Hybridization of Machine Learning Models for Alzheimers Disease Classification

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Abstract – Alzheimer's disease (AD), is a gradual cognitive decline and memory impairment. It is a major health concern worldwide. Despite intensive research efforts, accurate and early diagnosis remains difficult to achieve, largely due to the complexity of AD pathology and the absence of definitive biomarkers. Existing diagnostic approaches often rely on costly and invasive procedures, leading to delays in diagnosis and treatment initiation, and limiting the effectiveness of therapeutic interventions. To overcome these issues, this work suggests a novel approach for AD classification using EEG signals. EEG signals offer a non-invasive and cost-effective means of assessing brain activity, making them an attractive candidate for biomarker discovery and disease classification. The proposed work integrates preprocessing, feature extraction, and classification methodologies to accurately differentiate between AD, normal/healthy states, and Frontotemporal Dementia (FTD). The proposed solution begins with Sequential Savitzky-Golay filtering (SEQ-SG) to enhance the quality of EEG signals by reducing noise and enhancing relevant features. Subsequently, an Improved Principal Component Analysis (IPCA) approach is employed for feature extraction, incorporating feature scaling using StandardScaler to ensure uniform contribution from all features. Finally, classification is achieved using a hybrid approach named HMLCAD (Hybridization of Machine Learning for Classification of Alzheimer's Disease), which combines Random Forest and Gradient Boosting through a voting classifier ensemble. This methodology offers a promising framework for accurate and early detection of AD, enabling timely intervention and improved patient outcomes.

Keywords – Alzheimer's Disease, Hybrid Model, HMLCAD, SEQ-SG. Machine Learning, Mild Cognitive Impairment**,** Fronto Temporal Dementia.

I. INTRODUCTION

A long-term neurological disorder that damages the brain is identified as Alzheimer's disease (AD) [1]. In elderly people, Alzheimer's disease (AD) is a neurodegenerative disease that affects people more frequently [2]. Consequently, it is exceedingly challenging to identify AD in its initial stages with accuracy [3, 4], and clever strategies are required to assist medical professionals in the individualized diagnosis of this disease [5]. The urgency for timely and precise AD diagnosis cannot be overstated, as it is paramount for implementing effective management and intervention strategies. Among the various diagnostic modalities, Electroencephalography (EEG) has emerged as an essential tool for AD assessment, offering non-invasive access to brain activity and cognitive states [5].

Despite its promise, the analysis of EEG data for AD classification poses significant challenges. EEG signals exhibit a high degree of complexity, reflecting intricate neural dynamics and cognitive processes. Deciphering these signals necessitates sophisticated analytical methods and robust classification algorithms capable of distinguishing subtle differences associated with AD pathology. Moreover, EEG data are often contaminated with noise from various sources, further complicating the analysis and necessitating preprocessing steps to enhance signal quality [6].

In this context, the development of advanced classification algorithms tailored for EEG-based AD diagnosis becomes imperative. These algorithms should be capable of extracting relevant features from EEG signals, discerning distinctive patterns indicative of AD, and discriminating between different cognitive states with high accuracy [7]. Furthermore, they should be robust to variations in EEG data and capable of generalizing well to unseen samples.

Addressing these challenges requires a multidisciplinary approach that leverages insights from neuroscience, signal processing, and machine learning. By integrating domain knowledge with cutting-edge methodologies, researchers aim to develop innovative algorithms capable of unraveling the complexities of EEG data and advancing the frontier of AD diagnosis. Such advancements hold the promise of revolutionizing clinical practice, enabling earlier detection of AD, facilitating personalized treatment approaches, and ultimately improving outcomes for individuals affected by this debilitating condition.

This work presents a unique technique for EEG-based classification of cognitive states, including AD, FTD, and normal/healthy states is proposed. Leveraging advanced machine learning technique ensemble methods includes Random Forest (RF) Gradient Boosting (GB) aims for the accuracy improvement of AD. Building upon existing algorithms known for their efficacy in handling high-dimensional data and improving classification performance, the effective proposed methodology is demonstrated through experimental validation using real-world EEG datasets.

The paper is structured into several sections. Section II provides a review of related works, discussing prior research and methodologies in the field of EEG-based classification for cognitive states, including Alzheimer's disease. Section III elaborates on the proposed method, outlining the steps involved in preprocessing EEG data, extracting relevant features, and utilizing advanced machine-learning techniques for classification. In Section IV, the paper presents the results and discussion of the findings, including experimental validation and performance evaluation of the proposed methodology. In the last Section V offers the conclusion, summarizing the key findings of the study and highlighting upcoming pathways for research in EEG-based classification for cognitive states.

II. RELATED WORKS

Several approaches for predicting Alzheimer's disease (AD) by using electroencephalogram (EEG) signals have emerged in the last few decades. Many comprehensive review papers have provided light on this issue, and multiple studies addressing this field of research are mentioned in the research papers. For instance, Roy et al [8] showed an extensive review, providing insights into the diverse methodologies and advancements in EEG-based AD prediction. Similarly, Merlin Praveena et al. [9] offered a comprehensive overview of the existing literature, summarizing the key findings and methodologies employed in EEG-based AD prediction studies.

These review papers serve as valuable resources, synthesizing the collective knowledge and highlighting the advancements made in the field. Their systematic analyses and evaluations provide researchers and practitioners with a significant view into the current study to identify potential avenues for future exploration. EEG signal-based disease prediction and traditional machine-learning techniques are extensively used, particularly in the field of AD. Neto et al. [10] conducted a study for extracting features from EEG data, encompassing both frequency and time domains, which were utilized to identify AD and normal control (NC) by applying Support Vector Machine (SVM) with 67% accuracy, the trained model differentiates AD and NC groups, underscoring the potential of EEG-based features for disease classification.

Trambaiolli et al. [11] identified the important frequency bands for model training using the frequency waves for AD disease. Their research highlighted the significance of theta and alpha waves in connection to AD. By incorporating these relevant frequency bands into an SVM model and subjecting them to iterative training, the accuracy of AD classification significantly improved, achieving a notable accuracy rate of 71.18%.

This study shows the importance of selecting appropriate frequency bands to maximize classifier performance in identifying AD and NC patients. Kashefpoor et al. [12] investigated the pathological association between normal control (NC) subjects Using EEG data and the correlation modeling technique, persons suffering from frontotemporal dementia (FTD) were able to determine which signal had the highest level of correlation. This EEG signal was then used as input for a continuous Neuro-Fuzzy k-nearest Neighbor Classifier training process. 58.89% accuracy of FTD prediction on the test dataset was much improved by this method.

Rallabandi et al. [13] designed a machine learning algorithm to classify into four categories according to their cognitive status: late mild cognitive impairment, Alzheimer's disease, early mild cognitive impairment, and normal aging. Their approach utilized MRI images as input to classify these MCI classes. Employing a Support Vector Machine (SVM) 75% accuracy, 77% specificity, and 75% sensitivity is attained. However, a notable limitation of their model is the extended time required for disease progression analysis from one stage to another.

Kashefpoor et al. [14] presented a novel approach called Correlation-based label-consistent K-SVD (CLC-KSVD) applied to identify Mild Cognitive Impairment (MCI) using electroencephalography (EEG) data. Their approach, leveraging the MRI dataset, aimed to identify discriminative features (sparse coefficients) from EEG time series and spectral features. With this method, they achieved an accuracy of 88.9%. It is noted that the created approach is limited to identifying between the two mentioned groups, which limits its value to more general categorization tasks. While significant strides have been made in leveraging machine learning techniques to extract AD-related signals from EEG data, Recognizing the dependence on complex pre-processing techniques is essential. This dependence poses a serious challenge to accurate and flexible environmental screening for AD in the initial stages of its development. **Table 1** shows Accuracy of Related Words.

Table 1. Accuracy of Related Words

Author	Methodology	Key findings	Accuracy
A. Miltiadous et al. [15]	Resting-state EEG dataset	Provided detailed description of EEG dataset for individuals with AD and frontotemporal dementia, aiding in further research.	73%
Pirrone, et al [16]	DT, SVM, KNN	a novel, easy technique that uses a finite response filter (FIR) to efficiently extract features	70-97%
G. Biagetti et al. [17]	Robust-principal component analysis (R-PCA)	Effective extraction of features for classification of AD from EEG signals.	93.18%
W. Xia et al. [18[	EEG classification	Novel approach improves diagnosis accuracy of AD and MCI using EEG.	97.10%
Hülya AKKAŞ et al [19]	Analysis of publicly available EEG data	AD patients and healthy individuals were analyzed by using EEG signals for diagnostic purposes.	100%

III. PROPOSED METHODOLOGY

The proposed methodology aims to classify EEG signals into distinct categories representing, Alzheimer's disease (AD), normal/healthy states, and Frontotemporal Dementia (FTD) and. **Fig 1** describes the overall proposed flow of the process.

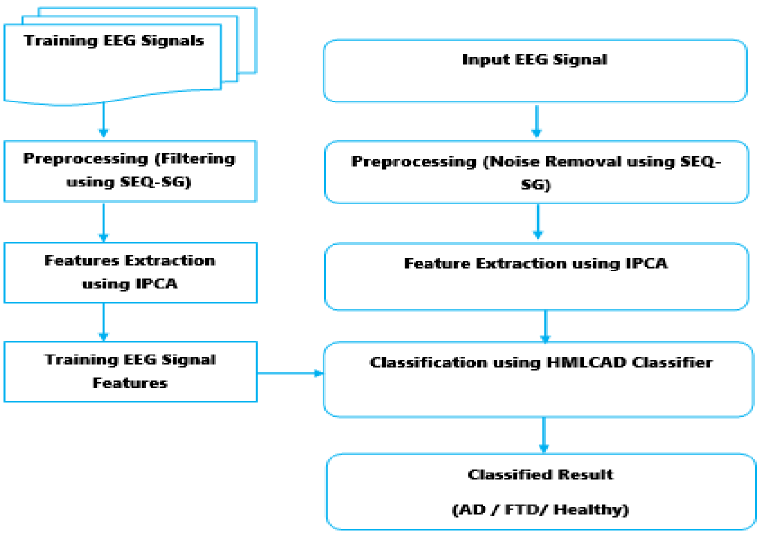

Fig 1. Overall Proposed Methodology for Alzheimer's Disease Classification.

Initially, EEG datasets are collected from diverse subjects to ensure representative samples. Following data collection, Sequential Savitzky-Golay filtering (SEQ-SG) is applied to preprocess the EEG signals. SEQ-SG filtering effectively enhances signal quality by reducing noise and smoothing the data, ensuring that subsequent analysis is conducted on clean and reliable signals. Feature extraction is then performed using an Improved Principal Component Analysis (IPCA) technique, which includes feature scaling using StandardScaler to normalize the data and ensure consistent feature contributions. PCA aids in reducing the dimensionality of the dataset while retaining crucial information, facilitating efficient feature extraction. Finally, classification is conducted using a hybrid approach known as HMLCAD (Hybridization of Machine Learning for Classification of Alzheimer's Disease). HMLCAD combines Random Forest and Gradient Boosting through a voting classifier ensemble, leveraging the strengths of both models for accurate classification. This comprehensive methodology integrates preprocessing, feature extraction, and classification techniques to provide a robust framework for EEG-based cognitive disorder classification.

Preprocessing

Sequential Savitzky-Golay filtering (SEQ-SG) [20] is a widely used technique in EEG signal processing for noise reduction and smoothing. This method applies a moving polynomial regression to the data, effectively reducing high-frequency noise while preserving important signal features. To implement SEQ-SG filtering on EEG signals, the following steps are typically followed:

Window Selection
Determine the window length and polynomial order for the filtering process. The window length specifies the number of data points over which the polynomial regression is applied, while the polynomial order defines the degree of the polynomial used in the regression.

Data Segmentation
Divide the EEG signal into overlapping segments of appropriate length. Overlapping segments help maintain continuity in the filtered signal and ensure that no information is lost during the filtering process.

Savitzky-Golay Filtering
Apply the Savitzky-Golay filter sequentially to each segment of the EEG signal. The filter performs a polynomial regression on each segment, effectively smoothing out noise and artifacts while retaining important signal features.

Overlap-Add Method
Combine the filtered segments using the overlap-add method to reconstruct the complete filtered EEG signal. This method ensures smooth transitions between segments and preserves the temporal structure of the original signal.

By applying Sequential Savitzky-Golay filtering to EEG signals, high-frequency noise, and artifacts are effectively removed, resulting in a cleaner and smoother signal for subsequent analysis. This preprocessing step is essential for improving the accuracy and reliability of feature extraction and classification algorithms applied to EEG data, ultimately enhancing the performance of cognitive state classification tasks such as distinguishing between frontal temporal Dementia, Alzheimer's disease, and normal/healthy states.

Feature Extraction using IPCA
To decrease the dimension of the data, Improved Principal Component Analysis (IPCA) is applied while preserving critical features for extracting features in EEG signals [21]. The process starts with feature scaling using StandardScaler, ensuring consistent contributions from all features by normalizing the data. Feature scaling transforms each feature x_{eeg} into a standardized form r_{scaled} using the formula:

$$\boldsymbol{x_{eeg\_scaled}} = \frac{x_{eeg} - \mu_{eeg}}{\sigma_{eeg}} \tag{1}$$

where μ_{eeg} represents the mean of the feature and σ_{eeg} denotes its standard deviation. Once the data is scaled, IPCA proceeds with covariance matrix calculation. The covariance matrix on ϵ_{eeg} is computed to capture relationships between different features. Eigenvalue decomposition is then performed on ϵ_{eeg}, yielding eigenvectors V_{eeg} and eigenvalues γ_{eeg}. These eigenvectors represent principal components, while eigenvalues denote the variance explained by each component. Next, dimensionality reduction occurs by selecting the top principal components that capture the majority of data variance. This involves sorting eigenvalues in descending order and retaining corresponding eigenvectors. Finally, feature extraction takes place by overlaying the scaled EEG data onto the selected principal components. This procedure yields a reduced-dimensional depiction of the original EEG signals, where each feature is a linear combination of principal components. Through IPCA, EEG data is effectively transformed into a compact and informative feature space, facilitating subsequent analysis.

Classification using the HMLCAD Model
The HMLCAD (Hybridization of Machine Learning for Classification of Alzheimer's Disease) integrates Random Forest and Gradient Boosting algorithms via a voting classifier ensemble to categorize EEG signals into distinct cognitive states: Alzheimer's disease, normal/healthy states, and Frontotemporal Dementia (FTD). Initially, EEG data needs to take place the preprocessing and feature extraction, followed by dataset division into training and testing subsets. The training data trains individual Random Forest and Gradient Boosting classifiers, with Random Forest adept at handling high-dimensional data and providing robust classification. At the same time, Gradient Boosting iteratively improves model performance by focusing on misclassified samples. The classifiers are then merged using a voting classifier ensemble, where each classifier's prediction carries equal weight. During classification, each classifier predicts the class label for a given EEG sample, and the final prediction results from a majority vote. This ensemble strategy ensures robustness and enhances classification accuracy by capitalizing on the combined strengths of Gradient Boosting and Random Forest. Overall, the HMLCAD module offers a robust EEG-based cognitive state classification framework, contributing to advancements in Alzheimer's disease and cognitive disorder diagnosis

Random Forest
The Random Forest is a powerful machine learning algorithm for classification that effectively handles high-dimensional datasets such as EEG features [23]. In the input phase, it takes a training dataset D comprising pairs of EEG features x_i and their corresponding class labels y_i, where i ranges from 1 to N, representing the number of samples. The output of the

algorithm is a trained Random Forest classifier RF. The procedure involves constructing a collection of decision trees. A subset of features in the ensemble for each tree is randomly selected, and with replacement, a subset of training data is sampled from the original dataset. Subsequently, a decision tree is trained on the selected subset of features and data. This process is repeated for a predefined number of iterations T, resulting in decision trees comprising the Random Forest classifier RF. Each decision tree in the ensemble learns different aspects of the data, contributing to the overall robustness and accuracy of the classifier. During the prediction phase, each decision tree predicts the class label on its own for a given input sample, and by taking the mean of each decision tree's predictions. the final prediction is identified in the ensemble. Through the combination of multiple decision trees trained on random subsets of features and data, the Random Forest Classifier offers robust classification performance.

Gradient Boosting

The Machine learning algorithms such as Gradient Boosting Classifiers used for classification tasks, are renowned for their capability to iteratively improve model performance by focusing on previously misclassified samples [22]. It takes as input a training dataset D comprising pairs of EEG features x_i and their corresponding class labels y_i where i ranges from 1 to N. The output of the algorithm is a trained gradient-boosting classifier GB. The procedure begins by initializing the ensemble prediction function $F_0(x)$ to zero. For each iteration t from 1 to T, the loss function's negative gradient concerning the previous ensemble prediction is computed, representing the residuals or errors in the predictions. A weak learner $h_t(x)$ is then fitted to these negative gradients using a loss function minimization approach, such as least squares. The learning rate $\propto$ controls each weak learner to the ensemble prediction, with smaller values typically leading to more conservative updates. The ensemble prediction function $F_t(x)$ is updated by adding the product of the learning rate and the predictions of the weak learner $h_t(x)$. The process iterates for a predefined number of iterations T, resulting in a series of ensemble prediction functions $F_1(x), F_2(x), \ldots, F_T(x)$. The final gradient-boosting classifier GB consists of these ensemble prediction functions, collectively leveraging the iterative refinement process to improve classification accuracy and robustness.

Voting Classifier

The Voting Classifier Ensemble combines the predictions from the Random Forest classifier RF and the Gradient Boosting classifier GB to classify EEG signals in the testing dataset D_{test}[23-25]. In the input phase, it takes as input the trained Random Forest classifier RF, the Gradient Boosting classifier GB, and the testing dataset D_{test}, consisting of EEG feature samples x_i where i ranges from 1 to M. The output of the algorithm is the predicted class labels for the testing dataset D_{test}. The procedure involves iterating through each sample x_i in the testing dataset D_{test}, where the class label prediction is obtained from each classifier in RF and GB.

These individual predictions are then aggregated using a majority voting scheme, where the final predicted class label for each sample is determined by selecting the class label with the highest frequency among the predictions. This ensemble approach ensures robustness and enhances classification accuracy by leveraging the collective insights from both the Random Forest and gradient-boosting classifiers. Finally, the Voting Classifier Ensemble returns the final predicted class labels for the testing dataset as shown in **Fig 2**, providing a reliable framework for cognitive state classification in EEG signals.

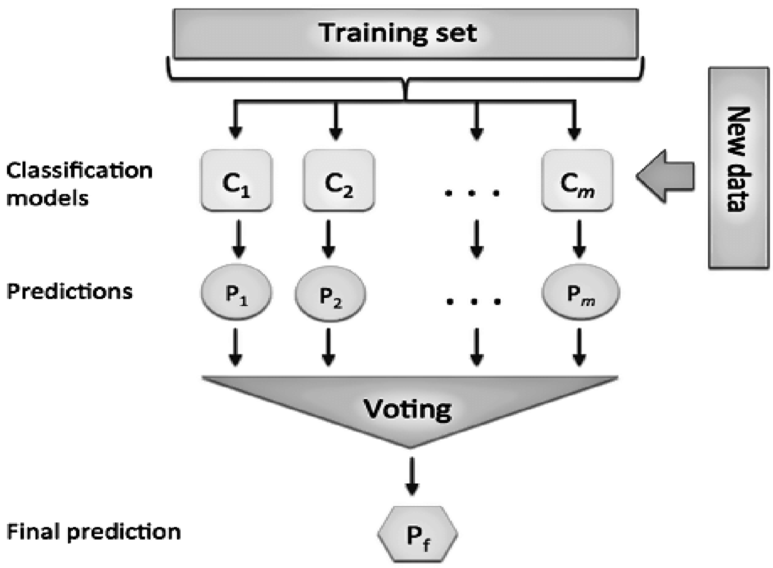

Fig 2. Voting Classifier Ensemble Working Structure.

IV. EXPERIMENTAL RESULTS

The experimental results presented in this section are designed and applied by the proposed method HMLCAD for classifying cognitive states using EEG, including Alzheimer's disease (AD), normal/healthy states, and Frontotemporal Dementia (FTD). Real-world EEG datasets were utilized for conducting the experiments, and the performance of the classification algorithms was evaluated based on various metrics.

Initially, an overview of the datasets used in the experiments, including their characteristics and preprocessing steps, is provided. Subsequently, the results of the classification experiments are presented, encompassing accuracy, F1-score, recall, and precision for each cognitive state in that accuracy represents the percentage of AD samples that were properly classified out of all the samples. It reflects the precision of the classifier in identifying AD cases accurately without falsely labeling healthy or other cognitive states as AD. Recall, within the context of AD classification, reflects the percentage of accurate positive predictions among all actual AD samples in the dataset. Lastly, the F1-score in AD classification serves as the harmonic mean of accuracy and recall, delivering a fair assessment of the classifier's overall performance in identifying AD cases while simultaneously considering both precision and recall. This metric provides insight into the classifier's ability to achieve both high precision and recall in AD classification tasks, thus indicating its robustness and effectiveness.

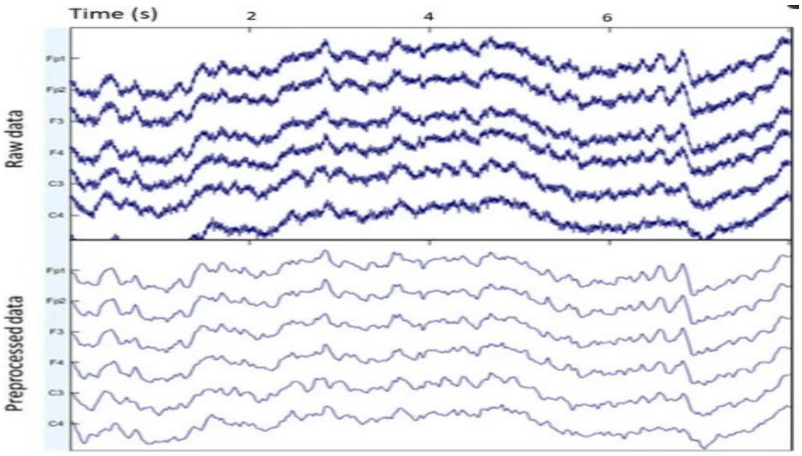

Fig 3. Sample Different Channels of EEG Signals from the Dataset (Raw and Preprocessed).

The dataset utilized for evaluating the effectiveness of the proposed methodology is the Alzheimer's disease and Fronto Temporal Diseases and healthy control dataset (AD-FTD-CN). It was obtained from the following link: https://openneuro.org/datasets/ds004504/versions/1.0.6. This dataset includes EEG records from 23 frontotemporal dementia patients, 36 Alzheimer's patients, and 29 healthy age-matched subjects. Specifically, it includes EEG closed-eye measurements from 88 participants during their resting state [15]. This dataset also contains preprocessed EEG signals from acquiring the raw signal, which is shown in **Fig 3**.

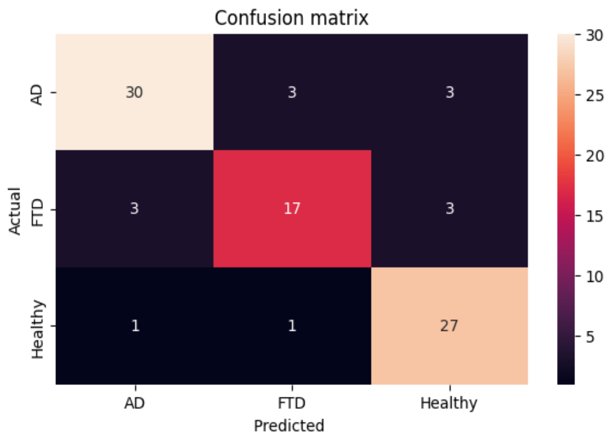

Fig 4. Confusion Matrix of HMLCAD Model.

Initially, we obtained a confusion matrix, depicted in **Fig 4**, focusing primarily on the positive class. A significant number of true positives contributed to the high performance in categorizing cognitive states. In the matrix, the proposed methodology accurately classified 30 signals of Alzheimer's disease, 17 FTD disease samples, and 27 healthy signals. Only a few signals were misclassified within the Alzheimer's disease and healthy classes.

Table 2. Performance Analysis of the HMLCAD Model

Metrics	Performance
Accuracy	84.09%
Precision	85.00%
Recall	83.00%
F1-score	84.00%

In **Table 2**, the performance metrics of HMLCAD are presented, including Accuracy, Precision, F1-score, and Recall. These metrics collectively assess the effectiveness of HMLCAD in accurately classifying cognitive states, such as AD, FTD, and healthy states. The obtained accuracy for EEG signal-based classification of cognitive states (AD, FTD, healthy) is 84.09%. The proportion of the samples that were correctly classified is the measure of accuracy that is measured among all samples in the dataset, indicating the overall effectiveness of the classifier in distinguishing between cognitive states based on EEG signals. The proportion of true positive predictions among all positive predictions is measured by precision, which is 85.00%. This metric assesses the classifier's ability to accurately identify specific cognitive states, such as AD, FTD, or healthy, without misclassifying other states. Recall, representing the proportion of true positive predictions among all actual samples of a particular cognitive state, is 83.00%. It evaluates the classifier's ability to capture instances of a specific cognitive state within the dataset. Lastly, the F1-score, calculated as the harmonic mean of precision and recall, provides an accurate measure of overall performance, considering both precision and recall simultaneously. The F1-score of 84.00% indicates the classifier's robustness in achieving a balance between accurate identification and comprehensive coverage of cognitive states. These metrics demonstrate the effectiveness of the EEG signal-based classification approach in accurately categorizing cognitive states, including AD, FTD, and healthy states, based on patterns observed in EEG signals.

Table 3. Comparative Analysis of Proposed HMLCAD Classifier and Single Classifier Model

Models	Accuracy
RF	82.46%
GB	81.24%
Proposed (HMLCAD)	84.09%

The accuracy scores of different models such as Gradient Boosting (GB), Random Forest (RF), and the proposed HMLCAD classifier are presented in **Table 3**. The HMLCAD classifier outperforms the single classifiers, RF and GB, with an accuracy of 84.09%, indicating its effectiveness in accurately classifying cognitive states based on EEG signals.

The Receiver Operating Characteristic (ROC) curve for the HMLCAD classifier is depicted in **Fig 5**. The ROC Area Under the Curve (ROC AUC) score for the HMLCAD classifier is 0.8767. This metric assesses the ability of the classifier, specifically HMLCAD, to differentiate between classes, with a higher ROC AUC indicating better discrimination performance. A value of 0.8767 suggests that the HMLCAD classifier performs well in separating the classes, further demonstrating its effectiveness in classifying cognitive states based on EEG signals.

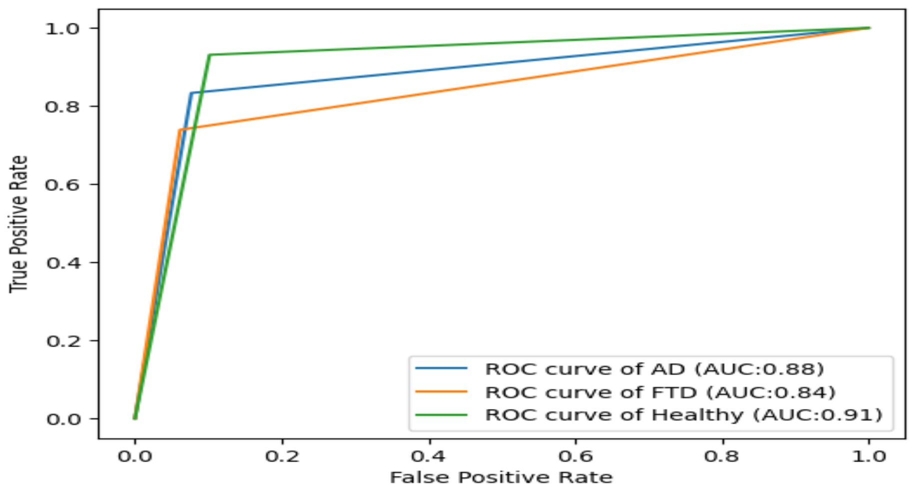

Fig 5. ROC Curve Analysis for AD Classification using HMLCAD Model.

V. CONCLUSION

The proposed HMLCAD approach demonstrates the promising performance of Cognitive states, including Alzheimer's disease (AD), Frontotemporal Dementia (FTD), and healthy states, which are classified using EEG data. Leveraging advanced machine learning techniques such as Random Forest and Gradient Boosting, the HMLCAD classifier achieves an accuracy of 84.09%, outperforming single classifiers like Random Forest (82.46%) and Gradient Boosting (81.24%). This high accuracy reflects the effectiveness of the HMLCAD classifier in distinguishing between these cognitive states based on patterns observed in EEG signals. Furthermore, recall, precision, and F1-score metrics validate the classifier's robustness, with recall at 83.00%, precision at 85.00%, and an F1-score of 84.00%. These metrics collectively showcase the classifier's ability to accurately identify specific cognitive states while maintaining comprehensive coverage of the dataset. Additionally, the HMLCAD classifier provides robust discrimination between different cognitive states, as evidenced by its high ROC AUC score of 0.8767. These results underscore the effectiveness of the proposed methodology in EEG-based classification, highlighting its potential for aiding in the early diagnosis of Alzheimer's disease and related cognitive disorders.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests
There are no competing interests.

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