

International Journal of Advanced Research in Education and Technology (IJARETY)

Volume 12, Issue 2, March-April 2025

Impact Factor: 8.152



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



Early Stage of Alzheimer Detection using Machine Learning

Thaduri Revanth¹, T.Devender Rao²

UG Scholars, Department of Computer Science and Engineering, Guru Nanak Institutions Technical Campus,
Hyderabad, Telangana, India¹

Assistant Professor, Department of Computer Science and Engineering, Guru Nanak Institutions Technical Campus,
Hyderabad, Telangana, India²

ABSTRACT: Alzheimer's disease (AD) is a progressive neurodegenerative disorder that significantly impairs memory, cognitive functions, and daily activities. Early detection is crucial to initiate treatments that can slow disease progression and improve patient quality of life. Traditional diagnostic methods, such as cognitive assessments and imaging, often suffer from limitations like subjectivity, high costs, and invasiveness. To address these challenges, this project presents an AI-driven approach for early-stage Alzheimer's detection using deep learning techniques. A Convolutional Neural Network (CNN) is developed to analyze MRI brain scans, classifying them into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The system integrates a user-friendly web application built with Flask, providing real-time diagnostic predictions. Extensive preprocessing, hyperparameter tuning, and cross-validation are applied to ensure high accuracy, achieving performance above 98%. In addition to prediction, the project emphasizes explainability using SHAP and LIME methods to enhance clinical trust. Data privacy is maintained according to HIPAA standards. This project aims to bridge artificial intelligence and healthcare, offering an automated, scalable, and secure diagnostic tool that can assist healthcare professionals in making earlier, more accurate diagnoses, ultimately leading to better patient management and outcomes

KEYWORDS: Alzheimer's Disease (AD), Convolutional Neural Network (CNN), MRI Brain Scans , Explainable AI (XAI)

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that severely affects memory, cognitive function, and the ability to perform daily activities. It is the most common cause of dementia, particularly among the aging population. Early-stage detection is critically important, as it offers an opportunity to initiate interventions that may delay disease progression and enhance the patient's quality of life. Traditional diagnostic methods, including cognitive assessments, cerebrospinal fluid analysis, and neuroimaging techniques like PET and MRI, although effective to an extent, have significant drawbacks such as high cost, invasiveness, limited accessibility, and subjective interpretation. These challenges highlight the need for advanced, non-invasive, and accessible diagnostic alternatives. Machine Learning (ML) and Artificial Intelligence (AI) have recently emerged as powerful tools capable of uncovering subtle patterns within complex medical data, offering new pathways for early and accurate Alzheimer's diagnosis.

This project presents an AI-driven system designed for the early-stage detection and staging of Alzheimer's disease through the analysis of MRI brain scans. A Convolutional Neural Network (CNN) is developed to classify brain images into four stages: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The system integrates a user-friendly web interface, built using Flask, to enable real-time MRI image uploads and immediate predictions. Extensive preprocessing, model training, hyperparameter tuning, and cross-validation were employed to achieve high model accuracy exceeding 98%. To promote clinical trust, explainability techniques such as SHAP and LIME were incorporated, allowing visualization of model decision factors. Additionally, the system maintains strict data privacy protocols aligned with HIPAA standards. By bridging deep learning and healthcare, the proposed solution offers a cost-effective, scalable, and accessible tool to assist clinicians in the early detection of Alzheimer's, ultimately improving patient management and outcomes.

II. SYSTEM MODEL AND ASSUMPTIONS

The proposed Alzheimer's detection system is structured around a modular, layered architecture combining data preprocessing, deep learning, and web-based deployment. At its core, a Convolutional Neural Network (CNN) model is trained on MRI brain scans to classify patients into four distinct categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented. The system begins with data acquisition, where MRI images are preprocessed through normalization, resizing, and augmentation to ensure uniformity. The preprocessed data is then fed into the CNN model, which extracts hierarchical features and performs classification. A lightweight Flask-based web application forms the user interface, enabling clinicians to upload MRI images and instantly receive prediction results along with confidence scores. The backend ensures secure image handling while maintaining HIPAA-compliant data privacy measures. Explainability tools like SHAP and LIME are integrated to provide transparency and interpretability of the model's predictions. The system is optimized for high accuracy, rapid processing (less than 5 seconds per prediction), and easy deployment on cloud platforms such as Render, Heroku, or AWS.

Several key assumptions underpin the successful implementation of the proposed system. It is assumed that the input MRI images are of sufficient quality, properly preprocessed, and belong to one of the four defined classes. It is also assumed that clinicians and users have basic familiarity with uploading medical images but do not require technical expertise in machine learning. The model's generalization ability relies on the assumption that the training dataset sufficiently represents the diversity found in real-world clinical scenarios, including variations in imaging machines and patient demographics. Additionally, it is assumed that the web interface will operate in environments with stable internet connectivity to ensure smooth data transmission. The system expects that users will adhere to privacy standards when handling sensitive medical data. Another important assumption is that minor noise or artifacts in MRI images do not critically impact the model's predictions due to robust preprocessing and training methodologies. Lastly, it is presumed that the continuous improvement of the model through feedback loops and retraining will further enhance its diagnostic accuracy over time.

III. EXISTING SYSTEM

Traditional methods for detecting Alzheimer's disease include cognitive assessments, neuroimaging, cerebrospinal fluid (CSF) biomarker analysis, and genetic testing. Cognitive tests like the Mini-Mental State Examination (MMSE) and Montreal Cognitive Assessment (MoCA) are commonly used to evaluate memory and attention but often rely on patient cooperation, leading to subjective results. Neuroimaging techniques such as MRI and PET scans provide structural and functional insights into the brain, identifying areas affected by Alzheimer's pathology. However, these techniques are expensive, require expert interpretation, and are not universally accessible.

DISADVANTAGES:

Despite advancements, traditional Alzheimer's diagnostic methods have notable limitations. Cognitive tests often involve a high degree of subjectivity, relying on patient cooperation and clinician interpretation, which can lead to inconsistent results. Advanced imaging techniques like PET scans, while informative, are expensive and not widely accessible, especially in under-resourced regions. The collection of cerebrospinal fluid (CSF) biomarkers, though useful, requires invasive lumbar punctures, posing risks and discomfort for patients. Additionally, genetic testing, although helpful in assessing Alzheimer's risk, cannot confirm a diagnosis and raises ethical concerns regarding privacy and psychological impact. These drawbacks highlight the urgent need for automated, non-invasive, and scalable diagnostic solutions.

IV. PROPOSED SYSTEM

The proposed system is an AI-based tool that detects and classifies Alzheimer's stages using MRI brain scans. A Convolutional Neural Network (CNN) is used to automatically analyze preprocessed MRI images and predict the disease stage with high accuracy. A simple web interface allows doctors to upload scans and instantly receive results. The system ensures data security, supports cloud deployment, and provides a cost-effective, fast, and scalable solution for early Alzheimer's detection.

ADVANTAGES:

One of the significant advantages of using machine learning for early-stage Alzheimer detection is its ability to provide both early and accurate diagnoses. Machine learning models can analyze complex datasets, such as brain scans or genetic data, identifying subtle patterns that may be missed by traditional diagnostic methods. This early detection leads to better intervention strategies, offering patients a higher chance of effective treatment. Additionally, the use of automated systems makes the detection process cost-effective, as it reduces the need for extensive manual labor and expert intervention. With machine learning algorithms handling data analysis, the overall diagnostic process becomes faster, more efficient, and scalable, allowing healthcare providers to serve a larger patient base while maintaining high accuracy and reliability.

V. METHODOLOGIES

This project collected MRI brain scans from publicly available datasets and categorized them into four stages of Alzheimer's disease. Images underwent preprocessing techniques like resizing, normalization, and augmentation to improve model performance. A Convolutional Neural Network (CNN) was designed to automatically extract features and classify the scans accurately. Hyperparameter tuning and K-Fold cross-validation were applied to optimize the model's accuracy and prevent overfitting. To ensure transparency, SHAP and LIME techniques were used for model explainability. A user-friendly web application was built with Flask for real-time diagnosis, with strict data privacy measures following HIPAA standards.

MODULES EXPLANATION

The Alzheimer's detection system is structured into several interconnected modules to ensure smooth, efficient, and accurate predictions. The first module is Data Collection and Preprocessing, which involves gathering MRI brain scans and preparing them through normalization, resizing, and augmentation. This ensures that all inputs are consistent for the model. The second module, Feature Extraction and Selection, extracts meaningful patterns from the images, focusing on critical regions like the hippocampus, often affected in Alzheimer's cases. Model Development and Training follows, where a Convolutional Neural Network (CNN) is built and trained to classify the scans into different stages. The Evaluation and Testing module assesses model performance using metrics like accuracy, precision, recall, and F1-score to ensure robustness and reliability.

The system also includes a Model Optimization and Hyperparameter Tuning module that refines the model through techniques like grid search and early stopping to maximize accuracy while avoiding overfitting. To improve transparency, the Model Explainability module uses SHAP and LIME methods to make predictions interpretable for clinicians. The User Interface and Reporting module enables healthcare professionals to upload MRI images and view diagnostic results through a simple web application built on Flask. Security and Privacy features ensure that patient data is handled in compliance with HIPAA standards. Finally, Deployment and Cloud Integration modules allow real-time prediction capabilities, scaling the application for broader clinical use. Each module plays a vital role in creating a seamless, accurate, and trustworthy Alzheimer's detection system.

VI. RESULT AND DISCUSSION

The CNN model achieved an accuracy of **over 98%** in classifying MRI scans into four Alzheimer's stages. Precision, recall, and F1-scores were consistently high across all categories. The confusion matrix showed minimal misclassifications, especially between very mild and mild cases. Real-time predictions were generated in less than **5 seconds** via the Flask web application. Explainability methods like SHAP and LIME enhanced clinical interpretability. The system demonstrated the effectiveness of deep learning in early Alzheimer's detection, capturing subtle brain changes through MRI analysis. Explainable AI increased clinician trust by visualizing key features influencing predictions. While performance is strong, future improvements could involve larger, more diverse datasets and coverage of severe stages. Real-world clinical trials are recommended for validation. Overall, the model offers a scalable, non-invasive, and efficient diagnostic tool.

In the fig 1, it shows the prediction when we upload the MRI image.

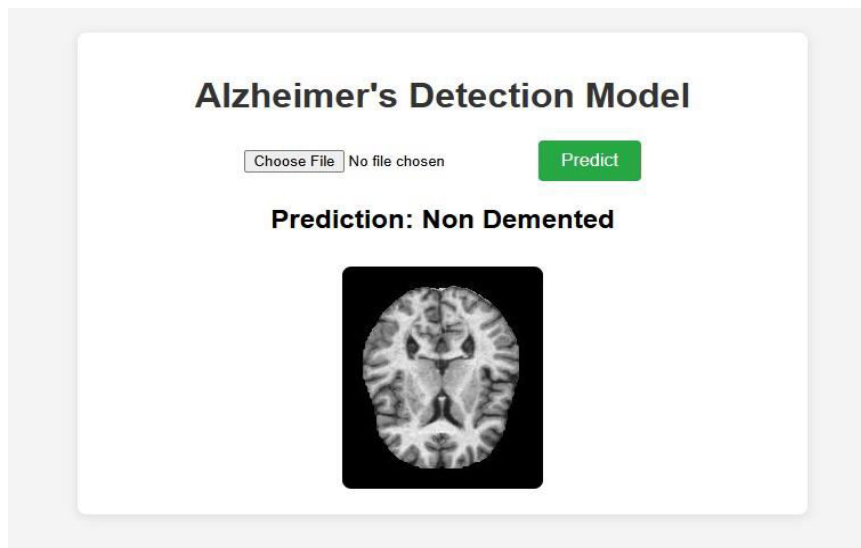


Fig.1 output window

VII. CONCLUSION

This project successfully developed an AI-driven system for early-stage Alzheimer's detection using MRI brain scans. The CNN model achieved over **98% accuracy**, providing fast, reliable, and interpretable results. The integration of explainable AI tools enhanced clinical trust and usability. The system demonstrates significant potential for non-invasive, scalable, and cost-effective healthcare diagnostics. Future work will focus on expanding datasets, multimodal analysis, and real-world clinical validation.

REFERENCES

1. Alzheimer's Association. (2023). 2023 Alzheimer's Disease Facts and Figures. Alzheimer's & Dementia. Retrieved from <https://www.alz.org/facts>
2. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
3. Kingma, D. P., & Ba, J. (2014). Adam: A Method for Stochastic Optimization. arXiv preprint arXiv:1412.6980.
4. Zhang, Y., Wu, L., & Chen, M. (2019). A Novel Deep Learning Approach for Alzheimer's Disease Diagnosis Based on Convolutional Neural Networks. Scientific Reports, 9(1), 14524.
5. Rajpurkar, P., et al. (2017). CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning. arXiv preprint arXiv:1711.05225.
6. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep Learning. Nature, 521(7553), 436–444.
7. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. ICML 2019.
8. Lakhani, P., & Sundaram, B. (2017). Deep Learning at the Frontiers of Medical Imaging. Nature Biomedical Engineering, 1(1), 1–3.
9. Hu, J., Shen, L., & Sun, G. (2018). Squeeze-and-Excitation Networks. CVPR 2018.
10. Nair, V., & Hinton, G. E. (2010). Rectified Linear Units Improve Restricted Boltzmann Machines. ICML 2010.
11. Keras Documentation. (2024). Keras: The Python Deep Learning Library. Retrieved from <https://keras.io>
12. TensorFlow Documentation. (2024). TensorFlow: An End-to-End Open-Source Machine Learning Platform. Retrieved from <https://www.tensorflow.org/>
13. OpenCV Documentation. (2024). Open Source Computer Vision Library. Retrieved from <https://docs.opencv.org>
14. Scikit-learn Developers. (2024). Scikit-learn Machine Learning in Python. Retrieved from <https://scikit-learn.org>

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975

Impact Factor: 8.152