

MindCareAI-Alzheimer's Disease Detection from Scan Using Machine Learning with Chatbot and Hospital Integration

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Abstract— Alzheimer's disease is an unrepairable degenerative brain disease. Every four seconds, someone in the world is diagnosed with Alzheimer's disease. The result is fatal, as it leads to death. As a result, it's crucial to catch the disease early on. The leading cause of dementia is Alzheimer's disease. Dementia causes a reduction in reasoning abilities and interpersonal coping skills, which affects people's ability to function independently. The patient will forget recent events in the early stages. If the illness progresses, they will gradually forget whole events. It is essential to diagnose the disease as soon as possible. This paper proposes a model that takes brain MRI sample images as input and determines whether a person has mild, moderate, or no Alzheimer's disease as an output. We are using the VGG19 and DenseNet169 architectures for this classification, providing a comparative analysis of which architecture shows promising results.

Index Terms— Alzheimer's, MRI images, VGG19, CNN DenseNet.

I. INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder that primarily affects memory, thinking, and behavior. It is one of the leading causes of dementia worldwide, with millions of individuals affected each year. Early and accurate detection of Alzheimer's is critical, as timely diagnosis enables better patient management, treatment planning, and improved quality of life. However, traditional diagnostic methods often rely on manual interpretation of MRI scans, clinical interviews, and cognitive tests, which can be time-consuming and prone to human error.

With the rapid advancements in artificial intelligence (AI) and medical imaging, machine learning (ML)

techniques have emerged as powerful tools for automated disease detection and diagnosis. Machine learning algorithms can analyze complex MRI brain scan patterns, identify early biomarkers of Alzheimer's, and provide predictive insights with high accuracy. This integration of AI with healthcare aims to support radiologists and neurologists by offering faster, more consistent, and data-driven diagnostic outcomes.

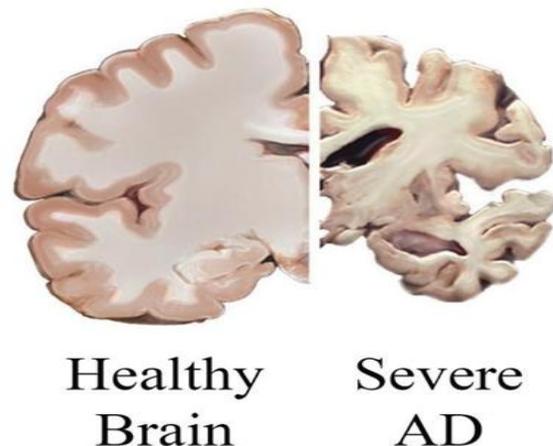


Fig. 1. Image representing a Healthy Brain vs. Severe AD Brain

The MindCareAI, combines machine learning-based Alzheimer's detection with a patient-interactive chatbot and hospital integration module. The system allows users to upload MRI scans, which are processed through a trained ML model to detect potential Alzheimer's indicators. The built-in chatbot enables users to interact with the system, receive disease predictions in an understandable format, and ask health-related questions for better awareness. Additionally, the platform is integrated with hospital and doctor databases to display nearby medical centers and specialists for immediate consultation.

By automating MRI scan analysis and providing a seamless communication bridge between patients and healthcare providers, MindCareAI aims to enhance early diagnosis, reduce diagnostic workload, and promote accessible healthcare through intelligent technology. This fusion of machine learning, conversational AI, and hospital networking represents a significant step toward smart, patient-centric medical solutions.

II. LITERATURE SURVEY

Several research studies have been conducted on the automated detection of Alzheimer's Disease (AD) using machine learning and deep learning models applied to MRI images. These studies primarily focus on improving diagnostic accuracy, interpretability, and computational efficiency.

Sharma et al. (2023) proposed a Deep Transfer Learning-Based Automated Alzheimer's Detection model utilizing the VGG16 architecture with Grad-CAM visualization. Their system achieved a high accuracy of 92%, effectively identifying critical brain regions associated with Alzheimer's. However, their approach required large datasets and lacked multimodal data integration, which limited its generalizability. Lee et al. (2024) introduced an Explainable Alzheimer's Diagnosis framework using Vision Transformers (ViT) combined with Grad-CAM. This study emphasized visual interpretability to enhance clinician trust in AI-based diagnosis. Although the interpretability improved significantly, the model required high computational power and GPU support for real-time inference, restricting its practical deployment in resource-constrained environments.

Ahmed et al. (2022) developed an Ensemble CNN model combining ResNet50 and VGG19 architectures for Alzheimer's stage classification. Their approach achieved higher accuracy in distinguishing mild and moderate stages of the disease. Despite its improved precision, the model suffered from increased computational complexity, making it less suitable for real-time clinical applications. Kumar and Patel (2023) proposed a Lightweight CNN model for Alzheimer's detection on edge devices. Their method achieved 88% accuracy with a significantly reduced inference time, demonstrating potential for deployment on portable systems. However, the model's performance

declined when dealing with noisy MRI images, highlighting the need for robust preprocessing techniques. Chen et al. (2023) explored multimodal deep learning by integrating MRI and genetic data using a Deep CNN framework. This study showed improved prediction accuracy by leveraging complementary data sources. Nonetheless, the approach was constrained by the limited availability of multimodal datasets, which restricted large-scale validation.

Lastly, Verma et al. (2022) implemented Grad-CAM Visualization for Interpretable Alzheimer's Diagnosis, emphasizing clinical explainability. Their system enhanced medical acceptance through transparent visual explanations but was limited to specific CNN layers, reducing its flexibility for broader applications. Overall, the reviewed literature demonstrates significant progress in Alzheimer's detection using deep learning models. However, there remains a gap in combining diagnostic accuracy, interpretability, and clinical integration. The proposed system, MindCareAI, aims to address these gaps by integrating machine learning-based MRI analysis, chatbot assistance, and hospital connectivity, providing an intelligent and user-centric diagnostic platform.

III. PROPOSED WORK

The proposed system, MindCareAI, is designed to create an intelligent and integrated platform that automates the detection of Alzheimer's Disease (AD) from MRI brain scans using machine learning techniques. In addition to disease prediction, the system incorporates an interactive chatbot and hospital integration module to provide comprehensive healthcare support. By combining artificial intelligence (AI), conversational interfaces, and hospital networking, MindCareAI aims to enhance diagnostic accuracy, accessibility, and patient engagement within a single unified web-based solution.

The system operates through three major components that function in coordination: the machine learning-based Alzheimer's detection module, the chatbot for prediction interaction and assistance, and the hospital and doctor integration system. The process begins when the user uploads an MRI brain scan to the system. The uploaded image undergoes preprocessing techniques such as resizing, noise removal, and

normalization to improve image clarity and consistency. The refined image is then analyzed by a trained deep learning model, which automatically extracts important spatial and structural features of the brain to identify Alzheimer’s-specific abnormalities. Based on the extracted features, the system classifies the scan into one of several diagnostic categories such as normal, mild, moderate, or severe Alzheimer’s disease.

Once the classification is completed, the results are communicated to the user through an intelligent chatbot interface. This chatbot acts as a virtual medical assistant, providing users with understandable explanations of the diagnosis, answering queries related to Alzheimer’s symptoms, prevention, and treatment, and offering general health guidance. Furthermore, to ensure timely medical attention, the system is connected to a hospital and doctor database that identifies nearby healthcare facilities and specialists. The chatbot presents users with this information, allowing them to seek professional consultation immediately if the results indicate possible Alzheimer’s detection.

In addition to diagnosis and consultation support, MindCareAI generates an automated diagnostic report summarizing the prediction outcome, confidence score, and critical brain regions identified by visualization techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM). This report can be downloaded or shared with healthcare professionals for further evaluation. By integrating deep learning-based MRI analysis with conversational AI and real-time hospital connectivity, MindCareAI seeks to provide a reliable, transparent, and accessible tool for early Alzheimer’s detection and patient-centered care.

A. Dataset

The data is sourced from an open online dataset library called Kaggle, which has not yet been used in various research projects and studies. It is an open-source dataset. This dataset contains nearly 6,000 images categorized into four classes labeled Mildly, Moderately, Very Mildly, and Non-Demented. The features are split into 80% training data and 20% testing data. Using 80% for training means that each deep learning model has two phases: training and testing, where it predicts the provided data. Both models use the same dataset, separate from the original Kaggle dataset, divided in an 8:2 ratio 80% for training

and 20% for validation. The datasets must have the same distribution to avoid discrepancies in comparing the predictions of both models, ensuring they receive similar types of input.

This removes the question upon both the models and brings them to the same inspection level that both were using, not the same dataset, and was trained and tested upon the exact distribution of the dataset.

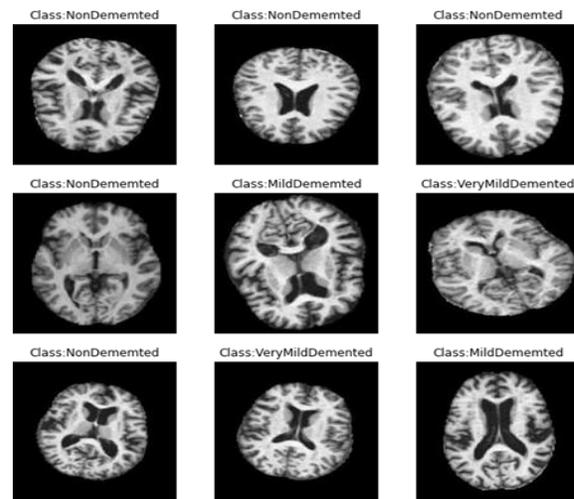


Fig. 2. Dataset after Pre-processing

B. Methodology

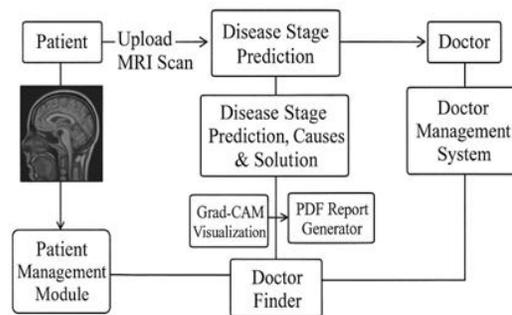


Fig. 3. Proposed Methodology

The system architecture diagram of MindCareAI illustrates the complete workflow from MRI scan input to disease prediction and hospital integration. The process begins when the patient uploads an MRI brain scan through the Patient Management Module, which stores and manages patient data securely. The scan is then analyzed in the Disease Stage Prediction module using a trained machine learning model to identify the presence and stage of Alzheimer’s Disease. The results, along with possible causes and

suggested solutions, are processed further for interpretability using Grad-CAM visualization, which highlights affected brain regions. A detailed diagnostic report is automatically generated through the PDF Report Generator for patient and doctor reference. The Doctor Finder module then locates nearby neurologists or hospitals based on the diagnosis results, ensuring timely medical consultation. Finally, the Doctor Management System connects patients with doctors for expert evaluation and follow-up treatment, creating a complete AI-driven healthcare loop that integrates automated diagnosis, explainability, and medical connectivity.

C. Convolutional Neural Network Alzheimer Disease

We used CNN to classify AD using MRI images. CNN is a special DL method for image CNN consists of multiple convolutional layers, pooling layers, and dense layers. In CNN, the convolutional layers and pooling layers perform feature extraction of AD (affected regions) to distinguish the features between the affected regions [33]. We mapped the features using multiple kernels because we only select one feature whether the regions are affected by AD or not. The rectified linear unit (ReLU) activation function was used to calculate the values. Then, pooling layers reduce the area from MRI that is not associated with Alzheimer's affected region. Moreover, pooling layers also reduce the computational cost. We applied Max Pooling in the query layers to increase the computational efficiency. We have used a number of convolutional layers and pooling layers that identify the features. The last pooling layer is connected with the dense layer with the flat layer which is fully connected. The learning process takes place in the dense layer and classifies our images.

IV. EXISTING BARRIERS AND LIMITATIONS

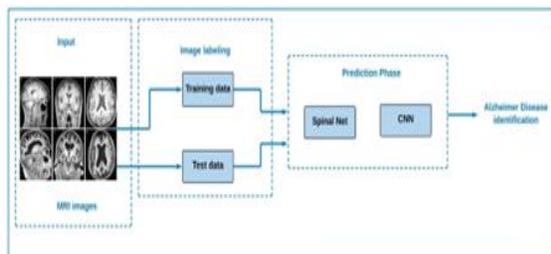


Fig. 4. Existing method for AD analysis from MRI images.

The existing system for Alzheimer's Disease detection primarily relies on deep learning models such as Convolutional Neural Networks (CNN) and Spinal Net for analyzing MRI brain scans. As shown in the diagram, the process begins with the input of MRI images, which are preprocessed and divided into training and testing datasets during the image labeling phase. These datasets are then used to train and evaluate the neural networks to identify Alzheimer's Disease based on learned patterns in the brain images. Although this method achieves reasonable accuracy, it faces several limitations that hinder its clinical applicability. The system lacks interpretability, as deep learning models often act as "black boxes," providing predictions without clear explanations of the decision-making process.

Additionally, it operates in isolation, without integration with hospitals, doctors, or patient management systems. There is also no interactive interface, such as a chatbot, to assist patients in understanding results or obtaining medical guidance. Moreover, the accuracy of the model depends heavily on the quality and size of the MRI dataset, which can lead to inconsistencies if data is limited or imbalanced. Finally, this approach is more suitable for research environments and lacks real-time diagnostic and healthcare integration capabilities. These limitations highlight the need for an advanced, user-centric, and integrated system like MindCareAI, which addresses these barriers by combining AI-based detection, chatbot interaction, and hospital connectivity.

V. CONCLUSION

In this project, we are going to integrate machine learning, medical imaging, and chatbot technology to create an intelligent platform for the early detection of Alzheimer's disease. By analyzing MRI brain scans using deep learning models, the system can accurately identify the presence and stage of the disease. The inclusion of a chatbot provides users with interactive support, explaining the diagnosis in simple terms and offering preventive healthcare tips.

Additionally, the system is designed with hospital and doctor data integration, enabling patients to easily locate nearby medical specialists for timely consultation. This end-to-end approach not only improves diagnostic accuracy but also enhances accessibility and patient awareness. Overall, MindCareAI

represents a significant step toward smarter, faster, and more patient-centered healthcare solutions for Alzheimer's disease detection and management.

REFERENCES

- [1] Sharma, R., Mehta, S., and Gupta, A., "Deep Transfer Learning-Based Automated Alzheimer's Detection Using MRI Images," Proceedings of the International Conference on Medical Imaging and Deep Learning, 2023.
- [2] Lee, J., Kim, H., and Park, S., "Explainable Alzheimer's Diagnosis Using Vision Transformers and Grad-CAM," IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2024.
- [3] Ahmed, T., Khan, M., and Yousaf, M., "Ensemble CNN for Alzheimer's Stage Classification," Journal of Computational Neuroscience, 2022.
- [4] Kumar, P., and Patel, D., "Lightweight CNN for Alzheimer's Detection on Edge Devices," International Journal of Artificial Intelligence and Applications, 2023.
- [5] Chen, L., Wang, Z., and Zhao, Y., "Alzheimer's Disease Detection Using Multimodal Data and Deep Learning," Frontiers in Computational Neuroscience, 2023.
- [6] Verma, R., Singh, N., and Bhatia, K., "Grad-CAM Visualization for Interpretable Alzheimer's Diagnosis," IEEE Access, 2022.