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Feature Engineering for Epileptic Seizure Classification Using SeqBoostNet

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Abstract: Epileptic seizure, a severe neurological condition, profoundly impacts patient's social lives, necessitating precise diagnosis for classification and prediction. This study addresses the need for reliable automated seizure detection in epilepsy by employing Artificial Intelligence (AI) driven analysis of Electroencephalography (EEG) signals. Key innovations include combining spectral and temporal features using Uniform Manifold Approximation and Projection (UMAP) with Fast Fourier Transformation (FFT), and the introduction of the Sequential Boosting Network (SeqBoostNet), a robust stacking model integrating machine learning and deep learning for effective seizure classification. Validated on benchmark datasets such as the BONN dataset from the UCI repository and the BEED from the Bangalore EEG Epilepsy Dataset, this approach achieved high accuracy, distinguishing Focal and Generalized seizure onsets with 95.91% accuracy and overall average accuracies of 96.71% on BEED and 97.11% on BONN. Existing models frequently struggle with the variability of seizure events. However, these findings underscore the model's strength in distinguishing between seizure onset types, even with the inherent fluctuations in seizure patterns. This research not only advances automated seizure detection but also underscores the value of integrating AI with EEG analysis to improve neurological diagnostics, offering the potential for significant enhancements in diagnostic accuracy and patient outcomes.

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

1. INTRODUCTION

An epileptic seizure is a neurological condition caused by an abnormality of the electrical activity of the brain. In recent years, there has been a wide focus on improving seizure prediction with AI, for more accurate predictive models [1]. Patients suffering from this disease are not only treated medically but also surgically. Thus, the precise prediction of future seizures becomes crucial to permit timely preventive medication to prevent their occurrence [2]. Seizures are classified into Focal, Generalized, or Unknown, which affect approximately 1% of the world population [3]. The focal seizures begin from an area of the brain on one side and a generalized seizure occurs when a seizure occurs simultaneously in both hemispheres of the brain [4]. Epilepsy imposes a tremendous personal burden of recurrent seizures, which further reduces the individual's ability to lead a normal social life. Epidemiological studies show that uncontrolled seizures can lead to sudden unexpected death, making epilepsy diagnosis a significant challenge. EEG is a recording of electrical brain activity which is an integral tool for diagnosing brain seizure disorders. During an EEG examination, a computer screen visualizes these electrical signals as wavy lines, representing a brain activity record. Electrodes are placed on different areas of the brain to record signals, with each channel representing a pair of electrodes; the data collected from a channel is referred to as a signal. The 10-20 International System is a standardized method for electrode placement in EEG [5].

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. Hence, recognizing these attributes poses a demanding task, and the observation of each EEG signal is both laborious and time-consuming [6]. 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. Hence, the primary objective of this research work is to develop the most accurate and efficient model possible.

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This research aims to enhance seizure detection and prediction using spectral and temporal features combined with advanced classification methods. A novel feature engineering technique integrates FFT for spectral analysis and UMAP for temporal data, improving feature learning and prediction. The proposed SeqBoostNet model, which merges machine learning and deep learning techniques, addresses accuracy challenges in multivariate data and supports both binary and multiclass classification. This study enhances EEG-based seizure classification by leveraging advanced spectral and temporal features, which provide critical information about the frequency and time dynamics of brain activity. Spectral features capture the frequency components of the EEG signals, enabling effective identification of distinct brain states, while temporal features highlight the changes in these signals over time, crucial for recognizing transient seizure patterns. The implementation of an efficient stacking model optimizes both classification accuracy and computational performance, establishing a new benchmark in seizure detection. By advancing feature engineering methods, this research not only enriches the field of computational neuroscience but also paves the way for broader applications in understanding various brain disorders.

Key Significance of the proposed work:

- The research enhances seizure detection and prediction, offering epilepsy patients greater reliability and potentially improving their quality of life by reducing uncertainty and better preparing for seizures.
- Combining spectral and temporal domain features with a stacking model introduces a novel approach to EEG analysis, with broader applications in neurological and medical fields, marking a shift in analyzing complex biological data.
- The stacking model leverages the strengths of various algorithms through a meta-model, optimizing classification tasks like EEG data analysis, leading to improved diagnostic accuracy.
- The stacking model integrates multiple algorithms via a meta-model, enhancing the classification of EEG data and improving diagnostic precision.
- This research sets a new standard for seizure classification accuracy, providing a reliable reference for researchers and clinicians while advancing computational neuroscience and informing future studies on neurological disorders.

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

In the realm of epilepsy diagnosis, automated seizure detection using EEG data has become essential, particularly for improving accuracy in diagnosis and supporting real-time clinical applications. Recent advances in deep learning and machine learning have enabled more accurate and efficient processing of EEG signals, providing better insights into seizure onset patterns and enhancing seizure classification. However, the challenges of accurately predicting seizures across varied datasets and patient demographics remain. To address this, various researchers have explored different preprocessing, feature extraction, and classification techniques to improve the generalizability and robustness of seizure prediction models.

Modern approaches to EEG-based seizure detection often rely on complex transformations to extract meaningful features. convolutional neural networks (CNN) are applied in [7][8] in combination with the fractional S-transform (FST) and dense convolutional blocks (DCB), respectively, for feature extraction and classification. These techniques have demonstrated high specificity and accuracy on controlled datasets like the BONN dataset, indicating that CNN architectures are effective for capturing critical EEG features. However, these studies faced limitations related to dataset diversity, which may restrict their effectiveness in real-world settings where EEG patterns are highly variable. This is a significant focus of our study, which incorporates robust spectral-temporal feature analysis to ensure model adaptability across different EEG datasets. Additionally, methods combining CNNs with traditional machine learning classifiers have gained popularity, showing promise in processing complex EEG signals. Mutual information-based feature estimation in CNN architectures could improve classification accuracy [9]. Meanwhile, [10] used a CNN-based approach with image-based representations of EEG signals. Although these methods achieved better accuracies, the dependency on specific preprocessing steps, such as image conversion, suggests that they may lack versatility for direct application to raw EEG time-series data. Our research aims to overcome this by integrating feature extraction techniques directly applicable to time-series EEG data, thereby enhancing computational efficiency and real-time performance. A three-step methodology for seizure prediction on EEG data, specifically targeting the CHB-MIT dataset. Their method includes preprocessing through notch filtering to improve the signal-to-noise ratio (SNR), followed by the extraction of statistical and CNN-based automated features [11]. Together, these studies emphasize the critical role of optimizing feature extraction and preprocessing in EEG-based seizure detection. The proposed model enhances these advancements by employing a stacked machine learning and deep learning approach for direct spectral-temporal feature extraction from EEG signals. This methodology improves accuracy and efficiency, providing a more adaptable solution for various EEG data sources without the need for extensive preprocessing, thereby advancing real-time seizure detection applications. Feature extraction techniques such as Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) have been widely applied to isolate frequency-domain characteristics of EEG signals, as seen in [12]. This approach has highlighted the value of spectral features in identifying seizure activity. However, as model complexity increases, computational requirements also escalate, which can be prohibitive in real-time scenarios. Our proposed model incorporates UMAP and FFT for optimized spectral and temporal feature analysis, striking a balance between computational efficiency and classification accuracy to facilitate real-time seizure detection. Some researchers have also focused on personalized seizure prediction models, such as [13], who tailored their model to individual patients by integrating a deep residual shrinkage network (DRSN) with a gated recurrent unit (GRU). While personalized models have shown strong sensitivity rates, they tend to have reduced generalizability across diverse populations, as they may overfit to specific patient data. To enhance generalizability, our research leverages a comprehensive multivariate dataset, which ensures the model's applicability across varied patient demographics and seizure types, thereby providing a robust solution for broader clinical use. For instance, [14] introduced a comprehensive method to differentiate between interictal and ictal states using multichannel EEG data. By employing a combination of five features—Variance, Pearson correlation coefficient, Hoeffding's D measure, Shannon entropy, and inter-quartile range—derived from maximal overlap discrete wavelet transform. While this study underscores the potential of these features in distinguishing different EEG states, it is limited by its reliance on a single clinical dataset, raising questions about the generalizability of the findings across broader patient populations. Building on this foundation, [15] developed an automated approach that integrates signal processing techniques with machine learning algorithms. Their methodology incorporates preprocessing using the Savitzky–Golay filter, feature extraction via discrete wavelet transform (DWT), and classification through a support vector machine (SVM). However, the need for further validation across diverse patient groups and real-time applicability remains critical for ensuring the method's effectiveness. The quest for improved accuracy led to the exploration of alternative neural network architectures, as highlighted by [16], utilizing a Random Neural Network (RNN) for seizure classification. Despite these encouraging results, the study emphasizes the importance of broader validation across various datasets to assess the model's robustness, particularly in real-time clinical scenarios where immediate responses are essential. Additionally, the integration of time-frequency analysis has shown promise in EEG classification. [17] combined time-frequency feature extraction with Relief feature selection techniques, analyzing the BONN dataset. Time-frequency features are crucial in EEG analysis as they capture both temporal and spectral information, enhancing the accuracy of brain activity and seizure detection. While effective, this approach's adaptability to varied EEG data sources remains a challenge, as its accuracy is constrained by the limited scope of the dataset, which could impact generalizability to different seizure patterns. The reliance on spectral features also presents advantages, as demonstrated by [18]. However, their sole focus on frequency-domain information without considering temporal aspects may hinder the model's ability to capture the complete dynamics of the EEG signal, resulting in moderate performance. In the area of deep learning, [19] showcased the effectiveness of a stacking ensemble-based deep neural network (DNN) approach. This method benefits from ensemble learning, which consolidates predictions from multiple models. Nonetheless, the computational demands of this approach present challenges for real-time seizure detection, limiting its clinical applicability where prompt diagnosis is critical. Wavelet transformation, combined with fractal dimension techniques, has also been explored in this context. [20] achieved using wavelet transformation alongside Petrosian Fractal Dimension and Singular Value Decomposition Entropy techniques on the BONN dataset. Although this comprehensive feature set allows for detailed signal analysis, the reliance on complex transformations may increase computational overhead, which could limit real-time deployment. Further advanced the field with their sliding window weighting approach [21], utilizing discrete wavelet transformation on the BONN dataset. By incorporating temporal elements through sliding windows, this method effectively captures changes in the EEG signal over time. However, the challenge of generalizability arises when applying this approach to diverse EEG datasets not used in the study. Lastly, a model that incorporates Discrete Wavelet Transform and Moth Flame Optimization-based Extreme Learning Machine [22], on the BONN dataset. While the optimization strategy enhances classification performance, its adaptability to larger and more varied datasets is limited, which could impact the robustness of the model across different populations.

In recent years, EEG-based seizure detection has drawn significant interest, especially in the application of machine learning and deep learning techniques to improve diagnostic accuracy and support early intervention. Previous studies have employed various feature extraction and classification methods on EEG datasets, such as BONN, to address this complex task with varying levels of success. While EEG-based seizure detection has significantly advanced, current models are facing limitations in scalability, adaptability, and computational demands, especially in the context of real-time applications. The proposed model builds upon the strengths of previous studies by addressing these limitations through a robust feature engineering and stacking approach. By combining UMAP and FFT-based feature extraction with stacked machine learning (ML) and deep learning (DL) methods, our approach aims to enhance robust feature engineering, computational efficiency, and seizure classification accuracy. This current research not only contributes to an adaptable model suitable for real-time applications but also

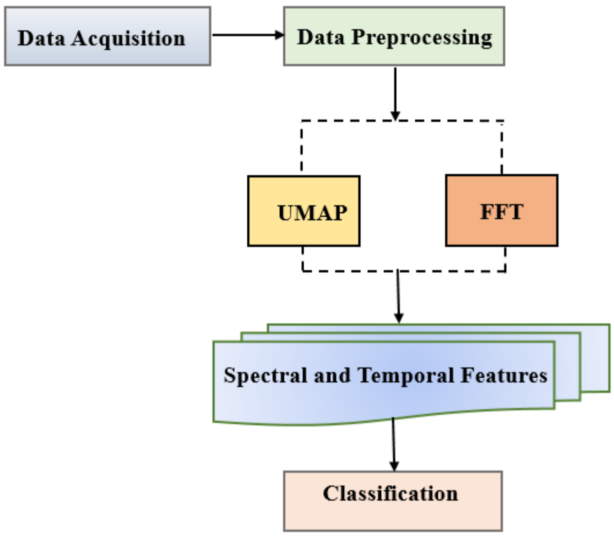

Figure 1. Proposed Framework

sets a foundation for improved clinical decision support in epilepsy diagnosis. Through systematic feature engineering, this model reduces dependency on extensive preprocessing and augmentation techniques, ensuring that it can adapt to a wide range of EEG data characteristics and patient profiles. It represents a significant step towards creating versatile, accurate, and computationally efficient seizure prediction models for use in diverse clinical settings.

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 four stages: Data Acquisition, Preprocessing, Spectral, and Temporal features and Classification illustrated in Figure 1. After acquiring data, data preprocessing is performed to enhance signal quality. FFT and UMAP are applied to extract spectral and temporal features, respectively. These extracted features are then combined into a unified feature set, and subsequently fed into the classification model for further analysis. For classification, SeqBoostNet, a novel stacked learning model is introduced. Further details on these techniques are provided in subsequent sections.

A. Data Acquisition

EEG data is acquainted using the brain's neuronal activity in the form of signals. The EEG signals are recorded over varying periods, from minutes to days, depending on research or clinical goals. The collected EEG data is digitally stored for subsequent analysis. 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. The choice of datasets enhances reliability and real-world relevance. The BEED dataset, with its real-time and dynamic recordings in physical movement and various seizure types, provides complexity in the application environment. The BONN dataset is one of the well-known benchmark datasets used, ensuring controlled conditions and standardization of the validation procedure, which affords a good comparison with other studies. By balancing real-time variability in this way with reliable and structured data for seizure prediction, a robust model can be created.

1) BEED EEG Dataset

The Bangalore EEG Epilepsy Dataset (BEED) was collected from an EEG clinic in Bangalore, which contains 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 [23].

B. Data Preprocessing

The proposed model aims to distinguish epileptic seizure onsets, seizure events, and healthy states through combined 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 selection, enhancing overall model performance. Data standardization ensures consistent scales across EEG channels and subjects, aiding in clearer interpretation of features and model coefficients [24]. 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 connectivity patterns. They illuminate how brain activity evolves, offering insights into cognitive processes like attention, memory, and perception, while also

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 hemispheres
Focal	Seizure recording in specific brain area

aiding in identifying neurological disorders, monitoring disease progression, and enhancing Brain-Computer Interfaces (BCI).

UMAP is an effective method that reduces the dimensionality of data while preserving its structural integrity. 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 [25]. UMAP is a method used to simplify complex data. It accomplishes this through four main steps in four key steps. It first examines the local relationships between each data point and its nearest neighbors. Next, it uses a fuzzy set to find each point's relationship to the other points in the data. After that, the data is adjusted to create a clearer picture called gradient descent. Ultimately, it combines all of this to present the data in an easier-to-visualize and analyze format. The equations 1, 2, and 3 provide the mathematical details for each step, helping us understand how UMAP works.

Fuzzy Set Membership Function (Fuzzifier)

$$\phi(d_{ij}, \sigma_i) = \exp\left(-\frac{d_{ij}^2}{2\sigma_i^2}\right) \tag{1}$$

Fuzzy Simplicial Set

$$S_{ij} = \phi(d_{ij}, \sigma_i) \cdot \phi(d_{ij}, \sigma_j) \cdot \text{Mutual\_knn}(i, j) \tag{2}$$

Objective Function

$$L = \sum(i) \sum(j) \cdot S_{ij} \cdot \log\left(\frac{S_{ij}}{Q_{ij}}\right) \tag{3}$$

Where; Equation 1 computes the similarity between two data points, where 'i' and 'j' represent the row indices in the input EEG data, 'd_{ij}' signifies the Euclidean distance between these data points. Equation 2 constructs a fuzzy simplicial set and Equation 3 defines an objective function, with the following key parameters. Where σ_i A scaling parameter determining the influence of distance on the similarity for a 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}'.

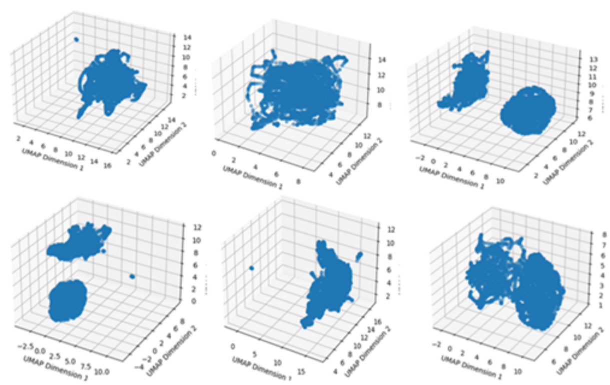

Figure 2. UMAP Visualization for BEED Data

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 show 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 the time domain. This transformation maintains the important structures in the data.

D. Spectral Features Using FFT

Spectral features, derived from the application of the Fast Fourier Transform (FFT) in EEG, have been of great use in understanding the frequency components of brain

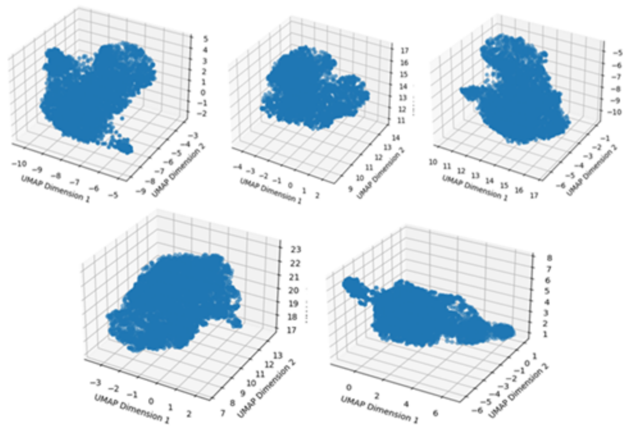

Figure 3. UMAP Visualization for BONN Data

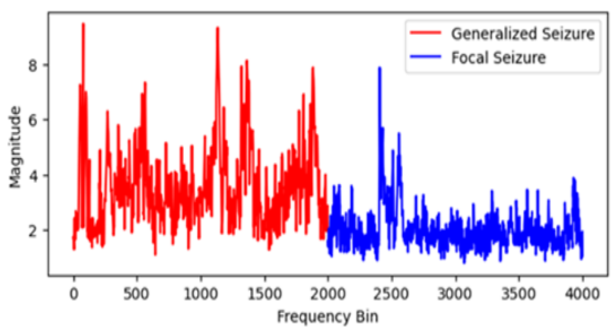

Figure 4. Frequency Response Spectrum for BEED Data

activity. FFT analyzes EEG signals in the frequency domain thus making their information visible, and critical to the brain's rhythm, such as delta, theta, alpha, beta, and gamma waves. These spectral features then give an ability to understand cognitive processes, neurological conditions, and states of consciousness. It observes and computes the frequency content of a signal given in a time-domain signal quite accurately. It transforms the signal from the time domain to the frequency domain through the computation of the DFT of a signal. The FFT, within the field of EEG data analysis, is very useful in showing how the frequency distribution for brainwave activity evolves with time [26]. 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. Figures 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.

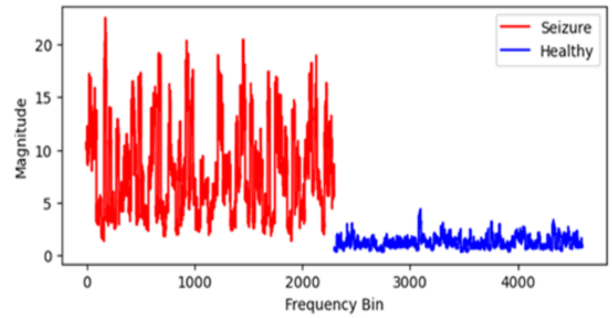

Figure 5. Frequency Response Spectrum for BONN Data

$$X_k = \sum_{n=0}^{n-1} x_j \cdot e^{-\frac{2\pi i jk}{N}} \tag{4}$$

Where; 'X_k' represents the input signal in the frequency domain, n represents the number of samples in the input signal, j represents the value of the signal at a specific feature index, N represents the total number of samples in the input signal, i represents the imaginary unit, which is $\sqrt{-1}$, k—represents the index for the frequency bins ranges from 0 to N-1 and the exponential term $e^{-\frac{2\pi i jk}{N}}$ represents phase shift introduced by k and j.

E. Model Selection Criteria

Combining UMAP and FFT for feature extraction manage to utilize the time-domain and frequency-domain analysis to improve the seizure classification with full complexity of the EEG signals. This transformation is very important because seizures tend to appear as changes in oscillatory behavior such as the power and frequency band and therefore the transformation helps capture patterns related to specific types of seizures. Even though many oscillations exist, FFT results are useful to scrutinize these oscillations as they contain prevalent spectral characteristics of seizures in the EEG dataset. While UMAP applied to the time-domain data, transforms high-dimensional data into lower-dimensional space that preserves important nonlinearity that might be hidden within the raw signal. It maintains important temporal structures and connections in the EEG data which is crucial for extracting seizures that have different temporal characteristics such as spike-like onset. When combined FFT is used to extract spectral features while temporal features come from UMAP, the methods take care of the non-stationariness of the EEG signals and then there are both rhythmic oscillations as well as temporal changes in the features. This dual representation not only strengthens the classifier by ensuring comprehensive seizure characterization but also improves robustness against noise commonly present in EEG signals. The combination of these features enhances model generalization across seizure subjects and their types by addressing both universal spectral properties and individual temporal variations.

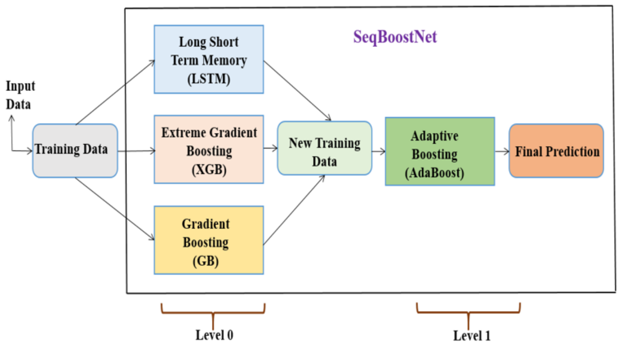

Figure 6. Sequential Boosting Network Architecture

F. Sequential Boosting Network (SeqBoostNet)

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, cognitive states, 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.

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 metamodel, thus combining 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) Long Short-Term Memory (LSTM)

LSTM processes EEG data sequentially, step by step, across all channels [27]. At every step, the cell state gets updated and the hidden state is computed by selectively retaining information through forget and input gates. Long-term dependency in a stream of input data that an LSTM can recognize makes it an excellent candidate for identifying patterns of seizure. The process of classification can assist it in identifying periods as seizure or non-seizure events. The LSTM's three main gates and cell state together manage the information flow effectively.

Cell State: The cell state in an LSTM acts as the memory, storing and transferring important information through the sequence. It is updated at each step based on the inputs and gate outputs, deciding whether to retain or discard information.

Forget Gate: Determines which information from the previous cell state to keep or discard using a sigmoid function.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$

Where: f_t: Output of the forget gate at time step t, W_f: Weight matrix for the forget gate, h_{t-1}: Previous hidden state, x_t: Current input, b_f: Bias term for the forget gate, σ: Sigmoid activation function.

Input Gate: Decides what new information to add to the cell state using a sigmoid function.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$

Where: i_t: Output of the input gate at time step t, W_i: Weight matrix for the input gate, b_i: Bias term for the input gate.

Candidate Cell State: Computes potential updates using the tanh function, mapping values between -1 and 1.

$$C_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{7}$$

Where: C_t: Candidate cell state at time step t, W_c: Weight matrix for the candidate cell state, b_c: Bias term for the candidate cell state, tanh: Hyperbolic tangent function.

Cell State Update: Combines the previous cell state with the new information from the input gate and candidate cell state.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{8}$$

Where: C_{t-1}: Previous cell state at time step $t-1$, $\tilde{C}_t$: Candidate cell state at time step t.

Output Gate: Regulates how much of the cell state to pass into the hidden state for the next step.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{9}$$

Where: o_t: Output of the output gate at time step t, W_o: Weight matrix for the output gate, b_o: Bias term for the output gate.

Hidden State: Calculated by applying the tanh function to the updated cell state, scaled by the output gate, which is then used for prediction or passed to the next time step.

$$h_t = o_t \cdot \tanh(C_t) \tag{10}$$

Where: h_t: Hidden state at time step t, $\tanh(C_t)$: tanh of the current cell state C_t.

2) Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting (XGBoost) is a highly effective gradient boosting algorithm known for its high predictive accuracy, particularly in analyzing EEG data.

While it excels in modeling complex, non-linear patterns in brain signals, it requires careful hyperparameter tuning to avoid overfitting. XGBoost operates as an ensemble learning method, combining multiple weak models (typically decision trees) to build a robust predictive model.

The algorithm's core components are the loss function and regularization:

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

Loss Function: Minimizes the error between actual labels (y_i) and predicted labels ($\hat{y}_i$) for EEG samples, ensuring accurate classification of signals, such as seizure types.

Regularization: The term $\Omega(f_k)$ controls model complexity to prevent overfitting, essential for handling high-dimensional EEG data.

$$\Phi(f) = \gamma T + \frac{1}{2}\lambda \sum \omega_j^2 \tag{12}$$

Regularization Details: Penalizes complexity by controlling tree parameters, where T is the number of leaves, ω_j are the leaf weights, and γ and λ are regularization parameters.

3) Gradient Boosting (GB)

Gradient Boosting is an ensemble learning technique that builds decision trees sequentially, making it well-suited for complex EEG data, including heterogeneous signals and outliers. Although slower in training compared to other algorithms, it is robust and effective. The model iteratively improves predictions by addressing residual errors from previous models. The learning rate α regulates the influence of each new tree on the final prediction.

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

Loss Function: Measures the error between actual labels and predictions, adjusting the model based on the residuals:

$$l(y, \hat{y}) = l(y, F_{m-1}(x) + \alpha h_m(x)) \tag{14}$$

4) Adaptive Boosting (AdaBoost)

AdaBoost enhances accuracy by combining weak learners into a strong model, effectively reducing bias and variance. However, it can be sensitive to noise and outliers. AdaBoost integrates predictions from LSTM, XGBoost, and Gradient Boosting base models in this framework. The process involves calculating a weighted loss, classifier weight, weight updates, and final prediction as shown in Equations 15-18.

Weighted Loss:

$$L_t = \sum_{i=1}^{n} \omega_i^{t-1} l(y_i, h_t(x_i)) \tag{15}$$

Classifier Weight:

$$\alpha_t = \frac{1}{2}\log\left(\frac{1 - \mathrm{err}_t}{\mathrm{err}_t}\right) \tag{16}$$

Weight Update:

$$w_i^t = w_i^{t-1} \cdot \exp\left(-\alpha_t \cdot y_i \cdot h_t(x_i)\right) \tag{17}$$

Final Prediction:

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

5) Stacking Classification Framework

In the SeqBoostNet stacking framework, LSTM, XGBoost (XGB), and Gradient Boosting (GB) serve as base models. Spectral and temporal features from EEG data are input into these models, which generate predictions. These predictions are aggregated by the AdaBoost meta-model for final classification. LSTM captures temporal dependencies, XGB ensures robustness and accuracy, and GB handles noise and outliers effectively. AdaBoost combines these base models to enhance classification performance by reducing bias and variance. SeqBoostNet, designed for seizure detection using BEED and BONN datasets, incorporates LSTM, XGB, and GB as base models and AdaBoost as the meta-model. The BEED dataset has 4,000 samples with 19 features, while the BONN dataset contains 4,600 samples with 181 features, both classifying seizures (1) vs. healthy (0). The data is normalized and split into training and testing sets. Each base model is trained to produce probabilistic predictions (Y_{LSTM}, Y_{XGB}, Y_{GB}).

These predictions are compiled into a matrix for AdaBoost, which is trained to improve classification accuracy. Once trained, SeqBoostNet processes new data with the base models, and AdaBoost makes the final prediction. Key hyperparameters for the models used in this study are as follows: For the LSTM, 128 cells are utilized with ReLU activation, a dropout rate of 0.5, Sigmoid output, Adam optimizer, Sparse Categorical Cross-Entropy loss, 100 epochs, and a batch size of 32. The XGBoost model is configured with 300 estimators, a maximum depth of 6, a learning rate of 0.05, and a Multi-Softmax objective. The Gradient Boosting (GB) model includes 100 estimators, a learning rate of 0.1, and a maximum depth of 3. Lastly, the AdaBoost model employs 50 weak learners with a learning rate of 1.0. These hyperparameters are crucial for optimizing SeqBoostNet's performance in EEG data classification.

6) Inferences

- Combining models significantly improves the classification of complex EEG patterns, leading to enhanced seizure detection accuracy.
- Each base model contributes specialized insights, effectively capturing unique spectral, temporal, and spatial characteristics of EEG signals.
- The stacked approach mitigates overfitting and enhances the model's ability to generalize across different EEG datasets and conditions.
- The meta-model integrates predictions from base models, yielding more reliable and robust EEG classifications.
- The model architecture is flexible, allowing for the incorporation of additional base models to refine EEG signal interpretation.
- By optimally weighting base model outputs, the meta-model boosts prediction accuracy for complex neurological conditions.
- This approach harnesses the complementary strengths of individual models, providing a comprehensive solution for EEG data analysis in clinical and research applications.

G. Performance Evaluation Metrics

Performance evaluation measures assess a model's effectiveness in various fields like machine learning, statistics, and information technology. These metrics gauge how well a model accomplishes its objectives [28]. 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 was 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 the time and frequency domain with SeqBoostNet for an automatic epileptic seizure classification, utilizing BEED and BONN datasets with different case scenarios provided in Table III and IV respectively.

A. Performance analysis of BEED Data

Table V presents the detailed performance metrics for BEED data. The results exhibit the performance metrics of six distinct cases (A1 to A6) applied in the classification of EEG data. Cases 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 cases demonstrate near-perfect classification capabilities, achieving perfect sensitivity and high specificity, indicating their proficiency in accurately identifying positive and negative cases. Moreover, their predictions yield low log loss values, suggesting high confidence and calibration. While cases 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, cases A4, A5, and A6 require marginally more processing time compared to A1, A2, and A3, which may be a consideration for real-time applications. Hence, 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, showing the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) for different cases (A1 to A6). Cases 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.

B. Performance analysis of BONN Data

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.

The models applied to EEG data for BONN cases

TABLE II. Performance Metrics and their Formulas

Metric	**Formula**
Accuracy (A)	$\frac{TS+TH}{TP}$
Chance Agreement (CA)	$\frac{TS\cdot(TS+FS)\cdot(TS+FH)+(TH+FS)\cdot(TH+FH)}{TP^2}$
F1-Score (F1)	$\frac{2\cdot P\cdot R}{P+R}$
F2-Score (F2)	$\frac{5\cdot P\cdot R}{4\cdot P+R}$
Kappa (K)	$\frac{A-CA}{1-CA}$
Log Loss	$-\frac{1}{N}\sum_{i=1}^{N}(y_i\log(p_i)+(1-y_i)\log(1-p_i))$
MCC	$\frac{(TS\cdot TH-FS\cdot FH)}{\sqrt{(TS+FS)\cdot(TS+FH)\cdot(TH+FS)\cdot(TH+FH)\cdot N}}$
Precision (P)	$\frac{TS}{TS+FS}$
Recall (R)	$\frac{TS}{TS+FH}$
Sensitivity	$\frac{TS}{TS+FH}$
Specificity	$\frac{TH}{TH+FS}$

TABLE III. BEED Cases

Dataset	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

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

TABLE V. Performance Analysis of BEED

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	1.00	1.00	93.89	93.56	1.00
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 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

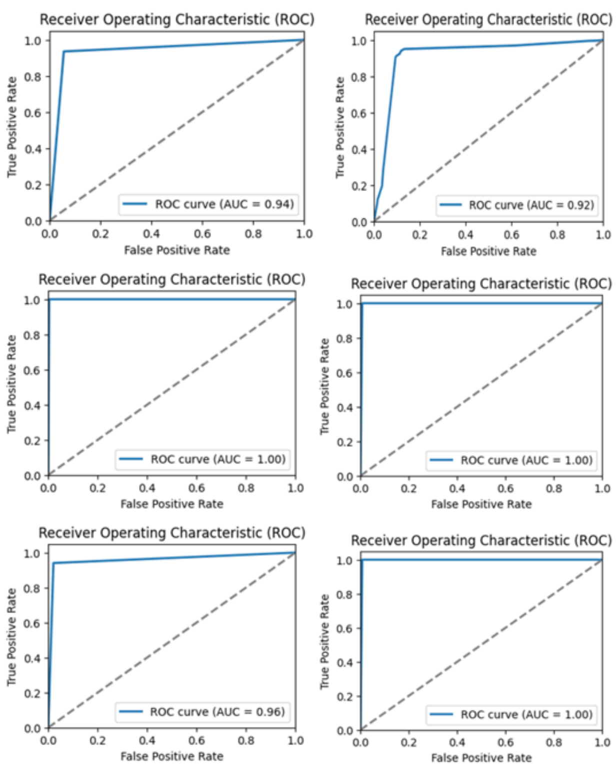

Figure 7. ROC curves for BEED Data

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 demonstrate the classification performance of cases B1 to B5, with AUC values indicating the ability to distinguish between true positive and false positive rates. Case B1 achieves perfect discrimination (AUC = 1.00), signifying excellent classification accuracy. B2 closely follows with a high AUC of 0.99, while B3 and B4 exhibit slightly lower discrimination with AUCs of 0.98 and 0.97, respectively. Case B5 demonstrates the lowest discrimination among the cases, with an AUC of 0.91, indicating relatively weaker classification performance.

C. Comparative Analysis

1) Comparision of existing literature with proposed model

Figure 9 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.

The time complexity details in Table VII provide insights into the computational efficiency of various techniques employed in the proposed work for EEG data anal-

TABLE VII. Time Complexity Details

Technique	Time Complexity
FFT	$O(N \log N)$
UMAP	$O(N \times D)$
LSTM	$O(N)$
XGB	$O(M \times T)$
GB	$O(M \times T)$
Ada	$O(M \times T)$
SeqBoostNet	$O(N \log N + N \times D + M \times T)$

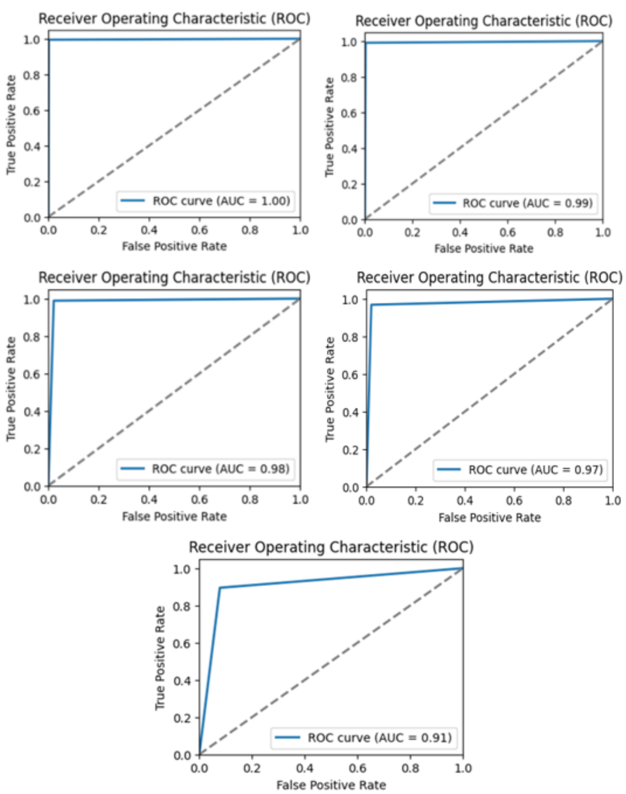

Figure 8. ROC curves for BONN Data

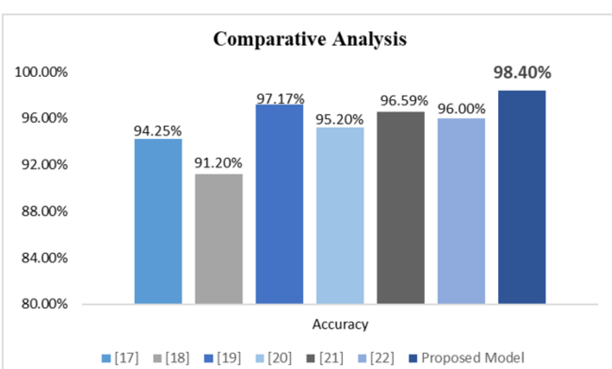

Figure 9. Comparision of existing literature with proposed model

ysis. FFT demonstrates the most efficient time complexity, making it well-suited for rapid processing of large datasets. UMAP's complexity is influenced by the number of data points (N) and dimensions (D), indicating its scalability for handling high-dimensional data. Recurrent neural networks, such as LSTM, exhibit linear time complexity, which can result in increased processing times with larger as datasets. In contrast, XGBoost, Gradient Boosting (GB), and AdaBoost share a complexity of $O(M \times T)$, reflecting their dependence on the number of features (M) and boosting iterations (T), suggesting moderate efficiency for these ensemble methods. The proposed SeqBoostNet model integrates the strengths of feature engineering techniques like UMAP and FFT, leading to an overall time complexity of $O(N \log N + N \times D + M \times T)$. This stacking approach effectively balances computational efficiency with deep learning capabilities, providing a robust and scalable solution for EEG data analysis. Hence, this overview emphasizes a range of methods, each with its trade-offs between speed and complexity, guiding the selection of suitable techniques for specific tasks and datasets.

2) *Comparison with Feature Extraction Techniques*

In the comparative analysis of the diverse feature-extracting techniques for seizure classification, the proposed method with spectral and temporal features outperforms all approaches by a wide margin in all cases as presented in Table VIII. It surpasses traditional techniques in the form of wavelet transform (WT) (89.81%), statistical features (STATS) (84.32%), short-time Fourier transform (STFT) (83.82%), principal component analysis (PCA) (89.82%), independent component analysis (ICA) (89.57%), Hilbert-Huang Transform (HHT) (80.90%), and empirical mode decomposition (EMD) (85.75%) with an average accuracy of 95.76%.

The proposed method has been compared with other techniques using the same, and actually, the proposed method has outperformed the existing methods in individual cases. Furthermore, for difficult cases, such as A2 and A3, the proposed method achieves 99.58% and 99.83% accuracy, respectively. Other techniques demonstrate similar performance but lack the strength of the presented model, especially in cases like A4 and A5, to which they break below 80%, while the proposed method maintains high accuracy. This will endorse the added capability of the combined feature extraction in a spectral and temporal sense to capture the complexity of seizure events.

Table IX represents a comparative feature extraction analysis for Bonn data. In all cases for the comparative analysis among feature extraction techniques, the proposed method, which fuses the spectral and temporal features, achieves superior performance. It has an impressive average accuracy of 96.97%, compared to conventional techniques such as wavelet transform (WT), 91.39%; statistical features, STATS, 89.95%; short-time Fourier transform, STFT, 89.25%; principal component analysis, PCA, 88.92%; independent component analysis, ICA, 89.00%; Hilbert-Huang Transform, HHT; and empirical mode decomposition, EMD; 91.%. Altogether, this approach can produce enhanced performance, particularly for challenging cases like B2, B3, and B4, in which approximate accuracies are around 98.47%, 99.42%, and 99.56%, respectively. Traditional methods remain comparable; however, this proposed technique is successful in endowing seizure pattern recognition with the facility to deal with complex presentations for the above analysis.

3) Comparison with Stacking Models

Stack Model 1 is the combination of base models such as XGBoost and LightGBM using a meta-learner of Bagging Classifier [29], and in Stack Model 2 base models are Random Forest, LightGBM, and Gradient Boosting; meta-learner is XGBoost [30].

The proposed SeqBoostNet model results in a significant outperformance of the stacking models on the BEED dataset as shown in Table X. It also boasts an average accuracy of 96.71%; more specifically, it outperforms other models in the specific cases of A2 (99.66%) and A3 (99.83%). Conversely, Stack Model 1 and Stack Model 2 display, on average, accuracies of 85.85% and 87.57%, respectively. The SeqBoostNet enhances much more challenging cases A4 and A5: stacking models fall below 80%, but the accuracy of SeqBoostNet is over 91% and shows its high robustness for seizure classification.

From Table XI it is observed that in the BONN data set, SeqBoostNet also outperforms with an accuracy of 97.11%, whereas Stack Model 1 shows 94.36% and Stack Model 2 shows 94.30%. In higher-accuracy cases such as B3 (99.34%) and B4 (99.63%), SeqBoostNet maintains high performance surpassing the stacking models every time. While the stacking models are performing well, relatively lower accuracy in cases like B5 further solidifies that SeqBoostNet has reliability and efficacy in accurately classifying seizure events across different cases.Hence, SeqBoostNet consistently outperforms existing stacking models in challenging scenarios. This exceptional performance highlights SeqBoostNet's robustness and reliability in accurately classifying seizure events, making it a strong classification model for enhanced diagnostic capabilities in healthcare settings.

5. Conclusions and Future Work

This study contributes significantly to seizure diagnostics by offering a robust SeqBoostNet stacking model's efficacy in classifying EEG data by leveraging both spectral and temporal features obtained through UMAP and FFT techniques. The proposed model accurately classifies seizure types, achieving a notable accuracy of 95.91% in distinguishing between focal and generalized seizures. Unlike existing models, which often struggle with variability in seizure presentations, this approach excels in classifying both seizure and healthy states and adapts well to varying patient conditions. By effectively capturing the temporal and spectral characteristics of EEG signals, the SeqBoostNet model demonstrates significant enhancement in classification performance across multiple metrics. Specifically, the model achieves an average accuracy of 96.71% for the BEED dataset and 97.11% for the BONN dataset, achieving a maximum accuracy of 99% for binary classification, distinguishing between seizure and healthy instances across both datasets. The proposed work demonstrates high performance due to its innovative integration of spectral and temporal features, which allows for a more comprehensive analysis of EEG signals. By employing the SeqBoostNet stacking model, the research effectively enhances classification accuracy through the combination of multiple algorithms, capitalizing on their strengths. Additionally, the use of advanced feature engineering techniques ensures that only the most relevant data is utilized, further improving the model's robustness. This meticulous approach not only boosts classification performance but also provides significant insights into distinguishing between various brain states. The exceptional precision, recall, and F1 scores achieved by the SeqBoostNet model highlight its reliability and robustness, marking a notable advancement in EEG data classification for clinical use. This strong performance emphasizes the model's potential for facilitating early detection and diagnosis of neurological disorders in both clinical and research contexts.

Limitations that are observed are dependency on the relevance of extracted features, which can differ significantly across datasets. Another key challenge related to the adaptability of stacked models is that combining multiple models or techniques can introduce complexity that may impact the model's performance across varied clinical datasets. Ensuring that stacked models maintain robust performance across different contexts remains a challenge. Future research should explore methods to improve the adaptability of stacking approaches, enhancing their applicability across diverse clinical contexts. Integrating the model into clinical practice could open avenues for innovations such as brain-computer interfaces and personalized medicine.

6. Acknowledgement

We would like to express our heartfelt appreciation to the management of the Bangalore EEG clinic for the BEED dataset, which comprises real-time EEG data collected from Bangalore. This dataset has been instrumental in our col-

TABLE VIII. Comparative Analysis with Feature Extraction Techniques For BEED Data

Cases	WT	STATS	STFT	PCA	ICA	HHT	EMD	Proposed
A1	89.91	83.83	81.42	85.83	85.67	78.75	83.58	**93.33**
A2	89.83	92.19	91.99	90.83	90.99	94.75	93.58	**99.58**
A3	92.30	91.42	92.51	93.67	92.75	94.42	94.33	**99.83**
A4	85.08	68.75	67.83	83.58	82.33	59.17	70.92	**89.91**
A5	89.91	76.42	75.42	90.33	90.92	66.25	78.08	**92.25**
A6	91.83	93.33	93.75	94.67	94.75	92.08	93.99	**99.66**
Average	89.81	84.32	83.82	89.82	89.57	80.90	85.75	**95.76**

TABLE IX. Comparative Analysis with Feature Extraction Techniques For BONN Data

Cases	WT	STATS	STFT	PCA	ICA	HHT	EMD	Proposed
B1	93.90	93.72	91.22	92.13	93.26	93.33	93.43	**97.10**
B2	90.41	91.46	91.25	90.58	90.22	90.23	91.26	**98.47**
B3	92.26	92.96	93.71	93.68	93.19	93.29	94.19	**99.42**
B4	93.64	94.93	94.28	91.99	91.55	93.71	94.78	**99.56**
B5	86.74	76.67	75.80	76.23	76.80	75.58	82.03	**90.28**
Average	91.39	89.95	89.25	88.92	89.00	89.23	91.14	**96.97**

TABLE X. Comparative Analysis with Stacking Classifiers For BEED Data

Cases	Stack 1	Stack 2	SeqBoostNet
A1	83.00	86.58	**95.91**
A2	91.75	90.92	**99.66**
A3	90.67	89.91	**99.83**
A4	71.67	75.58	**91.16**
A5	78.42	82.67	**94.01**
A6	99.58	99.75	**99.66**
Average	85.85	87.57	**96.71**

TABLE XI. Comparative Analysis with Stacking Classifiers For BEED Data

Cases	Stack 1	Stack 2	SeqBoostNet
B1	94.88	93.96	**97.39**
B2	96.26	95.04	**98.40**
B3	97.28	96.35	**99.34**
B4	95.49	96.71	**99.63**
B5	87.90	89.42	**90.79**
Average	94.36	94.30	**97.11**

laborative efforts to deepen our understanding of epilepsy. Without their generous support, our research would not have been feasible. Furthermore, we acknowledge Bangalore EEG clinic's notable contribution to our continued pursuit of knowledge in this domain.

References

[1] N. Kumari, U. Tiwari, S. K. Tripathi, R. Priyadarshini, and S. Naz, "Leveraging wearable sensors and supervised learning paradigm as a configurable solution for epileptic patients," *International Journal of Computing and Digital Systems*, vol. 14, no. 1, pp. 10 243–10 250, 2023.

[2] S. M. Usman, S. Khalid, and M. H. Aslam, "Epileptic seizures prediction using deep learning techniques," *Ieee Access*, vol. 8, pp. 39 998–40 007, 2020.

[3] E. Giourou, A. Stavropoulou-Deli, A. Giannakopoulou, G. K. Kostopoulos, and M. Koutroumanidis, "Introduction to epilepsy and related brain disorders," *Cyberphysical Systems for Epilepsy and Related Brain Disorders: Multi-parametric Monitoring and Analysis for Diagnosis and Optimal Disease Management*, pp. 11–38, 2015.

[4] M. D. Holmes, M. Brown, and D. M. Tucker, "Are "generalized" seizures truly generalized? evidence of localized mesial frontal and frontopolar discharges in absence," *Epilepsia*, vol. 45, no. 12, pp. 1568–1579, 2004.

[5] R. K. Maganti and P. Rutecki, "Eeg and epilepsy monitoring,"

CONTINUUM: Lifelong Learning in Neurology, vol. 19, no. 3, pp. 598–622, 2013.

[6] M. Gaik, M. Kojic, M. R. Stegeman, T. Öncü-Öner, A. Kościelniak, A. Jones, A. Mohamed, P. Y. S. Chau, S. Sharmin, A. Chramiec-Głabik *et al.*, "Functional divergence of the two elongator subcomplexes during neurodevelopment," *EMBO Molecular Medicine*, vol. 14, no. 7, p. e15608, 2022.

[7] S. Ashokkumar, S. Anupallavi, M. Premkumar, and V. Jeevanantham, "Retracted: Implementation of deep neural networks for classifying electroencephalogram signal using fractional s-transform for epileptic seizure detection," *International Journal of Imaging Systems and Technology*, vol. 31, no. 2, pp. 895–908, 2021.

[8] M. S. Islam, K. Thapa, and S.-H. Yang, "Epileptic-net: an improved epileptic seizure detection system using dense convolutional block with attention network from eeg," *Sensors*, vol. 22, no. 3, p. 728, 2022.

[9] F. Hassan, S. F. Hussain, and S. M. Qaisar, "Epileptic seizure detection using a hybrid 1d cnn-machine learning approach from eeg data," *Journal of Healthcare Engineering*, vol. 2022, no. 1, p. 9579422, 2022.

[10] T. S. Cleatus and M. Thungamani, "Epileptic seizure detection using spectral transformation and convolutional neural networks," *Journal of The Institution of Engineers (India): Series B*, vol. 103, no. 4, pp. 1115–1125, 2022.

[11] M. H. Aslam, S. M. Usman, S. Khalid, A. Anwar, R. Alroobaea, S. Hussain, J. Almotiri, S. S. Ullah, and A. Yasin, "Classification of eeg signals for prediction of epileptic seizures," *Applied Sciences*, vol. 12, no. 14, p. 7251, 2022.

[12] A. Altameem, J. S. Sachdev, V. Singh, R. C. Poonia, S. Kumar, and A. K. J. Saudagar, "Performance analysis of machine learning algorithms for classifying hand motion-based eeg brain signals." *Computer Systems Science & Engineering*, vol. 42, no. 3, 2022.

[13] X. Xu, Y. Zhang, R. Zhang, and T. Xu, "Patient-specific method for predicting epileptic seizures based on drsn-gru," *Biomedical Signal Processing and Control*, vol. 81, p. 104449, 2023.

[14] Y. Gao, Z. Zhao, Y. Chen, G. Mahara, J. Huang, Z. Lin, and J. Zhang, "Automatic epileptic seizure classification in multichannel eeg time series with linear discriminant analysis," *Technology and Health Care*, vol. 28, no. 1, pp. 23–33, 2020.

[15] S. Urbina Fredes, A. Dehghan Firoozabadi, P. Adasme, D. Zabala-Blanco, P. Palacios Játiva, and C. Azurdia-Meza, "Enhanced epileptic seizure detection through wavelet-based analysis of eeg signal processing," *Applied Sciences*, vol. 14, no. 13, p. 5783, 2024.

[16] S. Y. Shah, H. Larijani, R. M. Gibson, and D. Liarokapis, "Epileptic seizure classification based on random neural networks using discrete wavelet transform for electroencephalogram signal decomposition," *Applied Sciences*, vol. 14, no. 2, p. 599, 2024.

[17] D. Hernández, L. Trujillo, E. Z-Flores, O. Villanueva, and O. Romo-Fewell, "Detecting epilepsy in eeg signals using time, frequency and time-frequency domain features," *Computer science and engineering—theory and applications*, pp. 167–182, 2018.

[18] M. G. Tsipouras, "Spectral information of eeg signals with respect to epilepsy classification," *EURASIP Journal on Advances in Signal Processing*, vol. 2019, no. 1, pp. 1–17, 2019.

[19] K. Akyol, "Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection," *Expert Systems with Applications*, vol. 148, p. 113239, 2020.

[20] M. K. M. Rabby, A. K. Islam, S. Belkasim, and M. U. Bikdash, "Wavelet transform-based feature extraction approach for epileptic seizure classification," in *Proceedings of the 2021 ACM southeast conference*, 2021, pp. 164–169.

[21] J. Jing, X. Pang, Z. Pan, F. Fan, and Z. Meng, "Classification and identification of epileptic eeg signals based on signal enhancement," *Biomedical Signal Processing and Control*, vol. 71, p. 103248, 2022.

[22] S. Mishra, S. Kumar Satapathy, S. N. Mohanty, and C. R. Pattnaik, "A dm-elm based classifier for eeg brain signal classification for epileptic seizure detection," *Communicative & Integrative Biology*, vol. 16, no. 1, p. 2153648, 2023.

[23] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, p. 061907, 2001.

[24] D. Thara, B. PremaSudha, and F. Xiong, "Auto-detection of epileptic seizure events using deep neural network with different feature scaling techniques," *Pattern Recognition Letters*, vol. 128, pp. 544–550, 2019.

[25] T. Liu, M. Z. H. Shah, X. Yan, and D. Yang, "Unsupervised feature representation based on deep boltzmann machine for seizure detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 1624–1634, 2023.

[26] Y. Pan, X. Zhou, F. Dong, J. Wu, Y. Xu, and S. Zheng, "Epileptic seizure detection with hybrid time-frequency eeg input: A deep learning approach," *Computational and Mathematical Methods in Medicine*, vol. 2022, no. 1, p. 8724536, 2022.

[27] K. Singh and J. Malhotra, "Two-layer lstm network-based prediction of epileptic seizures using eeg spectral features," *Complex & Intelligent Systems*, vol. 8, no. 3, pp. 2405–2418, 2022.

[28] Aayesha, M. B. Qureshi, M. Afzaal, M. S. Qureshi, and M. Fayaz, "Machine learning-based eeg signals classification model for epileptic seizure detection," *Multimedia Tools and Applications*, vol. 80, no. 12, pp. 17 849–17 877, 2021.

[29] T. Islam, R. Islam, M. Basak, A. D. Roy, M. A. Arman, S. Paul, O. Shandra, and S. R. Ali, "Performance investigation of epilepsy detection from noisy eeg signals using base-2-meta stacking classifier," *Scientific Reports*, vol. 14, no. 1, p. 10792, 2024.

[30] S. Chatterjee and Y.-C. Byun, "Eeg-based emotion classification using stacking ensemble approach," *Sensors*, vol. 22, no. 21, p. 8550, 2022.