IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 12 August 2024, accepted 25 August 2024, date of publication 10 September 2024, date of current version 1 October 2024.

*Digital Object Identifier 10.1109/ACCESS.2024.3457018*

RESEARCH ARTICLE

# A Model for Epileptic Seizure Diagnosis Using the Combination of Ensemble Learning and Deep Learning

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**ABSTRACT** Epileptic seizures can be dangerous as they cause sudden and uncontrolled electrical activity in the brain which can lead to injuries if one falls or loss of control over physical functions. To mitigate these risks, machine learning and deep learning algorithms are being developed to anticipate seizure occurrences. Accurate prediction of seizures could enable patients to adopt preventive strategies or initiate medical interventions to halt seizures, thereby minimizing injuries and enhancing safety for individuals afflicted with epilepsy. This paper aims to combine neural networks and Ensemble learning to enhance the accuracy of diagnosing epileptic seizures. By leveraging the strengths of both techniques, the precision in seizure diagnosis can be significantly improved. It also improves the evaluation metrics used in machine learning methodologies for a more comprehensive assessment of diagnostic outcomes. This approach ensures a thorough understanding of the effectiveness of the proposed approach. In this paper, a model with a supreme precision rate is developed to detect epileptic seizures with the help of EEG signals. This study uses an ensemble method, which employs several algorithms, for instance XGB, SVM, RF, and BiLSTM. The used dataset is open access from Bonn University. The proposed methodology reached 98.52% accuracy, 97.37% precision, 95.29% recall, and 96.32% F1-score, respectively.

**INDEX TERMS** Epileptic seizure diagnosis, ensemble learning, deep learning, seizure.

## I. INTRODUCTION

Epilepsy plays a vital role in the overall disease burden on a global scale [1], affecting around 50 million people globally [2]. The projected proportion of the general populace experiencing active epilepsy varies from 4 to 10 per 1,000 individuals at any specific moment. In essence, this suggests that between 40 to 100 million people need ongoing treatment for epilepsy or grapple with recurring seizures worldwide [3].

The associate editor coordinating the review of this manuscript and approving it for publication was Domenico Rosaci.

A seizure is a sudden and unmanageable surge of electrical brain activity, leading to various changes in an individual's behavior, emotions, consciousness, and motor abilities during the episode [4]. Typical signs of a seizure encompass momentary confusion right after the event. Moreover, people might appear to gaze into nothingness or display sudden unwilling movements of their arms or legs. In more severe instances, the extensive electrical brain activity during a seizure can result in a complete loss of consciousness throughout its duration [5]. The neurological shifts happening during a seizure can bring about immediate as well as different effects on the person. If a person loses consciousness and falls because of disruptions during severe seizures, it can lead to big problems. Those with epilepsy encounter persistent challenges arising from recurrent seizures, such as jeopardized independent functioning, cognitive impairments, mood disorders, and an overall reduced quality of life. The paper aims to enhance comprehension of the condition and discover new treatment methods to alleviate the worldwide impact of epilepsy.

Unusual electrical neuron activities in the brain cells can be diagnosed by Electroencephalogram (EEG) signals which play a crucial role in evaluating brain activity during seizure occurrents. EEG serves as a widely utilized and efficient approach for diagnosing and assessing epilepsy [6]. In an EEG examination, minor metal discs named electrodes are affixed to different positions on the patient's scalp [7]. These electrodes collect the electrical signals generated by nerve cell firings in the brain. The electrodes transmit these signals through wires to a device, which amplifies the brain's electrical activity and submits it as wave patterns on paper or a computer. In comparison to alternative brain imaging techniques such as CT scans, MRI [8], PET [9], and SPECT scans [10], EEG signals shine due to several benefits. EEG tests are cost-effective, and portable, making them well-suited for use, and offer precise measurements of the brain's electrical activity with exceptional temporal resolution [11]. Through EEG recordings, abnormal brain wave patterns can be identified, potentially signaling underlying conditions like epilepsy. Researchers commonly analyze EEG recordings for epilepsy diagnosis, as distinctive patterns often manifest in the frequency domain of brain waves during seizure events, distinguishing them from regular brain activity.

Epileptic seizures pose significant challenges in both diagnosis and management, affecting millions of individuals worldwide. Despite advances in medical technology, traditional methods of seizure detection often fall short in terms of accuracy and timeliness. Accurate detection of seizures is crucial for effective treatment, as delayed or incorrect diagnosis can lead to severe consequences, including increased morbidity and impaired quality of life. This research aims to address these challenges by leveraging advanced machine learning techniques to enhance the precision of seizure detection from EEG signals. By improving the accuracy of detection, this work seeks to contribute to better patient outcomes and more efficient healthcare management.

In recent years, machine learning has been increasingly employed to analyze EEG recordings, showing encouraging outcomes. By training algorithms on extensive datasets of EEG data from both individuals without epilepsy and those experiencing seizures, machine learning models can learn to identify patterns that might signify an epileptic event. This automated analysis has the capacity to reduce interpretational errors and enhance diagnostic precision for conditions such as epilepsy. As machine learning becomes more integrated across diverse medical domains, it stands to enhance epilepsy diagnosis by enabling highly accurate analysis of EEG signals. This has the potential to streamline treatment and alleviate the global health impact of epilepsy.

Owing to the role played by precision which is one of the critical factors in evaluation metrics, this research makes use of the Ensemble method to increase this parameter.

The foremost focuses of this paper embrace the following:

- Improving the precision of epileptic seizure diagnosis by combining neural networks with Ensemble learning
- Enhancing the evaluation metrics of commonly used machine learning methods
- Comparing different Ensemble techniques to achieve the best possible results in diagnosing epileptic seizure

The following segments of this paper are organized as follows: The second section gives an overview of related works. In 3rd section, the proposed method is thoroughly explained. The 4th section presents the experimental results and discussions. The final part of the paper is dedicated to drawing conclusions based on the findings reported in the study.

## II. RELATED WORK

In today's world, due to the importance of diagnosing seizure epilepsy, researchers investigate various methods to increase the precision and accuracy and different evaluation metrics in diagnosing this disease. Owing to the advancement in technology and the use of computer science in various fields of wellness care, machine learning, and deep learning methods have shown the potential to detect this disease. Different research has been studied to achieve better results, which is explained in this section.

Handa et al. [12] divided the data into adults and children. They dealt with the available and usable datasets related to EEG signals in the field of seizure and epilepsy detection. Djemal et al. [13] tried to increase the accuracy by choosing appropriate features for the classification of tonic-myoclonic epileptic seizures based on surface electromyography and reached an accuracy of 93.33%. Dissanayake et al. [14] focused on the prediction of epileptic seizures considering its importance as an early detection method. The dataset used in this study is related to Boston Children's Hospital and MIT University. Researchers simulated two models in this paper: the first model has reached 88% accuracy, and the second one has reached 91.54% accuracy. In this paper, the CNN network is used to obtain the results. Reference [15] attempted to reduce the dimensions of tensor inputs. This paper aimed to evaluate the advanced approaches mentioned in the paper to determine their performance. Pale et al. [16], various strategies for improved HD computation learning, such as multi-pass learning, multi-center learning, and sample-weighted learning ("OnlineHD"), were used without considering the cost. A spectrum of learning methods was compared and finally, they reached 76% accuracy on test data. Hussain et al. [17] conducted three experiments in the study: two binary classifiers and one ternary classifier. By using the combination of LSTM and CNN methods, they reached the average accuracy of 94.71%, 93.99%, and 90.53%. The dataset used in the mentioned article is related to Freiburg Hospital in Germany, which has 21 subjects or the same patients. Beniczky et al. [18] recommended using wearable seizure detection devices and highlighted the role of the physician's decision. That's a clinical practice guideline that aims to provide recommendations for healthcare personnel dealing with patients with Epilepsy. Muhammad Usman et al. [19] proposed an ensemble learning method based on deep learning to predict epileptic seizures. In the proposed method, EEG signals are pre-processed using empirical mode decomposition and a bandpass filter to remove noise. They used a three-layer convolutional network to extract features. Group learning in this paper is the output of CNN, LSTM, and SVM, which reached 96% and 95% accuracy. Rasheed et al. [20] introduced machine learning techniques on EEG signals so that they can identify seizure disease early. To predict epileptic seizures, a group learning technique based on machine learning was proposed in [21]. It was created with the help of a group machine learning technique that uses several different algorithms such as support vector machine, decision tree, convolutional neural networks, and artificial neural networks. The introduced method achieved 91% accuracy. Kapoor et al. [22] introduced a combined optimization-driven ensemble classifier that includes the AdaBoost, RF, and DT classifiers. This ensemble approach aimed to automatically analyze EEG signal data and forecast epileptic seizures. The method achieved an accuracy of 96.6120%, sensitivity of 94.6736%, and specificity of 91.3684% when applied to the CHB-MIT database.

Escobar-Ipuz et al. [23] stated that the main objective of the research was to differentiate between individuals with idiopathic generalized epilepsy and those who are healthy. They accomplished this by employing machine learning techniques on interictal electroencephalography recordings. The outcomes of the study enabled the identification of patients with idiopathic generalized epilepsy through analysis of scalp EEG data. The research particularly emphasized the utilization of the extreme gradient boosting (XGB) method on scalp EEG recordings. The achieved results demonstrated an impressive accuracy level of 98.13%.

Kunekar et al. [24] employed machine learning techniques to devise a model that forecasted signal behavior and categorized seizures. The analysis was conducted using the Epileptic Seizure Recognition Data Set from the UCI Machine Learning Repository. Various models, including XGboost, Extra Tree Classifier, and Random Forest, were assessed using metrics such as F1 score, recall, and precision to evaluate the proposed approaches. Shen et al. [25] introduced a method for real-time epilepsy seizure detection using EEG signals, employing a combination of tunable-Q wavelet transform and CNN. Evaluation on the CHB-MIT database yielded promising results, including 97.57% accuracy, 98.90% sensitivity, a false positive rate of 2.13%, and a 10.46-second delay. Moreover, the method showed suitability for real-time application, suggesting its potential for clinical use in seizure detection. Kunekar et al. [26] explored the automated detection of epileptic seizures using both ML and DL techniques, alongside a comparative assessment of these methods and with the LSTM model demonstrating a validation accuracy of 97%, surpassing the performance of other algorithms examined in the research. The proposed system in [26] demonstrated high effectiveness in classifying EEG signals from both healthy individuals and seizure patients, achieving a validation accuracy of 97% and a false-negative rate of 2.06% using the LSTM model. Although conventional machine learning algorithms such as logistic regression, SVM, and KNN performed well in accuracy but fell short in classification precision compared to the proposed model.

Reference [27] utilized machine learning and deep learning algorithms, including XGBoost, TabNet, Random Forest, and a 1D CNN architecture, for classifying epileptic seizures within EEG signals. The primary innovation lies in the development of a model that emphasizes metrics such as precision, recall, and F1-score, which are crucial for medical applications. By incorporating these metrics, a comprehensive evaluation framework was introduced, highlighting improvements in model performance compared to previous approaches.

An optimized machine learning model for Alzheimer's and epilepsy detection was presented in [28]. The model incorporated particle swarm optimization for feature extraction, kernel principal component analysis for dimensionality reduction, and an optimized deep belief network for classification, with parameter tuning achieved through tuna swarm optimization. Experiments with the Bonn and Dementia datasets validated the model's superior precision, recall, F1-score, and accuracy, achieving classification accuracies of 94% and 95.05%, respectively.

## III. METHOD

This study provides a solution to increase evaluation metrics in detecting seizure epilepsy. This section offers a comprehensive explanation of the preprocessing phase and information on taking advantage of deep learning methods and machine learning algorithms. FIGURE 1. demonstrates an overview of the proposed epileptic seizure classification process via EEG signals.

As shown in FIGURE 1., after cleaning data and applying the preprocessing method, newly formed data is passed to various neural networks and machine learning algorithms. To boost the performance of models, the best algorithms are chosen and infused by the ensemble method. The novelty of this paper is rooted in the thorough and systematic investigation and integration of various techniques. It proposes a detailed strategy for feature extraction, selection, and combining models to enhance the overall performance.

### A. DATASET

The used data is from an open-access dataset from Bonn University [29] which consists of 5 folders, individually

**TABLE 1.** Summaries on detecting and classifying seizure epilepsy in another research.

| References | Methods | Dataset | Accuracy (%) |
|---|---|---|---|
| Djemal et al. [13] | ANN | SEMG | 93.33 |
| Dissanayake et al. [14] | Transfer learning | CHB-MIT | 96.00 |
| Taherisadr et al. [15] | TF-Tensor-CNN | CHB-MIT | 89.63 |
| Pale et al. [16] | RF + Weighted learning | CHB-MIT | - |
| Hussain et al. [17] | CNN-LSTM | Freiburg Hospital | 94.71-93.99-90.53 |
| Beniczky et al. [18] | - | - | - |
| Muhammad Usman et al. [19] | Ensemble learning | CHBMIT/AESKaggle | - |
| Ahmed et al. [21] | Ensemble learning | PhysioNet website | 91.00 |
| Kapoor et al. [22] | Ensemble learning | Siena Scalp/ CHBMIT | 96.61/95.30 |
| Escobar-Ipuz et al. [23] | XGB | Hospital Virgen | 98.13 |
| Kunekar et al. [24] | ML algorithms | UCI | 97.7 |
| Shen et al. [25] | TQWT and CNN | CHB-MIT | 97.57 |
| Kunekar et al. [26] | LSTM | UCI | 97 |
| Kunekar et al. [26] | ANN | UCI | 97 |
| Kode et al. [27] | 1D-CNN | UCI | 98-96-98-99 |
| Sharmila and Angel [28] | Deep belief network +Tuna swarm optimization | Bonn and Dementia | 94-95.05 |

containing 100 files, and each file in the folders represents a single person's information. One single data point corresponds to the EEG signal at a distinct time instance. The dataset has two classes, one as being affected by seizure and zero as being classified as non-seizure.

### B. PRE-PROCESSING STAGE

The preprocessing phase is a crucial step in optimizing the performance and evaluation metrics of machine learning algorithms for detecting seizures in EEG data [30]. This stage involves preparing the dataset and making it suitable to give into the machine learning model. In the context of EEG-seizure detection, the dataset typically consists of recordings from various classes, each representing different types of brain activity. In this specific case, the dataset is categorized into five classes denoted by labels 1 through 5.

Class 1 represents seizure activity, which is the primary target for detection in this context. Class 2 corresponds to EEG recordings from the hippocampus region of the brain associated with memory. Class 3 contains recordings from patients with epileptogenic brain regions prone to seizures. Patients with their eyes closed are in class 4, and class 5 comprises EEG data from patients with their eyes open.

The dataset comprises recordings that are approximately 23 seconds long, having a total of 4097 data points collected at different time intervals. To process the raw EEG data and make it suitable for training and evaluating machine learning models, a two-step preprocessing approach is implemented.

In the first step, each 23-second recording is divided into 23 smaller chunks, each containing 178 data points. Each of these chunks represents 1 second of brain activity. This segmentation of the recordings allows the machine learning models to analyze shorter time windows of the EEG signal, making the classification task more manageable. Analyzing shorter time segments is often more effective than attempting to classify the full 23-second recording in one go.

This segmentation process results in a substantial expansion of the dataset size. Specifically, it generates a total of 11,500 pieces of data from the original recordings. Each of these segments now contains 178 time-coded data points, effectively preserving the information of a single second of EEG recording. This initial preprocessing step significantly increases the dataset's size while preserving the essential information present in the original multisecond recordings.

The second step in the preprocessing phase involves normalizing the dataset. EEG can vary widely between different regions of the brain and across patients, making it essential to standardize the data to common units that can be fed into machine learning models. Standardization or min-max normalization techniques are commonly applied to transform the 178 values in each chunk into a common range, typically between 0 and 1.

By employing these preprocessing techniques, the raw EEG recordings are transformed into a standardized dataset. This standardized dataset is optimized for training machine learning algorithms to detect seizure activity with improved performance compared to using untreated data directly. Machine learning models trained on such standardized datasets often demonstrate enhanced accuracy, making them more effective in detecting seizure activity and aiding in epilepsy diagnosis.

Using machine learning alongside EEG analysis is a big step forward in detecting epilepsy [31]. By training machine learning algorithms on large datasets of EEG from both healthy people and those with seizures, they can learn to spot patterns that suggest epileptic events. This automated analysis can reduce human errors and improve how accurately epilepsy can be diagnosed.

As machine learning becomes more usable in the health area, it's making epilepsy diagnosis easier by analyzing EEG signals more precisely. This improvement could lead to better treatment plans and lessen the overall impact of epilepsy on health worldwide. By tapping into machine learning for

EEG analysis, doctors can diagnose and handle epilepsy more efficiently, improving the lives of people with this condition. By meticulously transforming raw EEG recordings into standardized datasets through meticulous preprocessing techniques, which involve segmentation and normalization processes, the machine learning models, including LSTM and its variant, BiLSTM, are equipped with meticulously prepared inputs. These inputs ensure that these sophisticated neural networks can effectively discern intricate patterns indicative of epileptic events within the EEG signals. As a result, they contribute significantly to the accurate diagnosis of epilepsy, marking a substantial leap forward in the realm of neurological healthcare.

### C. FEATURE EXTRACTION

Long Short-Term Memory (LSTM) represents a significant leap forward in the field of neural networks, mainly aimed at addressing a persistent challenge encountered during the training of deep networks: the vanishing gradient problem [32]. This issue is especially within recurrent neural networks (RNNs), where gradients reduce during the back-propagation process, impeding the network's ability to learn from extended sequences of data effectively. LSTM was innovatively designed to combat this concern by incorporating a memory cell, allowing the network to efficiently retain and utilize information over extended sequences. This characteristic lets LSTM to capture long-term dependencies in the data, rendering it an invaluable tool across various applications such as natural language processing, speech recognition, and time series analysis. The architecture of LSTM comprises three fundamental constituents: the input gate, the forget gate, and the output gate. These gates play a pivotal role in regulating the information flow within the cell, effectively overseeing both input and output processes. The input gate governs the degree to which new information should be integrated into the memory cell. On the other hand, the forget gate determines the data from the prior state that should be disregarded, addressing the challenge of information overload. Lastly, the output gate governs the impact of the current cell state on the network's output activation. Through the orchestration of these mechanisms, LSTM effectively manages the flow of information, discerningly storing and discarding data based on the contextual requirements, consequently adeptly addressing the vanishing gradient problem.

A noteworthy variant of LSTM is the Bidirectional LSTM (BiLSTM), a specialized category within RNN that has garnered significant attention due to its distinctive capabilities () [33]. Diverging from the conventional LSTM that processes input sequences unilaterally, a BiLSTM processes sequences both in forward and backward directions concurrently. This bidirectional processing empowers the network to assimilate information not only from the past but also from the future context of the current time step. Consequently, the model can encompass a broader context, leading to heightened performance on tasks requiring a comprehensive understanding of the input sequence.

The proficiency of BiLSTM in leveraging information from both past and future contexts makes it particularly effective in tasks such as named entity recognition, sentiment analysis, and speech recognition. Furthermore, in critical scenarios where a comprehensive grasp of the sequence's complete context is vital, such as in translation tasks, BiLSTMs have exhibited significant advantages over unidirectional LSTMs. The fusion of insights from both directions enriches the model's understanding to discern subtle nuances and dependencies in the data, ultimately resulting in superior performance.

LSTM and its variant, BiLSTM, have brought about a transformation in the neural network landscape, particularly in effectively managing sequential data that grapples with the vanishing gradient problem. By virtue of their proficient gating mechanisms and memory cells, LSTM can master the learning and utilization of long-term dependencies within the data. Conversely, BiLSTM takes these capabilities a step further by enabling bidirectional processing, enhancing the network's comprehension of intricate sequences and significantly elevating performance across a spectrum of applications. These advancements continuously fuel innovation across various domains, paving the way for the development of more potent and nuanced machine learning models. In the continually evolving realm of artificial intelligence, LSTM and BiLSTM emerge as pivotal instruments, pushing the boundaries of what is achievable in the realm of sequence modeling and analysis.

In this research, another neural network, known as the convolutional neural network [34], has also been employed as a classifier. Owing to the reason that BiLSTM is a much better fit with time-series data than CNN, BiLSTM demolished CNN, and therefore CNN has been neglected.

### D. FEATURE SELECTION

While LSTM and BiLSTM excel in understanding sequential data and discerning subtle patterns within EEG recordings, the utilization of Support Vector Machines (SVM), XGBoost, and Random Forest algorithms enhances the diagnostic process by capitalizing on their distinct capabilities in classification and predictive accuracy. In the domain of machine learning, specific algorithms have gained substantial recognition due to their distinct methodologies and effectiveness across various objectives. Notably, Support Vector Machines (SVM), XGBoost, and Random Forest have emerged as widely employed and impactful algorithms, each possessing unique strengths and tailored applications.

Support Vector Machines (SVM) have garnered a formidable reputation, particularly excelling in tasks involving binary classification [35]. Researchers and professionals have successfully applied SVM in diverse domains, showcasing its proficiency in achieving heightened accuracy in complex tasks. For example, [36] utilized SVM alongside

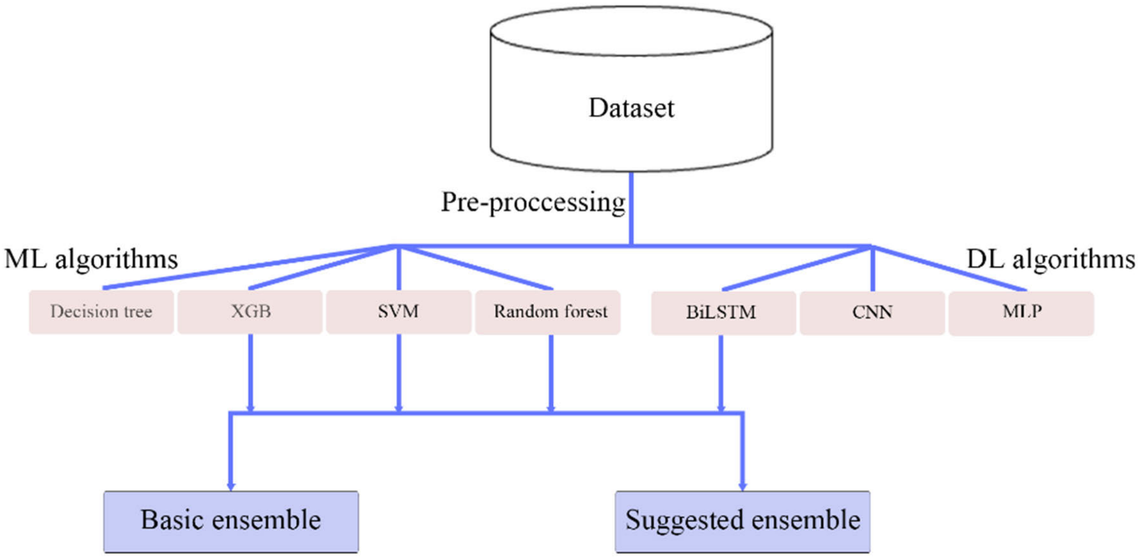


**FIGURE 1.** Flow of the suggested method.

other algorithms, resulting in a significant improvement in epilepsy detection accuracy. This serves as a prime example of Support Vector Machine's potential to enhance crucial medical diagnostic applications.

Conversely, XGBoost has attracted attention for its outstanding predictive precision and adaptability, proving highly effective in both classification and regression tasks [37]. The study conducted by Yossofzai et al. [38] emphasized the capabilities of XGBoost, solidifying its status as a preferred algorithm for tasks demanding superior predictive performance. Its versatility and precision make it an indispensable tool across various domains, spanning from financial analysis to healthcare and beyond.

Random Forest stands out as another algorithm renowned for effectively addressing overfitting concerns and skillfully managing high-dimensional data [39]. Its capacity to uphold model generalization while tackling intricate data structures positions it as a valuable asset in the toolkit of machine learning. By amalgamating insights from an ensemble of decision trees, Random Forest amalgamates collective knowledge, resulting in robust and precise predictions.

In this study, a deliberate choice has been made to deploy SVM, XGBoost, and Random Forest algorithms, capitalizing on their unique capabilities. Harnessing SVM's proficiency in binary classification, XGBoost's exceptional predictive accuracy, and Random Forest's aptitude to handle high-dimensional data without succumbing to overfitting, optimal outcomes for the specific task are sought. The amalgamation of these algorithms empowers the leveraging of diverse approaches, optimizing the potential to uncover patterns, make well-informed predictions, and propel understanding within the domain under scrutiny. Through this carefully considered selection of algorithms, valuable contributions are aspired to be made, continually extending the limits of what can be achieved within this research domain.

### E. CLASSIFICATION

Ensemble methods are a category of machine learning strategies that boost predictive accuracy by combining the predictions of multiple individual models [40]. Ensemble methods, a potent concept within machine learning and predictive modeling, have seen substantial application within the medical sector, transforming the approach to diagnostics, treatment strategy development, and healthcare administration [41]. These methodologies involve predictions from vast numbers of models to achieve the final prediction, resulting in better accuracy than relying on a single model. In medicine, where precision is essential, ensemble methods have emerged as a perfect alternative. A major domain where ensemble methods have made significant inroads in the medical industry is diagnostic decision-making. Medical practitioners often confront the task of accurately diagnosing patients based on an array of intricate variables, encompassing genetic indicators to imaging data. Ensemble methods, such as Random Forests or Gradient Boosting, facilitate the integration of diverse data sources and models to augment diagnostic precision. By aggregating forecasts from multiple models, ensemble methods mitigate the risk of individual model biases and errors, culminating in more dependable diagnoses.

Furthermore, ensemble methods are crucial in predictive modeling for devising treatment plans. Customizing treatments for individual patients based on their distinct attributes is a fundamental objective of contemporary medicine. Ensemble methods excel in crafting predictive models that guide treatment decisions by considering various patient-specific features, treatment alternatives, and potential outcomes. For example, ensemble techniques can be utilized to forecast a patient's response to a particular medication or therapy based on their medical history, genetic composition, and lifestyle aspects. This ensures a tailored approach to treatment, optimizing patient results.

**TABLE 2.** The performance metrics.

| Parameter | Value |
|---|---|
| **Accuracy** | $\frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}$ |
| **Precision** | $\frac{True\ Positive}{True\ Positive + False\ Positive}$ |
| **Recall** | $\frac{True\ Positive}{True\ Positive + False\ Negative}$ |
| **F1-Score** | $2 \cdot \frac{Precision\ \times\ Recall}{Precision +\ Recall}$ |

In addition to diagnostics and treatment strategy, ensemble methods are extensively applied in medical image interpretation. Analyzing medical imagery, like X-rays, MRIs, or CT scans, frequently necessitates advanced algorithms to precisely detect irregularities, tumors, or other medical conditions. Ensemble methods enhance the accuracy of image categorization and segmentation tasks by merging the outputs of multiple models, each specialized in different facets of image analysis. This not only enhances anomaly detection but also reduces erroneous positives and negatives, crucial for ensuring precise diagnoses.

Moreover, ensemble methods contribute to the burgeoning field of predictive healthcare analytics. By leveraging historical patient data, healthcare providers can foresee disease prevalence, patient rehospitalization rates, or resource utilization, aiding in efficient resource allotment and healthcare strategizing. Ensemble techniques boost the predictive efficacy of these models, enabling more accurate forecasts and ultimately contributing to superior healthcare provision and cost-effective decision-making.

Ensemble methods have gained swift traction within the medical industry due to their potential to enhance diagnostic precision, elevate treatment strategy formulation, optimize medical image interpretation, and advance predictive healthcare analytics. As healthcare continues improving, the accretion of machine learning methodologies such as ensemble methods is likely to play an increasingly pivotal role in enhancing the quality of patient care, ultimately leading to improved results and a healthier populace.

The fundamental principle of ensemble methods revolves around combining predictions from various models, effectively reducing the shortcomings of each model and ultimately having predictions that are more accurate and reliable. This study opts to leverage a combination of BiLSTM, SVM, XGBoost, and random forest through an average weighting mechanism to elevate the evaluation metrics. This approach enables harnessing the diverse strengths of each model, fostering a more comprehensive and robust predictive outcome.

In merging the strengths of different models, the aim is to capitalize on unique advantages and mitigate their respective weaknesses. BiLSTM, as a specialized recurrent neural network, excels in capturing bidirectional contextual information in sequences. SVM, known for its proficiency in binary classification tasks, emerges as a formidable tool in specific contexts. XGBoost, renowned for its superior predictive accuracy and adaptability across a range of tasks, contributes its strengths. Lastly, random forest's capability to effectively handle high-dimensional data and avoid overfitting stands out. Through a thoughtful integration of these models, the endeavor is to enhance the predictive prowess of the approach, pushing the boundaries of achievability in the research domain.

The ensemble approach involves averaging the predictions generated by each model, thereby creating a collaborative predictive output that benefits from the collective intelligence of the models involved. This technique helps to balance, ensuring that no single model dominates the prediction process, and instead, the collective insights of all models are incorporated. Consequently, the predictions are more robust, precise, and better suited to the intricacies of the task at hand.

The ensemble methodology chosen for this study includes a deliberate approach aimed at maximizing predictive accuracy by harnessing the strengths of multiple models. The combination of BiLSTM (Bidirectional Long Short-Term Memory), SVM (Support Vector Machine), XGBoost, and random forest through average weighting serves as a strategic effort to optimize evaluation metrics, promoting a comprehensive and predictive approach.

Each constituent model in this ensemble contributes a unique perspective and strengths to the predictive process. BiLSTM, with its ability to capture contextual information and long-term dependencies, is well-suited for sequential data analysis. SVM, known for effective classification, works optimally for distinct decision boundaries. XGBoost, a robust boosting algorithm, excels in ensemble learning and provides a robust framework for improving accuracy. Random forest, with its versatility and resilience to overfitting, contributes stability and reliability to the amalgamated model.

The fusion of these models leverages the collective intelligence of these varied approaches. Through average weighting, the ensemble method assigns appropriate importance to each model's predictions based on their respective strengths and performance. This strategic blending aims to create a unified predictive model that outperforms any individual model in terms of accuracy and robustness.

This concerted effort to amalgamate the best aspects of multiple models represents a significant stride in advancing machine learning within our research domain. The approach

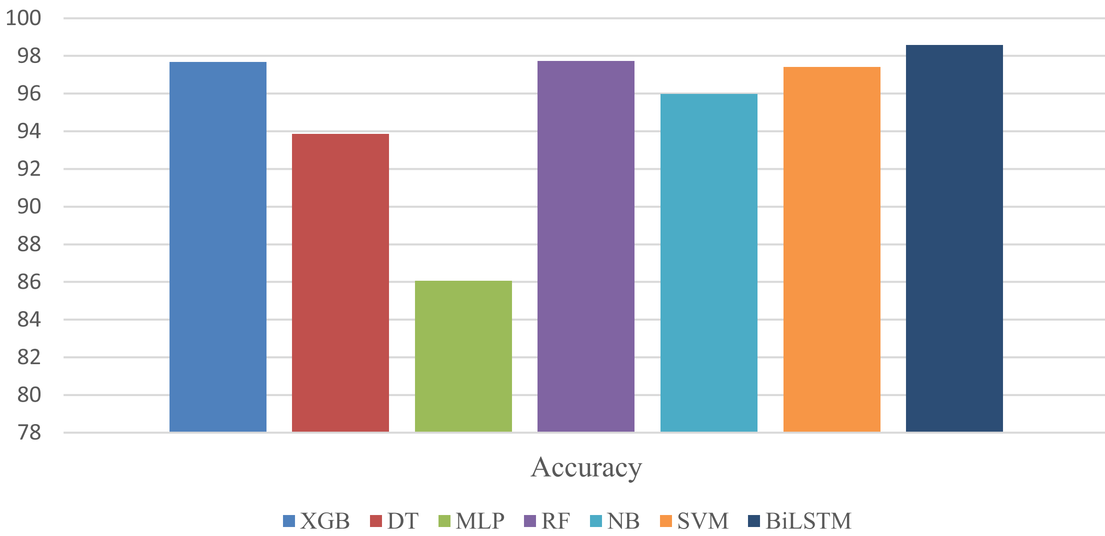


**FIGURE 2.** Achieved accuracy with different models.

not only optimizes predictive accuracy but also enhances the reliability of the results, which is important for informed decision-making in the specific field. It showcases the potential of ensemble methods to elevate the overall effectiveness of machine learning applications, underscoring the importance of leveraging a diverse range of models to achieve superior predictive outcomes.

## IV. RESULT AND DISCUSSION

This section provides an in-depth examination of the intermediate stages, procedures, and effectiveness of the proposed methodology for detecting seizure epilepsy through the utilization of machine learning and deep learning techniques. The procedures in this paper are simulated in Google Colab environment with Python language.

The assessment of this study relies on its ability to classify effectively, measured through various evaluation metrics. Accuracy, precision, recall, and F1-score are utilized in this research to evaluate the effectiveness of the proposed approach. The computation of these performance metrics is detailed in Table 2.

Owing to the errors faced while using raw data, preprocessing would be essential for better results. Eventually, after preprocessing, a collection of 11,500 chunks of data would be available. Each piece of data embraces 178 data points for 1 second of EEG signals.

Each individual EEG signal consists of 23.7 seconds of data points which are converted to one second, and each second includes 178 data points. There is a total of 500 patients, and to calculate the number of rows, the number of patients could be multiplied by 23.

In next step, different neural networks were applied and through achieved results, BiLSTM showed the potential and completely demolished CNN and Multi-Layer Perceptron, and BiLSTM was chosen to be used in the ensemble method. Simultaneous, different machine learning algorithms such as XGBoost, Decision Tree, Random Forest, Naïve Bayes, and SVM are compared. While BiLSTM, SVM, XGBoost, and Random Forest have shown promising results, each model has inherent limitations. BiLSTM, for instance, is computationally intensive and may require substantial training time, especially with large datasets. SVMs, though effective in binary classification, may struggle with high-dimensional data or when the class distributions are imbalanced. XGBoost is powerful but can be sensitive to hyperparameter settings, potentially requiring extensive tuning to achieve optimal performance. Random Forest, while robust, may become unwieldy with very high-dimensional data and can suffer from slower inference times due to the large number of trees. FIGURE 2. shows a quick overview of their performance.

As it is illustrated in FIGURE 2., MLP performed worst with 86.06% among all models, and BiLSTM, RF, XGB, and SVM showed the best performance, respectively, 98.58%, 97.74%, 97.68%, and 97.39%. By keeping results in mind, algorithms were chosen to be used in Ensemble.

In the next phase, different deep learning and machine learning models are used to select algorithms that showed high potential and then are combined via using ensemble methods. Two ensemble methods were employed. One is a simple ensemble in which all selected algorithms are stacked on each other, and if three out of four selected algorithms give the same result, it would be the final result. The second method is called average weighting, in which the potential shown by each algorithm sets the weights; for instance, if they show promising results, they would have a higher weight. In this paper, BiLSTM shined the most. Thus, its weight has been set as the highest with a value of 0.35. Among selected algorithms, Random Forest was in second place with a weight of 0.25, followed by XGBoost, and SVM with equal weights of 0.20. XGB and SVM had shown better results compared to others in the selecting phase; therefore, they were used in the ensemble method, but because they had nearly the same

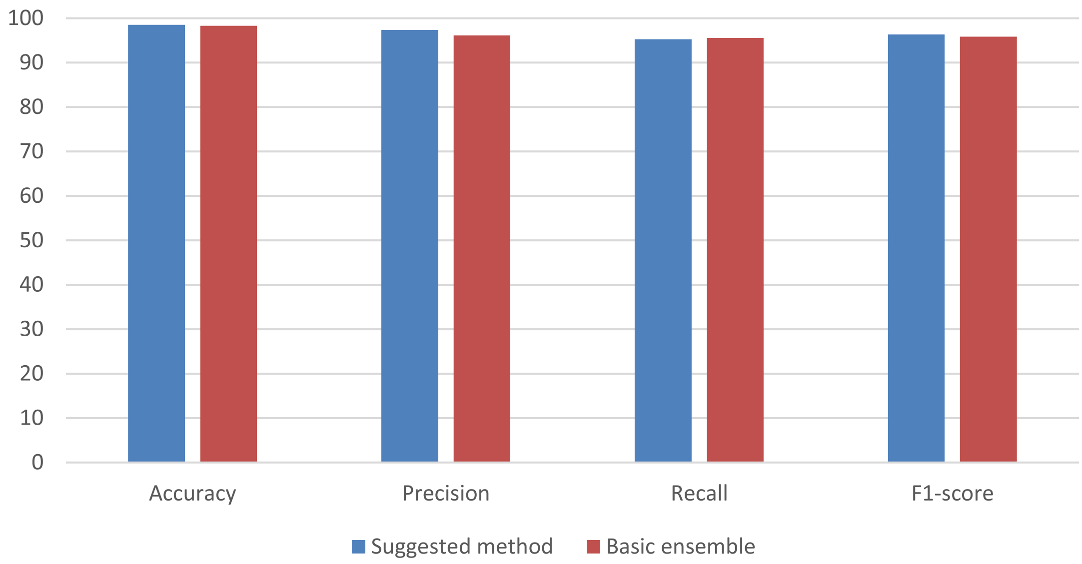


**FIGURE 3.** Comparison of applied ensembles.

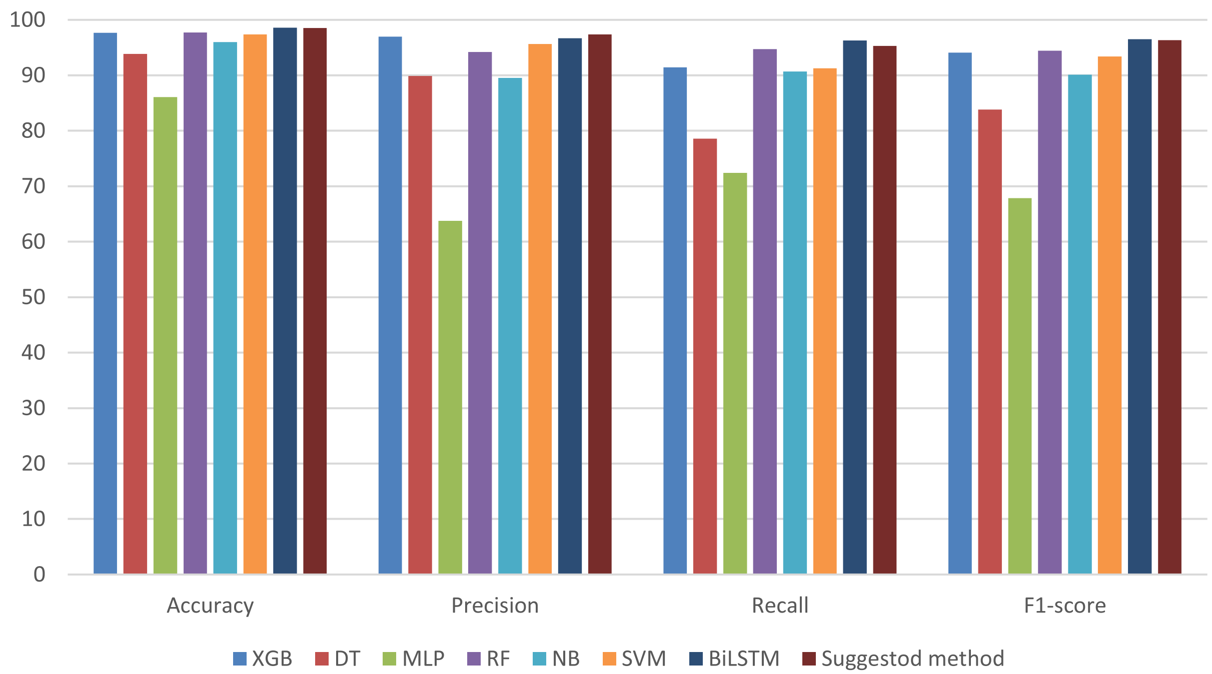


**FIGURE 4.** Classifiers comparison.

results, their weights were as equal as each other. FIGURE 3. illustrates a comparison between the simple ensemble and average weighting method that is suggested.

As described in FIGURE 3., three out of four parameters in the proposed ensemble work better. An increase in the precision criterion shows the decisive superiority of this method over the simple ensemble.

As mentioned, the average weighted ensemble method was chosen to classify seizure epilepsy in which BiLSTM, XGBoost, Random Forest, and SVM were used to achieve the best results as demonstrated in FIGURE 4.

FIGURE 4. conveys the used metrics in different algorithms, and it is concluded that the ensemble can achieve better results in most parameters compared to others, especially in precision.

Owing to the importance of precision rate in the health area, a higher rate is always in priority, so the suggested method would be a better fit than others. A comparison between precision rates has been illustrated in FIGURE 5.

The results indicate that MLP has the lowest precision with 63.77% among all the algorithms, and Ensemble has the highest precision with 97.37%. According to FIGURE 5.,

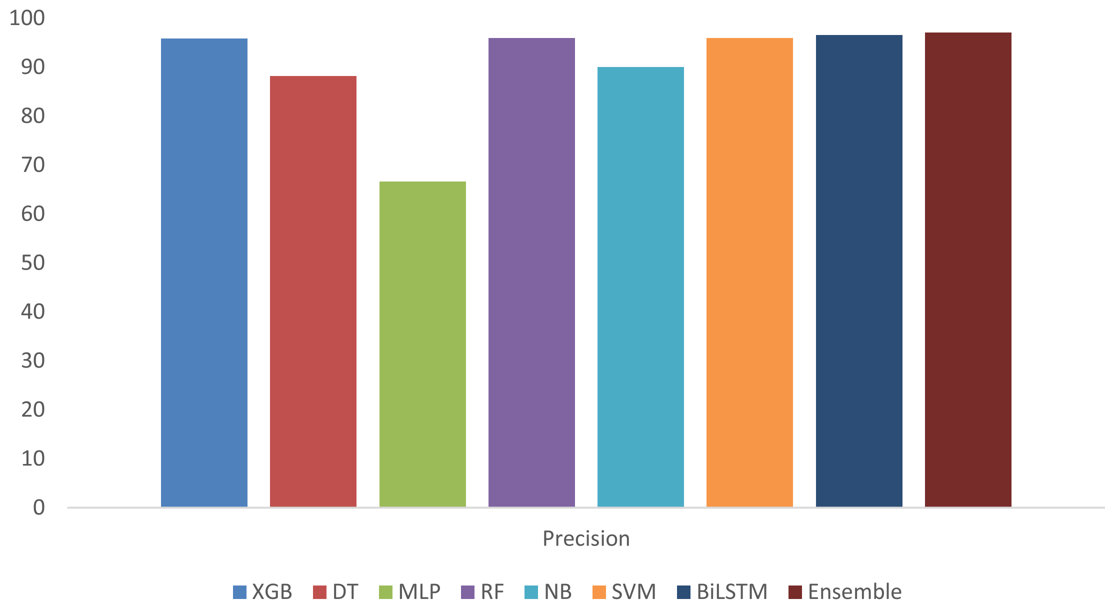


**FIGURE 5.** Classifiers comparison.

SVM and RF have performed similarly with a slight difference, and the highest level of precision achieved after the Ensemble method has been recorded by BiLSTM. According to the results obtained on the seizure epilepsy database, using MLP for diagnosing epilepsy is not recommended due to the weakness presented. Developing real-time EEG monitoring systems using wearable devices or hospital-based systems could significantly enhance seizure detection and management. Integrating the proposed model with clinical systems like EHRs and decision support systems will facilitate its adoption in medical practice.

## V. CONCLUSION

This research aims to detect seizure epilepsy with high precision which has a significant contribution among diseases all over the world. To achieve this goal, an ensemble method with the help of EEG signals is used. To detect seizure epilepsy using EEG signals, different methods were used. Different deep learning models such as BiLSTM, MLP, and CNN were compared, and by keeping the best results of accuracy in mind, BiLSTM was selected to be added to the ensemble method. To increase the evaluation metrics, different machine learning algorithms such as NB, XGB, RF, and SVM were applied too, and because XGB, RF, and SVM shined the most, they were selected to be in the Ensemble method. Eventually, BiLSTM, XGB, RF, and SVM were chosen as the backbone of the ensemble method. Although achieved results reveal that using an ensemble method would increase various metrics, it does not guarantee an increase in each metric; for instance, BiLSTM's accuracy was higher than the proposed method, with values of 98.58% and 98.52%, respectively. As precision plays a crucial role in evaluation metrics, especially in the medical field, it's been tried to keep the precision rate as high as possible. The suggested method shined the most here, because the achieved precision rate was higher than others, with the value of 97.37%.

While the dataset used in this study is comprehensive, has its limitations. The size and diversity of the dataset may not fully represent all potential variations in EEG signals from different populations or seizure types. Additionally, the preprocessing step of segmenting recordings into 1-second chunks may lead to the loss of some temporal context, potentially affecting the detection of longer-term patterns in the EEG data. Future works will be addressing these limitations by exploring more diverse datasets and developing methods to preserve temporal information during preprocessing.

## ACKNOWLEDGMENT

The authors would like to thank Michal Merta and Zdenek Truhlar for their help with the research connected with the topic of the article.

The result was created through solving the student project "Security analysis and developing lightweight ciphers and protocols" using objective-oriented support for specific university research from the University of Finance and Administration, Prague, Czech Republic.

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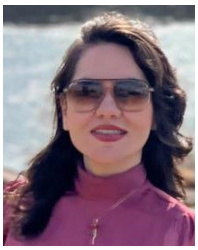

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