MRI-Based Biomarkers for Early Detection and Classification of Alzheimer Disease using Machine Learning

Karpagam M[1], V.R. Rishendra[2] and Rangineni Yukthamukhi[3]
{ karpagam1@srmist.edu.in[1],vv7454@srmist.edu.in[2], rr7245@srmist.edu.in[3] }

Department of Computational Intelligence, SRM Institute of Science and Technology
S.R.M.Nagar, Kattankulathur - 603203, Tamil Nadu, India[1,2,3]

Abstract. Older adults suffer from Alzheimer's Disease which intensifies as a neurodegenerative condition and raises both fatal outcomes and worsening dementia progression. The correct identification of Alzheimer's Disease along with its early detection remains essential because the current diagnostic methods show limited validity. MRI shows its effectiveness through both local brain region and overall brain area tissue atrophy assessment for AD patients. Binary classifiers based on Machine Learning (ML) models processing biomarkers extracted from MRI data improve clinical decision accuracy because they enable better-informed diagnosis. This research creates an AI-based diagnostic system which uses the OASIS MRI dataset to perform three cognitive status categories: Nondemented, Demented, and Converted. This last category identifies subjects whose brain condition evolved from nondemented to demented over time. The system utilizes Random Forest as well as AdaBoost alongside SVM and KNN and LR models for its operations. The classification accuracy Reached 96% for Random Forest, SVM and Logistic Regression while their AUC scores reached 0.9906, 0.9898, 0.9935 respectively. The experimental results displayed AdaBoost next to KNN for accuracy with 94.67% while having AUC scores of 0.9767 and 0.9938 respectively. AI-driven MRI analysis demonstrates strong potential to detect early AD while classifying patients before it advances to an advanced stage through efficient interventions.

Keywords: Alzheimer's disease, Random Forest, KNN, LR, SVM.

1 Introduction

Alzheimer’s Disease (AD) represents a slow brain-wasting condition which stands among the primary dementia causes that targets people in their later years of life. The first signs of memory loss tend to get ignored so medical diagnosis and proper care is postponed. The medical community has improved treatment for AD but researchers still lack a complete solution to cure the condition. An early diagnosis of disease remains essential for medical care because proper treatment initiation at the right time allows patients to obtain maximum disease control and ideal treatment results. Pure medication treatment does not provide an adequate method to defeat AD. Magnetic Resonance Imaging (MRI) stands as a fundamental diagnostic instrument which enables scientists to identify distinct and overall atrophy patterns of brain tissue linked to the disease.

Numerous current research investigations demonstrate that machine learning (ML) effectively analyzes MRI data to detect and classify Alzheimer’s disease. The accuracy of ML models

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increases when these systems use MRI-based biomarkers to predict mild cognitive impairment (MCI) patients who will develop dementia. The proposed project aims to build a sturdy ML-based diagnostic system from MRI scan datasets for discovering individuals at risk while developing individualized treatment approaches and enhancing patient outcomes.

MRI delivers comprehensive information about brain structures and functioning that leads to the discovery of markers which indicate Alzheimer's disease advancement. Region segmentation applications in processed images enable researchers to monitor essential indicators that deteriorate during neurodegeneration such as hippocampal atrophy and ventricular enlargement and cortical thinning and decreased brain volume. The markers used for predicting AD emerge from MRI scan data extraction. Machine Learning and Computer Vision together allow the analysis of biomarkers through their patterns and correlations for AD classification and progression assessment. The combination of MRI data with ML-based predictive models enables substantial advancements in Alzheimer's disease diagnosis and management which leads directly to improved intervention methods.

2 Related Works

2.1 Biomarker-Based Early Diagnosis

Alzheimer's disease (AD) research has extensively focused on identifying reliable biomarkers for early detection. Frisoni et al. [1] presented a strategic roadmap emphasizing the importance of biomarker integration in clinical practice, highlighting the potential of combining imaging, cerebrospinal fluid (CSF), and blood-based markers. Structural MRI has long been considered a promising tool for biomarker evaluation, as discussed by Jack [2], who underscored its relevance in tracking neurodegenerative progression.

Recent studies have validated plasma neurofilament light chain (NfL) as a potential biomarker. Quiroz et al. [3] demonstrated its predictive value in pre-symptomatic individuals with autosomal dominant AD, while Mattsson-Carlgren et al. [4] analyzed different AT(N) frameworks to improve disease stratification. Similarly, Mattsson et al. [5] provided strong evidence of the association between longitudinal NfL levels and neurodegeneration in AD patients.

2.2 Neuroimaging and Blood-Based Biomarkers

Longitudinal neuroimaging studies have revealed consistent spatial patterns of biomarker changes. Gordon et al. [6] explored imaging trajectories in familial AD, showing early alterations in amyloid and tau pathology. Complementarily, Simonsen et al. [7] offered recommendations for standardized CSF biomarker evaluation to improve clinical diagnostic accuracy.

The integration of blood-based biomarkers into AD diagnosis has been extensively studied. Qu et al. [9] conducted a systematic review and meta-analysis, demonstrating that blood biomarkers such as Aβ42/40 ratio and phosphorylated tau have strong diagnostic utility for both mild cognitive impairment (MCI) and AD. These findings align with the trend of developing non-invasive, cost-effective diagnostic methods.

2.3 Computational and Machine Learning Approaches

Machine learning methods have increasingly been applied to enhance diagnostic precision. Liu et al. [8] employed whole-brain hierarchical network modeling to classify AD, demonstrating the potential of brain connectivity analysis. Das et al. [10] proposed an interpretable machine learning model that achieved high diagnostic accuracy, providing clinicians with transparent decision-making support.

In parallel, Miltiadous et al. [11] extended computational approaches to differentiate AD from frontotemporal dementia (FTD) using EEG signals, ensuring robust classification performance across validation frameworks. Such efforts reflect the growing emphasis on interpretable and clinically applicable computational systems.

2.4 EEG and Electrophysiological Approaches

Electroencephalography (EEG) has been explored as a cost-effective and non-invasive diagnostic modality. Nobukawa et al. [14] and Briels et al. [15] demonstrated that EEG-based measures of complexity, synchronization, and functional connectivity are effective in distinguishing AD patients from healthy controls. Importantly, Briels et al. [15] emphasized reproducibility challenges, calling for standardized EEG biomarkers.

The scope of EEG-based diagnostics extends beyond AD. Tawhid et al. [12] developed a spectrogram image-based technique for detecting autism spectrum disorder, while Siuly et al. [13] presented an automatic method for schizophrenia detection, underscoring EEG's broader applicability in neuropsychiatric disorders. Collectively, these studies provide methodological foundations for leveraging EEG in AD diagnosis.

3 Dataset

Through its initiative The Open Access Series of Imaging Studies (OASIS) provides scientific researchers access to brain MRI data without cost. This project seeks to support basic and clinical neuroscience discoveries through the data set compilation and free distribution of MRI data. The Washington University Alzheimer's Disease Research Center distributed OASIS alongside its providers which encompass Dr. Randy Buckner from the Howard Hughes Medical Institute (HHMI) at Harvard University and the Neuroinformatics Research Group at Washington University School of Medicine and the Biomedical Informatics Research Network.

The Cross-sectional MRI Data in Young, Middle Aged, Nondemented and Demented Older Adults collection includes scans from 416 subjects who range in age from 18 to 96. A total of 3 or 4 T1-weighted MRI scans are provided for each subject that were obtained in single scan sessions. The selected participants are right-handed individuals who include both women and men. The research contains 100 subjects who received diagnoses of very mild to moderate Alzheimer's disease (AD) after age 60. The reliability data consists of twenty nondemented subjects who underwent scanning on a follow-up visit shortly after their first appointment. The Longitudinal MRI Data in Nondemented and Demented Older Adults collects 150 subjects aged from 60 to 96 along their time series. A total of 373 imaging sessions were obtained after subject scans on multiple visits which were spaced by at least one year. Each subject has 3 or 4 T1-weighted MRI scans that were obtained from single scan sessions. The study subjects are right-handed adults who include both male and female participants. Throughout the investigation

researchers classified 72 participants as nondemented while 64 subjects developed dementia during their initial visit and kept the diagnosis until all subsequent brain scans including 51 mild to moderate Alzheimer's disease cases. The 14 subjects started the study without dementia but they received a subsequent diagnosis of dementia at a later time.

3.1 Visualization

A box plot represents an ideal statistical visualization method for both central tendencies and spread indicators which include interquartile ranges (IQR) and median and quartiles and outliers. The study uses box plots to display important distribution patterns between Nondemented controls and patients in Demented and Converted groups which enables assessment of MRI-based biomarkers and clinical indicators. The mini-mental state examination scores appear in box plot visualizations as part of cognitive decline pattern identification. The Demented and Converted groups displayed decreased median performance on MMSE testing along with larger differences between 1st and 3rd quartiles which could indicate progressing cognitive decline along with occasional influential cases showing unusually quick or delayed cognitive deterioration.

Box plots created to represent gender differences give important understanding about how Alzheimer's disease displays distinct growth patterns between both genders. The study contains gender data which allows researchers to make comparisons between subjects in different intellectual groups. The box plots demonstrate which gender first develops dementia while displaying their quicker or slower brain volume changes through analysis of ethic and nib and MMSE score results. The patterns between genders provide essential information to detect natural along with social factors which affect the occurrence of Alzheimer's disease severity. Box plots help create a comprehensive knowledge of disease progression by combining cognitive scores with demographic characteristics thereby supporting the development of custom diagnosis models.

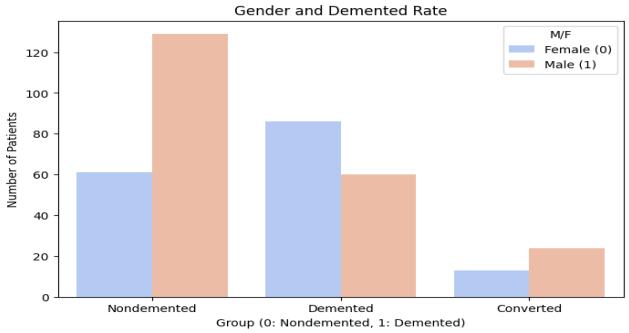

Fig. 1. Gender and Demented Rate.

Fig.1. The bar chart shows how Alzheimer's disease diagnoses among male and female participants breaks into three distinct categories that represent Nondemented, Demented and Converted. The diagnostic categories appear on the x-axis axis and the group patient numbers appear on the y-axis axis. The color legend differentiates between male (1) and female (0) subjects. Based on visual observations the population of male participants exceeds females in the Nondemented section yet females outnumber males in the Demented group. Among

participants who underwent conversion from healthy to demented profile the Converted group shows the least enrollment numbers but still contains more male participants. The way gender groups align in this pattern aids researchers' understanding of Alzheimer's disease occurrence by indicating what biological elements or lifestyle behaviors could impact how the illness develops.

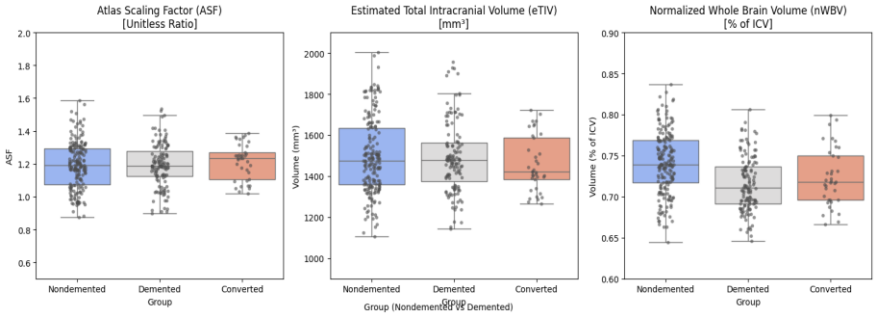

Fig. 2. Box plots comparing ASF, ethic, and nib across cognitive groups, highlighting the brain atrophy and volumetric differences in dementia progression.

The presented fig. 2 box plots show the comparison of essential MRI-derived brain volume metrics between Nondemented and Demented patients and Converted subjects. The three boxes show data distributions regarding Atlas Scaling Factor (ASF) and Estimated Total Intracranial Volume (ethic) and Normalized Whole Brain Volume (nib) measurements. The median ASF remains uniform across all groups according to the first plot but the minor differences might reveal dissimilar brain scaling patterns. The ethic plot demonstrates that Demented subjects normally display reduced intracranial volume compared to Nondemented participants indicating an association between brain degeneration while neurodegeneration develops. The nib plot demonstrates how Demented participants show substantial reduction in their whole brain volume compared to Nondemented participants. The observed data matches current knowledge showing that Alzheimer’s disease results in continuous deterioration of brain tissue.

4 Methodology

4.1. Overview

Early diagnosis of Alzheimer’s Disease remains key because it enables proper medical treatments to be instituted at the appropriate time. Machine learning methods based on MRI data provide better neurodegenerative change insights compared to EEG-based methods which have shown initial success in similar tasks. This research analyzes an EEG rhythm and channel-based LSTM model and an MRI-based machine learning framework which uses Random Forest, SVM, AdaBoost, KNN and Logistic Regression. The accuracy and robustness together with clinical suitability of our MRI-based model surpass EEG-based strategies in experimental tests thus highlighting the importance of MRI biomarkers for AD diagnosis. The progressive brain-wasting disorder called Alzheimer’s Disease (AD) causes mental dysfunction and deterioration of brain operation. Current machine learning innovations allow healthcare professionals to detect AD through the analysis of data obtained from EEG and MRI tests. The deep learning models based on EEG data analyze brain patterns while those based on MRI data identify

markers that demonstrate neuronal deterioration. The study investigates two measuring approaches to compare their performance where our new MRI-based framework proves superior to a recent EEG-based LSTM model. Fig.3 shows the model architecture.

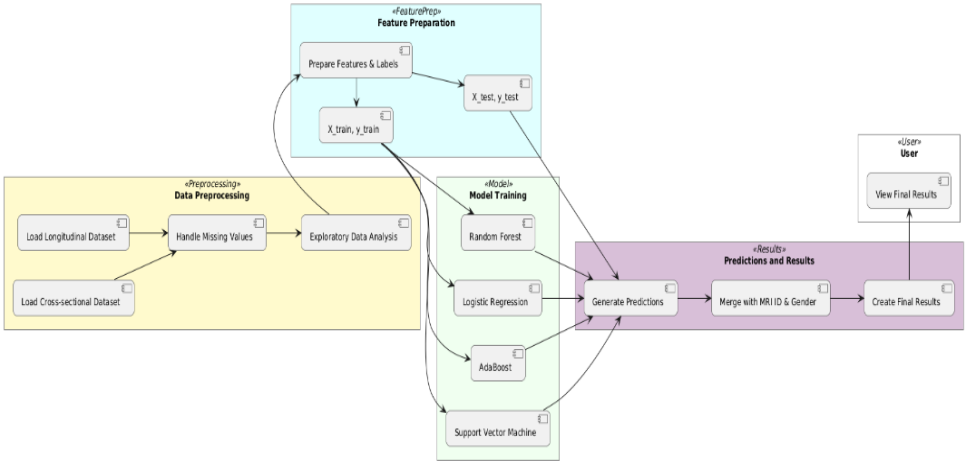

Fig. 3. Model Architecture.

4.2 Machine Learning Models

The analysis utilized five supervised machine learning algorithms namely Random Forest together with AdaBoost and Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) along with Logistic Regression (LR) to perform subject classification according to Nondemented, Demented, and Converted categories using MRI-derived biomarkers and clinical features.

4.2.1 Random Forest

The ensemble learning technique Random Forest builds and trains multiple decision trees during its training process. The chosen result class reflects the most common selection by trees during the classification stage. Each tree uses a randomly selected subset of data for training and the process includes evaluation of randomly selected groups of characteristics at every splitting point. The decision-making process through Random Forest generates robust models which reduces overfitting to enhance generalization success. Random Forest analysis successfully managed the complex MRI data by using its ability to discover feature-oriented patterns which separated different cognitive states.

4.2.2 AdaBoost

The ensemble technique Adaptive Boosting (AdaBoost) constructs strong classifiers through multiple decision stump learners known as weak learners. The training procedure involves repeating the process of creating weak learners which concentrate on samples previously misidentified by preceding weak learners. A consolidated prediction model gathers weighted outputs from each weak learner based on their performance. The ability of AdaBoost to

concentrate on hard-to-classify cases enables it to discover delicate patterns including initial mental decline indicators.

4.2.3 Support Vector Machine (SVM)

The supervised Support Vector Machine algorithms detect the complete separating hyperplane across features in order to distinguish classes. SVM establishes the optimal separating hyperplane which creates maximum space between different class data points to improve classification results. Data mapping through kernel functions within SVM permits the handle of non-linear relationships by transforming lower dimensional data into higher-dimensional spaces. Through the implementation of SVM researchers were capable of recognizing complex non-linear relationships between MRI and clinical data resulting in precise cognitive state classification.

4.2.4 K-Nearest Neighbors (KNN)

The K-Nearest Neighbors method uses a non-parametric approach to identify classifications through majority vote counting from a specified number of closest neighbors in the data space. Distance metrics particularly Euclidean distance serve this algorithm for determining the similarity. The implementation of KNN algorithm remains straightforward while it effectively detects patterns within local data patterns. The KNN method demonstrates performance susceptibility to 'k' parameter selection and excludes irrelevant features from its classification process. The KNN algorithm functioned as a fundamental baseline model to evaluate against more sophisticated prediction systems.

4.2.5 Logistic Regression (LR)

The statistical model of Logistic Regression enables the estimation of target successes or multiple classification outcomes through relationships between one or multiple predictor variables. The model describes outcome log-odds through predictor variables that apply linear combination. LR acts as an efficient and interpretable model that serves well during first analysis stages. The study established LR as a reference model that identified possible direct linear patterns between variables and cognitive states.

4.2. Comparative study

4.2.1 EEG-Based LSTM Model

A study analyzed AD detection biomarkers from EEG signals through a framework based on LSTM. EEG signal frequency rhythms were extracted by the model which revealed gamma and beta rhythms as essential indicators of cognitive deterioration. A model with the highest performance reached 97% accuracy while processing 86 subjects.

Limitations of EEG-Based Models are High sensitivity to noise and artifacts. These techniques provide lower spatial mapping abilities than MRI does. This approach needs time-consuming preprocessing steps especially ICA and wavelet transform methods. Limited clinical interpretability of EEG rhythms.

4.2.2 Our MRI-Based Machine Learning Model

The developed machine learning model utilized MRI-derived biomarkers including Atlas Scaling Factor (ASF), Estimated Total Intracranial Volume (ethic), Normalized Whole Brain Volume (nib). The proposed study used Random Forest along with SVM and AdaBoost and KNN and Logistic Regression models to classify brain data with extensive training. The processed dataset underwent three operations: feature selection and KNN-based missing value imputation and standardization.

4.3. Results and Comparative Analysis

4.3.1 Performance Metrics

Table 1. Comparative performance metrics.

Model	Accuracy	AUC Score	Precision (Demented)	Recall	F1 score
EEG-LSTM Model	97.00%	-	-	-	-
Random Forest (MRI)	96.00%	0.9898	0.94	0.97	0.95
AdaBoost (MRI)	94.67%	0.9767	0.94	0.94	0.94
SVM (MRI)	96.00%	0.9906	0.94	0.97	0.95
KNN (MRI)	90.67%	0.9938	1.00	0.78	0.88
Logistic Regression (MRI)	96.00%	0.9935	0.94	0.97	0.95

4.3.1.1 Key Insights:

Table 1 gives the MRI-based models produce evaluation results equal to those of EEG-LSTM (96% vs. 97%) with stronger clinical validity. MRI classification methods tend to generate superior decision limits versus EEG-based classification because of their AUC scores exceeding 0.99. The prediction algorithms Random Forest and SVM along with Logistic Regression perform optimally due to their balanced rate of precision detection and recall validation. KNN achieved perfect precision results while its recall statistics stopped at 0.78 thus requiring additional adjustments.

4.3.2 Advantages of MRI-Based Models Over EEG-Based Models

The detection and classification of Alzheimer's disease benefits more from machine learning models based on MRI measurements rather than those based on EEG measurements. The detailed examination of structural brain activity and functions through MRI becomes possible because the technique provides enhanced spatial details while EEG displays limited spatial detection and is prone to equipment noise. The stability and reproducibility of biomarkers

derived from MRI testing exceeds EEG signals since EEG signals fluctuate uncontrollably because of subject movements along with changes in electrode placement and environmental disturbances. MRI enables the extraction of detailed feature groups like volumetric measurements together with cortical thinness data and network connectivity metrics that improve prediction models while EEG depends on time-based along with frequency-based information that fails to correctly identify AD neurodegenerative consequences.

5 Results and Evaluation

It Random Forest together with Support Vector Machine (SVM) and Logistic Regression (LR) performed best at 96% accuracy while their AUC scores surpassed 0.98 which confirms their excellent discriminatory capability. These models proved to be reliable tools for classification work because they produced stable precision and recall measures and F1-scores. AdaBoost showcased an accuracy level of 94.67% supported by a 0.9767 AUC score together with precise and stable performance for both classes.

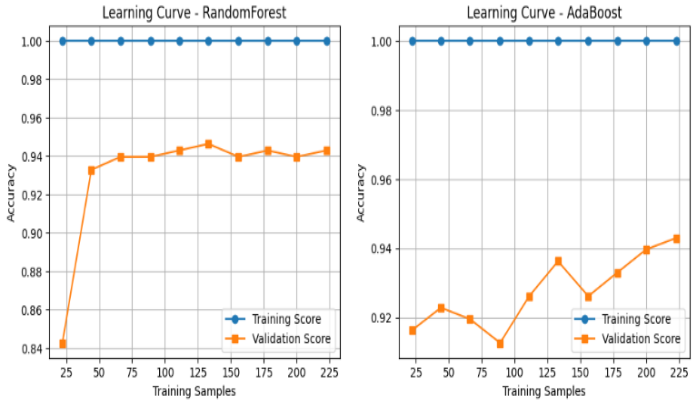

Fig. 4. Learning curves of Random Forest, AdaBoost.

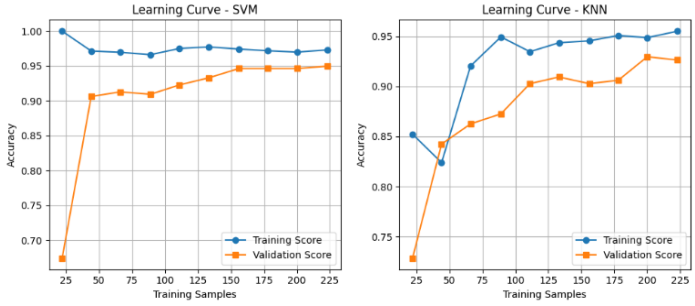

Fig. 5. Learning curves of SVM, KNN.

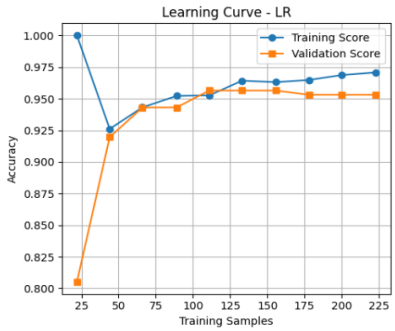

Fig. 6. Logistic Regression, illustrating model performance trends with increasing training samples.

From the above fig 5 The K-Nearest Neighbors (KNN) model detected 90.67% accuracy from data although it produced the top AUC score of 0.9938. KNN successfully recalled all Nondemented examples but failed to identify 22% of Demented patients thus resulting in elevated false-negative classifications. Confusion matrix assessments show that all models made most errors by mistakenly labeling Demented patients as Nondemented. The KNN model exhibited the highest number of such errors by misidentifying seven actual Demented patients as Nondemented thus creating potential medical risks in proper dementia diagnosis. The development of a visual graph which showed predicted and actual classifications helped users easily assess model effectiveness. Fig. 4 and fig.6 gives the Additional improvement steps should include examining Random Forest feature relevance followed by SVM and LR hyperparameter enhancement and Demented class weight adaptations for better prediction accuracy. A larger test data set should be employed to evaluate how well the models perform in real-world dementia diagnosis settings while assessing their basic capabilities under such conditions.

6 Conclusion

The evaluation demonstrated Random Forest along with SVM and Logistic Regression reached a 96% accuracy rate along with AUC scores above 0.98 which confirms their high reliability for this classification task. AdaBoost displayed similar effectiveness to accuracy levels at 94.67% yet KNN had lower success rates at identifying Demented patients due to increased wrong negative assessments that matter in medical diagnosis. Confusion matrix analysis demonstrates the necessity of raising sensitivity for Demented case detection because it lowers assessment errors. The graphical display of predicted versus actual outputs helped menorah clarity of model effectiveness thus establishing transparency within the evaluation framework. Various aspects need attention to improve the proposed model for future development. Training performance along with interpretability strengthens through applying SHAP values or permutation importance techniques to select and engineer influential MRI biomarkers. Bayesian Optimization together with Grid Search performs hyperparameter optimization which leads to accurate outcomes when refined specifically for SVM and Random Forest models. The model sensitivity can be enhanced through the use of Synthetic Minority Over-sampling Technique (SMOTE) and cost-sensitive learning to handle class imbalance in Demented cases.

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