Alzheimer's Disease Prediction Using Machine Learning

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Abstract- Alzheimer's disease is a progressive neurodegenerative condition that affects millions of people worldwide, causing memory loss, cognitive decline, and eventual loss of independence. Early detection is essential for slowing its progression and improving patient quality of life. This project presents a deep learning-based system for the automatic detection of Alzheimer's disease using medical imaging data, specifically MRI scans. Leveraging convolutional neural networks (CNNs), the model is trained to distinguish between healthy individuals and patients at different stages of the disease. It learns to identify subtle spatial and structural abnormalities in brain images that often go unnoticed in traditional analysis. The framework is developed and validated using benchmark datasets such as ADNI, ensuring robust and reliable performance. Experimental results show high accuracy, sensitivity, and specificity, highlighting the effectiveness of deep learning in detecting early signs of Alzheimer's. This approach represents a promising advancement toward automated, non-invasive, and efficient diagnosis, supporting clinicians in early intervention and personalized treatment planning.

Index Terms— Alzheimer, convolutional neural networks (CNNs), MRI, deep learning, ADNI

I. INTRODUCTION

Alzheimer's disease (AD) is the leading cause of dementia, marked by progressive cognitive decline, memory loss, and behavioral and personality changes. It accounts for 60–80% of dementia cases, predominantly affecting older adults. As global life expectancy rises, the prevalence of AD is increasing sharply, creating substantial emotional, social, and economic burdens for families, caregivers, and healthcare systems.

Early and accurate diagnosis is crucial for slowing disease progression, improving quality of life, and guiding effective treatment strategies. However, conventional diagnostic methods—such as cognitive testing, patient history assessment, and manual interpretation of neuroimaging—are often subjective, time-intensive, and prone to variability. Magnetic Resonance Imaging (MRI) offers valuable insights by revealing structural brain changes, such as hippocampal atrophy, but subtle abnormalities in the early stages can be difficult to detect, even for experienced radiologists.

Recent advancements in deep learning, a subfield of artificial intelligence, have transformed medical imaging analysis, often outperforming traditional machine learning in accuracy and robustness. Convolutional Neural Networks (CNNs), in particular, excel at identifying complex patterns in image data. This project investigates the use of CNN-based models for automated detection of Alzheimer's disease from MRI brain scans. The system is designed to classify individuals as cognitively normal, mildly cognitively impaired (MCI), or having Alzheimer's, enabling earlier and more reliable detection.

Trained on benchmark datasets such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), the proposed framework integrates advanced image processing and classification techniques to detect disease markers with high precision. The ultimate goal is to create a non-invasive, scalable, and efficient diagnostic tool that supports clinicians in making informed decisions and contributes to better management and early intervention in Alzheimer's disease.

II. LITERATURE SURVEY

Nanni et al. (2021), explored ensemble learning by combining multiple deep models to improve robustness in classifying Alzheimer's stages.
Limitations: Ensemble methods increased computational time and were difficult to interpret clinically.
Zhang et al. (2022) , a dual-attention mechanism was applied to CNNs for focusing on brain regions most affected by Alzheimer's. The system provided more interpretable results along with high accuracy.
Limitations: The attention maps were dependent on the training data and could mislead when encountering unseen anatomical anomalies.
Ravi et al. (2022) , they integrated clinical data with MRI images using a deep multimodal approach to enhance the Alzheimer's detection pipeline.
Limitations: Integration complexity and data heterogeneity posed challenges in real-world deployment.
Yu et al. (2023), developed a Transformer-based architecture for Alzheimer's diagnosis, capturing global dependencies in MRI volumes better than CNNs.
Limitations: Training Transformer models on 3D data was memory-intensive and lacked interpretability.
Joshi et al. (2023), used unsupervised pretraining with contrastive learning to improve feature representations of MRI data for Alzheimer's classification.
Limitations: Model performance relied heavily on careful augmentation and required fine-tuning with labeled data.
Gupta et al. (2024) , proposed a novel capsule network for detecting structural abnormalities in early Alzheimer's cases. It preserved spatial hierarchies better than CNNs.
Limitations: Capsule networks are harder to train, and the model needed more computational time than standard CNNs.
El-Gamal et al. (2024), focused on federated deep learning for Alzheimer's detection to preserve patient privacy while aggregating model knowledge across hospitals.
Limitations: Communication overhead and non-uniform data distribution affected learning consistency.
Singh et al. (2025), recently introduced a lightweight CNN model optimized for mobile diagnosis tools, with high speed and good accuracy using quantized models.
Limitations: Sacrificed some model depth for speed, which reduced accuracy slightly on borderline MCI cases.

III. PROPOSED SYSTEM

The proposed system introduces a deep learning-based framework for early detection of Alzheimer's disease using structural MRI brain scans. It automates the diagnostic process by classifying images into cognitively normal (CN), mild cognitive impairment (MCI), or Alzheimer's disease (AD) categories. Raw T1-weighted MRI images undergo preprocessing steps such as skull stripping, intensity normalization, resizing, and, if needed, slice extraction for 2D analysis.

The processed images are then input into a Convolutional Neural Network (CNN) that automatically learns spatial features associated with Alzheimer's-related structural brain changes. The CNN architecture typically includes multiple convolutional layers with ReLU activation, pooling layers, dropout for regularization, and fully connected layers for classification. A softmax or sigmoid activation function is applied at the output layer, depending on whether the task is multi-class or binary classification.

The model is trained on benchmark datasets such as ADNI, optimized using the Adam optimizer and categorical cross-entropy loss. For enhanced accuracy and adaptability, transfer learning with pre-trained models like VGG16 can be employed. The system outputs the predicted class with an associated confidence score, offering a non-invasive, scalable, and efficient tool to support clinicians in early diagnosis and intervention for Alzheimer's disease.

IV. METHODOLOGY

a) Step 1: Dataset Collection

- Source: Publicly available datasets like ADNI, OASIS, or Kaggle Alzheimer's datasets.
- Data Types: T1-weighted MRI or PET scans.

- Labels: Classified into groups such as:
  - CN (Cognitively Normal)
  - MCI (Mild Cognitive Impairment)
  - AD (Alzheimer's Disease)

b) Step 2: Data Preprocessing

- Image Resizing: Standardize all MRI slices to a fixed size (e.g., 224x224 pixels).
- Normalization: Normalize pixel values (0–1 or z-score).
- Data Augmentation: Rotation, flipping, shifting (to reduce overfitting).
- Slicing: If using 3D data (volumetric), convert to 2D slices or process as 3D.

c) Step 3: Deep Learning Model Design

OPTION 1: CNN FROM SCRATCH

- Input layer: (224x224x1)
- Conv2D → ReLU → MaxPooling → Dropout
- Multiple such convolutional blocks
- Flatten → Dense layers → Output layer (Softmax for multi-class)

OPTION 2: PRETRAINED MODEL (E.G., VGG16)

- Use pretrained VGG16 on ImageNet as a feature extractor
- Freeze initial layers, fine-tune top layers
- Add custom dense layers for classification

```
from TensorFlow. keras. applications import VGG16
base model = VGG16(weights='ImageNet', include_top=False,
input shape=(224,224,3)) for layer in base model. layers [:-4]:
 layer. Trainable = False
```

d) Step 4: Model Training

- Loss Function: categorical_crossentropy or binary_crossentropy (based on output classes)
- Optimizer: Adam or RMSProp
- Metrics: Accuracy, Precision, Recall, F1-score
- Epochs: 20–100 (with early stopping)
- Batch Size: 16/32

e) Step 5: Model Evaluation

- Use Confusion Matrix, AUC-ROC, and Accuracy scores.
- Evaluate on a separate test set (20–30% split).
- Perform k-Fold Cross Validation for reliability.

V. RESULTS

66	21	0.7	4195.2	F	MCI
79	27	1.5	4028.6	F	Normal
88	29	1.3	5926.5	M	Normal
74	25	1.7	5633.3	F	MCI
70	27	1.3	5499.3	M	Normal
67	18	1.1	5502.7	F	MCI
88	27	0.2	4990.2	M	Normal
80	21	0.7	4282.2	F	MCI
66	25	0.5	5060.6	M	MCI
85	17	0.5	4458.3	M	MCI
78	20	1.9	5780.1	F	MCI
82	26	0.8	4882.4	F	MCI
70	16	1.8	4339.6	F	Alzheimer
70	24	1.3	4742.9	F	MCI
83	27	1.6	5330.3	M	Normal
80	28	1.0	4549.0	F	Normal
63	23	1.2	4342.2	M	Alzheimer
67	19	1.0	5194.9	M	MCI
83	20	0.4	5196.0	F	MCI
62	26	1.4	4594.4	M	MCI
81	26	0.6	4623.2	M	MCI
80	26	0.0	5185.6	M	MCI
61	26	1.3	3841.5	M	MCI
83	18	0.4	3874.0	F	MCI

Figure 1: Read Dataset

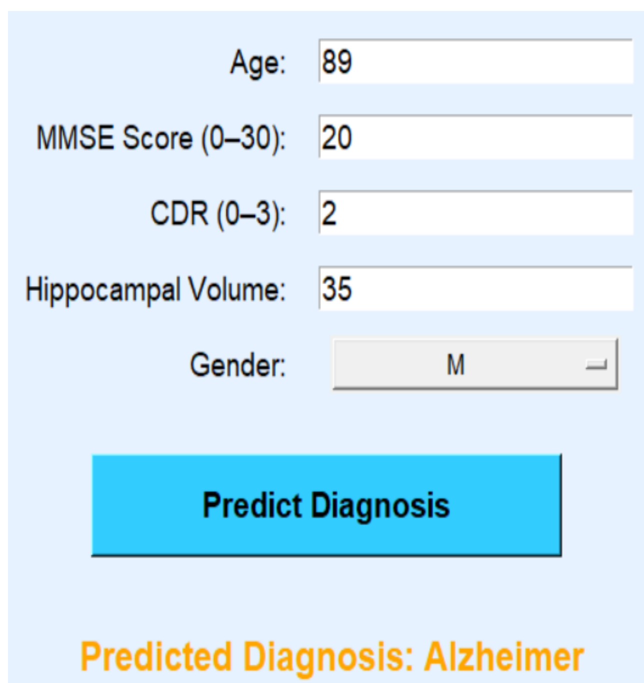

Figure 2: Predict Diagnosis

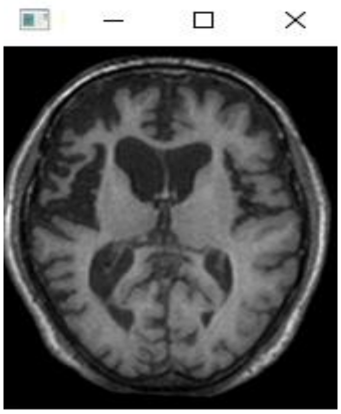

Figure 3: ReadImage
This module accepts the brain image of the patient

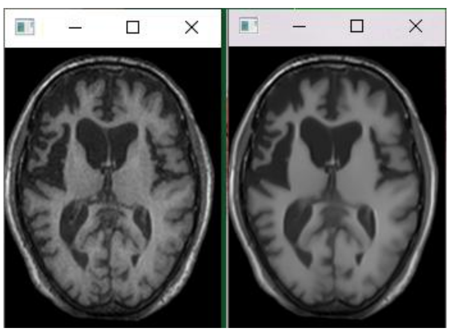

Figure 4: Preprocessing
This module removes noise and converts the image into gray color

Figure 5: Threshold

Displays the thresholded version of the given brain image, providing a simple yet effective method for separating the foreground from the background. This image analysis technique, a form of image segmentation, isolates objects by converting grayscale images into binary format.

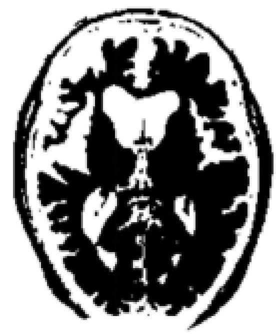

Figure 6: Prediction
Predicted as MCI

VI. CONCLUSION AND FUTURE WORKS

The use of deep learning—particularly Convolutional Neural Networks (CNNs) and transfer learning models such as VGG16—has demonstrated remarkable potential for the early and accurate detection of Alzheimer's disease from brain imaging modalities like MRI and PET scans. These models automatically extract and learn complex patterns from imaging data, often surpassing the performance of traditional manual analysis methods.

Through effective data preprocessing and fine-tuning of deep learning architectures, such systems can reliably differentiate between various stages of cognitive decline, including normal cognition, mild cognitive impairment (MCI), and Alzheimer's disease. This capability not only supports early diagnosis but also enhances clinical decision-making and facilitates more targeted treatment planning...

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