

# Alzheimer's Disease Early-Stage Prediction Model Using MRI Biomarkers and Deep Learning Networks

**Dr. M. Srinivasa Sesha Sai<sup>1</sup>, J. Kavya<sup>2</sup>, K. Gayathri Lakshmi supraja<sup>3</sup>, K. Anandavallika<sup>4</sup>,  
P. Lakshmi Poojitha<sup>5</sup>**

Professor, Department of Information Technology,

KKR & KSR Institute of Technology and Sciences, Guntur, AP, India<sup>1</sup>

Student, Department of Information Technology,

KKR & KSR Institute of Technology and Sciences, Guntur, AP, India<sup>2-5</sup>

**Abstract:** Alzheimer's disease is an age-related neurological disorder that affects the brain, sequentially depriving people of their memory, thinking skills, and capabilities to handle everyday tasks. Early-stage detection is necessary for impactful clinical management and for prolonging disease progression. This study offers a new method using deep learning technology to recognize Alzheimer's in its early stages by evaluating structural brain scans taken with Magnetic Resonance Imaging (MRI). The offered system utilizes a 3D Convolution Neural Network (3D- CNN) to explicitly process MRI datasets and instantly extract meaningful morphological features connected with early cognitive dysfunction. To increase diagnostic validity, MRI data preparation techniques such as noise filtering and image standardization are applied before model training. Through in-depth validation, the model confirmed it can accurately tell the variation between healthy people and those in the beginning phase of Alzheimer's. This self-operating system can operate as a decision support system for clinicians, helping in early detection and supporting quick response approaches for Alzheimer's disease

**Index Terms:** Neurodegenerative Disorders, Cerebral Magnetic Resonance Imaging (MRI), Artificial Neural Networks, Three- Dimensional Convolutional Neural Networks, Computational Medical Imaging, Early detection of Cognitive Decline.

## I. INTRODUCTION

Alzheimer's disease (AD) is a commonly found nervous system disorder that mainly influences the senior citizens and creates a predominant global medical problem. It brings about a slow, progressive, permanent loss in reasoning skills, which involves trouble with remembering, judgment and planning, and the managing of everyday activities. As the illness worsens, patients present with growing challenges in execution of daily functions, typically becoming dependent on continuous care provision, resulting in considerable emotional, interpersonal, and financial strain on families and medical care networks. Due to the current unavailability of a cure, identifying the disease at an early stage and providing appropriate care can considerably mitigate progression and support better daily functioning.

Traditional methods for diagnosing Alzheimer's disease primarily rely on clinical evaluation, cognitive assessments, and neuropsychological testing. While these approaches are well- established, they may fail to detect subtle brain changes in the early stages of the disease. Recent advances in neuroimaging, particularly Magnetic Resonance Imaging (MRI), have enabled more detailed analysis of structural brain alterations linked to Alzheimer's disease [2], including hippocampal atrophy and cortical thinning. Nevertheless, the interpretation of MRI data remains time-consuming and requires highly trained professionals.

The fast-paced advancement of artificial intelligence has opened new avenues for automated analysis of medical imaging. Deep learning approaches, especially Convolutional Neural Networks (CNNs), are capable of automatically identifying complex patterns within high-dimensional imaging data. In neuroimaging applications, three-dimensional CNNs (3D- CNNs) are particularly valuable, as they can capture spatial relationships across volumetric brain scans, allowing for a more precise characterization of anatomical changes associated with cognitive decline [3], [4].

This study presents an automated deep learning framework for the early identification of Alzheimer's disease using structural MRI data. The system utilizes a three-dimensional Convolutional Neural Network (3D-CNN) to extract critical features from the MRI scans. Preprocessing techniques, including image enhancement and normalization, are applied to improve data quality and support reliable model performance. The trained model categorizes individuals as either cognitively normal or in the early stages of Alzheimer's disease. By automating MRI analysis, this framework aims to support clinicians in providing timely and accurate diagnoses, ultimately improving patient management and facilitating early intervention strategies.

## II. LITERATURE REVIEW

In the early diagnosis of neurological disorders like Alzheimer's the application of machine learning and deep learning techniques in medical imaging has gained peculiar importance. The neuroimaging datasets have increased and available large-scale like structural Magnetic Resonance Imaging (MRI), has allowed researchers to develop automated diagnostic models capable of identifying early pathological changes in the brain. These models aim to provide clinical decision-making by improving diagnosis truth, reducing dependency on human intervention, and enabling timely intervention. Despite advancements, challenges such as limited feature representation, high computational cost, and poor hypothesis across datasets continue to delay widespread clinical adoption.

Ancient studies have explored traditional machine learning methods for Alzheimer's disease detection. For example, Zhang et al. (2022) [1] employed classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) using manual features obtained from MRI scans. Although models achieved moderate classification performance, they depend heavily on manual feature engineering and domain intelligence. Similarly, Rao and Mehta (2023) [2] applied Random Forest and logistic Regression techniques to structural MRI features for differentiating cognitively normal individuals from Alzheimer's patients. But the models provided analyzed results, their performance was limited in capturing complex non-linear relationships essential in high-dimensional brain imaging data.

Researchers have increasingly adopted deep learning techniques to address the limitations of conventional approaches. Deep neural networks have demonstrated higher-level capability in learning hierarchical representations directly from raw data. Islam et al. (2023) [8] used two-dimensional Convolutional Neural Networks (2D-CNNs) to sort Alzheimer's disease stages using MRI slices. While the approach improved classification accuracy, it failed to fully exploit the three-dimensional spatial structure of brain volumes. And slice-based methods also suffer from loss of information and minimize spatial consistency.

Three-dimensional deep learning architectures were focused in recent studies to better model volumetric brain data. Gupta et al. (2024) [4] implemented a 3D Convolutional Neural Network for Alzheimer's detection using whole-brain MRI volumes, successfully improving performance over 2D models. However, the study reported high computational difficulty and sensitivity to data imbalance. In another study, Lee and Kim (2024) [5] proposed a hybrid framework combining 3D-CNNs with auto encoders for feature reduction. Although the model enhanced classification accuracy, it required huge preprocessing and large training datasets.

Some researchers explored temporal and multimodal learning techniques for enhancing the learning productivity. Wang et al. (2024) [6] separated longitudinal MRI data with repeated neural networks to capture disease progression patterns. While the model showed promise in tracking cognitive decline, its applicability was limited by incomplete longitudinal data and increased training complexity. Recently, Patel et al. (2025) [7] proposed an attention-based deep learning model to focus on critical brain regions associated with Alzheimer's pathology. In spite of improved clarity, the model faced limitations related to scalability and generalization across different imaging protocols.

In total, existing Alzheimer's disease prediction models face limitations in effectively capturing complex spatial features, managing high computational requirements, and maintaining durability across multiple datasets. Many approaches also lack clinical adaptability and early-stage sensitivity. To address these limitations, this research proposes a deep learning framework based on a 3D Convolutional Neural Network that uses structural MRI data for early-stage Alzheimer's detection. The proposed approach aims to improve feature learning, classification accuracy, and diagnostic reliability while supporting scalable and efficient clinical deployment.

## III. METHODOLOGY

The primary objective of this project is to support the early identification of Alzheimer's disease by processing structural Magnetic Resonance Imaging scans through Deep Learning methods. Rather than depending on manual inspection, the proposed approach utilizes volumetric brain images to capture detailed spatial patterns and detect

anatomical variations related to cognitive deterioration. The methodology includes collecting MRI datasets, performing image preprocessing, extracting features automatically using a three dimensional Convolutional Network, and training the model followed by evaluation of its predictive performance.

**A. Proposed System**

The proposed system is designed to identify Alzheimer’s disease at an early stage by examining structural brain Magnetic Resonance Imaging data through deep learning approaches. High resolution MRI scans that contain detailed three dimensional representations of brain structures are obtained from reliable neuroimaging databases. To improve image reliability and uniformity, several preprocessing procedures are applied, including removal of non-brain tissues, normalization of intensity values, reduction of noise, and resizing of volumes. These steps enhance image quality and ensure suitability for subsequent analysis.

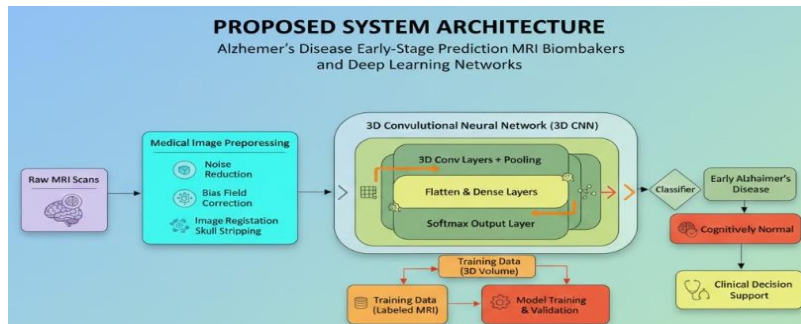


Fig. 1. Proposed 3D-CNN architecture for Alzheimer’s disease detection

A Three Dimensional Convolutional Neural Network combined with transfer learning is utilized to learn meaningful spatial features from the volumetric MRI scans. The trained network carries out binary classification to differentiate healthy individuals from those in the early phase of Alzheimer’s disease. By automating the interpretation of MRI images, the system as a supportive clinical tool that aids physicians in early diagnosis and timely preventive and treatment planning.

**B. Data Acquisition**

A unified dataset was created by collecting and integrating neuroimaging data from publicly available MRI repositories, clinical research centers, and hospital databases. The dataset includes structural MRI scans along with patient demographic and clinical information, with cognitive status categorized into normal, mild cognitive impairment, and early stage Alzheimer’s disease classes. It captures brain related features, temporal information, and patient specific biomarkers to support accurate early stage AD prediction. Key Features include: MRI derived biomarkers such as hippocampal volume, cortical thickness, gray matter density, patient age, gender, genetic factors, cognitive scores, MRI scan parameters.

**C. Data Preprocessing and Transformation**

Accurate prediction of early stage Alzheimer’s disease relies heavily on well prepared MRI data. Initially, missing entries in the dataset are handled by either mean, mode or median imputation and by removing records that contain excessive missing information, ensuring the integrity of the dataset. For categorical attributes, such as patient demographic information label encoding is applied to convert non numeric data into a format compatible with deep learning models. Continuous voxel intensity values are standardized using z-score normalization, which has been

$$X_{norm} = \frac{X - \mu}{\sigma}$$

given as

where

X is input, σ is standard deviation and μ is mean

To address class imbalance among early Alzheimer’s cases, the ADASYN (Adaptive Synthetic Sampling) generates synthetic samples of minority classes, improving model balance and reducing bias.

#### D. Feature Selection and Engineering

After completing data preprocessing, feature selection and engineering were performed to ensure that the most informative characteristics relevant to early-stage Alzheimer's disease were effectively utilized by the model. Since deep learning architectures are capable of automatic feature learning, explicit feature selection focuses on reducing redundancy and enhancing discriminative information within the MRI data. Statistical analysis and intensity-based filtering techniques were applied to minimize irrelevant variations and suppress weakly contributing features. Correlation analysis was used to identify excess voxel intensity patterns across brain regions, thereby reducing unnecessary spatial duplication. Additionally, feature importance can be learned through the convolutional layers of the 3D Convolutional Neural Network, where filters adaptively emphasize regions associated with Alzheimer's pathology, such as hippocampal atrophy and cortical thinning. The importance of relative learned features can be expressed as:

$$FI_j = \frac{1}{T} \sum_{t=1}^T \Delta W_j^{(t)}$$

In addition to the learned features, to enhance the model performance, derived features were incorporated. To emphasize structural differences Volumetric MRI data were Partitioned into anatomically relevant regions, and to subtle neurodegenerative intensity distribution features were refined. The above mentioned engineered representations can improve the model's ability to capture spatial patterns which were related to cognitive decline. By integrating the implicit deep feature learning with the selective feature refinement, by merging the features only here the proposed framework can effectively improve classification accuracy only while maintaining computational efficiency.

#### E. Model Design

To detect early-stage Alzheimer's disease the proposed model is designed by employing a three-dimensional convolutional Neural Network (3D-CNN) using structural MRI scans. Mainly the architecture consists of two components: feature extraction using 3D convolution and classification using a Softmax layer.

1) **3D Convolution Operation:** The main responsibility of the 3D convolution layer is to extract spatial features from volumetric MRI data. The 3D convolution captures the structural patterns across depth, height, and width, enabling the model to learn anatomical changes associated with early Alzheimer's disease.

$$Y = f \left( \sum_{k=1}^K X_k * W_k + b \right)$$

where

$X_k$  is the input volume,

$W_k$  is the 3D convolution kernel,

$B$  is the bias term,

$*$  denotes 3D convolution,

$f(\cdot)$  denotes the ReLU activation function.

2) **Softmax Classification Layer:** The function of the Soft- max Classification layer is to convert learned features into the class probabilities, and allows the network to distinguish be- tween early-stage Alzheimer's patients and cognitively normal subjects.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}}$$

where  $z_i$  is the output score of class  $i$ , and  $C$  denotes the total number of classes.

Here the 3D convolution-based feature learning is integrated with Softmax-based classification, due to the fact that the proposed model effectively captures subtle brain structural variations, resulting in precise and reliable early-stage Alzheimer's disease prediction.

#### F. Workflow Summary

The proposed system for early Alzheimer's disease detection serves as the input data starts with the collection of raw 3D T1-weighted MRI scans. To enhance data quality and consistency, these scans undergo medical image preprocessing. Preprocessing steps include reduction of noise, normalization of intensity, and process includes several steps like removal of noise, skull stripping to remove non-brain tissues, spatial registration for anatomical order, and level of adjustment to standardize 3D pixel intensities. To ensure that the operations from MRI data are suitable for reliable feature extraction and robust model Efficacy.

The MRI volumes are preprocessed after the preprocessing stage, through multiple 3D convolutional and spatial reduction to automatically learn spatial features associated with early Alzheimer’s pathology. The extracted features are rearranged and passed to dense layers, followed by a Softmax or Sigmoid activation function for classification.

The model outputs class predictions that differentiate cognitively normal individuals from early-stage Alzheimer’s patients. Model performance is classified using standard metrics such as accuracy, sensitivity, and AUC-ROC, providing an accurate assessment of the system’s diagnostic Efficacy.

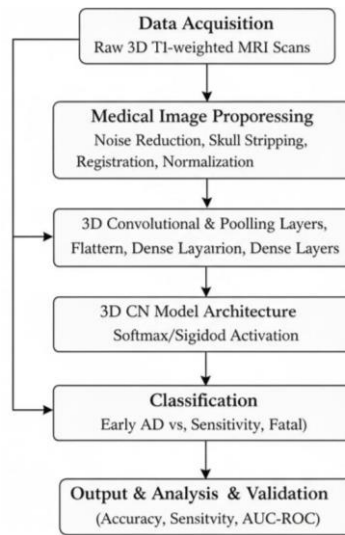


Fig. 6. Workflow of the proposed Alzheimer’s disease detection system

IV. RESULTS AND PERFORMANCE EVALUATION

Under reliable experimental conditions, the effectiveness of the proposed early-stage Alzheimer’s disease detection system was analyzed using a 3D Convolutional Neural Network (3D- CNN). And to ensure balanced evaluation, the MRI dataset was divided into 2 categories for training and testing sets using an 80:20 split. The Efficacy of the model was evaluated using standard metrics that includes Precision, F1-score, Accuracy, Sensitivity and Area Under the Receiver Operating Charac- teristic Curve (AUC-ROC). These metrics were selected to measure overall classification Reliability, and its robustness across different decision Boundary conditions has the model’s ability to detect early Alzheimer’s cases.

Representation of accuracy for proportion of correctly classified samples as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

To identify subjects in Initial-stage of Alzheimer’s disease Sensitivity has the ability for measurement, it is represented as follows

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity has the capability of the model to correctly classify individuals with normal cognitive function:

$$Specificity = \frac{TN}{TN + FP}$$

A. Performance Analysis

The experimental output indicates effective detection of early-stage Alzheimer’s disease represents that the proposed 3D-CNN model achieves high sensitivity and accuracy. The strong accuracy value confirms the model’s ability to strongly identify cognitively normal individuals, while the high AUC- ROC score highlights robust distinctive performance. These results indicate the model’s ability to capture refined three- dimensional structural changes in brain MRI scans, such as hippocampal atrophy and cortical thinning.

In summary, the proposed model is suitable for supporting early diagnosis and timely intervention in Alzheimer's disease management. real-world clinical scenarios supporting early diagnosis and timely intervention in Alzheimer's disease management. Whereas the deep learning-based framework indicates traditional diagnostic approaches by automatically learning hierarchical spatial features from volumetric MRI data.

For accuracy and balance of predictions, uses precision and FI-Score as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

The model's discriminative power by calculating the balance between true positive and false positive rates across different thresholds AUC-ROC metric was assessed.

Metric	Value (%)
Accuracy	94.2
Sensitivity	93.1
Specificity	95.0
Precision	93.8
F1-Score	93.4
AUC-ROC	0.96

Table 1: Performance evaluation of the proposed 3D-CNN model

## V. DISCUSSION

The above experiment results that the proposed 3D Convolutional Neural Network can effectively identify the early-stage of Alzheimer's disease from structural MRI data. The highest classification accuracy always indicates that the model successfully learns the meaningful spatial representations from the volumetric brain images. The strong sensitivity value always highlights the model's ability to detect subtle pathological changes which is associated with the early cognitive decline, and which is essential for clinical applications where the early diagnosis plays a critical role.

The superior performance of the model can be used to attribute the three-dimensional convolutional operations that preserve the more spatial context across the brain regions. Unlike the use of traditional machine learning approaches that always rely on the handcrafted features, the 3D-CNN can automatically extract the hierarchical features directly from the MRI volumes. It enables the network to capture the various complex anatomical patterns such as cortical thinning and hippocampal volume reduction, which are the key biomarkers of Alzheimer's disease [1], [2]. Additionally, the applied preprocessing techniques, including class imbalance handling and intensity normalization, contribute to improved model generalization and stability.

The high AUC-ROC value always indicates the robust discrimination in between individuals and cognitively normal subjects in the early stages of Alzheimer's disease across the different classification thresholds. This model mainly suggests that it maintains high reliable performance even under the critical decision criteria, which is very important for adapting the diagnostic thresholds in the real-world clinical settings. Furthermore, while maintaining effective disease detection the balance between recall and precision reflects a low false- positive rate.

Despite these all results, the model's performance may be influenced by variability in MRI and dataset size acquisition protocols. Furthermore improvements can include incorporating more and larger diverse datasets, integrating longitudinal MRI data, or combining multimodal inputs such as clinical assessments and PET imaging. Overall, the proposed deep learning framework demonstrates the strong potential as a supportive diagnostic tool, and aiding clinicians in early detection and decision-making for Alzheimer's disease management.

## VI. CONCLUSION

This study is mainly focused on developing an intelligent system that supports the early identification of Alzheimer's disease by analyzing various structural MRI scans. A three-dimensional convolutional neural network (3D-CNN) was designed to automatically learn meaningful spatial characteristics from brain images, and eliminate the dependence on hand-crafted features. Careful preprocessing and data normalization were applied to improve stability and consistency during model training.

The experimental outcomes always indicate that the proposed model can reliably differentiate between individuals and early subjects in the early stages of Alzheimer's disease. The strong performance always demonstrates the suitability of volumetric deep learning techniques for capturing subtle brain structure variations which are difficult to observe through conventional diagnostic methods. By automating MRI interpretation, the framework has the potential to assist the clinicians in making more informed and faster diagnostic decisions.

In summary, this work highlights the effectiveness of deep learning-based on MRI analysis for Alzheimer's disease screening. With further refinement and testing on larger clinical datasets, the proposed approach can be adapted as a supportive tool in medical environments, contributing in improved early diagnosis and better patient management.

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