Proceedings of the Second International Conference on Smart Electronics and Communication (ICOSEC).
IEEE Xplore Part Number: CFP21V90-ART; ISBN: 978-1-6654-3368-6

2021 2nd International Conference on Smart Electronics and Communication (ICOSEC) | 978-1-6654-3368-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/ICOSEC51865.2021.9591824

Classification Algorithms Used In The Study of EEG-Based Epileptic Seizure Detection

* Umme salma M
department of Computer Science,(Assistant Professor)
CHRIST (Deemed To Be University)
Bangalore, India
ummesalma.m@christuniversity.in

Najmusseher
department of Computer Science,(Research Scholar)
CHRIST (Deemed To Be University)
Bangalore, India
najmusseher@res.christuniversity.in

***Abstract*—Epilepsy is a neurological illness that has become more frequent around the world. Nearly 80% of epileptic seizure sufferers live in low- and middle-income nations. In persons with encephalopathy, the risk of dying prematurely is three times higher than in the general population. Three-quarters of people with brain illnesses in low-income countries do not receive the treatment they require. Recurrent seizures are a symptom of epilepsy, characterized by strange bursts of excess energy in mind. Experts agree that most people diagnosed with epilepsy may be managed successfully, provided the episodes are discovered early on. As a result, machine learning plays an essential role in seizure detection and diagnosis. Support Vector Machine(SVM), Extreme Gradient Boosting(Xgboost), Decision Tree Classifier, Linear Discriminant Analysis(LDA), Perceptron, Naive Bayes Classifier, k-Nearest Neighbor(k-NN), and Logistic Regression are eight of the most widely used machine learning classification algorithms used to classify EEG based mostly Epileptic Seizures. Almost all classifiers, according to the study, give an efficient process. Despite this, the results show that SVM is the most effective method for detecting epileptic seizures, with a 96.84% accuracy rate. For diagnosing Epileptic Seizures using EEG signals, the perceptron model has a lower accuracy of 76.21% percent.**

***Index Terms*—EEG, Epileptic Seizures, Classification, SVM, XGBOOST, Linear Discriminant Analysis, kNN, Decision Tree Classifier.**

I. Introduction

Epilepsy is a neurological illness that has become more frequent around the world. According to WHO (World Health Organization)[**6**], Epilepsy is a chronic brain disease that affects fifty million people worldwide, resulting in encephalopathy, a common neurologic illness. EEG is a popular technique that employs more than one conductor positioned on the brain's scalp to monitor the electrical activity of nerve cells in the cortex. On the other hand, a medical specialist evaluates the prognosis of seizure detection; so, it is difficult to detect in the early stages. Manual EEG-based observation takes time[**16**], and having correct visual images is a complex effort. As a result, computer-assisted epileptic seizure detection has been considered a perfectly appropriate generation for seizure prediction[**3**]. Seizures appear in the EEG as seizure attacks or events, defined by monotonous perpetual waveforms that increase in amplitude and frequency until eventually dissipating. On the other hand, seizures should be discovered as soon as possible so that medicine can be administered swiftly to manage the seizure without side effects. Growing computational approaches known as classifiers is one of the most exciting strategies in epileptic seizure prediction and detection. The following is how the paper is structured: Section 2 discusses the Background Information, Section 3 discusses Seizure Classification Methodology, Section 4 discusses Preprocessing and Feature Selection, Section 5 discusses Classification Algorithms, Section 6 discusses Performance Metrics of Classifiers, and Section 7 discusses the Conclusion and Future Work.

II. Background

In the EEG signal, there are a lot of ambiguous information about perpetual seizures.The EEG develops into a large area of the brain seizure. EEG signals are the electrical activity of the brain structure. The EEG signal represents a superposition of brain processes as a variety of electrical activities throughout the scalp. The EEG signals absorb a significant quantity of data related to brain function[**5**]. On the other hand, the Signal technique is used to deal with issues related to EEG analysis, such as information compression, detection, relegation, noise reduction, and signal disseverment. The EEG is also a scalp recording of electrical activity in the brain. The recorded waveforms are used to investigate the electrical activity of the brain. Microvolts are commonly used to measure EEG activity (mV). Human EEG waves are classified depending on their signal frequency. Delta, Theta, Alpha, Sigma, and Beta, in that order, are the best frequencies. The frequencies associated with each type of EEG band are listed in the table I.

TABLE I
Frequency of EEG waves in Hertz(Hz)

EEG Waves	Frequency in Hertz
Delta	0.5 to 4 Hz
Theta	4 to 7 Hz
Alpha	8 to 12 Hz
Sigma	12 to 16 Hz
Beta	13 to 30 Hz

III. Seizure Classification Methodology

The technology offers clinicians with particular seizure data for the management of epileptic seizures. Seizures can occur in a localized area of the brain or throughout the entire brain. Seizures are discovered from time to time and unpredictably. Hence automated seizures detection using machine learning techniques may be possible. Here, we have provided a comprehensive overview of the various supervised learning classification algorithms. As illustrated in Fig 1, we follow the typical workflow used in the literature.

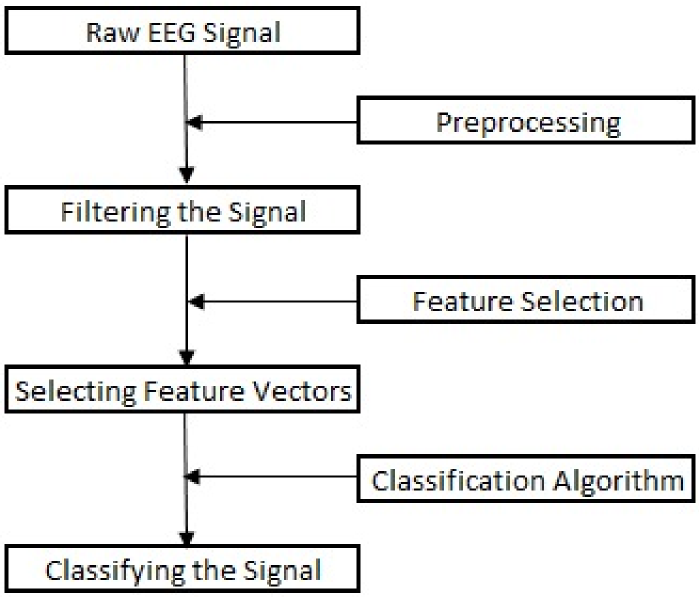

Fig. 1. General Workflow for The Classification of Epileptic Seizures

We follow the steps given in Fig 1, To implement and compare eight different classification techniques used in this proposed work to check their behaviour on EEG Epileptic Seizure data.

TABLE II
EEG based Epilepsy dataset description

EEG Data Folder	EEG Based Epilepsy Dataset Description
A	Recordings of Epileptic Seizures
B	Recordings of the area where the tumor was located
C	Recording from the healthy brain area
D	Recording of EEG signals when patient had closed their eyes
E	Recording of EEG signals when patient had opened their eyes

An EEG epileptic detests from Bonn University[**8**] in Germany was used in this investigation. It is divided into five classes, numbered A–E. Each class has 100 single-channel EEG segments with a duration of 23.6 seconds.

IV. Pre-processing and Feature Selection

The process of changing raw data into well-formed data sets is known as data preprocessing. As a result, processing analytics are used. Raw data is frequently incomplete and formatted inconsistently. Every data validation and data imputation are included in preprocessing. The goal of data validation is to determine whether or not the data in question is comprehensive and accurate. The purpose of data imputation is to fill in missing numbers and fix errors. Feature selection, also known as spatial property reduction, tries to extract a small collection of useful alternatives from a large amount of data by deleting irrelevant, redundant, or undesirable aspects. Higher learning performance, higher learning accuracy, reduced computational value, and higher model interpretability are often the results of feature selection[**9**]. Random Forests are commonly utilised in a unique information processing workflow for feature selection. The idea is that random forests' tree-based methods naturally rank well by increasing the purity of the node. We can create a collection of the initial required options by cutting trees below a specific node. Random Forest, on the other hand, could be a reliable algorithmic solution when properly hyper-parametrized (optimizing every vary of plait and range of options at each node).

V. Classification Algorithms

Machine learning algorithms use various algorithms to classify future datasets by acknowledging, understanding, and combining ideas and objects into planned categories or" subpopulations." Using pre-categorized training datasets, machine learning algorithms classify future datasets using various algorithms. It predicts the likelihood of preset trajectories using training datasets. In a nutshell, classification is a form of "Pattern Recognition," with classification algorithms applied to training datasets to detect same patterns[**4**],(similar phrases or attitudes, range sequences, and so on) in subsequent sets of data. In this paper, we look at eight different classification strategies that are commonly employed in epileptic data categorization research. We used Bonn university EEG data to train and test the eight classification models, with 66% of the data used for training and 34% for testing, and the accuracies gained are listed in table III.

A. Support Vector Machine

Support Vector Machine (SVM) could possibly be a supervised learning formula for classification and regression problems. It is, however, mostly used in categorization difficulties. We tend to plot every data item in the n-dimensional area using the SVM formula to some extent (where n is additionally many features you have). Finding the hyper-plane that distinguishes the two classes well[**2**] is one way to classify using SVM. Individual observation coordinates are represented as vectors in SVM. In addition, the SVM classifier is a frontier that best separates the two classes (hyper-plane/line). It works well in areas with many dimensions, and it's still beneficial when the variety of dimensions matters more than the quantity of samples. It employs a set of training points known as support vectors as part of the decision function. As a result, it is collectively memory efficient.SVM is very versatile in that it offers a variety of kernel functions for decision-making. The fundamental drawback of SVM is that they do not provide probability estimates directly.

B. Extreme Gradient Boosting

Extreme Gradient Boosting (XGBOOST) algorithm is a gradient boosting-based decision tree-based ensemble Machine Learning technique. Artificial neural networks tend to outperform all other algorithms or frameworks in prediction problems[**10**] involving unstructured data (pictures, text, etc.). When dealing with small-to-medium structured or tabular data, however, decision tree-based algorithms are considered best-in-class. XGBOOST has the advantage of being quite versatile. It took advantage of parallel processing. It's quicker than upping the gradient. It is in pursuit of batch normalization. With its built-in alternatives, it's geared to deal with missing data. The key problem is that XGBOOST takes a long time to train the model, lacks scalability, and overfits if the model isn't stopped at the right time.

C. Decision Tree Classifier

A Decision Tree is a tree-like tool that models likely outcomes, resource value, utility, and potential consequences. Decision trees can be used to provide conditional control statements in algorithms[**11**]. They embrace branches that reflect phases in decision-making that will lead to a positive outcome. These are the only kind of learning algorithms that are supported by a variety of learning methods. Because the tools will address data-fitting difficulties like regression and classifications, they will also effectively fit nonlinear connections. A decision tree has the advantage of considering all possible outcomes of a decision and tracing each path to a conclusion. The main downside is that it is prone to over-fitting.

TABLE III
COMPARISON BETWEEN THE PERFORMANCE OF CLASSIFICATION ALGORITHMS FOR EEG-BASED EPILEPTIC SEIZURE DETECTION

Classification Algorithm	**Train Accuracy %**	**Test Accuracy %**
Decision Tree	100	92.89
XGBoost	98.81	94.24
Support Vector Machine	98.31	96.84
k-Nearest Neighbor	96	93.86
Naive Bayes	95.85	95.47
Logistic Regression	83.15	81.32
Linear Discriminant Analysis	83.87	81.74
Perceptron	77.30	76.21

D. Linear Discriminant Analysis

The idea behind Linear Discriminant Analysis (LDA) is simple. Mathematically speaking, we need to seek a new feature space to project the data to maximize classes disjunction. The primary step is to determine how to measure this separation capability of every new feature space candidate. The space between the projected suggests that every category can be one amongst the measures. Still, solely this distance wouldn't be a sensible metric because it doesn't take the unfold of data under consideration[**1**]. If the distribution of your data is significantly non-Gaussian, the LDA may not perform well. The advantage of LDA lies in its easy, quick, and portable algorithmic rule, which used data from each of the features to form a new axis that successively minimizes the variance and maximizes the class distance of the two variables. The main limitation is that it needs a standard distribution assumption on features/predictors, which may not be the case always.

E. Perceptron

The perceptron is a simplified model of biological neurons in human brain and is known as the building block of artificial neural networks. A perceptron is that the most straightforward neural network, one that's comprised of only one nerve cell. Perceptron is typically accustomed classify the data into two components[**12**]. Therefore, it's conjointly referred to as a Linear Binary Classifier. A perceptron model can be a single layer or multi-layered. In our work, we implement a single perceptron model. The advantage of the perceptron is that they classify an unknown pattern with different known ways that share similar distinctive features. They can learn solely linearly separable patterns. The limitation of the perceptron is that the output values can take just one of the two weights [0 or 1]. Owing to the exhausting limit transfer function, it'll entirely classify the linearly separable set of vectors.

F. Naive Bayes classifiers

Naive Bayes classifiers are a bunch of classification algorithms supported Bayes' theorem. It's not one algorithmic rule; but a family of algorithms, where all of them share a typical principle, i.e., each pair of classified features is independent of each other. Naive Bayes rule may be a kind of classifier that uses the Bayes Theorem[**13**]. It predicts membership possibilities for each class, just like the probability that a given record or data point belongs to a particular category with the very best probability taken into account the major possible category. Naive Bayes classifiers may be an easy approach and straightforward to implement. It doesn't want the most quantity of training data. It handles each continuous and categorical data. It's incredibly ascendible with the number of predictors and data points. The main disadvantage is that it implicitly assumes that everyone amongst the attributes is reciprocally independent and has data deficiency.

G. k-Nearest Neighbors

The k-Nearest Neighbors (k-NN) algorithmic rule is a straightforward, supervised machine learning rule that will solve each classification and regression issue. However, it is simple to implement and perceive; however, it encompasses a significant downside of considerably slowing because its size in use grows. The k-NN method saves all of the data that is available and classifies a new data point that supports the similarity[**14**]. This implies that once new data appears, it will be organized into a well-suited class using the k-NN algorithm. Hence k-NN is used for this identification because it works on a similarity measure. The advantage of kNN includes its simplicity, usefulness for missing value imputation, Regression and classification, High accuracy compared to better-supervised learning models. The main limitation is that it is sensitive to the dimensions of the data and needs high memory ought to store all of the training data.

H. Logistic Regression

Logistic Regression is also a supervised learning rule mainly accustomed to determine binary classification tasks. The main point of interest in logistical Regression is the word logistic, which may be a function that performs the classification task. Logistic Regression is also treated as a simple but effective classification algorithmic rule most fitted to binary type[**7**]. It's even used as an activation function for neural network layers. The logistic regression, often known as the sigmoid function, is a logistic function that takes any real-valued range and maps it to a range between zero and one. The benefits of logistic Regression embrace it's easier to implement, interpret, and highly effective to train, and best suited for binary classification tasks. The limitations assume it's typically quite prone to noise and should result in over-fitting.

VI. Performance Metrics of Classifiers

The primary goal of the proposed work is to shed light on classification techniques that aid in the diagnosis of epileptic seizures, as well as to demonstrate how quickly and reliably the classification algorithms used for the EEG, which are based primarily on epileptic seizure prediction, will be useful for automatic epileptic seizure diagnosis, and to be able to yield a precise classification and translation. Table III shows the performance of the used classifiers, which represents the classifiers' overall training and testing accuracy in the suggested study. 66% of the data is used for training, while 34% is used for testing. The SVM outperforms all alternative models with a test accuracy of 96.84%, with the least accurate model being a single layer perceptron model with a test accuracy of 76.21%, according to the experimental data.

VII. Conclusion and Future Work

Epilepsy is a frequent neuromuscular condition that results in several deaths each year. EEG is used to detect encephalopathy. These signals are highly complex, non-stationary, and multi-varying. For diagnostic and prognostic purposes, EEG research necessitated the use of combined feature selection approaches and, as a result, the most powerful machine learning classifiers. We use the most robust machine learning classifiers to classify epileptic seizure data, which is supported by the nature of these signals. During this research, several widely used classifiers such as SVM, Xgboost, decision Tree, LDA, Perceptron, Naive Bayes, kNN, and logistical Regression are investigated. SVM outperform the other eight techniques with a 96.84% accuracy, followed by Naive Bayes 95.47% and XGBOOST 94.24%. Clinicians can deploy this data-driven technique to distinguish healthy and epileptic people from standard procedures for diagnostic purposes. To determine epileptic seizures, provide the most effective evaluation performance. The advancement of deep learning meta-heuristic-based classifiers will be the focus of future studies.

References

[1] M. Li, W. Chen, and T. Zhang, "FuzzyEn-based features in FrFT-WPT domain for epileptic seizure detection," Neural Computing and Applications, vol. 31, no. 12, pp. 9335–9348, Sep. 2018.
[2] A. Subasi, J. Kevric, and M. Abdullah Canbaz, "Epileptic seizure detection using hybrid machine learning methods," Neural Computing and Applications, vol. 31, no. 1, pp. 317–325, Apr. 2017.
[3] Y. Paul, "Various epileptic seizure detection techniques using biomedical signals: a review," Brain Informatics, vol. 5, no. 2, Jul. 2018.
[4] L. Hussain, "Detecting epileptic seizure with different feature extracting strategies using robust machine learning classification techniques by applying advance parameter optimization approach," Cognitive Neurodynamics, vol. 12, no. 3, pp. 271–294, Jan. 2018.
[5] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," EURASIP Journal on Advances in Signal Processing, vol. 2015, no. 1, Aug. 2015.
[6] Q. Yuan, W. Zhou, Y. Liu, and J. Wang, "Epileptic seizure detection with linear and nonlinear features," Epilepsy Behavior, vol. 24, no. 4, pp. 415–421, Aug. 2012.
[7] A. Alkan, E. Koklukaya, and A. Subasi, "Automatic seizure detection in EEG using logistic regression and artificial neural network," Journal of Neuroscience Methods, vol. 148, no. 2, pp. 167–176, Oct. 2005.
[8] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," Physical Review E, vol. 64, no. 6, Nov. 2001.
[9] F. Alzami et al., "Adaptive Hybrid Feature Selection-Based Classifier Ensemble for Epileptic Seizure Classification," IEEE Access, vol. 6, pp. 29132–29145, 2018.
[10] L. Torlay, M. Perrone-Bertolotti, E. Thomas, and M. Baciu, "Machine learning–XGBoost analysis of language networks to classify patients with epilepsy," Brain Informatics, vol. 4, no. 3, pp. 159–169, Apr. 2017.
[11] K. D. Tzimourta et al., "A robust methodology for classification of epileptic seizures in EEG signals," Health and Technology, vol. 9, no. 2, pp. 135–142, Sep. 2018.
[12] S. Raghu and N. Sriraam, "Optimal configuration of multilayer perceptron neural network classifier for recognition of intracranial epileptic seizures," Expert Systems with Applications, vol. 89, pp. 205–221, Dec. 2017.
[13] A. Sharmila and P. Geethanjali, "DWT Based Detection of Epileptic Seizure From EEG Signals Using Naive Bayes and k-NN Classifiers," IEEE Access, vol. 4, pp. 7716–7727, 2016.
[14] W. Mardini, M. M. Bani Yassein, R. Al-Rawashdeh, S. Aljawarneh, Y. Khamayseh, and O. Meqdadi, "Enhanced Detection of Epileptic Seizure Using EEG Signals in Combination With Machine Learning Classifiers," IEEE Access, vol. 8, pp. 24046–24055, 2020.
[15] W. Zhao et al., "A Novel Deep Neural Network for Robust Detection of Seizures Using EEG Signals," Computational and Mathematical Methods in Medicine, vol. 2020, pp. 1–9, Apr. 2020.
[16] V. T, V. R, and D. M, "Fusion based Feature Extraction Analysis of ECG Signal Interpretation - A Systematic Approach," March 2021, vol. 3, no. 1, pp. 1–16, Mar. 2021.