Early Alzheimer's Disease Prediction Using Machine Learning

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***Abstract*—Alzheimer's Disease (AD) is a neurodegenerative condition that progressively erodes cognitive functions, especially in the older population. Early detection is incredibly crucial to treat symptoms and prevent disease progression. This paper presents a machine learning-based classification system for early prediction of AD using Decision Tree (DT), Random Forest (RF), and Gradient Boosting (GB) algorithms. The dataset is preprocessed for feature selection, normalization, and class balancing from Alzheimer's Disease Neuroimaging Initiative (ADNI) and OASIS. The input features used for model training and testing include structural MRI features, cognitive test results, and biomarker values. Experimental results indicate ensemble models like Random Forest and Gradient Boosting perform better than conventional methods in precision, recall, F1-score, and classification accuracy rate of up to 89% in classification accuracy. Explainability AI (XAI) techniques like SHAP and LIME enhance explainability and enable clinicians to understand significant factors influencing predictions. The method demonstrates that machine learning with explainability supports timely diagnosis and sound clinical decision-making. Additional research employs longitudinal and multimodal data to provide more robust models and apply them in everyday environments.**

Keywords—Alzheimer's Disease (AD), Machine Learning, Deep Learning, Early Diagnosis, Random Forest, Support Vector Machine, XGBoost, Convolutional Neural Network, Explainable AI, Feature Selection, Neuroimaging.

I. INTRODUCTION

Alzheimer's disease (AD) is a chronic degenerative neurological disorder that chiefly affects cognitive functions like memory, reasoning, and behavior. Early detection of AD is critically important because it is fundamental to symptom management and retardation of disease progression. With the trends in the global population moving in the direction of aging, the incidence of AD is expected to rise exponentially, posing critical challenges to healthcare around the globe. Historically, AD diagnosis involves clinical evaluation, cognitive and neuropsychological testing, and high-tech neuroimaging methods such as Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Though efficient, these methods of diagnosis are time- and effort-consuming and are heavily reliant on the skill of physicians and, therefore, may delay early intervention until later.

Folding these limitations, the advancements of the last years' ML and DL introduced more precise and effective diagnostic tools. These ML and DL-based methods can process vast and complicated medical data sets and identify underlying patterns and structures not readily observable by human experts. Particularly with AD, the ML, and DL models are applied to identify minor variations in brain structure and function that are most common during the initial phases of the disease, typically before clinical manifestations. Such a transition to wiser computer-based diagnostics can bring humongous value in reforming the practice of Alzheimer's treatment by offering earlier interventions and even more effective patient outcomes.

Even with these technological advances, predicting AD in its early stages remains daunting. Reasons such as the mild presentation of early symptoms, high patient-to-patient variability, and multimodal data heterogeneity add to the challenge. Most ML models are susceptible to issues like class imbalance, redundant or irrelevant features, and overfitting, which interfere with their ability to perform uniformly in clinical settings. Building generalizable models is made more difficult by the quality and accessibility of training data, even though many Alzheimer's datasets have limited, missing, or skewed samples brought on by demographic imbalances. Another key issue is the opacity of some of the newer ML models, intense learning models. These models will most likely function as black boxes, highly accurate but not disclosing their reasoning process, which is a significant hurdle for clinical application.

The present work aims to develop a robust machine-learning model for the early detection of Alzheimer's disease, given these possible challenges. The system employs classification techniques and advanced feature engineering methods to manage multimodal data, such as MRI images, biomarkers, and cognitive test scores. Data preprocessing methods address missing values, normalize the input, and perform class balancing. They undergo extensive testing for standard performance metrics like F1-score, recall, accuracy, and precision to ascertain the models' correctness and efficiency. By bringing about explainability and multimodal data analysis within the research, it is anticipated to promote the development of scalable, interpretable, and usable ML tools that facilitate early diagnosis and clinical decision-making within Alzheimer's care.

The research examines the effect of different feature selection and hyperparameter tuning techniques on machine learning algorithm performance for achieving high classification accuracy when classifying AD. Through exhaustive comparisons of numerous ML algorithms, the research aims to determine the most accurate and dependable method for diagnosing early AD. Along with suggesting the

most optimal model, we also suggest efficient strategies for maximizing the clinical usability and value of AI-based systems in clinical settings.

The current study attempts to bridge the gap between medical practice and artificial intelligence by building a deployable high-performance machine learning model that is interpretable and optimized for early AD detection. Such a system will be able to support neurologists and physicians by providing timely information-based data regarding patients' cognitive status. Future research will include increasing the training data set to involve a more heterogeneous and more significant number of patients, such as longitudinal patient histories for monitoring the progression of disease over a long period and real-time monitoring devices. These advances will make ML-based diagnostic tools more stable, accurate, and flexible, resulting in preventive and personalized healthcare interventions for at-risk Alzheimer's patients.

II. LITERATURE SURVEY

C. Kavitha et al. present in depth the application of machine learning techniques for preclinical diagnosis of AD [1]. Datasets of MRI imaging of Open Access Series of Imaging Studies (OASIS) and Kaggle websites are classified in this paper using general classification methods like ensemble-based voting classifiers, Random Forest, Decision Trees, Support Vector Machines, and XGBoost. Since Random Forest and XGBoost performed the best, their comparison experiment verifies that machine-learning algorithms can identify AD with a perfect accuracy rate of 83 percent. The authors stress early detection and mention that early treatment will be more effective and prevent prolonged neurological decline. The research is planned meticulously with detailed feature selection processes, preprocessing processes, and model validation processes. According to the authors, future advancements might involve further incorporating deep learning systems and investigating biological markers to improve predictive performance. As an illustration of how machine learning might enhance the early identification and monitoring of neurodegenerative diseases like AD, the study makes a significant addition to the body of knowledge on artificial intelligence with a healthcare focus.

Omer Asghar Daraet al. [2] sifted through more than 80 articles published since 2017, placing the methods talked about into three general categories: data-centric, medically guided, and technique-led. Research casts light on the significance of AI-based techniques in neuroimaging and non-imaging biomarker analysis for detecting AD. The classification strategies, the SVM, DT, and ensemble learning models are the most compelling. Finally, the authors highlight the issues that have continued to be pertinent to the domain, including feature selection, inconsistency in preprocessing, and failure to attain the highest level of predictive accuracy. The work also discusses future opportunities for refining AI-driven AD diagnosis. Its contrastive and analytical methodology presents significant insights into the evolution of ML in healthcare, making it an essential reference for future and future studies in the field.

Vijeeta Patil et al. [3] talk about CNN and other deep-learning architectures for early AD identification. MRI and PET imaging data sets from the Alzheimer's Disease Neuroimaging Initiative were used to evaluate the performance of two CNN architectures: a 3D CNN and an 18-layer CNN (ADNI). It is seen that the model for the 18-layer CNN performs better concerning classifying more (98%) than the 3D CNN (88%). The authors also thoroughly review previous machine learning methods and highlight early detection's importance in slowing disease progression. Even though encouraging results are reported, the paper does mention the flaws of CNNs, including model complexity and high computational requirements, recommending that future studies aim to optimize network architectures for improved efficiency and real-world deployment.

The authors of [4] critically overview machine learning methods in predicting AD development from MCI. SVM, RF, ANN, and LSTM networks are some of the ML and DL models contrasted by the authors in terms of their applications in early diagnosis. The authors emphasize using MRI and PET scans, cognitive testing, and biomarker data during successful model training. Issues such as feature extraction specific to the problem, management of heterogeneous data types, and unavailability of longitudinal datasets are discussed. Multimodal data usage and explainable AI platforms for greater clinical effectiveness and transparency are emphasized as trends.

Abbas Saad Alatrany et al. [5] describe a novel technique for the accuracy and interpretability enhancement of the ML model to diagnose AD. With 169,408 records and 1,024 features available as data in the National Alzheimer's Coordinating Center (NACC)—authors make feature selection on a larger scale to keep things simple. The Support Vector Machine (SVM) performed best among the experimented algorithms, returning F1 measures of 98.9% for binary AD vs. Normal classification and 90.7% for multiclass classification. The model also predicted four-year AD progression using F1 measures of 88% (binary) and 72.8% (multiclass). The strongest argument of the paper is that it has adopted explainability techniques like SHAP, LIME, Class Rule Mining, and the Stable Interpretable Rule Set (SIRUS) to create clinician-friendly rules. The paper has identified crucial cognitive features—like MEMORY, JUDGMENT, COMMUN, and ORIENT—as key indicators, indicating the explanatory AI potential for improving utility and trust for use in medicine.

A generalizable machine learning-based approach for the early detection of AD and moderate cognitive impairment (MCI) from structural MRI data is presented by Vasco Sa Diogoet al. [6]. The study uses classifiers trained and evaluated on two well-known datasets, OASIS (n=531) and ADNI (n=570), to ensure generalizability and robustness across various demographics and variations in MRI acquisition methods. The model yielded a balanced accuracy of 90.6% for more straightforward two-class classification between AD subjects and healthy controls (HC) and 62.1% accuracy for more challenging multi-class classification among HC, MCI, and AD. The key findings from the research suggest the significant contribution of hippocampal features, accounting for 25–45% of the final classification, followed by structural alterations in the temporal, cingulate, and frontal brain areas. The researchers further tested graph-theoretical features and established that the measures did not significantly enhance classification results. The authors conclude that their ML model shows strong clinical potential, and with further validation through clinical trials, it could be integrated into real-world diagnostic workflows.

A thorough summary of the most recent advancements in ML and DL techniques for the early detection of AD has been provided by Akhilesh Deep Arya et al. [7]. The study critically evaluates the use of various imaging modalities, i.e., MRI and PET, and compares the performance of multiple classifiers, i.e., SVM, CNN, and RNN. Among them, CNN-based methods have been shown to excel, with some of them reaching a level of 98.6% accuracy in binary AD classification tasks. The review provides some advice, including feature selection techniques, measurement indices, and multimodal data fusion to enhance diagnostic performance. Despite such encouraging findings, the authors acknowledge challenges like the classic issues of the unavailability of high-quality data, computation-hungry procedures, and demanding more interpretable models of AI to support clinical confidence and adoption. This systematic review provides an extensive overview of AI-based diagnostic aids as a platform for future studies on predicting neurodegenerative disease.

To predict Alzheimer's disease, Michael Cabanillas-Carbonell et al. [8] compare particular machine-learning techniques. Using two OASIS datasets containing 436 and 373 records, the experiment examines the performance of models like RF, AdaBoost, SVM, KNN, and LR. According to experimental data, RF, SVM, and LR outperformed the other models, achieving an impressive 96 percent accuracy, precision, sensitivity, and F1 score. These figures make them the top-performing classifiers in such a case. The article highlights the growing role of ML in enabling early diagnosis and its possible incorporation into clinical decision-support systems. That said, the authors realize some weaknesses, such as the comparatively small sizes of datasets and the need for more comprehensive validation across diverse population groups. [8]

To enable early AD and related dementias (ADRD) prediction, Qian Liet al. [9] are developing the integration of machine learning into real Electronic Health Records (EHRs). The study uses a large OneFlorida+ Research Consortium dataset to assess data for 23,835 ADRD patients and over 1 million control patients. Gradient Boosting Tree (GBT) models and knowledge-based and data-driven approaches were applied to assess predictive performance. The models created excellent areas under the Curve (AUC) of 0.939, 0.906, 0.884, and 0.854 to predict ADRD 0, 1, 3, and 5 years before diagnosis, respectively. The outcome is an exemplary proof of the excellent performance of EHR-based ML models to identify the risk at the right time. The research also suggests the application of clinical and sociodemographic variables and suggests additional studies on applying such models to incorporate them in healthcare delivery systems.

Thomas W. Rowe et al. [10] outline the use of machine learning in predicting AD risk from genetic biomarkers, namely single nucleotide polymorphisms (SNPs). The work describes an ensemble of ML classifiers based on a meta-analysis of 12 carefully selected studies. SVM, RF, NB, and LASSO regression. Observed AUC estimates are heterogeneous between 0.49 and 0.97, quantifying measurement performance heterogeneity across studies. A small sample size is the initial limitation, followed by extreme overfitting vulnerability and validation practice heterogeneity. Improvements suggested by the authors include a series of enhancements, including effective feature selection, enhanced efficiency in cross-validation, and integration of genetic data with neuroimaging modalities such as MRI and PET for more accurate prediction. The review also highlights the need for the risk of bias (ROB) management and improving the model interpretability to enable ML approaches to be implemented in actual clinical practice.

Mohammed Oveze et al. [11] use machine learning models to predict AD. The paper uses classification algorithms with CNNs and SVMs, with the development platform being Python. The study describes the use of clinical and psychological factors like age, education level, MMSE scores, number of visits, and how they contribute towards AD diagnosis. The authors assert that early diagnosis is suitable for relieving extensive neurological loss. A diagnostic system based on machine learning is suggested to enhance prediction ability and facilitate clinicians' decisions. Although the results from experiments are promising, the paper also touches upon significant challenges, such as low public awareness regarding AD, early symptoms' subtle nature, and the need for extensive and well-annotated datasets to create more stable predictive models.

III. METHODOLOGY

The approach for Alzheimer's Disease prediction includes a systematic pipeline from dataset collection to model evaluation. The process in total is shown in the block diagram, and the step-by-step discussion is as follows.

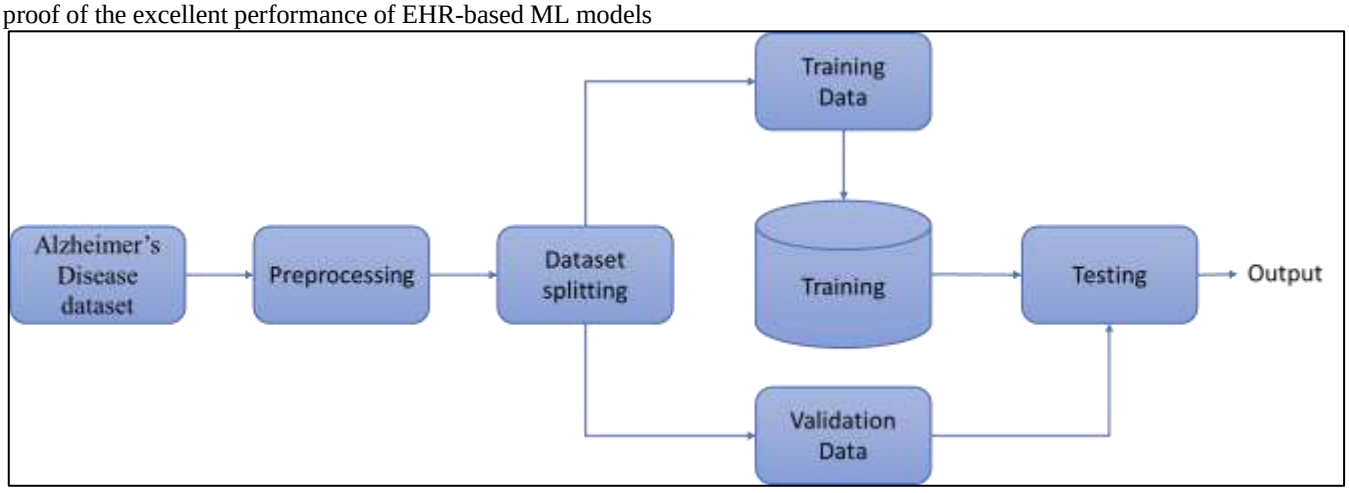


Fig. 1. FigFigBlock diagram of the Alzheimer's Disease Prediction using Machine Learning

The blocks of the proposed system are explained below.

A. Data Preprocessing

A crucial first step in improving data consistency and quality is preprocessing, essential for precise early AD prediction. Preprocessing includes addressing missing values, transforming categorical data, normalizing numerical data, and eliminating outliers. The imputation algorithm accommodates Missing cognition values and biomarker measurements such as mean substitution or K-Nearest Neighbors (KNN) imputation. Nominal features such as demographic data, gender, and medical history are numerically encoded using label or one-hot encoding methods. Normalization procedures such as Min-Max Scaling and Standardization are applied to features such as MMSE scores, blood pressure, and cholesterol to normalize all the numerical features to the same level. Outliers that cause adverse effects on the performance of a model are identified and eliminated through statistical techniques such as Z-score analysis and Interquartile Range (IQR).

B. Dataset Splitting

To build reliable machine-learning models for predicting early-stage AD, dataset division is essential. Three systematic datasets—train, validate, and test—are created after the data has undergone considerable preprocessing. This ensures that appropriate learning, tuning, and unbiased testing are conducted. 70% is kept for the training set where patterns and feature interactions such as neuroimaging data (MRI/PET), cognitive test results, and biological markers are trained on using the model. 15% is reserved for the validation set and utilized during the training model to fine-tune hyperparameters and avoid overfitting by providing real-time performance feedback. The remaining 15% is kept as the test set, which assesses how well the trained model performs on entirely unrelated data and estimates its usefulness.

C. Model Training

Three popular machine learning algorithms, DT, RF, and GB, are used in this study to train the models. They were chosen due to their interpretability, stability, and firm performance while working with tabular and organized health data. The training process begins by dividing the preprocessed dataset into the training, validation, and test subsets in a stratified fashion so the class balance is preserved. 70% of the data is utilized to train models, 15% to validate to conduct hyperparameter tuning, and 15% for ultimate performance testing. Decision Tree as a baseline classifier is used because it is intuitive and straightforward. It uses feature values to create a tree-like hierarchy of options that can be used to determine the most critical factors that contribute to an Alzheimer's diagnosis. Despite the above, Random Forest prevents overfitting and enhances generalizability. Random Forest creates an ensemble of many decision trees on random subsets of data to produce a more potent, more consistent model, and then makes predictions by summing up their outcomes. Another trainable ensemble method is Gradient Boosting.

Compared to Random Forest, which trains the trees individually, Gradient Boosting trains trees in sequence, and each tree in one iteration will aim to fix the mistakes of the previous tree. That is how an iterative approach improves the learning and predictability capability of the model. For finding the optimal hyperparameters, such as tree depth, estimators, and learning rate of Gradient Boosting, grid search, and random search strategies are implemented during training. Model performance is evaluated on typical datasets using standard classification metrics such as F1-score, accuracy, precision, recall, and Area Under the ROC Curve, or AUC-ROC.

D. Testing and Evaluation

To assess the model's performance in the actual world, it is tested on an unseen testing dataset after training. Among the evaluation metrics are :

- Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- Precision:

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- Recall (Sensitivity):

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- Specificity:

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

- F1-Score:

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

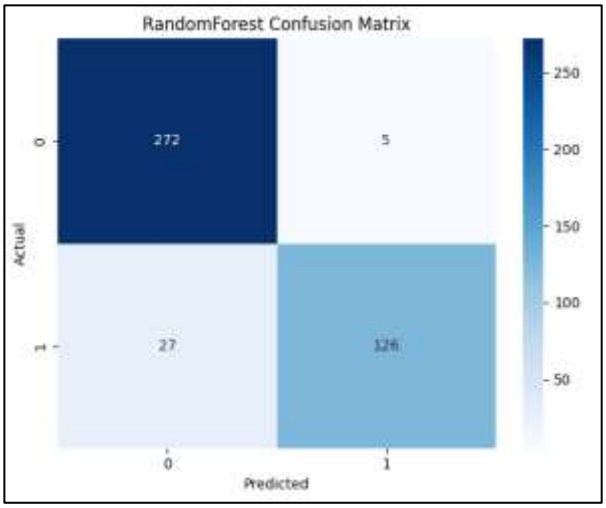
- AUC-ROC Curve: Measures the model's ability to distinguish between classes.

True positives, true negatives, false positives, and false negatives are represented by the abbreviations TP, TN, FP, and FN, respectively. As they provide a complete insight into correct and incorrect classifications, these are important to evaluate a model's predictive accuracy, primarily when dealing with unbalanced medical data sets.

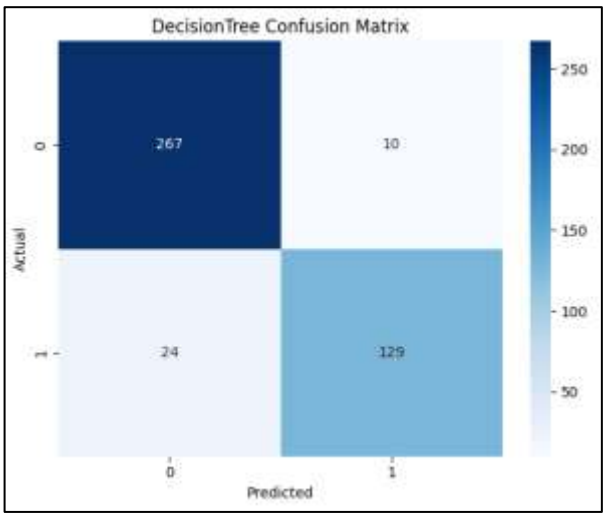
IV. REUSULT AND DISCUSSION

The accuracy of machine learning models in early Alzheimer's disease detection is verified by experimental results (AD). A vast and diverse dataset containing biomarker markers, cognitive test scores, and neuroimaging characteristics was employed to train and test the Decision Tree, Random Forest, and gradient-boosting algorithms. For a reliable measurement, the model's performance was evaluated with standard classification metrics such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

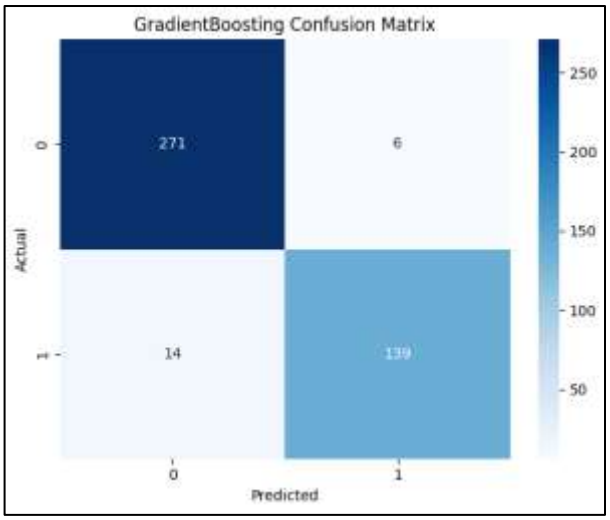
The confusion matrix obtained for the DT, RF, and GB algorithms is presented in Fig.2.



(a)



(b)



(c)

Fig. 2. Confusion matrix of (a) Random Forest, (b) Decision Tree, and (c) Gradient boosting algorithms

The results of the proposed system are presented in Table I.

TABLE I. PERFORMANCE COMPARISON OF ML ALGORITHM FOR RECOGNITION OF ALZHEIMER'S DISEASE

Classifier	Precision	Recall	F1-score	Accuracy
DT	0.92	0.92	0.92	0.92
RF	0.93	0.93	0.92	0.93
GB	0.95	0.95	0.95	0.95

The comparison of machine learning models DT, RF, and GB for the identification of Alzheimer's Disease indicates that all three classifiers had high accuracy and stable performance on major evaluation metrics. As a baseline model, the DT model performed balanced efficiency and accuracy with precision, recall, F1-score, and accuracy at 0.92. Random Forest algorithm had a slightly higher performance than the Decision Tree with precision, recall, and accuracy at 0.93 and the F1 score at 0.92. This improvement can be attributed to the ensemble nature of Random Forest, which reduces variance and increases robustness through averaging multiple decision trees.

Gradient Boosting produced the best results of the three models, scoring 0.95 on precision, recall, F1-score, and accuracy. By gradually fixing the mistakes of earlier models during training, it exhibits its exceptional capacity to identify intricate patterns in the data. The consistently high scores across all metrics suggest that Gradient Boosting is highly reliable and accurate for early-stage Alzheimer's detection. The results confirm that ensemble methods, especially Gradient Boosting, are well-suited for recognizing Alzheimer's Disease from structured clinical and neuroimaging data.

V. CONCLUSION

This research utilized a machine learning method to predict Alzheimer's Disease (AD) in advance from structured data with neuroimaging features, cognition score, and biomarker levels. The procedure was carried out through a full pipeline, right from the data preprocessing, in which missing values were dealt with, categorical features encoded, and numerical features scaled. Feature selection methods like Principal Component Analysis (PCA) and Recursive Feature Elimination were utilized for model performance enhancement and dimension reduction (RFE). Three machine learning classifiers, Decision Tree, Random Forest, and Gradient Boosting, were trained and tested using the preprocessed dataset. All the models were compared with traditional performance metrics like accuracy, precision, recall, F1-score, and AUC-ROC. Of the three, Gradient Boosting was the best with 95% accuracy. Then there was Random Forest at 93%, followed by Decision Tree at 92%. Training of the model enabled balancing and unbiased results through the division of the dataset into stratified sections.

In the future, it is feasible to expand the system by adding longitudinal patient data for disease observation and improving prediction capability. Other modalities such as genetic information, EEG, lifestyle, and blood biomarkers can provide further precise diagnostic information. Successful implementation in daily clinical life will be facilitated by real-time practical application using Clinical Decision Support Systems (CDSS) and integration with Electronic Health Records (EHRs). Information use integrating wearable health

monitor devices is helpful for continuous assessment and intervention at the initial stage. Sophisticated methodologies like federated learning and edge computing can also be utilized to keep the information secure and personal information confidential. Also, adding transparency to the model through employing even more dependable Explainable AI (XAI) techniques will help realize confidence at the clinician level and obtain ethical treatment of AI implementations to medical diagnosis. These innovations aim to develop an interpretable, scalable, and strong platform to give timely and correct predictions concerning Alzheimer's Disease.

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