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A systematic review of ensemble learning approaches for improving the accuracy of epilepsy seizure detection using wavelet transform and artificial neural network

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***Abstract*—This paper presents an extensive systematic review of recent developments in EEG-based ML/DL technologies for epileptic seizure diagnosis. The paper covers recent developments in the diagnosis of seizures, different statistical feature extraction techniques, ML/DL models, their capabilities, constraints, and fundamental difficulties in the diagnosis of epileptic seizures based on EEG data. In addition, criteria for choosing the best ML/DL models and feature extraction methods for epileptic seizure diagnosis are covered.**

The study's findings will assist researchers in selecting efficient ML/DL models and appropriate feature extraction methods to improve the performance of EEG-based epileptic seizure detection.

I. INTRODUCTION

EPILEPTIC seizures are a well-known recurring neurological disease that affects a significant number of individuals worldwide, with a prevalence ranging from 4% to 16% among organ recipients [1]. About 60–70 million individuals worldwide are afflicted by this noncommunicable disease, which can strike at any age but is more common in young children and the elderly [1-4]. An epileptic seizure is characterized by sudden abnormal electrical activity in the brain, resulting in excessive neuronal discharges in the cerebral cortex and affecting the entire body [2]. Early epilepsy diagnosis and treatment are essential for slowing the disease's course and enhancing patients' quality of life. By analysing EEG patterns with a keen eye, neurologists can identify characteristic changes associated with seizures, allowing for timely intervention. However, the manual interpretation of EEG recordings is a resource-intensive endeavor, prone to fatigue and potentially missing subtle anomalies.

In order to overcome this difficulty, machine learning algorithms have emerged as the bold new captains of the detection ship. Trained on vast datasets of labelled EEG signals, these algorithms can learn to discern the subtle electrical whispers of a brewing seizure. Techniques like wavelet decomposition and feature extraction allow them to pinpoint the unique signatures of these episodes, enabling real-time detection and even seizure type classification.

Recent advancements in deep learning architectures are pushing the boundaries, showing promising results in seizure prediction and early warning systems. But EEG isn't the only vessel navigating these stormy waters. Peripheral signals like electrocardiograms (ECGs) and accelerometers are also being explored as potential predictors.

Electroencephalogram (EEG) is a widely used method for recording the brain's neural electrophysiological activity by placing electrodes on the subject's scalp [5, 6]. EEG signals are frequently used in the identification and diagnosis of epileptic seizures because they offer useful information about the electrical activity of the brain [10, 11]. EEG provides portability, cost-effectiveness, and the capacity to evaluate data in both the time and frequency domains as compared to other methods used in epilepsy monitoring [5, 6]. Neurologists analyse various characteristics of EEG signals, such as waveform, frequency, and amplitude, to diagnose epilepsy and identify specific indications of seizure activity, such as spikes [10, 11]. However, manual epilepsy diagnosis based on EEG signals is time-consuming, prone to human error, and subject to interobserver variability [4]. Manual diagnosis has a number of drawbacks, including the requirement for skilled medical professionals with specific skills, susceptibility to noise interference leading to decreased signal-to-noise ratio, and the large amount of EEG data that clinicians have to review [4, 12, 13]. These drawbacks emphasize how critical it is to create strategies to deal with these issues and raise the effectiveness and precision of epileptic seizure detection.

Artificial intelligence (AI) methods, especially those involving machine learning (ML) and deep learning (DL) algorithms, have drawn interest recently due to their potential to improve disease detection, including epilepsy seizures [14, 15]. ML/DL classifiers have the ability to analyze large volumes of EEG data, automate the detection process, and

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provide objective and accurate diagnoses [14, 15]. The application of ML/DL in epilepsy detection has rapidly expanded, and numerous studies have been conducted to explore the effectiveness of these techniques.

Our goal in conducting this systematic study is to present a thorough examination of ensemble learning techniques that use artificial neural networks and wavelet transform to increase the precision of epileptic seizure identification. The findings of this review will shed light on the effectiveness of ensemble learning approaches and guide future research efforts in developing more accurate and reliable seizure detection systems.

II. Epilepsy Seizure Detection Methods

A. Traditional Approaches and Limitations

Traditional seizure detection methods, often relying on a single algorithm, can struggle with the inherent variability and non-linearity of EEG signals. Epileptic seizure identification has always relied on manual analysis by skilled medical professionals. These clinicians visually inspect EEG signals and interpret various characteristics, such as waveform patterns, frequencies, and amplitudes, to identify seizure activity [4, 12].

Firstly, the subjective nature of visual inspection and the reliance on individual expertise make the diagnosis susceptible to interobserver variability and possible misdiagnosis [4]. Different clinicians may reach inconsistent conclusions when analysing the same EEG signals, leading to inconsistencies in diagnosis and treatment decisions.

Secondly, EEG signals are weak and easily contaminated by noise, which can significantly degrade their signal-to noise ratio [12]. Noise interference can alter the waveform characteristics of EEG signals, making it challenging to accurately identify seizure patterns and distinguish them from artifacts or background noise.

Lastly, the sheer volume of EEG data required for diagnosis poses a significant challenge for clinicians. To obtain additional behavioral indications, EEG signals are usually captured concurrently with video signals, which adds to the clinician's workload [11]. Large-scale EEG data reviews take a lot of time and can make one tired, which can impair diagnosis accuracy and even result in a false positive [13].

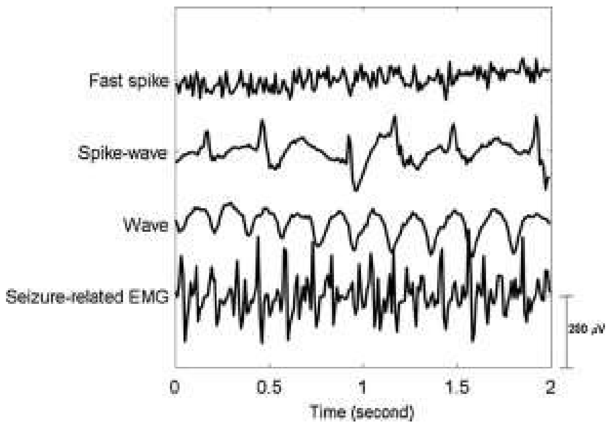

Figure 1. An example of four typical EEG patterns during seizures from ID patients.

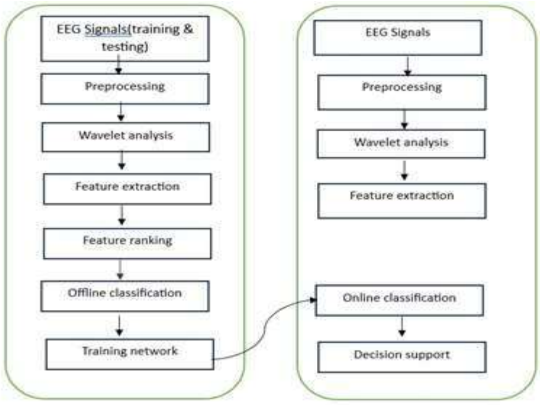

Figure 2. Diagram for computer aided epilepsy diagnosis system.

B. Ensemble Learning Approaches: An Overview

In the relentless battle against epilepsy, ensemble learning methods emerge as powerful weapons, leveraging the combined strength of diverse individual learners to conquer the complexities of EEG signal analysis and achieve superior seizure detection accuracy. Imagine a team of skilled detectives, each having a unique area of skill and perspective, collaborating to solve a puzzling crime. Ensemble learning operates in a similar fashion, combining the insights of multiple machine learning models to paint a clearer picture of epileptic activity within the brain's electrical symphony.

Ensemble learning techniques have emerged as a viable option for epileptic seizure detection due to its ability to overcome the limitations of existing methodologies. Multiple independent classifiers are combined in ensemble learning to make collective decisions, often resulting in improved accuracy and robustness compared to standalone classifiers [16]. Ensemble learning methods leverage the diversity and complementary strengths of individual classifiers to enhance overall performance. By aggregating predictions from multiple classifiers, ensemble models can reduce the impact of individual classifier biases and errors, leading to more reliable and accurate seizure detection.

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Numerous group learning strategies have been used in epilepsy seizure detection, including bagging, boosting, and stacking. Bagging algorithms, such as Random Forest, construct multiple classifiers from bootstrap samples of the data's training and combine their predictions through voting or averaging [16]. Boosting algorithms, such as AdaBoost, iteratively train weak classifiers and assign higher weights to misclassified samples, thereby improving their performance [16]. Stacking, conversely, involves training multiple classifiers and uses a meta-classifier to combine their outputs and make the final prediction [16].

III. WAVELET TRANSFORM AND ARTIFICIAL NEURAL NETWORKS

A. Wavelet Transform in Epilepsy Seizure Detection

As wavelet transform can extract frequency and temporal information from EEG data, it has drawn a lot of interest in the field of epileptic seizure detection. There have been several WT-based feature extraction methods proposed recently for the identification of epilepsy [17]. The Discrete Wavelet Transform (DWT) has been a widely used method for extracting features from non-stationary data in WT [17]. A more thorough examination of the nonstationary character of EEG signals—which change in frequency components over time during seizure episodes—is made possible by the application of wavelet transform. [18]. Each wavelet family has its own characteristics and is suitable for capturing specific features of EEG signals. The choice of wavelet family depends on the desired resolution and frequency localization required for accurate seizure detection.

Where other signal processing techniques fail or are less successful, the wavelet transform is especially useful for expressing different features of non-stationary signals, such as trends, discontinuities, and repetitive patterns. Transient characteristics are precisely recorded and localized in both time and frequency context using wavelet decomposition of the EEG recordings [19].

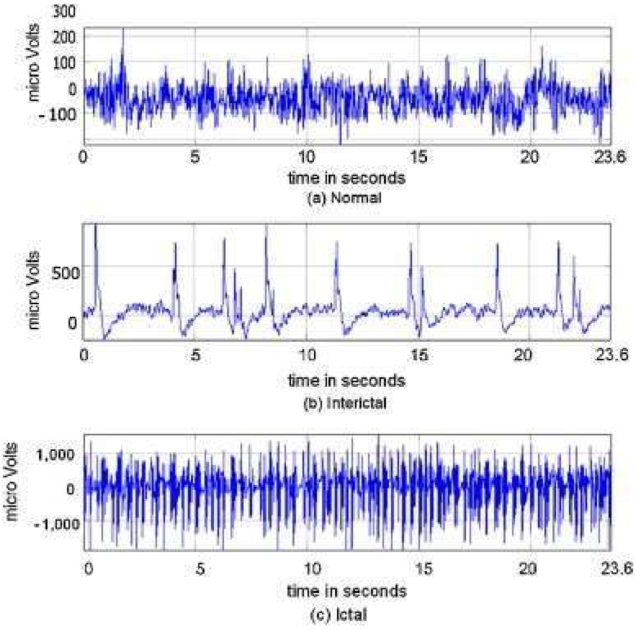
EEG signals are broken down into several frequency subbands using the wavelet technique, providing a detailed representation of signal components at different scales. This decomposition helps in identifying specific frequency patterns associated with seizures, such as spikes or sharp waveforms. Seizures can be identified more precisely by examining the wavelet coefficients in the time-frequency domain. The primary benefit of the WT is its variable window size, which allows for excellent time-frequency resolution across all frequency ranges by being large at low frequencies and narrowing at high frequencies [20].

Studies on the identification of epileptic seizures have made use of a number of wavelet families, including the Daubechies, Symlets, and Haar wavelets. Every wavelet family has unique properties and can be used to capture particular EEG signal components. Which wavelet family to choose depends on the required resolution and the frequency localization required for accurate seizure detection.

B. Artificial Neural Networks for Seizure Detection

Artificial Neural Networks (ANNs) have demonstrated significant promise in a range of medical applications, such as the detection of epileptic seizures. ANNs are computer models that are based on the composition and operation of the human brain. They are made up of networked neurons or nodes that process and send information via weighted connections.

Computer systems known as artificial neural networks are inspired by the functioning of the human nervous system and brain. The biological neurons dispersed and parallel processing architecture has been linked to the biological neural system's remarkable ability to carry out complicated tasks. The



artificial neural network (ANN) mimics these systems, in which computation is handled by means of basic units known as artificial neurons that are connected to form a network [21].

Figure 3. Wavelet based EEG processing for computer-aided seizure detection and epilepsy diagnosis.

In the context of epilepsy seizure detection, ANNs can learn the complex relationships between input features extracted from EEG signals and the corresponding seizure patterns. By training on labeled seizure and non-seizure data, ANNs can

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learn to classify new EEG signals as either normal or indicative of seizure activity.

For the purpose of detecting epileptic seizures, several ANN topologies, including feedforward neural networks, recurrent neural networks, and convolutional neural networks, have been investigated. Every architecture offers benefits of its own and is suitable for different aspects of seizure analysis, such as temporal dependencies, spatial patterns, or local feature extraction.

C. Integration of Wavelet Transform and Artificial Neural Networks

Artificial neural networks combined with wavelet transforms have demonstrated encouraging results in increasing the precision of epileptic seizure detection. By breaking down EEG signals into frequency subbands, the wavelet transform offers a reliable feature extraction mechanism, and ANNs pick up the discriminative patterns to determine the final seizure prediction. Prediction accuracy can be increased by combining many dynamical recurrent neural networks, each of which aims to capture the dynamics of multiple multi-resolution versions of a given data signal.

With this novel method, prediction and data analysis are combined seamlessly. It results in a natural combination of connectionist engines, with their outputs merged. As a result, information fusion and problem decomposition are both carefully managed and integrated. [22].

ANNs can use the wavelet coefficients that are produced when EEG data are broken down using the wavelet transform as input characteristics. By training the ANN model on these wavelet coefficients, the network can learn to effectively discriminate between normal and seizure EEG patterns. The integration of wavelet transforms and ANNs enhances the ability to capture both time and frequency information, leading to improved seizure detection performance.

IV. Ensemble Learning Approaches for Epilepsy Seizure Detection

A. AdaBoost-based Approaches

Adaptive Boosting, or AdaBoost, is a well-liked ensemble learning method that builds a powerful classifier by combining several weak classifiers. AdaBoost-based strategies have been extensively investigated in the area of epileptic seizure detection to enhance the precision and resilience of seizure prediction models.

Any given learning algorithm can be made more accurate in general by using a technique called "boosting." This chapter, which mostly focuses on the AdaBoost algorithm, provides an overview of some of the recent work on boosting. This work includes analyses of the training and generalization errors of AdaBoost, the relationship between boosting and logistic regression, game theory and linear programming, extensions of AdaBoost for multiclass classification problems, techniques for integrating human knowledge into boosting, and experimental and applied work utilizing boosting [23].

In AdaBoost, weak classifiers are iteratively trained on different subsets of the training data. The weights of samples that are incorrectly classified are increased with each iteration, which compels weaker classifiers to concentrate on these difficult instances. All of the weak classifiers' predictions are combined and weighted according to how well each one performed on its own to produce the final forecast.

AdaBoost-based methods have been used with many kinds of weak classifiers, including artificial neural networks, decision trees, and support vector machines, in the context of epileptic seizure detection. These methods have demonstrated encouraging outcomes in precisely identifying seizure events and reducing false alarms.

B. Bagging-based Approaches

Bagging, also known as Bootstrap Aggregation, is another widely used ensemble learning approach that focuses on improving machine learning model performance and generativity. Bagging approaches have been used extensively in the field of epilepsy seizure detection to reduce variability and enhance the stability of prediction models.

Using the initial training set of data, bagging generates several bootstrap samples, each of which is produced by randomly choosing samples with replacement. Each bootstrap sample then trains a different classifier. Finally, the final result is calculated by aggregating all classifier predictions using majority voting. Bagging is an ensemble method commonly applied to classification cases, with the aim of improving classification accuracy by combining single classifications, and the outcomes outperform those of random sampling. [24].

Bagging-based techniques have been used with different base classifiers, including decision trees, random forests, and k-nearest neighbours, in the context of epileptic seizure detection. These methods have demonstrated enhanced accuracy performance, sensitivity, and specificity, effectively capturing the complex patterns associated with seizure events.

C. Stacking-based Approaches

Stacking, also called stacked generalization, is an ensemble learning method that uses a meta-classifier to integrate the predictions of several base classifiers. In the context of epilepsy seizure detection, stacking-based approaches have been explored to leverage the strengths of different classifiers and improve the overall performance of seizure prediction models. Stacking works by training multiple base classifiers on the training data, and then using their predictions as input features to train a meta-classifier. With consideration for each base classifier's unique advantages and disadvantages, the meta-classifier learns to aggregate the predictions of the individual classifiers. The final prediction is made by the

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meta-classifier based on the combined information from the base classifiers.

Stacking is an ensemble learning method that uses a metaclassifier to integrate several underlying classification models. This method creates a single generalized machine learning model by combining several traditional classifiers. [25]. These approaches have demonstrated improved accuracy and robustness in seizure detection, effectively leveraging the complementary information provided by different classifiers.

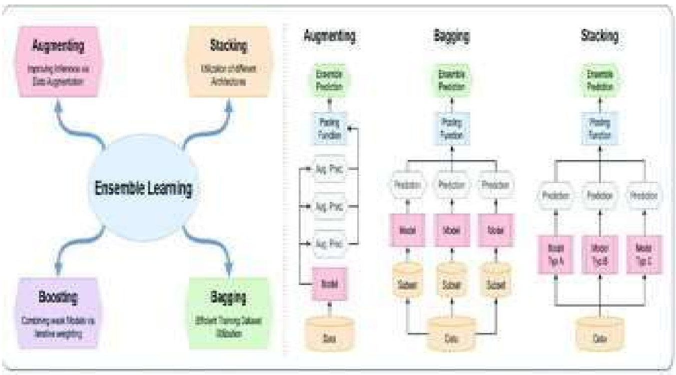

Figure 4. Diagram showing the four ensemble learning techniques: Augmenting, Stacking, Boosting and Bagging.

V. Performance Evaluation and Comparative Analysis

A. Evaluation Metrics for Epilepsy Seizure Detection

To assess efficiently the performance of ensemble learning approaches for epilepsy seizure detection, it is essential to define appropriate evaluation metrics. The literature has widely employed a number of metrics to assess the efficacy of seizure detection models. Machine learning approaches are intensely being applied to this problem due to their ability to classify seizure conditions from a large amount of data, and provide pre-screened results for neurologists. Several features, data transformations, and classifiers have been explored to analyze and classify seizures via EEG signals [26].

Accuracy is a commonly employed metric that evaluates the overall precision of the models' predictions. Accuracy is calculated as the ratio of correctly classified cases to the total number of cases in the dataset. However, accuracy alone may not provide a comprehensive assessment, especially when dealing with imbalanced datasets where the number of seizure and non-seizure instances is significantly different.

Figure 5. Performance metrics: Epileptic seizure prediction based on Convolutional neural networks and optimization techniques

To overcome the limitations of accuracy, other evaluation metrics are often considered, such as sensitivity (also known as recall), specificity, precision, and F1 score. Specificity gauges the model's capacity to accurately classify nonseizure occurrences, whereas sensitivity gauges the model's capacity to accurately identify seizure cases. The F1 score offers a balanced measurement between sensitivity and precision, while precision is defined as the percentage of properly diagnosed seizure cases among all instances projected to be seizures.

B. Datasets for Performance Evaluation Previous research has used many datasets to evaluate ensemble learning systems' efficacy in identifying epileptic seizures. The EEG recordings from people with epilepsy, including both seizure

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and non-seizure episodes, are included in these databases. The goal of this, is to develop an efficient segment-based approach to EEG signal classification that can be used in the design of automated interval-based seizure prediction systems (or onset detection systems) [27].

One commonly used dataset is the Freiburg EEG dataset, which contains EEG recordings from multiple patients with epilepsy. This dataset provides a valuable resource for the performance evaluation seizure detection models, as it includes a diverse range of seizure types and seizure-related EEG patterns.

Another widely used dataset is the CHB-MIT Scalp EEG Database, which consists of EEG recordings from pediatric patients with epilepsy. This dataset includes long-term EEG recordings captured during both seizure and non-seizure periods, allowing for the assessment of seizure detection models under realistic conditions.

Additionally, other publicly available datasets, such as the Bonn University EEG dataset and the Temple University Hospital EEG dataset, have also been utilized for performance evaluation in epilepsy seizure detection studies.

C. Comparative Analysis of Ensemble Learning Approaches

In the literature, several ensemble learning approaches have been proposed for epilepsy seizure detection, including AdaBoost-based approaches, bagging-based approaches, and stacking-based approaches. These approaches have been evaluated and compared based on their performance using various evaluation metrics and datasets. Because of its excellent categorization performance, ensemble learning has grown to be one of the most often used machine learning techniques. This paper presents the application of four core ensemble learning techniques (voting, stacking, bagging, and boosting) with five distinct classification algorithms that have the best parameter values on signal datasets [28].

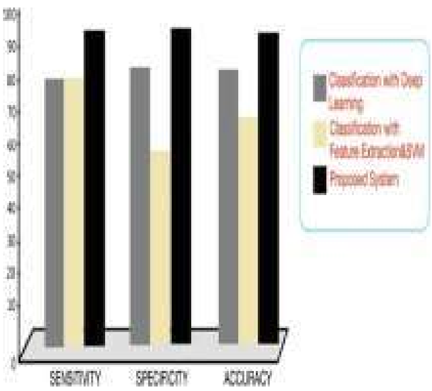

Figure 6. Bar graph showing the results of performance and accuracy analysis based on a comparison of the methods.

A comparative analysis of these ensemble learning approaches provides insights into their strengths and limitations. It enables practitioners and academics to determine the best methods for seizure detection tasks by accounting for variables including computational efficiency, sensitivity, specificity, and accuracy.

Furthermore, comparative analysis can shed light on the impact of different ensemble learning techniques on the performance of seizure detection models. It aids in comprehending the benefits and drawbacks of each strategy, making it possible to choose the best method for a particular application circumstance.

VI. LIMITATIONS AND CHALLENGES

A. Limited Generalizability

Despite the promising results achieved by ensemble learning approaches for epilepsy seizure detection, there are still several limitations and challenges to be addressed.

The major challenges in developing ensemble learning models for seizure detection is the limited generalizability of the models. Most studies in this field utilize specific datasets collected from controlled environments, which may not fully represent the real-world scenarios. The performance of ensemble learning models trained on one dataset may not be consistent when applied to different datasets with varying characteristics, such as different patient populations or recording conditions.

Therefore, it is important to evaluate the generalizability of the proposed models on diverse datasets to ensure their robustness and reliability in real-world applications.

B. Feature Selection and Extraction

An important aspect of designing effective ensemble learning models for seizure detection is the selection and extraction of relevant features from EEG signals. The success of ensemble learning heavily relies on the quality and informativeness of the selected features. However, identifying the most discriminative features from the complex EEG signals remains a challenge. Additionally, the choice of feature extraction techniques can significantly lack of interpretability hinders the acceptance and trust in the models, particularly in clinical settings where explainability is crucial for decision-making. Developing methods to enhance the interpretability and explainability of ensemble learning models for epilepsy seizure detection is necessary to facilitate their adoption in clinical practice.

Addressing these limitations and challenges is crucial for the further advancement and practical deployment of ensemble learning approaches in epilepsy seizure detection. Overcoming these hurdles will lead to more accurate, reliable, and interpretable models, enabling better management and treatment of epilepsy patients.

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VII. Recent Advancements and Future Directions

A. Advanced Ensemble Techniques

The utilization of sophisticated ensemble methods to improve seizure detection model performance has been studied recently. Methods like rotation forest, random subspace, and gradient boosting have demonstrated encouraging outcomes in enhancing the ensemble learning procedure. By combining more complex ensemble algorithms, feature selection mechanisms, and model combination procedures, these techniques seek to deal with the shortcomings of conventional ensemble methods. These sophisticated ensemble approaches can be further explored and improved in future studies to obtain even greater accuracy and dependability in seizure detection.

B. Integration with Other Modalities

Although EEG signals are widely used to detect seizures, the integration of other methods can provide additional

impact the performance of ensemble learning models. information and improve the overall performance of

Thus, there's a requirement for further research on developing advanced feature selection and extraction methods specifically tailored for seizure detection to improve the accuracy and robustness of the models.

C. Imbalanced Data Distribution

Unbalanced data distribution, wherein the proportion of seizure occurrences is much lower than that of non-seizures, is a common problem in epilepsy seizure datasets. The performance of ensemble learning models may be impacted by this imbalance, which may result in biased learning. Furthermore, misclassifying seizure cases might have serious repercussions because they belong to the minority class, which is typically more significant in seizure detection. Consequently, to improve the efficacy and dependability of ensemble learning models in the detection of epileptic seizures, it is imperative to tackle the problem of unequal data distribution and devise practical methods for managing class imbalance.

D. Interpretability and Explainability

Another challenge associated with ensemble learning approaches is the lack of interpretability and explainability.
Ensemble models often produce complex decision boundaries that are difficult to interpret and understand. This ensemble learning models. For example, combining EEG signals with electrocardiogram (ECG), electromyogram (EMG), or other physiological signals can enhance the discriminative power of the models and enable more comprehensive analysis of seizure activity. Integrating multimodal data sources can result in a more holistic understanding of seizures and enable more dependable and accurate detection.

C. In Real-Time and Mobile Applications

Creating mobile and real-time applications for seizure detection is an important area for future research. For those experiencing seizures to receive appropriate interventions and help, real-time detection is essential. To enable continuous monitoring and seizure detection in real-world scenarios, ensemble learning models can be implemented on portable devices and tailored for real-time processing. The accessibility and usability of ensemble learning-based seizure detection systems can be further improved by integrating wearable technology with Internet of Things (IoT) technologies.

D. Explainable and Trustworthy Models

As ensemble learning models become more complex and powerful, it is important to ensure their explainability and trustworthiness. Interpretability and explainability of seizure detection models are crucial for gaining the trust of clinicians, patients, and caregivers. Future research should focus on developing techniques to interpret and explain the decision-making process of ensemble models, providing transparent and understandable insights into the detected seizures. Explainable ensemble learning models will facilitate the adoption and acceptance of these models in clinical practice.

To sum up, the precision and dependability of epilepsy seizure detection have been greatly enhanced by the latest developments in ensemble learning methodologies. Still, there are a number of directions that could be explored and improved. Promising paths for future study include deep learning methodologies, real-time and mobile applications, explainable models construction, advanced ensemble techniques, and interaction with other modalities. By addressing these problems, ensemble learning models have the potential to greatly enhance epilepsy therapy and management, ultimately leading to an improvement in the quality of life for individuals with the condition.

VIII. Conclusion

In conclusion, this systematic review provided a comprehensive overview of the recent development of EEG based machine learning (ML) and deep learning (DL) techniques in the diagnosis of epileptic seizures. We have explored traditional approaches and their limitations, highlighting the need for more efficient diagnostic methods. Ensemble learning approaches, such as AdaBoost, bagging, and stacking, have been examined, demonstrating their potential in improving seizure detection accuracy.

It is imperative to emphasize that the recommendations and conclusions drawn from this review study will assist researchers and practitioners in selecting appropriate feature extraction techniques and efficient ML/DL models to increase the precision of EEG-based epileptic seizure diagnosis. We may work toward reliable and consistent diagnosis results by overcoming the obstacles and constraints mentioned, which will ultimately improve the lives of those who are impacted by epilepsy. In conclusion, this study has clarified the developments, constraints, and potential paths for EEG-based ML/DL systems in order to diagnose seizures caused by epilepsy. By pushing the envelope in this area of study and research, we can support ongoing initiatives to lessen the effects of epilepsy and improve treatment for those afflicted with this long-term neurological condition.

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