Feature Engineering for Epileptic Seizure Classification Using SeqBoostNet

Najmusseher[1], Nizar Banu P K[2]

[1, 2] Department, of Computer Science, CHRIST (Deemed to be University)
Central Campus Bangalore-560029, India
E-mail address: najmusseher@res.christuniversity.in, nizar.banu@christuniversity.in

Abstract: Epileptic seizure, a severe neurological condition, profoundly impacts patient's social lives, necessitating precise diagnosis for classification and prediction. This research addresses the critical gap in automated seizure detection for epilepsy patients, aiming to improve diagnostic accuracy and prediction capabilities through Artificial Intelligence driven analysis of Electroencephalography (EEG) signals. The system employs innovative feature combination such as spectral and temporal features, combining Uniform Manifold Approximation and Projection (UMAP) with Fast Fourier Transformation (FFT), and a classification technique called Sequential Boosting Network (SeqBoostNet). SeqBoostNet is a groundbreaking stacked model that integrates machine learning (ML) and deep learning (DL) approaches, leveraging the strengths of both methodologies to swiftly differentiate seizure onsets, events, and healthy brain activity. The method's efficacy is validated on benchmark datasets such as BONN from the UCI repository and real-time data BEED from the Bangalore EEG Epilepsy Dataset, achieving remarkable accuracy rates of 98.40% for BONN and 99.66% for BEED datasets. The practical significance of this study lies in its potential to transform epilepsy care by providing a precise automated seizure detection system, ultimately enhancing diagnostic accuracy and patient outcomes. Furthermore, it underscores the importance of integrating advanced AI techniques with EEG analysis for more effective neurological diagnostics and treatment strategies.

Keywords: Epileptic Seizure, UMAP, Machine Learning, Deep Learning, FFT, LSTM, AdaBoost

1. Introduction

In recent years, epilepsy has become a focal point of research due to its lack of cure. Researchers are leveraging Artificial Intelligence to predict seizures more accurately by refining data collection methods and utilizing past and present data for predictive modeling [43]. Seizures represent a common occurrence in individuals with epilepsy, a neurological disorder characterized by bursts of uncontrolled electrical activity among nerve cells. This phenomenon leads to temporary abnormalities and alterations in behavior. Patients afflicted by this condition have access to both medical and surgical treatments.

Unfortunately, for significant portion of individuals experiencing recurring seizures, traditional medical and surgical interventions are insufficient to manage their condition, even when they have already experienced seizures. Consequently, accurately predicting future seizures becomes of paramount significance, enabling timely preventive medication to avert their occurrence [1].

Epileptic seizures result from disruptions in the brain's electrical activity, which are categorized as Focal, Generalized, or of Unknown, which affects around 1% of the global population [2] [3]. Focal seizures initiate on one side of the brain and are further classified based on the patient's level of awareness during the seizure, distinguishing between simple partial and complex partial seizures [4][5].

Generalized seizure takes place when the irregular electrical activity triggering a seizure initiates simultaneously in both hemispheres of the brain [6]. Generalized seizures are further categorized by motor and non-motor symptoms that involve movement [7]. Unknown seizures occur when the onset and origin of the seizure are unclear [8][9]. Individuals living with epilepsy experience the profound personal burden of recurrent seizures, affecting their ability to lead a normal social life [10].

Uncontrolled seizures can even result in sudden unexpected death, making epilepsy diagnosis a significant challenge [11]. EEG involves the recording of electrical brain activity, a valuable tool in the diagnosis of brain seizure disorders [12] [13]. During an EEG examination, a computer screen visualizes these electrical signals as wavy lines, which represent a record of brain activity. Electrodes are positioned on various regions of the brain to capture signals, and each channel corresponds to a pair of electrodes, with a signal being the data obtained from that channel. The 10-20 International System is a standardized method for electrode placement in EEG [14].

Neurologists still rely on manual analysis of EEG signals and lengthy video monitoring, which requires multi-day recordings, posing a laborious task. EEG signals resulting from seizures exhibit distinctive patterns that differentiate them from signals caused by other factors. These patterns often include high amplitude repetitive activities characterized by a combination of slow and spike waves [15]. Hence, recognizing these attributes poses a demanding task, and the observation of each EEG signal is both laborious and time consuming [16]. Automatic detection methods are vital for helping neurologists diagnose accurately. These systems could save neurologists from spending hours reviewing EEG records manually. Despite ongoing research efforts, many neurologists continue to rely on manual diagnosis, reflecting their lack of confidence in computerized methods. While achieving perfect seizure detection, prediction may remain an aspiration. Hence, the primary objective of this research work is to develop the most accurate and an efficient model possible.

This research study strives to create a method that ensures an accurate seizure detection and prediction by utilizing the spectral and temporal features and classification technique. In this research we have introduces feature engineering such as combination of spectral and temporal features of EEG signals and stacked classification model for an accurate seizure detection and prediction. The first approach addresses the challenges of intricate features and information preservation by employing both spectral and temporal data transformations, integrating FFT for spectral features and applying UMAP on time series data for temporal features to enhance feature learning and prediction efficiency. In the second approach, a Stacked model called SeqBoostNet is employed, combining ML and DL techniques to overcome diminished accuracy issues in multivariate data and to support binary and multiclass classification for accurate seizure detection. Epileptic Seizure detection and prediction are persistently challenging research domains, and this work represents a dedicated effort to advance the current boundaries of knowledge in this field. The research conducted in this study significantly contributes to several key areas. Firstly, it advances EEG based seizure classification through the introduction of an innovative features, integrating spectral and temporal nothing but time and frequency domain features. This comprehensive approach provides a deeper understanding of brain activity, crucial for accurate seizure detection and prediction. Secondly, the study optimizes classification efficiency and accuracy with a sophisticated stacking model, combining LSTM and gradient boosting models.

This tailored model not only improves computational method's performance but also sets a new standard in seizure classification. Lastly, by offering innovative methods, the research broadens the horizons of computational neuroscience. These methods, adaptable beyond epilepsy research, hold promise for diverse neurological data analysis tasks, potentially revolutionizing our understanding of the brain and related disorders.

Key Significance of the proposed work are as follows:

- The research offers concrete advantages to individuals with epilepsy by providing more dependable seizure detection and prediction. This has the potential to substantially improve the quality of life for epilepsy patients, alleviating daily challenges and anxieties through reduced uncertainty and better preparedness for seizures.
- The innovative approach of this study is combining spectral and temporal domain features with stacking model, has broader implications beyond epilepsy. It catalyzes advancements in EEG analysis techniques applicable to various neurological and medical applications, representing a paradigm shift in approaching the analysis of complex biological data.
- Stacking amalgamates predictions from various base models using a meta model, capitalizing on diverse algorithm strengths to boost overall performance, crucially optimizing classification tasks such as EEG data analysis for enhanced insights and diagnostic accuracy through aggregated modeling.
- This research establishes a new standard for seizure classification accuracy, offering a reliable reference for researchers, practitioners, and clinicians, potentially reshaping seizure detection and prediction methods.
- Furthermore, it advances computational neuroscience by expanding the possibilities in understanding and diagnosing neurological disorders, potentially inspiring future research and innovation in unraveling the complexities of the brain.

The manuscript's organization is structured as follows: In Section 2, related work is presented, focusing on the utilization of EEG data for classifying epileptic seizures. Section 3 offers a comprehensive overview of dataset preparation and discusses the proposed methodology. Section 4 presents the proposed method results and discussions. Lastly, Section 5 concludes with final remarks and outlines the future scope of the research.

2. RELATED WORK

Various machine learning and deep learning methods have been applied to automatize the diagnosis of epilepsy. Below, we provide a few instances of relevant studies in this field.

Tzimourta et al. [17] presents a method for automated seizure detection in EEG signals, using the Discrete Wavelet Transform (DWT) and the Random Forest classifier to achieve a classification accuracy exceeding 95%. Nevertheless, the method's dependence on this specific DWT and Random Forest combination could limit its adaptability to different classification algorithms or signal processing methods. Furthermore, characteristics of the data and computational time for processing is not provided in the study.

Gao et al. [18] presents a method for distinguishing multichannel EEG's for health control and identifying interictal and ictal EEG's in epileptic patients. The approach relies on five features Variance, Pearson correlation coefficient, Hoeffding's D measure, Shannon entropy, and inter-quartile range, all derived from the maximal overlap discrete wavelet transform, are calculated and employed in linear discriminant analysis for the purpose of classification, achieving a high accuracy of 94.33% in distinguishing interictal EEG data from normal EEG recordings, underscoring its efficacy in EEG signal differentiation. However, the study has limitations, as it was tested on a single clinical dataset, and its generalizability to larger databases is unverified.

Mardini et al. [19] suggests a framework to detects epileptic seizures in EEG signals using 54-DWT wavelets and machine learning (SVM, KNN, ANN, NB). The ANN classifier achieves a high 97.82% accuracy across diverse datasets. The process includes EEG preprocessing, DWT-based feature extraction, genetic algorithm feature selection, and classification. However, limitations involve dataset diversity, sensitivity in feature selection, and the absence of deep learning exploration for complex EEG signal analysis.

Kumar et al. [20] conducted research focused on automating the detection of epileptic seizures in EEG signals. Their approach integrates the fractional S-transform (FST) and entropic features with deep convolutional neural networks (CNN) for classification. They first preprocess the EEG signals using discrete wavelet transform (DWT) with Db4 wavelets. The outcomes indicate strong performance, achieving a specificity of 98.70%, sensitivity of 97.71%, and an accuracy of 99.70% for multichannel EEG segments. However, the study's reliance on the Bonn EEG dataset from 21 patients raises questions about its applicability to a broader range of epilepsy cases. The model's adaptability to larger and more diverse EEG datasets remains untested.

Islam et al. [21] presented a study "Epileptic-Net", a deep learning model created to identify epileptic seizures using EEG data. The model incorporates elements like dense convolutional blocks (DCB), feature attention modules (FAM), residual blocks (RB), and the hyper column technique (HT) to efficiently extract crucial information from EEG samples. In evaluations conducted on the University of Bonn EEG dataset, Epileptic-Net exhibits remarkable accuracy, outperforming existing seizure detection models. This innovation is anticipated to enhance diagnostic precision, support medical professionals, and reduce misdiagnosis rates. Nonetheless, the research acknowledges certain limitations related to data augmentation, indicating a marginal reduction in performance when not employed.

Hassan et al. [22] presented a study that integrates convolutional neural networks (CNN) with machine learning classifiers to automatically detect epileptic seizures using EEG data. This approach aims to efficiently and effectively analyze complex EEG signals by pre-processing the data and extracting features with CNN. The use of mutual information based estimators helps improve classification accuracy. The results indicate high accuracy across various classification scenarios, showcasing the model's promise for seizure prediction. However, the study does not investigate the adaptability of the approach to diverse EEG datasets from different sources and patient groups, which may constrain its broader applicability.

In contrast to certain previously discussed research studies, our proposed work effectively addresses their limitations by incorporating a comprehensive multivariate dataset, thus mitigating issues like the absence of real-time data and small sample sizes. Our research systematically tackles gaps in the domains of spectral-temporal analysis, computational efficiency, multivariate data handling, and robust feature selection. This multifaceted approach yields substantial advantages, including enhanced support for clinical decision-making, real-time seizure prediction, and increased applicability to a wide array of EEG datasets, consequently amplifying its significance within the realm of epilepsy diagnosis and treatment.

The research serves as a noteworthy contribution to the field of epileptic seizure classification. It introduces innovative feature combination techniques, notably the integration of the UMAP and FFT method, which significantly improves spectral and temporal analysis, resulting in a more effective capture of dynamic seizure aspects. Efficiency and generalization are key focuses of the study, addressing common computational challenges that frequently hinder the performance of existing models, ultimately facilitating robust classification suitable for real-time applications. Furthermore, the research extends its influence by accommodating diverse types of seizure data, thus ensuring its suitability for a broad spectrum of epilepsy cases. Additionally, the model employs advanced feature engineering methodologies grounded in mutual information, consequently leading to heightened classification accuracy and the successful mitigation of limitations previously encountered in similar studies.

3. METHODOLOGY

This section outlines our research framework for EEG signal analysis, focusing on seizure classification (Focal, Generalized, and healthy episodes). The framework consists of three stages: Data Acquisition, Preprocessing, Spectral and Temporal features and Classification illustrated in Figure 1.

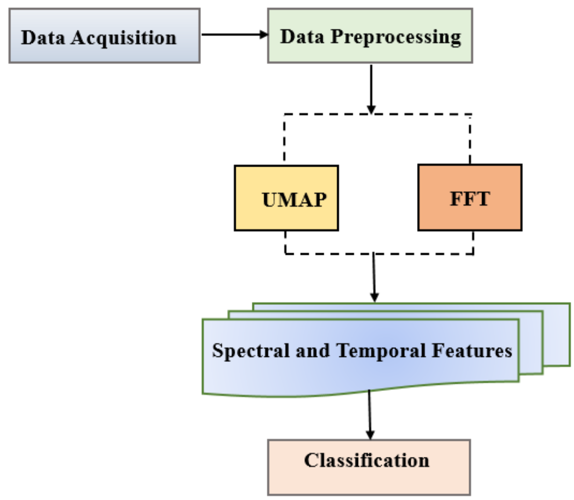

Figure 1. Proposed Framework

After acquiring data, we perform data preprocessing to enhance signal quality. Next, we use FFT and UMAP for extracting spectral and temporal features, respectively. These extracted features are then amalgamated into a feature set, which is subsequently fed into the classification model for further analysis. For classification, we introduce SeqBoostNet, a novel stacked learning model. Further details on these techniques are provided in subsequent sections.

A. *Data Acquisition*

EEG data acquisition involves collecting electrical brain activity using electrodes placed on the scalp. During EEG data acquisition, electrodes are positioned on the scalp following a standardized system like the International 10-20 placement, secured with a conductive gel for optimal electrical connectivity. The EEG signals are then recorded over varying time spans, from minutes to days, depending on research or clinical goals. The collected EEG data is digitally stored for subsequent analysis, leveraging modern digital storage systems for more efficient processing and examination. In this study, two distinct datasets were employed. The first dataset comprises the benchmark dataset BONN data obtained from the UCI repository, while the second dataset consists of real-time data obtained from BEED.

1) BEED EEG Dataset: The Bangalore EEG Epilepsy Dataset (BEED) was collected from an EEG clinic in Bangalore.

TABLE I. BEED DATASET DESCRIPTION

Dataset	Description
Seizure Events	Seizure recording during physical movement
Healthy subject	Recordings from seizure free participants
Generalized	Seizure recording in both brain hemisphere
Focal	Seizure recording in specific brain area

Which containing raw waveform signals from 16 EEG channels with a sampling rate of 256 Hz. The dataset is categorized into four distinct types, detailed in Table I, each lasting 20 seconds. These recordings adhere to the internationally recognized 10–20 electrode placement method and encompass EEG data of seizure onsets, seizure events, and data from healthy individuals for comparison.

2) BONN EEG Dataset: The BONN dataset, sourced from BONN University in Germany and archived in the UCI repository, comprises five subsets, each containing 100 individual channel recordings from 500 subjects. These recordings, lasting 23.6 seconds each, were sampled at 173.61 Hz, enabling frequency analysis spanning 0.53 to 40 Hz. Collected via the international 10-20 electrode placement technique, the dataset comprises 11,500 rows and 179 columns. The final column serves as class labels, categorized into five distinct groups: 1 denotes seizure activity recordings, 2 indicates tumor location recordings, 3 represents healthy brain recordings, while 4 and 5 signify recordings with eyes closed and opened, respectively [44].

B. *Data Preprocessing*

The proposed model aims to distinguish epileptic seizure onsets, seizure events, and healthy states through innovative features and classification techniques tailored for EEG signals. Initial preprocessing involves Exploratory Data Analysis (EDA) and data standardization, pivotal for understanding EEG data attributes, identifying anomalies, and enhancing data quality. EDA facilitates informed decisions on feature extraction and model selection, enhancing overall model performance [25]. Data standardization ensures consistent scales across EEG channels and subjects, aiding in clearer interpretation of features and model coefficients [26]. This preprocessing approach is crucial for constructing a precise and resilient EEG data classification model.

C. *Temporal Features using UMAP*

Temporal features extracted from time series EEG data, particularly by applying UMAP, are pivotal for comprehending brain activity's dynamic nature. These features reveal patterns and variations in brain signals across different time points, encompassing crucial aspects such as temporal dynamics, and temporal connectivity patterns. They illuminate how brain activity evolves over time, offering insights into cognitive processes like attention, memory, and perception, while also aiding in the identification of neurological disorders, monitoring disease progression, and enhancing Brain-Computer Interfaces (BCI's). Overall, these temporal features provide a comprehensive understanding of brain function and dysfunction, driving advancements in neuroscience research and clinical applications.

UMAP is a powerful technique that reduces data dimensionality while maintaining its structural integrity, making it ideal for tasks like visualization and clustering. It combines manifold learning and topological data analysis methods to capture intricate patterns in complex datasets. The process involves constructing a nearest neighbor graph, computing fuzzy set memberships, optimizing the UMAP objective function through gradient descent, and generating low-dimensional embeddings for visualization and analysis [27]. UMAP is a method used to simplify complex data so we can understand it better. It does this through four main steps. First, it looks at each data point's closest neighbors to see how they relate locally. Then, it determines how each point is connected to others in the data using a fuzzy set. After that, it adjusts the data to create a clearer picture called gradient descent. Finally, it puts all this together to show the data in a simpler way that we can easily visualize and analyze. The equations (1), (2), and (3) provides the mathematical details for each step, helping us understand how UMAP works.

Fuzzy Set Membership Function (Fuzzifier)

$$\boldsymbol{\phi(d_{ij}, \sigma_i) = exp\left(-\frac{d_{ij}^2}{(2 * \sigma_i^2)}\right)} \qquad \textbf{\textit{(1)}}$$

Fuzzy Simplicial Set

$$\boldsymbol{S_{ij} = \phi(d_{ij}, \sigma_i) * \phi(d_{ij}, \sigma_j) * Mutual\_knn(i, j)} \quad \textbf{\textit{(2)}}$$

Objective Function

$$\boldsymbol{L = \sum(i)\sum(j) S_{ij} * log(S_{ij} \backslash Q_{ij})} \qquad \textbf{\textit{(3)}}$$

Where; Equation (1) computes the similarity between two data points, where *'i'* and *'j'* represent the row indices in the input EEG data, and 'd_{ij}' signifies the Euclidean distance between these data points. Equation (2) constructs a fuzzy simplicial set and Equation (3) defines objective function, with the following key parameters. Where, 'σ_i' A scaling parameter determining the influence of distance on the similarity for data point, *'i'*. Notably, smaller distances and larger 'σ_i' values yield higher similarity, 'S_{ij}' is the pairwise similarity between data points *'i'* and *'j'* in the high-dimensional space incorporating the fuzzy set membership function, distance, and mutual k-nearest neighbors, *'Mutual_knn (i, j)'* is a function checking whether *'i'* and *'j'* are mutual k-nearest neighbors considering their proximity in the EEG data and 'Q_{ij}' is the pairwise similarity in the low-dimensional space, representing the optimization target sought by UMAP during the dimensionality reduction process. 'S_{ij}' is the value in a specific position *(i, j)* in a matrix, often representing a probability or frequency and 'Q_{ij}' is the corresponding value in a specific position *(i, j)* in another matrix, used for comparison with 'S_{ij}'.

The Fuzzy Set Membership Function helps to find similarities between data points, the Fuzzy Simplicial Set creates a graph, and the Objective Function guides the optimization process for effective simplification. UMAP reduces the dimensions of EEG data while keeping its essential relationships intact. Figures [2] and [3] shows visual representations of the transformed BEED and BONN data, illustrating the outcomes for three embedding dimensions, respectively.

In this study, UMAP uses equations (1), (2), and (3) to simplify and condense high-dimensional EEG data. The original data, with dimensions 4000*16 for BEED and 4600*178 for BONN, gets transformed into lower-dimensional representations and forms temporal features, 4000*3 for BEED and 4600*3 for BONN in time domain. This transformation maintains the important structures in the data.

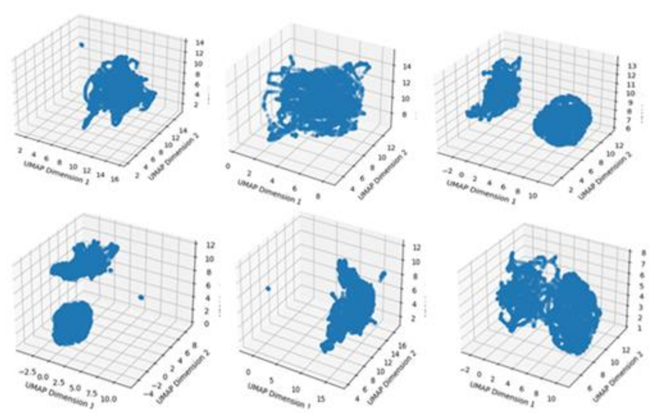

Figure 2. UMAP Visualization for BEED Data

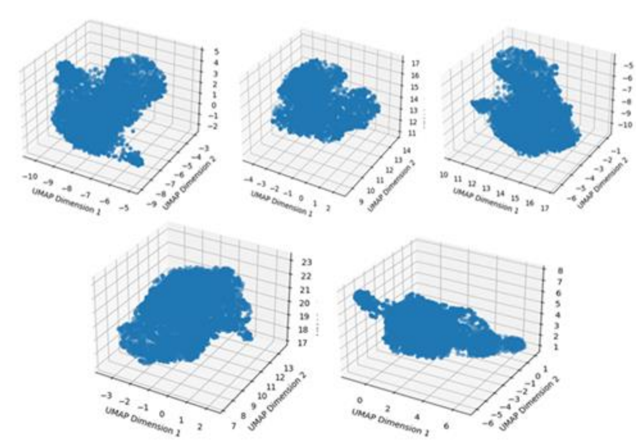

Figure 3. UMAP Visualization for BONN Data

D. Spectral Features using FFT

Spectral features extracted using Fast Fourier Transform (FFT) from EEG data plays a crucial role in understanding brain activity's frequency components.

FFT analyzes EEG signals in the frequency domain, revealing important information about brain rhythms such as delta, theta, alpha, beta, and gamma waves. These spectral features provide insights into various cognitive processes, neurological conditions, and states of consciousness. The FFT is a computational method widely used in signal processing to analyze the frequency components present in a time-domain signal. It effectively calculates the Discrete Fourier Transform (DFT) of a signal, allowing for the transformation of the signal from the time domain to the frequency domain [28].

In the realm of EEG data analysis, the FFT is notably beneficial, assisting in understanding the temporal evolution of the frequency distribution of brainwave activity [29]. The initial data from BEED, sized 4000*16, and BONN, sized 4600*178, undergo transformation through FFT into spectral features, maintaining the dimensions of 4000*16 for BEED and 4600*178 for BONN in the frequency domain. This process integrates the spectral features with the existing temporal features, resulting in combined features known as spectral and temporal features, with dimensions of 4000*19 for BEED and 4600*181 for BONN, respectively. Figure [4] and [5] depicts the frequency response spectrum representation of Generalized and Focal seizure signals using BEED data, seizure and healthy signals for BONN and data. Equation (4) provides the mathematical expression for the FFT.

$$X_K \sum_{\eta=0}^{n-1} x_j e^{\frac{-2\pi i_{jk}}{N}} \qquad \textbf{\textit{(4)}}$$

Where; X_K —represent input signal in frequency domain, *n* represents the number of samples in the input signal, *j* represents the value of the signal at specific feature index, *N* represents the total number of samples in the input signal, *I* represents the imaginary unit, which is √ (-1), *k*—represents the index for the frequency bins ranges from 0 to N-1 and $e^{\frac{-2\pi i_{jk}}{N}}$ --represents the phase shift introduced by *K* and *j*.

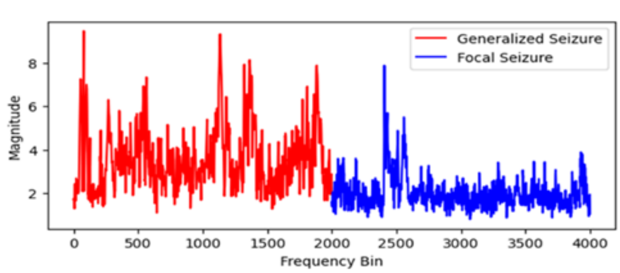

Figure 4. Frequency Response Spectrum for BEED Data

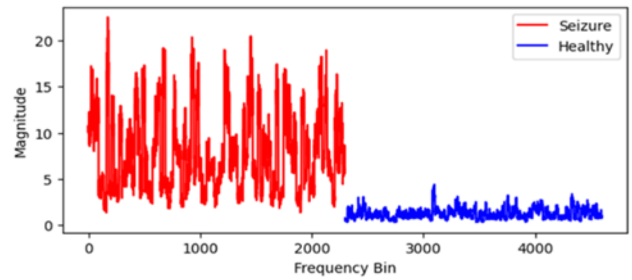

Figure 5. Frequency Response Spectrum for BONN Data

E. Sequential Boosting Network (SeqBoostNet) Classification

After assembling the spectral and temporal feature sets, the data proceeds to the classification stage. EEG classification entails sorting EEG signals according to their distinctive features, encompassing the identification of neurological events (e.g., seizures), cognitive states (e.g., attention or drowsiness), and patterns associated with mental and neurological conditions. Traditional machine learning (ML) approaches for binary and multiclass classification didn't yield significant accuracy. Therefore, we propose a novel classification method employing a stacking model, which combines ML and deep learning (DL) approaches for more robust classification results.

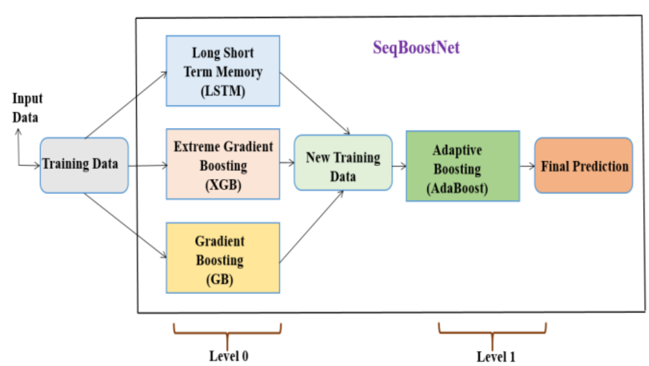

Figure 6. Sequential Boosting Network Architecture

SeqBoostNet is a classification model that employs stacking ensemble learning to improve predictive performance by combining multiple base models. This method involves training a meta learner, also known as a blender, to effectively merge predictions from these base models. The Stacking algorithm consists of two stages: in the first stage (level 0), base models like LSTM, XGB, and GB are trained individually to predict target class labels. In the second stage (level 1), the meta model synthesizes these predictions to generate the final prediction. SeqBoostNet combines predictions from diverse machine learning models using AdaBoost to construct a meta-model, thus leveraging the strengths of different base models to enhance predictive accuracy. This technique effectively captures complex patterns and improves performance across various classification scenarios. Figure 6, illustrates the SeqBoostNet architecture used in this research study.

1) LSTM (Long Short-Term Memory): A type of recurrent neural network known for handling sequential data, advantageous for capturing long-term dependencies, but computationally intensive and prone to vanishing gradient problems [31]. The LSTM network processes EEG data as sequential input, analyzing time series data from EEG recordings. The data contains 19 columns per row in BEED and 181 columns per row in BONN, with each row representing a sequence of readings over time. The LSTM architecture includes a forget gate, input gate, candidate cell state, and an output gate.

$$f_t = \sigma\left(w_f \,.\, [h_{t-1}, x_t] + b_f\right) \qquad (5)$$

Equation (5) provides the mathematical expression for forget gate.

Forget Gate calculates a decision on which information to retain or forget from the previous cell state using the sigmoid activation function. This gate decides how much information from the previous state should be kept. Where; f_t is the output of the forget gate at time step t, σ is the sigmoid function mapping input values to a range of 0-1, W_f is the weight matrix for the forget gate, h_{t-1}, x_t represents concatenation of previous hidden state and current input.

$$i_t = \sigma(w_i \,.\, [h_{t-1}, x_t] + b_i) \qquad (6)$$

Input Gate determines what new information should be added to the cell state using the sigmoid function. Equation (6) represents expression for input gate. It controls how much new information from the current input is allowed into the cell state. Where; i_t is the output of the input gate at time step t, W_i is the weight matrix for the input gate and b_i is Bias term for the input gate.

$$C_t = tanh(w_c \,.\, [h_{t-1}, x_t] + b_c) \qquad (7)$$

Candidate Cell State helps to updates the cell state in an LSTM network using the hyperbolic tangent function, which maps input values to a range between -1 and 1. Equation (7) represents candidate cell state. It allows the model to consider both past and present information. Where; C_t is candidate cell state at time step, tanh is hyperbolic tangent function mapping input values to a range of -1 to 1, W_c is the weight matrix for the candidate cell state and b_c is the bias term for the candidate cell state.

$$C_t = (f_t \,.\, C_{t-1} + i_t \,.\tilde{}C_t) \qquad (8)$$

Updating cell state combines the previous cell state and new information from the input gate and candidate cell state to update the current cell state. Equation (8) provides the expression for candidate cell state update. Where; C_t is the updated cell state at time step t, C_{t-1} Previous cell state at time step t-1, ~c_t candidate cell state at time step t.

$$O_t = \sigma(w_0 \,.\, [h_{t-1}, x_t] + b_0) \quad (9)$$

Output Gate Regulates the amount of current cell state used to calculate the current hidden state and output. It uses the sigmoid function to map the input values to a range between 0 and 1. Equation (9) represents the expression for output gate. Where; O_t is the output gate value at time step t, W_0 is the weight matrix for the output gate, b_0 is the bias term for the output gate.

$$h_t = O_t \,.\, tanh(C_t) \qquad (10)$$

Hidden state Calculated by multiplying the output gate value by the hyperbolic tangent of the current cell state. This determines how much information from the current cell state should pass to the hidden state. Equation (10) represents hidden state computation. Where; h_t is the hidden state at time step t, $tanh(C_t)$ is the hyperbolic tangent of the current cell state and O_t is the output gate value at time step t.

In this way, the LSTM processes the input sequentially, incorporating new information and retaining useful past information to manage and predict time series data effectively.

2) XGBoost (Extreme Gradient Boosting): A powerful gradient boosting algorithm with regularization, advantageous for high predictive accuracy, but may require tuning of hyperparameters and can be sensitive to overfitting [32]. XGBoost is an ensemble learning method that uses gradient boosting to build a strong predictive model by combining multiple weak models. It constructs a series of decision trees to model non-linear relationships in the input data. It consists of loss function and regularization. Equation (11) and (12) represents the mathematical expression for loss function and regularization.

$$L = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{k} \Omega(f_k) \qquad (11)$$

The loss function minimizes the error between actual and predicted labels. Where; y_i is the actual label of the i^{th} sample, $\hat{y}_i$ is the predicted label for the i^{th} sample, $l(y_i, \hat{y}_i)$ is the loss function that measures the difference between actual and predicted labels, $\Omega(f_k)$ is the regularization term that controls the complexity of the decision trees.

$$\boldsymbol{\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2} \quad \textit{(12)}$$

Regularization helps to controls model complexity and overfitting. Where; T is the tree, w_j is the leaf weights and γ and λ are regularization parameters.

*3) **Gradient Boosting (GradientBoost):*** An ensemble learning technique that builds trees sequentially, advantageous for handling heterogeneous data and robustness to outliers, but slower training time compared to other algorithms [33]. Gradient boosting is similar to XGBoost in that it builds a strong predictive model by combining weak models (typically decision trees). The model iteratively refines it's predictions based on the residual errors from the previous models. The model is updated iteratively by adding new decision trees to correct the errors from the previous iteration and α is the learning rate, controlling how much each tree influences the final prediction. Equation (13) and (14) represents mathematical expressions for loss functionand regularization.

$$\boldsymbol{F_m(x) = F_{m-1}(x) + \alpha h_m(x)} \quad \textit{(13)}$$

Loss Function measures the loss or error of the model's predictions and adjusts the model based on the residuals.

$$\boldsymbol{l(y, \hat{y}) = l\left(y, F_{m-1}(x) + \alpha h_m(x)\right)} \quad \textit{(14)}$$

In both XGBoost and gradient boosting, the model leverage the input data and iteratively improve predictions through adjustments based on errors. Regularization controls complexity to avoid overfitting.

*4) **AdaBoost (Adaptive Boosting):*** AdaBoost offers a multitude of advantages and tends to achieve higher accuracy compared to alternative supervised machine learning algorithms [42]. An ensemble learning method that combines weak learners to create a strong learner, advantageous for reducing bias and variance, but sensitive to noisy data and outliers [34]. AdaBoost takes the predictions from the three base models (LSTM, XGBoost, and Gradient Boosting) as input. It is computed using weigthed loss, classifier weight, weight update and final prediction represented in Equation [15-18] . Where; ω_i^{t-1} is the weight assigned to the i[th] sample in the previous iteration, $l\left(y_i, h_t(x_i)\right)$ is the loss function (e.g., log loss) for the i[th] sample, given its actual label y_i and $h_t(x_i), err_t$ is the weighted error rate of the base model at iteration *t*, w_i^t is the updated weight of the i[th] sample for the next iteration and *H(x)* is the final prediction, which is the weighted sum of the base model predictions across iterations. In each of the models, the equations process the input data (features and labels) to calculate the loss function and adjust the model's parameters accordingly.

Weighted loss

$$\boldsymbol{L_t = \sum_{i=1}^{n} \omega_i^{t-1} l\left(y_i, h_t(x_i)\right)} \quad \textit{(15)}$$

Classifier Weight

$$\boldsymbol{\alpha_t = \frac{1}{2} log\left(\frac{1-err_t}{err_t}\right)} \quad \textit{(16)}$$

Weight Update

$$\boldsymbol{w_i^t = w_i^t - 1. exp\left(-\alpha_t . y_i . h_t(x_i)\right)} \quad \textit{(17)}$$

Final Prediction

$$\boldsymbol{H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)} \quad \textit{(18)}$$

In the stacking classification framework, the base models LSTM, XGB, and GB are utilized. The input feature set, comprising spectral and temporal features, is fed into the SeqBoostNet classification model. Here, LSTM, XGB, and Gradient Boost generate their respective predictions, which are subsequently forwarded to the meta model AdaBoost for the final prediction process. In this stacking model LSTM is recognized for its ability to capture temporal dependencies within sequential data like EEG signals, which aids in achieving accurate classification results. XGBoost, on the other hand, provides robustness and high predictive accuracy specifically tailored for EEG data classification tasks, making it well suited for handling intricate and diverse feature sets. Gradient Boosting showcases resilience to outliers and noise present in EEG data, contributing to consistent classification performance. Lastly, AdaBoost proves effective in enhancing the classification performance of EEG data by amalgamating multiple weak learners, thereby mitigating bias and variance in the predictions.

The SeqBoostNet model, tailored for seizure detection using BEED and BONN datasets, capitalizes on the amalgamation of LSTM, XGBoost, and Gradient Boost as base models, augmented by AdaBoost as the meta model. The BEED dataset encompasses 4000 samples characterized by 19 features, while the BONN dataset comprises 4600 samples with 181 features. Both datasets exhibit classification, distinguishing between seizures (1) and healthy instances (0) and other case scenarios as well.

Initiating with data normalization and partitioning into training and testing sets. Subsequently, individual base model LSTM, XGBoost, and Gradient Boost are trained independently on the training data. Through this process, each base model generates probabilistic predictions (Y^{LSTM}, Y^{XGB} *and* Y^{GB}) for the target classes.

The next phase involves constructing the input matrix for the meta-model AdaBoost. By concatenating the predictions from the base models, S_{META} is formed, where each row represents a sample, and each column signifies the predicted probabilities for each class. Hence, S_{META} assumes dimensions (4000*(3*2) for the BEED data and (4600*(3*2) for the BONN data, owing to the binary classification nature (2 classes).

Following this, the AdaBoost meta-model is trained and the corresponding target labels y. AdaBoost iteratively amalgamates predictions from the base models, refining its ensemble to enhance classification accuracy. Once the training concludes, the SeqBoostNet model is fully primed for inference.

During prediction, new input data undergoes processing by the base models to yield predictions, which are subsequently concatenated to form meta model features. The AdaBoost meta model then employs this meta features to predict the final class labels $Y_{pred.}$

In essence, SeqBoostNet leverages an ensemble of diverse base models to discern intricate patterns in BEED and BONN datasets, culminating in robust seizure detection capabilities. By harnessing the collective intelligence of individual models through meta model, SeqBoostNet delivers heightened accuracy and reliability in classifying seizures against healthy instances, thereby fostering advancements in epilepsy diagnosis and treatment.

The hyperparameter configurations plays a crucial role in shaping the behavior and efficacy of the SeqBoostNet model in this research study. Specifically, for the LSTM model, 128 LSTM cells are employed with ReLU activation, accompanied by a dropout rate of 0.5 to mitigate overfitting. The output layer utilizes Sigmoid activation, Adam optimization, Sparse Categorical Cross-Entropy loss, and is trained over 100 epochs with a batch size of 32. In the case of the XGBoost model, 300 estimators are utilized with a maximum depth of 6 and a learning rate of 0.05, while employing the Multi-Softmax objective. The Gradient Boosting model is configured with 100 estimators, a learning rate of 0.1, and a maximum tree depth of 3. Additionally, the AdaBoost meta-model integrates 50 weak learners with a learning rate of 1.0, dynamically adjusting based on the performance of the LSTM, XGBoost, and Gradient Boosting models. These Hyperparameters govern the learning and prediction processes of each model, collectively influencing their individual and collaborative performance within this research context.

Inferences of SeqBoostNet are as follows:

- Combining different models can improve overall prediction accuracy.
- Each base model offers a different approach, providing varied insights.
- Mixing models can help avoid overfitting and improve generalization.
- The meta-model integrates predictions to create a more reliable final outcome.
- Allows easy inclusion of additional models or modifications to existing ones.
- The meta-model weighs the base model predictions for better accuracy.
- Different models capture unique aspects of the data, such as temporal patterns and feature relationships.
- The stacked approach leverages complementary strengths for comprehensive learning.

F. Performance Evaluation Measures

TABLE II.PERFORMANCE EVALUATION METRICS FORMULA

Sl.NO	Metric	Formula
1	Accuracy (A)	$\frac{TS+TH}{TP}$
2	Precision (P)	$\frac{TS}{TS+FS}$
3	Recall (R)	$\frac{TS}{TS+FH}$
4	F1-Score (F1)	$\frac{2*P*R}{P+R}$
5	Kappa (K)	$\frac{A-CA}{1-CA}$
6	Chance agreement (CA)	$\frac{TS(\mathrm{TS}+\mathrm{FS})*(\mathrm{TS}+\mathrm{FH})+(\mathrm{TH}+\mathrm{FS})*(\mathrm{TH}+\mathrm{FH})}{TP^2}$
7	MCC	$\frac{(TS*TH-FS*FH)}{\sqrt{((\mathrm{TS}+\mathrm{FS})*(\mathrm{TS}+\mathrm{FH})*(\mathrm{TH}+\mathrm{FS})*(\mathrm{TH}+\mathrm{FH}))N}}$
8	F2-Score (F2)	$\frac{5*P*R}{4*P*R}$
9	Sensitivity	$\frac{TS}{TS+FH}$
10	Specificity	$\frac{TH}{TH+FS}$
11	Log loss	$-\left[\frac{1}{N}\right]\sum_{I=1}^{N}(y_i\log(p_i)+(1-y_i)\log(1-p_i))$

Performance evaluation measures assess model's effectiveness in various fields like machine learning, statistics, and information technology. These metrics gauge how well a model accomplishes its objectives [35].

Various performance evaluation metrics are essential for assessing the effectiveness of classification models in handling both seizure and healthy subjects.

Table II provides the formulae used in this study. The acronyms used in the table are as follows; TS-True Seizures, TH-True Healthy, TP-True positives, FS- False Seizures, FH-False Healthy and A- Agreement.

4. RESULTS AND DISCUSSION

This section interprets the results of the proposed feature engineering approach such as spectral and temporal features, which utilizes techniques like UMAP and FFT. It includes an analysis showcasing the efficacy of the SeqBoostNet classifier in epileptic seizure classification.

The analysis carried out using a Python tool on a Windows 10 operating system with a 64-bit architecture and 8 GB of RAM. The system was equipped with an Intel(R) Core(TM) i3- 6006U CPU operating at 2.00 GHz. The study introduces a model combining different features from time and frequency domain with SeqBoostNet for an automatic epileptic seizure classification, utilizing BEED and BONN datasets with different case scenarios is provided in Table III and IV respectively.

TABLE III. BEED CASES

BEED Cases	Description
A1	Generalized Vs Focal
A2	Generalized Vs Healthy
A3	Focal Vs Healthy
A4	Focal Vs Seizure Events
A5	Generalized Vs Seizure Events
A6	Seizure Events Vs Healthy

TABLE IV. BONN CASES

BONN Cases	Description
B1	Seizure Vs Tumor
B2	Seizure Vs Healthy
B3	Seizure Vs Eye Closed
B4	Seizure Vs Eye Opened
B5	Eye Closed Vs Eye Opened

A. Performance analysis of BEED Data

The results displayed in the table exhibit the performance metrics of six distinct models (A1 to A6) applied in the classification of EEG data. Models A2, A3, and A6 emerge as the top performers, showcasing exceptional accuracy, precision, recall, F1-score, ROC-AUC, Kappa, MCC, sensitivity, specificity, and F2-score, with values consistently exceeding 99%.

These models demonstrate near-perfect classification capabilities, achieving perfect sensitivity and high specificity, indicating their proficiency in accurately identifying both positive and negative cases. Moreover, they yield low log loss values, suggesting high confidence and calibration in their predictions. While models A1, A4, and A5 also exhibit commendable performance, they present slightly lower values across most metrics, hovering around the mid to high 90% range. Notably, models A4, A5, and A6 require marginally more processing time compared to A1, A2, and A3, which may be a consideration for real-time applications. Overall, the findings underscore the effectiveness of models A2, A3, and A6 in accurately classifying EEG data, making them highly suitable candidates for practical implementation in neuroscience and clinical settings. The detailed performance metrics for BEED data are presented in Table V.

Metrics	A1	A2	A3	A4	A5	A6
Accuracy	95.91%	99.66%	99.83%	91.16%	94.01%	99.66%
Precision	96.01%	99.66%	99.83%	91.25%	94.01%	99.66%
Recall	95.91%	99.66%	99.83%	91.16%	94.01%	99.66%
F1-score	95.91%	99.66%	99.83%	91.15%	94.01%	99.66%
Kappa	91.83%	99.33%	99.66%	82.27%	87.98%	99.33%
MCC	91.91%	99.33%	99.66%	82.38%	87.99%	99.33%
ROCAUC	95.98%	99.65%	99.82%	91.06%	94.01%	99.65%
Sensitivity	94.05%	100%	100%	93.89%	93.56%	100%
Specificity	97.92%	99.30%	99.65%	88.23%	94.46%	99.30%
F2-score	95.93%	99.66%	99.83%	91.18%	94.01%	99.66%
Log Loss	1.47	0.12	0.06	0.61	2.16	0.12
Time	28s	28s	28s	30s	31s	48s

TABLE V. PERFORMANCE ANALYSIS OF BEED

The performance metrics for classifying EEG data in the table V indicate exceptional results across different tasks. Notably, models that differentiate between Generalized vs. Healthy (Case A2), Focal vs. Healthy (Case A3), and Seizure Events vs. Healthy (Case A6) achieve outstanding classification performance, with accuracy, precision, recall, and F1-scores consistently close to or at 99.66% or higher. These models also maintain high sensitivity and specificity, highlighting their precision in identifying both positive and negative cases. In contrast, Generalized vs. Focal (Case A1), Generalized vs. Seizure Events (Case A5), and Focal vs. Seizure Events (Case A4) offer strong, yet slightly lower, accuracy and specificity compared to the top-performing models. Although these models remain effective for classification tasks, they demonstrate slightly longer processing times. Overall, the exceptional performance of these models in classifying EEG data positions them as highly reliable for use in clinical and neuroscience settings, providing significant insights for future applications and research advancements.

Figure 7, illustrates the ROC curves for BEED cases, the ROC curves illustrate the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) for different models (A1 to A6). Models A3, A4, and A6 achieve perfect discrimination (AUC = 1.00), indicating excellent performance in distinguishing between positive and negative cases. A2 and A5 also demonstrate strong discrimination, with AUC values of 0.92 and 0.96 respectively, while A1 shows slightly lower discrimination with an AUC of 0.94.

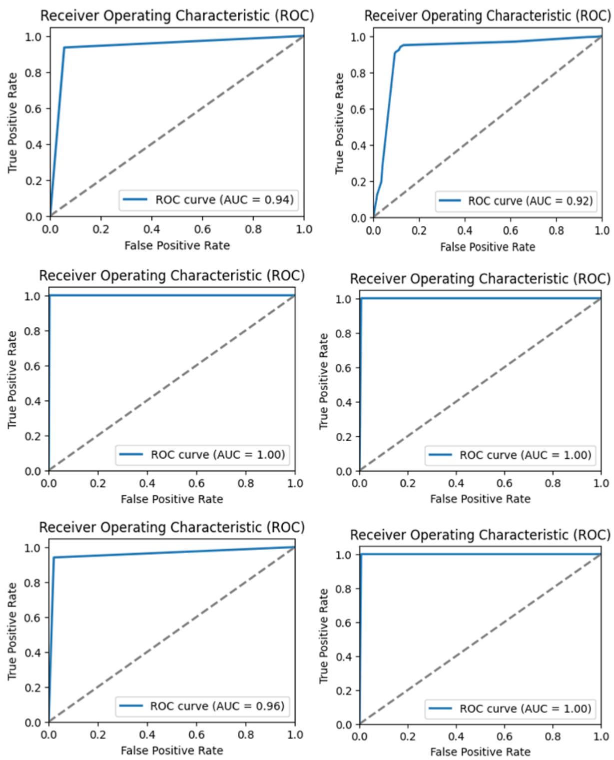

Figure. 7. ROC curves for BEED data for different cases

B. Performance analysis of BONN Data

The table VI presents the comprehensive performance metrics of five distinct models (B1 to B5) employed for EEG data classification. Notably, models B3 and B4 consistently exhibit exceptional performance across various evaluation criteria, including accuracy, precision, recall, F1-score, Kappa, MCC, ROC-AUC, sensitivity, specificity, and F2-score, with values consistently exceeding 99%. These models demonstrate robust agreement between predicted and actual classifications, with high sensitivity and specificity, indicating their proficiency in correctly identifying both positive and negative cases.

Furthermore, B3 and B4 achieve low log loss values, reflecting high confidence and calibration in their predictions. In contrast, while models B1 and B2 also perform well, they exhibit slightly lower metrics compared to B3 and B4, while B5 demonstrates relatively lower performance across most evaluation criteria. Overall, the findings underscore the effectiveness of models B3 and B4 in accurately classifying EEG data, suggesting their suitability for practical applications in neuroscience and clinical settings. The detailed performance metrics for BONN data are presented in Table VI.

TABLE VI. PERFORMANCE ANALYSIS OF BONN

Metrics	**B1**	**B2**	**B3**	**B4**	**B5**
Accuracy	97.39%	98.40%	99.34%	99.63%	90.79%
Precision	97.40%	98.40%	99.35%	99.63%	90.85%
Recall	97.39%	98.40%	99.34%	99.63%	90.79%
F1-score	97.39%	98.40%	99.34%	99.63%	90.79%
Kappa	94.77%	96.80%	98.69%	99.27%	81.59%
MCC	94.78%	96.81%	98.69%	99.27%	81.63%
ROCAUC	97.41%	98.38%	98.69%	99.64%	90.84%
Sensitivity	96.77%	98.87%	99.01%	99.43%	89.49%
Specificity	98.04%	97.89%	99.69%	99.84%	92.19%
F2-score	97.39%	98.40%	99.34%	99.63%	90.80%
Log Loss	0.94	0.57	0.23	0.13	3.31
Time	2m 58s	2m 19s	2m 53s	2m 56s	2m 32s

The models applied to EEG data for BONN cases exhibit excellent performance in classifying various conditions. The tasks involving Seizure vs. Eye Closed (Case B3) and Seizure vs. Eye Opened (Case B4) excel with top-tier accuracy, precision, recall, and F1-scores, reaching 99.34% and 99.63% respectively. These models also showcase high sensitivity and specificity, effectively identifying both positive and negative cases with near-perfect accuracy. Seizure vs. Healthy (Case B2) also performs exceptionally well, maintaining high accuracy and strong ROC-AUC, indicating its efficiency in distinguishing seizure data from healthy cases. The Seizure vs. Tumor (Case B1) classification task exhibits strong accuracy and reliability, though slightly lower than the top performers. Eye Closed vs. Eye Opened (Case B5) has the lowest performance of the set but still delivers strong results in distinguishing between these two conditions. Overall, these models provide highly reliable and accurate classification of EEG data across different tasks, making them valuable tools for use in clinical and research settings.

Figure 8, illustrates the ROC curves for BONN cases The ROC curves illustrate the classification performance of models A1 to A5, with AUC values indicating the ability to distinguish between true positive and false positive rates. Model A1 achieves perfect discrimination (AUC = 1.00), signifying excellent classification accuracy. A2 closely follows with a high AUC of 0.99, while A3 and A4 exhibit slightly lower discrimination with AUCs of 0.98 and 0.97 respectively. Model A5 demonstrates the lowest discrimination among the models, with an AUC of 0.91, indicating relatively weaker classification performance.

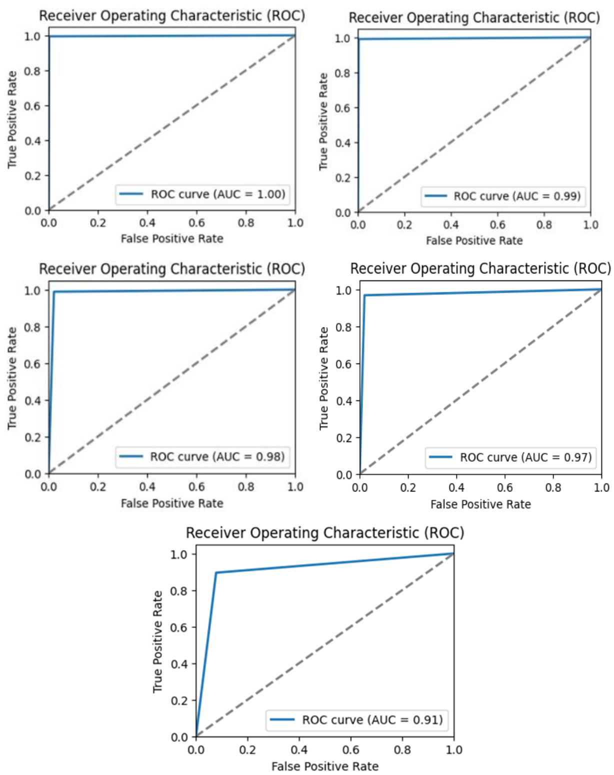

Figure. 8. ROC curves for BONN data for different cases

TABLE VII. COMPARISION OF THE RESULTS OF PROPOSED MODEL WITH THE RELEVANT LITERATURE

Previous studies	**Dataset**	**Technique**	**Accuracy**
Hernández et al. [36]	BONN	Time frequency feature extraction and Relief feature selection method	94.25%
Tsipouras et al. [37]	BONN	Spectral feature extraction	91.20%
Akyol et al.[38]	BONN	Stacking ensemble based Deep Neural Network	97.17%
Rabby et al. [39]	BONN	Wavelet Transformation, Petrosian Fractal Dimension, Higuchi Fractal Dimension and Singular Value Decomposition Entropy.	95.20%
Jing et al.[40]	BONN	Sliding window weighting with discrete wavelet transformation	96.59%
Mishra et al.[41]	BONN	Discrete Wavelet Transform and Moth Flame Optimization-based Extreme Learning Machine	96.00%
Proposed Model	**BONN**	**Spectral and temporal with stacked ML and DL model**	**98.40%**

Table VII provides a comparison of the results obtained by the proposed system in the study with the findings from previous relevant research. The proposed model demonstrated outstanding performance with an accuracy of 98.40%, surpassing the accuracy levels achieved by previous studies on the same BONN dataset. This remarkable accuracy highlights the effectiveness and superiority of the proposed model in EEG signal classification. This study offers valuable insights into the early diagnosis of epileptic seizures through the application of artificial intelligence and classification algorithms. It underscores the importance of timely seizure diagnosis, considering the global prevalence of this health issue, and the positive impact it can have on patient outcomes.

TABLE VIII. TIME COMPLEXITY DETAILS

Technique	**Time Complexity**
FFT	O (N log N)
UMAP	O (N * D)
LSTM	O (N^2)
XGB	O (M*T)
GB	O (M*T)
Ada	O (M*T)
SeqBoostNet	**O (N log N)+ O(N^2)**

The time complexity details in Table VIII outline the computational efficiency of various techniques used in the proposed model and existing models for EEG data analysis. Fast Fourier Transform (FFT) offers the most efficient time complexity ideal for processing large datasets quickly. UMAP's complexity depends on the number of data points (N) and dimensions (D), indicating scalability in high-dimensional data analysis. Recurrent neural networks, such as LSTM, have a quadratic time complexity of which may lead to higher processing times with larger datasets. XGBoost, Gradient Boosting (GB), and AdaBoost all share a linear complexity dependent on the number of data points (M) and iterations (T), suggesting moderate efficiency for boosting algorithms.

The proposed model combines the strengths of feature engineering such as UMAP and FFT with SeqBoostNet, with an overall time complexity of O(N log N) + O(N^2). This hybrid approach balances efficiency and deep learning capabilities, offering a powerful yet scalable solution for EEG data analysis. Overall, it highlights a variety of methods with trade-offs between speed and complexity, guiding the selection of appropriate techniques for specific tasks and datasets.

5. CONCLUSION AND FUTURE SCOPE

In this study, we conducted a comprehensive analysis focusing on two main areas: the efficacy of spectral and temporal features and the performance of the SeqBoostNet stacking model in EEG data classification. By integrating spectral and temporal features, which combines UMAP and FFT data, we observed a significant enhancement in classification model's capabilities. This combined method effectively captured both temporal and spectral characteristics of EEG data, leading to improved classification accuracy and precision. Moreover, the SeqBoostNet model demonstrated remarkable effectiveness by leveraging outputs from UMAP and FFT, resulting in superior classification performance across various metrics.

The models evaluated for classifying EEG data across various tasks demonstrate remarkable performance and reliability, particularly in distinguishing between different types of brain activity such as generalized, focal, and seizure events in the BEED cases and seizure, tumor, and eye state distinctions in the BONN cases. The top-performing models, especially those differentiating between generalized, focal, and seizure events from healthy states, consistently achieve near-perfect accuracy, precision, and recall. This outstanding performance highlights the model's potential for application in clinical and research environments, aiding in the early detection and diagnosis of neurological disorders.

Despite these successes, future work could focus on refining model processing times and optimizing specificity metrics. For example, improving distinctions between eye closed and eye opened conditions could enhance overall classification accuracy. The integration of these models into clinical practice promises to transform EEG analysis, providing faster and more precise diagnostics.

Looking ahead, future research avenues could explore feature engineering techniques, alternative dimensionality reduction methods, real-world applications, interpretable model development, efficient handling of large-scale datasets, and detailed case studies on waveband computation for seizure data. These potential areas offer exciting prospects for further advancement in EEG data analysis and classification.

In addition, by incorporating advanced data fusion techniques and real-time processing, these models could pave the way for novel applications in personalized medicine and brain-computer interface development. Collaborations between clinicians and data scientists will be essential to fine-tune these models for specific medical challenges and maximize their impact. Further research can explore alternative feature engineering, dimensionality reduction methods, and handling large datasets to elevate EEG data analysis and classification even further.

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