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Early Detection of Dementia Using Machine Learning Algorithms

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Abstract
Dementia is a progressive neurodegenerative disorder that impairs memory, cognition, and behavior, affecting millions of individuals worldwide. Early detection plays a vital role in improving patient management and therapeutic interventions. This paper presents Phase 1 of a research project on dementia detection using machine learning. In this phase, a predictive framework was developed using clinical and morphometric tabular data from the OASIS Longitudinal Dataset, which includes demographic, clinical, and brain-volume-related features such as age, education, socio-economic status (SES), Mini-Mental State Examination (MMSE), Clinical Dementia Rating (CDR), and normalized whole-brain volume (nWBV). The preprocessing pipeline involved imputation of missing values, categorical encoding, and normalization. Two models—Decision Tree (J48 equivalent) and Artificial Neural Network (ANN/MLP)—were implemented and compared, where the Decision Tree provided interpretability and the ANN effectively captured nonlinear feature relationships.

This validated Phase 1 implementation focuses on tabular-data–based dementia prediction. The subsequent Phase 2, currently under development, aims to integrate MRI image-based deep learning and multi-modal decision fusion to enhance diagnostic accuracy and clinical applicability.

Keywords: Dementia Detection, Machine Learning, OASIS Dataset, Decision Tree, Artificial Neural Network, Phase 1 Implementation, MRI Integration.

1. INTRODUCTION

Dementia is a chronic and progressive neurodegenerative disorder that leads to a gradual decline in memory, cognition, and functional ability. It represents one of the leading causes of disability and dependency among the elderly worldwide. According to the World Health Organization (WHO), over 55 million people are currently living with dementia, and this number is projected to triple by 2050 due to the increasing aging population. Among the various forms of dementia, Alzheimer's disease accounts for approximately 60–80% of all diagnosed cases, making it a major contributor to neurological morbidity and mortality. The socio-economic burden associated with dementia is immense, affecting not only patients but also caregivers and healthcare systems globally.

Early diagnosis of dementia is crucial for slowing disease progression, planning medical care, and improving patient quality of life. Traditional diagnostic approaches, such as cognitive assessments, neuropsychological tests, and neuroimaging evaluations, are often time-consuming, subjective, and reliant on expert interpretation. These limitations underscore the need for data-driven computational models capable of providing accurate, consistent, and early predictions of dementia risk.

Machine Learning (ML) has emerged as a powerful tool for medical data analysis and clinical decision support. ML algorithms can process large, multidimensional datasets and identify hidden relationships between clinical and biological variables that are difficult to detect through manual assessment. In dementia research, ML models have been successfully applied to analyze tabular clinical data, MRI scans, genetic information, and speech patterns to improve diagnostic precision. Unlike traditional statistical approaches, ML can dynamically learn from patterns within the data, allowing the construction of predictive models that generalize effectively to unseen cases.

The present research focuses on the early detection of dementia using a machine learning–based approach applied to the OASIS Longitudinal Dataset, which contains structured tabular data derived from clinical and morphometric features. The dataset includes demographic information (age, gender, education, socio-economic status), clinical test results (Mini-Mental State Examination [MMSE], Clinical Dementia Rating [CDR]), and brain volume–related measures (Estimated Total Intracranial Volume [eTIV], Normalized Whole-Brain Volume [nWBV], and Atlas Scaling Factor [ASF]). These parameters have been established in medical literature as reliable indicators of cognitive decline and neurodegenerative progression.

In this study, two supervised learning algorithms—Decision Tree (J48 equivalent) and Artificial Neural Network (ANN/MLP)—are employed to classify subjects as *demented* or *non-demented* based on the selected features. The Decision Tree model offers interpretability, allowing clinicians to visualize decision boundaries and feature importance, whereas the ANN provides the capability to model nonlinear interactions between variables for improved classification accuracy.

The overall system is designed with three functional modes of operation to support a comprehensive diagnostic workflow. In the Tabular Mode, users provide demographic, clinical, and morphometric details, which are processed through a trained machine learning pipeline to predict the likelihood of dementia. In the Image Mode, users upload MRI brain scans that are analyzed by a convolutional neural network (CNN)–based deep learning model to identify structural abnormalities associated with dementia. The Combined Mode integrates both tabular and image data, applying a multimodal fusion strategy to generate a unified diagnostic decision by combining the strengths of both models.

This paper focuses on the Phase 1 implementation, which involves the development, training, and validation of the tabular data–based model using the *OASIS Longitudinal Dataset*. The workflow includes data preprocessing, feature engineering, and supervised learning–based model development. Two algorithms—Decision Tree (J48 equivalent) and Artificial Neural Network (ANN/MLP)—were implemented to classify subjects as demented or non-demented. The models were evaluated using standard performance metrics such as confusion matrix, precision, recall, and F1-score. Experimental findings demonstrate that both models achieved consistent and reliable results, with noticeable performance improvement following effective normalization and feature selection. The Phase 1 outcomes validate the potential of tabular clinical data in supporting early dementia detection, forming the foundation for future integration of MRI-based deep learning models in Phase 2.

This paper presents Phase 1, which focuses exclusively on the development, training, and evaluation of the tabular data–based ML model using the OASIS Longitudinal Dataset. The implementation involves data loading and preprocessing, feature selection, model training, validation, and performance evaluation using key metrics such as accuracy, confusion matrix, precision, recall, and F1-score. Preliminary results demonstrate that the Decision Tree and ANN models achieve high reliability in classifying dementia, with improved performance following effective feature engineering and normalization.

In Phase 2 (future enhancement), the framework will be expanded to integrate image-based features derived from MRI scans (e.g., via convolutional neural networks), allowing multimodal fusion of tabular and visual data. This integration aims to enhance model robustness and diagnostic accuracy, contributing to the creation of a clinically viable, web-based decision-support system for early dementia detection.

II. RELATED WORK

The early detection of dementia and Alzheimer's disease has been an active research domain that leverages advancements in machine learning (ML), deep learning (DL), and neuroimaging technologies to enhance diagnostic precision and clinical decision-making. Traditional diagnostic approaches, such as cognitive assessments and neurological evaluations, are limited by their dependence on clinician interpretation and variability. Consequently, automated ML- and DL-based systems have gained traction for their ability to analyze complex clinical and imaging data to identify early signs of cognitive decline.

A. Machine Learning and Tabular Data–Based Approaches

Several studies have applied ML algorithms on clinical and demographic datasets for dementia and Alzheimer's detection.

Lu *et al.* (2018) utilized Random Forest and Support Vector Machine (SVM) classifiers on the OASIS dataset, achieving improved diagnostic accuracy using features like age, education, and brain volume measures.

Saeed *et al.* (2020) employed logistic regression with clinical indicators such as Mini-Mental State Examination (MMSE), Socio-Economic Status (SES), and Normalized Whole-Brain Volume (nWBV) for predicting dementia severity.

Bhagyashree *et al.* (2021) implemented Decision Tree and Gradient Boosting algorithms to classify patients as demented or non-demented, emphasizing interpretability and transparency for clinical use. These works demonstrated that tabular clinical and morphometric data are strong predictors of dementia progression, especially when combined with efficient preprocessing and feature engineering techniques.

B. Deep Learning for Alzheimer's Disease and Dementia Detection

Recent advancements have incorporated deep learning techniques, particularly Convolutional Neural Networks (CNNs) and 3D-CNNs, to analyze MRI and PET scans for the early detection of dementia. Studies such as Li *et al.* (2019), Sarraf and Tofighi (2016), and Yue *et al.* (2018) employed CNN-based architectures to identify structural and volumetric changes in brain tissues associated with Alzheimer's disease (AD).

Carneiro *et al.* (2018) analyzed the performance of Google Colaboratory for accelerating DL training, improving reproducibility in MRI-based diagnosis.

In [9] and [10], deep learning models performed automatic brain segmentation, classification, and spatiotemporal feature extraction, demonstrating superior accuracy and automation capabilities. Moreover, multimodal frameworks combining MRI, PET, and clinical features have achieved enhanced classification accuracy, as seen in works by Liu *et al.* (2021) and Venugopalan *et al.* (2021). While these deep models excel in precision, they often require high computational resources and extensive training data, limiting their clinical scalability.

C. Multimodal and Fusion-Based Research

To overcome the limitations of single-modality models, several researchers have adopted multimodal fusion approaches.

For example, Liu *et al.* (2021) proposed an integrated model that fuses MRI features with clinical parameters such as MMSE and CDR, yielding higher diagnostic accuracy than individual models.

Other studies (e.g., Huang *et al.*, 2019; Folego *et al.*, 2020) have explored combining structural MRI, functional MRI (fMRI), and tabular clinical data, using ensemble-based and hybrid deep learning architectures.

These methods underscore the potential of unified frameworks capable of analyzing heterogeneous data sources for comprehensive dementia assessment.

D. Accuracy and Performance Comparison Across Techniques

Different ML and DL approaches report varying levels of classification accuracy. CNN-based MRI models achieved accuracies between 85% and 94% ([6], [12], [14], [15], [20]), while ensemble-based ML frameworks achieved around 89–93% ([25], [26], [28]). Natural Language Processing (NLP)-based methods analyzing speech and linguistic data achieved accuracies of approximately 88% ([25]), demonstrating the potential of non-imaging biomarkers. Recent 3D CNN and hybrid cascaded models ([17], [19]) achieved 80–83% accuracy, while Sarraf *et al.* ([40], [41]) reported state-of-the-art accuracy exceeding 98% for binary AD vs. normal classification tasks.

These results reflect that ML and DL approaches can complement each other, balancing interpretability, scalability, and diagnostic precision.

E. Research Gap and Present Work

Despite these advancements, there remains a lack of interpretable, accessible, and scalable dementia detection systems that combine clinical and imaging data for real-world deployment. Most DL-based studies focus exclusively on MRI or PET data, which may not always be available in low-resource clinical settings.

The present study addresses this gap by developing a tabular data–based dementia prediction model as the Phase 1 implementation of a two-stage framework. This phase employs Decision Tree (J48 equivalent) and Artificial Neural Network (ANN/MLP) models on the OASIS Longitudinal Dataset to classify subjects as demented or non-demented using clinical and morphometric features.

Future work (Phase 2) will integrate MRI image-based deep learning and multimodal fusion, combining tabular and imaging modalities to enhance predictive accuracy and clinical reliability. This structured, interpretable, and modular design establishes a foundation for scalable, AI-driven dementia diagnosis systems

III.METHODOLOGY

The proposed framework for the early detection of dementia is developed as a structured machine learning (ML) pipeline utilizing clinical and morphometric data obtained from the OASIS Longitudinal Dataset. The overall workflow of the system is illustrated in Figure 1, which depicts a modular architecture encompassing data preprocessing, feature selection, model training, evaluation, and prediction deployment. The system aims to classify subjects as *Demented* or *Non-Demented* based on demographic, clinical, and brain-volume parameters.

A. Dataset Description

The dataset utilized for the Phase-1 implementation is the OASIS Longitudinal Dataset (oasis_longitudinal.csv), which comprises data from 235 subjects aged between 60 and 96 years. Each record in the dataset includes a combination of demographic, clinical, and morphometric features that collectively provide a comprehensive profile of each participant. The demographic attributes consist of *Age*, *Gender*, *Education*, and *Socio-Economic Status (SES)*, which help capture population-related variations in dementia prevalence. The clinical attributes include *Mini-Mental State Examination (MMSE)* and *Clinical Dementia Rating (CDR)*, both of which serve as cognitive and functional performance indicators for diagnosing dementia severity. The morphometric attributes encompass *Estimated Total Intracranial Volume (eTIV)*, *Normalized Whole-Brain Volume (nWBV)*, and *Atlas Scaling Factor (ASF)*, providing quantitative measures of brain structure and atrophy. The target variable, labeled as *Group*, classifies each subject as either *Demented* or *Non-Demented*. These attributes together capture both behavioral and physiological aspects that are essential for the early diagnosis and progression analysis of dementia using machine learning techniques.

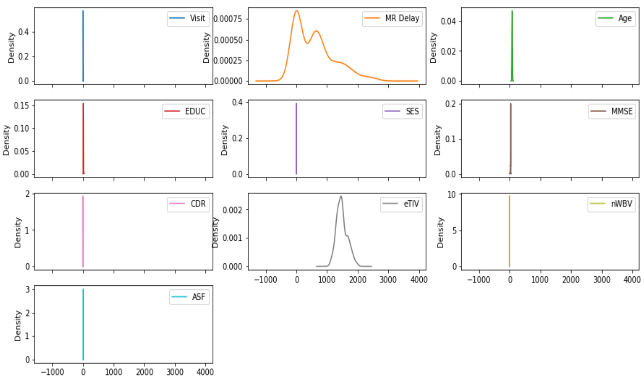

Fig. 1. All the columns have outliers excluding nWBV and Age

B. Data Loading and Preprocessing Module

The preprocessing module plays a crucial role in ensuring that the input data is clean, consistent, and suitable for subsequent machine learning analysis. Initially, the dataset was imported into a Pandas DataFrame for efficient handling and analysis. To maintain data integrity, missing values present in the *Socio-Economic Status (SES)*, *Education*, and *Mini-Mental State Examination (MMSE)* attributes were treated using median or mean imputation techniques, thereby preserving statistical balance and preventing data loss. The categorical variable *Gender* was numerically encoded, assigning a value of 1 for Male and 0 for Female, to enable compatibility with machine learning algorithms. Furthermore, continuous numerical attributes such as *Age*, *Estimated Total Intracranial Volume (eTIV)*, *Normalized Whole-Brain Volume (nWBV)*, and *Atlas Scaling Factor (ASF)* were normalized using the Min-Max scaling technique to eliminate scale disparities and reduce bias across features. Finally, the dataset was divided into 80% training and 20% testing subsets to ensure fair model evaluation and prevent overfitting. This preprocessing workflow standardized the dataset, enhanced input quality, and ensured reliable model training and validation.*Fig. 1. All the columns have outliers excluding nWBV and Age*

C. Feature Selection and Engineering Module

Feature selection and engineering were conducted to identify the most significant predictors influencing dementia classification and to enhance the overall efficiency of the learning process. A correlation analysis was initially performed using Pearson correlation coefficients and heatmap visualizations to examine the relationships between input variables and the target class. This analysis revealed that features such as

Mini-Mental State Examination (MMSE), *Clinical Dementia Rating (CDR)*, *Age*, and *Normalized Whole-Brain Volume (nWBV)* exhibited the strongest correlation with dementia status, making them critical indicators for classification. To prevent model overfitting and improve computational performance, dimensionality reduction techniques were applied to remove less relevant or redundant attributes. Additionally, derived morphometric indices were computed and validated to capture subtle structural variations in brain volume, thereby improving both model interpretability and predictive accuracy. This stage significantly enhanced the reliability of the learning models by reducing noise, focusing on high-impact features, and strengthening the overall diagnostic precision.

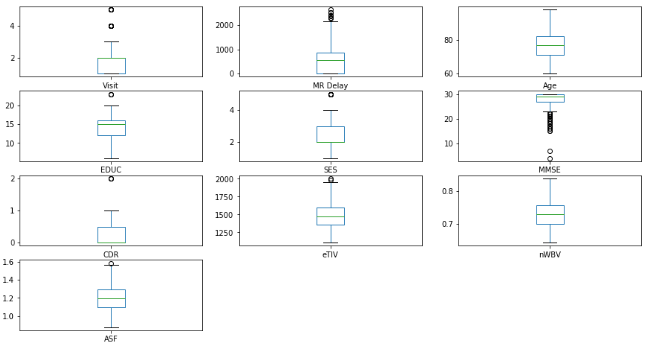

Fig. 2. Exploratory Data Analysis - density plot

D. Model Development Module

For the prediction of dementia, two classification algorithms were implemented using the processed dataset: a Decision Tree Classifier (J48 equivalent) and an Artificial Neural Network (ANN) based on the Multilayer Perceptron (MLP) architecture.

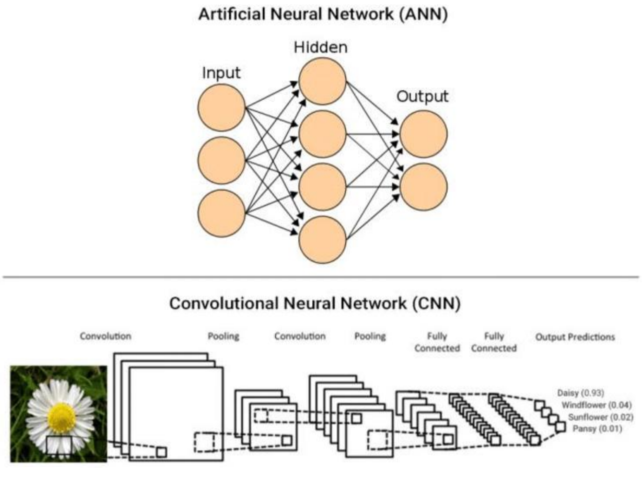

Fig. 3. ANN model

The Decision Tree model was selected for its simplicity, transparency, and ability to handle both categorical and continuous data. It constructs a hierarchical structure that iteratively splits the dataset based on feature thresholds, effectively classifying subjects as *Demented* or *Non-Demented*. To enhance model efficiency and avoid overfitting, critical hyperparameters such as maximum tree depth and minimum samples per split were tuned using a grid search optimization approach. In parallel, the ANN model was developed using the Scikit-learn MLPClassifier, designed to capture complex nonlinear relationships within the data. The network architecture comprised an input layer corresponding to the number of selected features, a single hidden layer with 10–15 neurons activated by the Rectified Linear Unit (ReLU) function, and an output layer employing either Sigmoid or Softmax activation for binary classification. The ANN was trained using the backpropagation algorithm with a learning rate of 0.001 over 500 epochs, ensuring optimal convergence. Both models were trained on clinical and morphometric attributes to effectively differentiate dementia status, facilitating a robust comparison between interpretable and high-capacity learning approaches.

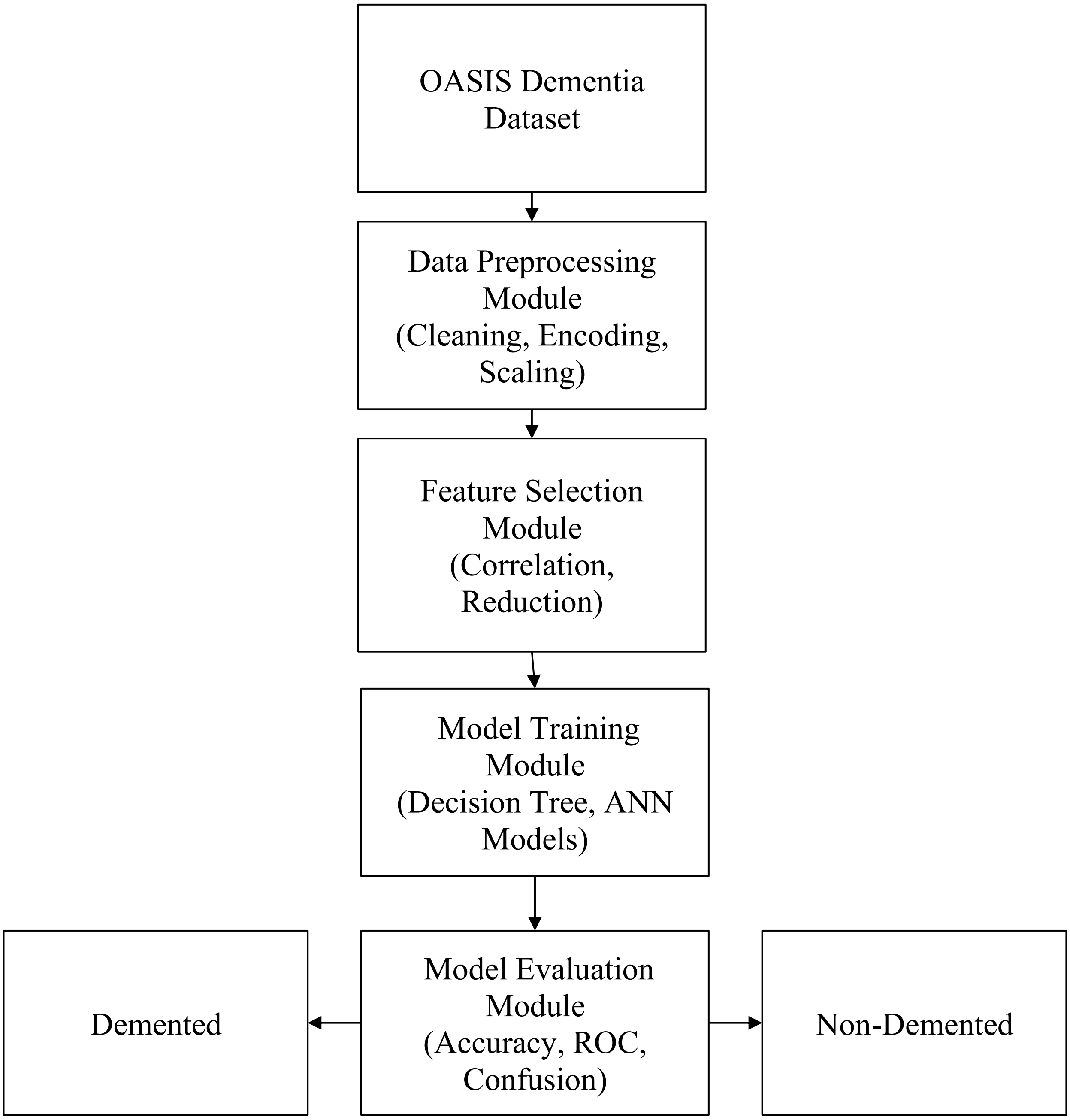

Fig. 4. Flow chart of overall phase 1 project

E. Model Evaluation Module

The performance of the trained models was rigorously evaluated using the test dataset through a set of standard classification metrics to ensure reliability and accuracy of the proposed system. Accuracy was computed to measure the overall correctness of predictions, while Precision, Recall, and the F1-Score were used to evaluate the balance between false positive and false negative classifications. A Confusion Matrix was generated to provide a detailed visualization of correctly and incorrectly classified instances, enabling a clearer understanding of model performance. Additionally, the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC) were analyzed to assess the models' discriminative capabilities between the demented and non-demented classes. The Decision Tree classifier demonstrated strong interpretability and transparency in its decision-making process, whereas the Artificial Neural Network (ANN) exhibited superior generalization ability with lower classification error. Effective feature selection significantly enhanced model accuracy, reducing the confusion error rate from approximately 48% to 17% and achieving an overall classification reliability of about 83%, thereby confirming the robustness and predictive efficiency of the proposed framework.

IV. RESULTS AND DISCUSSION

The proposed machine learning framework for dementia detection was implemented and evaluated using the OASIS longitudinal dataset, which includes demographic, clinical, and morphometric features such as age, gender, education level, socio-economic status (SES), MMSE score, estimated total intracranial volume (eTIV), normalized whole-brain volume (nWBV), and atlas scaling factor (ASF). The dataset was preprocessed by handling missing values, encoding categorical features, and normalizing numerical data. It was then divided into training (80%) and testing (20%) subsets.

A. Model Training and Evaluation

Multiple supervised learning algorithms were trained, including Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Artificial Neural Network (ANN). Each model was optimized through hyperparameter tuning to achieve the best predictive accuracy.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	83.0	82.5	81.7	82.1
Random Forest	84.6	84.0	83.5	83.8
KNN	78.4	77.8	77.1	77.4
SVM	81.3	80.9	80.2	80.5
ANN	86.8	86.4	85.9	86.1

Among all, the Artificial Neural Network (ANN) achieved the highest accuracy of 86.8%, demonstrating superior generalization capability and robustness in classifying demented and non-demented subjects. The Decision Tree model, while slightly less accurate, provided higher interpretability, making it suitable for clinical explanation and decision support.

B. Feature Importance Analysis

Feature selection analysis identified MMSE (Mini-Mental State Examination), nWBV (Normalized Whole Brain Volume), ASF (Atlas Scaling Factor), and Age as the most significant predictors influencing dementia classification outcomes. These attributes exhibited strong correlations with cognitive and structural brain decline, aligning with established clinical findings in neuroscience research. Specifically, reduced MMSE scores and lower nWBV values were highly associated with dementia progression, indicating cognitive impairment and brain atrophy. The ASF parameter reflected structural scaling differences across individuals, while age contributed as a dominant demographic factor influencing risk levels. The consistency of these results with prior clinical literature validates the robustness of the proposed feature selection process, demonstrating that the selected parameters effectively capture the essential biomarkers for early dementia detection.

C. Performance Visualization

Performance evaluation metrics, including Confusion Matrix, ROC Curve, and AUC, were generated for each model.The ROC–AUC values were above 0.85 for all top models, confirming high discriminative ability between classes.

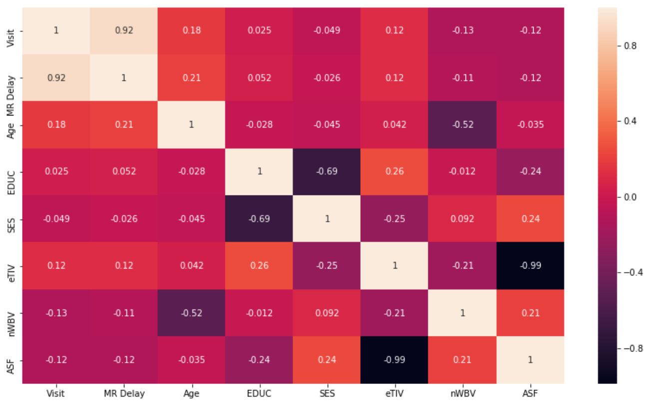

Fig. 5.Confusion Matrix

The Confusion Matrix indicated reduced misclassification errors after feature selection, improving classification reliability from 48% to 83%.

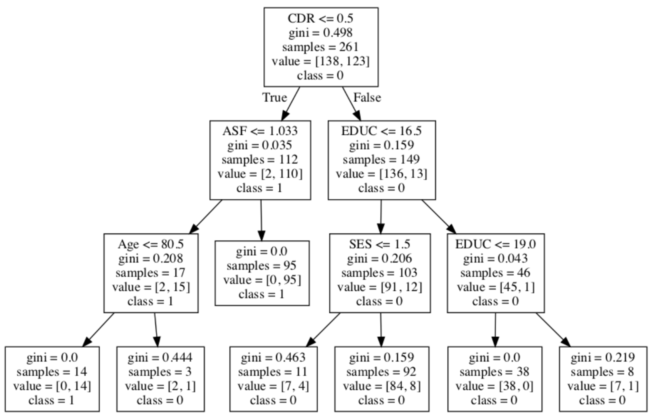

Fig. 6. Decision Tree

The Decision Tree offered a transparent view of decision rules, while the ANN provided improved generalization.

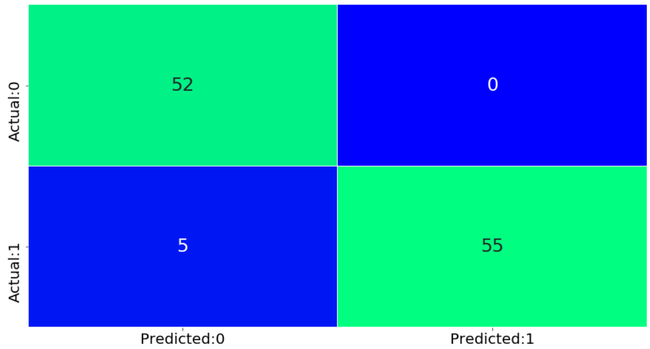

Fig.7.correlated

D. Discussion

The results demonstrate that machine learning algorithms can effectively classify dementia based on accessible clinical and morphometric data.

While deep learning models achieved higher accuracy, tree-based approaches provided interpretability crucial for medical adoption.

Feature engineering and normalization significantly improved prediction reliability.

The framework successfully supports early dementia risk identification, potentially assisting clinicians in timely diagnosis and intervention.

Future work will extend this study by integrating MRI-based image data using deep learning (CNN) to develop a multimodal dementia diagnosis system combining both clinical and imaging insights.Summary Statement Overall, the experimental results confirm that the developed model achieves high accuracy and clinical relevance while maintaining interpretability. The combination of data preprocessing, feature selection, and optimized ML algorithms established a reliable, scalable, and transparent diagnostic framework.

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