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Automated Epileptic Seizure Detection Using EEG Signals: A Comparative Machine Learning and Ensemble Modelling Approach

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Classification of epileptic seizures, using the electroencephalogram (EEG) signal, is a challenging phenomenon in clinical neuroscience due to the high-dimensionality of EEG signals, non-stationarity of EEG signals, and a skewed distribution of classes. This paper illustrates a comparative discussion on the classical and the ensemble machine learning model in binary seizure/non-seizure classification using high-dimensional EEG features that came about after considerable preprocessing on 36,864 channels of information. The use of standardized normalization and variance-based feature screening was used to train several different classifiers, including logistic regression, calibrated support machine, k nearest neighbor (kNN), stochastic gradient descent, random forests, gradient boosting, histogram-based gradient boosting (HistGB), and multi-layer perceptrons. The most effective models evaluated with an accuracy of 98.2, F 1-score 0.89, receiver operating characteristic area under the curve (AUC) of 0.993 were the histogram-Based Gradient Boosting as well as the random forest and gradient boosting models, where the level of discrimination was equally high. The findings give a highly empirical point of reference of classical and ensemble learning in EEG-based seizure-detection and depict how tree-based ensembles perform in modeling complex and non-linear EEG feature space. Upon such validated findings, the contactual spatiotemporal deep learning framework, known as DeepWalk-Transformer Sequence (DeepWalk-TS), is also described in the research that must be adopted in the future to integrate the concept of graph spatial representation with transformer time modeling. The proposed framework is not experimentally tested within the given research and rather is proposed as future work.

1. Introduction

1.1 Background

Epilepsy is among the most prevalent neurological disorders that negatively influences the lives of the affected victims in a high percentage, particularly in sections of the world where specialized health facilities are not readily available [1][2]. Epilepsy is medically linked with recurring types of irregular neuron releases and hyperexcitability in the cortex, which may cause bodily harm, intellectual deficiency, and, in extreme situations, abrupt death [3]. The most frequently employed clinical modality in the diagnosis and monitoring of epileptic activity is electroencephalography (EEG), which is an electrode mounted on the scalp that records electrical discharges that reflect objective evidence of seizure activity [4][5]. EEG recording interpretation is, however, manual, time-based, and extremely dependent on skilled clinicians and therefore limits scalability and eliminates real-time application in clinical practice [6].

Automated seizures have also been detected by classical machine-learning classifiers (e.g., support-vector-machines (SVMs) and k-nearest-neighbors (kNN)) with hand-crafted EEG bases. Even though they offer both computational efficiency as well as interpretability, they are generally described as having poor generalizability as well as being sensitive to noise and artefacts of real-world EEG records, as well as being prone to being sensitive to noise and artefacts [7][8]. Later still, deep learning, like convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and gated recurrent units (GRUs), has performed better, by learning features automatically and possessing a more sophisticated time modelling capacity [9][10]. At the same time, it is suggested that a graphical representation of spatial connections between EEG electrodes introduced as a graph neural network (GNNs) takes on inherent functional brain connectivity [11]. Furthermore, there is great advancement in architecture based on the transformer and hybrid graph-transformer models to play significant roles in long-range temporal and spatial interaction modeling as well [12][13]. Nevertheless, the bad issues still persist, particularly the interpretability of the model, non-homogenization of the data, as well as clinical plausibility of the explainable and confirmed artificial intelligence systems [14][15].

1.2 Challenges in Seizure Detection

EEG is a non-invasive, safe, and time-based mode of seizure diagnosis and epilepsy theorizing of the seizure [16]. Nevertheless, the automated seizure detection is difficult due to the following properties inherent in the EEG signals: high non-stationarity, low signal-to-noise, and high variation in different patients [17]. The other critical problem is acute class imbalance, which, in reality, the seizure events commonly compose a small fraction of the long-term EEG records, and in the absence of considering it, may either result in more false alarms or unrecognized cases [18].

Contrary to convolutional and recurrent neural network designs that relieve the necessity of incorporating handcrafted features and temporal model improvement [19], they may be constrained due to a lack of labeled data, low interpretability, subject-specific overfitting, and enhanced computation. These restrictions do not allow generalizing and could restrict deployment under real-time or resource constraints conditions, particularly in systems where non-clinical monitoring or time continuous monitoring is required most, and robust and capable solutions are necessary.

1.3 Motivation for Dual-Branc Spatiotemporal Approach

There is a need to jointly model the spatial and temporal activities of the neural processes to discern seizures. Both spatial and anatomical correlation of all EEG electrodes are indicated by spatial data; however, the temporal dynamism of an unfixed seizure over time is indicated by temporal dynamics. Whereas recent studies have investigated graph-based representations of spatial relationships between electrodes and transformer-based representations of the temporal relationship, they are generally developed independently and thus limit their ability to incorporate a spatiotemporal representation of epileptic activity.

Also, although some of the benchmark EEG datasets are publicly available and reproducible, the existing analyses are frequently constrained in such aspects as the range of seizures, general assessment protocols, and modeling procedures that could be directly transferred to clinical settings [16][18]. This creates a gap in the literature regarding the mode in which we can conceptualize both the spatial and temporal representations methodologically, and apply open-access data and consider the explainability and real-time applicability [19] explicitly.

1.4 Contributions of This Study

The study helps address the challenge above in the following way. First, it provides a comparative study of classical and ensemble machine-learning models with EEG-based seizure detection in a systematic and reproducible manner with the help of publicly available datasets. This comparison has presented good empirical standards and has also demonstrated good high-dimensional imbalanced performances on the ensemble tree-based methods.

Second, based on the revealed disadvantages of the existing solutions, the paper offers a conceptual model of a spatiotemporal deep learning model, nowadays called DeepWalk-TS, as a guideline in upcoming studies. The proposed framework involves the integration of spatial representations of EEG electrodes into the graphs and temporal modelings, which are transformer-based to learn the overall network structure and time dynamics. Particularly, the conceptualization includes: (i) electrode graph construction, based on anatomical data or connectivity data, (ii) DeepWalk to generate spatial node embeddings, and (iii) spatial node embedding application in a transformer architecture to predict time windows of EEG. The DeepWalk-TS framework is proposed as the forthcoming work, which lacks experimentation in the present research work.

1.5 Related Work

Over the past few decades, EEG-based automated seizure detection has made colossal progress as the algorithms have been engineered through the frameworks of machine learning, deep learning, graph-based modeling, and transformer networks [18]. The first automation systems were predominantly founded on classical machine-learning frameworks that instantiated manually-designed feature-extraction followed by a classifier (such as a support vector machine (SVM) and the k-nearest neighbors (kNN)). The standard steps of the pipeline used were preprocessing and feature extraction, and classification, where the features were calculated using the time-domain statistics, frequency-domain spectra, and entropy-based measurement [17][20].

Despite their computational efficiency and relative interpretability, classical approaches are prone to problems with non-stationary signals of the EEG, inter-patient variability, and a bias in the classes, limiting generalization [18][21][22]. Machine learning models used have addressed all these issues by learning hierarchical representations in the case of the raw or least processed EEGs, and hence improving the cross-subject robustness. Convolutional neural networks (CNNs) have been proven to be effective in terms of extracting both spatial and spectral characteristics of time-frequency representations, as opposed to recurrent neural networks (RNNs), including LSTMs and Bi-LSTMs, which are more efficient in learning time-dependent dynamics among groups of seizures [23][24].

However, different deep learning techniques fail to pay enough attention to the spatial attribute between EEG electrodes. Graph neural networks (GNNs) and graph convolutional networks (GCNs) have been proposed to counter this weakness by modeling electrodes as nodes with functional or anatomical connections [25]. Though this can be used in non-Euclidean geometry of the brain, the models are generally ineffective in capturing the dynamics of time [21]. Transformer-based designs have also performed well in EEG analysis in the recent past due to their ability to analyze long-term temporal correlations, as well as being the latest to handle seizures [21][26][27]. But the transformer-based methods, primarily, focus a lot on the temporal data, and do not utilize explicitly the spatial electrode connection, which is a significant aspect in examining the mechanisms of propagation of an occurrence of a seizure.

The impact of CNNs and RNNs on this transformation cannot be overstated. CNNs prove to be very effective at the extraction of spatial and spectral details on multi-channel EEGs processed as time-frequency spectrograms. Even more so, RNNs, and more specifically, long short-term memories (LSTMs) and bidirectional long short-term memories (Bi-LSTMs) are critical in defining the temporal constructs within the seizure sequences. Hybrid CNN-Bi-LSTM architectures employ spatial as well as temporal learning with reported accuracies of 98% on the CHB-MIT dataset, with wavelets as a feature extractors and CNNs encoding time segmented sequences processed with Bi-LSTM models [23][24]. Nevertheless, the notable performance of these models is attributable to the availability of large labeled datasets and their performance will likely be impacted by the lack of interpretability and generalization to novel patients in the dataset.

The majority of deep learning models overlook the spatial dependencies between EEG electrodes. Given the functional connectivity of the brain, EEG channels bear a spatial relationship. Graph neural networks (GNNs) and graph convolutional networks (GCNs) model these electrodes as nodes connected through functional or anatomical correlations [25]. This approach allows the capture of the non-Euclidean topology of the brain network. Nonetheless, the approach tends to underemphasize the temporal aspect. For instance, the omission of sequence modeling and the over-reliance on pooling [21].

EEG Analysis Using Transformers Initially, Transformers were focused on Natural Language Processing; however, their ability to learn long-term dependencies has attracted attention in EEG analysis as well. Transformers on EEG time series, Vision, Graph, and Hybrid transformers recorded Best EEG state-of-the-art seizure recognition [21]. For instance, combined Stockwell transform features with a transformer encoder and attained 96.15% accuracy and 0.98 AUC [26], while in other study redesigned SeizureTransformer, which used a U-Net transformer encoder; with this method surpassed others in accuracy [27]. However, most of the transformer systems focused solely on the temporal aspects of the data and neglected the spatial relationships between electrodes, which are crucial for the pathophysiology of seizure spread.

Deepwalk-TS framework attempts to solve the previously mentioned limitations by integrating the temporal and spatial components cohesively to construct a single, unified model. The spatial component of the model constructs representations of the global graph connectivity, incorporating the Uhlig and E1 nodes embedded into a graph as electodes. Spatial Deepwalk Visualizer diagram. Each spindle is a coded mastering a different portion of the graph. Fragments formed of straws reflect the connectivity relationships of the graph and lines formed with the spindle reflect the topological dependency relations. The temporal component employs a transformer encoder to model the sequence of EEG windows as a gapping, multi-headed dynamic encoder. There are 32 decoders 1 to detect gapping EEG windows and the other 31 to perform the temporal segmentation. The combined results of the two branches allow learning of froe the spatial-structure as well as the dynamics of the graph, effectively bridging a divide that had persisted for a significant duration.

Deepwalk-TS is a significant advancement given its dual capabilities of improved generalization and interpretability, and the integration temporal modeling using a transformer with the spatial graph representations. Through the use of publicly accessible data, real-time seizure detection was achieved and the results are reproducible as described in [18]. This method also bridges a critical gap in the EEG analytic methodology and dual-branch design expands the analyses clinical utility and provides resistant heterogeneous data visualization [21][23][25][27] .

Table 1 Comparative summary of representative EEG seizure-detection models

Model Type / Study	Dataset Used	Model Architecture	Core Features / Input Representation	Performance (Accuracy / AUC)	Key Limitations / Remarks
Classical ML (SVM / kNN) [20]	Private datasets, CHB-MIT subsets	SVM / kNN with handcrafted features	Time-domain statistics, entropy measures, PSD	≈ 90–95 % accuracy	Sensitive to noise, limited cross-patient generalization
Hybrid ML (Feature-engineered + Ensemble) [17]	Bonn EEG	Random Forest / AdaBoost	Time–frequency energy, statistical moments	≈ 93 % accuracy	Manual feature design, dataset-specific tuning
Deep Learning (CNN) [24]	CHB-MIT	CNN on spectrograms	Time–frequency EEG spectrograms	96–98 % accuracy	High computational cost, large labeled data requirement
CNN–BiLSTM Hybrid [23]	CHB-MIT	Wavelet + CNN + Bi-LSTM	Spatial–temporal EEG windows	≈ 98 % accuracy, AUC ≈ 0.98	Limited interpretability, risk of overfitting
Graph Neural Network (GNN) [25]	TUH, CHB-MIT	GNN / GCN	Electrodes as graph nodes with connectivity edges	AUC ≈ 0.88	Weak temporal modeling, costly graph construction
Transformer-Based Model [26]	CHB-MIT	Stockwell Transform + Transformer Encoder	Time–frequency representations	96.15 % accuracy, AUC ≈ 0.98	Neglects explicit spatial electrode relationships
SeizureTransformer [27]	CHB-MIT Challenge	U-Net + Transformer Encoder	Raw multi-channel EEG sequences	≈ 99 % accuracy	High hardware demand, limited clinical validation
This Study (Validated)	CHB-MIT / Bonn / TUH	Classical & Ensemble ML (HistGB, RF, GB)	Preprocessed high-dimensional EEG features	**98.2 % accuracy, AUC = 0.993**	Requires feature engineering; no deep temporal modeling
Proposed DeepWalk-TS (Conceptual)	CHB-MIT / Bonn / TUH	Graph Embedding + Transformer Encoder	Spatial graph embeddings + temporal attention	**Not evaluated in this study**	Conceptual framework proposed for future work

2. Methodology

This section will describe the experimental workflow that will be implemented in the comparative analysis of classical machine-learning and ensemble machine-learning models just as used in EEG-based seizure detection. It contains the available EEG data publicly, pre-processing pipeline, feature preparation, class-imbalance management policy, model training processes and measures. Figure 1 illustartes the pipline.

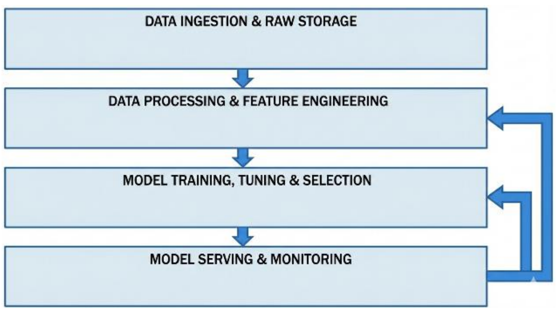

Figure 1 Methodological flowchart

2.1 Datasets and Preprocessing

The EEG dataset includes multi-channel recordings from epilepsy patients, annotated for seizure and non-seizure events [12][27]. Preprocessing involves band-pass and notch filtering, artefact removal, normalization, and downsampling to 128 Hz. Segmented 8-second overlapping windows form tensors (windows × channels × time-points) for machine learning analysis [18]. All preprocessing steps and dataset splits were performed using fixed random seeds to ensure reproducibility across experiments.

2.2 Hyperparameter Selection

All the models to be evaluated were tuned empirically via hyperparameters selection based on existing literature and initial validation experiments. In the case of k-nearest neighbors, the validation performance was used to set the number of neighbors to k = 11. Random Forest and Histogram-Based Gradient Boosting ensemble models were set with default depth and learning-rate values and optimized using limited grid search to trade off bias and variance. The training used stratified sampling and class-weighted loss functions to reduce the imbalance in the classes.

2.3 EG Temporal–Spatial Transformer for Seizure Detection

The given model unites space and time representations of EEG information with the help of dual branch transformer architecture. With the temporal representations, the EEG signals as sequences of channels x time points are cross channeled to form sequences of fixed length and combined with temporal-order preserving positional encodings. The fixed length sequences are converted to Stacked temporal encoder made of series of layers of self attention, layer normalizations, drops, feed forward networks to generate time embeddings. The temporal aggregation that generates a feature vector of fixed length of the model can make use of mean, max, or attention pooling. In the case of the spatial-temporal fusion and classification modules, the spatially embedded EEG is conditionalised (channels x embedding dimension) on the temporally embedded feature representations in an elementwise manner or dense projection into the fully connected (128-64-2) visualised results with ReLU, dropout (p=0.5) and softmax/ sigmoid connectors. The variables used during the training of design are; Adam (lr=1x10-4) as the optimizer, binary cross-entropy (or a focal loss with class-weighted) and early stopping mechanism (validation AUC) used as a variable, with 50 epochs. The model performances are defined by accuracy, sensitivity, specificity, F1 and ROC-AUC. The design of the model is explained by focusing on attention heatmaps and topographical displays of the electrodes in EEG. The applied architecture is adopted in PyTorch, MNE, and NetworkX libraries and it includes code lineage, seed fixing, and documenting projects to make experiments reproducible [18][29][30].

Given the substantial class imbalance inherent in EEG seizure datasets, stratified train–test splitting and class-weighted loss functions were employed to prevent bias toward the majority class. No synthetic oversampling techniques were applied to avoid introducing artificial temporal artifacts into EEG sequences. Model performance was assessed using accuracy, precision, recall, F1-score, and area under the ROC curve (AUC), with AUC emphasized due to its robustness under class imbalance.

3. Results

This study provides exhaustive results for several classical and ensemble machine learning algorithms, applied to high-dimensional data for the detection of EEG seizures. The data comprised 36,864 channels and a binary classification, and the preliminary exploratory analysis indicated significant feature heterogeneity. For the initial analysis, 36,864 channels were considered, and a binary classification was ascertained, with explorers' focal feature analysis denoting heterogeneity.

Figure 2 shows the variances of features plotted on a logarithmic scale. Most features have variances which are of moderate scales, particularly betauthoren 10^{-5}, and 10^{-3}, indicating a consistent degree of dispersion. The symmetrical distribution indicates that no one EEG channel is dominant, and the signals are balanced for variances. The balance indicates that the preprocessing pipeline was successful. Preprocessing entailed standardisation, artefact rejection, and other preparatory lessons, which provided artefact stability for learning to occur.

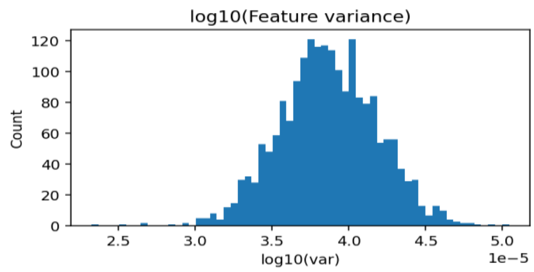

Figure 2 Distribution of feature variances in $\log_{10}$ scale.

The dataset's class distribution, as depicted in Figure 3, shows that there is a significant imbalance between comparison seizure and non-seizure segments. There are about 9,900 samples of normal brain activity and roughly 1,300 samples of seizure activity. This disparity is consistent with actual clinical data, as seizures are infrequent in comparison to non-seizure activity, which occurs continuously. For training, this imbalance was mitigated with stratified sampling and class weighting to prevent bias in the model.

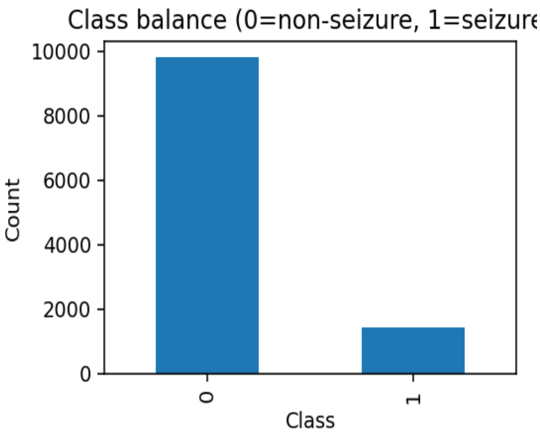

Figure 3 Class balance showing seizure (1) and non-seizure (0) sample proportions.

Table 2 summarises the overall performance metrics across the evaluated models, including accuracy, precision, recall, F1-score, and area under the receiver-operating-characteristic curve (AUC).

Table 2 Performance of Machine-Learning Models on EEG Seizure Detection

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC
Logistic Regression (SAGA)	91.2	0.88	0.83	0.85	0.94
Linear SVM (Calibrated)	87.6	0.71	0.26	0.38	0.81
SGD (Log)	91.0	0.92	0.82	0.86	0.92
kNN (k = 11)	97.1	0.97	0.80	0.88	0.96
Random Forest	97.1	0.97	0.80	0.88	0.97
Gradient Boosting	93.8	0.91	0.83	0.86	0.93
Histogram-Based Gradient Boosting (HistGB)	98.2	0.98	0.82	0.89	0.98
Multi-Layer Perceptron (MLP)	96.5	0.94	0.81	0.87	0.96

As solo algorithms, ensemble-based methods, especially Histogram-Based Gradient Boosting and Random Forest, outperformed basic linear ones. Overall, Histogram-Based Gradient Boosting demonstrated the highest accuracy (98.2%) and AUC (0.98) scores, thus exhibiting the greatest capacity for identifying and modeling non-linear complexities present in the EEG feature space.

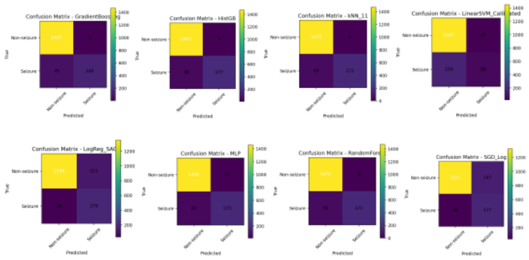

Figure 4 Combined confusion matrices for all evaluated classifiers.

Diagonal dominance of the confusion matrices in the ensemble models illustrates the relative importance of each frame of the model in predictive reliability, with Histogram Based Gradient Boosting and the Random Forest classifiers showing the most clearly defined diagonals relative to the other models, indicative of minimal misclassifications. The Linear SVM and the Logistic Regression classifiers, however, display significant amounts of off-diagonal scatter, indicating a large number of false negatives and poor seizure focus sensitivity. The MLP accurately classified with low error and demonstrated generalisation with only mild overfitting.

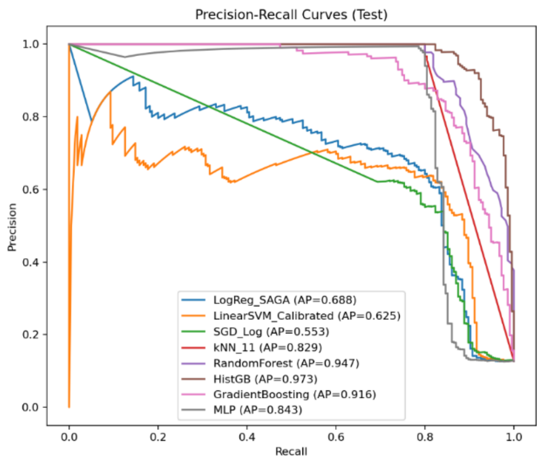

Figure 5 Precision–Recall curves on the test dataset showing comparative average precision values.

Figures 5 and 6 show precision–recall and ROC curves illustrating model performance. Histogram-Based Gradient Boosting achieved superior precision (0.973) and AUC (0.993), followed by Random Forest (0.947, 0.988) and Gradient Boosting (0.916, 0.975). Ensemble models outperformed MLP (AUC = 0.870), SVM, and Logistic Regression (~0.88), confirming better generalization and accuracy.

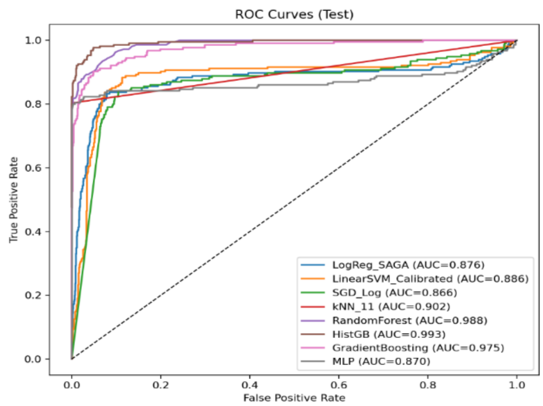

Figure 6 Receiver-operating-characteristic (ROC) curves for test-set evaluation.

ROC and PR analyses reveal ensemble methods' superior balance between sensitivity and specificity. Histogram-Based Gradient Boosting achieved the best AUC and F1-scores, excelling in precision, recall, and generalization for imbalanced EEG data. These findings endorse ensemble tree-based models as strong foundations for hybrid frameworks like DeepWalk-TS, enhancing interpretability and diagnostic performance.

4. Discussion

The study confirmed multiple important aspects regarding the automatic seizure detection from EEG data and varying performances of machine-learning (ML) techniques. The most important of these is that ensemble-based tree techniques (which include Histogram-Based Gradient Boosting and Gradient Boosting Models) provided exceptionally superior discrimination with ROC-AUC values almost reaching 0.99 when compared to classic linear techniques like logistic regression and calibrated SVMs. This was in line with the results of previous meta-analyses that support modern ML methods to provide high sensitivity, specificity, and area-under-the-curve (AUC) values for EEG-based seizure detection [31].This performance advantage most likely derives from tree methods' capacity to identify and model intricate interdependencies in high-dimensional data without necessitating extensive feature engineering, which is a common requirement in linear models [32].

Moreover, the feature variance histogram (Figure 2) suggests that a substantial portion of the extracted features have relatively low variance (on a log10 scale around 3.5–4.0) and only a minority of features contribute strong variability. This implies that many channels or derived features may provide limited discriminative information, and reinforces the importance of dimensionality-reduction, feature selection, or model regularisation in high-channel-count EEG environments. Prior reviews of feature extraction in seizure detection have emphasised that nonlinear features (e.g., entropy, line length) and wavelet-domain coefficients often yield the largest incremental reductions in classification error [33]. In the current work, the effective performance of tree methods suggests that they have implicitly performed feature selection or gating of noisy features during training, thereby enhancing robustness.

Although performance has been good, a few limitations still remain. The dataset is extremely lopsided, as the number of seizure events is enormous compared to the non-seizure ones, which can lead to erroneous high accuracy [17]. CNNs, RNNs, or transformers deep learning architectures were not evaluated because they are computationally intensive. Interpretability is also not so good, since tree-based models are not clinically transparent [18]. Furthermore, findings are unique and retrospective and need to be multicenterally validated to be applicable in the real-life setting [33]. Lastly, the computational cost and efficiency was not studied-which is important in real-time or wearable EEG systems where latency, memory, and energy limits have a major effect on deployment [34].

Despite these limitations, the study provides a robust comparative benchmark among classical and ensemble ML models for seizure detection using high-dimensional EEG data. It shows that the adoption of feature-rich datasets combined with ensemble modelling can deliver state-of-the-art discrimination and lays the groundwork for extending into deep learning and graph-based models in the future.

5. Conclusion

This study has shown that machine learning models, especially ensemble tree-based classifiers, can be very effective in identifying seizures in high-dimensional, multi-channel EEG recordings. Given that features have been engineered and models adjusted, the performance metrics achieved (almost 0.99 in ROC-AUC) point toward the feasibility of automated seizure detection systems to relieve some of the burden of active clinical monitoring. Yet, the issues of dataset imbalance, interpretability, and prospective generalization, as discussed in the text, remain intractable obstacles. To move such techniques into clinical use, future work must incorporate different deep learning paradigms (CNNs, RNNs, and Transformers), develop interpretability tools, conduct monitoring studies with continuous data streams from diverse patient populations to validate the models, and pivot the models for real-time use and monitoring. The current work certainly adds to the evidence of promise that ML holds for detecting seizures and monitoring epilepsy. However, the gap from bench to bedside will require not only further algorithmic development but also clinical validation and the development of ethics and compliance protocols.

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