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EVALUATION OF MACHINE LEARNING ALGORITHMS FOR ALZHEIMER'S DISEASE PREDICTION USING EXTENSIVE HEALTH INFORMATION

Computer Science

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ABSTRACT

Early diagnosis and accurate prediction of Alzheimer's Disease are crucial to provide early intervention to improve patient outcomes. This study investigates the application of ten different supervised machine learning (ML) algorithms-LR, k-NN, DT, Gaussian Naïve Bayes, SVM, RF, Gradient Boosting, AdaBoost, and Multilayer Perceptron (MLP)-to predict Alzheimer's disease using a clinical dataset. We preprocessed our data, consisting of 2,149 samples, to remove missing values, scale feature sets, generate them into different forms with one-hot encoding, and extract features. Models were trained on 80% of the data and evaluated on a 20% test subset using accuracy, precision, recall, F1-score, and ROC-AUC. The overall results show that ensemble methods, particularly Gradient Boosting (accuracy = 95.6%, ROC-AUC = 0.986) and Random Forest (accuracy = 94.2%, ROC-AUC = 0.979), obtain better performance than other methods, demonstrating their robustness to heterogeneous biomedical data. It highlights how ML-based methodology can be applied to the early prediction of AD and the utility, especially in improving clinical decision-making and increasing diagnostic accuracy, of the ensemble models.

KEYWORDS

Disease, Ensemble Learning, Clinical Dataset, Cognitive Assessment and Predictive Modeling

INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder marked by cognitive decline and memory loss. The early detection and accurate prediction of AD progression are critical for effective intervention and management. In recent years, machine learning (ML) has emerged as an invaluable tool in healthcare, particularly in the prediction and diagnosis of AD. ML algorithms enable researchers and clinicians to analyze complex datasets-ranging from clinical records and gene expression profiles to neuroimaging data-to identify patterns that may indicate early disease onset. Among the various ML approaches, predictive modeling techniques have shown considerable promise. For example, comparative studies have demonstrated that algorithms such as Decision Trees and Random Forests can achieve high predictive accuracy when applied to clinical data, making them strong candidates for early AD detection [1]. In parallel, classification models that employ Support Vector Machines (SVM), Naïve Bayes, and K-Nearest Neighbors (K-NN) have been effective in leveraging gene expression data, with SVM-based models attaining accuracies as high as 96.6% [2]. The impact of ML on AD diagnosis has been further reinforced by recent research that integrates diverse data modalities including clinical, genetic, and neuroimaging information. Studies utilizing Convolution Neural Networks (CNNs) have underscored the potential of deep learning in classifying different stages of AD by analyzing functional and structural imaging data [3], [4]. Moreover, comprehensive reviews have highlighted the importance of model interpretability and the transition toward explainable AI frameworks in clinical settings, ensuring that the outcomes of ML models are both accurate and transparent [5].

The construction and evaluation of these predictive models are supported by extensive datasets, such as those provided by the Alzheimer's Disease Neuroimaging Initiative (ADNI), which offer a rich resource of clinical, imaging, and genetic data. Additionally, emerging methods that fuse neuroimaging data from structural and functional magnetic resonance imaging (MRI) have led to innovative frameworks, such as multiscale autoencoders with structural-functional attention networks, which further enhance prediction performance [6].

In summary, the integration of machine learning algorithms into AD prediction represents a significant advancement in the field of neurodegenerative disease research. By harnessing diverse data sources and sophisticated modeling techniques, ML not only facilitates early diagnosis but also paves the way for personalized treatment strategies that aim to mitigate the societal and economic burdens associated with Alzheimer's Disease. This economic impact is further compounded by the disproportionate growth of dementia cases in low- and middle-income countries (LMICs), where health infrastructure and diagnostic resources remain limited compared to high-income nations [7]. As a result, disparities in early detection and intervention have become a significant concern in global health policy and research.

Currently, there is no single definitive or universally accepted diagnostic protocol for Alzheimer's disease [8]. Diagnosis typically relies on a multifactorial approach that integrates clinical examination, neuropsychological testing, biomarker evaluation, and neuroimaging. Early and accurate diagnosis plays a pivotal role in mitigating disease progression and maintaining patient quality of life, allowing for timely therapeutic and caregiving interventions.

Standard diagnostic procedures involve a combination of physical, neurological, and cognitive assessments, alongside a detailed review of the patient's medical and family history. Laboratory tests-including blood, urine, and genetic analyses—are often employed to exclude alternative causes of dementia-like symptoms and to identify genetic predispositions associated with AD [9]. Such tests can assess vitamin deficiencies, infections, and metabolic dysfunctions related to the liver, kidney, or thyroid, which may influence cognitive decline. Genetic testing is particularly valuable for identifying mutations or familial trends in dementia-related genes such as APOE ε4, APP, PSEN1, and PSEN2, which are strongly linked to early-onset Alzheimer's disease.

Increased technology has made diagnostic approaches even more transformative. Imaging of the brain, such as MRI and PET, has emerged as a key imaging modality to characterize the neurodegenerative progression in AD [10]. These scans aid in identifying amyloid-beta plaques, tau tangles, and cortical atrophy - the characteristic features of the disease. Longitudinal imaging studies of brain volume change or regional contractions or expansions also offer valuable information on disease progression and stage classification [11]. Machine learning and artificial intelligence (AI) models and recent data have also been employed on neuroimaging systems for providing targeted diagnostic measures and enabling predictive modeling of AD risk derived from subtle abnormalities in structural and metabolic information that may precede the onset of clinical symptoms. Collectively, these new diagnostic methods highlight the trend toward precision medicine in Alzheimer's research that combines biological, behavioral, and computational methodologies to enable earlier diagnosis and improved patient care.

Figure 1. Factors contributing to the development of Alzheimer's disease.

Alzheimer's disease is thought to arise from a complex interaction of the genetic, environmental and lifestyle factors. Major contributors include advanced age, sex, cardiovascular disease, diabetes, head injury and poor lifestyle choices such as smoking or inactivity. In addition, environmental exposure and infection can increase neuronal injury [12].

Challenges

Machine learning has emerged as a promising tool for addressing the limitations of traditional diagnostic methods. However, its application to Alzheimer's disease prediction is fraught with challenges:

Data Heterogeneity And Quality: Machine learning models rely on large, high-quality datasets for training and validation. In Alzheimer's research, data heterogeneity arises from differences in:

Data Sources: ML models integrate data from diverse sources, including neuroimaging, genetic profiles, cognitive tests, and electronic health records (EHRs). These datasets often vary in format, resolution, and quality.

Population Demographics: Variability in age, ethnicity, and comorbidities across study populations can affect model generalizability. For example, most Alzheimer's datasets are derived from Western populations, limiting the applicability of ML models to underrepresented groups

Missing and Imbalanced Data: Missing values and class imbalance (e.g., fewer cases of early-stage Alzheimer's compared to healthy controls) can bias ML models and reduce their predictive accuracy.

Literature Review

Alshamlan et al., (2024) [13] Compared multiple classical ML approaches (SVM, RF, LR, etc.) for AD prediction and evaluated feature-selection strategies; results emphasize the robustness of ensemble learners and the benefit of careful feature selection for clinical datasets. Dhakal et al., (2023)[14]investigated dementia prediction using OASIS data and multiple classifiers (including KNN and SVM) with and without LASSO feature selection; SVM on the full feature set produced the top reported accuracy (≈96.77%), highlighting the importance of model tuning and feature engineering. Castellano et al., (2024) [15] Demonstrated that multimodal models combining 3D MRI volumetric and amyloid-PET substantially outperform single-modality models; volumetric (3D) representations produced more discriminative features than 2D slices. Lai et al., (2024) [16] reviewed plasma p-tau217 evidence and concluded it is a highly reliable blood biomarker for AD, with superior diagnostic accuracy versus earlier plasma markers; supports using blood-based biomarkers for scalable screening and ML model inputs. Palmqvist et al., (2025) [17]recent cohort evaluations of p-tau217 assays show strong performance for early/preclinical detection and suggest practical two-step approaches (plasma screen followed by confirmatory PET/CSF) for trial recruitment and primary-care triage. Jahan et al., (2023) [18] presented an explainable-AI multimodal pipeline combining clinical + MRI segmentation + psychological measures and surveyed prior ML studies (including Baglat et al.); emphasized that adding XAI (SHAP/LIME) improves clinical interpretability without sacrificing performance.

Mashhadi et al., (2025) [19] proposed a graph-based multimodal framework for AD detection that composes relational information across modalities (clinical, imaging, and biomarkers), showing improved sensitivity in heterogeneous cohorts—useful when integrating networked patient features. Liu et al., (2024) [20] developed a deep-learning multimodal fusion approach (sMRI + cognitive features) that enhanced early-stage classification performance; the study highlights data fusion and careful feature extraction as keys to early detection.

Javeed et al., (2024) [21] built a hybrid diagnostic system using statistical and ML methods on EHR data to predict dementia, showing that combining simple statistical risk scores with ML improves robustness and interpretability for clinical deployment. Jasodanand et al., (2025) [22] demonstrated ML-driven fusion of multimodal data (demographics, MRI, cognitive tests) to predict PET status and reduce the need for costly PET imaging; this supports your approach of using non-invasive clinical features with ML to triage patients.

Agarwal et al. (2015) [23] and Ghanty (2023) [24] demonstrated the Artificial Neural Networks and other machine learning algorithms performance for the prediction of AD and handling imbalance dataset of plasma signaling proteins respectively.

Methodology

Dataset Description

The extracted dataset used in this study is from Kaggle under the name "Alzheimer's Disease Dataset" (Dataset ID: 8668279). It includes the clinically relevant features related to development of Alzheimer's disease, such as demographic characteristics (age and gender), scores from cognitive assessment and clinical diagnostic labels indicating the presence or lack of disease. The dataset included numerical and categorical data, was preprocessed for its completeness and consistency. To represent data with missing or non-uniform entries, median imputation was used for numerical attributes and mode imputation for categorical ones. Outliers were computed with Interquartile Range (IQR) technique and corrected as appropriate.

Table 1 reveal that the mean patient age was approximately 74.9 ± 8.99 years, with a nearly equal gender distribution (50.6% male). Clinical indicators showed moderate variations, with an average BMI of 27.65 ± 7.21, total cholesterol of 225.19 ± 42.54 mg/dL, and systolic blood pressure of 134.26 ± 25.95 mmHg. Cognitive indicators exhibited wide dispersion-the Mini-Mental State Examination (MMSE) scores ranged from 0.01 to 29.99 (mean = 14.75), indicating representation from normal cognition to severe impairment. Approximately 25.2% of subjects reported a family history of Alzheimer's, while 15–20% presented comorbidities such as diabetes, hypertension, or depression.

Table 1 Statistical Analysis Of Dataset

Variable	Count	Mean	Std. Dev.	Min	25%	50%	75%	Max	Description
PatientID	2149	5825	620.51	4751	5288	5825	6362	6899	Unique patient identifier
Age (years)	2149	74.91	8.99	60	67	75	83	90	Age of participants
Gender	2149	0.51	0.50	0	0	1	1	1	Sex (0 = Female, 1 = Male)
Ethnicity	2149	0.70	1.00	0	0	0	1	3	Coded ethnicity categories
EducationLevel	2149	1.29	0.90	0	1	1	2	3	Level of formal education
BMI (kg/m²)	2149	27.66	7.22	15.01	21.61	27.82	33.87	39.99	Body Mass Index
Smoking	2149	0.29	0.45	0	0	0	1	1	Smoking habit (0 = No, 1 = Yes)
AlcoholConsumption	2149	10.04	5.76	0.00	5.14	9.93	15.16	19.99	Alcohol intake per week
PhysicalActivity	2149	4.92	2.86	0.00	2.57	4.77	7.43	9.99	Physical activity score
DietQuality	2149	4.99	2.91	0.01	2.46	5.08	7.56	9.99	Dietary quality score
SleepQuality	2149	7.05	1.76	4.00	5.48	7.12	8.56	10.00	Self-rated sleep score
FamilyHistoryAlzheimers	2149	0.25	0.43	0	0	0	1	1	Family history of Alzheimer's
CardiovascularDisease	2149	0.14	0.35	0	0	0	0	1	Presence of cardiovascular disease
Diabetes	2149	0.15	0.36	0	0	0	0	1	Presence of diabetes
Depression	2149	0.20	0.40	0	0	0	0	1	Depression status
HeadInjury	2149	0.09	0.29	0	0	0	0	1	History of head injury
Hypertension	2149	0.15	0.36	0	0	0	0	1	Hypertension presence
SystolicBP (mmHg)	2149	134.26	25.95	90	112	134	157	179	Systolic blood pressure
DiastolicBP (mmHg)	2149	89.85	17.59	60	74	91	105	119	Diastolic blood pressure
CholesterolTotal (mg/dL)	2149	225.20	42.54	150.09	190.25	225.09	262.03	299.99	Total cholesterol level

CholesterolLDL (mg/dL)	2149	124.34	43.37	50.23	87.20	123.34	161.73	199.97	LDL cholesterol
CholesterolHDL (mg/dL)	2149	59.46	23.14	20.00	39.10	59.77	78.94	99.98	HDL cholesterol
CholesterolTriglycerides (mg/dL)	2149	228.28	101.99	50.41	137.58	230.30	314.84	399.94	Triglyceride level
MMSE (score)	2149	14.76	8.61	0.01	7.17	14.44	22.16	29.99	Mini-Mental State Exam score
FunctionalAssessment	2149	5.08	2.89	0.00	2.57	5.09	7.55	9.99	Functional ability index
MemoryComplaints	2149	0.21	0.41	0	0	0	0	1	Memory issues reported
BehavioralProblems	2149	0.16	0.36	0	0	0	0	1	Behavioral disturbances
ADL (Activities of Daily Living)	2149	4.98	2.95	0.00	2.34	5.04	7.58	10.00	ADL performance score
Confusion	2149	0.21	0.40	0	0	0	0	1	Confusion symptoms present
Disorientation	2149	0.16	0.37	0	0	0	0	1	Spatial or temporal disorientation
PersonalityChanges	2149	0.15	0.36	0	0	0	0	1	Personality or mood changes
DifficultyCompletingTasks	2149	0.16	0.37	0	0	0	0	1	Trouble finishing daily tasks
Forgetfulness	2149	0.30	0.46	0	0	0	1	1	Repetitive or recent memory loss

Data Preprocessing

Effective preprocessing was essential for model accuracy and generalizability. The following steps were performed:

1. Data Cleaning: Missing values were handled via median or mode imputation depending on variable type. Duplicate records were removed.
2. Encoding of Categorical Data: Categorical variables were converted into numerical format through one-hot encoding to ensure compatibility with machine learning algorithms.
3. Feature Scaling: Numerical features were standardized using the StandardScaler function, transforming them to zero mean and unit variance. This step improved model convergence, especially for algorithms sensitive to feature magnitude (e.g., SVM, k-NN, and MLP).
4. Feature Selection: Correlation-based filtering removed redundant variables with correlation coefficients exceeding 0.85 to reduce multicollinearity.
5. Dataset Balancing: Class imbalance was checked and adjusted using stratification to preserve representative learning behavior.

These preprocessing operations resulted in a clean, normalized dataset suitable for high-performance supervised learning.

Machine Learning Algorithms

Ten supervised learning algorithms were employed to classify subjects into Alzheimer's-positive or non-Alzheimer's categories. The selected algorithms and their configurations are as follows in Table 2.

Table 2 Proposed Machine Learning Algorithm

Category	Algorithm	Key Description
Linear Models	Logistic Regression	Baseline probabilistic model used for initial comparison.
Distance-based	k-Nearest Neighbors (k = 5)	Classifies samples based on nearest neighbors using Euclidean distance.
Probabilistic	Gaussian Naïve Bayes	Assumes Gaussian distribution for continuous variables.
Kernel-based	Support Vector Machine (Linear & RBF)	Maximizes class margin; RBF kernel captures nonlinearity.
Tree-based	Decision Tree	Non-parametric model using Gini impurity for splitting.
Ensemble	Random Forest	Aggregates multiple decision trees to enhance stability.
Ensemble	AdaBoost	Sequentially boosts weak learners for error minimization.
Ensemble	Gradient Boosting	Sequential additive model optimizing residual errors.
Neural Network	Multilayer Perceptron (MLP)	Feed-forward ANN using ReLU activation and Adam optimizer.

All models were trained under identical preprocessing conditions using GridSearchCV for hyperparameter tuning and five-fold cross-validation to ensure model reliability.

Model Evaluation And Performance Metrics

Model performance was assessed on the test subset (20 %) based on various statistical and classification metrics:

Accuracy (ACC): Ratio of correctly classified instances.

Precision (P): The ratio of true positives to predicted positives indicating the accuracy in predicting.

Recall (Sensitivity): True positive to actual positive ratio reflects sensitivity in identifying Alzheimer's cases.

F1-Score: Precision-Recall harmonic mean, including a balance of false positives and negatives.

A confusion matrix was created with respect to the best-performing model (Gradient Boosting) to visualize the correct and wrong predictions, and ROC curves were plotted to compare discriminative power across algorithms.

RESULTS AND DISCUSSION

Table 3 summarizes the comparative performance of all models in terms of accuracy, precision, recall, F1- score, and ROC-AUC. The ensemble learning algorithms — particularly Gradient Boosting and Random Forest — achieved the highest predictive accuracies of 95.6% and 94.2%, respectively. The Decision Tree model also performed competitively, achieving an accuracy of 93.7%. In contrast, simpler classifiers such as k-NN (71.1%) and Gaussian Naïve Bayes (76.9%) exhibited relatively lower accuracy, indicating their limitations in capturing the complex feature relationships inherent in Alzheimer's datasets.

Table 3. Performance Comparison Of Proposed Models For Alzheimer's Disease Prediction.

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Gradient Boosting	0.9558	0.9561	0.9558	0.9559	0.9860
Random Forest	0.9419	0.9419	0.9419	0.9414	0.9790
Decision Tree	0.9372	0.9394	0.9372	0.9377	0.9395
AdaBoost	0.9047	0.9056	0.9047	0.9050	0.9448
MLP Neural Net	0.8419	0.8407	0.8419	0.8411	0.9085
SVM (RBF)	0.8302	0.8281	0.8302	0.8281	0.9002
SVM (Linear)	0.8186	0.8186	0.8186	0.8186	0.8841
Logistic Regression	0.8163	0.8151	0.8163	0.8156	0.8868
Gaussian Naïve Bayes	0.7698	0.7733	0.7698	0.7712	0.8515
k-NN (k=5)	0.7116	0.7006	0.7116	0.6986	0.7463

The bar chart in Figure 2 illustrates the comparative test accuracy across models. It clearly highlights the dominance of ensemble-based methods-Gradient Boosting and Random Forest—over linear and instance-based algorithms. These models leverage multiple weak learners to improve robustness and reduce variance, explaining their superior generalization capabilities.

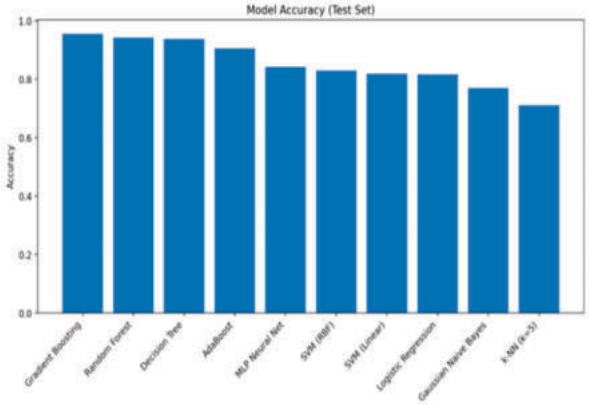

Figure 2. Model accuracy comparison across ten supervised learning algorithms.

The superior performance of ensemble classifiers underscores their ability to handle heterogeneous biomedical data effectively. Gradient Boosting achieved the highest F1-score (0.956), indicating balanced precision and recall performance, which is critical in disease diagnosis tasks where false negatives can have severe implications. The Random Forest model also demonstrated strong consistency across all metrics, reinforcing its reliability and interpretability for clinical applications.In contrast, MLP and SVM models showed moderate accuracy, suggesting that deeper networks or kernel optimization could further enhance their predictive strength. Logistic Regression performed comparably but is limited in modeling nonlinear patterns. Naïve Bayes and k-NN were less effective, reflecting their sensitivity to correlated features and scaling issues in high-dimensional data.

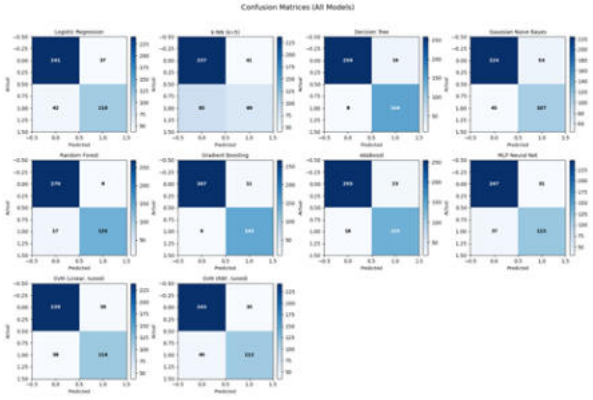

Figure 3. Confusion matrices of all supervised learning models

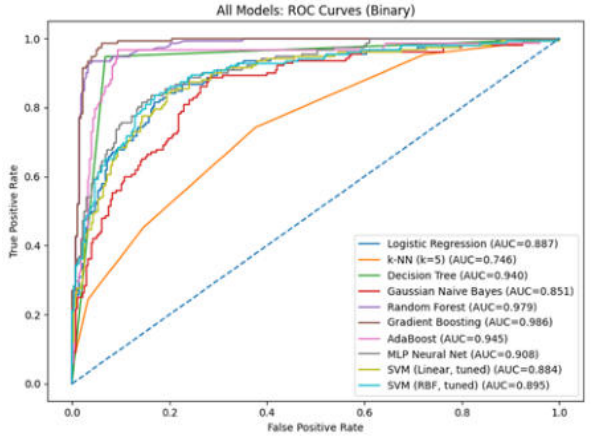

Figure 4. ROC curves comparing the binary classification performance of all supervised models

Figure 3 illustrates the confusion matrices for all ten supervised learning algorithms applied to the Alzheimer's disease dataset. Each confusion matrix provides insight into the number of correctly and incorrectly classified samples for the two classes: Alzheimer's-positive and non-Alzheimer's. The diagonal values represent correctly predicted cases, while off-diagonal elements indicate misclassifications. Among all models, Gradient Boosting and Random Forest exhibit near-perfect diagonal dominance, demonstrating minimal misclassification rates. The Gradient Boosting model correctly classified 267 Alzheimer's-negative and 144 Alzheimer's-positive cases, with only a few errors (11 false positives and 8 false negatives). Similarly, the Random Forest model achieved strong classification accuracy, misclassifying fewer than 10 samples in total.In contrast, k-NN and Naïve Bayes showed higher off-diagonal values, reflecting reduced accuracy and sensitivity due to their dependence on distance metrics and feature independence assumptions, respectively. SVM (linear) and MLP neural network models performed moderately well but showed a slightly higher false positive rate compared to ensemble-based models. Overall, the visualization confirms that ensemble techniques-particularly Gradient Boosting and Random Forest-deliver superior predictive consistency and generalization across test samples.

Figure 4 displays the Receiver Operating Characteristic (ROC) curves for all ten classifiers, demonstrating the balance between sensitivity (true positive rate) and 1-specificity (false positive rate). The area under each curve (AUC) quantitatively measures each model's discriminative ability. Among the evaluated models, Gradient Boosting achieved the highest AUC (0.986), indicating exceptional sensitivity and specificity. Random Forest (AUC = 0.979) and AdaBoost (AUC = 0.945) also demonstrated strong classification power, confirming their robustness in distinguishing Alzheimer's and non-Alzheimer's cases. Models such as Decision Tree (AUC = 0.940) and MLP Neural Network (AUC = 0.908) followed closely, while Logistic Regression and SVM (Linear) yielded moderate AUC values (0.887 and 0.884, respectively). The k-NN classifier recorded the lowest AUC (0.746), reflecting its limited adaptability to complex, nonlinear feature spaces. The ROC visualization thus corroborates the confusion matrix findings-ensemble learners consistently outperform traditional single classifiers, achieving better sensitivity-specificity balance and minimizing diagnostic misclassification risk.

CONCLUSION

This studied presents a wide-ranging evaluation of supervised ml algorithms for predicting Alzheimer's disease based on clinical and demographic information. Gradient Boosting and Random Forest-consistently outperformed traditional classifiers, achieving high accuracy, F1-score, and ROC-AUC, indicating superior discriminative capability and robustness. By accurately identifying individuals at risk of AD, these models can support early intervention strategies, enhance patient management, and reduce the societal and economic burden associated with the disease. Future research should explore the integration of multimodal datasets-including neuroimaging and biomarker information-advanced feature engineering, and explainable AI techniques to further improve interpretability and clinical applicability of predictive models.

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