3D Convolutional Neural Network for Early Detection of Alzheimer's Disease using Structural MRI

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ABSTRACT:- Alzheimer's disease is a progressive neurological disorder where early detection is critical. This study proposes a deep learning approach using a custom 3D Convolutional Neural Network (3D CNN) to classify MRI brain images into Alzheimer's Disease (AD), Cognitively Normal (CN), and Mild Cognitive Impairment (MCI). Minimal preprocessing is applied to standardize the data, and the model is trained using the Adam optimizer with CrossEntropy loss. A simple graphical user interface (GUI) is also developed to enable easy image input and result visualization. The results demonstrate that 3D CNNs can effectively capture spatial features from MRI data for reliable classification.

Keywords :Alzheimer's Disease Detection , Deep Learning,3D CNN, structural MRI

I. INTRODUCTION

Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, thinking, and behavior, and is one of the leading causes of dementia worldwide. Early diagnosis is essential for effective treatment and slowing disease progression, but traditional diagnostic methods are often time-consuming and dependent on expert analysis.

Recent advancements in deep learning have enabled automated analysis of medical imaging data, particularly Magnetic Resonance Imaging (MRI). Convolutional Neural Networks (CNNs) have proven effective in extracting complex features from images, reducing the need for manual feature engineering.

In this study, a deep learning-based system using a custom 3D Convolutional Neural Network (3D CNN) is proposed to classify MRI brain images into Alzheimer's Disease (AD), Cognitively Normal (CN), and Mild Cognitive Impairment (MCI). The system uses minimally preprocessed MRI data in .pt format and focuses on extracting volumetric spatial features for accurate classification.

Additionally, a graphical user interface (GUI) is developed to allow users to upload MRI data and visualize prediction results, making the system more practical and user-friendly for real-world applications.

II. LITERATURE REVIEW

Traditional Alzheimer's disease detection methods relied on manual analysis of brain MRI scans and handcrafted feature extraction techniques such as:

- Intensity-based features
- Texture analysis (GLCM, LBP)
- Region-based segmentation
- Statistical feature extraction

While these approaches provide useful insights, they often fail to capture complex spatial relationships in brain structures. Variations in MRI scans, noise, and subtle changes in brain regions make manual feature extraction less reliable and time-consuming.

Sr.no.	Paper name	Author name	Key points	Advantages	Disadvantages
1	Alzheimer's Disease Prediction Using 3D-CNNs	Rahman et al. (2022)	Uses 3D CNN to capture volumetric MRI features	High accuracy using 3D CNN	High computational cost
2	Attention-Based 3D CNN for Brain Imaging	Zhang et al. (2023)	Uses attention mechanism for better accuracy	Focuses on important brain regions	Complex architecture
3	Alzheimer's Detection from MRI: Deep Learning Perspective	Armonaite et al. (2023)	Highlights importance of 3D CNN in MRI analysis	Comprehensive overview of DL methods	Data scarcity issue

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Recent research has demonstrated the effectiveness of 3D CNN models for Alzheimer's disease detection using MRI scans. These models can automatically extract relevant features from volumetric brain images and improve classification performance. The proposed work builds upon these advancements for AD, CN, and MCI classification.

III. METHODOLOGY

A. Dataset

The dataset used in this research was obtained from ADNI (Alzheimer's Disease neuroimaging initiative) consists of 1012 3D MRI brain scans categorized into three classes:

- Alzheimer's Disease (AD) - 185 scans
- Cognitively Normal (CN) – 298 scans
- Mild Cognitive Impairment (MCI) – 529 scans

The dataset was divided into:

- 80% Training Samples
- 20% Testing Samples

This division ensures proper model training and unbiased evaluation of the proposed 3D CNN model.

B. Preprocessing

To prepare the MRI data for model input, minimal preprocessing techniques were applied:

Data Conversion:
MRI data is converted into floating-point format for computation.

Normalization:
Pixel intensity values are scaled between 0 and 1 to improve training stability.

Dimension Adjustment:
A channel dimension is added to match the input requirement of the 3D CNN model.

Data Formatting:
All MRI scans are structured into consistent tensor shapes for efficient processing.

These steps ensure uniformity and reduce computational complexity.

C. 3D CNN Architecture

The proposed model is a custom 3D Convolutional Neural Network designed to extract volumetric features from MRI data.

1. **Convolution Layer 1:**
   32 filters with a 3×3×3 kernel are used to extract basic spatial features from MRI scans.

2. **ReLU Activation:**
   Introduces non-linearity into the network and removes negative values to improve feature learning.

3. **MaxPooling Layer (2×2×2):**
   Reduces the spatial dimensions of the feature maps while retaining the most important features for efficient processing.

4. **Convolution Layer 2:**
   64 filters with a 3×3×3 kernel are used to capture deeper structural patterns and more complex features from MRI scans.

5. **ReLU Activation + MaxPooling**

6. **Convolution Layer 3:**
   128 filters with a 3×3×3 kernel are used to extract high-level volumetric features from different brain regions for accurate Alzheimer's disease classification.

7. **Global Average Pooling:**
   Reduces the feature maps to a fixed-size representation by averaging spatial information across the entire volume.

8. **Fully Connected Layer:**
   Converts the extracted features into a one-dimensional feature vector for final classification.

9. **Softmax Output Layer:**
   Produces probability scores for the Alzheimer's Disease (AD), Cognitively Normal (CN), and Mild Cognitive Impairment (MCI) classes.

D. Training Configuration

Loss Function (Cross-Entropy Loss):

Used for multi-class classification.

Optimizer (Adam):

Adaptive optimizer for faster convergence.

Batch Size (4):

Processes small groups of MRI scans.

Epochs (20):

Number of training iterations over the dataset.

E. Feature Extraction & Prediction

After training, the model is used to extract deep features from MRI scans using intermediate layers. These features are then passed through the fully connected layer to perform final classification.

Additionally, a Graphical User Interface (GUI) is developed to:

- Upload MRI data in .pt format

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• Display image slices
• Show classification results with confidence score

The graphical user interface provides a simple and user-friendly platform for MRI analysis. It allows users to upload MRI data, visualize image slices, and obtain classification results without requiring technical knowledge of the underlying deep learning model.

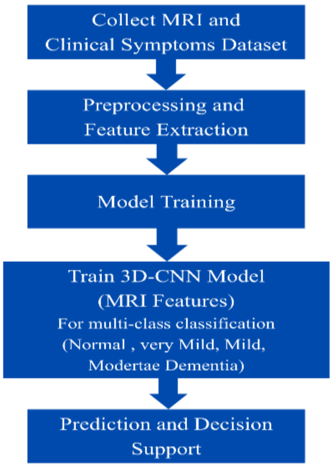

Fig.a: Architecture diagram

IV. RESULTS

During training, the model showed:
• Continuous decrease in training loss
• Improvement in training accuracy
• Effective learning of spatial features from 3D MRI scans

The model was able to distinguish between different classes such as Alzheimer's Disease (AD), Cognitively Normal (CN), and Mild Cognitive Impairment (MCI). It successfully captured subtle variations in brain structures, which are difficult to identify manually.

The system outputs confidence scores for each prediction. These scores help in understanding the reliability of classification and identifying uncertain cases.

However, some misclassifications occurred between MCI and AD due to their similar brain patterns. Variations in MRI quality, noise, and limited dataset size also affected overall performance.

Metric	Value
Testing Accuracy	84.21%
Testing Loss	0.0805
Validation Accuracy	80.55%
Validation Loss	0.0336

Table 1 : Quantitative Performance of Metrics of Model

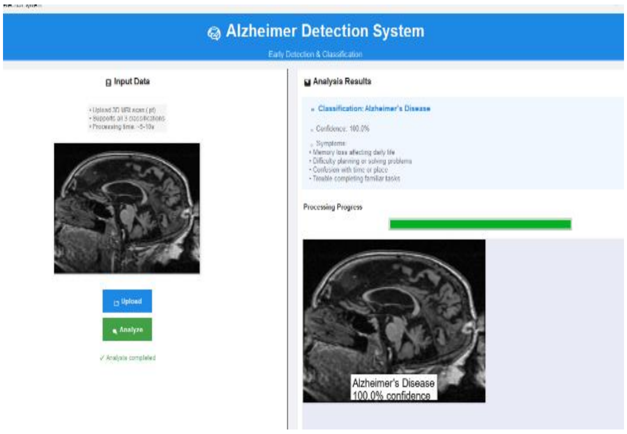

Fig.1:Output for AD

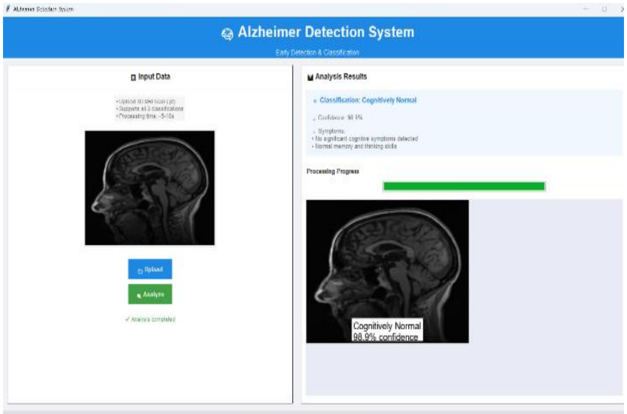

Fig.2:Output for CN

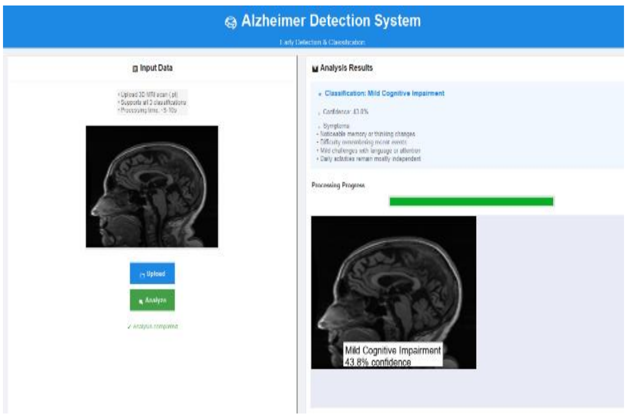

Fig.3:Output for MCI

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V. DISCUSSION

The 3D CNN-based model proves to be an effective technique for Alzheimer's disease classification using MRI data. Some key observations include: CNNs automatically extract meaningful volumetric features without manual intervention. The model is capable of identifying subtle structural changes in brain regions. Performance depends on the quality and diversity of MRI data. Minimal processing simplifies the pipeline while maintaining the efficiency.

This approach is highly beneficial in the healthcare domain, where early and accurate detection of Alzheimer's disease is critical. It can assist doctors in diagnosis and reduce manual workload. The system also provides a scalable and automated solution for medical image analysis.

The integration of a graphical user interface (GUI) makes the system user-friendly, allowing easy upload of MRI data and visualization of prediction results. The model demonstrates reliable classification performance by learning complex spatial patterns directly from 3D brain images.

The performance of the proposed model may be affected by class imbalance and the limited size of the MRI dataset.

VI. FUTURE WORK

To further improve the system, advanced architectures such as ResNet, DenseNet, or attention-based 3D CNNs can be used. The model can be trained on larger and more diverse MRI datasets such as ADNI to improve generalization and classification performance. Multimodal data, including PET scans along with MRI images, can be incorporated to enhance diagnostic accuracy. Model interpretability can be improved using explainable AI techniques, and real-time web-based or cloud-based diagnostic systems can be developed for practical clinical applications.

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