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RESEARCH ARTICLE

# Epileptic Seizure Detection in EEG Signals Using Machine Learning and Deep Learning Techniques

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**ABSTRACT** This research presents a novel approach to detecting epileptic seizures leveraging the strengths of Machine Learning (ML) and Deep Learning (DL) algorithms in EEG signals. Epileptic seizures are neurological events with distinctive features found in Electroencephalography (EEG) that lend considerable credibility to researchers. Machine Learning (ML) and Deep learning (DL) algorithms have emerged as powerful feature extraction and classification tools in EEG signal analysis. Many studies have converted the EEG signals into either images and /or calculated time-frequency domain features and performed classification. This study focuses on classifying time-series data representation of EEG signals with machine learning-based classifiers by tuning parameters and deep learning-based One-Dimensional Convolutional Neural Network (1D CNN) methods. The primary objective is not only to determine the optimal classifier but also to emphasize critical metrics such as sensitivity, precision, and accuracy, which are critical in medical investigations, particularly for the early detection of diseases and patient care optimization. The UCI Epileptic Seizure Recognition dataset used in this study consists of time-series data points extracted from the EEG signals. The dataset has been preprocessed and fed to the classifiers, namely Extreme Gradient Boosting (XGBoost), TabNet, Random Forest (RF), One Dimensional Convolutional Neural Network, and achieved encouraging accuracies of 98%, 96%, 98%, and 99%, respectively. The proposed 1D-CNN model performed better than other state-of-the-art models concerning accuracy, sensitivity, precision, and recall.

**INDEX TERMS** XGBoost, TabNet, deep learning (DL), machine learning (ML), random forest (RF), epileptic seizures, 1D CNN, data points, time series.

## I. INTRODUCTION

Epilepsy, a neurological disorder affecting approximately 50 million individuals globally, stands as one of the most prevalent neurological diseases worldwide, as reported by the World Health Organization. It is characterized by recurrent and unpredictable seizures. Epileptic seizures pose a significant challenge to the quality of life for affected individuals [1]. It is marked by a tendency for recurrent episodes across one's lifespan. Epileptic seizures can manifest under diverse circumstances, encompassing factors such as skull fractures, genetic predisposition, tumors, and other contributing factors [2]. It is found that anyone can be affected at any age, but it is most initiated in childhood or over the age of 65 [3].

An epileptic seizure is a sudden and temporary disturbance in the normal functioning of the brain, characterized by abnormal and excessive electrical activity. This electrical activity can result in various physical and mental manifestations, ranging from subtle sensations to convulsions and loss of consciousness, and sometimes leads to sudden, unexpected death [4]. Accurate detection of seizures in epilepsy patients

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is vital for diagnosing the condition correctly and devising personalized treatment strategies. A better quality of life and reduced life risks can be ensured through early diagnosis and continuous monitoring of seizures.

The purpose of analyzing the electroencephalogram (EEG) signals, which record electrical activity in the brain, is to evaluate patients with known seizures to detect the accurate seizure type [5]. Epileptic EEG signals provide a dynamic representation of neural activity, capturing the intricate patterns associated with seizures. EEG signals are recorded using electrodes attached to the scalp. These electrodes detect the electrical impulses generated by neurons in the brain.

Raw EEG signal data often contains noise and irrelevant information. Preprocessing steps, such as filtering, artifact removal, and baseline correction, are applied to clean the signals and enhance their quality. Once preprocessing is done, feature selection and extraction play a crucial role in epileptic seizure detection using EEG signal classification [6]. Extracting relevant features from the signal data provides more discriminative information than the raw signal alone. Machine learning and Deep learning techniques have shown remarkable potential in extracting relevant features and classifying them in various medical applications, including epilepsy diagnosis.

Epileptic seizures can vary widely in their presentation, severity, and duration. The brain's regular activity results from intricate communication between neurons through electrical signals. In individuals with epilepsy, there is a tendency for the brain's neurons to fire excessively and abnormally, leading to a seizure. Seizures can be classified into different types based on their characteristics and the brain regions from which they originate. In Figure 1, we observe the diverse patterns of EEG signals recorded from different brain regions: the healthy brain area, the region affected by a tumor, and during a seizure event. In healthy brain areas, we typically observe regular, rhythmic patterns characterized by consistent frequency and amplitude, which reflect normal electrical activity. At the tumor site, the EEG signals exhibit alterations compared to those from the healthy brain area. These can manifest in various ways depending on the nature and location of the tumor. However, during a seizure event, the EEG signals exhibit distinctive patterns that reflect abnormal neuronal activity with high frequency and amplitude.

The X-axis in the above figure represents the EEG signal at a particular time interval, and the Y-axis represents the signal amplitude.

This study employs various ML classifiers and a 1D- CNN network to classify EEG time-series data. This approach allows for a comprehensive comparison of different classification techniques, enabling insights into which methods are most effective for seizure detection. The aim of this study is not only to acquire the best accuracy but also to demonstrate a commitment to addressing the real-world needs of healthcare practitioners and patients. The focus is on the critical metrics relevant to medical diagnosis and decision-making, such as sensitivity, the ability to identify seizures and specificity

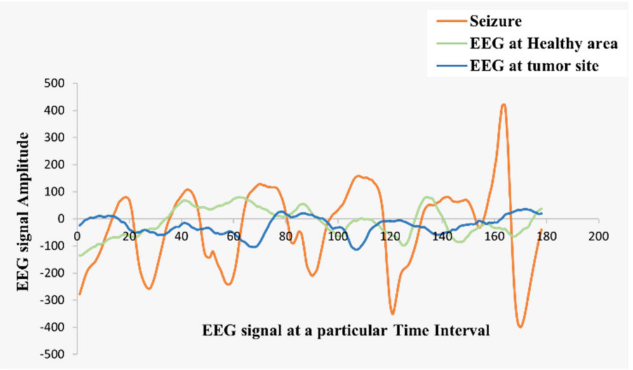



**FIGURE 1.** Variation in EEG signals at different instances.

correctly, and the ability to correctly identify non-seizures to classify EEG time-series data, explicitly targeting the accurate prediction of epileptic seizures. The dataset used in this study consists of time series data points that represent the value of the EEG signal at a particular time. Further, the data was preprocessed and classified using XGBoost, TabNet, Random Forest, and 1D CNN methods. The parameters of the classifiers are tuned according to the nature of the dataset to acquire qualitative results and high-performance evaluations.

The subsequent sections of this research paper are outlined as follows: Section II briefly discusses existing works relevant to this study, Section III discusses the methodology with details about the dataset employed, and offers insight into the methodology utilized in this research. Section IV illustrates the evaluation process, presents graphical analyses, and compares our findings with pertinent state-of-the-art research. Lastly, Section V concludes the study, highlighting the limitations and challenges encountered and outlining potential avenues for future research.

## II. RELATED WORK

The EEG signal, characterized by non-stationary behavior and notable time variations, necessitates applying non-linear analytical methods. To address this, [7] employed the discrete wavelet transform (DWT) to extract the intricate frequency components inherent in EEG signals. Their proposed approach utilizes an optimized k-nearest neighbors (KNN) algorithm for enhanced detection accuracy.

The quantitative features have been extracted from the EEG data using a one-dimensional local binary pattern (IDLBP) in [8], and these features were fed to various classifiers, which include logistic regression, BayesNet, SVM, ANN, and functional tree. The authors in [9] introduced a novel seizure detection algorithm that employs principal component analysis (PCA) for feature extraction. The algorithm compares these features with other machine learning (ML) algorithms, incorporating four prediction models: logistic regression (LR), dense trees, 2D-support vector machine (2D-SVM), and cosine k-nearest neighbor (cos-KNN). The algorithm enhanced training and test datasets' performance by leveraging PCA to reduce data dimensions.

Furthermore, The authors in [10] introduce an innovative approach to identifying epileptic seizures in EEG signals through the application of the Improved Correlation-based Feature Selection method (ICFS) in conjunction with the Random Forest classifier (RF). The methodology entails an initial step of employing ICFS to extract key features from the time domain, frequency domain, and entropy-based features. Subsequently, the Random Forest ensemble is trained on a refined set of selected features. Furthermore, the authors in [11] chose fourteen highly correlated features using the Chi-square tests. They applied classifiers such as random forest, decision tree, support vector machine, k-nearest neighbor, and TabNet. Extraction of meaningful features from EEG signals will directly impact the classification of the model's performance [12].

The Convolutional Neural Network (CNN) employs various filters in its convolutional layers to extract a distinctive and rich set of meaningful features. However, one-dimensional CNNs are suitable for tasks where the input data is structured in a sequence, time-series data. In [13], the author proposed a 1D-CNN approach by converting EEG signals into 2D/3D images and achieved an accuracy of 96.30%.

In [14], nineteen EEG data channels were selected, and then the signals were resampled at a frequency of 256Hz. Subsequently, these signals were partitioned into time frames of 3 seconds each. Further, we feed the data into the ConvLSTM model for epileptic seizure identification. Another study [15] proposed an innovative method capable of autonomously extracting features from deep within a CNN and generating easily interpretable rules for classifying seizures in EEG signals. Their objective is to elucidate the internal logic, providing neurologists with valuable insights for decision-making, whereas [16] proposed a 13-layer deep CNN algorithm to detect normal, preictal, and seizure classes. Their proposed method achieved accuracy, sensitivity, and specificity of 88.67%, 95.00%, and 90.00%, respectively.

A supervised deep convolutional autoencoder (SDCAE) model [17] was proposed to detect seizures in children with epilepsy. The Bi-LSTM-based classifier used in this model with an EEG signal segmented to 4s length achieved an accuracy of 98.79%.

## III. METHODOLOGY

This section describes the dataset and methods we propose to detect epileptic seizures, including the machine learning algorithms such as extreme gradient boosting classifier (XGBoost), TabNet classifier, Random Forest classifier with fine-tuning their parameters, and a 1D- CNN based deep learning algorithm.

### A. DATASET DESCRIPTION

The dataset used in this study is a publicly available UCI Epileptic Seizure Recognition [18] dataset, which is a processed version of the original Bonn dataset [19]. The Bonn dataset is organized into five folders. Each folder corresponds to a unique individual, with 100 files per folder, each representing brain activity over 23.6 seconds. The corresponding time series are sampled into 4097 datapoints, where each point reflects the EEG value at a specific time. So, a total of 500 individuals with 4097 data points each are available.

The UCI Epileptic Seizure Recognition [18] dataset partitioned the above 4097 datapoints (from Bonn dataset) into 23 segments, each containing 178 data points, representing a 1-second time interval. This process was applied to all 500 individuals, resulting in 11500 (23 *500) data instances. This process was made to make it available for the users to use for different classification purposes. This dataset has five classes. Each is represented as below.

Class 1: Seizure activity recordings.

Class 2: EEG signal captured from the tumor's region.

Class 3: EEG recordings were from the healthy brain area.

Class 4: EEG recordings were captured when patients closed their eyes.

Class 5: EEG recordings were captured when patients opened their eyes.

All the non-seizure class values (2,3,4 and 5) were uniformly set to 0 and the seizure class to 1. The graphical representation in Figure 2 illustrates the distinct nature of the EEG signal data present in the dataset, categorized into epileptic and non-epileptic. The binary classification is denoted by the label 'y', where y = 0 signifies non-epileptic instances, and y = 1 represents epileptic seizures.

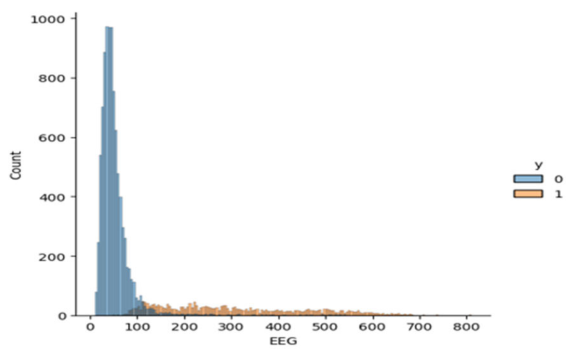



**FIGURE 2.** Histogram representation of the epileptic and non-epileptic seizures in the dataset.

### B. PROPOSED APPROACH

This study employs a comprehensive approach utilizing four distinct classifiers: XGBoost, TabNet, decision tree, and 1D-Convolutional Neural Network (CNN). Before model training, the dataset underwent preprocessing steps to ensure data quality and consistency. The dataset was strategically divided into an 80% training set and a 20% validation set.

Figure 3 illustrates the framework of the proposed methodology representing data processing, classifiers, and a set of evaluation metrics employed in the approach. In the feature extraction process, the authors in [18] extracted data points from the EEG signals. In our study, we considered those extracted datapoints as features and further preprocessed and

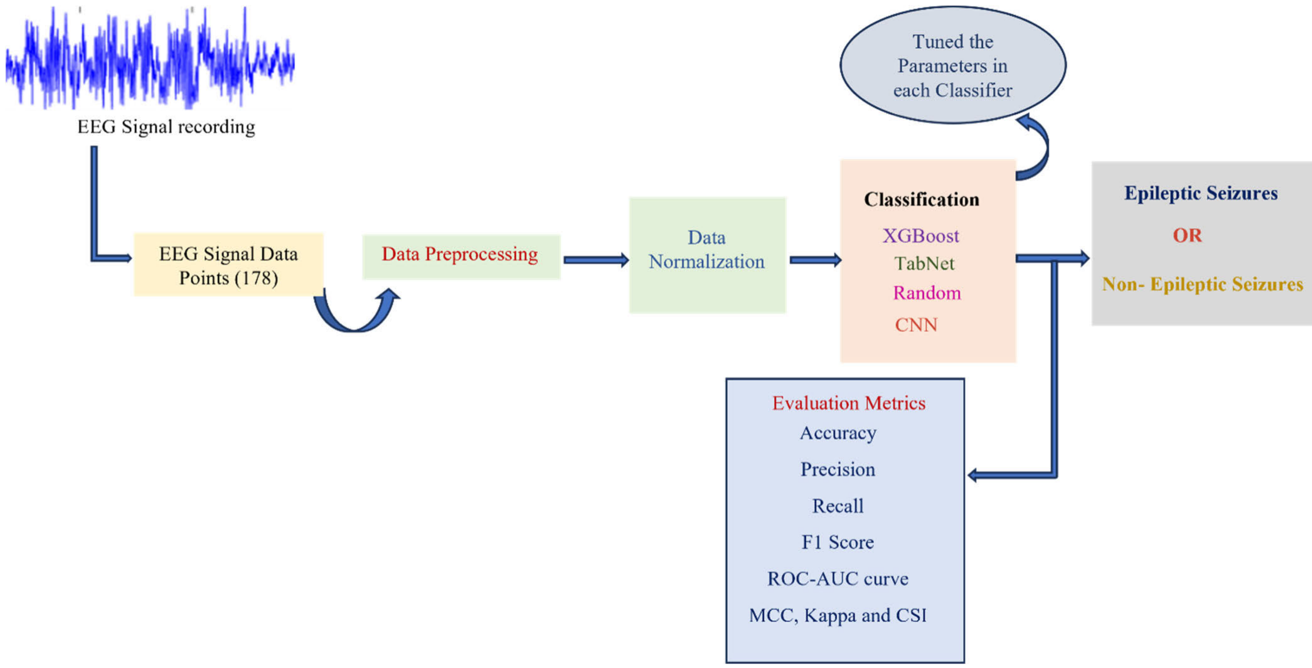



**FIGURE 3.** The Block diagram for the proposed method.

**TABLE 1.** Experimental configuration.

| *Component* | *Specification* |
|---|---|
| GPU | Google Colab T4 GPU |
| CPU | AMD Ryzen7 5700u |
| Operating System | 64-bit OS, Windows |
| RAM | 16.0 GB |
| Language | Python 3.8 |
| Development Platform | Google Colab |
| Libraries | Keras, Pandas, Scikit Learn, Pytorch, TensorFlow. |

normalized to ensure all the features are on a consistent scale, preventing certain features from dominating others in the learning process. Further, the data was fed to the classifiers and evaluated with the following metrics as shown in Figure 3.

Table 1 details the hardware and software configuration utilized for developing this proposed method. We used Google Colab for both code development and execution.

### C. XGBOOST CLASSIFIER

Extreme Gradient Boosting (XGBoost) [20] is a robust and widely used machine learning algorithm, particularly in gradient boosting frameworks. This classifier can capture temporal dependencies in time series data due to its ensemble of decision trees. Each tree can recognize patterns and trends within the temporal sequence of data points. Epileptic seizures may exhibit non-linear patterns that can be effectively captured by XGBoost's decision trees, allowing the model to learn complex relationships between features across different time steps. Also, the regularization techniques in this classifier help prevent overfitting, which is crucial for modeling epileptic seizures where noisy data or outliers might be present. In this study, we configured the parameters of XGBoost as follows: a learning rate was set to 0.01 as it controls the contribution of each tree to the overall model. A lower learning rate makes the model more robust. In the context of epileptic seizure detection, setting a small learning rate suggests a cautious and deliberate learning approach. Regularization parameter 'alpha' is used, which helps avoid fitting noise in the data. A booster tree specified as 'gbtree' is suitable for capturing non-linear relationships and temporal dependencies present in the time-series data of epileptic seizures. The maximum depth of individual trees was set to 8. A depth indicates a relatively deep tree structure allowing the model to capture intricate patterns in the data, and the number of estimators (n_estimators) is set to 1000, which indicates a commitment to build a sufficiently large ensemble to capture diverse patterns in the epileptic seizure time-series data.

### D. TABNET CLASSIFIER

Tabular Neural Network is an architecture designed for tabular data with sequential dependencies. TabNet [21] combines the elements of deep learning with attention mechanisms

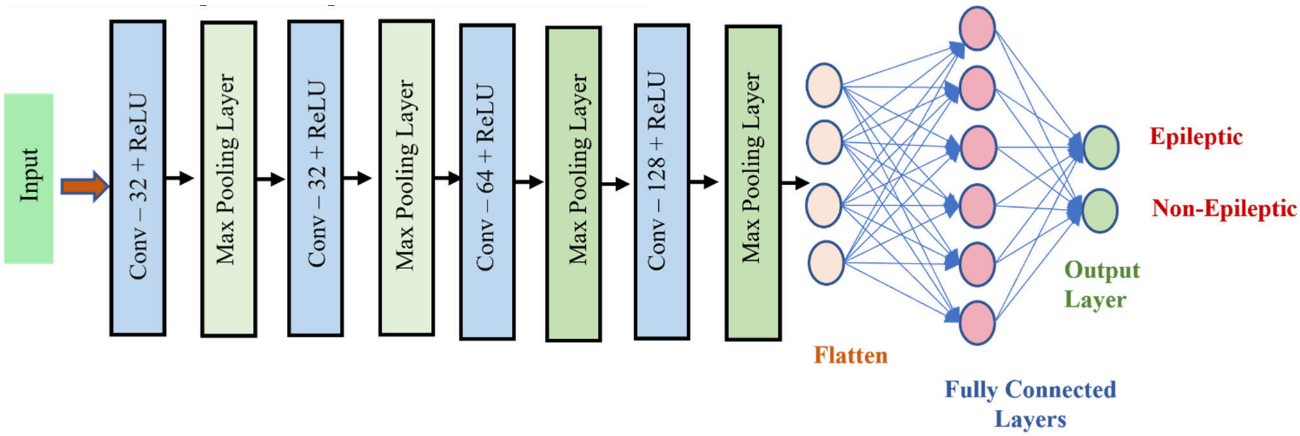



**FIGURE 4.** CNN architecture of the proposed method.

to handle structured data efficiently. In epileptic seizures, where the order of observations matters, TabNet's attention mechanism allows the model to focus on relevant time steps while considering their sequential relationships. The attention mechanism in this classifier provides transparency into the decision-making process, enabling researchers to understand which time steps contribute most to the seizure classification. In our study, we imported the TabNet classifier from PyTorch and adjusted the parameters as follows: patience was set at 20, and maximum epochs (max_epochs) were set to 100. Combining these two parameters indicates a strategy of early stopping that allows the training process to stop automatically when the model's performance on the validation set stops improving, preventing unnecessary computation and potential overfitting.

### E. RANDOM FOREST CLASSIFIER

Random Forest is an ensemble learning like XGBoost method that operates by constructing a multitude of decision trees during training and outputting the class, which is the mode of classes of the individual trees. This classifier has high predictive accuracy, robustness to overfitting, and the ability to handle large amounts of data with high dimensionality. Combining multiple decision trees enhances the model's ability to generalize well to different temporal patterns observed in epileptic seizure data. This classifier can identify the most important features at different time points, aiding in identifying crucial factors contributing to seizure occurrences. In this study, the parameters of the Random Forest are set as follows: a number of estimators (n_estimators) set to 1000 to create a large and diverse ensemble of trees leads to more robust and stable models reducing the risk of overfitting and improving generalization performance. random state at 42, and the criterion parameter specifies the function used to measure the quality of a split in the decision tree. We used 'gini' criterion measures of how often a randomly chosen element would be incorrectly classified.

### F. CONVOLUTIONAL NEURAL NETWORK

Convolutional Neural Networks (CNNs) can be used for various data types, not just images. In the case of one-dimensional data, such as sequences or time series, 1D convolutions are employed. In this study, 1D CNN is used with kernel_size = 2 to capture relatively short-term features in EEG data, max pooling layer helps reduce the spatial dimensions of the data, and activation function "ReLU" is used to learn complex relationships in the data. Four layers of convolutions were used in this model with filters of 32, 32, 64, and 128. The progressive increase in the number of filters across the convolutional layers implies a hierarchical feature learning process. Deep layers with more filters learn more abstract and high-level representations. This architecture allows the model to extract hierarchical features at different levels of abstraction from the EEG data. The dropout rate of 0.2 used in this model indicates a regularization strategy to prevent overfitting. The first fully connected layer has 64 neurons with activation function ReLU and a dropout rate 0.5. The final FC layer has one neuron with the activation function 'Sigmoid.' Here, Adam Optimizer is used with a 'learning_rate' equal to 0.0005 and 'binary_crossentropy' as a loss function. FIGURE.4 represents the architecture of the 1D- CNN model proposed in this study.

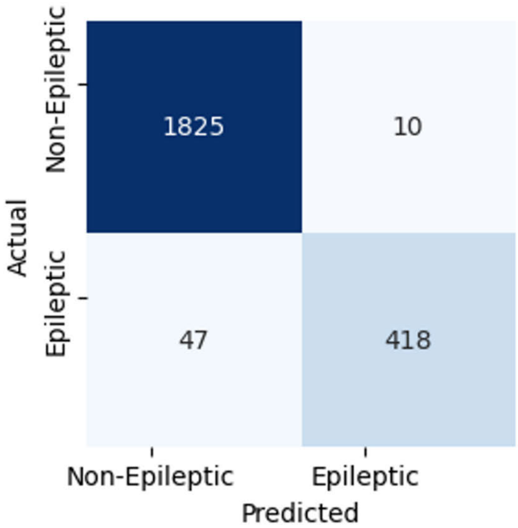
The equations below represent the mathematical form of the Sigmoid, ReLU, and Binary cross-entropy functions used in the CNN model.

$$Sigmoid\,(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

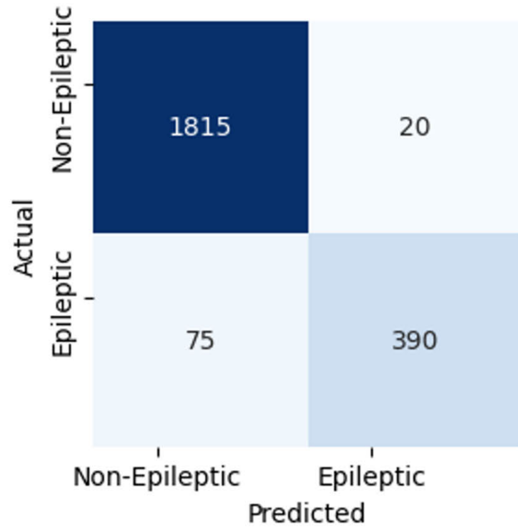
Here, $x$ is the input to the function, $e$ is the base of the natural logarithm (Euler's number, approximately equal to 2.71828), $Sigmoid\,(x)$ is the output, which has a value between 0 and 1.

$$ReLU\,(x) = \max\,(0, x) \tag{2}$$

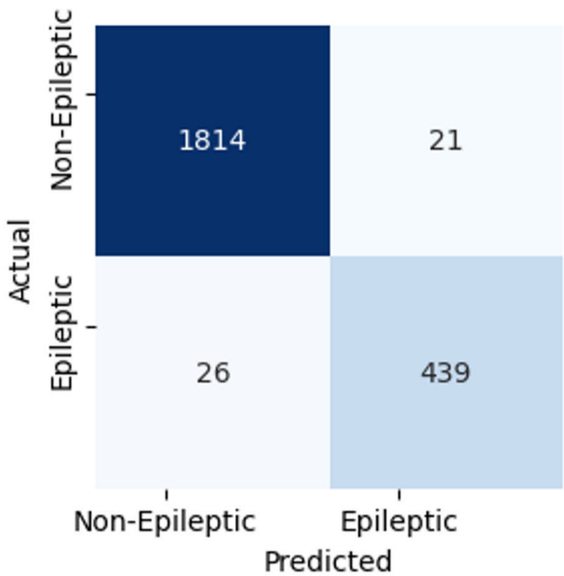
The ReLU activation function outputs the input value $x$ if $x$ is positive or zero, and zero if $x$ is negative. Graphically,



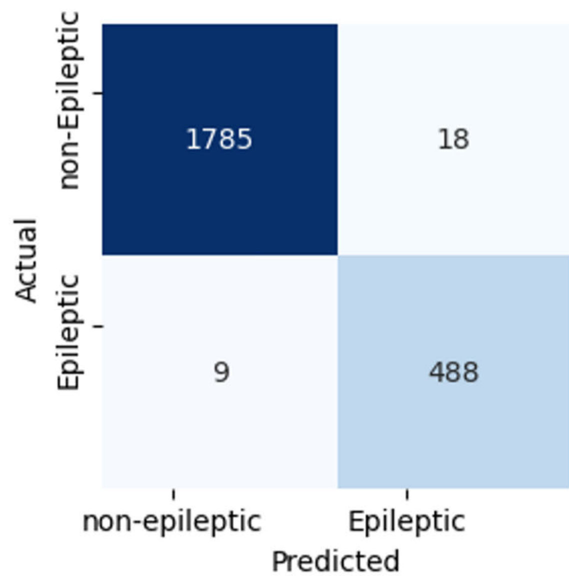

(a)




(b)




(c)




(d)

**FIGURE 5.** Confusion matrices of four classifiers. (a) XGBoost classifier, (b) TabNet classifier, (c) RF classifier, and (d) 1D-CNN.

it looks like a ramp, allowing positive values to pass through unchanged while converting negative values to zero.

$$L\left(y,\hat{y}\right) = -\left(y.log\left(\hat{y}\right) + (1-y)\,.log\left(1-\hat{y}\right)\right) \quad (3)$$

From the above equation $L\left(y,\hat{y}\right)$ is the binary cross-entropy loss, $y$ is the true label (either 0 or 1) and $\hat{y}$ is the predicted probability that the instance belongs to class 1.

## IV. PERFORMANCE EVALUATION AND RESULTS

The evaluation metrics accuracy, precision, recall, and F1 score, CSI, MCC, and Kappa are computed below to assess the performance of the proposed method to differentiate seizures and non-seizures accurately. The mathematical representation of these metrics is shown below:

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (4)$$

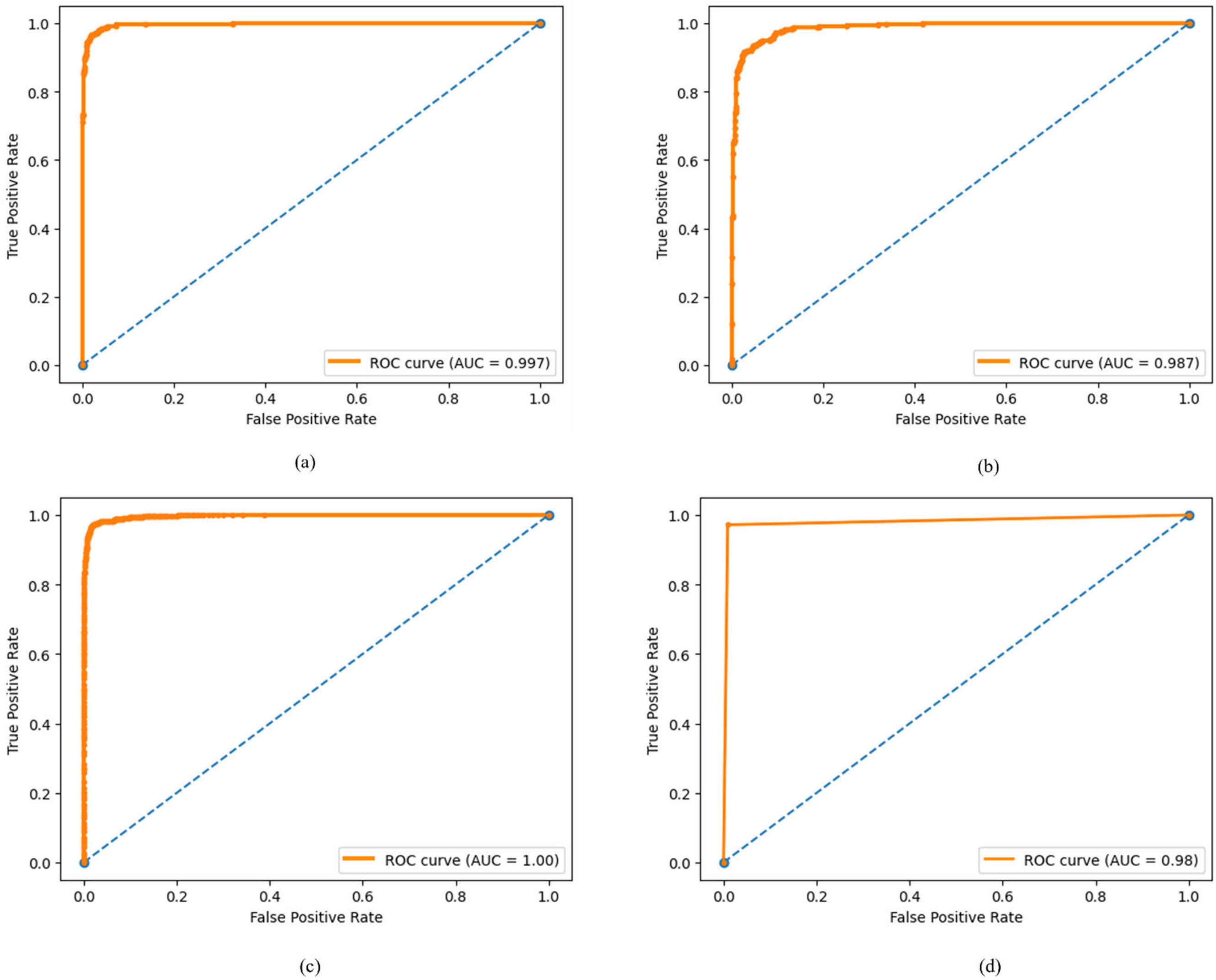



**FIGURE 6.** ROC-AUC curve of four classifiers. (a) XGBoost, (b) TabNet, (c) Random Forest, and (d) CNN.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1\ Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \tag{7}$$

$$CSI = \frac{TP}{TP + FN + FP} \tag{8}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{9}$$

where TP is true positive, correctly predicts as positive.

TN is true negative, correctly predicts as negative.

FP is false positive, incorrectly predicts as positive also called as Type 1 error.

FN is false negative, incorrectly predicts as negative also called as Type 11 error.

$$Cohen's\ Kappa = \frac{P_o - P_e}{1 - P_e} \tag{10}$$

where, $P_o$ is the relative observed agreement and

$P_e$ is the expected agreement.

### A. CONFUSION MATRIX

The key evaluation metrics, such as accuracy, precision, sensitivity (Recall), and specificity, were derived from the confusion matrix. FIGURE 5 illustrates the visual representation of the confusion matrices generated for all four classifiers. It serves as a comprehensive tool for assessing the performance of the model by revealing the distribution of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. Based on the

|  | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.97 | 0.99 | 0.98 | 1835 |
| 1 | 0.98 | 0.90 | 0.94 | 465 |
| accuracy |  |  | 0.98 | 2300 |
| macro avg | 0.98 | 0.95 | 0.96 | 2300 |
| weighted avg | 0.98 | 0.98 | 0.97 | 2300 |

(a)

|  | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.96 | 0.99 | 0.97 | 1835 |
| 1 | 0.95 | 0.84 | 0.89 | 465 |
| accuracy |  |  | 0.96 | 2300 |
| macro avg | 0.96 | 0.91 | 0.93 | 2300 |
| weighted avg | 0.96 | 0.96 | 0.96 | 2300 |

(b)

|  | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.99 | 0.99 | 0.99 | 1835 |
| 1 | 0.95 | 0.94 | 0.95 | 465 |
| accuracy |  |  | 0.98 | 2300 |
| macro avg | 0.97 | 0.97 | 0.97 | 2300 |
| weighted avg | 0.98 | 0.98 | 0.98 | 2300 |

(c)

|  | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.99 | 0.99 | 0.99 | 1803 |
| 1 | 0.96 | 0.98 | 0.97 | 497 |
| accuracy |  |  | 0.99 | 2300 |
| macro avg | 0.98 | 0.99 | 0.98 | 2300 |
| weighted avg | 0.99 | 0.99 | 0.99 | 2300 |

(d)

**FIGURE 7. Classification report of four classifiers. (a) XGBoost, (b) TabNet, (c) Random Forest, and (d) 1D-CNN.**

**TABLE 2. Weighted average values of the proposed method.**

| Classifier | Accuracy | Precision | Recall | F1 score | Kappa | MCC | CSI |
|---|---|---|---|---|---|---|---|
| XGBoost | 0.98 | 0.98 | 0.98 | 0.97 | 0.920 | 0.922 | 0.88 |
| TabNet | 0.96 | 0.96 | 0.96 | 0.96 | 0.86 | 0.86 | 0.80 |
| Random Forest | 0.98 | 0.98 | 0.98 | 0.98 | 0.93 | 0.93 | 0.90 |
| CNN | 0.99 | 0.99 | 0.99 | 0.99 | 0.96 | 0.96 | 0.94 |

results shown in FIGURE 5, 5(a) shows the XGBoost classifier predicts ten non-epileptic instances as epileptic and 47 epileptic instances as non-epileptic, 5(b) shows the TabNet classifier predicts 20 non-epileptic instances as epileptic and 75 epileptic instances as non-epileptic whereas, 5(c) shows the Random Forest classifier predicts 21 non-epileptic instances as epileptic and 26 epileptic instances as non-epileptic. Finally, 5(d) shows the 1D-CNN predicts 18 non-epileptic instances as epileptic and 9 epileptic instances as non-epileptic. These results provide insights

**TABLE 3.** Comparison table with previous works.

| Datasets | Classification Type | Accuracy % | Precision % | Recall % | F1-Score % |
|---|---|---|---|---|---|
| Bonn<br>CHB-MIT [22], **2023** | CNN + RNN | 99<br>96 | - | - | - |
| CHB-MIT [17], **2021** | Bi-LSTM | 98.79 | 98.86 | 98.72 | 98.79 |
| Bonn Dataset [23], **2022** | CNN<br>Bi-LSTM | 93.9<br>97.2 | - | - | - |
| Epileptic Seizure Recognition-UCI [24], **2020** | 1D CNN -LSTM<br>CNN | 99.39<br>97.13 | 98.39<br>94.24 | 98.79<br>92.34 | 98.59<br>0.93 |
| AdventHealth [25], **2020** | 1D -CNN | 89.73 | | | |
| Data from Shiraz University of Medical Sciences, Iran [11], **2022** | Random Forest<br>TabNet | 64.8<br>70.36 | 64.1<br>68.12 | 68.25<br>80.95 | -<br>- |
| Bonn Dataset [26], **2014** | Fuzzy approximate entropy, SVMRBF, SVML | 97.36<br>97.38 | - | 98.3<br>98.17 | |
| Epileptic Seizure Recognition- UCI [15], **2021** | CNN | 98 | - | 96 | |
| Epileptic Seizure Recognition- UCI [27], **2020** | RF | 97.08 | - | - | - |
| Epileptic Seizure Recognition- UCI [28], **2023** | 1D-CNN-BiLSTM+TBPTT | 99.41 | - | 98.99 | - |
| Bonn dataset [10], **2017** | Improved Correlation Feature selection and Random Forest | 97.4 | - | 97.4 | - |
| Bonn dataset [29], **2022** | Fuzzy Random Forest | 99.4 | 98.8 | 99.4 | 96.3 |
| Epileptic Seizure Recognition-UCI [24], **2020** | 1D CNN -LSTM | 99.39 | 98.39 | 98.79 | 98.59 |
| Proposed Approach | XGBoost<br>Tabnet<br>Random Forest<br>1D- CNN | **98**<br>**96**<br>**98**<br>**99** | **98**<br>**96**<br>**98**<br>**99** | **98**<br>**96**<br>**98**<br>**99** | **97**<br>**96**<br>**98**<br>**99** |

into the performance and characteristics of each classifier in terms of their ability to correctly classify instances as epileptic or non-epileptic. For instance, TabNet classifier exhibits more misclassifications than the other classifiers, particularly in falsely identifying epileptic instances as non-epileptic. On the other hand, the 1D-CNN model demonstrates relatively fewer misclassifications among all the proposed classifiers.

### B. ROC-AUC CURVE

The Receiver Operating Characteristic Area Under the Curve (ROC AUC) is a metric used to assess the performance of a classification model, mainly in binary class classification. It is a graphical representation between sensitivity (true positive rate) and specificity (true negative rate) across various threshold settings.

The ROC curve plots the true positive rate against the false positive rate, whereas AUC is the area under the ROC curve. In FIGURE 6, (a), (b), (c), and (d) have the AUC values of 0.997, 0.98, 1.00, and 0.98, respectively, which indicate that a has the AUC value of 0.997 and c has an AUC value of 1.00 which represents those proposed approaches reflects the perfect discrimination.

### C. CLASSIFICATION REPORT

A classification report is a valuable tool for model evaluation. It helps guide adjustments to the model parameters to improve performance, especially for imbalanced datasets where one class dominates the other, which becomes crucial for assessing the model's performance. FIGURE 7 shows that the classification report clearly indicated the precision, recall, and f1-score of epileptic and non-epileptic seizures individually. It also shows the effective results of accuracy, macro average, and weighted average of the proposed approach.

### D. CSI, MCC AND COHEN'S KAPPA

Additional metrics like the Critical Success Index (CSI), Mathews Correlation Coefficient (MCC), and Cohen's Kappa gave additional insights into the classifiers and 1D-CNN model performance. For the XGBoost classifier, the results achieved for the CSI, MCC, and Cohen's Kappa are 0.88, 0.92, and 0.92, respectively. For the TabNet classifier, the results were 0.80, 0.86, and 0.86, respectively. For the Random Forest classifier, the results were 0.90, 0.93, and 0.93, respectively, and for the 1D-CNN model, the results achieved were 0.94, 0.96, and 0.96, respectively.

Table 2 provides a comprehensive overview of the experimental outcomes derived from the proposed approach. The table encapsulates the achieved accuracies of the employed classifiers, namely XGBoost, TabNet, Random Forest, and 1D CNN, which achieved 98%, 96%, 98%, and 99% accuracies, respectively. In this analysis, we opted for weighted average values for Precision, Recall, and F1 score calculations due to the imbalance class distribution within the dataset. Weighted average metrics consider the class imbalances, providing a more representative evaluation of the model's performance. The values in Table 2 were obtained from FIGURE 7. The validation loss values were highlighted for additional insight into the model's generalization. Specifically, the validation loss of the XGBoost classifier is 0.06, the tabNet classifier is 0.13, and the 1D- CNN model showcased a notably lower validation loss of 0.02. These loss values indicate how well each classifier in our proposed approach generalizes to unseen data. Numerous studies have delved into Epileptic Seizure detection using EEG signals, achieving encouraging results. The efficacy of the models has consistently hinged on the characteristics of the datasets, each with its unique set of features. While some studies use 1D-CNN models, as shown in Table.3, additional layers were added to make the model more efficient and accurate. In our proposed 1D-CNN model, only convolutional, pooling, and classification layers show similar outcomes concerning accuracy. Still, our investigation stands out by achieving the highest sensitivity, precision, and recall values.

## V. CONCLUSION

This research used machine learning and deep learning algorithms to classify epileptic seizures effectively within the EEG signals. We meticulously tuned the parameters of classifiers, namely XGBoost, TabNet, Random Forest and developed a 1D CNN architecture. Our primary innovation lies in creating a best model that not only predicts epileptic and non-epileptic seizures with high accuracies but places a special emphasis on metrics such as precision, recall, and f1 score, which are crucial in the medical field but may have been overlooked in previous studies. By focusing on these metrics, we have highlighted the importance of correctly identifying positive cases (seizure events) and negative cases (non-seizure events) in the context of medical diagnosis. By incorporating these additional metrics, we have introduced a comprehensive evaluation framework that captures various aspects of the model's effectiveness. Despite similar accuracies achieved in previous studies using comparable classifiers, our research demonstrates superior precision, recall and f1-score performance. This comparison highlights the novelty and significance of our findings, indicating a substantial improvement over existing approaches. Accurate and reliable seizure detection is essential for timely intervention and personalized treatment planning in epilepsy patients, and our findings contribute to advancing the state-of-the-art in this domain in Epileptic Seizure Detection.

### A. LIMITATIONS AND CHALLENGES

Our study used the UCI epileptic seizure recognition dataset, consisting of extracted data from the Bonn University dataset stored in.csv format rather than raw signal data; nuances and features may be lost during the extraction process. Relying on the preprocessed data means that the model's performance highly depends on the quality of the preprocessing steps applied to the original EEG signals. If the preprocessing steps do not adequately capture relevant features or introduce biases, it could affect the accuracy and reliability of the classification model. While tuning parameters may have led to the acquisition of the best results, there may still be unexplored areas of the feature space that could potentially improve the model's performance. There may be a gap between its performance in a controlled experimental setting and its practical applicability in real-time seizure detection scenarios since the model's performance is evaluated using preprocessed data (UCI epileptic seizure detection).

Despite the progress presented in this paper, Epileptic seizure detection poses several challenges, ranging from the complexity of EEG signals to the need for real-time monitoring. Some key challenges include variability in seizure patterns. Epileptic seizures can manifest in various patterns, making it challenging to develop a universal algorithm that can accurately detect all types of seizures. Another challenge is that EEG signals vary significantly between individuals. Creating a personalized model for each patient to improve accuracy is a challenge, especially considering the diversity of seizure presentations. Addressing these challenges requires interdisciplinary collaboration between neuroscientists, clinicians, and machine learning experts.

### B. FUTURE DIRECTIONS

Integrating data from multiple sources, such as EEG, electrocardiography (ECG), accelerometry, and other physiological signals, provides a more comprehensive view of a patient's condition. Multimodal approaches can improve the specificity and sensitivity of seizure detection.

Deep Learning and domain adaptation techniques can leverage information from related tasks to enhance model generalization. Exploring explainable AI methods will contribute to the interpretability of these models in a clinical setting. As technology continues to evolve and interdisciplinary collaborations flourish, the future of epileptic seizure detection holds the promise of more effective, personalized, and accessible solutions that positively impact the lives of individuals with epilepsy and their caregivers.

## CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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