Emergency call systems that require actively pushing an alarm button are inappropriate for most epilepsy patients and alternative approaches are needed.
- Diagnostic accuracy is still missing so multimodal approaches which combine the measurement of autonomous parameters (e.g., heart rate, or muscular activity) will be required to detect these seizures.

- The trade-off between seizure detection algorithm (SDA) accuracy vs. detection speed, such improvements may come at the expense of increased invasiveness of monitoring.
- Dealing with non-stationarity and noise. EEG is prone to many different artifacts which obstruct the view of underlying brain activity.
- Minimizing computational cost.
- SDA Performance Assessment. Extensive prospective validation of any SDA is required to properly assess its performance

VII CONCLUSION

The automation of epileptic seizure detection using EEG signals represents a major advancement in the management and treatment of epilepsy. Through the integration of sophisticated signal processing and classification techniques, it is possible to accurately identify and classify seizures, thereby reducing the burden on healthcare professionals and enhancing patient care. However, challenges such as noise interference, the need for long-term monitoring, and computational cost remain significant obstacles in the development of effective and real-time systems. Despite these hurdles, hybrid approaches that combine multiple feature extraction methods and machine learning algorithms show promising results in improving detection accuracy and reducing false positives. Moreover, the prediction of seizures before their occurrence remains an area of active research, with patient-specific prediction models offering a potential solution. Future developments in multimodal systems and the continued refinement of algorithms are expected to improve the reliability and usability of automated seizure detection systems, leading to better outcomes for patients and a shift towards more personalized treatment approaches.

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