
RESEARCH ARTICLE

Epilepsy Seizures Classification with EEG Signals: A Machine Learning Approach

Sajad Ulhaq¹, Gul Zaman Khan² ✉, Imran Ulhaq³, Inam Ullah⁴ and Fazal Rabbi⁵

^{1,3,5}Department of Computer Science Ghazi Umara Khan Degree Collage Sammarbagh Dir(L), Pakistan

²Department of Computer Software Engineering, UET Mardan, Pakistan

⁴Department of Computer Science Abdul Wali Khan University Mardan, Pakistan

Corresponding Author: Gul Zaman Khan, **E-mail:** gulzamankhan726@gmail.com

ABSTRACT

Epilepsy is a neurological disorder characterized by recurrent seizures, which can significantly impact a person's life. Early and accurate diagnosis of epilepsy is crucial for effective management and treatment. The traditional methods for diagnosing epilepsy are deemed ineffective and costly. Epilepsy disease detection at an early stage is crucial. Machine learning techniques have shown promise in automating the classification of epilepsy based on various data sources, such as electroencephalogram (EEG) signals, clinical features, and imaging data. This paper presents a machine learning approach to epilepsy disease classification using EEG signal data. We have applied various machine learning models, including Random Forest, XGBoost, GradientBoost, Naive Bayes, Decision Tree, and Extra Tree, with some pre-processing and feature selection techniques. XGBoost achieved 98.93% training accuracy and 98.23% testing accuracy; Gradient Boost achieved 98.40% training and 98.20% testing accuracy; Extra Tree achieved 98.65% training and 97.85% testing accuracy; Random Forest achieved 97.42% training and 96.52% testing accuracy; Decision Tree achieved 92.6% training and 92.4% testing accuracy; Navies Bayes achieved 93.52% training and 92% testing accuracy. The XGBoost classifier achieved the highest accuracy among all other classifiers applied in the proposed research experiment.

KEYWORDS

Classification, epilepsy disease classification, machine learning approaches

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1. Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent and unprovoked seizures. It is one of the most common neurological conditions, affecting people of all ages and backgrounds. Epileptic seizures occur due to abnormal electrical activity in the brain, leading to a wide range of symptoms that can vary from mild to severe. Seizures are the hallmark of epilepsy and can manifest in different forms, including convulsions, loss of consciousness, altered sensations, or abnormal behaviors. These seizures can be spontaneous or triggered by certain factors, such as flashing lights, sleep deprivation, or stress. The frequency and severity of seizures can vary greatly among individuals, making epilepsy a highly heterogeneous condition. According to a recent report published by the WHO in 2023, epileptic seizures affect approximately 5 million individuals worldwide every year. The average prevalence of epilepsy in Pakistan is estimated to be between 9.99 and 14.8 cases per 1000 individuals (Zarine & Hassan, 2020). According to estimates, epilepsy affects 49 out of every 100,000 people in nations with higher incomes each year. This ratio can reach 139 per 100,000 in low- and middle-income nations (WHO, 2022). The underlying causes of epilepsy are diverse and can include genetic factors, brain injuries, infections, developmental disorders, and structural abnormalities in the brain. In some cases, the exact cause may be unknown, leading to a diagnosis of idiopathic or cryptogenic epilepsy. Understanding the underlying cause is essential for appropriate treatment and management strategies.

Accurate diagnosis is crucial to differentiate epilepsy from other conditions that may present with seizures and to determine the type of epilepsy, as there are various subtypes based on seizure characteristics and brain activity patterns. Diagnosing epilepsy involves a comprehensive evaluation of an individual's medical history, physical and neurological examinations, and specialized tests such as electroencephalography (EEG) and neuroimaging. The aforementioned traditional methods for epilepsy disorder diagnosis can be time-consuming, and there is a potential for incorrect results. While traditional diagnostic methods are generally effective, they do have limitations, and the diagnosis of epilepsy can sometimes be challenging (Ahmed, Hisam, & Magdy, 2018). Machine learning for brain disease diagnosis has gained attention in recent years. Researchers are making several fruitful attempts at automated diagnosis. These approaches are based on artificial intelligence strategies that make use of time- and frequency-based methods of feature extraction. Recent advancements in machine learning and deep learning have transformed the fields of computational intelligence and the healthcare sector, particularly in the field of disease detection, yielding excellent results that have resulted in state-of-the-art brain-computer interfaces. The proposed research work suggests an epileptic seizure detection system that uses both machine learning models and EEG data. We have applied various machine learning and deep learning models to a recently uploaded EEG dataset to diagnose epilepsy disease early and accurately. The key contributions of the suggested approach are as follows:

- To develop a system for epilepsy seizure recognition that is efficient and results in less computation time and cost.
- To apply machine learning models to the EEG dataset and then compare their performance.
- To improve the existing methods and suggest new methods for early and accurate epilepsy disease diagnosis.

This paper is organized into five sections. Section 2 discusses the previous work done on epilepsy seizure classification and detection. Section 3 presents the material and methods applied in the proposed experiment. Section 4 discusses the result and analysis, while Section 5 gives a conclusion and features work.

2. Literature Review

Epilepsy is a continuous spontaneous seizure that disturbs normal brain function and appears as an unexpected electrical irregularity of the human brain. This brain abnormality is detected by examining the EEG for disease investigation, which implies seizures. To classify EEG signals, various machine learning and deep learning techniques have been proposed. Table 1 depicts the previous work done on epilepsy seizure classification and detection.

Table I. Literature Review With Pros And Cons

Reference	Models/Algorithm applied	Contribution	Weakness	Dataset Used	Result
(Ezequiel et al. 2002)	CNN, DAG-CNN	Detection	Accuracy can be improved	MRI dataset	87%
(Ahmad & Magdy, 2021)	Magnet	Classification	High time complexity	MRI dataset	99%
(Taku, Noboru, & Toshihisa, 2021)	SDCAE, BiLSTM	Classification	Used small dataset	CHB-MIT dataset	98%
(Anwar et al., 2022)	DCSAE-ESDC	Detection	High time complexity	UCI dataset	98%
(Marlen et al., 2022)	CNN, TL	Classification	Accuracy can be improved	BWII EEG dataset	95%
(Marina, Juan & Helbert, 2021)	ANN, LR, SVM, CNN	Compared various ML models	Accuracy can be improved	CHB-MIT dataset	86%
(Yunguan et al., 2020)	DCNN	Classification	Accuracy can be improved	CHB-MIT dataset	90%

(Khaled, 2020)	Random Forest, K-NN, NB, LR, DT, J48, S.G.D	Classification and detection	Accuracy can be improved	UCI dataset	97%
(Thomas et al. , 2020)	t-VGG	Classification	Accuracy can be improved	TUH EEG dataset	70.38%
(Shanta et al. , 2023)	LR, SVM, KNN, CNN, DT, GB Classifier, NB, RF.	Classification	Accuracy can be improved	EEG dataset	97.91%
(Saif et al. , 2022)	SVM, KNN, NB, DT	Compared various ML models	Accuracy can be improved	UCI dataset	96.5%
(Xin, Maokun & Tingting, 2022)	RF+GBDT	Classification and detection	Accuracy can be improved	CHB-MIT dataset	92.5%
(Loukas, Dimitris, John, 2023)	Alex Net, DenseNet201, ResNet18, EfficientNet,	Detection	Used small dataset	Bonn dataset	98.7%
(Wasem et al. , 2023)	DCAE-ESD-Bi-LSTM	Classification	High time complexity	CHB-MIT dataset	99.8%
(Summaya et al. , 2023)	KNN, SVM, NB, LR	Detection	Used small dataset	KAUH dataset	97.11%
(Muhammad, 2021)	SVM	Classification	Accuracy can be improved	CHB-MIT dataset	91%
Shuaicing et al. , 2023)	Hybrid Transformer	Classification and detection	Used small dataset	CHB-MIT dataset	91%

In the above-mentioned table, several studies focus on the EEG signal dataset using various ML and DL models. Finding an effective method to address all of these challenges is useful and important. The proposed research work focuses on a large EEG signal dataset with various preprocessing, feature selection, and cross-validation techniques to tackle these challenges.

3. Methodology

The main objective of the suggested strategy is to identify people with epilepsy seizure disease accurately and at an early stage. This study uses Logistic Regression, K-NN, Random Forest, Decision Tree, Naive Bayes, Extra Tree, and XGBoost classifiers employing an EEG signal dataset to identify epilepsy seizures early and accurately. Data preprocessing, feature extraction, and feature selection are important steps before feeding data into classifiers (Gul, Inam, 2023). It ensures that the input data for the classifiers is noise-free and in a normalized form, which increases the model detection accuracy. The proposed experiment consists of six steps, as shown in Figure 1.

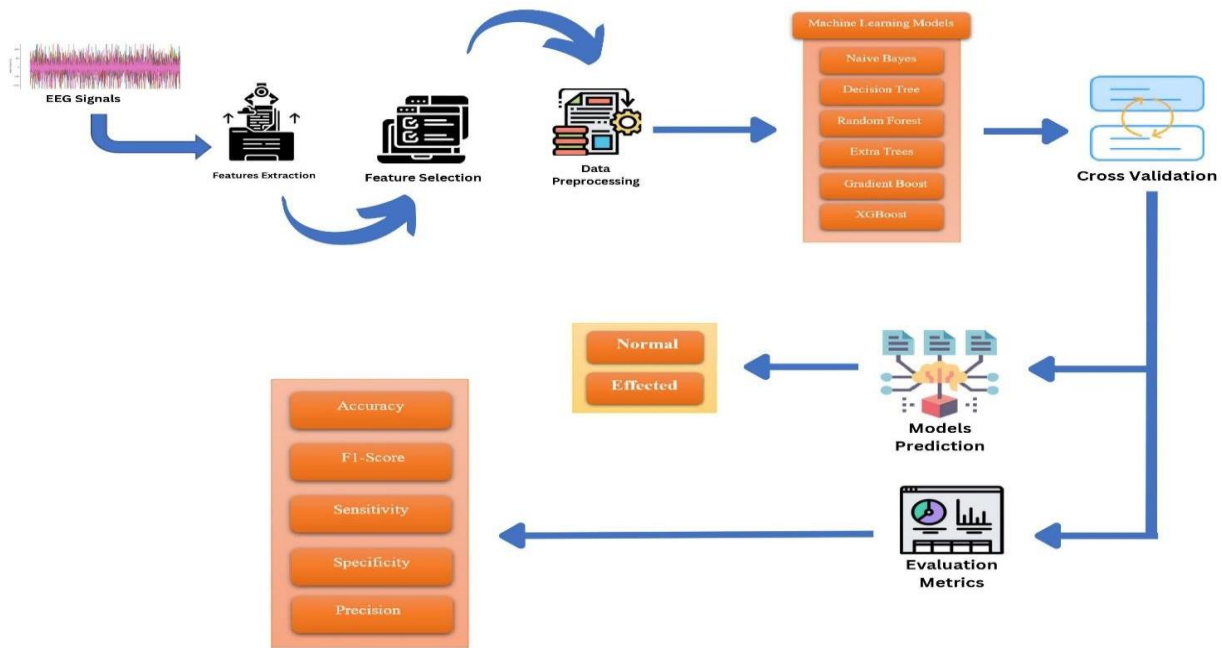


Fig.1 Proposed methodology

3.1 Dataset Acquisition

The first and most important step in developing an intelligent system is to gather more pertinent data precisely and effectively (Ahmad et al.,2023). We have made use of a dataset collected by UCI machine learning repository using EEG electrodes with a 23.6-second time frame to record brain activity. Table II shows the details of the dataset used.

Table II. Detail of Uci Eeg Dataset

Characteristics	Attribute type	Instances	Attributes	area
Multivariate	Integer, real	11500	179	life

3.2 Pre-Processing

Preprocessing is a critical step in machine learning research that involves transforming raw data into a format suitable for training and improving the performance of machine learning models (Gul et al., 2023). It plays a crucial role in extracting meaningful information, reducing noise, and addressing various challenges associated with real-world datasets. In addition, the standard scalar transforms the features of the dataset to have a zero mean and unit variance, whereas min-max scalar scales the features to a specific range, typically between 0 and 1(Shah et al., 2022). This technique shifts the feature values proportionally, preserving the relationships between them while ensuring that all features fall within a consistent range. Finally, data with missing or invalid values is removed from the dataset.

3.3 Feature Selection

Feature selection is crucial in ML research as it enables the identification and inclusion of the most relevant and informative features while excluding irrelevant or redundant ones (Gul et al., 2023). By selecting the optimal subset of features, we can enhance the performance of models and reduce overfitting. mRMR, ReliefF, and variance threshold feature selection techniques are used to find out the most essential and related features that accurately reflect the structure of the target we desire.

3.3 Classification Models

The proposed research work used various machine learning algorithms, including Random Forest, Decision Tree, Extra Tree, XGBoost, Gradient Boost, and Naive Bayes, on the UCI EEG signal dataset.

4. Result and Discussion

4.1 Result of the proposed classifiers

We have applied various machine learning models to classify epilepsy seizure patients and normal people. Figure 2 shows the confusion matrix of XGBoost. In Figure 2, we see that out of records, the XGBoost predicted 1737 records correctly and 26 records incorrectly. Similarly, out of 1857 records, XGBoost successfully predicted 1819 records of them.

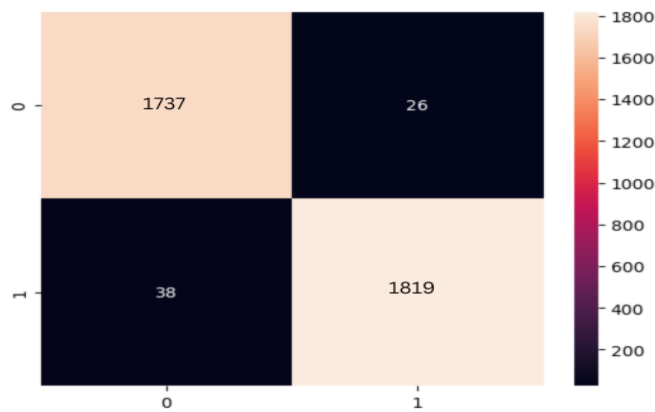


Fig.2.Confusion matrix of XGBoost

Figure 3 shows the confusion matrix of the Gradient Boost. In Figure 3, we see that the Gradient Boost predicted 1734 records correctly and 24 records incorrectly. Similarly, out of 1862 records, the Gradient Boost successfully predicted 1821 records of them.

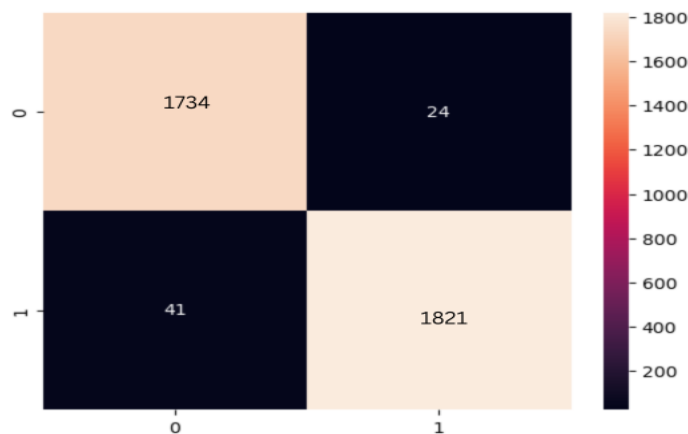


Fig.3.Confusion matrix of Gradient Boost

Similarly, Figure 4 shows the confusion matrix of Extra Trees. In Figure 4, we see that the Extra Trees predicted 1720 records correctly and 23 records incorrectly. Similarly, out of 1877 records, the Extra Trees successfully predicted 1822 records of them.

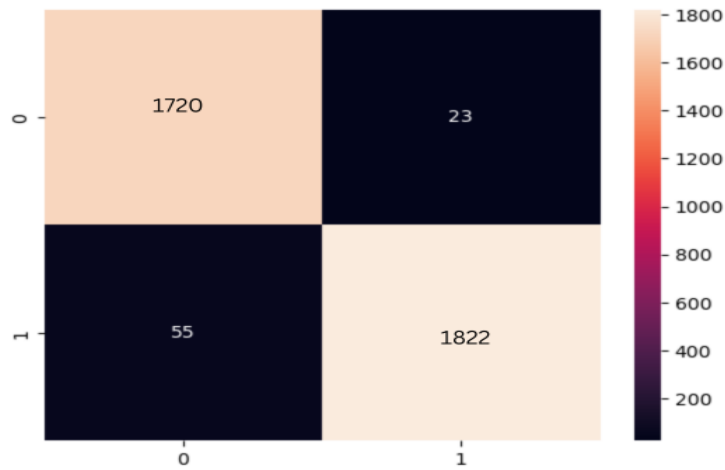


Fig.4.Confusion matrix of Extra tree

Figure 5 shows the confusion matrix of Random Forest. In Figure 5, we see that the Random Forest predicted 1733 records correctly and 84 records incorrectly. Similarly, out of 1803 records, the Random Forest successfully predicted 1761 records of them.

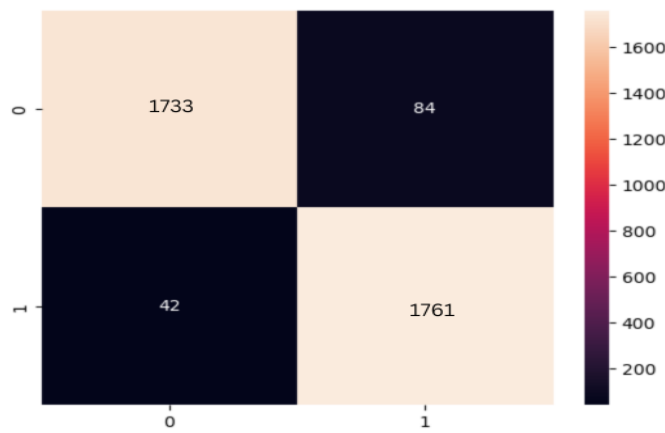


Fig.5.Confusion matrix of Random Forest

Figure 6 shows the confusion matrix of the Decision Tree. In Figure 6, we see that the Decision Tree predicted 1653 records correctly and 152 records incorrectly. Similarly, out of 1815 records, the Decision Tree successfully predicted 1693 of them.

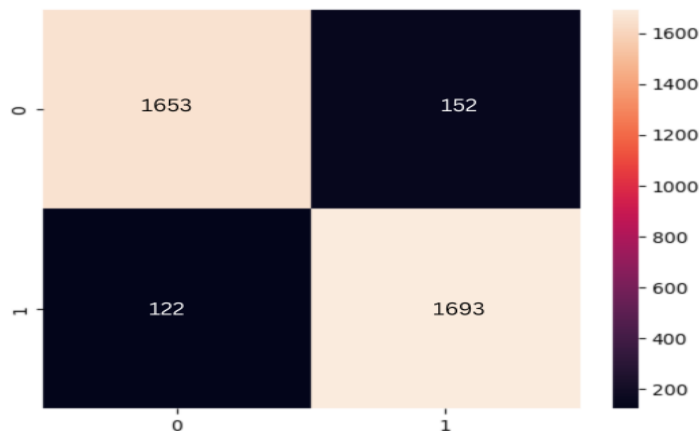


Fig.6.Confusion matrix of Decision Tree.

Figure 7 shows the confusion matrix of Naive Bayes. In the figure 7, we see that the Decision Tree predicted 1727 records correctly and 246 records incorrectly. Similarly, out of 1647 records, the Decision Tree successfully predicted 1599 of them.

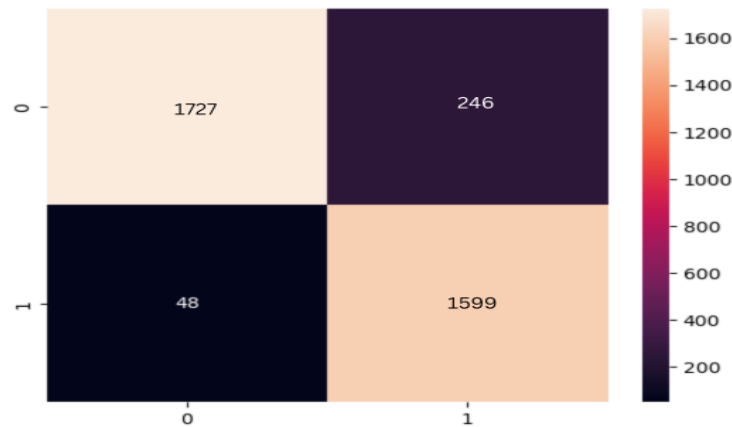


Fig.7.Confusion matrix of Navies Bayes

Table 2 shows various evaluation matrices calculated for XGBoost, Gradient Boost, Extra Tree, Random Forest, and Decision Tree.

Table III. Evaluation Matrix of the Proposed Classifier

Model Name	Training accuracy (%)	Testing accuracy (%)	F1 Score (%)	Sensitivity (%)	Specificity (%)	Precision (%)
NB	93.5	92.0	92.0	87.5	97.2	97.0
Decision Tree	92.6	92.4	92.2	91.5	93.2	93.1
Random Forest	97.42	96.52	96.4	95.3	97.6	97.6
Extra Trees	98.65	97.85	97.7	98.6	97.0	96.9
Gradient Boost	98.40	98.20	98.4	98.6	97.6	97.6
XGBoost	98.93	98.23	98.1	98.5	97.9	97.8

XGBoost achieved the highest accuracy among all classifiers applied in the proposed experiment. Gradient Boost accuracy was 2nd in the list, while the Decision tree achieved less accuracy among all classifiers. The evaluation metrics are graphically represented in Figure 8.

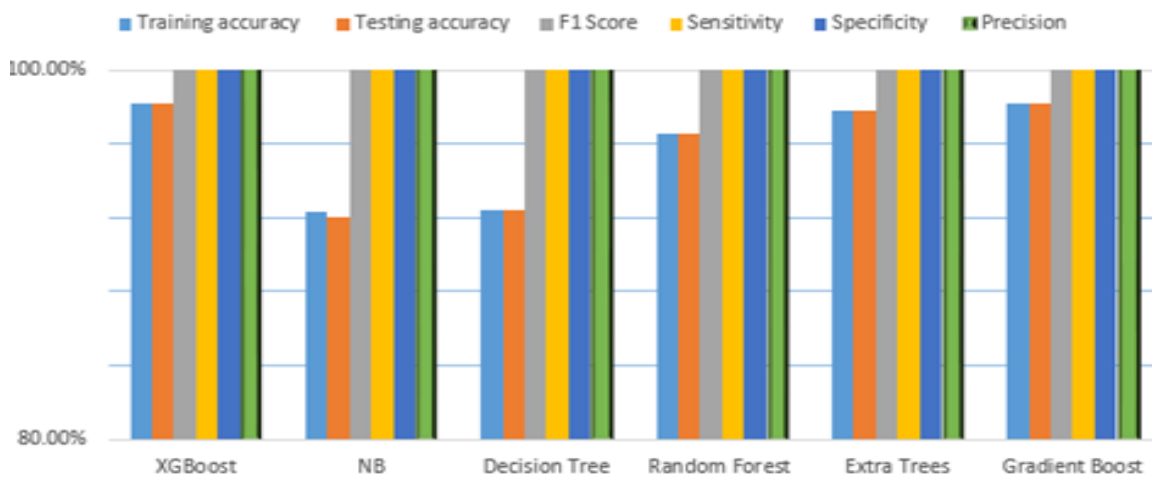


Fig.8. Performance Evaluation Metrics

The ROC curve is created by plotting the true positive rate (TPR) on the y-axis against the false positive rate (FPR) on the x-axis. Each point on the curve corresponds to a particular classification threshold applied to the model's predicted probabilities or scores. Figure 9 depicts the ROC curves of all classifiers used in the proposed experiment.

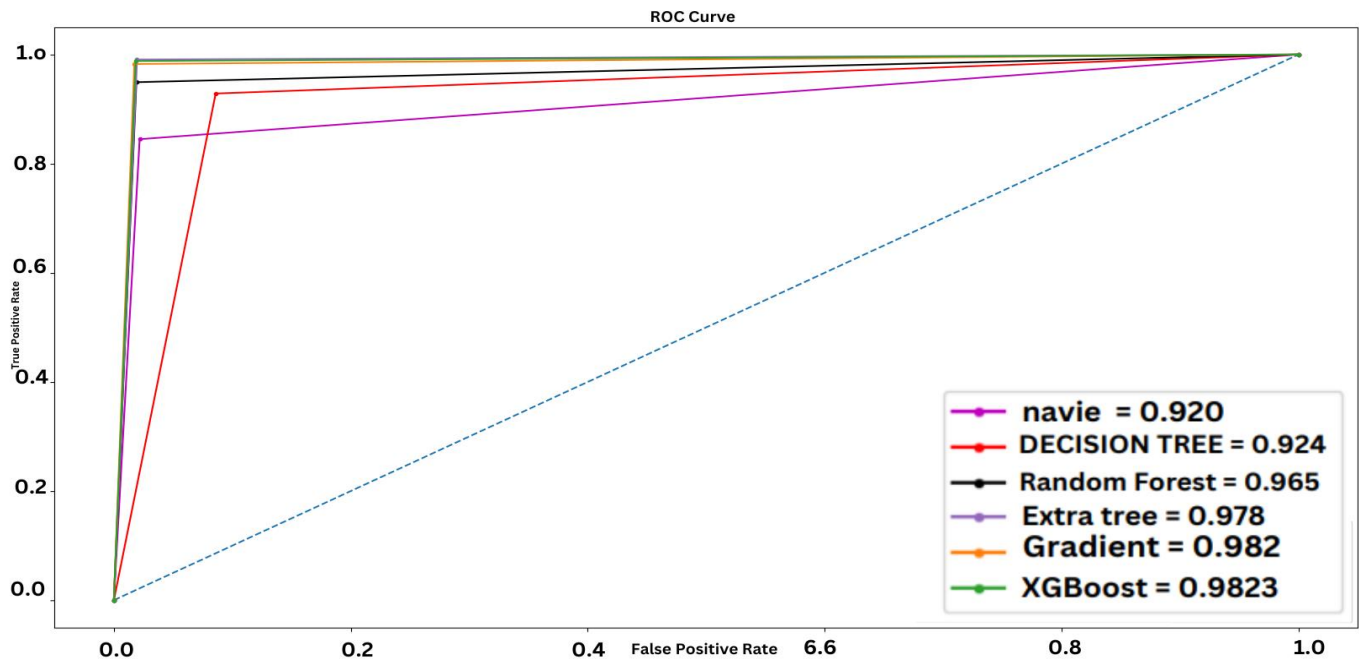


Fig.9. Roc curves of all classifiers

4.2 Comparison with previous studies

The results of our proposed approach demonstrated significant improvements across all performance metrics while maintaining minimal computation time. Based on the statistical findings presented in Table 3, we can conclude that the efficiency of the algorithms has increased. These findings validate the effectiveness and practicality of our approach, highlighting its potential for real-world applications.

Table IV. Comparative Analysis

Reference	Models/Algorithm applied	Weakness	Result
(Ezequiel et al. 2002)	CNN, DAGCNN	Accuracy can be improved	87%
(Taku et al. , 2021)	SDCAE, BiLSTM	Used small dataset	98%
(Anwar et al., 2022)	DCSAE-ESDC	High time complexity	98%
(Marlen et al., 2022)	CNN, TL	Accuracy can be improved	95%
(Marina et al. , 2021)	ANN, LR, SVM, CNN	Accuracy can be improved	86%
(Yunguan et al. , 2020)	DCNN	Accuracy can be improved	90%
(Thomas et al. , 2020)	t-VGG	Accuracy can be improved	70.38%
(Saif et al. , 2022)	SVM, KNN, NB, DT	Accuracy can be improved	96.5%

(Xin, et al. , 2022)	RF+GBDT	Accuracy can be improved	92.5%
(Muhammad, 2021)	SVM	Accuracy can be improved	91%
Shuaicing et al. , 2023)	Hybrid Transformer	Used small dataset	91%
Proposed	RF, DT, XGBOOST, ET,	-	98.23

5. Conclusion

This paper provides an approach for diagnosing epilepsy seizures disorder based on a machine learning model with an EEG signal dataset. The objective of this paper is to propose an approach for diagnosing epilepsy seizures disorder using a machine learning model with an EEG signal dataset. We have applied various machine learning models, including Random Forest, XGBoost, Gradient Boost, Naive Bayes, Decision Tree, and Extra Tree, to the EEG dataset for the classification of epilepsy seizures. XGBoost achieved 98.93% training accuracy and 98.23% testing accuracy; Gradient Boost achieved 98.40% training and 98.20% testing accuracy; Extra Tree achieved 98.65% training and 97.85% testing accuracy; Random Forest achieved 97.42% training and 96.52% testing accuracy; Decision Tree achieved 92.6% training and 92.4% testing accuracy; Navies Bayes achieved 93.52% training and 92% testing accuracy. The proposed experiment achieved high accuracy, which is acceptable. The novelty of this paper lies in the application of multiple machine learning models to diagnose epilepsy seizures using EEG signals. The comparative analysis of various algorithms provides valuable insights into their performance in this specific medical context. Additionally, achieving high accuracy with the proposed approach is noteworthy, as it suggests the potential for using machine learning in medical diagnostics. The proposed study uses a small EEG signal dataset, and still, its computation time is high. In the future, we will apply some hybrid machine learning and deep learning models with large datasets and transformers to improve accuracy and reduce computation time.

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