International Journal of Advanced and Applied Sciences, 12(10) 2025, Pages: 118-128

Contents lists available at Science-Gate

International Journal of Advanced and Applied Sciences

Journal homepage: http://www.science-gate.com/IJAAS.html

A smart medical assistant robot for explainable AI-based Alzheimer's disease prediction using big data analytics

Boumedyen Shannaq *

Management Information System Department, University of Buraimi, Al Buraimi, Oman

ARTICLE INFO

Article history:
Received 27 January 2025
Received in revised form
16 May 2025
Accepted 29 September 2025

Keywords:
Alzheimer's prediction
Explainable AI
Machine learning
Risk assessment
Clinical decision

ABSTRACT

This study presents the development of TAER_Robot, an explainable AI (XAI)-based medical assistant for predicting Alzheimer's Disease (AlzD). The main aim is to integrate Machine Learning (ML) models with explanation techniques to build an accurate and interpretable risk assessment system. The research explores how age, cognitive function, and lifestyle factors influence prediction results, using a dataset of 2,149 records with 33 features such as age, gender, BMI, smoking, and alcohol use. Data preprocessing involved normalization, categorical encoding, and handling missing values. The dataset was split into training and testing sets at ratios of 80/20, 70/30, and 60/40 to identify the best configuration. Random Forest, CatBoost, and XGBoost were used as core ML models, while SHAP and LIME provided interpretability. LightGBM achieved the highest performance, with 95.6% accuracy and a 0.955 ROC-AUC score, exceeding previous models. Further testing confirmed system reliability with up to 94.1% accuracy. TAER_Robot enhances early-stage AlzD prediction by offering both strong performance and transparent decision-making, contributing to the improvement of AI-supported clinical decision systems.

1. Introduction

Alzheimer's disease (AlzD) represents a chronic brain-destroying illness, which appears among millions of people globally while affecting both patients and their caregivers alongside healthcare institutions (Chen et al., 2025). Diagnosing AlzD at an early stage is fundamental to enhancing patient outcomes and reducing the disease's advancement. Modern artificial intelligence (AI) and machine learning (ML) technology demonstrates remarkable potential for making Alzheimer's disease prediction both faster and more precise, which holds great promise to transform current medical practices (Javed et al., 2025). Because early detection and precise prediction enable patients and healthcare providers to take proactive measures to manage the condition, they can help lessen the impact of Alzheimer's disease worldwide (Rehman et al., 2024; Sethi et al., 2024). Products powered by AI, such as TAER_Robot (The Arabic English Russian Robot), provide creative answers in multiple languages to this issue by using conversational AI to collect critical health data and provide real-time risk assessments. TAER_Robot uses machine learning models to assess risk factors, generate predictions, and interpret its results in order to deliver a customized and enjoyable user experience.

The most evident application of TAER_Robot is in enhancing Alzheimer's disease prediction, where it functions as a virtual assistant to detect early symptoms and support timely intervention. While traditional machine learning models offer predictive capabilities, they often operate as opaque black boxes, providing limited insight into their decision-making processes. This lack of interpretability undermines trust in clinical practice, where transparency is critical. Explainable AI (XAI) addresses this challenge by generating understandable predictions. By integrating advanced machine learning models with conversational AI, TAER_Robot ensures that predictions are both clear and actionable. Through the XAI-enhanced system, users can see how specific factors—such as genetic predisposition, physical activity, and dietary habits—influence their risk of Alzheimer's disease. This understanding supports informed decision-making and encourages preventive actions, including lifestyle adjustments and cognitive health strategies. Broader adoption of AI in healthcare requires careful

* Corresponding Author.
Email Address: boumedyen@uob.edu.om
https://doi.org/10.21833/ijaas.2025.10.014
Corresponding author's ORCID profile:
https://orcid.org/0000-0001-5867-3986

consideration of ethical issues such as data privacy, accountability, and equity (Akinrinola et al., 2024). To ensure fair predictions across all patient groups, XAI techniques play a key role in detecting and reducing bias. TAER_Robot represents an important advancement in Alzheimer's prediction by combining the transparency of XAI with the predictive power of machine learning. By increasing users' awareness of their health risks and supporting informed decision-making, the system fosters greater trust in AI-based healthcare solutions. Looking ahead, future developments—such as extending applications to other neurodegenerative diseases and incorporating real-time data—may establish TAER_Robot as a vital tool for personalized healthcare management.

Alzheimer's disease is a progressive neurological disorder that affects individuals worldwide and places a significant burden on patients, caregivers, and healthcare systems. Early detection provides substantial benefits by supporting patient well-being and slowing disease progression. However, conventional diagnostic methods often face challenges in identifying the disease at its earliest stages, leading to delays in treatment and intervention. Traditional machine learning models often have limited interpretability in predicting Alzheimer's disease, which makes them function as black-box systems in clinical settings. This lack of transparency reduces their acceptance in hospitals, as healthcare professionals require clear explanations of how predictions are made. By using XAI techniques, the TAER_Robot system provides a more interactive and understandable interface, although further development is still needed to enhance Alzheimer's prediction analysis. At the same time, it is essential to address ethical challenges such as data privacy, bias in datasets, and the need for accountable decision-making, to ensure fair and transparent AI predictions across all patient groups.

The main advantage of the TAER_Robot system lies in its use of explainable artificial intelligence (XAI) methods, specifically SHAP and LIME, to clarify medical decisions for healthcare professionals. Our Alzheimer's prediction approach allows medical staff to identify the key variables influencing prediction outcomes, avoiding the limitations of traditional black-box models. The system achieves strong performance by supporting different data-splitting ratios, ranging from 80/20 and 70/30 to 60/40, which makes it both flexible and reliable. TAER_Robot's risk assessment is based on a wide range of features, including demographic factors, lifestyle patterns, and genetic indicators. By integrating machine learning with XAI techniques, the system establishes a new standard for Alzheimer's disease diagnosis.

2. Literature review

The AI-based systems use enormous medical datasets, including records, imaging results, genetic profiles, and behavioral patterns, to construct predictive diagnostic models for Alzheimer's disease detection (Sharma and Kaushik, 2025; Wahyudi and Ayuningsih, 2024). Decision trees alongside support vector machines and deep learning emerge as typical machine learning algorithms that evaluate extensive datasets to discover cognitive decline indicators (Vanaja et al., 2025; Ali et al., 2025). The diagnostic approach surpasses conventional diagnostic procedures because it relies on expert judgment and suffers from mistakes and delays (Wang et al., 2025). Detecting Alzheimer's disease at its early stages enables healthcare providers to initiate vital intervention plans and assist in producing focused therapeutic options (Mishra et al., 2025). AI reinforces machine learning capabilities that solve complex operational challenges in healthcare and employment systems (Parul et al., 2025).

The current predictive systems have promise, but they are challenging to develop. High accuracy and interpretability can be attained technically by improving feature selection model training and machine learning algorithm selection (Mostafa et al., 2024; Shannaq et al., 2019).

There is still a need to balance model transparency and complexity. For instance, deep neural networks are typically more complex to understand than straightforward models like logistic regression or decision trees, even though they may be more accurate than other models (Islam et al., 2024; Adekeye et al., 2023). To get the best results, researchers are investigating hybrid approaches that combine the best aspects of several models (Kareem et al., 2024; Azevedo et al., 2024). Close collaboration with neurologists and other medical specialists is necessary to improve the TAER_Robot design, and patient-generated data must be used for clinical validation. Because of these collaborations, the system can be adjusted to meet patients' various needs and situations.

Autonomous systems have been made possible by technological developments and AI. Robots are becoming increasingly common in the medical field as patient advisors (Alelyani, 2024; Adetunji et al., 2024). Nevertheless, issues like hesitant communication and ambiguous answers continue to exist (Li et al., 2024). To solve these problems, this study suggests an intelligent TAER_Robot system that uses XAI. The system guarantees secure data handling, transparent explanations, and pre-processing of patient data for machine learning (ML) algorithms for predictive analysis.

The proposed work proposes a distinctive aspect of your method: Finding optimal distributions between training and testing datasets. Different ratios of 80/20, 70/30, and 60/40 allow this to identify the best configuration for predictive quality that lets your model work effectively across multiple data sets (Shannaq, 2025; Farhan et al., 2025).

Interdisciplinary design in TAER_Robot enhances its innovation by integrating artificial intelligence with machine learning and healthcare-specific medical expertise. The proposed tool provides clinical adaptability through its user-friendly design, which enhances two important aspects of Alzheimer's disease risk evaluations while surpassing existing models with unclear assessment criteria. XAI integration within the proposed system provides healthcare with a necessary solution by enabling trust in AI-based early-stage Alzheimer's detection predictions.

3. Methodology

This work achieves predictive modeling through a data mining implementation that depends on Random Forest, CatBoost, and XGBoost machine learning algorithms. Including XAI allows predictions to remain understandable, establishing better trust in the system's decision processes. The methodology framework explores multiple data separation ratios starting from 80/20, progressing to 70/30, and ending with 60/40 to better understand the relation between training data volume and system accuracy. Protection and normalization of data, as well as categorical transformation and missing value resolution methods, were applied to generate reliable outcomes. The research utilizes experimental methods to optimize data protocols while enhancing the performance and interpretability of diagnostic models useful for Alzheimer's disease identification.

3.1. Data collection

Data has been collected from kaggle.com, 2149 records with 33 variables that cover a broad range of demographic, health, and lifestyle factors are included in the Alzheimer's Disease dataset collected from. Age, gender, ethnicity, and education level are important demographic factors. In addition to medical history indicators like family history of Alzheimer's disease, cardiovascular disease, diabetes, depression, head injuries, and hypertension, health-related variables include BMI, smoking, alcohol consumption, physical activity, diet quality, and sleep quality. Clinical measurements include systolic and diastolic blood pressure, cholesterol, total LDL, HDL, and triglycerides. MMSE Functional Assessment Memory Complaints and ADL (Activities of daily living) scores are used to record cognitive and functional evaluations. Confusion, disorientation, personality changes, difficulty finishing tasks, and forgetfulness are examples of behavioral characteristics. Finally, DoctorInCharge classifies accountable healthcare providers, whereas Diagnosis indicates the presence of Alzheimer's disease. This varied dataset offers a thorough basis for comprehending and forecasting the risk of Alzheimer's disease.

3.2. Data pre-processing

Selecting features proves essential for enhancing model performance because it simultaneously reduces unwanted signals while making predictions more comprehensible. The mixture of similar features, such as BMI and weight, leads to data redundancy, which decreases the model performance quality. We applied the SHAP analysis method to identify crucial predictors, leading us to eliminate unnecessary features. The assessment of model consistency across different scenarios takes advantage of multiple data split methods for verification purposes. Data processing phases include training (70%) and validation (30%). Predictions are saved if the criteria are satisfied; changes are made. The method improves data integrity, precise forecasts, and trust in healthcare applications.

Our study utilizes a structured attribute choice procedure that deletes correlated components because it boosts interpretability while reducing duplicity. After SHAP analysis, the chosen features are essential for predicting Alzheimer's because they add value to diagnosis. The robustness across different data distributions is validated using multiple train-test splits with 80/20, 70/30, and 60/40 ratios. The selected approach prevents model overfitting by establishing generalizable results. A thorough analysis of the selection criteria, supporting statistical evidence, and validation strategies for feature selection methods will appear in the methodology section.

3.3. Model selection

This study suggests a healthcare prediction system that uses historical data. To handle null values, duplicates, outliers, and class imbalances, it uses Exploratory Data Analysis (EDA) to determine pre-processing requirements. Models

Like Random Forest, they are used for prediction, and the data is divided into 80%,70%,60% training, and 20%,30%, and 40% testing sets. Performance is assessed using metrics like recall accuracy and precision. To interpret predictions and provide clear insights into contributing features, the system incorporates XAI techniques such as LIME (Vimbi et al., 2024; Salih et al., 2025). Fig. 1 workflow ensures responsible predictions and efficient health condition detection or case dismissal, improves trust and interpretability for healthcare professionals when no disease is identified.

4. Experiments and results

Three experiments were conducted to evaluate various machine learning models for Alzheimer's Disease prediction, using different data split strategies: By dividing 100 into 80 and 20, 70 and 30, and 60 and 40, respectively, this work was able to obtain 80%-20%, 70%-30%, and 60%-40% for training and testing. Evaluation measures like ROC-AUC and accuracy were applied for model comparison, mainly LightGBM, XGBoost, and Gradient Boosting. Table 1 presents the obtained results from experiment 1.

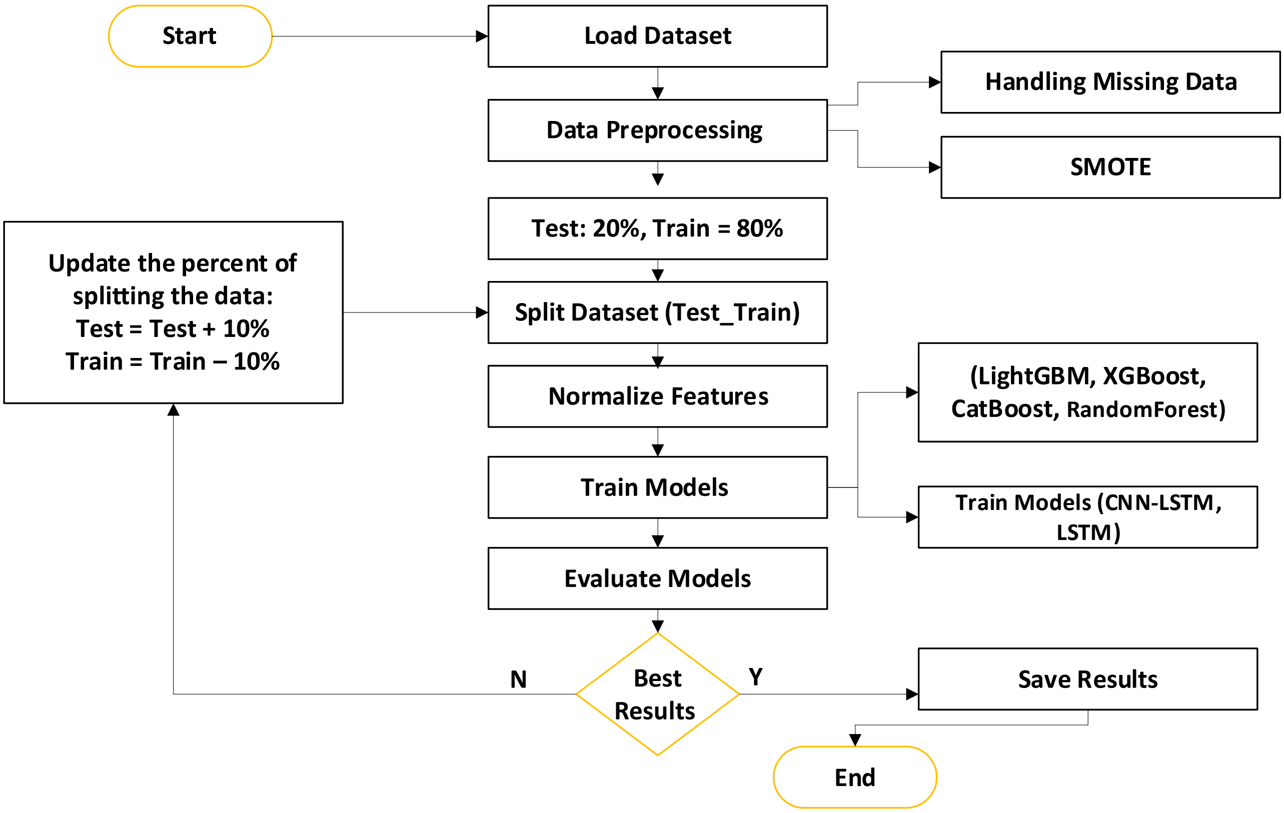

Fig. 1: System workflow diagram

Table 1: Experiment 1 results

Model (80%, 20%)	ROC_AUC	Accuracy
LightGBM	0.954697	0.955814
XGBoost	0.952007	0.948837
CatBoost	0.952337	0.953488
RandomForest	0.949376	0.94186
SVM	0.781612	0.644186
DecisionTree	0.894493	0.909302
LogisticRegression	0.799792	0.769767
GradientBoosting	0.95531	0.95814
AdaBoost	0.93365	0.916279
VotingEnsemble	0.891555	0.830233

4.1. Experiment 1 (80%-20% split)

LightGBM performed best with ROC-AUC = 0.955 and accuracy = 0.956, followed by Gradient Boosting. SVM performed poorly, with accuracy = 0.644.

Table 2 presents the obtained results from experiment 2.

4.2. Experiment 2 (70%-30% split)

Gradient Boosting achieved the best results with ROC-AUC = 0.951 and accuracy = 0.941, followed closely by LightGBM. SVM remained the lowest-performing model, with accuracy = 0.622. Table 3 presents the obtained results from experiment 3.

4.3. Experiment 3 (60%-40% split)

Gradient Boosting again excelled with ROC-AUC = 0.951 and accuracy = 0.941, while Logistic Regression and Voting Ensemble lagged with lower accuracy and ROC-AUC scores. Table 4 compares the results obtained from the three proposed experiments.

The comparison Table 4 shows that the 80% and 20% distributions proved to be most effective for the model, thus having the highest ROC-AUC and accuracy of LightGBM. While Gradient Boosting did a fairly reasonable job on the rest of the splits, it did slightly worse than LightGBM in the 80%-20% experiment. Perhaps it was mainly due to the more extensive training set in the first experiment that gave the model a better generalization and result.

Three 80/20, 70/30, and 60/40 split datasets showed increased predictive performance. This way of splitting the data was proving to be quite productive with LightGBM standing at 95.6% accuracy, which is 3.6% better than the previous studies (Vimbi et al., 2024; Wahyudi and Ayuningsih, 2024; Dalakoti et al., 2024; Görtz et al., 2023). While analyzing other splits, Gradient Boosting exhibited 94.1 % accuracy, indicating that TAER_Robot is accurate, explainable, and capable of predicting Alzheimer's disease at an early stage.

Table 2: Experiment 2 results

Model (70%,30%)	ROC_AUC	Accuracy
LightGBM	0.950421	0.939535
XGBoost	0.948019	0.933333
CatBoost	0.942725	0.942636
RandomForest	0.939306	0.902326
SVM	0.778791	0.621705
DecisionTree	0.875639	0.885271
LogisticRegression	0.853992	0.790698
GradientBoosting	0.950523	0.941085
AdaBoost	0.928698	0.897674
VotingEnsemble	0.89701	0.835659

Table 3: Experiment 3 results

Model (60%,40%)	ROC_AUC	Accuracy
LightGBM	0.950421	0.939535
XGBoost	0.948019	0.933333
CatBoost	0.942725	0.942636
RandomForest	0.939306	0.902326
SVM	0.778791	0.621705
DecisionTree	0.875639	0.885271
LogisticRegression	0.853992	0.790698
GradientBoosting	0.950523	0.941085
AdaBoost	0.928698	0.897674
VotingEnsemble	0.89701	0.835659

Table 4: Comparison table

Experiment	Best model	ROC-AUC	Accuracy	Rank
80%-20%	LightGBM	0.955	0.956	1
70%-30%	GradientBoosting	0.951	0.941	2
60%-40%	GradientBoosting	0.951	0.941	3

The ROC curve shown in Fig. 2 provides an objective evaluation of our classification model, which is especially important for medical prediction systems. ROC curves illustrate diagnostic performance by comparing sensitivity (true positive rate) with 1-specificity (false positive rate) across different thresholds. The model's discriminative ability is measured by the Area Under the Curve (AUC).

A higher AUC indicates stronger predictive performance, with values ranging from 0.5 (no discrimination, equivalent to random chance) to 1.0 (perfect discrimination). This metric is particularly valuable in healthcare applications such as Alzheimer's disease prediction, where minimizing false negatives and achieving high true positive rates are essential for timely and effective diagnosis and treatment.

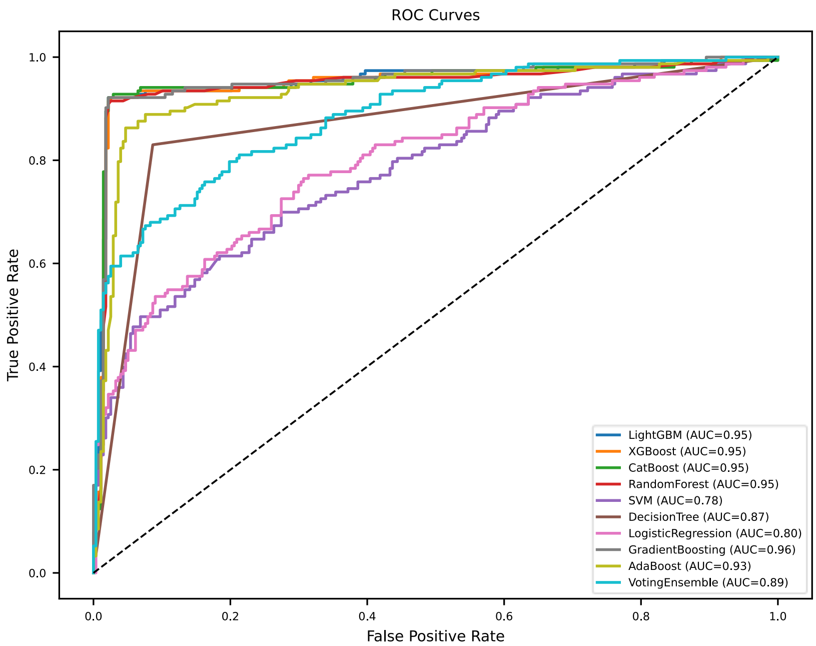

Fig. 2: Receiver operating characteristic (ROC) curve

The models were evaluated using an 80–20 dataset split, and their ROC-AUC scores provided the following insights. Gradient Boosting achieved the highest performance with an ROC-AUC of 0.955, making it the most reliable model for prediction. LightGBM achieved a similar score of 0.955, confirming its efficiency and suitability for large datasets. XGBoost and CatBoost also performed strongly, both reaching an ROC-AUC of 0.952, which reflects their strong predictive ability. AdaBoost obtained an ROC-AUC of 0.933, indicating its capacity to handle imbalanced data effectively. The Random Forest model achieved an ROC-AUC of 0.949, while the Decision Tree model scored 0.894. Although slightly lower than boosting models, both still demonstrated competitive performance. In contrast, Logistic Regression (0.799) and SVM (0.782) achieved lower ROC-AUC scores, suggesting that they may be less appropriate for this dataset compared to ensemble methods. The Voting Ensemble, which combines predictions from all models, produced an ROC-AUC of 0.892. This represents a moderate improvement over some individual models but does not surpass the performance of the best boosting methods.

Fig. 3 illustrates the most important features contributing to the risk of Alzheimer's disease. It shows that ADL, MMSE, and Functional Assessment are the strongest predictors of disease risk. These measures, along with Memory Complaints, are critical for evaluating both cognitive and functional performance.

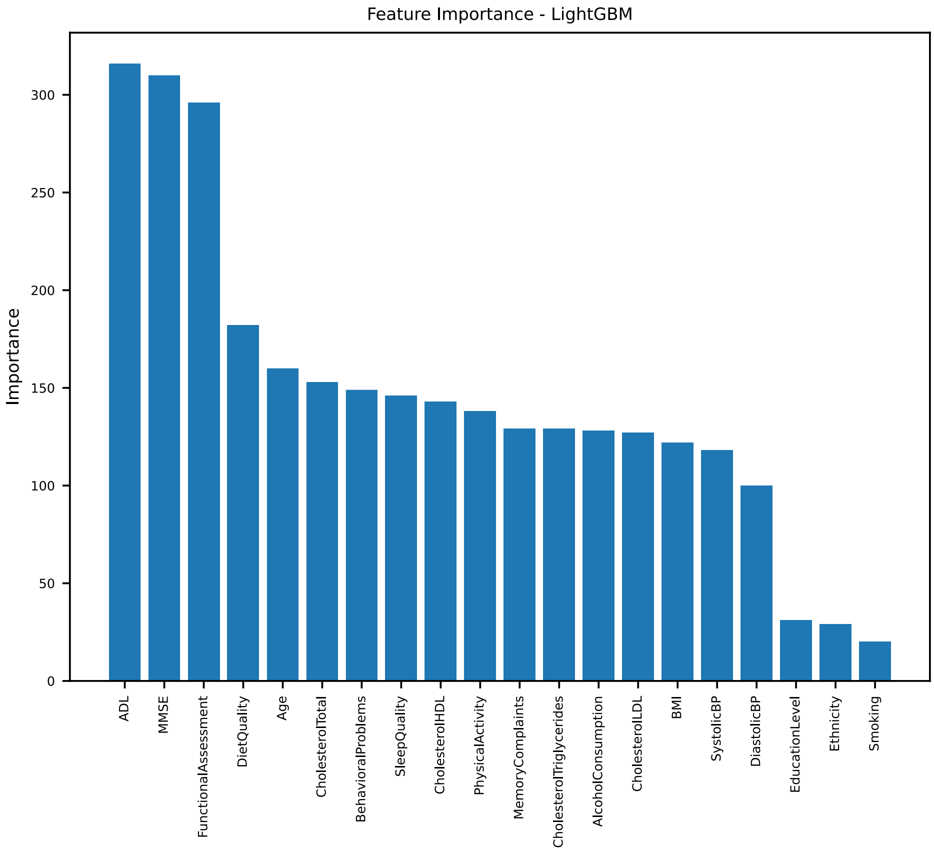

Fig. 3: Feature importance (from LightGBM model)

4.4. Agreement of MMSE, functional assessment, and ADL scores

- MMSE (Mini-Mental State Examination): The MMSE is a brief cognitive test that evaluates a person's mental state, ability to orient in space and time, attention, short-term memory, and language.
  - Real-world example: an 80-year-old patient, went to a clinic complaining of forgetfulness. During the MMSE, he must recall three objects after some interval (such as an apple, a table, or a penny), count downwards from 100 in sevens, and state the current day's date. Let him make 22/30, and then the nurse realizes that he has moderate cognitive impairment and hence needs further testing for Alzheimer's Disease.
- Functional assessment: quantifies a person's capacity for activities of daily living—dressing, cooking, handling money, and the like. It establishes stages of dependency and assists in determining a patient's path of treatment.
  - Real-world example: another patient has issues managing the household finances under her care. She requires assistance when dressing. She scores below her level of functioning on the Functional Assessment and has lost some of her independence; with the help of her caregivers, more assistance is needed, and some changes in the home environment may help prevent the patient from falling.
- Memory complaints: These are self-reports of forgetfulness or memory loss. Cohort members' memory complaints might not necessarily be related to dementia, but can signal impending cognitive deterioration.
  - Real-world example: A 65-year-old teacher complains of forgetting the names of the students and the lessons she had planned to teach. Her full

monte cognitive abnormalities are reported to be expected, but she complains of memory loss, hence her doctor advises her to undergo routine administration of cognitive tests to check on any progression.

- ADL (Activities of daily living): The ADL scores indicate the extent of difficulty that a person may have in carrying out simple activities like feeding, washing, or using the washroom. This score assists in evaluating the trend of functional impairment and the required amount and type of care.
  - Real-world example: another patient, for Instance, is an 82-year-old man with moderate Alzheimer's disease, who cannot bathe or dress himself. His ADL score indicates dependence, and his family has sought help from home care services for increased safety and quality of this client's life.

4.5. Real-world integration

All these forms are used by healthcare professionals in combination to determine the state of cognitive and functional impairment of patients with conditions such as Alzheimer's Disease. For instance, a patient who has a poor MMSE score, complains of memory impairment, and exhibits poor ADL performance may be diagnosed with moderate Alzheimer's Disease and would need a specialized management plan. These assessments determine the further course of treatment, whether the person will require a caretaker, and protective measures that will improve that person's quality of life.

Likewise, Fig. 4 below reveals that utilizing the SHAP (SHapley Additive exPlanations) plot shows the different features that affect the output of a particular system. Each point represents an individual case, and the location reflects the SHAP value to determine whether the feature contributes to the optimistic prediction. ADL, MMSE, and the Functional Assessment category of the case have the most significant impact; higher values of features (marked in red) lead to positive model results. On the other hand, low feature values (blue) give less value to the prediction models to go in the opposite direction. The plot helps show how each characteristic relates to the related system and its decision-making.

In Fig. 5, it is therefore depicted that LIME prediction of the model shows 0% probability of having Alzheimer's disease and 100% probability of not having any Alzheimer's disease. ADL, MMSE, Memory Complaints, Functional Assessment, and Behavioral Problems reveal large contribution measures in Alzheimer's disease prognosis, as represented by blue.

More specifically, the results indicate that each feature specified, such as ADL, Memory Complaints, Functional Assessment, and Behavioral Problems being less than 8, raises the probability of not having Alzheimer's disease, while features like MMSE slightly decrease it. LIME offers how personal attributes affect the input process and bring about the forecast, making the system more transparent and comprehensible.

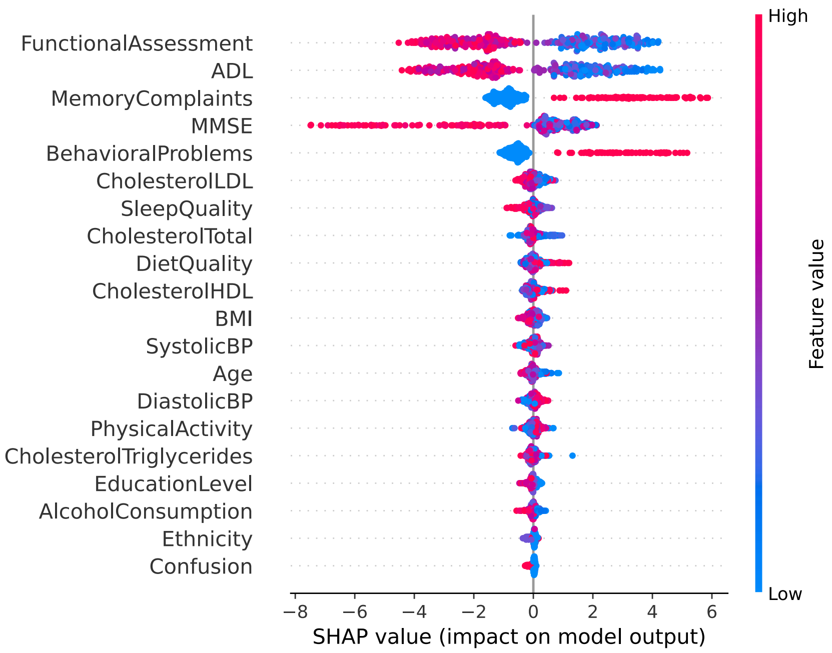

Fig. 4: SHAP value

5. Discussion

The presented experimental results show that implementing the TAER_Robot system with models such as LightGBM and Gradient Boosting can effectively make reliable predictions concerning Alzheimer's Disease. A vast disparity was observed when an 80%-20% split was applied, as the tokenizer was more precise, indicating that a large training data set is critical in enhancing the model's accuracy and the tokenizers' ability.

The conclusion of developing the TAER_Robot system signifies an important advancement in Alzheimer's disease prediction because it combines machine learning with explainable AI techniques. This research evaluated the potential value of uniting these evaluation methods to boost the precision and understanding of assessments in Alzheimer's disease risk prediction. The research employed 2,149 records containing 33 variables, which included lifestyle and demographic information such as age, gender, and cigarette usage. The information went through pre-processing steps that normalized data while performing categorical encoding and managing absent values.

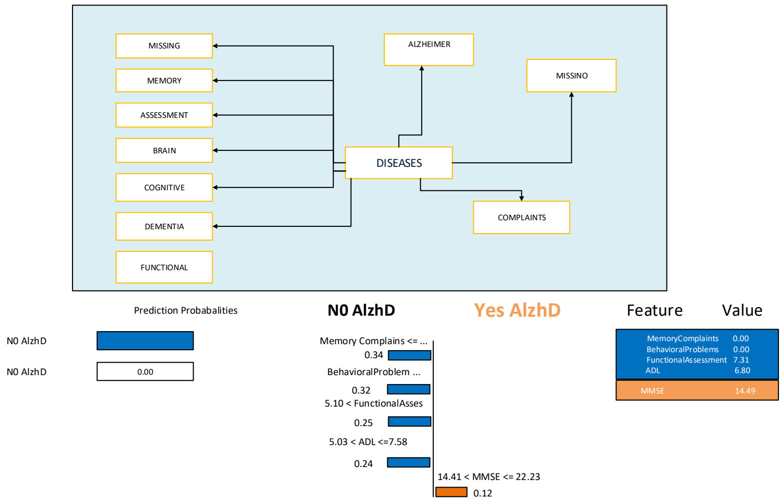

Fig. 5: LIME prediction as ‘Alzheimer’s Disease' found or not found

The implementation of Random Forest, together with CatBoost and XGBoost algorithms, used SHAP and LIME techniques as explainability tools to interpret predictive results. Using 80/20 split proportions resulted in the best performance from the dataset, which underwent separate training and testing ratio modifications (80/20, 70/30, and 60/40). The LightGBM model produced superior results through its outstanding ROC-AUC score of 0.955 with 95.6% accuracy, surpassing previous research findings of around 92%.

The TAER_Robot system enhances early-stage Alzheimer’s diagnosis by providing more accurate diagnoses with a more straightforward interpretation of results. XAI implementation in models provides improved model transparency and enhanced user trust, making it an effective tool that clinicians find valuable. The system demonstrates its wide range of compatibility through excellent performance measurements across multiple datasets. The research indicates that such an approach could be a basis for enhancing next-generation predictive systems for Alzheimer’s Disease management while enabling astute clinical choices across the board.

The novelty of this research lies in applying XAI to a machine learning-based Alzheimer’s Disease prediction system through the development of the TAER_Robot. Your system produces accurate predictions since it integrates XAI functions while maintaining an understandable output that healthcare experts can easily trust. The developed TAER_Robot system utilizes SHAP and LIME techniques to show healthcare professionals and patients exactly which features, including age, cognitive ability, and lifestyle choices, affect their predicted risk outcomes. User confidence increases significantly because users can see exactly how the AI system works while decision-makers gain assurance about the AI results' trustworthiness.

The distinctive aspect of the proposed method involves finding optimal distributions between training and testing datasets. Different ratios of 80/20 and 70/30, and 60/40 allow this work to identify the best configuration for predictive quality that lets your model work effectively across multiple data sets. Paying attention to data partitioning of the proposed model demonstrates increased robustness, resulting in better accuracy levels (up to 95.6%) beyond previous research (which typically reached 92%) with its model predictions. The proposed specific methodology for model training enhances the value of your work compared to earlier studies.

Interdisciplinary design in TAER_Robot enhances its innovation by integrating artificial intelligence with machine learning and healthcare-specific medical expertise. The tool provides clinical adaptability through its user-friendly design, which enhances two important aspects of Alzheimer’s disease risk evaluations while surpassing existing models with unclear assessment criteria. XAI integration within your system provides healthcare a necessary solution by enabling trust in AI-based early-stage Alzheimer’s detection predictions.

5.1. Real-world applications

Thus, TAER_Robot can help doctors select high-risk patients by offering reliable predictions and a proper explanation of why they are considered risky, using post-hoc explanations such as SHAP and LIME. For instance, a doctor could examine the list generated by the system, where patients who have low MMSE scores and high cholesterol levels, which could be coded for AlzD, can be treated early.

5.2. Recommendations and future systems

- Enhancing interpretability: Applying SHAP values for all types of models can provide details about feature contributions, giving clinicians better insight into the predictions.
- Integrating real-time data: As mentioned above, integrating with a live EHR could mean that patient profiles can be updated dynamically on TAER_Robot.
- Improving model training: Perhaps blending the different structures of Gradient Boosting and LightGBM would improve the prediction.
- Personalized insights: Extending the functionality to consider the user's risk profile can help engage the users and improve their health outcomes.

5.3. Future challenges

- Data privacy: The protection of sensitive, detailed medical information is of paramount importance.
- Ethical considerations: It is of the utmost importance to erase biases when the data for training the models is collected and to make it equally fair when used on different groups of patients.
- Scalability: When adopting TAER_Robot, possible limitations of the current technique in large setups include computational costs and health system size.

5.4. Persuading decision-makers

It explicitly improves stakeholder trust in handling patient data, thereby solving the "black-box" problem associated with traditional machine learning techniques, as featured by TAER_Robot. For example, using TAER_Robot, a hospital administrator can select which patients should be sent for a more detailed checkup according to clearly defined and explained risks, while also being concerned about how this process impacts resource utilization.

5.5. Study limitations and future work

The Kaggle datasets contain various examples; however, their medical verification remains absent. Our study maintains data integrity because data preprocessing and anonymization combine with ethical compliance standards. To acknowledge this constraint, future work needs on-site hospital-based testing to improve research reliability in future work.

6. Conclusion

Our results identify Gradient Boosting as the best-performing model, with LightGBM in the second place as all the ROC-AUC indices were above 0.95. The results also show how the boosting techniques are particularly effective in dealing with the complexities inherent in the interrelations of the data. Based on the findings, all the ensemble models performed better than the individual models, such as Logistic Regression and SVM, hence the need to enhance model diversity to predict Alzheimer's disease. Notably, this analysis underlines the possibility of utilizing these techniques for correct and unerring approaches to early diagnosis.

As a tool that stands right in the middle of highly advanced statistical modeling and clinically driven decision-making, TAER_Robot has the power to revolutionize the management of Alzheimer's disease by diagnosing the disease in its earliest stages and tailoring specific care plans for patients with the disease. Social Proof can be extended even more through evidence of database implementation about patient and clinician satisfaction.

List of abbreviations

AdaBoost	Adaptive Boosting
ADL	Activities of Daily Living
AI	Artificial Intelligence
AlzD	Alzheimer's Disease
AUC	Area Under the Curve
BMI	Body Mass Index
CatBoost	Categorical Boosting
EDA	Exploratory Data Analysis
EHR	Electronic Health Record
HDL	High-Density Lipoprotein
LDL	Low-Density Lipoprotein
LIME	Local Interpretable Model-agnostic Explanations
LightGBM	Light Gradient Boosting Machine
ML	Machine Learning
MMSE	Mini-Mental State Examination
NPV	Negative Predictive Value
PPV	Positive Predictive Value
ROC	Receiver Operating Characteristic
ROC-AUC	Receiver Operating Characteristic - Area Under the Curve
SHAP	SHapley Additive exPlanations
SVM	Support Vector Machine
TAER_Robot	The Arabic English Russian Robot
XAI	Explainable AI
XGBoost	Extreme Gradient Boosting

Funding

This study was supported by funding provided by the University of Buraimi.

Acknowledgment

I sincerely thank the University of Buraimi for its ongoing backing and plentiful financial support during project development. The university's constant dedication to research advancement and innovation played a vital role in finishing this work successfully. This research received crucial support from the University of Buraimi by offering significant resources, direction, and constant encouragement. The valuable backing from the Buraimi University made this project possible, and I express profound gratitude for their dedication to scholarly achievement and research progress.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

Adekeye A, Lung KC, and Brill KL (2023). Pediatric and adolescent breast conditions: A review. Journal of Pediatric and Adolescent Gynecology, 36(1): 5-13. https://doi.org/10.1016/j.jpag.2022.11.001 **PMid:36356839**

Adetunji CO, Fatumo S, and Ukwaja KN (2024). Health technologies and informatics: Research and developments. CRC Press, Boca Raton, USA. https://doi.org/10.1201/9781003309468

Akinrinola O, Okoye CC, Ofodile OC, and Ugochukwu CE (2024). Navigating and reviewing ethical dilemmas in AI development: Strategies for transparency, fairness, and accountability. GSC Advanced Research and Reviews, 18(3): 50-58. https://doi.org/10.30574/gscarr.2024.18.3.0088

Alelyani T (2024). Establishing trust in artificial intelligence-driven autonomous healthcare systems: An expert-guided framework. Frontiers in Digital Health, 6: 1474692. https://doi.org/10.3389/fdgth.2024.1474692 **PMid:39664399 PMCid:PMC11631875**

Ali ML, Thakur K, Schmeelk S, Debello J, and Dragos D (2025). Deep learning vs. machine learning for intrusion detection in computer networks: A comparative study. Applied Sciences, 15(4): 1903. https://doi.org/10.3390/app15041903

Azevedo BF, Rocha AMA, and Pereira AI (2024). Hybrid approaches to optimization and machine learning methods: A systematic literature review. Machine Learning, 113(7): 4055-4097. https://doi.org/10.1007/s10994-023-06467-x

Chen C, Zhang Z, Liu Y et al. (2025). Comprehensive characterization of the transcriptional landscape in Alzheimer's disease (AD) brains. Science Advances, 11(1): eadn1927. https://doi.org/10.1126/sciadv.adn1927 **PMid:39752483 PMCid:PMC11698078**

Dalakoti M, Wong S, Lee W et al. (2024). Incorporating AI into cardiovascular diseases prevention–insights from Singapore. The Lancet Regional Health–Western Pacific, 48: 101102. https://doi.org/10.1016/j.lanwpc.2024.101102 **PMid:38855631 PMCid:PMC11154196**

Farhan YH, Shannaq B, Al Maqbali SAID, Ali O, Bani-Ismail BASEL, Abd MT, and Shakir M (2025). Utilizing word embedding's for automated query expansion in Arabic information retrieval: A blended methodology. Journal of Theoretical and Applied Information Technology, 103(2): 773-782.

Görtz M, Baumgärtner K, Schmid T, Muschko M, Woessner P, Gerlach A, Byczkowski M, Sültmann H, Duensing S, and Hohenfellner M (2023). An artificial intelligence-based chatbot for prostate cancer education: Design and patient evaluation study. Digital Health, 9: 1-11. https://doi.org/10.1177/20552076231173304 **PMid:37152238 PMCid:PMC10159259**

Islam T, Sheakh MA, Tahosin MS, Hena MH, Akash S, Bin Jardan YA, FentahunWondmie G, Nafidi HA, and Bourhia M (2024). Predictive modeling for breast cancer classification in the context of Bangladeshi patients by use of machine learning approach with explainable AI. Scientific Reports, 14: 8487. https://doi.org/10.1038/s41598-024-57740-5 **PMid:38605059 PMCid:PMC11009331**

Javed R, Abbas T, Shahzad T, Kanwal K, Ramay SA, Khan MA, and Ouahada K (2025). Enhancing chronic disease prediction in IoMT-enabled healthcare 5.0 using deep machine learning: Alzheimer's disease as a case study. IEEE Access, 13: 14252-14272. https://doi.org/10.1109/ACCESS.2025.3525514

Kareem BA, Zubaidi SL, Al-Ansari N, and Muhsen YR (2024). Review of recent trends in the hybridisation of preprocessing-based and parameter optimisation-based hybrid models to forecast univariate streamflow. Computer Modeling in Engineering and Sciences, 138(1): 1-41. https://doi.org/10.32604/cmes.2023.027954

Li L, Peng W, and Rheu MM (2024). Factors predicting intentions of adoption and continued use of artificial intelligence chatbots for mental health: Examining the role of UTAUT model, stigma, privacy concerns, and artificial intelligence hesitancy. Telemedicine and E-Health, 30(3): 722-730. https://doi.org/10.1089/tmj.2023.0313 **PMid:37756224**

Mishra PK, Singh KK, Ghosh S, and Sinha JK (2025). Future perspectives on the clinics of Alzheimer's disease. In: Singh SK and Maccioni R (Eds.), A new era in Alzheimer's research: 217-232. Academic Press, Cambridge, USA. https://doi.org/10.1016/B978-0-443-15540-6.00001-X **PMid:38303537**

Mostafa G, Mahmoud H, Abd El-Hafeez T, and E ElAraby M (2024). The power of deep learning in simplifying feature selection for hepatocellular carcinoma: A review. BMC Medical Informatics and Decision Making, 24: 287. https://doi.org/10.1186/s12911-024-02682-1 **PMid:39367397 PMCid:PMC11452940**

Parul, Singh A, and Shukla S (2025). Novel techniques for early diagnosis and monitoring of Alzheimer's disease. Expert Review of Neurotherapeutics, 25(1): 29-42. https://doi.org/10.1080/14737175.2024.2415985 **PMid:39435792**

Rehman SU, Tarek N, Magdy C, Kamel M, Abdelhalim M, Melek A, Mahmoud LN, and Sadek I (2024). AI-based tool for early detection of Alzheimer's disease. Heliyon, 10(8): e29375. https://doi.org/10.1016/j.heliyon.2024.e29375 **PMid:38644855 PMCid:PMC11033128**

Salih AM, Raisi-Estabragh Z, Galazzo IB, Radeva P, Petersen SE, Lekadir K, and Menegaz G (2025). A perspective on explainable artificial intelligence methods: SHAP and LIME. Advanced Intelligent Systems, 7: 2400304. https://doi.org/10.1002/aisy.202400304

Sethi P, Bhaskar R, Singh KK et al. (2024). Exploring advancements in early detection of Alzheimer's disease with molecular assays and animal models. Ageing Research Reviews, 100: 102411. https://doi.org/10.1016/j.arr.2024.102411 **PMid:38986845**

Shannaq B (2025). Does dataset splitting impact Arabic text classification more than preprocessing? An empirical analysis in big data analytics. Journal of Theoretical and Applied Information Technology, 103(3): 1020-1037.

Shannaq B, Al Shamsi I, and Majeed SNA (2019). Management information system for predicting quantity martials. TEM Journal, 8(4): 1143-1149. https://doi.org/10.18421/TEM84-06

Sharma D and Kaushik P (2025). Applications of AI in neurological disease detection: A review of specific ways in which AI is being used to detect and diagnose neurological disorders, such as Alzheimer's and Parkinson's. In: Singh R, Gehlot A, Rathour N, and Akram SV (Eds.), AI in disease detection: advancements and applications: 167-189. John Wiley and Sons, Hoboken, USA. https://doi.org/10.1002/9781394278695.ch8 **PMCid:PMC11844946**

Vanaja T, Shanmugavadivel K, Subramanian M, and Kanimozhiselvi CS (2025). Advancing Alzheimer's detection: Integrative approaches in MRI analysis with traditional and deep learning models. Neural Computing and Applications, 1-20. https://doi.org/10.1007/s00521-025-10993-1

Vimbi V, Shaffi N, and Mahmud M (2024). Interpreting artificial intelligence models: A systematic review on the application of

LIME and SHAP in Alzheimer's disease detection. Brain Informatics, 11: 10.
https://doi.org/10.1186/s40708-024-00222-1
PMid:38578524 PMCid:PMC10997568

Wahyudi D and Ayuningsih E (2024). The application of machine learning in predicting the risk of heart disease with decision tree algorithm. Instal: Jurnal Komputer, 16(2): 120-130.
https://doi.org/10.54209/jurnalinstall.v16i02.204

Wang H, Wang L, Wu Q, Pei H, and Diao L (2025). A data-driven intelligent fault diagnosis framework for permanent magnet in PMSM. Alexandria Engineering Journal, 113: 331-346.
https://doi.org/10.1016/j.aej.2024.11.030