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REVIEW ARTICLE

Essentials of Predicting Epileptic Seizures Based on EEG Using Machine Learning: A Review

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Abstract:

Objective:

Epilepsy is one of the chronic diseases, which requires exceptional attention. The unpredictability of the seizures makes it worse for a person suffering from epilepsy.

Methods:

The challenge to predict seizures using modern machine learning algorithms and computing resources would be a boon to a person with epilepsy and its caregivers. Researchers have shown great interest in the task of epileptic seizure prediction for a few decades. However, the results obtained have not clinical applicability because of the high false-positive ratio. The lack of standard practices in the field of epileptic seizure prediction makes it challenging for novice ones to follow the research. The chances of reproducibility of the result are negligible due to the unavailability of implementation environment-related details, use of standard datasets, and evaluation parameters.

Results:

Work here presents the essential components required for the prediction of epileptic seizures, which includes the basics of epilepsy, its treatment, and the need for seizure prediction algorithms. It also gives a detailed comparative analysis of datasets used by different researchers, tools and technologies used, different machine learning algorithm considerations, and evaluation parameters.

Conclusion:

The main goal of this paper is to synthesize different methodologies for creating a broad view of the state-of-the-art in the field of seizure prediction.

Keywords: Epilepsy, EEG, Machine learning, Seizure prediction, India, Behavioral, Health.

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1. INTRODUCTION

Epilepsy is a chronic non-communicable disease of the brain that affects people of all ages. According to the World Health Organization (WHO), around 50 million people suffer from epilepsy worldwide. It is estimated that there are more than 10 million people with epilepsy in India. Globally, an estimated five million people are diagnosed with epilepsy each year. Epilepsy leads to behavioral, health, and economic consequences. Efficient diagnosis and treatment are very much essential for the quality of life of the person with epilepsy and its caregivers.

With the increasing computing availability and storage, machine learning algorithms have been widely explored in the area of epileptic seizure prediction. However, because of the diversified research approaches, dataset considerations, evaluation parameters, and implementation approaches, the reproducibility of the results is limited. The work presented here focuses on the essential aspects of epileptic seizure prediction. The future research approaches may consider the presented comparative analysis of datasets, implementation tools, and methodologies for evolved epileptic seizure prediction methodology.

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The organization of this paper is as follows: Section-2 describes the fundamentals of epilepsy and treatment. Section-3 and 4 describe the use of electroencephalogra-phy (EEG) for epileptic seizure prediction and the need for algorithms. Section-5 gives the comparative analysis of various approaches for epileptic seizure detection and prediction, followed by Section-6 with the research gaps. Section-7 gives a detailed understanding of datasets used in prior research of epileptic seizure prediction. Section-8 gives a comparative analysis of tools and libraries used for the implementation of epileptic seizure prediction systems, which is followed by the conclusion.

2. EPILEPSY AND TREATMENT

Seizures are due to excessively synchronous and/or excessively intense activity of neuronal circuits in the brain, particularly in the cerebral cortex. In epilepsy, seizures occur spontaneously, repeatedly, and usually suddenly. The unpredictability of seizures represents one of the main disabling features of epilepsy [1]. To date, the causes of epilepsy have not been identified. However, conditions like severe head injury, stroke and blood vessel diseases, tumors, changes in brain structure, and brain infections could provoke seizures [2]. Epileptic seizures can be classified into three groups [3]. *Generalized Onset Seizures:* These seizures affect both sides of the brain or groups of cells on both sides of the brain at the same time. This term still includes seizure types like tonic-clonic, absence, or atonic. *Focal Onset Seizures:* It can start in one area or group of cells on one side of the brain. *Unknown Onset Seizures:* When the beginning of a seizure is not known, it is called an unknown onset seizure.

Epileptic seizures have four different states: the preictal state, which is a state that appears before the seizure begins, the ictal state that begins with the onset of the seizure and ends with an attack; the postictal state that starts after ictal state, and interictal state that starts after the postictal state of first seizure and ends before the start of the preictal state of consecutive seizure [4]. The effect of epilepsy is different in each individual. So, recognizing and diagnosing the type of seizure or epilepsy affecting a person can sometimes be challenging. However, there are a few common ways of testing and determining an epilepsy diagnosis [3]. Various methods, like electroencephalography (EEG), Computerized Tomography (CT) scans, Magnetic Resonance Imaging (MRI), and functional imaging studies, are used to evaluate a person with epilepsy [5, 6]. EEG is the most common method amongst all for the diagnosis and treatment of epilepsy. Persons with epilepsy are generally treated with Anti-Epileptic Drugs (AEDs). A high dosage of AEDs optimally controls epileptic seizures. However, regular consumption of AEDs generally shows side effects like tiredness, headache, dizziness, or blurred vision. It may also lead to behavioral changes in the person with epilepsy [7]. About 20-40% of persons with epilepsy are drug-resistant, *i.e.*, they do not respond to AEDs even though a variety of drugs are available for decades [8, 9], of whom only a small minority can be helped by epilepsy surgery [10].

3. ELECTROENCEPHALOGRAPHY(EEG)

An electroencephalogram (EEG) is the flow of neuronal ionic currents recorded using a pair of electrodes either inside or outside the scalp [11]. The applications of EEG signal processing are brain-computer interface, seizure detection, seizure prediction, schizophrenia detection and classification, diagnosis of Parkinson's disease, *etc.* EEG is significantly used in the diagnosis, classification, and treatment of epileptic seizures [8]. If an invasive technique is used to record the EEG signal from inside the skull, it is called intracranial EEG (iEEG). In a non-invasive technique, EEG signals are recorded from the scalp, called scalp EEG (sEEG). EEG waveforms are generally classified into normal and abnormal signals using frequency parameters [12]. EEG signals can be categorised into the following based on frequency: Delta (0.1 - 4 Hz), Theta (4 - 8 Hz), Alpha (8- 13 Hz), Beta (13 - 30 Hz), and Gamma (30 - 100 Hz). Different EEG frequency corresponds to different behavior and mental state of the brain [12]. Due to the high complexity of EEG signals, a single prediction feature can only quantify some of its properties [7].

The popularity of EEG is because of the following advantages: scalp EEG (sEEG) is a non-invasive technique which records the waveforms without much effort or active response by the subject/patient, EEG recording kit is portable and financially affordable, EEG recording devices do not make any noise and no special environment is needed to set it up [11]. Though EEG techniques are widely evolved, there are still a few limitations that need to be addressed. Such as, EEG is prone to low spatial resolution and low signal-to-noise ratio (SNR) [11]. Preprocessing of EEG is also very challenging. To have an artefact-free EEG to extract the control signals, the EEGs have to be restored from the artefacts, such as eye-blinking, electrocardiograms (ECGs), and any other internal or external disturbing effects [13].

4. THE NEED FOR EPILEPTIC SEIZURE PREDICTION ALGORITHMS

With the evolving EEG technology and resource advances, there has been huge interest in the EEG waveform-based research for brain-computer interface (BCI), disease detection, and treatment. Characterization of EEG waveforms plays a vital role in the field of epileptic seizure detection and classification. With the use of sEEG or iEEG signals, certain patterns can be found to detect the preictal state of seizure. The detection of a preictal state would trigger an alarm for the patient or patient's caregivers to take precautions or medicine beforehand to avoid the ill effect of seizure [7]. Seizure detection methods can be used for the offline analysis of EEG waveforms or seizure-abortion devices. Whereas the seizure prediction system identifies the occurrence of seizure before a certain period called the occurrence period [7].

With rapidly increasing computing power and storage, the availability of EEG data has become easier. Researchers have started using the power of modern machine learning algorithms to improve the results of seizure prediction algorithms [14 - 27]. Though ample research has already been done, there is no clinical applicability yet [28, 29]. This is because of the sensitivity of the seizure prediction algorithms. One of the challenges in the study of epileptic seizure detection and prediction is to achieve the results to apply the same for clinical applicability [7]. The statistical justification is also desirable for a complete understanding of existing approaches that achieve significant results [7]. For clinical applicability of seizure prediction approaches, the alarm shall trigger prior to a considerable time period. So, the seizure prediction horizon needs to be one of the important evaluation parameters of such systems [7]. Researchers have incorporated various approaches for epileptic seizure prediction. The following sections review the datasets incorporated, tools and libraries used and different algorithms considered for the same. This would help novice ones to explore and improve machine learning-based epileptic seizure prediction algorithms.

5. MACHINE LEARNING ALGORITHMS AND EVALUATION PARAMETERS

The work for epilepsy seizure prediction has evolved drastically since its inception. Based on various methodologies followed and algorithms used, epilepsy seizure prediction can be categorized into four approaches as follows. Also, Fig. (**1**) shows all four approaches:

[1] The traditional machine learning approach
[2] Deep learning approach
[3] Signal processing approach
[4] Hybrid approach

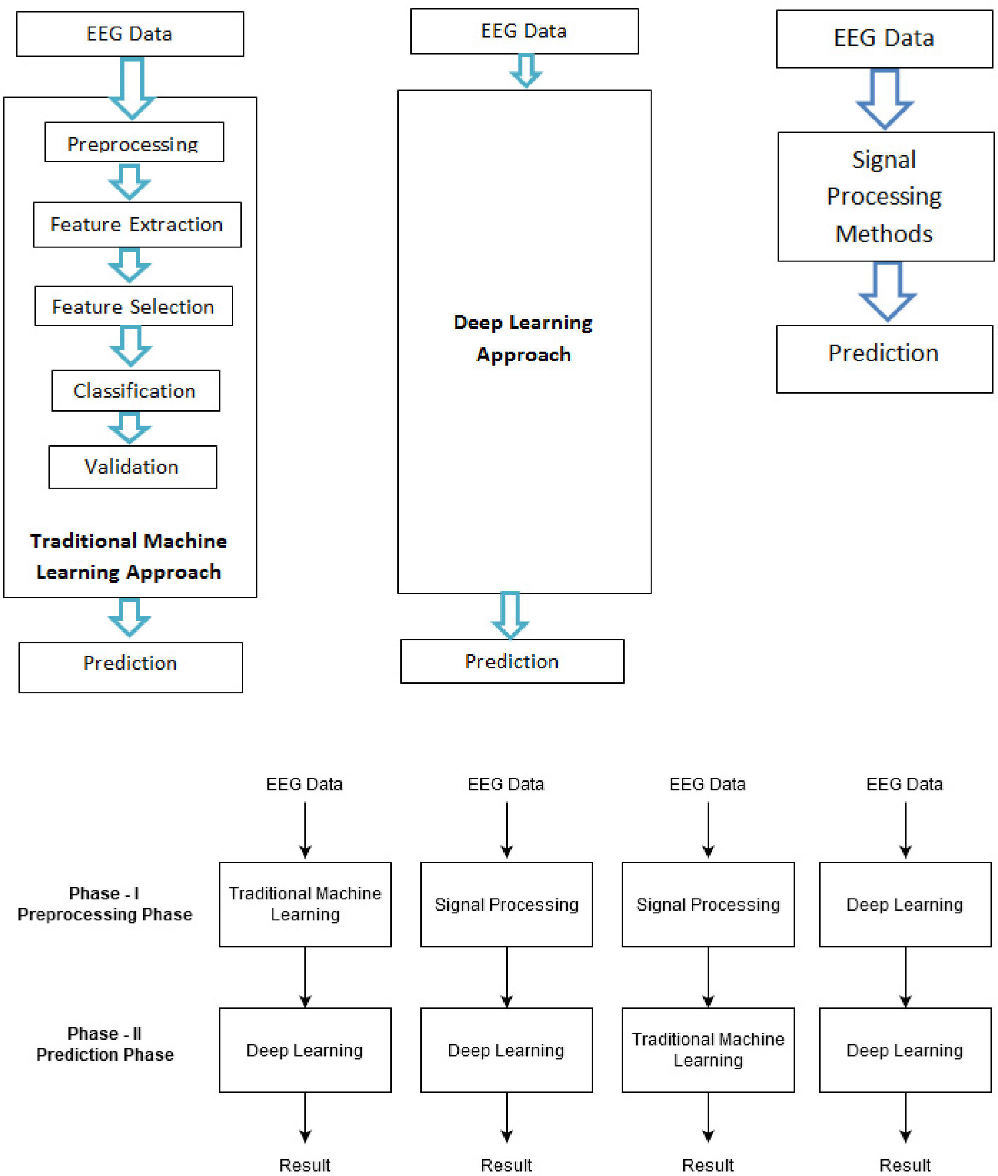

Fig. (1). Diagrammatic representation of commonly used approaches for epileptic seizure prediction.

5.1. The Traditional Machine Learning Approach

The traditional machine learning approach includes various stages like preprocessing, feature extraction, feature selection, classification, and validation. Handcrafted features are being used for the detection of the preictal state. A brief description of all the stages is as follows: *Data Cleaning*, EEG data is nonstationary and prone to artefacts, it requires high preprocessing. This is the phase that takes maximum effort to read, interpret, and clean the noise. *Feature Extraction*, using different signal processing techniques, features are extracted in time domain, frequency domain, or time and frequency domain. *Feature Selection*, a huge amount of features is being generated from the feature extraction phase. It is important to find the feature of importance for a specific task. Some of the features considered by researchers are entropy, approximate entropy, Hjorth parameters, spectral moments, mobility, energy, entropy, correlation coefficients, Fast Fourier Transform (FFT), variance, skewness, kurtosis, mean, fractal dimension, frequency band power, peak amplitude, zero crossing, average spectral power, line length, and maximal and minimal values. *Classification*, the problem of epileptic seizure prediction and detection is actually to differentiate the pre-ictal state of EEG signal from the interictal and ictal state. Different classification algorithms like Support Vector Machine, k-nearest neighbor, Gaussian Naive Bayes, random forest, multi-layer perceptron are used for this purpose, *Validation*, the hyperparameters are not trained by classification models, it would be predefined. Model performance depends highly on the selection of hyperparameters. The best model amongst various values of hyperparameters is chosen in the validation stage. *Prediction* is the last phase that performs the task of prediction based on the optimal performing model. Table **1** gives the detailed comparative analysis of various studies conducted using the traditional machine learning approach for epileptic seizure state detection and prediction.

5.2. Deep Learning Approch

Deep learning-based models are end-to-end models, *i.e.* once EEG signals are given as input, an automated approach for feature extraction and selection is done. Based on the learning and validation, the model would converge and give the prediction results. Another noticeable approach for epileptic seizure prediction is based on signal processing methods. The large amount of data recorded from even a single EEG electrode pair presents a difficult interpretation challenge. Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and variations of these algorithms have been used by researchers in the past for the task of seizure prediction. This approach is trending because of the availability of resources. Table **2** gives the detailed comparative analysis of various studies conducted using the deep learning approach for epileptic seizure state detection and prediction.

5.3. Signal Processing Approach

In this approach, traditional signal processing methods are used to highly process the data. Signal processing methods are needed to automate signal analysis and interpret the signal phenomena [30]. The prediction stage of this approach uses a basic classification algorithm for signal state classification. Table **3** gives the detailed comparative analysis of various studies conducted using the signal processing approach for epileptic seizure state detection and prediction.

5.4. Hybrid Approach

The combination of all three methods, *i.e.*, traditional machine learning, deep learning, and signal processing leads to a hybrid approach, which takes best of all. Literature provides the data related to the combination of traditional machine learning and deep learning models, deep learning, and signal processing models, machine learning and signal processing methods deep learning methods. References for some hybrid approaches provides the detailed comparative analysis of various studies conducted using the hybrid approach to epileptic seizure state detection and prediction.

To evaluate the performance of various models, different evaluation parameters like sensitivity, specificity, false-positive rate, accuracy, prediction time, AUC, ROC, and F1 score have been considered in the past by other researchers. However, there is no clear consensus regarding which parameter signifies the performance of epileptic seizure detection or prediction algorithms best. Yannick Roy *et al.* [31] and Alexander Craik *et al.* [32] have presented a vast comparison of all work done in the field of epileptic seizure prediction. Along with the comparison, various aspects for future research are also mentioned.

6. RESEARCH GAPS

To increase the reliability of seizure prediction results and clinical applicability of the same, evolved models of EEG signal analysis are the need of the time [11]. This section describes some of the improvement areas which could aid in the performance of seizure detection and prediction models, which may lead to clinical applicability. No methods have exhibited both high sensitivity and zero false alarms per hour to achieve the reliability of results [28]. Also, existing machine learning algorithms unnecessarily reduce the number of parameters in feature selection for simplistic classification [28]. The advanced techniques can be used for preprocessing of EEG data to get increased sensitivity of the results [4]. Identification of proper matrices for the evaluation of seizure prediction model is also a big challenge for highly imbalanced data. Most of the work done in the field of epileptic seizure detection and prediction focuses on patient-specific approaches. The concept of domain adaptation and transfer learning can be used for cross-patient research, *i.e.* generalized models [28]. A better generalization performance between subjects will be necessary to truly make BCIs useful [31]. All prediction methods have been developed and tested on different EEG data pools, making it difficult to compare their performance [101, 119].

Table 1. Comparative analysis of the traditional machine learning approach.

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2009	Theoden Netoff *et al.* [33]	European Epilepsy Database	Removing artefacts, filtering	Power of spectral bands	N/M	Cost-effective SVM	Sensitivity = 77.8% False positive rate per hour = 0
2013	Ning Wang *et al.* [34]	European Epilepsy Database	N/M	Averaged Instantaneous Envelope (AIE), Averaged Instantaneous Frequency (AIF)	RFE-SVM (Recursive feature elimination - SVM)	SVM	Average Sensitivity = 98.8% Average False alarm per hour = 0.054 AUC = 0.784
2014	Peyvand Ghaderyana *et al.* [35]	European Epilepsy Database	Removing artefacts, normalized power	Spectral bands, statistical moments, median, and Power Spectral Density (PSD), Feature Change Ratio (FCR)	PCA, KNN-based undersampling	SVM	Sensitivity = 100% Average false alarm rate per hour = 0.13 G-mean = 0.97 F-measure = 0.90
2015	P. Fergus *et al.* [36]	CHB-MIT	Delta, theta, alpha, and beta signal bands filtering	Peak Frequency, Median Frequency, variance, root mean squares, sample entropy, skewness, and kurtosis	Linear discriminant analysis backward search	LDC, QDC, UDC, POLYC, LOGLC, KNCC, TREEC, PARZENC, SVC	Best results with KNNC: Sensitivity = 84% Specificity = 85% AUC = 91% Global error = 15%
2015	Cristian Donos *et al.* [37]	European Epilepsy Database	N/M	mean, mean absolute deviation, variance, skewness, kurtosis, autocorrelation, line length, power, power ratio	N/M	Random forest classifier	Mean sensitivity = 93.84% Mean detection delays = 3.03s False detections per hour = 0.33/h mean
2015	Zisheng Zhang *et al.* [38]	Kaggle - American Epilepsy Society Seizure Prediction Challenge	N/M	PSD features: Relative Spectral Powers, Spectral Power Ratios	CART	SVM	Sensitivity = 100% Mean False Positive (FP) rate = 0.073 FP/hour Mean prediction horizon = 58 minutes AUC = 0.979
2016	Bruno Direito *et al.* [39]	European Epilepsy Database	Butterworth Infinite Impulse Response (IIR) filter to remove the noise	AR Modeling predictive error, Decorrelation time, Energy Hjorth, Spectral power, Spectral edge, Energy wavelet coefficients, Mean, Variance Skewness, Kurtosis	N/M	SVM	false predictions per hour = 0.20 sensitivity = 38.47%
2016	Lung-Chang Lin *et al.* [40]	Real-time personal dataset	EEG epoch acquisition	Autoregressive modeling predictive error, Decorrelation time, Energy, Entropy, Hjorth, Relative power, Spectral edge, Statistics, Energy of the wavelet coefficients	Correlation based Feature Selection (CFS) approach	SVM	Correctness = 97.50%, Sensitivity = 96.92%, Specificity = 97.78%, Precision = 95.45%
2016	Khurram I. Qazi *et al.* [41]	Real-time personal dataset	Seizure, pre-seizure and seizure-free labelling	Energy (E), range (R), standard deviation (SD), the sum of absolute values (SAV), mean absolute values (MAV) and variance (Var)	N/M	SVM, ANN with supervised learning, K means clustering combined with unsupervised learning algorithms	Accuracy = 85 - 90%

(Table 1) contd.....

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2017	Syed Muhammad Usman *et al.* [4]	CHB-MIT	Surrogate channel creation, Empirical Mode Decomposition	Statistical features of time-domain and spectral features of frequency domain	N/M	Support Vector Machine, Naïve Bayes, K nearest neighbor	Best results with SVM: Sensitivity = 92.23% and average prediction time = 23.61 minutes
2017	Han-Tai Shiao [42]	Mayo Clinic dataset	N/M	Spectral features	N/M	SVM	Sensitivity = 90-100% Average False positive rate per day = 0-0.3
2018	Yanli Yang *et al.* [43]	European Epilepsy Database	Filtering and sampling	Permutation entropy	N/M	SVM	Average sensitivity = 94% False prediction rates per hour(FPRh) = 0.111 Average prediction horizon = 61.93min
2019	Amirhossein Ahmadi *et al.* [44]	CHB-MIT	N/M	Shannon entropy	Statistical one-sample t-test	SVM,KNN	Sensitivity = 83.8% (SVM & KNN) Specificity = 71% (SVM), 67.8 (KNN)
2019	Xiashuang Wang *et al.* [45]	Bonn University Dataset	Digital filtering, removing artefacts, re-referencing, and baseline corrections	Fourier transform, multitaper spectral analysis, PACF, and STFT	N/M	Random forest algorithm based on grid search optimization	Accuracy = 96.7% AUC = 99.0%
2019	Yuxing Wang *et al.* [46]	CHB-MIT	Pre-ictal state partition	Wavelet Packet Decomposition (WPD)	N/M	Random forest	Accuracy = 84.8%

Table 2. Comparative analysis of the deep learning approach.

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2016	Mohammad-Parsa Hosseini *et al.* [17]	The University of Pennsylvania and the Mayo Clinic	Dimensionality reduction	N/M	N/M	Stacked auto encoder	Accuracy = 0.94 Precision = 0.95 Sensitivity = 0.93 False Positive Rate = 0.05 False Negative Rate = 0.06
2017	Sachin Talathi [16]	Bonn University database	N/M	N/M	N/M	Gated Recurrent Unit (GRU) RNNs for seizure detection	Accuracy = 100% Sensitivity = 98%
2017	U. Rajendra Acharya *et al.* [47]	Bonn University database	Normalization	N/M	N/M	CNN	Accuracy = 88.67% Sensitivity = 95% Specificity = 90%
2017	Haidar Khan *et al.* [48]	1) Mount Sinai Epilepsy Center dataset 2) CHB-MIT	N/M	N/M	N/M	Convolutional filters on the wavelet transformation	Sensitivity = 87.8% False prediction rate = 0.142/h
2018	Isabell Kiral-Kornek *et al.* [20]	Cook *et al.*,2013	Spectrogram generation	N/M	N/M	Deep neural network	Mean sensitivity = 69% Mean time in warning = 27%
2018	Matthias Eberlein *et al.* [19]	Kaggle	N/M	N/M	N/M	CNN	AUC = 0.73

(Table 2) contd.....

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2018	David Ahmedt-Aristizabal *et al.* [21]	Bonn University database	N/M	N/M	N/M	LSTM	Accuracy = 95.54% Sensitivity = 91.83 Specificity = 90.50 Precision = 91.50 AUC = 0.9582
2018	Nhan Duy Truonga *et al.* [49]	CHB-MIT, European Epilepsy Database, Kaggle	Short-time Fourier transform, Windowing	N/M	N/M	CNN	Sensitivity = 81.4% - 81.2% - 75% False prediction rate = 0.06/h, 0.16/h, 0.21/h
2018	Mengni Zhou *et al.* [50]	European Epilepsy Database, CHB-MIT	Spectrogram generation	N/M	N/M	CNN	Accuracy = 93-97.5%
2018	R. Schirrmeister *et al.* [15]	The Temple University Hospital (TUH) EEG Abnormal Corpus	Artefact removal and resampling	N/M	N/M	CNN	Accuracy = 84.5-85.4% Sensitivity = 75.1-77.3% Specificity = 90.5-94.1% Accuracy = 81.7-82.5%
2019	Xinghua Yao *et al.* [51]	CHB-MIT	Bidirectional Long Short-Term Memory (BiLSTM)	N/M	N/M	Softmax function	Sensitivity = 87% Specificity = 88.60% Precision = 88.63%
2019	Xinghua Yao *et al.* [23]	CHB-MIT	Independently recurrent neural network (IndRNN)	N/M	N/M	N/M	Sensitivity = 87.3% Specificity = 86.7% Precision = 87.08% F1 score = 87.07%
2019	Ali Emamia *et al.* [27]	NTT Medical Center Tokyo	2-D image construction	N/M	N/M	CNN	Median of detected seizure rate by minutes = 100% False alarm 0.2 per hour
2019	Ibrahim Aliyu *et al.* [52]	Bonn University database	Discrete wavelet transform			RNN-LSTM	Accuracy = 99%
2019	Chien-Liang Liu *et al.* [53]	Kaggle, CHB-MIT	PCA, FFT, and data augmentation	N/M	N/M	Multi-view CNN	AUC = 0.84 (Kaggle), 0.82-0.89 (CHB-MIT)
2020	Fabio Pisano *et al.* [54]	European Epilepsy Database	Manual channel selection, EEG segmentation and data augmentation	N/M	N/M	CNN	Accuracy = 96.39% Specificity = 96.81% Sensitivity = 93.20% Gmean = 89.92-98.83%

Table 3. Comparative analysis of the signal processing approach.

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2012	James R. Williamson *et al.* [55]	European Epilepsy Database	Filtering and normalization	High-dimensional feature vectors are extracted from space–delay covariance and correlation matrices	N/M	SVM	Sensitivity = 95-86% AUC = 0.973
2012	Mojtaba Bandarabadi *et al.* [56]	European Epilepsy Database	Filtering and windowing	Normalized spectral power features, relative features using bi-variate approach	normalized difference of the percentiles	SVM	Sensitivity = 76.09% False positive rate per hour = 0.15 No. of sleeted features = 8.75 Seizure occurrence period = 31.6 min
2013	Sun-Hee Kim *et al.* [57]	Bonn University Dataset	N/M	Detection of special characteristics	N/M	coercively adjusted auto regression (CA-AR)	Root mean square error = 0.029

(Table 3) contd.....

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2013	Yang Zheng *et al.* [58]	European Epilepsy Database	Artefact removal and filtering	Bivariate empirical mode decomposition, Mean Phase Coherence (MPC)	A quantitative method based on the seizure prediction characteristic was proposed for the feature selection	The preictal changes of the MPC time courses were used to raise the seizure alarms	Sensitivity = 70-80% with Seizure Prediction Horizon = 10 min and False Prediction Rate(max) = 0.15 FP/h.
2014	Zhen Zhang *et al.* [59]	Real-time personal dataset	Optimal channel selection	Approximate entropy	N/M	N/M	Prediction accuracy = 94.59% False prediction rate = 0.084/h Mean prediction time = 26.64 min
2014	Nilufer Ozdemir *et al.* [60]	European Epilepsy Database	Artefact Removal and Segmentation	Hilbert Huang Transform, total energy	Filtering feature selection and Correlation-based Feature Selection (CFS) with the best first search algorithm	Bayesian network	Sensitivity = 96.55% Mean detection latency = 33.21 False positives per hour (FPs/h) = 0.21 Time spent in warning (FP%) = 13.896 min
2015	Hamidreza Namazi *et al.* [61]	Real-time personal dataset	Filtering	Hurst exponent and fractal dimension	N/M	N/M	Seizure occurrence period = 25.76 seconds
2015	Kohtaroh Edakawa *et al.* [62]	Real-time personal dataset	N/M	Phase–amplitude coupling (PAC)	θ -high γ, α -high γ, β -high γ, θ phase of 10–80 Hz amplitude, High γ amplitude alone	Synchronisation index (SI)	Sensitivity = 100, False detection rate per hour = 0.713
2016	A. Sharmila *et al.* [63]	Bonn University Dataset	N/M	Statistical features from Discrete Wavelet Transform (DWT)	N/M	Naïve Bayes, K-nearest neighbor	Accuracy = 100% (with Naïve Bayes)
2016	Mark H. Myers *et al.* [64]	CHB-MIT	Filtering	Phase Locking Thresholds	N/M	N/M	Sensitivity = 77% Precision = 88% False positive per hour = 0.17
2017	Turky N. Alotaiby *et al.* [65]	CHB-MIT	N/M	Common Spatial Pattern (CSP)	N/M	Linear discriminant analysis (LDA)	Average sensitivity = 0.89 Average specificity = 0.37 Average False Prediction Rate = 0.39 Average prediction time = 68.71 minutes
2017	Amirmasoud Ahmadi *et al.* [66]	Bonn University Dataset	N/M	Wavelet packets transform	Standard Deviation, Root mean square	SVM with the radial basis function	Accuracy = 97.85%
2018	Ahmed I. Sharaf *et al.* [67]	Bonn University Dataset	Tunable Q-Wavelet Transformation (TQWT)	Chaotic features, statistical features, power spectrum features, Co-occurrence matrix	Firefly algorithm	Random forest	Accuracy = 99% Precision = 97% Specificity = 97% Recall = 98% F-measure = 98% Matthew's correlation coefficient = 95%
2019	Naghmeh Mahmoodian *et al.* [68]	European Epilepsy Database	Filtering and windowing	Cross-bispectral analysis	N/M	SVM	Sensitivity = 100% False positive rate (FPR) = 0.044 Prediction time = 51-96 minutes

(Table 3) contd.....

Year	Research Group	Dataset Used	Preprocessing	Feature Extraction	Feature Selection	Classifier Used	Performance
2019	Agustina Garcés Correa *et al.* [69]	CHB-MIT	Adaptive filter and signal averaging	N/M	N/M	N/M	Sensitivity = 90.29% Specificity = 73.7%
2019	Hafeez A. Agboola *et al.* [70]	CHB-MIT	N/M	Low-level feature extraction	High level feature extraction	SVM, ANN	Sensitivity = 87.26% (SVM), 75.5% (ANN) False alarm per hour = 0.09 (SVM), 0.13 (ANN) Seizure occurrence period = 31 min (SVM), 29 min (ANN)

Table 4. Comparative analysis of the hybrid approach.

Year	Research Group	Dataset used	Preprocessing	Feature Extraction	Feature selection	Classifier used	Performance
2005	Nihal Fatma Guler *et al.* [71]	Bonn University database	N/M	Lyapunov exponents	N/M	RNN	Sensitivity = 96.88-96.13% Specificity = 97.38% Accuracy = 96.79%
2015	Khalid Abualsaud *et al.* [72]	Bonn University database	Compressive Sensing (CS), Discrete Cosine Transform (DCT)	DWT	N/M	Noise-aware Signal Combination (NSC) ensemble classifier	Accuracy = 80% (for SNR=1dB), 84% (for SSNR=5dB), 88% (for SNR=10dB)
2018	Kostas M. Tsiouris *et al.* [73]	CHB-MIT	Segmentation	Cross-correlation, time domain, frequency domain, graph theory	N/M	LSTM	Sensitivity = 99.84% Specificity = 99.86% FPR per hour = 0.02 Preictal duration = 120
2018	Punjal Agarwa *et al.* [74]	Kaggle	Image sampling, dimensionality reduction	FFT, CNN	N/M	Hybrid CNN-SVM	Accuracy = 97.07% Sensitivity = 96.47% Specificity = 98.81%
2018	Farrikh Alzami *et al.* [75]	Bonn University database	N/M	DWT	rank-aggregation (RA)	Adaptive hybrid feature selection-based ensemble	Accuracy = 96-100% Sensitivity = 96.58-100% Specificity = 97.47-100%
2018	J.B. Schiratti *et al.* [76]	European Epilepsy Database	Down sampling	Time and frequency domain features	N/M	Logistic regression, Weighted Ensemble (WE) classifier	ROC AUC score = 0.87
2018	Lal Hussain [77]	Bonn University database	Wavelet threshold demonising method, Daudechies (db4) wavelet, PCA	Time domain, frequency domain and complexity	N/M	SVM, KNN, Decision tree, Ensemble	Accuracy = 99.5% (with SVM) AUC = 0.9991 (with SVM)
2018	Debdeep Sikdar *et al.* [78]	Bonn University database	Wavelet-based decomposition	Multifractal Detrended Fluctuation Analysis (MF-DFA)	N/M	SVM	Accuracy = 99.6% Precision = 99.3% Recall = 99.3% Specificity = 99.7 F-score = 99.3

(Table 4) contd.....

Year	Research Group	Dataset used	Preprocessing	Feature Extraction	Feature selection	Classifier used	Performance
2019	Hisham Daoud *et al.* [22]	CHB-MIT	N/M	N/M	N/M	MLP DCNN+MLP DCNN+Bi-LSTM DCAE+Bi-LSTM DCAE+Bi-LSTM+CS	Sensitivity = 99.72% Specificity = 99.60% Accuracy = 99.60% False Alarm per hour = 0.004 Prediction time = 1 hour
2019	Omer Turk *et al.* [79]	Bonn University database	N/M	Continuous Wavelet Transform (CWT)	Resize image	CNN	Accuracy = 90.50-100%
2020	Yunyuan Gao *et al.* [80]	CHB-MIT	Signal denoising	Power spectrum density analysis	N/M	Inception-v3, ResNet152, Inception-ResNet-v2	Accuracy = 92.6% Sensitivity = 97.1% Preictal duration (Minutes) = 30

7. DATASETS

Table **5** shows the comparative analysis of datasets used by various researchers for epileptic seizure detection and prediction. The datasets considered are highly unlike each other. The differences are in terms of EEG recording mechanism used *i.e.*, sEEG or iEEG, number of subjects used, number of channels used, duration of the recordings, and number of recordings with the true positive case. The '*' in the Table **5** suggests that the parameter has not been specified by the researchers. The research is also diversified in intra-subject (subject-specific), and inter-subject (adaptive) approaches. The selection of the dataset is highly dependent on these parameters. As derived from Table **5**, majorly used datasets in the field of epileptic seizure detection/prediction are CHB-MIT [81, 82], Kaggle competition dataset [83], Bonn university dataset [84], and BCI competition dataset [85]. Apart from these, available significant datasets are the TUH dataset [86], European epilepsy dataset [87], and EEG epilepsy dataset [88]. Based on the subject-specific or adaptive approach of epileptic seizure prediction, the selection of the dataset is done [89]. For reproducibility of the results, utilization of the dataset must be clearly mentioned.

Table 5. Epilepsy seizure prediction datasets used by different researchers.

References	Dataset	Type of EEG	No. of Subjects	No. of Channels
Syed Muhammad Usman *et al.* [4]	CHB-MIT	sEEG	22	23
Pouya Bashivan *et al.* [14]	Collected by authors	sEEG	13	64
Robin Tibor Schirrmeister *et al.* [15]	BCI competition-IV	sEEG	*	*
Sachin Talati *et al.* [16]	Bonn University	sEEG	*	128/ single
Mohammad-Parsa Hosseini *et al.* [17]	BCI competition	iEEG	9	15
Mohammad-Parsa Hosseini *et al.* [18]	Kaggle competition	iEEG	5 Dog and 2 Human	16 and varying channels
Matthias Eberlein *et al.* [19]	Kaggle competition	iEEG	5 Dog and 2 Human	16 and varying channels
Isabell Kiral-Kornek *et al.* [20]	Cook *et al.* [89]	iEEG	10	16
David Ahmedt-Aristizabal *et al.* [21]	Bonn University	sEEG	*	128/Single
Hisham Daoud *et al.* [22]	CHB-MIT	sEEG	22	18/23
Xinghua Yao *et al.* [23]	CHB-MIT	sEEG	22	18/23
Nick Hershey *et al.* [24]	Stanford hospital and Lucile Packard Children Hospital	sEEG & iEEG	1,36,363	3-142
Ghulam Muhammad *et al.* [25]	CHB-MIT	sEEG	22	18/23
Xiaoyan Wei *et al.* [26]	Xinjiang Medical University	sEEG	13	*
Ali Emamia *et al.* [27]	NTT Medical Center Tokyo	sEEG	16	19
Turky N. Alotaiby *et al.* [65]	CHB-MIT	sEEG	22	18/23
P. Fergus *et al.* [90]	CHB-MIT	sEEG	22	18/23
Lung-Chang Lin *et al.* [40]	Kaohsiung Medical University Hospital	sEEG	5	21

(Table 5) contd.....

References	Dataset	Type of EEG	No. of Subjects	No. of Channels
Julius Hulsmann [91]	PhysioNet	sEEG	109	64
Benjamin H. Brinkmann [92]	Kaggle competition	iEEG	8	16
Ricardo Aler [93]	BCI-III competition	sEEG	3	32
Ning Wang *et al.* [34]	Freiburg dataset	iEEG	21	128
Xinghua Yao *et al.* [51]	CHB-MIT	sEEG	22	18/23
Nipun Dilesh Perera *et al.* [94]	CHB-MIT	sEEG	22	23
Fayas Asharindavida *et al.* [95]	CHB-MIT, EPILEPSIAE-purchased	sEEG & iEEG	22/125	22/217
Yinxia Liu *et al.* [96]	Bonn University	sEEG	*	128/Single
Gurwinder Singh *et al.* [97]	Bonn University	sEEG	*	128/Single
I. Omerhodzic *et al.* [98]	Bonn University	sEEG	*	128/Single
Punjal Agarwal *et al.* [74]	Kaggle competition	iEEG	5 Dog and 2 Human	16 and varying channels
Omer Turk *et al.* [79]	Bonn University	sEEG	*	128/Single
Debdeep Sikdara *et al.* [78]	Bonn University	sEEG	*	128/Single
Kostas M. Tsiouris *et al.* [73]	CHB-MIT	sEEG	22	23
Maarten Larmuseau *et al.* [99]	Kaggle competition	iEEG	4 Dog	16
Kaat Vandecasteele *et al.* [100]	Hospital ECG, Wearable ECG, Wearable PPG	*	11	1
Ehsan Dadgar-kiani *et al.* [101]	Kaggle competition	iEEG	1	16
M. Stella Mercy [102]	Bonn University	iEEG	2	1
Sharanreddy *et al.* [103]	CHB-MIT	sEEG	22	23
U. Rajendra Acharya *et al.* [47]	Bonn University	sEEG	*	128/Single
Ibrahim Aliyu *et al.* [52]	Bonn University	sEEG	*	128/Single

8. TOOLS AND LIBRARIES USED FOR IMPLEMENTATION

Though an ample amount of work has already been done in the field of epileptic seizure detection and prediction, the available published work does not contain much information related to the implementation environment used by the researchers. Table **6** summarizes the details available in past work on epileptic seizure detection and prediction.

It can be derived from Table **6** that most of the work is implemented using Matlab or Python. Various popular tools provided by Matlab are EEGLAB [104], Brainstorm [105], FieldTrip [106], EEGVIS [107], NFT [104], and BCILAB [104]. Python provides different libraries like MNE [108], MNE-Python [109], PyEEG [110], and Pyprep [111]. Whereas R provides packages like eegkit [112], eegUtils [113], eegR [114], erpR [115], and ERP [116]. While undertaking any research project which includes EEG signal analysis, researchers spent an ample amount of time in finalizing the platform to adapt for implementation. Following detail shows a comparison of Matlab, Python, and R concerning various parameters useful for implementation:

Table 6. Frameworks used by various researchers for epileptic seizure prediction.

References	Framework Used
Syed Muhammad Usman *et al.* [4]	Matlab
Pouya Bashivan *et al.* [14]	Lasagne
Mohammad-Parsa Hosseini *et al.* [18]	Pytorch
Xiaoyan Wei *et al.* [26]	Python with Tensorflow
Ali Emami *et al.* [27]	Python
Lung-Chang Lin *et al.* [40]	Weka
Julius Hu¨lsmann *et al.* [91]	Numpy, Scipy, MNE
Benjamin H. Brinkmann *et al.* [92]	LibSVM
Ricardo Aler *et al.* [93]	Weka
Ning Wang *et al.* [34]	Matlab spiderbox toolbox
Fayas Asharindavida *et al.* [95]	Matlab
Maarten Larmuseau [99]	Sci-kit learn, keras
Ehsan Dadgar-Kiani *et al.* [101]	Sci-kit learn, keras
M. Stella Mercy [102]	LibSVM
Sharanreddy *et al.* [103]	Matlab
U. Rajendra Acharya *et al.* [47]	Matlab
Ibrahim Aliyu *et al.* [52]	Python with Tensorflow and Keras

Open Source: The major advantage of using Python and R over Matlab is that they are open source, making them quite attractive solution to many applications. Applications developed in Python and R can be widely distributable, making it easier to enable collaboration between scientists at various locations. *Maturity of Tools:* The tools supported by Matlab are quite mature to use compared to Python and R. It is best suitable for detailed analysis of the EEG signals. *Flexibility of Manipulation:* The maturity makes it less flexible to manipulate and extend features in Matlab. *Community Support:* Community support has important significance in selecting the specific platform for research. Matlab and Python both have huge community support when it comes to EEG signal processing. This area is quite evolving in R; however, the statistical analysis performed by R is no comparable.

One of the best solutions could be to use the best feature of each platform and use it in integration. Python has an Oct2py library [117], which converts Python data structures to Matlab or Octave data structures and vice versa. It is the simplest and most stable way to run Matlab functions on Python, and most EEGLAB functions may be called from within python using this method. R provides the reticulate package [118], which allows running Python code directly within R.

CONCLUSION

EEG-based epilepsy detection and prediction using a machine learning approached has taken a boost following the technology evolution. The essential aspects of EEG waveform-based research for epileptic seizure detection and prediction have been discussed in detail. The comparative analysis of various datasets and implementation platforms considered in the past approaches along with details of traditional machine learning, deep learning, and combination of both - the hybrid approach is given, which would help novice to begin. The selection of dataset and implementation environment is highly dependent on requirement of the research. Various criteria play an important role, such as for datasets: subject-specific research or generalized research to be carried out, number of channels to consider, number of patients to consider; and for implementation environment: budget, programming expertize, and size of the dataset. Shortcomings of epileptic seizure prediction approaches are also discussed to shed light on future enhancements.

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