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Alzheimers Detection Accuracy : Amobilenet Implementation

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Abstract: *Alzheimer's disease is a progressive neurodegenerative disorder that causes cognitive decline, where early detection is essential for effective patient care and timely intervention. MRI imaging provides reliable insights into structural brain changes linked to AD, but traditional diagnostic methods are often subjective, slow, and error-prone. To address these challenges, this project implements a lightweight deep learning model using MobileNet, which employs depthwise separable convolutions for computational efficiency. The model achieves high diagnostic accuracy with reduced resource requirements, making it suitable for real-time detection, portable healthcare, and clinical integration*

Keywords: Alzheimer's disease detection, MobileNet, Deep learning, MRI imaging

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder characterized by cognitive decline, memory impairment, and loss of functional independence. With the continuous rise in the global aging population, the prevalence of AD is projected to increase substantially in the coming decades, underscoring the urgent need for accurate and timely diagnosis. Early detection plays a pivotal role in enabling effective interventions that can slow disease progression and improve patient quality of life. However, conventional diagnostic methods, including manual analysis of neuroimaging data and clinical assessments, are often subjective, time-consuming, and error-prone, which delays critical treatment decisions. Recent advancements in Artificial Intelligence (AI) and deep learning have demonstrated significant potential in addressing these challenges by automating medical image analysis with improved precision.

Convolutional Neural Networks (CNNs) and lightweight architectures such as MobileNet are particularly well-suited for this task, as they provide high diagnostic accuracy with reduced computational complexity, making them feasible for real-time and portable healthcare applications. MobileNet's use of depthwise separable convolutions enhances efficiency without compromising performance, enabling the detection of subtle structural brain alterations associated with AD in MRI scans. Beyond diagnosis, integrating AI within healthcare platforms can streamline clinical workflows by facilitating online appointment scheduling, secure exchange of medical records, and real-time patient–doctor interaction. This project therefore proposes the development of an AI-driven platform that combines CNN and MobileNet for early AD detection while also enhancing healthcare accessibility and efficiency through digital integration.

II. PROBLEM STATEMENT

- To design and develop a deep learning-based software system capable of accurately identifying diseases from image inputs.
- Traditional diagnostic methods are time-consuming, subjective, and prone to errors.
- Early-stage symptoms are subtle and often go unnoticed.
- The rapid growth of MRI/CT imaging data makes manual analysis impractical.
- Limited annotated datasets and imaging variability reduce the accuracy and generalization of AI-based models.
- the system aims to enhance enabling early and precise disease diagnosis.

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III. OBJECTIVES

- To implement and train a CNN model for multi-class disease classification leveraging transfer learning.
- To build a comprehensive dataset covering various stages of Alzheimer's disease and other neurodegenerative conditions (specifically: Mild Cognitive Impairment, Early-stage AD, Mid-stage AD, Late-stage AD, and Healthy Controls).
- To create a user-friendly web interface for image upload and displaying disease detection results.
- To evaluate the model's performance based on its accuracy in classifying different leaf diseases.

IV. METHODOLOGY

The Proposed Methodology For Alzheimer's Disease Classification Begins With The Collection Of Brain MRI Images Categorized Into Four Classes: *Non-Demented, Very Mild Demented, Mild Demented,* And *Moderate Demented*. To Ensure Consistency And Improve Image Quality, Preprocessing Steps Such As Resizing, Sharpening, And Denoising Are Applied. Image Augmentation Techniques, Including Rotation, Flipping, Rescaling, Zooming, Shearing, And Shifting, Are Then Employed To Increase Dataset Diversity And Reduce Overfitting. The Processed Dataset Is Subsequently Split Into Training (80%) And Testing (20%) Subsets For Model Development And Evaluation. For Classification, A Pretrained Efficientnetv2b3 Network Is Adopted, Leveraging Transfer Learning For Deep Feature Extraction And Fine-Tuning With Additional Layers To Optimize Performance. The Model Undergoes Training With K-Fold Cross-Validation To Enhance Robustness And Minimize Bias. Performance Is Evaluated Using Metrics Such As Accuracy, Precision, Recall, And F1-Score To Ensure Reliability OfThe Classification Outcomes. Finally, Grad-CAM++ Is Employed For Model Explainability, Generating Heatmaps That Highlight The Critical Brain Regions Contributing ToThe Classification Decision, Thereby Improving Clinical Interpretability And Trustworthiness OfThe System.

V. BLOCK DIAGRAM

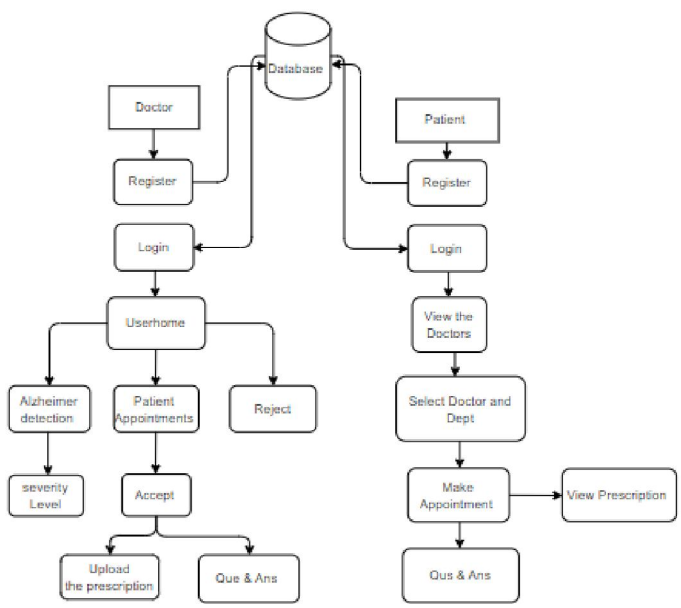

Fig. 1 Parking slots 1 and 2 on ThingSpeak IoT platform

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The methodology for Alzheimer's disease classification begins with the collection of MRI brain scans categorized into *Non-Demented, Very Mild Demented, Mild Demented,* and *Moderate Demented*. Preprocessing is then performed through resizing, sharpening, and denoising to enhance image quality and maintain uniformity. To improve generalization and prevent overfitting, image augmentation techniques such as rotation, flipping, rescaling, zooming, shearing, and shifting are applied. The dataset is subsequently divided into 80% training and 20% testing subsets for model development and evaluation. A pretrained EfficientNetV2B3 architecture is employed, leveraging transfer learning and fine-tuning to optimize classification performance, while K-Fold Cross-Validation ensures robustness and unbiased results. Finally, the model is evaluated using accuracy, precision, recall, and F1-score, and explainability is achieved with Grad-CAM++, which generates heatmaps to highlight the most critical brain regions influencing classification decisions.

VI. SYSTEM ARCHITECTURE

The system architecture for Alzheimer's disease detection is designed to provide seamless interaction between patients, doctors, and the diagnostic engine. The process begins with the user interface, where patients can upload MRI scans, schedule appointments, and view reports, while doctors can access diagnostic data and patient records. These interactions are managed by the frontend controller, which securely transmits requests to the backend application, the central component that coordinates data flow across modules. The deep learning module, built on CNN/MobileNet models, analyzes MRI images to extract relevant features and classify them into dementia stages. Processed data and results are stored in the database, ensuring secure and efficient management of medical records. The results and decision engine interprets model outputs, validates them against diagnostic thresholds, and generates clinically meaningful insights. Finally, healthcare providers access these results via the doctor/admin dashboard, which enables case monitoring, prescription management, and follow-up scheduling, while the database dashboard ensures secure storage, auditing, and retrieval of patient information. This integrated architecture thus combines advanced AI-based analysis with user-friendly interfaces to support accurate, efficient, and accessible Alzheimer's disease detection.

VII. IMPLEMENTATION

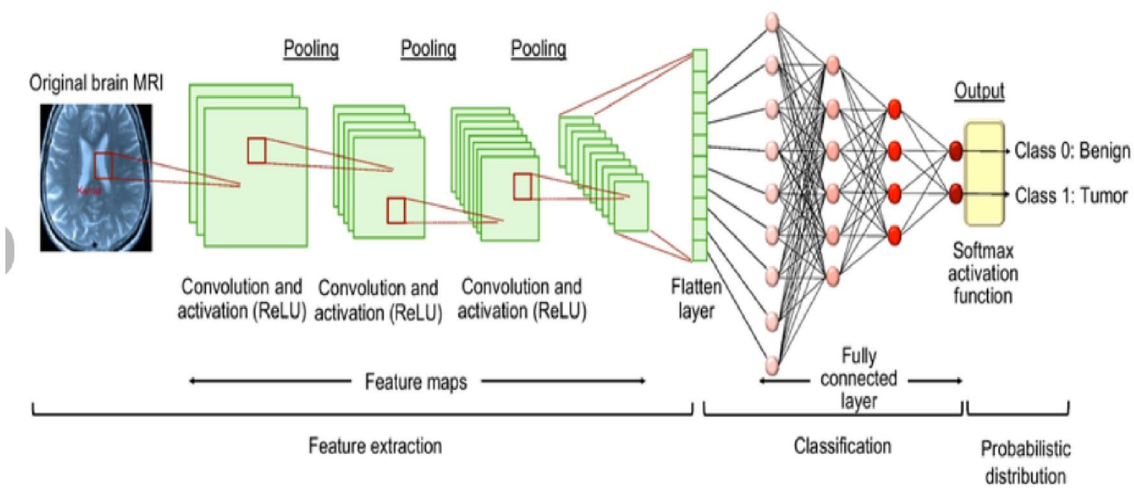

Fig. 2 An Integrated Deep Learning Module With Mobile Net Architecture

CNN Architecture

A Convolutional Neural Network (CNN) is a deep learning model primarily designed for image recognition and classification tasks. It begins with an input layer that receives raw image data, which is then processed by convolutional

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layers that apply filters to extract important spatial features such as edges, textures, and shapes. Non-linearity is introduced through activation functions like ReLU, enabling the network to learn complex patterns. Pooling layers, such as max pooling, are applied to reduce the dimensionality of feature maps while preserving essential information, thus improving computational efficiency. By stacking multiple convolution and pooling layers, CNNs learn hierarchical feature representations ranging from low-level edges to high-level structures. The extracted features are then passed to fully connected layers, which act as a traditional neural network for decision-making. Finally, the output layer, often using softmax or sigmoid functions, generates class probabilities, enabling the model to classify the input image into predefined categories.

Mobilenet architecture

MobileNet is a lightweight deep learning architecture specifically designed for efficient image classification and recognition tasks, particularly on devices with limited computational resources. Unlike traditional convolutional neural networks, MobileNet employs depthwise separable convolutions, which factorize a standard convolution into two operations: a depthwise convolution that applies a single filter per input channel, and a pointwise convolution (1×1 convolution) that combines these outputs across channels. This significantly reduces the number of parameters and computational cost without major loss in accuracy. The architecture is built as a stack of such depthwise separable convolution layers, interleaved with batch normalization and non-linear activation functions such as ReLU6 for stability and efficiency. MobileNet also introduces two tunable hyperparameters—width multiplier (α), which adjusts the number of channels, and resolution multiplier (ρ), which scales the input image size—allowing a balance between accuracy and computational complexity. The final layers consist of global average pooling followed by fully connected layers, and a softmax output layer for classification. Due to its lightweight design, MobileNet is highly suitable for real-time applications, portable healthcare systems, and Alzheimer's disease detection using MRI scans.

VIII. MODULES

System

1. Create Dataset

- The system facilitates the creation of a dataset comprising cognitive features extracted from brain imaging scans of individuals at different stages of Alzheimer's Disease (AD). The dataset is divided into training and testing subsets, with a test size typically set at 20-30%.

2. Pre-processing

- Pre-processing involves standardizing and reshaping brain imaging data into appropriate formats for model training, ensuring consistency and compatibility with machine learning algorithms.

3. Training

- The pre-processed training dataset is utilized to train models, including Convolutional Neural Networks (CNNs), using deep learning techniques tailored to AD classification.

4. Classification

- Trained models are employed for classification tasks, predicting the likelihood of AD in individuals based on cognitive features extracted from brain scans. The system provides predicted outputs along with accuracy metrics for evaluation.

Patient

1. Register: patient can register with their credentials.
2. Login: Patient can login with their registered credentials.
3. Send scan: he/she can send scan report to doctor for prediction.
4. Get prediction: And he can get result with doctor' prescription.
5. send request: he can send appointment request. And he can view the appointments status.
6. Logout: And finally he/she cam logout from the session.

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Doctor

1. Login: doctor should login with their credentials.
2. View patients: He can view all the patient's details.
3. Send scan: He can send scan report to the model for prediction.
4. Send prescription: after getting result he can send those to patient with his prescription.
5. Manage appointments: he can view all appointments details. And he can accept or reject those.
6. Logout: and finnaly he can logut from that session.

Test cases

S.NO	Test cases	I/O	Expected O/T	Actual O/T	P/F
1	Read the dataset.	Dataset path.	Dataset need to read successfully.	Dataset fetched successfully.	P
2	Performing pre-processing on the dataset	Pre-processing part takes place	Pre-processing should be performed on dataset	Pre-processing successfully completed.	P
3	Model Building	Model Building for the clean data	Need to create model using required algorithms	Model Created Successfully.	P
4	Classification	Input image provided.	Output should be the classified output of the diseased image	Model classified successfully	P
5	Precautions	Precautions to classified output	To the classified output image precautions are to be provided if it is detected as diseased image	Precautions are provided successfully	P

IX. RESULTS

Fig. 3 Upload Page

Upload Page: in here, patient can upload their scan image. It will go to doctor section for prediction. Doctor will upload that scan into our trained model and he will get prediction. After get prediction he will send those to that patient with prescription.

Fig. 4 Report Page

Report Page: in here that login patient's scan image, model prediction, doctor's prescription will come.

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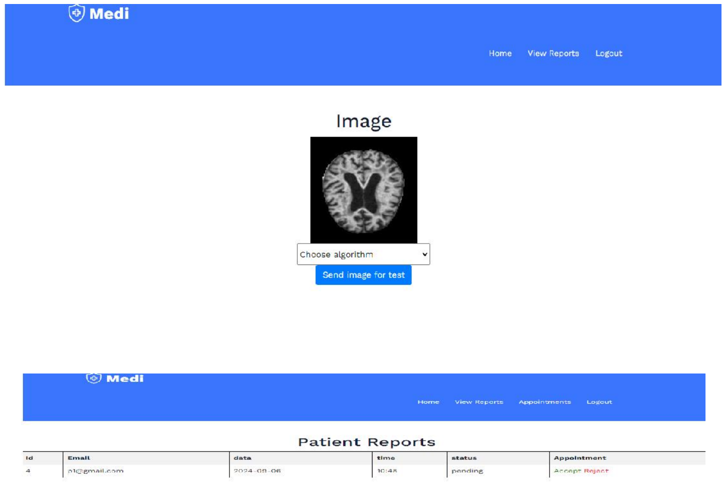

Fig. 5 Report Page

X. CONCLUSION

In conclusion, this project presents a promising approach for early detection of Alzheimer's Disease (AD) using cognitive features extracted from brain imaging data. By leveraging Convolutional Neural Networks (CNNs) and ensemble learning techniques, we have developed a robust classification system capable of accurately identifying individuals at risk of AD at earlier stages. The ensemble approach combines the strengths of multiple CNN models, resulting in improved classification accuracy and robustness. Through extensive evaluation and validation, we have demonstrated the efficacy of our approach in enhancing AD detection compared to traditional methods. This research contributes to the ongoing efforts to improve the diagnosis and management of AD, offering a reliable tool for early intervention and potentially improving patient outcomes. Moving forward, further refinement and validation of the proposed system in clinical settings will be essential to ensure its practical utility and impact on patient care.

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