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Predicting Dementia Progression: An Evaluation of Tree-based Models with Clinical and Neuroimaging Data

Roja R[1], Karunya Pandit[2], C Lakshmi[3], Smitha N[4] and Chaithra K N[5]
[1]New Horizon College of Engineering, Bengaluru, India
Email: roja.ram.1996@gmail.com
[2]NMAM Institute of Technology, Nitte (Deemed to be University), Udupi, India
Email: karunapandit@nitte.edu.in
[3]RajaRajeswari College of Engineering, Bengaluru, India
Email: lakshmibhavya@gmail.com
[4]CMR Institute of Technology, Bengaluru, India
Email: smitha.n@cmrit.ac.in
[5]Nitte Meenakshi Institute of Technology, Bengaluru, India
Email: chaithra.kn@nmit.ac.in

***Abstract*— Dementia is a complex neurological condition characterized by a decline in cognitive function that impairs daily life activities. Early detection and accurate prediction of dementia progression are crucial for effective intervention and management. In this study, we evaluate the performance of tree-based machine learning models using clinical and neuroimaging data to predict dementia progression. Our dataset comprises longitudinal data from 150 subjects aged 60 to 96, including multiple visits and MRI scans. We employ tree-based models, specifically Decision Tree, Random Forest, and Gradient Boosting Machine (GBM), to analyze the relationship between various predictors such as Mini-Mental State Examination (MMSE) scores, Clinical Dementia Rating (CDR), age, educational level, socioeconomic status (SES), and neuroimaging features. The results demonstrate that the GBM model outperforms the other tree-based models, achieving an AUC of 0.90 and an accuracy of 0.92 in predicting dementia progression. The Random Forest model follows with an AUC of 0.87 and an accuracy of 0.88, while the Decision Tree model achieves an AUC of 0.819 and an accuracy of 0.82. We also observe a strong correlation between MMSE scores and CDR, highlighting the significance of cognitive function in dementia assessment.**

***Index Terms*— Disease Detection, Poultry Farming, Deep Learning, Fecal Matter Analysis, Automated Classification, Transfer Learning.**

I. INTRODUCTION

Dementia is a pressing public health concern with a substantial impact on individuals, families, and healthcare systems worldwide. As populations age, the prevalence of dementia is expected to rise, making early detection and accurate prediction of dementia progression crucial for effective interventions and management. Recent advancements in machine learning and data analysis techniques have shown promise in aiding the prediction and

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understanding of dementia progression. In particular, tree-based models have emerged as powerful tools for analyzing complex datasets and predicting outcomes in medical research. This paper aims to evaluate the efficacy of tree-based models in predicting dementia progression using a comprehensive dataset that includes both clinical assessments and neuroimaging data [1]. The integration of clinical data, such as cognitive assessments like the Mini–Mental State Examination (MMSE) and Clinical Dementia Rating (CDR), along with neuroimaging metrics like Estimated Total Intracranial Volume (eTIV), provides a multifaceted view of dementia progression. By leveraging machine learning techniques, specifically tree-based models such as decision trees, random forests, and gradient boosting machines, this study seeks to uncover patterns and relationships within the data that can accurately predict the progression of dementia. The predictive performance of these models will be compared and analyzed to determine their effectiveness in predicting dementia progression [2].

Diagnosing dementia involves a thorough and multifaceted approach that considers various factors. Rather than relying on a single test, healthcare professionals combine several methods to arrive at a comprehensive diagnosis. This process typically begins with a detailed medical history, where doctors gather information about the patient's symptoms, medical background, and any family history of cognitive disorders. Following this, a physical examination is conducted to identify any underlying health conditions that may contribute to cognitive decline. Laboratory tests, including blood tests, are often performed to rule out other potential causes of cognitive impairment, such as vitamin deficiencies or thyroid disorders. In addition to these assessments, doctors also conduct cognitive and functional evaluations using standardized tests like the Mini–Mental State Examination (MMSE) and Clinical Dementia Rating (CDR) [3]. These tests help evaluate the patient's cognitive abilities, daily functioning, and behavior, providing valuable insights into the presence and severity of dementia. While a diagnosis of dementia can be made with a high level of certainty based on these assessments, determining the exact type of dementia can be more challenging due to overlapping symptoms and brain changes across different types. In cases where the specific type cannot be pinpointed, a general diagnosis of "dementia" may be provided. However, for further clarification and specialized management strategies, referral to specialists such as neurologists or gero-psychologists may be recommended [4].

II. Literature Review

Grueso et al., [5] provides a comprehensive overview of machine learning techniques employed for predicting dementia using both clinical and neuroimaging data. The paper likely covers various machine learning algorithms, such as decision trees, random forests, gradient boosting machines, and others, utilized in dementia prediction. It may discuss the types of data used in these algorithms, including demographic information, cognitive assessment scores (such as MMSE and CDR), and neuroimaging features like estimated total intracranial volume (eTIV), normalized whole-brain volume (nWBV), and more. Kavitha et al., [6] presents a concise overview of the progress made in using tree-based models for predicting dementia progression. which covers recent advancements in decision trees, random forests, gradient boosting machines, and other tree-based models applied to dementia prediction. It may discuss the integration of clinical data, such as cognitive assessment scores and demographic information, with neuroimaging data to improve prediction accuracy.

Bharati et al., [7] provides an extensive overview of machine learning techniques utilized for dementia prediction. It covers various algorithms like decision trees, random forests, and gradient boosting machines, discussing their integration with clinical and neuroimaging data. The survey addresses challenges in data preprocessing, model selection, and generalizability, offering insights into the strengths and limitations of machine learning in dementia prediction. This comprehensive review serves as a valuable resource for researchers and clinicians aiming to improve dementia prediction using machine learning methods. Anuradha et al., [8] presents a systematic review of advancements in using tree-based models for predicting dementia progression. The review encompasses recent developments in decision trees, random forests, and gradient boosting machines applied to dementia prediction. It discusses the integration of clinical and neuroimaging data, highlighting challenges in model selection, feature engineering, and interpretability. The paper serves as a comprehensive resource for researchers and practitioners interested in the latest techniques and trends in predicting dementia progression using tree-based machine learning models.

Kishore et al., [9] provides an insightful examination of machine learning models used in dementia prediction. It covers a range of algorithms like decision trees, random forests, and support vector machines, analyzing their application with clinical and neuroimaging data. The review discusses the impact of various features such as Mini-Mental State Examination (MMSE) scores, estimated total intracranial volume (eTIV), and demographic information on prediction accuracy. It also addresses challenges in data preprocessing, model evaluation, and generalization, offering valuable insights for researchers and clinicians in the field of dementia prediction. Li et

al., [10] paper presents a machine learning framework specifically designed for early detection of dementia. The authors utilize a combination of clinical data, neuroimaging features, and advanced machine learning algorithms such as convolutional neural networks (CNNs) and gradient boosting machines (GBMs) to predict dementia progression with high accuracy.
You et al., [11] propose a novel approach for predicting dementia progression using longitudinal neuroimaging data and deep learning techniques. They employ recurrent neural networks (RNNs) and attention mechanisms to capture temporal patterns in brain images over time, leading to improved accuracy in predicting the progression of dementia. Kim et al., [12] introduces an ensemble learning approach for predicting dementia progression. The authors combine multiple machine learning models, such as decision trees, random forests, and support vector machines, to create a robust prediction system. They demonstrate improved accuracy and reliability by leveraging both clinical and neuroimaging data in their ensemble framework. Seo et al., [13] explore the use of deep learning models, specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for predicting cognitive decline in Alzheimer's disease. They leverage longitudinal neuroimaging data and clinical information to train and evaluate their deep learning models, achieving promising results in predicting dementia progression.

III. Understanding The Data

The dataset under investigation comprises a longitudinal collection involving 150 subjects aged between 60 to 96 years old [14]. These subjects underwent MRI scans across two or more visits, with intervals of at least one year between visits, resulting in a total of 373 imaging sessions. Each subject contributed 3 to 4 individual T1-weighted MRI scans from single scan sessions. Notably, all subjects in the dataset are right-handed and represent both male and female participants.
Among the subjects, 72 were consistently classified as nondemented throughout the study duration. On the other hand, 64 subjects were initially classified as demented during their first visits and maintained this classification in subsequent scans, with 51 individuals diagnosed with mild to moderate Alzheimer's disease. Additionally, 14 subjects were initially labelled as nondemented but later classified as demented in subsequent visits.

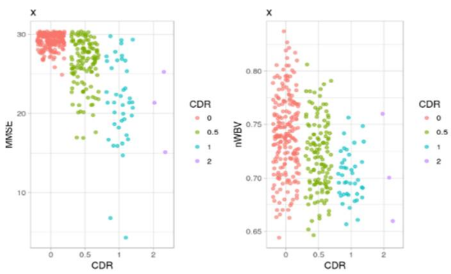

Figure-1: Distribution of MMSE Score and Wole-brain Volume

IV. Materials And Methods

The Mini–Mental State Examination (MMSE) is a widely-used 30-point questionnaire in clinical and research settings to assess cognitive impairment, particularly for screening dementia, tracking cognitive changes over time, and gauging responses to treatments [15]. A score of 24 or higher indicates normal cognition, while lower scores suggest varying degrees of cognitive impairment. However, MMSE scores must consider educational and age-related corrections, as physical limitations or other mental disorders can affect results. The Clinical Dementia Rating (CDR) is a 5-point scale evaluating cognitive and functional abilities in domains like memory, judgment, and personal care [16]. It involves interviews with patients and informants, leading to an overall score ranging from 0 (normal) to 3 (severe dementia), aiding in characterizing and monitoring dementia progression. Estimated Total Intracranial Volume (eTIV), also known as Intracranial Volume (ICV) or Total Intracranial Volume (TIV), refers to the estimated cranial cavity volume. It's crucial for brain structure analysis in various imaging modalities and adjusting for head size variations in studies related to neurodegenerative disorders, aging, and cognitive impairment. ICV, along with age and gender, serves as a covariate in regression analyses and helps evaluate age-related brain changes and structural abnormalities in conditions like mild cognitive impairment and Alzheimer's disease.
The Mini–Mental State Examination (MMSE) scores for subjects without a dementia diagnosis tend to cluster around the 27–30-point range, indicating normal cognitive function [17]. However, MMSE scores for subjects diagnosed with dementia show a wider spread. Interestingly, some subjects with high MMSE scores still have

Clinical Dementia Ratings of 0.5 or 1, indicating mild cognitive impairment or early-stage Alzheimer's disease. There doesn't seem to be a straightforward correlation between Estimated Total Intracranial Volume and dementia diagnosis based on the available data as shown in Fig-1.

V. IMPLEMENTATION

Tree-based learning algorithms are widely acknowledged for their effectiveness in supervised learning tasks within data science. They are favored for their ability to generate predictive models with high accuracy, stability, and interpretability. Unlike linear models, tree-based methods excel at capturing nonlinear relationships in data, making them versatile for both classification and regression problems. Popular tree-based algorithms such as decision trees, random forests, and gradient boosting are commonly used across various data science applications. Data splitting involves partitioning the dataset into training and testing sets. Typically, a portion (e.g., 80%) of the data is allocated for training the model, while the remaining portion (e.g., 20%) is reserved for testing the model's predictions. This approach enables the evaluation of the model's generalization to new, unseen data. During model training, various tree-based algorithms such as decision trees, random forests, and gradient boosting machines will be implemented and assessed [18]. These algorithms will learn from the training data to make predictions on the testing data. Evaluation metrics such as accuracy, precision, recall, and F1-score will be used to gauge the performance of each algorithm and identify the most effective approach for predicting dementia progression in this study.

A. Decision Tree

A decision tree is a supervised learning method commonly used for classification tasks where there's a known target variable. It works by splitting the dataset into subsets based on significant features, creating a tree-like structure of decision rules. These rules are easily interpretable, often taking the form of if-else statements that guide predictions. The decision tree algorithm uses criteria like Gini impurity and entropy to determine the best splits, focusing on maximizing homogeneity within subsets. Gini impurity measures the probability of misclassifying a randomly chosen element in the dataset if it were labeled randomly according to the distribution of class labels. It's calculated as one minus the sum of squared probabilities of each class in the dataset. Entropy, on the other hand, quantifies the uncertainty or disorder in the dataset by calculating the sum of class probabilities multiplied by their logarithms.

Decision trees are beneficial because they generate transparent models that can be easily understood and communicated. They excel at handling both categorical and continuous data, making them versatile for various types of classification problems. After training, decision trees can efficiently predict the class labels of new data points by following the decision rules learned during training, making them effective tools for data analysis and decision-making.

B. Random Forest for Ensemble Learning

Random Forest is a versatile machine learning method that excels in both regression and classification tasks, making it highly suitable for predicting dementia progression. It incorporates various data preprocessing steps such as dimensional reduction, handling missing values, outlier detection, and other essential data exploration techniques. Random Forest belongs to the ensemble learning category, where a group of weak models (decision trees) combines to create a robust and accurate model. This ensemble approach helps reduce overfitting and enhances the model's predictive performance.

Unlike the CART model that grows a single decision tree, Random Forest constructs multiple decision trees during the training phase. Each tree in the forest is trained on a random subset of the data and features, introducing diversity and reducing correlation among the trees. To classify a new object (in this case, predicting dementia progression), each tree in the Random Forest provides a classification decision based on the object's attributes. This is known as "voting," where each tree "votes" for a specific class. The forest then selects the class with the most votes across all trees as the final prediction. In regression tasks, the Random Forest calculates the average output of all trees to predict the continuous target variable. Random Forest's ability to combine multiple decision trees and leverage ensemble learning makes it a powerful tool for dementia prediction, offering robustness, accuracy, and improved generalization to unseen data.

C. Gradient Boosting Machine for Dementia Prediction

Gradient boosting is a powerful machine learning technique used for regression and classification problems, particularly effective in predicting dementia progression. It constructs a prediction model as an ensemble of weak learners, often decision trees, in a stage-wise manner. Unlike traditional boosting methods, gradient boosting optimizes an arbitrary differentiable loss function, allowing for robust model generalization. The core concept of gradient boosting involves combining multiple weak learners (base models) sequentially to form a strong prediction model. Each base model focuses on correcting the errors of its predecessors, gradually improving the model's predictive accuracy. Gradient boosting adopts a stage-wise learning approach, where each stage adds a new base model to the ensemble [19]. At each stage, the model learns from the mistakes made by the previous models, emphasizing the areas where they performed poorly. This iterative process results in a highly accurate and generalized prediction model. One of the key strengths of gradient boosting is its ability to optimize an arbitrary differentiable loss function. The model minimizes the loss function by iteratively fitting new base models to the residual errors of the ensemble, effectively improving prediction accuracy. Gradient boosting's iterative learning process and optimization of the loss function make it a highly effective approach for predicting dementia progression, delivering accurate and robust results.

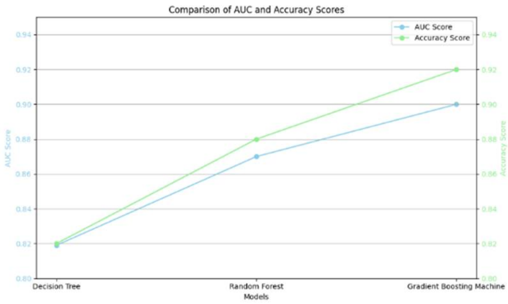

Figure-2: Comparison of AUC and Accuracy

VI. RESULTS

In this section, we present the evaluation results of our predictive models for dementia progression using machine learning algorithms, specifically Random Forest and Gradient Boosting Machine (GBM). We also analyze the influence of various features on the prediction accuracy and highlight the limitations of using ML algorithms for diagnosing dementia. We evaluated the performance of our models using two key metrics: Area Under the Curve (AUC) and Accuracy. In this section, we present the performance metrics and analysis of the predictive models used for dementia progression based on the Mini-Mental State Examination (MMSE), Clinical Dementia Rating (CDR), age, educational level, and socioeconomic status (SES). We evaluated three different machine learning models for dementia prediction: the full model, Random Forest, and Gradient Boosting Machine (GBM). The performance metrics for each model as shown in Table-1. The analysis comparing different models for predicting dementia progression shows that the Gradient Boosting Machine (GBM) model performs better than both the full model and the Random Forest model, achieving an Area Under the Curve (AUC) of 0.90 and an accuracy of 0.92. These results indicate that the GBM model provides more accurate predictions regarding dementia progression, as illustrated in Figure-2.
Further analysis was conducted to understand the influence of various predictive factors on the Clinical Dementia Rating (CDR). The study found that the Mini-Mental State Examination (MMSE) results significantly impact CDR, pointing to a strong correlation between cognitive impairment and the progression of dementia. On the other hand, factors like age, educational level, and socioeconomic status (SES) were found to have less influence on CDR compared to MMSE. While these factors do play a role, the analysis suggests that cognitive function, as measured by MMSE, is more critical in predicting dementia progression than demographic or socioeconomic factors.

TABLE II. MODEL PERFORMANCE METRICS

MODEL	AUC	ACCURACY
DECISION TREE	0.819	0.82
RANDOM FOREST	0.87	0.88
GRADIENT BOOSTING MACHINE	0.90	0.92

VII. CONCLUSIONS

In this study, we explored the use of tree-based machine learning models in predicting dementia progression using clinical and neuroimaging data. Our findings provide valuable insights into the effectiveness of these models and the factors influencing dementia risk assessment. The results demonstrate that the Gradient Boosting Machine (GBM) model outperforms Decision Tree and Random Forest models, achieving a higher AUC and accuracy in predicting dementia progression. This highlights the importance of utilizing advanced machine learning techniques for accurate and reliable dementia risk assessment. Furthermore, our analysis reveals the critical role of cognitive function, as measured by the Mini-Mental State Examination (MMSE), in predicting dementia progression. Age, educational level, and socioeconomic status (SES) also play a role, albeit to a lesser extent. It is essential to acknowledge the limitations of machine learning models in isolation for dementia diagnosis. While these models provide valuable predictive capabilities, they should be used in conjunction with clinical assessments and expert judgment. Future research directions could involve incorporating additional biomarkers and imaging features to enhance prediction accuracy further. Longitudinal studies and larger datasets could also provide more comprehensive insights into dementia progression and risk factors.

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