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Performance Comparison of Five Machine Learning Algorithms for Early Detection of Alzheimer's Disease

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Abstract

Alzheimer's disease (AD) is the most common form of dementia, posing an enormous social and economic burden globally, necessitating the development of efficient and objective early detection methods. This study aims to predict Alzheimer's disease diagnosis by conducting a comprehensive comparative analysis of five Machine Learning (ML) algorithms: XGBoost, Decision Tree, Logistic Regression, Support Vector Machine (SVM), and Random Forest. The research utilized the "Alzheimer's Disease Dataset" (2,149 records with 35 features), which contains demographic, lifestyle, medical factors, and cognitive symptoms, with the methodology involving data pre-processing (including imputation, cleaning, and feature selection) and model evaluation using k-fold cross-validation (70:30, 80:20, and 90:10 splits). Unlike previous studies that performed only partial evaluations, this research conducts head-to-head performance tests on five algorithms representing various classification paradigms. The evaluation prioritized maximizing the Recall (Sensitivity) value to minimize the critical risk of false-negative diagnoses in early detection. The results show that the XGBoost algorithm achieved superior performance across all evaluation metrics. With an 80:20 split, XGBoost achieved the highest performance, with Accuracy, Precision, and Recall of 95.1%. This outcome confirms the efficacy of XGBoost for patient classification and supports the development of faster, more objective medical decision-support systems.

Keywords: Alzheimer's Disease, Classification, Early Detection, Machine Learning, XGBoost

1. INTRODUCTION

Alzheimer's disease (AD) is the most common form of dementia and a global public health crisis. The social and economic burden of AD is enormous, and the number of cases is expected to triple by 2050 [1]. Delayed diagnosis hinders the effectiveness of therapeutic interventions. Therefore, there is an urgent need to develop objective, efficient, and noninvasive methods to predict the transition from normal to cognitive decline Mild Cognitive Impairment (MCI) and AD [2]. Early identification of individuals at risk is crucial for enabling timely clinical intervention and slowing disease progression. Furthermore, the heterogeneity of disease progression among patients necessitates robust predictive tools that can generalize across diverse populations. Advances in computational methods have opened new opportunities to detect subtle patterns associated with early neurodegeneration.

The economic burden of AD is massive, encompassing both direct care costs (medical and social) and indirect costs (lost productivity). A report by Alzheimer's Disease International (ADI) indicates that the global cost of dementia has exceeded $1 trillion USD and is expected to double in the coming decade [1]. This escalating financial burden places significant pressure on healthcare systems, particularly in low- and middle-income countries. In addition, families and caregivers experience substantial emotional and financial strain due to long-term care requirements. Consequently, improving early diagnosis and intervention strategies may help reduce long-term economic impacts.

Chandra et al. used Magnetic Resonance Imaging (MRI) to describe distinct patterns of brain damage that can differentiate AD from other brain disorders, brain abnormalities associated with an increased risk of developing AD from MCI, and other behavioral outcomes [3]. However, manual diagnostic approaches have proven unsatisfactory [4]. Therefore, a better diagnostic approach is needed. Manual interpretation of MRI data is often time-consuming and subject to inter-observer variability. In addition, subtle structural changes in early-

stage AD may not be easily detectable through conventional analysis methods. This limitation underscores the importance of automated, data-driven approaches to improve diagnostic accuracy and consistency.

Therefore, this study aims to predict Alzheimer's disease diagnosis using five machine learning algorithms: XGBoost, Decision Tree, Logistic Regression, Support Vector Machine (SVM), and Random Forest. The selection of these algorithms is motivated by their proven performance in previous studies for classification tasks. For instance, ensemble-based methods such as XGBoost and Random Forest have demonstrated superior accuracy and robustness, particularly in handling complex and imbalanced datasets [5][9][10]. Meanwhile, Decision Tree and Logistic Regression are widely utilized due to their interpretability and simplicity, which are essential for clinical decision support systems [6], [7]. In addition, SVM has been effectively applied in medical diagnosis problems due to its capability to construct optimal decision boundaries in high-dimensional data spaces [8]. Several previous studies have explored the effectiveness of these algorithms in predicting Alzheimer's disease diagnoses. A study by Yi et al. (2023) using XGBoost, Random Forest, and Naïve Bayes reported that XGBoost achieved the highest accuracy.of 87.57% with a train-test split of 80:20, followed by Random Forest at 86.83% and Naive Bayes at 74.39% [10].

This study aims to develop a predictive model for Alzheimer's disease diagnosis using a dataset that incorporates demographic characteristics, lifestyle factors, medical history, and cognitive symptom indicators of patients. Several machine learning algorithms, namely XGBoost, Decision Tree, Logistic Regression, Support Vector Machine (SVM), and Random Forest, are systematically evaluated to identify the most effective model for distinguishing between Alzheimer's and non-Alzheimer's cases. Model performance is assessed using multiple evaluation metrics, including accuracy, precision, recall, and F1-score. Furthermore, this study investigates the relative importance of features to determine the most influential factors contributing to diagnostic outcomes. The results are expected to enhance understanding of early detection indicators and support the development of efficient, objective, and reliable clinical decision support systems.

The novelty of this study lies in its comprehensive and systematic comparative framework, which extends beyond prior research. Unlike studies such as Yi et al. (2023) and Tomita et al. (2023), which evaluated only a limited number of models, this research conducts a direct comparative analysis of five machine learning algorithms representing diverse classification paradigms within a unified experimental setting. Moreover, this study addresses a gap in application domains by examining the effectiveness of advanced algorithms, particularly XGBoost, on Alzheimer's clinical datasets. This contrasts with prior studies by Zhang et al. (2025) and Ghosh et al. (2024), which primarily focused on applications in cancer and kidney disease. Additionally, this research shifts the evaluation emphasis from solely maximizing accuracy toward optimizing recall (sensitivity), thereby reducing the likelihood of false negative predictions, which is critically important in the early detection of degenerative diseases.

2. MATERIAL AND METHOD

This research methodology was designed to conduct a comparative analysis of the performance of five classification algorithms XGBoost, Random Forest, Logistic Regression, Support Vector Machine (SVM), and Decision Tree in predicting Alzheimer's disease diagnosis using the Alzheimer's Disease Data dataset. Each algorithm was evaluated on accuracy, precision, recall, F1-score, and other performance metrics to assess the model's ability to classify patients as having Alzheimer's or not. The complete flow of the research methodology is shown in Figure 1. Tables and Figures are presented center, as shown below and cited in the manuscript.

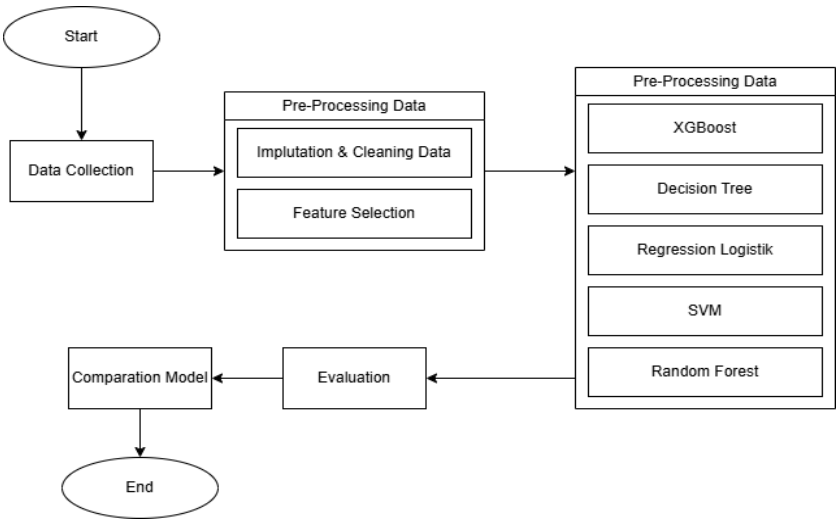

Figure 1. Research Methodology

2.1. Data Collection

The dataset used in this study is the Comprehensive Health Information for Alzheimer's Disease dataset available on the Kaggle platform under the name "Alzheimer's Disease Dataset." This dataset contains 2,149 patient data with 35 features, including demographic information (age, gender, ethnicity), lifestyle (smoking, alcohol consumption, physical activity, sleep quality), medical variables (diabetes, hypertension, stroke, cholesterol), and cognitive symptoms such as memory impairment, disorientation, behavioral changes, and communication difficulties. These features are used as predictors for determining an Alzheimer's diagnosis. According to the 2021 World Alzheimer's Report, the number of patients with AD will reach 131 million globally, and the estimated cost will reach one trillion dollars by 2050, posing a heavy financial burden on society [7].

Table 1. Attribute and description

Attribute	Description
Age	Subject's chronological age.
Gender	Subject's sex (e.g., Male, Female).
Ethnicity	Subject's racial or cultural background.
Education Level	Highest level of formal education completed.
BMI	Body Mass Index (weight relative to height).
Smoking	Current or historical smoking status.
Alcohol Consumption	Frequency or amount of alcohol intake.
Physical Activity	Level of regular exercise or movement.
Diet Quality	Assessment of usual dietary habits.
Sleep Quality	Subjective or objective measure of sleep health.
Family History Alzheimers	Presence of Alzheimer's disease in first-degree relatives.
Cardiovascular Disease	History of heart and blood vessel conditions.
Diabetes	Presence or history of high blood sugar levels.
Depression	Diagnosis or symptoms of a mood disorder.
Head Injury	History of traumatic brain injury.
Hypertension	Presence or history of high blood pressure.
Systolic BP	Systolic blood pressure reading.
Diastolic BP	Diastolic blood pressure reading.
Cholesterol Total	Overall measured cholesterol level.
Cholesterol LDL	Level of 'bad' low-density lipoprotein cholesterol.
Cholesterol HDL	Level of 'good' high-density lipoprotein cholesterol.
Cholesterol Triglycerides	Level of blood fats (triglycerides).
MMSE	Mini-Mental State Examination score (cognitive screening).
Functional Assessment	Evaluation of the ability to perform daily tasks.
Memory Complaints	Subjective reporting of memory problems.
Behavioral Problems	Presence of disruptive or challenging behaviors.
ADL	Activities of Daily Living (basic self-care tasks).
Confusion	State of impaired orientation or thinking.
Disorientation	Loss of awareness of person, place, or time.
Personality Changes	Notable alterations in usual character or temperament.
Difficulty Completing Tasks	Trouble finishing complex or sequential activities.
Forgetfulness	Tendency to frequently forget information or events.
Diagnosis	Final medical conclusion or classification of the condition.

2.2. Data Processing

Data preprocessing aims to clean, transform, and standardize raw data from clinical sources (such as demographic, cognitive, or biomarker features) so that it is ready for use by a Machine Learning model. This stage is crucial for reducing noise, handling bias, and ensuring optimal model performance. In a classification task, scaling, also called normalization, is an essential preprocessing step that ensures every feature varies within the same range [7]. The data preparation stage includes many tasks, such as removing outliers and noise, integrating data from diverse sources, handling missing data, and transforming data to a scale suitable for analysis. This stage aims to eliminate the impact of systematic sources of variation as much as is feasible [11].

2.3. Material and Literature Review

2.3.1 XGBoost

XGBoost stands for extreme gradient boosting, which is a supervised EL algorithm that implements a generalized gradient boosting method that includes a regularization term to yield accurate models with multicore and distributed settings for classification, regression and ranking tasks [12]. XGBoost (Extreme Gradient Boosting) is a very efficient, flexible, and portable implementation of the Gradient Boosting Machine

(GBM) framework, designed to accelerate the performance and scalability of tree-based models. XGBoost is widely known for frequently providing superior results in structured classification and regression tasks. Chen & Guestrin (2016) define XGBoost as a "boosting tree system (tree boosting) which is measurable (scalable) and efficiently designed to improve the speed and performance of algorithms, boosting existing ones [13]. One strength of XGBoost is its ability to handle noise and outliers, ensuring reliable performance. It also helps identify significant variables and provides insights into the underlying processes driving urban patterns through feature importance ranking [9].

The history of XGBoost is intertwined with the broader evolution of machine learning, particularly the field of ensemble learning techniques. Ensemble methods, which combine multiple models to improve predictive performance, have been around since the early days of machine learning [14]. Overall, XGBoost uses a DT as a booster, and has demonstrated excellent performance in many classification, regression, and ranking tasks. However, XGBoost has not been widely studied in classification tasks that incorporate spectral and spatial features from views, including classification accuracy, computational efficiency, and the influence of crucial parameters [15].

2.3.2 Random Forest

Random Forest (RF) is an ensemble learning method that falls under the homogeneous base learner category of constructive classifiers. As the name implies, all base learners are decision trees, and therefore, they have a simpler structure than similar methods [16]. RF is a classifier consisting of a collection of tree-shaped classifiers with the same distribution for all trees in the forest. The random forest is characterized by aggregating votes from multiple decision trees based on the Gini Coefficient [17]. As a base learner, RF builds an ensemble of K decision trees (DTs). Each DT individually predicts the output, and these predictions are then averaged to produce the final output [18].

2.3.3 Logistic Regression

Regression analysis is one of the data analyses that aims to determine the effect of a variable on another variable, namely, the independent variable on the dichotomous dependent variable. The logistic regression model was created to describe the probability of the dependent variable between 0, stating "disagree," and 1, stating "agree." Logistic regression has an accurate classification accuracy [19]. Logistic Regression is a linear statistical model used to model the probability of a dichotomous (binary) outcome occurring, where the outcome is assumed to follow a Bernoulli distribution (David W. Hosmer, Stanley Lemeshow, n.d). Although its name contains the word "Regression," its primary function is as a classification algorithm. The logistic regression used is a simple, non-optimized model [20].

2.3.4 Support Vector Machine (SVM)

SVM is a nonprobabilistic classification and regression algorithm based on the principles of Vapnik-Chervonenkis (VC) theory [22]. SVM is a supervised machine learning technique that requires input from an existing dataset. For the known input, it constructs a model. For fresh data, it forecasts the result based on the model. The main goal of SVM, especially in classification, is to find the optimal plane of separation (hyperplane) that separates data classes in high-dimensional space. On the record, an SVM constructs a hyperplane in high-dimensional space, where separated regions with well-defined boundaries correspond to the largest distance between selected support vectors [22].

2.3.5 Decision Tree

A decision tree is defined as a hierarchical classification model that prioritizes interpretability, where the model structure consists of internal nodes(which perform tests on the feature) and leaf nodes(which provide the final decision). The creation of this tree is based on minimizing the loss function, taking into account the limitations (constraints) to maintain the validity of medical decisions [9].

A decision tree is a classification algorithm in machine learning that provides an easily interpretable mechanism [23] and is commonly used in image classification and pattern recognition [25]. Structurally, this algorithm builds a predictive model as a decision tree, where each node represents a condition (test on data attributes) and each branch represents the result of that condition [26]. As a basic model, Decision Tree also serves as a base learner or a homogeneous constructive classifier, a key component in more complex ensemble algorithms such as Random Forest [27].

Decision Trees operate using the “greedy” (top-down divide-and-conquer) method and use criteria such as Information Gain to optimally split the data at each node. Although this algorithm is suitable for datasets with both categorical and numerical features [25], its traditional versions (such as ID3 and CART) inherently exhibit a bias towards the majority class, resulting in lower accuracy when applied to unbalanced data.

2.3.6. Literature Review

Several studies have applied machine learning techniques to early detect and predict Alzheimer's Disease (AD), addressing the urgent need for accurate, efficient automated diagnostic systems. As highlighted by Kavitha et al. (2022), early diagnosis of Alzheimer's disease remains challenging for humans and often requires costly medical procedures, even though early intervention is crucial to slow the progression of brain damage. In response to this challenge, recent research has demonstrated that machine learning models can provide faster and more objective diagnostic support, with predictive performance that, in some cases, exceeds that of traditional human assessment. Various classification algorithms, such as Support Vector Machines (SVMs), Random Forests, and Logistic Regression, have been widely explored and have shown promising performance in medical diagnosis tasks using clinical and cognitive datasets. In particular, ensemble-based approaches have attracted significant attention for their ability to capture complex patterns in high-dimensional healthcare data. For instance, Kavitha et al. (2022) reported that the Random Forest model achieved optimal performance, with an average validation accuracy of 83% in Alzheimer's disease classification. These findings are consistent with other studies that highlight the effectiveness of ensemble learning methods, including bagging and boosting algorithms such as Random Forest and XGBoost, which demonstrate strong predictive capability and improved robustness when handling complex medical datasets. However, despite these promising results, several challenges remain in applying machine learning to Alzheimer's disease prediction. Clinical datasets, such as the OASIS dataset, often contain inconsistencies, redundant information, and a large number of missing values, which require extensive data preprocessing before machine learning models can be effectively applied. Therefore, building reliable predictive systems not only depends on the choice of algorithm but also on proper data preparation and preprocessing strategies to ensure optimal model performance.

2.4. ROC Curve

The Receiver Operating Characteristic (ROC) curve is a graphical plot that illustrates the diagnostic capability of a binary classification system as its discrimination threshold varies. This curve plots the True Positive Rate (TPR), also known as Sensitivity or Recall, on the Y-axis against the False Positive Rate (FPR), which equals 1 minus Specificity, on the X-axis, for each possible threshold. The most common summary metric of this curve is the Area Under the Curve (AUC), where a value close to 1.0 indicates that the model has excellent ability to distinguish between positive and negative classes. ROC curves are crucial in medical research and Machine Learning because they allow researchers to visually compare the performance of multiple models and identify which model provides the best trade-off between sensitivity and specificity for a specific classification task [10].

3. RESULTS AND DISCUSSION

The first step in this study was data collection. The dataset used in this study contained 2,149 records on Alzheimer's disease predictions, obtained from Kaggle. This dataset includes 35 attributes. Before entering the classification stage, data analysis is performed first to understand each variable. This process involves pre-processing the data to ensure it is ready for comprehensive processing. The Alzheimer's disease predictions dataset can view Table 2.

Table 2. Alzheimer's disease predictions dataset

PatientID	Age	Gender	...	Memory Complaints	Behavioral Problems	Diagnosis	DoctorInCharge
4751	73	0	...	0	0	0	XXXConfid
4752	89	0	...	0	0	0	XXXConfid
4753	73	0	...	0	0	0	XXXConfid
4754	74	1	...	0	1	0	XXXConfid
4755	89	0	...	0	0	0	XXXConfid

3.1. Pre-Processing

Pre-processing is a stage in which inappropriate data is removed or data is converted into a form that is easier for the system to process. The processed data will first be cleaned to remove unwanted data, such as data without names, IDs, etc. In the data pre-processing stage, this study used the Python programming language and the Google Colab platform. The initial data preparation process included steps such as cleaning, filtering, and trimming. Several features that were not used in this study were Unnamed Feature: 0, id, and the name of the doctor in charge, which were irrelevant to the analysis.

3.2. Evaluation

This is supported by the confusion matrix results for the XGBoost algorithm with the best accuracy in k-fold cross-validation with a value of 80:20. The confusion matrix results can be seen in Figure 3.

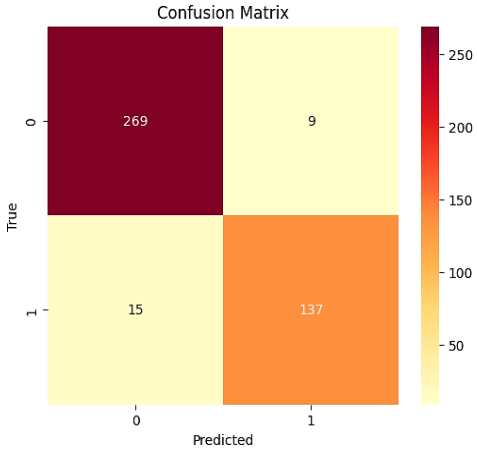

Figure 3. Confusion Matrix Evaluation

The sample shows a very balanced demographic distribution, with 50.00% being women and 50.00% being men, which minimizes potential gender bias in the comparison of risk factors. On average, the subjects' age is 60 years, confirming that this research sample is relevant because it represents the older adult age group, which is the population at high risk for Alzheimer's disease. Furthermore, the dataset is evenly distributed in the Diagnosis variable, with 50.00% of subjects diagnosed with Alzheimer's and 50.00% diagnosed without Alzheimer's. This balance ensures that subsequent analysis and modeling will be based on equal proportions of positive and negative cases, increasing the reliability of the results obtained.

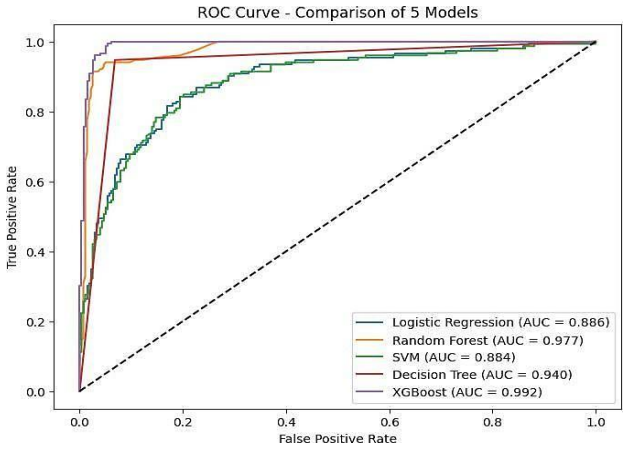

Figure 4. AUC Evaluation

Based on the comparison of the five models, the XGBoost algorithm achieved the highest AUC of 0.992. This performance was followed by Random Forest (AUC = 0.977) and Decision Tree (AUC = 0.940). The Logistic Regression model (AUC = 0.886) and SVM (AUC = 0.884) showed the lowest discriminatory ability among the five models. Visually, the XGBoost curve was closest to the upper left corner, which clearly validated that this model was the most effective and had the highest ability to distinguish between positive and negative classes in this classification problem.

3.3. Comparison Model

In this study, the classification process was carried out using the Google Colab platform, and the algorithm models used were XGBoost, Random Forest, SVM, Logistic Regression, and Decision Tree. Model validation was performed using the k-fold cross-validation method with splits of 70:30, 80:20, and 90:10. These splits were chosen because the dataset was quite large (2,149 records), ensuring representative training and test data. This method allows each subset to be used alternately as training and test data. This approach is designed to provide a more comprehensive evaluation of model performance, reduce the risk of overfitting, and ensure more accurate and reliable results. The results of the XGBoost algorithm are shown in Figures 5, 6, and 7.

Based on Figure 5, the analysis shows that the XGBoost classification model achieves 93.8% accuracy, 93.8% precision, and 93.8% recall. These results reflect that the model performs quite well in classifying data, with high accuracy and precision. The higher precision than recall indicates that most of the model's positive predictions are correct (low false positives), although some positive cases are still missed (false negatives).

This shows that the model tends to be more selective in predicting positive classes, resulting in more precise predictions, but potentially losing some important data. To improve the model's performance, further optimization is needed, especially to increase the recall value. This step will help the model become more sensitive in detecting all positive cases consistently. Optimization can be done by adjusting parameters, choosing a more appropriate distance metric, or performing better data preprocessing, such as normalization or feature selection.

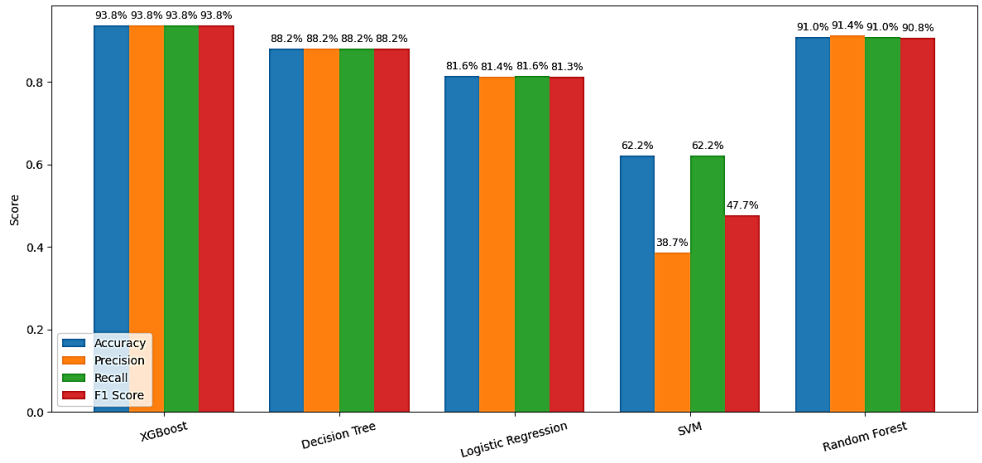

Figure 5. Model comparison on the data splitting test on 30%

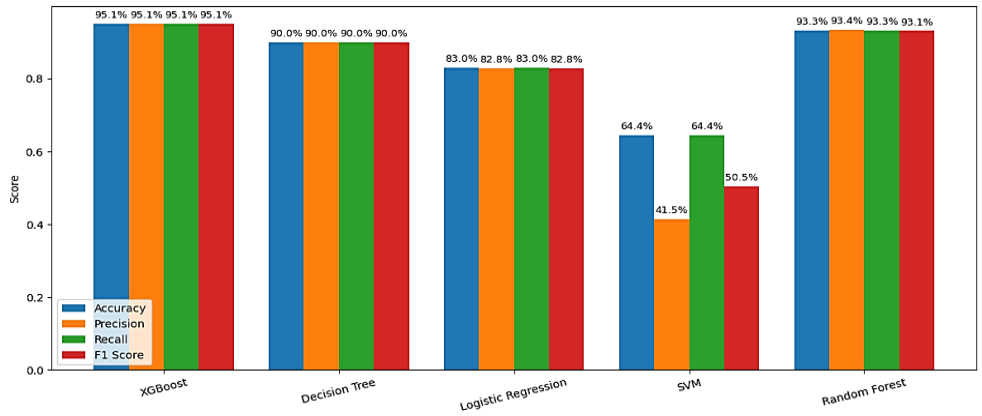

Figure 6. Model comparison on the data splitting test on 20%

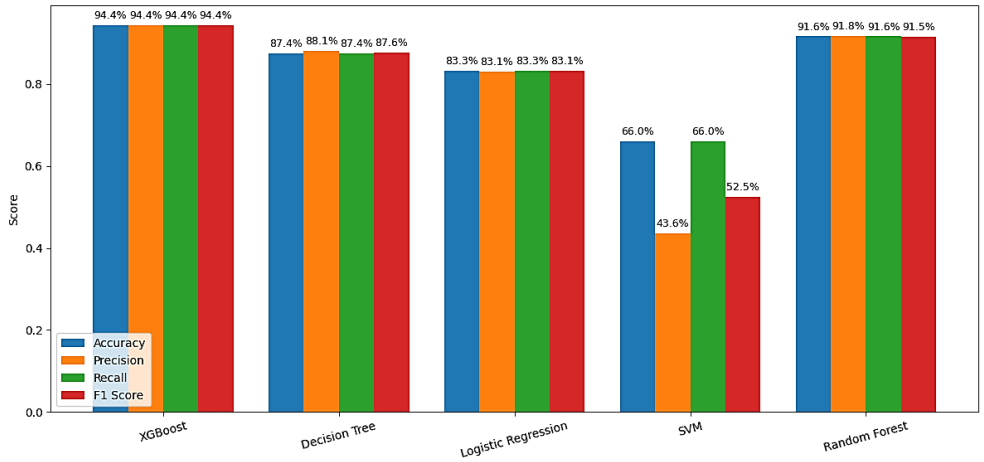

Figure 7. Model comparison on the data splitting test on 10%

The results of this study show that XGBoost consistently outperforms other algorithms with Accuracy, Precision, and Recall values reaching 95.1% on an 80:20 data split. These findings confirm and exceed those of Yi et al. (2023), who reported an XGBoost accuracy of 87.57% in the same domain. Technically, XGBoost's

superiority in this study can be explained by its ability to handle complex structured data through a regulated boosting mechanism.

Unlike standard Decision Trees, which tend to overfit when many features are present, XGBoost includes regularization parameters to control model complexity. In addition, since this dataset has 35 features ranging from demographic factors to cognitive symptoms, XGBoost can capture non-linear relationships between these variables more effectively than linear models such as Logistic Regression or SVM, which had the lowest scores in this experiment. XGBoost's ability to optimize the loss function via gradient descent makes it more sensitive to accurately classify Alzheimer's patients.

4. CONCLUSION

This study successfully concluded that the XGBoost algorithm is the most effective model for early detection of Alzheimer's disease compared to four other algorithms. The main findings indicate that at an 80:20 data ratio, XGBoost achieves peak performance with a 95.1% score across all evaluation metrics. The most significant aspect is the high Recall value (95.1%), which demonstrates the model's ability to minimize the risk of false negatives and detection failures in patients who indeed have Alzheimer's.

Recommendations for Further Research (1) Hyperparameter Optimization: Conduct a search for optimal parameters (such as learning rate and maximum depth) on the XGBoost model to further improve diagnostic accuracy. (2) Feature Importance Analysis: Conduct a more in-depth identification of the existing 35 features to determine which clinical factors are most dominant in triggering Alzheimer's. (3) External Dataset Validation: Test the developed model on a larger clinical dataset to ensure the consistency of the model's performance across various patient populations.

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