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ALZHEIMER'S DISEASE PREDICTION USING XGBOOST MACHINE LEARNING MODEL WITH SHAP EXPLAINABILITY

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Abstract: Alzheimer's disease (AD) is a progressive neurodegenerative disorder that impairs memory, cognition, and behavior. Early diagnosis is vital for timely treatment, yet traditional clinical and neuroimaging methods are often costly and time-consuming. This study proposes an explainable machine learning framework using the Extreme Gradient Boosting (XGBoost) algorithm for accurate and interpretable AD prediction. The dataset includes demographic, lifestyle, medical, and cognitive features such as age, gender, BMI, cholesterol, blood pressure, MMSE score, and behavioral symptoms. Exploratory data analysis and visualizations were performed to identify key patterns and correlations. The XGBoost model achieved high accuracy, precision, recall, F1-score, and ROC-AUC in distinguishing healthy and AD subjects. SHAP (SHapley Additive exPlanations) analysis provided interpretability by identifying the most influential features. The proposed XGBoost–SHAP framework ensures reliable early AD detection and supports personalized clinical decisions.

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that causes memory loss, cognitive decline, and behavioral impairment, primarily affecting older adults. It accounts for about 60–70% of dementia cases worldwide and poses a major global health and economic challenge. According to the World Health Organization, over 55 million people live with dementia, and this number may triple by 2050. AD is marked by amyloid plaques and neurofibrillary tangles in the brain, leading to neuronal death and brain atrophy. Current treatments such as cholinesterase inhibitors and NMDA antagonists offer only temporary relief without halting disease progression, making early detection crucial. The disease arises from multiple factors including age, genetics (e.g., APOE ε4), cardiovascular issues, diabetes, obesity, depression, and unhealthy lifestyles.

Traditional diagnostic methods—such as cognitive assessments (MMSE, MoCA), neuroimaging (MRI, PET), and CSF biomarker tests—are effective but costly, invasive, and limited in accessibility. Additionally, overlapping symptoms with other disorders make early diagnosis difficult. Machine Learning (ML) has emerged as a powerful tool in medical diagnosis, capable of identifying hidden patterns in large, complex datasets. Algorithms like Random Forest, Support Vector Machine, and Gradient Boosting have shown strong potential in predicting diseases, including AD. However, most ML models lack interpretability, which is essential for clinical acceptance. To overcome this limitation, Explainable Artificial Intelligence (XAI) methods such as SHAP (SHapley Additive exPlanations) provide transparency by showing how each feature influences model predictions.

This study proposes an interpretable Alzheimer's prediction framework using the Extreme Gradient Boosting (XGBoost) algorithm with SHAP analysis. The model uses demographic, clinical, and cognitive features to classify Healthy and AD subjects accurately while ensuring transparency for clinical decision-making.

II. LITERATURE SURVEY

Several studies have explored machine learning and deep learning techniques for Alzheimer's disease (AD) detection and diagnosis. N. Chedid et al. developed an automated EEG-based machine learning pipeline using logistic regression with an accuracy of 81%, addressing challenges such as manual preprocessing, large data dependency, and lack of model transparency. Their approach demonstrated the potential for scalable and automated AD diagnosis in clinical settings. O. A. Dara et al. conducted a comprehensive survey of over 80 publications since 2017, highlighting the role of genetic, environmental, and nutritional factors in AD development and emphasizing the value of machine learning and AI-based models in integrating neuroimaging and non-imaging biomarkers for improved diagnosis. Similarly, Isra Malik et al. reviewed 116 research papers across multiple databases, covering deep learning methods, datasets, and feature extraction techniques for AD prediction. The study emphasized the importance of interpretability and explainability in AI-based diagnostic systems to enhance clinical trust. V. Adarsh et al. proposed

a CNN-based multimodal framework integrated with a Multi-feature Kernel Supervised Discriminative Dictionary Learning (MKSCDDL) technique, achieving a remarkable 98.27% accuracy in classifying AD, Mild Cognitive Impairment (MCI), and cognitively normal subjects with transparent decision-making. Likewise, Ghassan Al Rahbani et al. combined ResNet and EfficientNet architectures with post-processing heuristics for multiclass AD detection, enhancing model robustness, interpretability, and diagnostic accuracy. Collectively, these studies demonstrate that explainable machine learning and hybrid deep learning approaches significantly improve early Alzheimer's detection, accuracy, and clinical applicability.

III. PROPOSED METHODOLOGY

3.1 Problem Statement

Existing Alzheimer's disease (AD) diagnostic systems primarily rely on clinical evaluations, neuropsychological tests, and neuroimaging techniques such as MRI, PET, and CT scans. While effective, these methods are costly, time-consuming, and invasive, making them unsuitable for large-scale or early screening. Cognitive tools like MMSE and CDR often fail to detect early pathological changes, leading to delayed diagnosis. Machine learning models such as Logistic Regression, SVM, and Random Forest have been applied to improve accuracy, but they struggle to capture complex nonlinear relationships and often rely on small datasets, limiting generalization. Moreover, most deep learning-based models function as black boxes with limited interpretability, which restricts their clinical trust. They also neglect behavioral and lifestyle factors, offering a fragmented view of AD progression. Hence, there is a need for an interpretable, efficient, and holistic diagnostic model that integrates multi-domain data for early detection.

3.2 Proposed System

The proposed system introduces a hybrid, data-driven diagnostic framework based on the Extreme Gradient Boosting (XGBoost) algorithm integrated with SHAP (SHapley Additive exPlanations) for transparency. Unlike imaging-based systems, it uses clinical, demographic, behavioral, and physiological features such as age, BMI, cholesterol, MMSE score, and lifestyle factors to provide a cost-effective and comprehensive risk evaluation. The workflow includes data preprocessing (missing value handling and normalization), data splitting (80:20 ratio), model training using XGBoost, and performance evaluation through accuracy, precision, recall, F1-score, and ROC-AUC. SHAP analysis enhances interpretability by quantifying each feature's contribution to predictions, helping clinicians understand the impact of factors like age, MMSE score, and family history on AD risk. This combination ensures a high-performing, explainable, and reliable diagnostic tool.

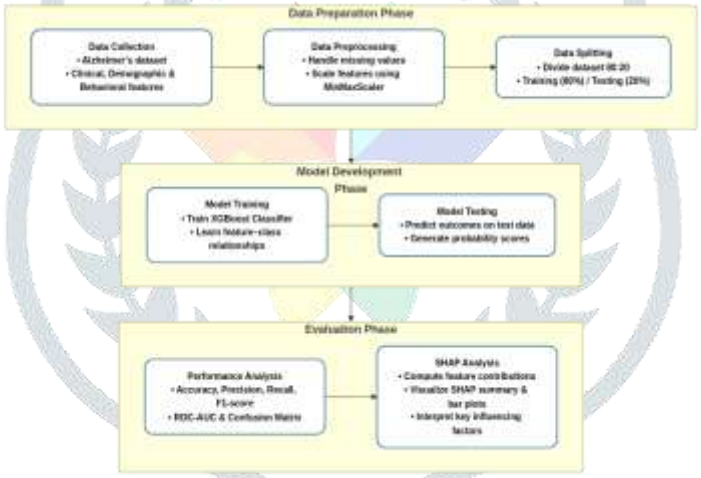


FIG 1: SYSTEM ARCHITECTURE

Proposed Modules:

The system consists of seven key modules: (1) Data Collection from Kaggle (clinical, demographic, and behavioral features), (2) Data Preprocessing using imputation and MinMax scaling, (3) Data Splitting into training and testing sets, (4) XGBoost Model Training to learn complex patterns, (5) Model Testing to validate generalization, (6) Performance Evaluation through standard metrics and visualization, and (7) SHAP Analysis for feature interpretability. Together, these modules enable efficient learning, robust validation, and transparent prediction of Alzheimer's disease.

Proposed Algorithm – XGBoost:

XGBoost is an optimized gradient boosting algorithm that combines multiple decision trees to minimize prediction error iteratively. It applies gradient descent and second-order derivatives for faster and more accurate optimization. Regularization (L1 and L2) prevents overfitting, while pruning and subsampling enhance generalization. XGBoost's ability to handle nonlinear relationships, missing data, and large datasets makes it ideal for biomedical prediction tasks. In this study, it is employed to classify subjects as Healthy or AD, providing reliable probabilistic predictions supported by SHAP-based interpretability.

IV. SOFTWARE AND DOMAIN DESCRIPTION

This project utilizes Python as the primary programming language due to its simplicity and extensive support for machine learning and data analysis. Essential libraries such as NumPy, Pandas, Scikit-learn, TensorFlow, Keras, Matplotlib, and Seaborn are employed for data preprocessing, model training, and visualization. NumPy and Pandas enable efficient data manipulation, Scikit-learn supports classical ML algorithms, while TensorFlow and Keras facilitate deep learning model development. Visualization tools like Matplotlib and Seaborn help interpret results effectively. The project lies within the domain of Data Mining and Machine Learning, focusing on discovering useful patterns and knowledge from large datasets. Data mining integrates methods from databases, statistics, and artificial intelligence to perform classification, clustering, and pattern recognition. Machine learning enhances this process by enabling systems to automatically learn and make predictions from data. The data mining process involves stages such as preprocessing, modeling, testing, and evaluation to ensure accuracy and reliability. By combining these tools and techniques, the system efficiently extracts meaningful insights from complex data and supports intelligent decision-making.

4.1 SYSTEM DESIGN

The system design defines the structure and functionality of the proposed model, ensuring smooth data flow and process interaction. The Data Flow Diagram (DFD) illustrates how input data is processed and transformed into output, showing relationships among processes, data stores, and external entities. The Unified Modeling Language (UML) provides standardized visual models, including Use Case, Class, Sequence, and Activity Diagrams, which represent system behavior and structure. Input design focuses on collecting, validating, and processing user data efficiently while minimizing errors and ensuring ease of use. Output design emphasizes clear and accurate presentation of processed information for effective decision-making. System testing validates system performance through various test types—Unit, Integration, Functional, and System Testing. White Box and Black Box testing approaches ensure both internal logic and external functionality are verified. Finally, User Acceptance Testing confirms that the system meets all functional requirements and operates as expected. The overall testing results ensure reliability, efficiency, and correctness of the system.

V. EXPERIMENTAL SYSTEMS

MODULE 1- Data Loading and EDA

Dataset

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholConsumption	PhysicalActivity	DietQuality	...	FunctionalAssessment	MemoryCompl
0	4751	73	0	0	2	22.927749	0	13.297218	6.327112	1.347214	...	6.518877	
1	4752	89	0	0	0	26.827681	0	4.542524	7.619885	0.518767	...	7.118696	
2	4753	73	0	3	1	17.796882	0	19.555085	7.844988	1.826335	...	5.895077	
3	4754	74	1	0	1	33.800817	1	12.209266	8.428001	7.435604	...	8.965106	
4	4755	89	0	0	0	20.716974	0	18.454356	6.310461	0.795498	...	6.045039	
5	4756	86	1	1	1	30.626886	0	4.140144	0.211062	1.584922	...	5.510144	
6	4757	68	0	3	2	38.387622	1	0.646047	9.257695	5.897388	...	6.062124	
7	4758	75	0	0	1	18.776009	0	13.723826	4.649451	8.341903	...	3.401374	
8	4759	72	1	1	0	27.833188	0	12.167848	1.531360	6.736882	...	7.396061	
9	4760	87	0	0	0	35.456302	1	16.028688	6.440773	8.086019	...	1.148904	

10 rows × 34 columns

Dataset shape / Dataset input features / Statistical Analysis

```
df.shape
```

```
(2149, 34)
```

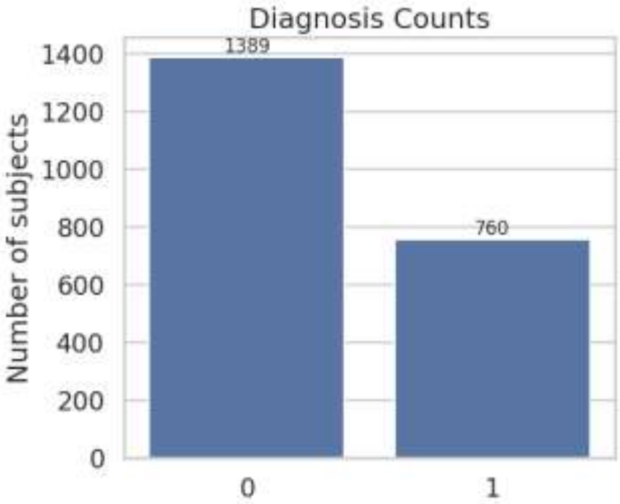
```
df.columns
```

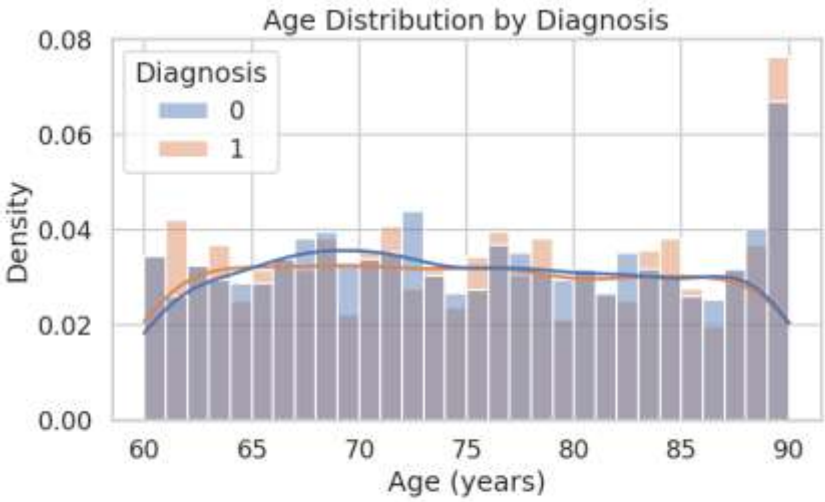
```
Index(['PatientID', 'Age', 'Gender', 'Ethnicity', 'EducationLevel', 'BMI',
       'Smoking', 'AlcoholConsumption', 'PhysicalActivity', 'DietQuality',
       'SleepQuality', 'FamilyHistoryAlzheimers', 'CardiovascularDisease',
       'Diabetes', 'Depression', 'HeadInjury', 'Hypertension', 'SystolicBP',
       'DiastolicBP', 'CholesterolTotal', 'CholesterolLDL', 'CholesterolHDL',
       'CholesterolTriglycerides', 'MMSE', 'FunctionalAssessment',
       'MemoryComplaints', 'BehavioralProblems', 'ADL', 'Confusion',
       'Disorientation', 'PersonalityChanges', 'DifficultyCompletingTasks',
       'Forgetfulness', 'Diagnosis'],
      dtype='object')
```

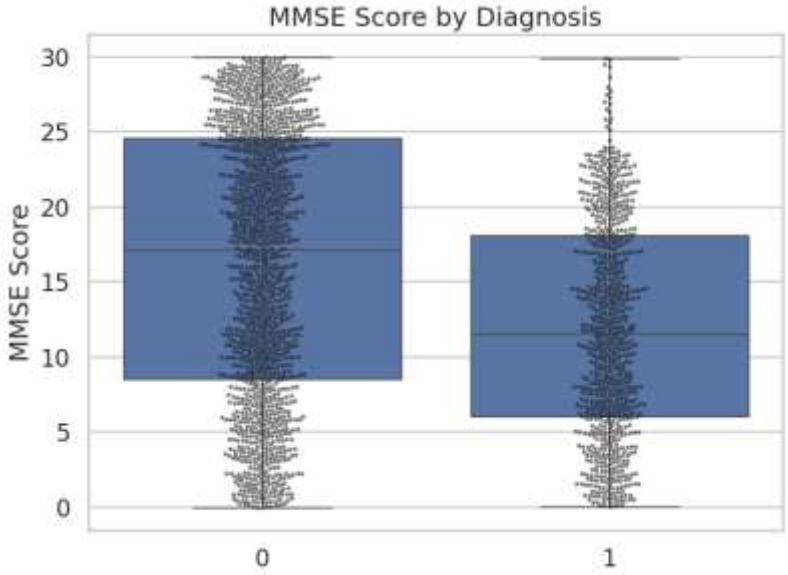
index	count	mean	std	min	25%	50%	75%	max
PatientID	2149.0	5825.0	620.507180024208	4751.0	5288.0	5825.0	6362.0	6899.0
Age	2149.0	74.90879478827361	8.990221362749964	60.0	67.0	75.0	83.0	90.0
Gender	2149.0	0.5062819916240112	0.5000788996325778	0.0	0.0	1.0	1.0	1.0
Ethnicity	2149.0	0.6975337366216845	0.9961277282688679	0.0	0.0	0.0	1.0	3.0
EducationLevel	2149.0	1.2866449511143065	0.9044280784061679	0.0	1.0	1.0	2.0	3.0
BMI	2149.0	27.655696980794788	7.2174380913686238	15.00885110	21.61140792	27.82392369	33.86977772	39.99276746
Smoking	2149.0	0.28850628199162404	0.45317732237757467	0.0	0.0	0.0	1.0	1.0
AlcoholConsumption	2149.0	10.039441769844232	5.757910289122869	0.002003090	5.139809509	9.934412376	15.15793891	19.98929336
PhysicalActivity	2149.0	4.920202144377116	2.857191118993296	0.003616817	2.579526476	4.766424262	7.427898828	9.987429413
DietQuality	2149.0	4.993137913656376	2.909054899060648	0.009338472	2.458454902	5.076087317	7.558624794	9.998346079
SleepQuality	2149.0	7.051081071502884	1.763572954905148	4.002628600	5.482997209	7.115646231	8.562520838	9.999840317
FamilyHistoryAlzheimers	2149.0	0.25221033038622614	0.4343024148949425	0.0	0.0	0.0	1.0	1.0
CardiovascularDisease	2149.0	0.14425314099581202	0.3514200352649634	0.0	0.0	0.0	0.0	1.0
Diabetes	2149.0	0.15076779897626082	0.3579856820657977	0.0	0.0	0.0	0.0	1.0
Depression	2149.0	0.20055839925546767	0.40041130744383027	0.0	0.0	0.0	0.0	1.0
HeadInjury	2149.0	0.09260120986505352	0.28994622423797087	0.0	0.0	0.0	0.0	1.0
Hypertension	2149.0	0.14890646812470917	0.35608791058834406	0.0	0.0	0.0	0.0	1.0
SystolicBP	2149.0	134.26477431363428	25.949352110615084	90.0	112.0	134.0	157.0	179.0
DiastolicBP	2149.0	89.84783620288506	17.592492106826576	60.0	74.0	91.0	105.0	119.0
CholesterolTotal	2149.0	225.19751067054816	42.54223264939179	150.0933166	190.2529671	225.0864298	262.0316596	299.9933526
CholesterolLDL	2149.0	124.33594418511482	43.366584053432074	50.23070690	87.19575802	123.342593	161.7337326	199.9656651
CholesterolHDL	2149.0	59.46353314107928	23.13917387780342	20.00343401	38.8956988	59.7682375	78.93804963	99.98032408
CholesterolTriglycerides	2149.0	228.28149617049978	101.98672078041567	50.40719362	137.5832224	230.3019826	314.6396482	399.9418616
MMSE	2149.0	14.755132197526036	8.613151282063026	0.005312146	7.167602257	14.44166061	22.16102791	29.99138066
FunctionalAssessment	2149.0	5.080054971165153	2.8927434741712776	0.000459604	2.566280915	5.094438729	7.546081388	9.996467073

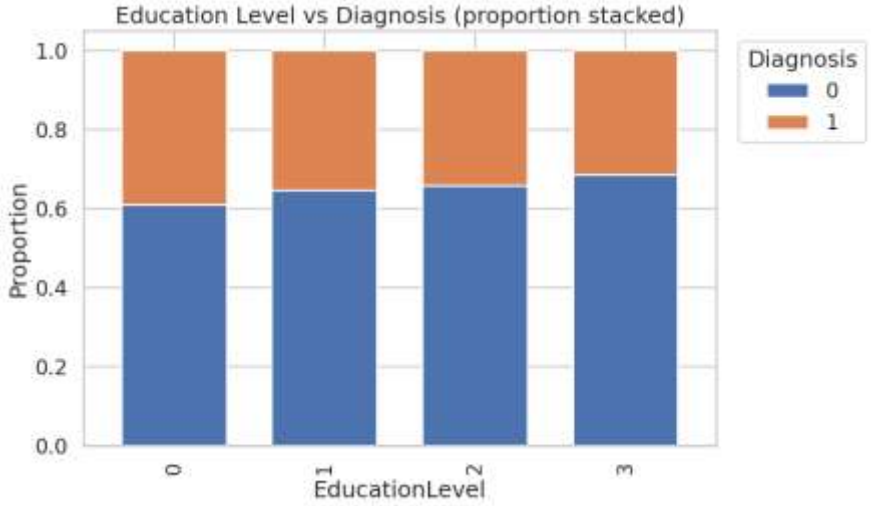
Show 25 per page

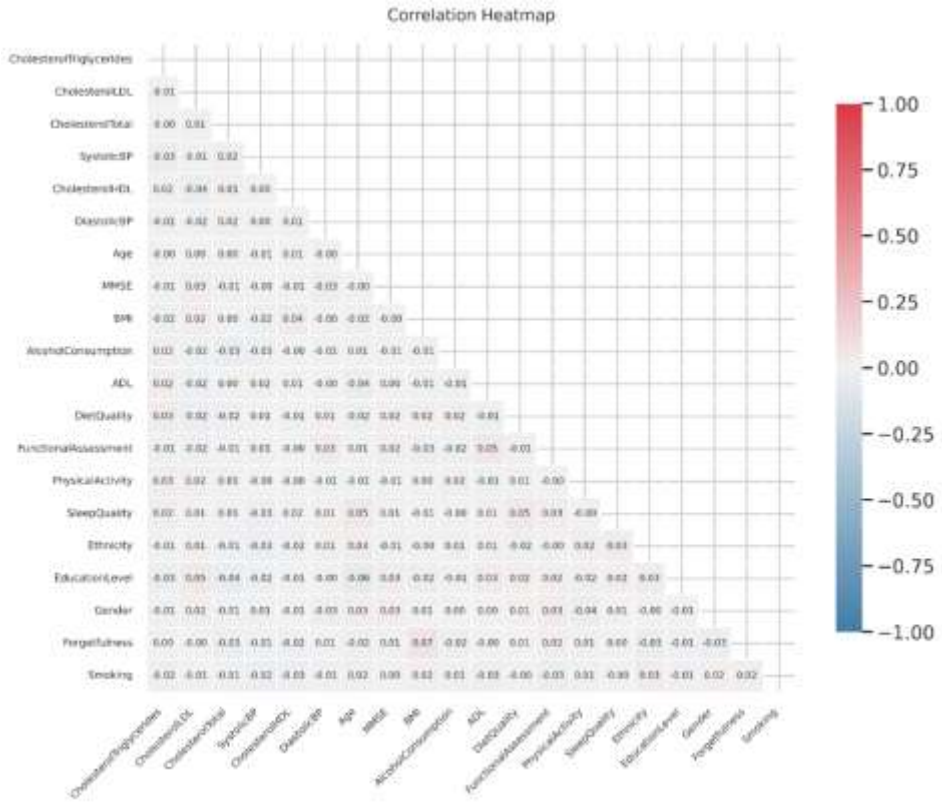
Data Visualization











MODULE 2 - Data Preprocessing

Data Cleaning

Null Value Checking Result

	0
PatientID	0
Age	0
Gender	0
Ethnicity	0
EducationLevel	0
BMI	0
Smoking	0
AlcoholConsumption	0
PhysicalActivity	0
DietQuality	0
SleepQuality	0
FamilyHistoryAlzheimers	0
CardiovascularDisease	0
Diabetes	0
Depression	0
HeadInjury	0
Hypertension	0
SystolicBP	0
DiastolicBP	0
CholesterolTotal	0
CholesterolLDL	0
CholesterolHDL	0
CholesterolTriglycerides	0
MMSE	0
FunctionalAssessment	0
MemoryComplaints	0
BehavioralProblems	0
ADL	0
Confusion	0
Disorientation	0
PersonalityChanges	0
DifficultyCompletingTasks	0
Forgetfulness	0
Diagnosis	0

dtype: int64

Data Scaling using MinMax Scaler

```
[[0.00000000e+00 4.33333333e-01 0.00000000e+00 ... 0.00000000e+00
  1.00000000e+00 0.00000000e+00]
 [4.65549348e-04 9.66666667e-01 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 1.00000000e+00]
 [9.31098696e-04 4.33333333e-01 0.00000000e+00 ... 0.00000000e+00
  1.00000000e+00 0.00000000e+00]
 ...
 [9.99068901e-01 5.66666667e-01 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 0.00000000e+00]
 [9.99534451e-01 6.00000000e-01 1.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 1.00000000e+00]
 [1.00000000e+00 4.00000000e-01 0.00000000e+00 ... 0.00000000e+00
  0.00000000e+00 1.00000000e+00]]
```

MODULE 3 – Data Splitting

Data Splitting – 80:20

```
Train shape: (1719, 33) Test shape: (430, 33)
```

MODULE 4 – XGBoost Model Training

```
Model training completed!
```

MODULE 5 – Model Testing

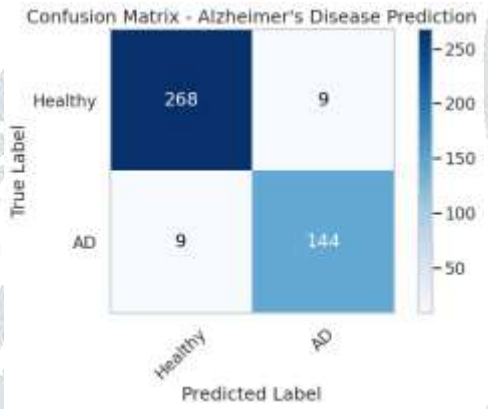
Testing Set Prediction Result

```
=== Actual vs Predicted Results ===
      Actual_Label  Predicted_Label  Prediction_Probability(AD)
1159             0                0                    0.000457
1822             0                0                    0.005930
978              0                0                    0.041175
759              0                0                    0.006287
874              0                0                    0.000714
109              0                0                    0.000621
1177             1                1                    0.999171
259              0                0                    0.002463
1697             0                0                    0.000775
479              1                1                    0.997960
1107             0                0                    0.009242
836              1                1                    0.984047
2008             1                1                    0.886231
70               0                0                    0.012086
231              0                0                    0.009077
290              0                0                    0.000507
1192             1                1                    0.899700
618              1                1                    0.947771
297              0                0                    0.006166
1738             0                0                    0.013179
```

The testing phase evaluates the XGBoost model's performance using unseen data. The model generates predicted labels and probability scores indicating Alzheimer's likelihood. Results show clear separation between healthy and AD subjects, with high probabilities (near 1) for Alzheimer's cases and low values (near 0) for healthy individuals. Most predictions accurately match actual labels, confirming strong learning and generalization. The model demonstrates high precision, reliability, and robustness, making it effective for early Alzheimer's detection and clinical decision support.

MODULE 6 – Performance Evaluation

Confusion Matrix



The confusion matrix shows that the XGBoost model accurately classified 268 healthy individuals and 144 Alzheimer's patients, with only 9 false positives and 9 false negatives. These results indicate high accuracy, strong sensitivity, and specificity. The model effectively minimizes classification errors and reliably distinguishes between healthy and AD cases. Overall, the confusion matrix confirms the model's robustness and precision, demonstrating its potential as a reliable tool for early Alzheimer's detection.

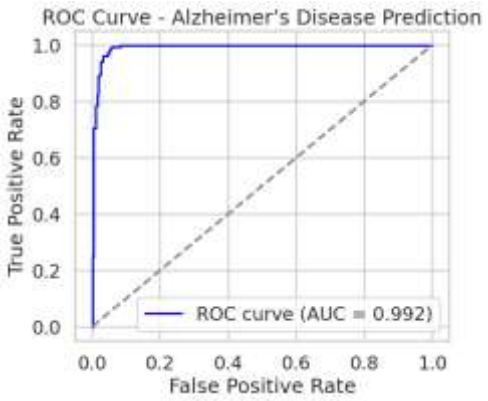
Performance Metrics

```
=== Evaluation Metrics ===
Accuracy:  0.9581
Precision: 0.9543
Recall:    0.9543
F1-Score:  0.9543
ROC-AUC:   0.9916

Classification Report:
              precision    recall  f1-score   support

     Healthy     0.9675    0.9675    0.9675       277
          AD     0.9412    0.9412    0.9412       153

    accuracy                         0.9581       430
   macro avg     0.9543    0.9543    0.9543       430
weighted avg     0.9581    0.9581    0.9581       430
```

The evaluation metrics confirm the high performance and reliability of the proposed XGBoost-based Alzheimer's prediction model. It achieved 95.81% accuracy, with precision, recall, and F1-score all at 0.9543, showing consistent and balanced performance. The ROC-AUC value of 0.9916 indicates excellent separability between healthy and AD cases. Slightly higher precision and recall

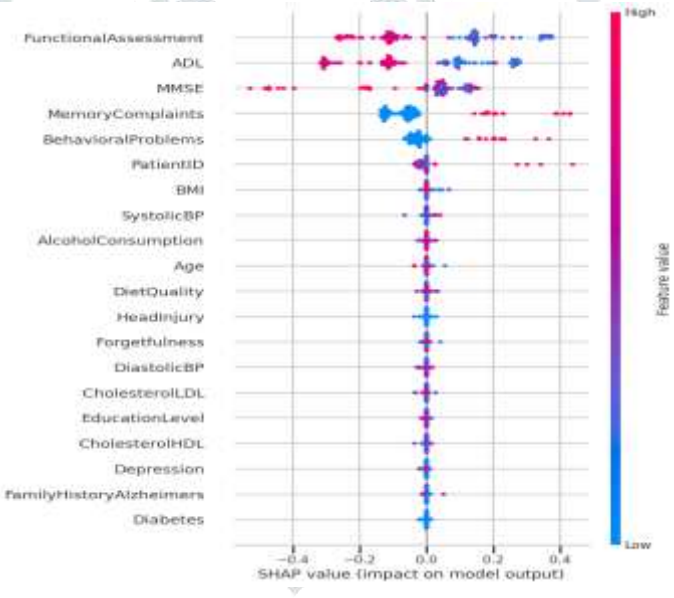
for healthy subjects suggest strong overall classification stability. These results validate the model's efficiency, robustness, and suitability as a reliable tool for early Alzheimer's detection.

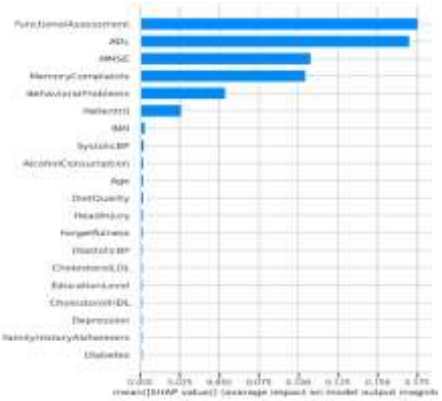
ROC Curve



The ROC curve illustrates the strong classification ability of the proposed XGBoost-based Alzheimer's prediction model, showing a steep rise toward the top-left corner, which indicates high sensitivity and low false positives. The AUC value of 0.992 confirms near-perfect discrimination between Alzheimer's and healthy cases. This demonstrates the model's robustness, reliability, and excellent balance between sensitivity and specificity, making it a highly effective tool for accurate early detection and clinical decision support in Alzheimer's diagnosis.

SHAP Analysis





The SHAP analysis highlights how each feature influences the XGBoost model's Alzheimer's predictions. Key factors include Functional Assessment, ADL, and MMSE — where lower scores increase disease risk. Memory Complaints and Behavioral Problems also strongly affect outcomes. Overall, the SHAP results confirm that the model is accurate, interpretable, and clinically reliable.

VI. CONCLUSION

The proposed XGBoost-SHAP model provides an intelligent and interpretable framework for Alzheimer's disease prediction. Using a Kaggle dataset with clinical and behavioral features such as age, BMI, MMSE, and daily activities, the model achieved 95.81% accuracy and an AUC of 0.992, showing excellent classification performance. SHAP analysis identified Functional Assessment, ADL, and MMSE as key predictors, enhancing transparency and clinical trust. Overall, the model proves to be a robust and explainable tool for early Alzheimer's detection and effective clinical decision support.

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