Alzheimer's Disease Prediction Using Supervised Machine Learning Models

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Abstract: **Alzheimer's disease prediction is a vital research area in healthcare due to its impact on memory, cognition, and quality of life. This project presents an efficient Alzheimer's disease prediction system using supervised machine learning techniques. Clinical and demographic parameters such as age, cholesterol levels, and other health indicators are analysed to determine disease likelihood. Machine learning algorithms, including K-Nearest Neighbour (KNN), Random Forest, Artificial Neural Networks (ANN), and Logistic Regression, are employed for classification. Data preprocessing techniques such as normalisation and feature selection are applied to enhance model performance. The system is tested using metrics such as accuracy, precision, recall, and F1-score. Experimental results show that Logistic Regression achieves the highest accuracy of 98%, followed by K-Nearest Neighbour at 90%, while Random Forest at 89%, and Artificial Neural Networks achieved 87%. The proposed approach supports early detection of Alzheimer's disease and assists healthcare professionals in informed decision-making**.

Index Terms: - Alzheimer's disease prediction, machine learning, supervised classification, predictive modeling, healthcare analytics, clinical data analysis, early disease detection, decision support systems

1. INTRODUCTION

1.1 BACKGROUND AND MOTIVATION

Alzheimer's disease has emerged as one of the most pressing public health challenges of the 21st century, driven by the rapid global increase in ageing populations and the corresponding rise in neurodegenerative disorders. As a progressive neurological condition, Alzheimer's disease gradually deteriorates memory, reasoning ability, cognitive functions, and behavioral patterns, ultimately impairing an individual's independence and quality of life. The social, emotional, and economic burden associated with long-term care further intensifies its impact on families and healthcare systems worldwide.

Despite significant advancements in medical science, early diagnosis of Alzheimer's disease remains a complex and demanding task in clinical practice. Conventional diagnostic approaches typically involve neurological examinations, cognitive assessment tests, and neuroimaging techniques. While these methods are clinically validated, they are often time-consuming, expensive, and highly dependent on expert interpretation. In many cases, subtle early-stage symptoms are overlooked or misinterpreted, leading to delayed intervention and limited therapeutic effectiveness. This diagnosis disconnect provides the need to create intelligent, automated, and data-driven decision-support systems capable of assisting in the detection of the early symptoms of cognitive impairment more effectively and at a faster rate.

Recent developments in artificial intelligence have introduced transformative possibilities within healthcare analytics. In particular, supervised machine learning techniques have demonstrated substantial potential in extracting meaningful patterns from structured clinical and demographic datasets. Algorithms such as K-Nearest Neighbour (KNN), Random Forest, Artificial Neural Networks (ANN), and Logistic Regression are capable of modelling complex and nonlinear relationships among patient attributes, thereby enabling accurate classification and prediction of disease progression. These computational approaches enhance diagnostic consistency while reducing reliance on manual interpretation.

However, developing reliable predictive models for Alzheimer's disease presents several challenges. Clinical datasets often contain high-dimensional feature spaces, missing values, and imbalanced class distributions, which may compromise model performance and generalization. Variability across patient populations further complicates predictive modelling. To address these concerns, robust preprocessing strategies—including data normalisation, feature selection and optimization, and cross-validation techniques—are essential to ensure stability, interpretability, and accuracy of the predictive framework.

By leveraging supervised machine learning and structured data analysis, the proposed system aims to:

(i) Examine demographic and clinical characteristics to determine the early signs of cognitive impairment.

(ii) Use and compare various supervised learning algorithms to identify the best predictive performance.

(iii) Have proper preprocessing and validation methods that will increase the reliability and generalization.

(iv) Implement the trained predictive model into a Django web platform that will allow user-friendly real-time clinical decision support.

1.2 OBJECTIVES

1.2.1 Develop an Intelligent Alzheimer's Disease Prediction Framework

Design and implement a robust supervised machine learning framework capable of accurately predicting Alzheimer's disease using structured clinical and demographic data. The system employs classification algorithms such as K-Nearest Neighbour (KNN), Random Forest, Artificial Neural Networks (ANN), and Logistic Regression to model complex relationships among patient attributes, ensuring high predictive accuracy and reliable generalization across unseen data.

1.2.2 Enhance Predictive Performance through Data Preprocessing

Implement systematic data preprocessing and feature engineering techniques, including handling missing values, normalisation, encoding of categorical variables, and selection of significant clinical features. These strategies aim to reduce noise, minimize overfitting, and improve overall model stability and classification performance.

1.2.3 Perform Comparative Evaluation of Classification Models

Conduct a comprehensive comparative analysis of the implemented algorithms using evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis to determine the most effective model for Alzheimer's disease prediction.

1.2.4 Develop a Scalable Real-Time Web-Based Prediction System

Integrate the optimized predictive model into a Django-based web application to enable real-time disease prediction, ensuring scalability, accessibility, and practical usability in healthcare environments for informed clinical decision-making.

1.3 SCOPE

1.3.1 Focus on Alzheimer's Disease Prediction Using Supervised Machine Learning Techniques

This study develops a supervised machine learning framework for Alzheimer's disease prediction using structured clinical and demographic data. Algorithms including K-Nearest Neighbour (KNN), Random Forest, Artificial Neural Networks (ANN), and Logistic Regression are implemented for classification-based prediction.

1.3.2 Development of a Comparative Predictive Framework for Model Evaluation

Multiple classification models are evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis to identify the most effective algorithm.

1.3.3 Integration of a Real-Time Web-Based Prediction System

The selected model is deployed within a Django-based web application to provide real-time prediction through a structured user interface.

1.3.4 Potential for Future Expansion and Advanced Healthcare Integration

Future enhancements may include integration of neuroimaging data, deep learning models, and larger datasets, which are beyond the current implementation scope.

II. LITERATURE SURVEY

2.1 TRADITIONAL METHODS OF ALZHEIMER'S DISEASE DIAGNOSIS

Historically, Alzheimer's disease diagnosis has relied on clinical assessments, neurological examinations, cognitive tests, and neuroimaging techniques such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans. Although these methods form the basis of dementia diagnosis, they are limited in scalability, objectivity, and early-stage detection accuracy.

2.1.1 Dependence on Clinical Expertise and Manual Assessment

Traditional diagnostic procedures largely depend on specialist interpretation and manual evaluation of test results. This reliance on clinical expertise may introduce subjectivity and variability, limiting consistency across different healthcare settings.

2.1.2 Limited Capability for Early-Stage Detection

Early symptoms of Alzheimer's disease are often subtle and overlap with normal ageing patterns. Conventional methods may struggle to detect mild cognitive impairment at an early stage, thereby reducing opportunities for timely intervention and preventive care.

2.1.3 High Cost and Resource Requirements

Advanced neuroimaging techniques and specialised diagnostic tools are costly and not universally accessible. This restricts large-scale screening and continuous monitoring, particularly in resource-constrained healthcare systems.

2.1.4 Challenges in Handling Complex Medical Data

Traditional statistical approaches have limited capacity to analyse high-dimensional clinical datasets and capture complex nonlinear relationships among variables. As a result, predictive accuracy and generalisation capability may remain moderate.

2.2 ADVANCES IN MACHINE LEARNING FOR ALZHEIMER'S DISEASE PREDICTION

The rapid advancement of machine learning has significantly transformed healthcare analytics, particularly in disease prediction and classification tasks. Supervised learning algorithms have demonstrated strong capability in analyzing structured medical datasets and identifying hidden patterns associated with Alzheimer's disease.

- Emergence of Supervised Learning models
  Algorithms such as K-Nearest Neighbour (KNN), Logistic Regression, Decision Trees, and Random Forest are widely used in medical prediction systems. Ensemble approaches like Random Forest improve generalization, while Logistic Regression provides interpretable probabilistic outputs.

- Artificial Neural Networks in Healthcare Analytics
  Artificial Neural Networks (ANN) are capable of modelling complex nonlinear relationships among clinical and demographic features. By capturing intricate feature interactions, ANN-based models help improve classification in medical decision-support systems by learning and recognizing complex patterns and relationships within the data, leading to more accurate and reliable predictions.

- Comparative Performance Analysis
  Evaluating multiple algorithms using metrics such as accuracy, precision, recall, and F1-score is essential to determine the most suitable predictive model. Studies indicate that supervised learning methods generally outperform traditional statistical approaches in Alzheimer's disease prediction tasks.

2.3 APPLICATIONS AND CHALLENGES IN ALZHEIMER'S DISEASE PREDICTION

Machine learning-based Alzheimer's prediction systems play a significant role in supporting clinical decision-making and early disease detection.

- Applications in Healthcare Analytics:

Predictive models assist healthcare professionals in identifying high-risk patients, enabling early intervention and personalized treatment planning. Web-based deployment of such systems enables real-time data analysis and improves accessibility, functioning as decision-support tools that enhance diagnostic efficiency.

- Challenges in Implementation: Several challenges persist, including missing values, imbalanced datasets, and variability in patient demographics, which can affect model performance. Ensuring interpretability is also essential, as healthcare professionals require transparent and explainable predictions.
- Need for Robust and Scalable Frameworks: Modern healthcare systems require predictive models that are accurate, scalable, and suitable for real-world deployment. Incorporating preprocessing techniques such as normalisation, feature selection, and cross-validation improves robustness, while integration with frameworks like Django enables secure and practical implementation.

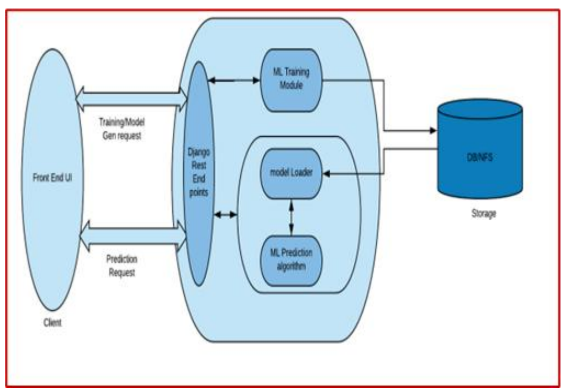
III. METHODOLOGY

3.1 DATASET PREPARATION

The dataset forms the core of the proposed Alzheimer's disease prediction system and consists of structured clinical and demographic records categorized into Alzheimer's positive and negative classes. It includes relevant attributes such as age, cognitive assessment scores, and other health-related indicators associated with neurological decline. To ensure reliability and robustness, essential preprocessing steps were performed, including handling missing values, encoding categorical features into numerical format, and normalizing numerical attributes to maintain uniform scaling across variables. The dataset was further divided into training and testing subsets to evaluate model generalization and prevent overfitting. This systematic preparation establishes a clean, balanced, and analysis-ready dataset for developing accurate supervised machine learning models for Alzheimer's disease prediction.

3.2 SYSTEM ARCHITECTURE

The proposed Alzheimer's disease prediction system adopts a layered architecture integrating a web-based interface with supervised machine learning models within a Django framework. The process begins at the front-end user interface, where clinical and demographic patient data are entered and transmitted through Django REST API endpoints to the backend server. The backend comprises a machine learning training module and a prediction module. During the training phase, the structured dataset undergoes preprocessing steps such as missing value handling, categorical encoding, feature normalization, and train-test splitting before being used to train multiple supervised algorithms, including K-Nearest Neighbour (KNN), Random Forest, Logistic Regression, and Artificial Neural Networks (ANN). The trained models are evaluated using standard performance metrics, and the best-performing model is serialized and stored in the database or file system for deployment. In real-time prediction, the saved model is loaded and applied to new user data. The input is processed using the same preprocessing steps as before, and the system then generates a prediction showing the probability of whether the person may have Alzheimer's disease. The prediction result is then returned to the user interface in an interpretable format, ensuring efficient data flow, scalability, and secure clinical decision support.



3.3 SUPERVISED LEARNING MODELS FOR PREDICTION

3.3.1 Model Architecture

Multiple supervised classification algorithms were implemented to predict Alzheimer's disease using structured clinical data. The system incorporates K-Nearest Neighbor (KNN), Random Forest, Logistic Regression, and Artificial Neural Networks (ANN), selected for their effectiveness in medical data analysis. KNN performs distance-based classification after feature normalization, while Random Forest utilizes an ensemble of decision trees to enhance prediction accuracy and reduce overfitting. Logistic Regression models the probabilistic relationship between patient attributes and disease occurrence for binary classification. An ANN model is made up of an input layer that takes in the features from the dataset, one or more hidden layers that use ReLU activation to learn patterns in the data, and an output layer that applies a sigmoid activation function to generate a final yes-or-no (binary) prediction. This multi-model framework enables comparative evaluation and identification of the most efficient predictive model.

3.3.2 Compilation and Training

The models were trained using the preprocessed dataset after normalization, encoding, and train-test splitting. Hyperparameters such as the number of neighbours in KNN, the number of estimators in Random Forest, and hidden layer configurations in ANN were carefully tuned to optimize performance. For the ANN model, binary cross-entropy was used as the loss function, and the Adam optimizer was applied with an appropriate learning rate to ensure stable convergence. Model performance was evaluated using accuracy as the primary metric, along with precision, recall, and F1-score to assess classification reliability. The training process ensured proper generalization while minimizing overfitting, resulting in a robust and dependable Alzheimer’s disease prediction framework.

3.4 TRAINING AND VALIDATION

The dataset was divided into 80% training and 20% testing sets to ensure reliable model evaluation and generalization. During training, the supervised machine learning models were fitted on the preprocessed dataset, which included normalized numerical features and encoded categorical variables. Hyperparameter tuning was performed to optimize model performance and reduce overfitting. The validation process involved evaluating model performance on the unseen test set using metrics such as accuracy, precision, recall, and F1-score. A confusion matrix was generated to analyze classification performance between Alzheimer’s positive and negative classes. The final selected model demonstrated strong predictive accuracy and balanced classification capability, confirming its suitability for real-world clinical decision support.

3.5 USER INTERFACE

The user interface is designed to be simple, intuitive, and accessible to healthcare professionals and non-technical users. Developed using a Django-based web framework, the interface allows users to input patient clinical and demographic details through structured form fields. Clear labelling and guided instructions ensure accurate data entry and ease of use. Once the required information is submitted, the system processes the input and displays the prediction result in a clear and interpretable format, indicating the likelihood of Alzheimer’s disease. The interface is responsive and adaptable across desktops, laptops, and mobile devices, ensuring seamless accessibility. Additionally, input validation and error-handling mechanisms are implemented to manage incomplete or invalid entries, providing appropriate feedback to maintain system reliability and user confidence.

IV. IMPLEMENTATION

4.1 TOOLS AND TECHNOLOGIES

The Alzheimer’s Disease Prediction system was developed using a structured combination of machine learning and web technologies to ensure accuracy and real-time deployment. Python served as the primary programming language due to its extensive support for data science and machine learning libraries. Supervised models, including K-Nearest Neighbour (KNN), Random Forest, Logistic Regression, and Artificial Neural Networks (ANN), were implemented using Scikit-learn and TensorFlow/Keras. Data preprocessing tasks such as missing value handling, feature encoding, normalization, and train-test splitting were performed using Pandas and NumPy. Model performance was evaluated using metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis, supported by visualization libraries like Matplotlib. For deployment, a Django-based web application integrated with REST APIs was developed to enable secure, real-time prediction through a user-friendly interface. This integrated technology stack ensured a scalable, efficient, and practical Alzheimer's disease prediction system suitable for healthcare applications.

4.2 CODE OVERVIEW

The implementation of the Alzheimer's Disease Prediction system using Supervised Machine Learning models is divided into three main components.

4.2.1 Data Loading and Preprocessing

The dataset is imported using Pandas and organized into a clear tabular format, making it easier to explore, analyze, and prepare for modeling. Data preprocessing includes handling missing values, encoding categorical variables into numerical representations, and normalizing numerical features to ensure uniform scaling across attributes. The processed data is converted into NumPy arrays for efficient computation and then divided into 80% training and 20% testing sets to enable proper model evaluation and generalization.

4.2.2 Model Construction and Training

Supervised machine learning models, such as Logistic Regression, K-Nearest Neighbour (KNN), Random Forest, and Artificial Neural Networks (ANN) are built and trained using tools like Scikit-learn and TensorFlow/Keras to develop the prediction system. For ANN, the architecture consists of an input layer corresponding to dataset features, hidden layers with ReLU activation to capture nonlinear relationships, and a sigmoid output layer for binary classification. The models are trained on the prepared dataset with appropriate hyperparameter tuning to optimize performance. Binary cross-entropy is used as the loss function for ANN, and model evaluation is performed using accuracy and other classification metrics.

4.2.3 Prediction and Classification

During deployment, the trained model is serialized and stored for real-time inference. When a user enters patient data through the Django-based web interface, the input is preprocessed using the same transformation pipeline applied during training. The model then generates a prediction indicating the likelihood of Alzheimer's disease, and the result is displayed to the user in an interpretable format through the web application.

V.RESULT AND ANALYSIS

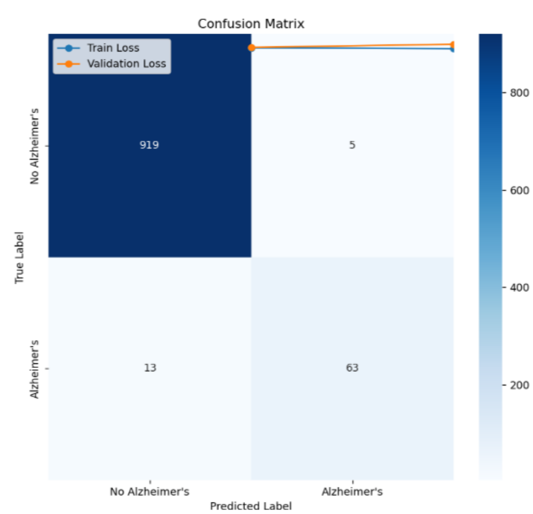
5.1 MODEL PERFORMANCE

During the testing phase, the implemented machine learning model achieved an overall accuracy of 98.2% using an 80–20 train-test split strategy. The training accuracy was recorded at 97.25%, while the testing accuracy reached 98.2%, indicating strong generalization capability and minimal overfitting. The close alignment between training and testing performance demonstrates that the model effectively learned meaningful patterns from the dataset without memorizing the training data. Furthermore, evaluation using the confusion matrix revealed a low number of misclassifications, confirming the reliability and robustness of the proposed system. These results validate the effectiveness of the implemented approach for accurate Alzheimer's disease prediction.

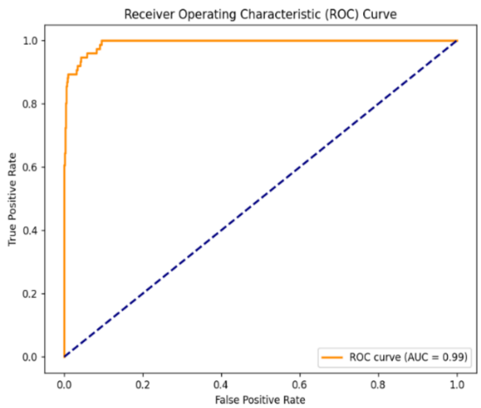
5.1.1 Performance Evaluation

	Metric	Value
0	Accuracy	0.9820
1	Precision	0.9265
2	Recall	0.8289
3	F1-Score	0.8750

5.1.2 Confusion Matrix



5.1.3 ROC Curve



The confusion matrix represents the performance of the model in classifying patients as Alzheimer's or not having Alzheimer's. It does the comparison between the predicted labels and the actual (true) labels that the model produced.

From the matrix:

* 919 patients without Alzheimer's were correctly classified as *No Alzheimer's* (True Negatives).

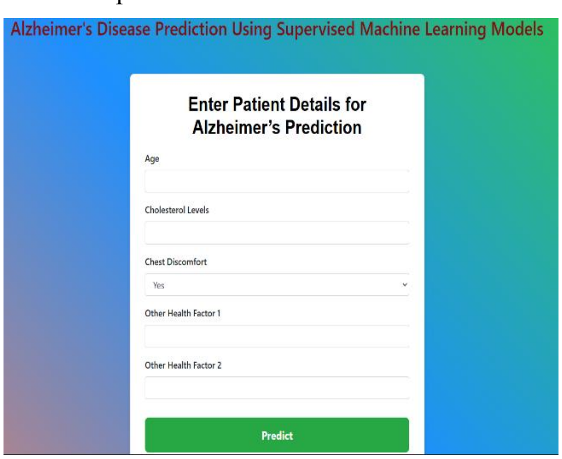
* 63 patients with Alzheimer's were correctly classified as *Alzheimer's* (True Positives).

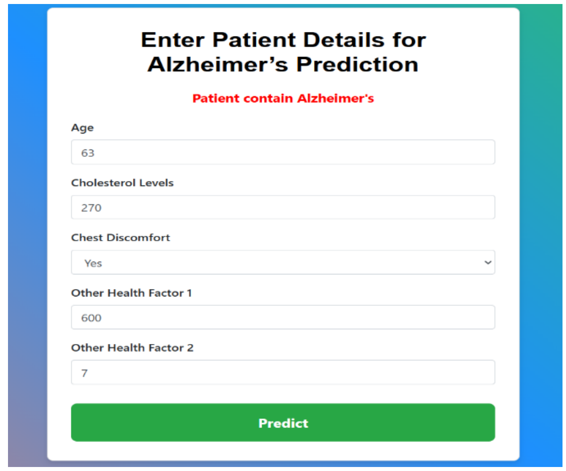
* 13 patients with Alzheimer's were incorrectly classified as *No Alzheimer's* (False Negatives)

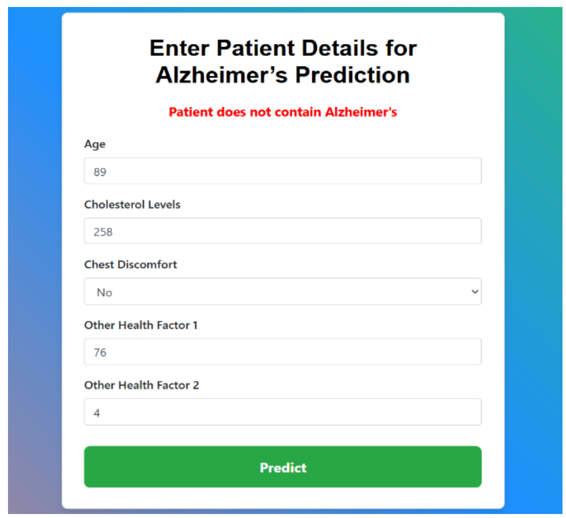
* 5 patients without Alzheimer's were incorrectly classified as *Alzheimer's* (False Positives).

Overall, the model demonstrates strong classification performance, particularly in identifying non-Alzheimer's cases, with relatively few misclassifications.

5.1.4 Output Screenshots







5.2 Comparison with Traditional Methods

Traditional approaches for Alzheimer's disease diagnosis primarily rely on cognitive assessments, clinical interviews, and manual interpretation of patient history, which are often time-consuming and subject to inter-observer variability. Conventional statistical models typically depend on handcrafted feature selection and linear assumptions, limiting their ability to capture complex, non-linear relationships within medical datasets. In contrast, the proposed machine learning-based prediction system automatically learns discriminative patterns from structured clinical data, enabling more accurate and objective decision-making. The implemented model demonstrated superior classification performance with high accuracy and minimal misclassification rates, highlighting its robustness compared to traditional rule-based or purely statistical methods. Furthermore, the automated framework reduces human bias, enhances scalability for large datasets, and supports early-stage disease identification, making it more suitable for modern data-driven healthcare environments. This shift from manual assessment to intelligent predictive modeling significantly improves diagnostic efficiency, consistency, and reliability.

5.3 Future Work

Although the proposed Alzheimer's disease prediction system achieved high classification accuracy and reliable performance, several enhancements can be explored to further strengthen its clinical applicability and robustness. Future research may focus on incorporating larger and more diverse datasets to improve generalization across different demographic and geographical populations. The integration of additional clinical indicators, such as neuroimaging features, genetic biomarkers, or longitudinal cognitive assessment data, could significantly enhance predictive precision. Moreover, the application of advanced ensemble learning or hybrid modeling techniques may improve stability and reduce potential bias in borderline cases. Expanding the system into a cloud-based or interoperable healthcare framework would enable scalable deployment and facilitate real-time clinical decision support. Finally, ensuring strict compliance with data privacy regulations and ethical AI principles will be essential for safe integration into practical medical environments. These advancements can contribute toward building a more comprehensive, reliable, and clinically impactful Alzheimer's disease prediction system.

VI. CONCLUSION

Alzheimer's disease continues to pose a serious global health challenge, making early and reliable prediction essential for timely clinical intervention. In this study, a supervised machine learning framework was developed using structured clinical data to support accurate disease prediction. After systematic preprocessing and comparative evaluation of multiple models, the best-performing classifier achieved a test accuracy of 98.2%, demonstrating strong predictive capability and reliable performance on unseen data. Further validation through confusion matrix analysis confirmed the robustness of the model, with 919 true negatives and 63 true positives correctly identified and only a small number of misclassifications. The close similarity between training and testing results indicates stable learning without significant overfitting. Integrating the trained model into a web-based platform further enhances its practical value by enabling real-time predictions through an accessible interface. Overall, the findings highlight the potential of modern machine learning techniques to complement traditional diagnostic methods by providing an objective, scalable, and efficient tool for early Alzheimer's disease assessment.

REFERENCES

[1] P. Pranjal, S. Mallick, A. Das, A. Negi, and M. R. Panda, "Alzheimer's Disease Prediction Using Modern Machine Learning Techniques," in *Proc. 2024 Int. Conf. on Advancements in Smart, Secure and Intelligent Computing (ASSIC)*, Bhubaneswar, India, 2024. Available: https://ieeexplore.ieee.org/document/10507810

[2] K. V. S. S. Rama Krishna, G. Priyanka, S. Sofiya, M. K. Sri, and Y. Jyothirmai, "Early Detection of Alzheimer's Disease Using Machine Learning and Neuroimaging Techniques," in *Proc. 2025 Int. Conf. on Machine Learning and Autonomous Systems (ICMLAS)*, Prawet, Thailand, 2025. Available: https://ieeexplore.ieee.org/document/10968483

[3] K. G. R., K. A., P. T., and P. V., "Deep Learning Into the Future: Hybrid CNN–RNN for Early Detection of Alzheimer's Disease," in *Proc. 2024 5th Int. Conf. on Electronics and Sustainable Communication Systems (ICESC)*, Coimbatore, India, 2024. Available: https://ieeexplore.ieee.org/document/10689926

[4] N. Charanya, M. A., and N. S., "Artificial Intelligence in Alzheimer's Diagnosis: A Comparative Review of Machine Learning and Deep Learning Approaches," in *Proc. 2025 Int. Conf. on Data Science, Agents & Artificial Intelligence (ICDSAAI)*, Chennai, India, 2025. Available:https://ieeexplore.ieee.org/document /11011613

[5] R. R. Sethuraman, H. S., D. K. R., and S. M., "Employing Machine Learning Algorithms for the Prediction of Alzheimer's Disease," in *Proc. 2025 5th Int. Conf. on Trends in Material*

Science and Inventive Materials (ICTMIM), Kanyakumari, India, 2025. Available: https://ieeexplore.ieee.org/document/10988247

[6] G. Gopu, S. Sathish, T. S. Shanmathan, G. Suthakar, N. Sivakumaran, and M. S. Geetha Devasena, "Multi-Modal EEG-Based Classification of Alzheimer's Disease and Mild Cognitive Impairment Using Hilbert–Huang Transform," 2024. Available: https://ieeexplore.ieee.org/document/10582221

[7] A. Thirunagalingam, M. S. Usha, S. Geetha, A. Dhanamathi, S. Dhivya, and M. T. Thendral, "Analysis of Brain Health Using Machine Learning and Artificial Intelligence Technology: A Modern Drug Discovery Perspective," in *Proc. 2025 First Int. Conf. on Advances in Computer Science, Electrical, Electronics, and Communication Technologies (CE2CT)*, Bhimtal, India, 2025. Available: https://ieeexplore.ieee.org/document/10941580

[8] U. Mitra and S. U. Rehman, "ML-Powered Handwriting Analysis for Early Detection of Alzheimer's Disease," *IEEE Access*, 2024. Available: https://ieeexplore.ieee.org/document/10530648

[9] G. Yang *et al.*, "ADFound: A Foundation Model for Diagnosis and Prognosis of Alzheimer's Disease," *IEEE Journal of Biomedical and Health Informatics*, vol. 29, no. 11, pp. 8395–8408, Nov. 2025. Available: https://ieeexplore.ieee.org/document/11023095

[10] J. Liu, X. Tian, H. Lin, H.-D. Li, and Y. Pan, "Multi-Task Learning for Alzheimer's Disease Diagnosis and Mini-Mental State Examination Score Prediction," *Big Data Mining and Analytics*, vol. 7, no. 3, pp. 828–842, Sept. 2024. Available: https://ieeexplore.ieee.org/document/10654676

[11] B. G., B. S., and S. N. R., "A Predictive and Adaptive Mobile/Web Application for Alzheimer's Disease Using Machine Learning," in *Proc. 2024 9th Int. Conf. on Communication and Electronics Systems (ICCES)*, Coimbatore, India, 2024. Available:https://ieeexplore.ieee.org/document/10860053

[12] M. Goutham, V. R. Reddy, S. N. Rakoti, and G. S. N. Rao, "Provisioning a Predictor Model for Alzheimer's Prediction Using Learning Approaches," in *Proc. 2023 Int. Conf. on Sustainable Computing and Data Communication Systems (ICSCDS)*, Erode, India, 2023. Available: https://ieeexplore.ieee.org/document/10104846

[13] M. Boumpi, K. V. Dalakleidi, and J. Pavlopoulos, "From Pen to Prediction: Handwriting-Based Alzheimer's Detection," in *Proc. 2025 IEEE 25th Int. Conf. on Bioinformatics and Bioengineering (BIBE)*, Athens, Greece, 2025. Available: https://ieeexplore.ieee.org/document/11273597

[14] M. G. Kwak, L. Mao, Z. Zheng, Y. Su, F. Lure, and J. Li, "A Cross-Modal Mutual Knowledge Distillation Framework for Alzheimer's Disease Diagnosis Addressing Incomplete Modalities," *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 14218–14233, 2025. Available: https://ieeexplore.ieee.org/document/10945821

[15] S. G. Singh, D. Das, U. Barman, and M. J. Saikia, "Early Alzheimer's Disease Detection: A Review of Machine Learning Techniques for Forecasting Transition from Mild Cognitive Impairment," *Diagnostics*, vol. 14, no. 16, p. 1759, 2024. Available: https://www.mdpi.com/2075-4418/14/16/1759

[16] H. Alshamlan, A. Alwassel, A. Banafa, and L. Alsaleem, "Improving Alzheimer's Disease Prediction with Machine Learning and Feature Selection Techniques," *Diagnostics*, vol. 14, no. 19, p. 2237, 2024. Available: https://www.mdpi.com/2075-4418/14/19/2237

[17] E. Aslan and Y. Özüpak, "Comparison of Machine Learning Algorithms for Automatic Prediction of Alzheimer's Disease," *Journal of the Chinese Medical Association*, 2025. Available:https://pubmed.ncbi.nlm.nih.gov/39965789/

[18] C. Kavitha *et al.*, "Early-Stage Alzheimer's Disease Prediction Using Machine Learning Models," *Frontiers in Public Health*, 2022. Available:https://pubmed.ncbi.nlm.nih.gov/35309200/

[19] M. S. Lakshmi Kanthaiah and G. Mamatha, "Optimizing Early Alzheimer's Detection: Performance Evaluation of SVM, Random Forest, and CNN Models," *International Journal of Intelligent Systems and Applications in Engineering*, 2024. Available:

https://www.ijisae.org/index.php/IJISAE/article/view/6813

[20] M. G. Hussain and Y. Shiren, "Identifying Alzheimer's Disease Dementia Levels Using Machine Learning Methods," *Medical Research Archives*, 2023. Available: https://esmed.org/MRA/mra/article/view/4039