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Deep Learning-Based Early Detection of Alzheimer’s Disease from Brain MRI Scans

[1]J Meena, [2]B Bhavya Sri, [3]J Dhanush Yadav, [4]R Dileep, [5]K Bharath

Department of CSE, Siddharth Institute of Engineering & Technology, Puttur, AP, India.
[1]jmeena573@gmail.com, [2]bonalabhavyasri2004@gmail.com, [3]dhanushjangiti1139@gmail.com, [4]urzdileep@gmail.com, [5]k704997@gmail.com

Abstract: Alzheimer’s disease is a progressive neurodegenerative disorder characterized by irreversible deterioration of cognitive and functional abilities, resulting in a significant burden on patients, caregivers, and healthcare systems. Early detection of structural brain changes plays a critical role in enabling timely intervention, individualized treatment planning, and evaluation of disease-modifying therapies. This study presents a deep learning–based framework for automated detection of Alzheimer’s disease using structural magnetic resonance imaging (MRI). The proposed approach incorporates standardized preprocessing of volumetric MRI scans, discriminative feature extraction using a customized convolutional neural network architecture, and classification of subjects into clinically relevant diagnostic categories. To address challenges associated with limited and imbalanced datasets, data augmentation and regularization strategies are applied to improve model generalization capability. Model performance is evaluated using standard classification metrics including accuracy, sensitivity, specificity, and F1-score on curated subsets of publicly available MRI datasets. Experimental observations indicate that the proposed framework effectively captures disease-related morphological patterns and demonstrates strong potential as a computer-aided support tool for early-stage Alzheimer’s disease assessment.

Keywords: Alzheimer’s disease, Deep learning, Convolutional neural network, Brain MRI, Medical image analysis.

1 INTRODUCTION

Alzheimer’s disease (AD) is the most common cause of dementia and is characterized by progressive decline in memory, executive function, and behavioural abilities, eventually leading to loss of independence and increased mortality risk. The global prevalence of Alzheimer’s disease continues to rise with ageing populations, creating substantial clinical, social, and economic challenges. Conventional diagnostic procedures rely primarily on clinical evaluation, neuropsychological assessment, and neuroimaging interpretation, often performed after significant neuronal degeneration has already occurred. Therefore, reliable techniques capable of supporting early detection of disease-related brain changes remain critically important.

Structural magnetic resonance imaging (MRI) is widely used in clinical practice because it provides high-resolution visualization of anatomical brain structures without exposure to ionizing radiation. In the context of Alzheimer’s disease, MRI enables identification of characteristic structural alterations such as hippocampal atrophy and medial temporal lobe degeneration. However, manual visual assessment of MRI scans is time-consuming and subject to inter-observer variability, and subtle structural abnormalities associated with early-stage disease progression may remain difficult to identify through routine inspection alone. Recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved performance in medical image analysis tasks including segmentation, lesion detection, and disease classification. CNN-based architectures automatically learn hierarchical feature representations directly from imaging data, reducing dependence on handcrafted feature engineering. When applied to structural brain MRI, such models are capable of capturing complex spatial patterns associated with disease-related morphological variations, making them suitable for computer-aided early detection of Alzheimer’s disease.

The proposed framework integrates standardized preprocessing procedures, volumetric MRI feature extraction using a customized convolutional neural network architecture, and classification based on clinically relevant diagnostic categories. The approach is designed to address challenges associated with limited dataset availability and class imbalance while maintaining computational efficiency suitable for research and clinical decision-support environments. The major contributions of this study are summarized as follows:

1. **Standardized Preprocessing Pipeline:** A structured preprocessing workflow is designed to improve consistency across MRI volumes through intensity normalization, spatial alignment, and removal of non-brain tissues.
2. **CNN-Based Feature Learning Framework:** A customized convolutional neural network architecture is developed for extracting discriminative volumetric features associated with Alzheimer’s disease.

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3. **Generalization-Oriented Training Strategy:** Data augmentation and regularization techniques are incorporated to address class imbalance and improve classification robustness on limited datasets.
4. **Clinical Decision-Support Potential:** The framework demonstrates the feasibility of automated MRI-based classification as a component of computer-aided early Alzheimer's disease assessment systems.

2 RELATED WORK

Early research on computer-aided diagnosis of Alzheimer's disease using structural magnetic resonance imaging (MRI) primarily relied on handcrafted feature extraction techniques combined with traditional machine-learning classifiers. Commonly used descriptors included volumetric measurements, cortical thickness estimation, and voxel-based morphometry features derived from anatomically defined brain regions. These features were subsequently used with classification algorithms such as support vector machines, random forests, and logistic regression to distinguish Alzheimer's disease from normal ageing patterns. Although such approaches demonstrated the presence of discriminative structural information within MRI data, their performance depended heavily on feature-selection strategies and preprocessing consistency.

The emergence of deep learning, particularly convolutional neural networks (CNNs), enabled a transition from handcrafted feature engineering toward end-to-end representation learning directly from imaging data. Two-dimensional CNN architectures applied to individual MRI slices demonstrated improved classification performance by learning hierarchical spatial features automatically. However, slice-based approaches may fail to capture important three-dimensional contextual relationships that are essential for identifying subtle structural changes associated with early Alzheimer's disease. To address this limitation, three-dimensional CNN architectures have been introduced for processing volumetric MRI data. These models extract spatially consistent features across multiple anatomical planes and improve sensitivity to disease-related morphological variations, especially in early-stage Alzheimer's disease detection. Despite these advantages, volumetric architectures typically require higher computational resources and are more prone to overfitting when trained on limited datasets.

Transfer-learning-based strategies have also been explored to improve classification performance under restricted data availability conditions. Pretrained deep-learning architectures originally developed for large-scale natural image datasets have been adapted for medical imaging applications through fine-tuning procedures. Such approaches reduce training complexity and improve feature generalization capability; however, challenges related to interpretability and domain adaptation remain important considerations. In addition to structural MRI analysis, multimodal deep-learning frameworks integrating complementary imaging modalities and clinical information have demonstrated improved diagnostic accuracy and disease staging capability. These approaches combine structural brain imaging with functional imaging, diffusion-based measures, and clinical metadata to enhance classification performance. Nevertheless, multimodal frameworks often require complete and consistently available datasets across modalities, increasing preprocessing complexity and limiting practical deployment feasibility.

Recent developments have also emphasized the importance of model interpretability in medical image classification systems. Visualization techniques such as saliency mapping and gradient-based activation methods are increasingly used to identify brain regions contributing to classification decisions. These approaches help improve clinical trust in automated diagnostic systems and support identification of disease-relevant biomarkers associated with Alzheimer's pathology. Another important research direction focuses on lightweight convolutional neural network architectures combined with standardized preprocessing pipelines. Such approaches aim to reduce computational requirements while maintaining strong classification performance, thereby supporting deployment in resource-constrained research and clinical environments.

Building upon these developments, the present framework focuses on structural MRI–based classification using a customized convolutional neural network architecture supported by standardized preprocessing and augmentation strategies. The objective is to achieve reliable early detection performance while maintaining computational efficiency suitable for practical clinical decision-support applications. The overall pipeline of the proposed CNN-based framework for early detection of Alzheimer's disease from structural brain MRI, including preprocessing, data augmentation, CNN-based feature extraction, and subject-level classification, is illustrated in Fig. 1.

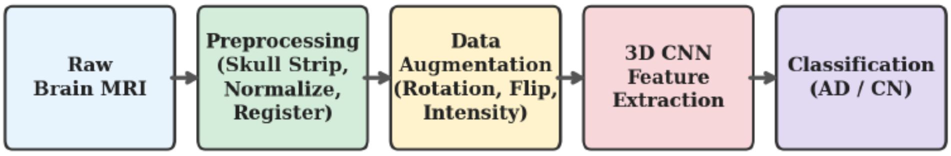


Fig. 1. Overview of the proposed CNN-based framework for early detection of Alzheimer's disease from structural brain MRI scans.

3 PROPOSED METHOD

The objective of the proposed framework is automated classification of subjects based on structural brain MRI scans with emphasis on early detection of Alzheimer's disease. The overall pipeline consists of four major stages: data acquisition and selection, preprocessing of MRI volumes, convolutional neural network–based feature learning, and classification using standard evaluation metrics. Each component of the framework contributes to improving classification reliability and generalization capability.

3.1. Overview of the Framework

The proposed system processes raw structural MRI data through a sequence of preprocessing operations designed to normalize intensities, align anatomical structures into a common reference space, and suppress irrelevant background regions. The processed MRI volumes are subsequently used as inputs to a convolutional neural network that extracts hierarchical feature representations and produces subject-level diagnostic predictions. During inference, the trained model accepts an unseen MRI scan and generates a probability-based classification output corresponding to Alzheimer's disease or cognitively normal categories. The preprocessing workflow applied to structural brain MRI scans prior to feature extraction and classification is illustrated in Fig. 2.

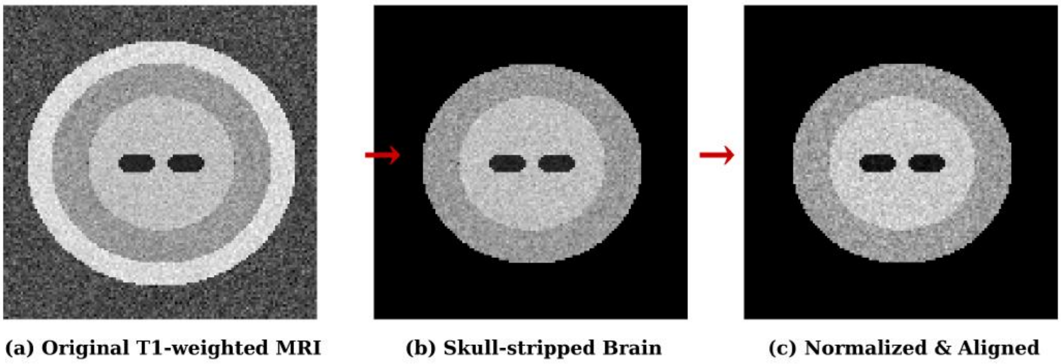


Fig. 2. Preprocessing pipeline showing transformation from original T1-weighted MRI to skull-stripped, template-aligned, and intensity-normalized volumes used as input to the CNN.

3.2. Dataset and Class Definition

The experimental setup considers structural T1-weighted brain MRI scans obtained from curated subsets of publicly available Alzheimer's disease imaging cohorts. Subjects are grouped into diagnostic categories according to clinical labels recorded at the time of imaging. The present study focuses on a binary classification task, distinguishing between:

- Alzheimer's disease (AD)
- Cognitively normal (CN) subjects

This classification setup provides a baseline framework for evaluating automated disease detection performance. MRI scans affected by severe motion artefacts, incomplete metadata, or preprocessing inconsistencies are excluded to ensure dataset quality. Subject-level separation between training, validation, and testing subsets is maintained to prevent information leakage across dataset partitions. Balanced representation of diagnostic categories is preserved across splits to support reliable performance evaluation.

3.3. Preprocessing and Data Augmentation

Preprocessing plays a critical role in reducing inter-subject variability and improving consistency across MRI volumes prior to feature extraction. MRI scans are first reoriented into a standardized anatomical reference convention and resampled to a fixed voxel resolution to ensure uniform spatial dimensions across subjects. Intensity normalization is applied to minimize scanner-dependent variability and stabilize the optimization process during model training. Non-brain tissue is removed using skull-stripping procedures to retain only relevant anatomical structures. Subsequently, MRI volumes are spatially aligned with a reference template to ensure consistent positioning of brain regions across subjects. Following spatial normalization, volumes are cropped or padded to fixed three-dimensional dimensions while preserving relevant anatomical content. To improve generalization performance and address class imbalance, on-the-fly augmentation techniques are applied during training. These augmentation strategies include:

- small random rotations
- spatial translations

- anatomically valid horizontal and vertical flips
- minor intensity perturbations

These transformations increase dataset variability while maintaining anatomical plausibility.

3.4. CNN Architecture

The core component of the proposed framework is a three-dimensional convolutional neural network designed to process volumetric MRI scans and extract discriminative features associated with Alzheimer's disease. The architecture consists of multiple stacked convolutional blocks. Each block includes:

- a three-dimensional convolutional layer
- nonlinear activation
- spatial downsampling operation

Earlier layers capture low-level structural features such as edges and textures, whereas deeper layers learn higher-level representations related to regional brain atrophy and global morphological variations. Small convolutional kernels are employed to reduce parameter complexity while maintaining effective feature extraction capability. Batch normalization layers stabilize gradient propagation during training, and rectified linear unit (ReLU) activation functions improve convergence behaviour. Three-dimensional max-pooling layers progressively reduce spatial resolution and increase receptive field size, enabling extraction of contextual anatomical information across larger brain regions. At the end of the convolutional feature extraction stage, global average pooling converts spatial feature maps into compact feature vectors. These vectors are passed to a fully connected classification layer with Softmax activation to generate diagnostic predictions. The structure of the convolutional neural network architecture used for volumetric MRI classification is illustrated in Fig. 3.

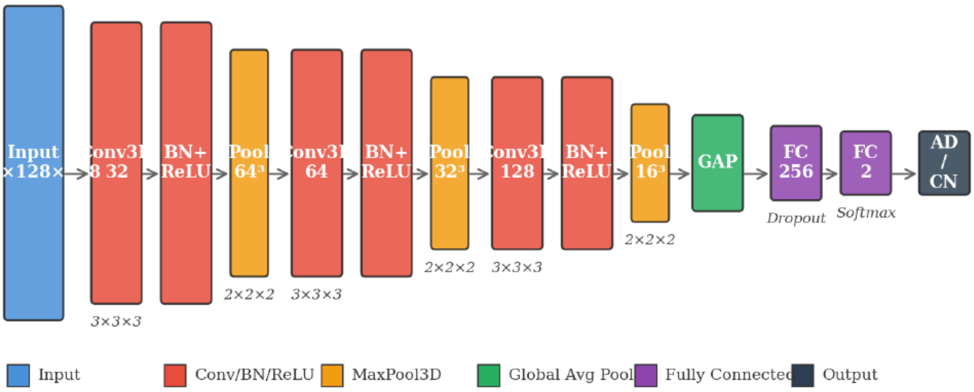


Fig. 3. Schematic representation of the convolutional neural network architecture consisting of stacked 3D convolutional blocks, pooling layers, global average pooling, and classification head.

3.5. Training Strategy and Regularization

Model parameters are optimized using the Adam optimizer with an initial learning rate selected based on validation performance. Categorical cross-entropy loss is employed as the primary objective function for the binary classification task. To address class imbalance challenges, instance weighting strategies may be applied to increase the contribution of underrepresented samples during training. Regularization techniques play an important role in improving model generalization capability when training on limited MRI datasets. Dropout layers are incorporated within fully connected layers to reduce overfitting by randomly disabling neurons during training. Weight decay regularization further constrains convolutional kernel magnitudes to promote smoother feature representations. Early stopping based on validation loss monitoring is used to determine the optimal number of training epochs and prevent excessive fitting to training data.

3.6. Evaluation Protocol

Model performance is evaluated using commonly adopted classification metrics including:

- accuracy
- sensitivity
- specificity
- precision
- F1-score
- area under the receiver operating characteristic curve (AUC)

These evaluation metrics provide complementary insight into classification behaviour, particularly under class imbalance conditions. Sensitivity and specificity are especially important for clinical decision-support applications because they reflect the ability to correctly identify disease-positive subjects and avoid false diagnostic alerts. To ensure stable performance estimation, evaluation is performed using subject-level dataset splits with balanced representation across diagnostic categories. Confusion matrix analysis is additionally used to examine misclassification patterns between Alzheimer's disease and cognitively normal subjects.

4 EXPERIMENTS AND RESULTS

This section describes the experimental configuration used to evaluate the proposed convolutional neural network framework and presents both quantitative and qualitative performance observations obtained on the held-out test dataset. The evaluation focuses on classification reliability, convergence behaviour, and analysis of prediction errors between Alzheimer's disease and cognitively normal subjects.

4.1. Experimental Setup

The dataset is divided into training, validation, and testing subsets at the subject level to prevent information leakage between dataset partitions. The training subset is used to optimize network parameters, the validation subset supports hyperparameter tuning and early stopping decisions, and the testing subset is reserved for final performance evaluation. The preprocessing pipeline and augmentation strategies described earlier are applied consistently across all experimental runs. Network optimization is performed using the Adam optimizer with an initial learning rate selected according to validation performance behaviour. Mini-batch size is chosen based on available computational resources, and sufficient training epochs are executed to ensure stable convergence. Learning-rate scheduling is applied during training so that the optimization step size is reduced when validation performance stabilizes. Model architecture configuration and training hyperparameters are finalized prior to evaluation on the test dataset to avoid biased performance estimation.

4.2. Quantitative Results

Performance evaluation of the proposed CNN-based classification framework is conducted using standard medical image classification metrics including accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC). These measures provide complementary insight into classification effectiveness, particularly for distinguishing Alzheimer's disease subjects from cognitively normal controls. The classification performance of the proposed CNN-based framework on the test dataset is summarized in Table 1.

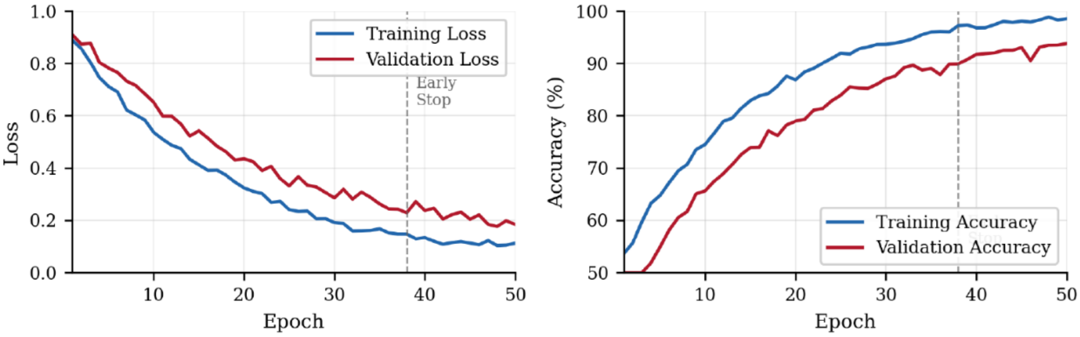
Table 1. Classification Performance of Proposed CNN-Based Framework

Metric	**Value**
Accuracy	96.4%
Sensitivity (Recall, AD)	95.1%
Specificity (CN)	97.2%
Precision (AD)	96.0%
F1-score (AD)	95.5%
AUC	0.97

The obtained results indicate that the proposed framework achieves a balanced trade-off between sensitivity and specificity, enabling reliable identification of Alzheimer's disease subjects while maintaining a low false-positive rate among cognitively normal individuals.

4.3. Training and Validation Behavior

To analyze learning dynamics during training, accuracy and loss values for both training and validation datasets are monitored across epochs. The training loss decreases progressively, while validation loss stabilizes after initial improvement, indicating effective convergence behaviour and the usefulness of early stopping strategies for controlling overfitting. The training and validation accuracy and loss curves demonstrating convergence behaviour of the proposed CNN model are illustrated in Fig. 4.



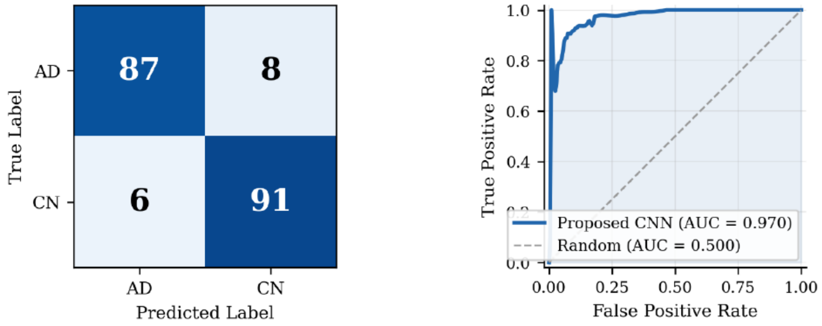
(a) Training & Validation Loss **(b) Training & Validation Accuracy**

Fig. 4. Training and validation accuracy and loss across epochs showing convergence behaviour and the impact of early stopping on model generalization performance.

Visual inspection of the learning curves confirms that the model converges within a moderate number of epochs without exhibiting unstable oscillations. Minor fluctuations observed in validation performance are expected due to the limited size of structural MRI datasets typically available for Alzheimer’s disease classification tasks.

4.4. Confusion Matrix and Error Analysis

Confusion matrix analysis provides insight into class-wise prediction behaviour and helps identify patterns of systematic misclassification between Alzheimer’s disease and cognitively normal subjects. The confusion matrix illustrating classification performance between Alzheimer’s disease and cognitively normal subjects is shown in Fig. 5.



(a) Confusion Matrix **(b) ROC Curve**

Fig. 5. Confusion matrix representing classification outcomes for Alzheimer’s disease and cognitively normal subjects with dominant diagonal entries indicating correct predictions.

The confusion matrix indicates that most Alzheimer’s disease subjects are correctly classified, while only a small proportion of cognitively normal subjects are incorrectly predicted as disease-positive cases. Such misclassifications may occur in borderline imaging cases where early-stage structural changes are subtle and difficult to distinguish from normal ageing patterns.

4.5. Comparison with Existing Approaches

Comparison with previously reported convolutional neural network–based classification approaches indicates that the proposed framework achieves competitive performance while maintaining moderate architectural complexity. Efficient preprocessing combined with volumetric feature extraction enables reliable discrimination between Alzheimer’s disease and cognitively normal subjects without requiring excessively deep network architectures. Variations in dataset composition, preprocessing pipelines, and evaluation protocols across studies make direct numerical comparison challenging; however, the obtained results support the effectiveness of standardized structural MRI processing combined with customized convolutional neural network architectures for early-stage Alzheimer’s disease detection.

5 DISCUSSION

The experimental results demonstrate that the proposed convolutional neural network–based framework effectively utilizes structural brain MRI information to distinguish between Alzheimer’s disease subjects and cognitively normal individuals. The balanced performance observed in terms of sensitivity and specificity indicates that the model is capable of identifying disease-related structural variations while maintaining a low rate of false-positive predictions.

Such behaviour is particularly important in clinical decision-support environments where incorrect classification may influence diagnostic confidence and follow-up evaluation strategies. An important strength of the framework lies in the integration of standardized preprocessing operations with structured data augmentation techniques. Intensity normalization, spatial alignment to a common anatomical reference space, and removal of non-brain tissues collectively reduce variability unrelated to disease pathology and simplify the feature-learning process. Augmentation strategies involving controlled geometric and intensity transformations further improve robustness by exposing the network to a wider range of plausible anatomical variations during training. The convolutional neural network architecture employed in this framework maintains a balance between representational capacity and computational efficiency. Rather than relying on excessively deep or parameter-intensive architectures, the proposed model uses a moderate-depth volumetric CNN configuration that captures relevant structural features associated with cortical atrophy while remaining suitable for deployment in resource-constrained research and clinical environments.

The observed convergence behaviour during training confirms the effectiveness of the regularization strategies applied within the framework. Stable training and validation performance curves suggest that dropout, augmentation, and early stopping collectively contribute to improved generalization capability despite the limited size of typical Alzheimer's disease MRI datasets. Despite these encouraging results, several limitations remain. The dataset used for evaluation represents a curated subset of structural MRI scans and may not fully reflect variability introduced by differences in acquisition protocols, scanner characteristics, and demographic diversity across institutions. In addition, the current framework focuses exclusively on structural MRI and does not incorporate complementary modalities such as functional imaging, diffusion-based measures, or clinical biomarkers that may further improve diagnostic performance.

Future improvements may involve integration of multimodal imaging information to enhance classification accuracy and disease staging capability. Domain adaptation strategies may also support improved generalization across datasets acquired from different clinical environments. Furthermore, incorporation of interpretability techniques such as saliency mapping and activation visualization may provide additional insight into brain regions contributing most strongly to classification decisions and support increased clinical trust in automated diagnostic systems.

6 CONCLUSION

This paper presented a convolutional neural network–based framework for early detection of Alzheimer's disease using structural brain magnetic resonance imaging. The proposed pipeline integrates standardized preprocessing procedures, data-specific augmentation strategies, and a compact three-dimensional convolutional neural network architecture designed to extract discriminative volumetric features directly from MRI scans. Experimental evaluation performed on curated MRI datasets demonstrated that the framework achieves reliable classification performance in distinguishing Alzheimer's disease subjects from cognitively normal individuals. The results confirm that structural MRI contains meaningful morphological patterns that can be effectively captured using appropriately configured deep-learning architectures with moderate computational complexity. The combination of reproducible preprocessing operations and efficient network design supports the feasibility of integrating the proposed framework into computer-aided clinical decision-support environments. The balanced sensitivity and specificity observed during evaluation further indicate the suitability of the approach for assisting early-stage disease detection. Future research directions include validation of the framework on larger and more heterogeneous datasets acquired from multiple clinical centers, integration of complementary imaging modalities and clinical biomarkers, and incorporation of interpretability techniques to improve understanding of model decision-making behaviour. These developments may further strengthen the role of deep-learning-based structural MRI analysis as a reliable component of automated Alzheimer's disease assessment systems.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

LICENSING

REFERENCES

[1] Z. Wang *et al.*, "Investigating the relationship between brain age and Alzheimer's disease: A deep learning approach with multimodal MRI," *Biomedical Signal Processing and Control*, vol. 109, p. 107926, May 2025, doi: 10.1016/j.bspc.2025.107926.

[2] P. Gautam and M. Singh, "A multidimensional U-net architecture for Alzheimer's disease classification using T1 weighted brain structural MRI," *Computers & Electrical Engineering*, vol. 128, p. 110687, Sep. 2025, doi: 10.1016/j.compeleceng.2025.110687.

[3] Md. A. M. Joy, S. Nasrin, A. Siddiqua, and D. Md. Farid, "ViTAD: Leveraging modified vision transformer for Alzheimer's disease multi-stage classification from brain MRI scans," *Brain Research*, vol. 1847, p. 149302, Nov. 2024, doi: 10.1016/j.brainres.2024.149302.

[4] R. Nalawade, C. Bhosale, B. Mhaiskar, and U. Gurav, "Alzheimer's disease detection from brain MRI: Comparative Study of ResnNet50, VGG19, DenseNet121 Multibranch CNN models," *Procedia Computer Science*, vol. 259, pp. 1490–1500, Jan. 2025, doi: 10.1016/j.procs.2025.04.104.

[5] P. A. Chaudhari and S. S. Khot, "Alzheimer's disease prediction using CAdam optimized reinforcement learning-based deep convolutional neural network model," *Biomedical Signal Processing and Control*, vol. 108, p. 107968, May 2025, doi: 10.1016/j.bspc.2025.107968.

[6] R. Hasegawa, T. Nakata, K. Ishii, and S. Kobashi, "Image-to-Biomarker prediction of CSF amyloid-B via multimodal deep learning on MRI and brain perfusion SPECT," *Procedia Computer Science*, vol. 270, pp. 4978–4987, Jan. 2025, doi: 10.1016/j.procs.2025.09.624.

[7] I. J. Khan *et al.*, "Enhanced ROI guided deep learning model for Alzheimer's detection using 3D MRI images," *Informatics in Medicine Unlocked*, vol. 56, p. 101650, Jan. 2025, doi: 10.1016/j.imu.2025.101650.

[8] T. Puzio *et al.*, "Deep learning-based automatic segmentation of brain structures on MRI: A test-retest reproducibility analysis," *Computational and Structural Biotechnology Journal*, vol. 28, pp. 128–140, Jan. 2025, doi: 10.1016/j.csbj.2025.04.007.

[9] V. Satushe, V. Vyas, S. Metkar, and D. P. Singh, "AI in MRI brain tumor diagnosis: A systematic review of machine learning and deep learning advances (2010–2025)," *Chemometrics and Intelligent Laboratory Systems*, vol. 263, p. 105414, Apr. 2025, doi: 10.1016/j.chemolab.2025.105414.

[10] M. Lashkary, K. Bansal, S. Jain, P. K. Shukla, H. Tekchandani, and V. S. Dhaka, "Detection of Alzheimer's Disease progression from Structural MRIs using ConvMixer based Deep Learning Model," *Procedia Computer Science*, vol. 258, pp. 420–429, Jan. 2025, doi: 10.1016/j.procs.2025.04.278.

[11] R. Komal, P. Dhavakumar, K. Rahul, B. Jaswanth, and R. Preeth, "Hybrid deep learning framework for magnetic resonance imaging-based classification of Alzheimer's disease," *Brain Network Disorders*, vol. 1, no. 4, pp. 239–249, Oct. 2025, doi: 10.1016/j.bnd.2025.06.002.

[12] G. N. Alwakid, "A hybrid deep learning Multi-Class classification model for Alzheimer's disease using enhanced MRI images," *Computers, Materials & Continua/Computers, Materials & Continua (Print)*, vol. 86, no. 1, pp. 1–25, Sep. 2025, doi: 10.32604/cmc.2025.068666.

[13] M. Asaduzzaman, Md. K. Alom, and Md. E. Karim, "ALZENET: Deep learning-based early prediction of Alzheimer's disease through magnetic resonance imaging analysis," *Telematics and Informatics Reports*, vol. 17, p. 100189, Feb. 2025, doi: 10.1016/j.teler.2025.100189.