

“EARLY PREDICTION OF ALZHEIMER’S DISEASE USING CONVOLUTIONAL NEURAL NETWORK - REVIEW PAPER”

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Abstract— Alzheimer’s disease (AD) is a progressive condition that affects the brain, and early and accurate diagnosis is essential for timely treatment. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown great promise in analyzing brain MRI scans for early detection of AD. This paper presents a review of recent approaches using CNNs for predicting Alzheimer’s disease before symptoms become severe. A thorough search was conducted across major scientific databases for studies published between 2018 and 2025. The reviewed methods were assessed based on the data used, the structure of the model, performance metrics, and their applicability in real-world clinical settings. The analysis reveals that advanced CNN models, such as 3D CNNs and transfer learning techniques, can achieve high accuracy, ranging from 85% to 97%. However, several challenges remain, including the lack of diverse data, class imbalances, high computational demands, and the difficulty in understanding how these models make decisions. This study outlines current trends, identifies existing problems, and proposes directions for future research to develop more reliable and effective.

KEYWORDS: Alzheimer’s disease, CNN, Deep AI systems for diagnosing Alzheimer’s disease. Learning, MRI Imaging, Early Diagnosis, Medical Image Classification.

INTRODUCTION:

Alzheimer's disease is a progressive and irreversible condition that affects memory, thinking, and daily activities. It is the most common form of dementia and has a growing impact on society due to the aging population. Early and accurate diagnosis is critical for timely treatment, better patient care, and slowing the disease's progression. However, detecting Alzheimer's in its early stages, especially in Mild Cognitive Impairment (MCI), remains a significant challenge in clinical settings. Neuroimaging techniques like MRI and PET scans are often used to detect brain changes linked to the disease. MRI is preferred due to its non-invasive nature, widespread availability, and detailed brain imaging. However, traditional methods often rely on expert interpretation of images, which can be time-consuming, subjective, and inconsistent between different experts. Detecting subtle changes in early stages through manual analysis is difficult. In recent years, AI and deep learning techniques have shown potential in medical image analysis. CNNs, in particular, have proven effective in automatically learning and extracting important features from imaging data. Unlike traditional machine learning methods that require manually designed features, CNNs can process raw MRI data directly and produce better classification results. As a result, many studies have explored various CNN architectures, such as 2D CNNs, 3D CNNs, transfer learning models, and hybrid frameworks, for automated detection and classification of Alzheimer's. Despite these advancements, several challenges persist, including limited and unbalanced data, lack of multi-center validation, poor model interpretability, and inconsistent preprocessing and evaluation methods. With the rapid growth of deep learning in this field, there is a need for a comprehensive and up-to-date review of current methods, performance trends, and research gaps. This paper presents a systematic review of CNN-based approaches for the early prediction of Alzheimer's disease using MRI data. The review critically analyzes recent literature, compares datasets and model architectures, identifies key challenges, and outlines future research directions. The aim is to provide researchers and clinicians with a clear understanding of current advancements and opportunities for developing more robust, interpretable, and clinically applicable AI-based diagnostic systems. The rest of the paper is organized as follows: Section II provides background and context, Section III summarizes the functional aspects of CNN-based approaches, Section IV identifies research gaps, and subsequent sections discuss findings, limitations, and future research directions.

II. Review Methodology

This review follows a systematic literature review approach to identify relevant studies on CNN-based early prediction of Alzheimer's disease. Major scientific databases including IEEE Xplore, Science Direct, SpringerLink, and PubMed were searched for articles published between 2018 and 2025. Keywords such as "Alzheimer's disease," "convolutional neural network," "deep learning," and "MRI classification" were used. Only peer-reviewed journal and conference papers focusing on MRI-based AD detection using CNN models were included. Studies lacking experimental validation or not related to deep learning-based neuroimaging were excluded.

Paper Title	Author(s)	Year	Journal / Site	Method Used	Limitations
Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks	Basaia et al.	2020	NeuroImage: Clinical	Deep CNN model using single MRI modality for AD and MCI classification	Limited dataset size and lack of multi-modal data
Convolutional neural network based Alzheimer's disease classification from magnetic resonance brain images	Jain et al.	2019	Cognitive Systems Research	CNN-based image classification using MRI brain scans	Overfitting due to small dataset and lack of regularization
DeepAD: Alzheimer's disease classification via deep convolutional neural networks using MRI and fMRI data	Sarraf et al.	2021	bioRxiv	CNN architecture trained on both MRI and fMRI modalities	Lack of cross-validation with real clinical datasets
Alzheimer's disease diagnostics by adaptation of 3D convolutional network	Hosseini-Asl et al.	2016	IEEE ICIP	3D CNN-based feature extraction for diagnosis of AD	High computational cost and training time
Multimodal and multiscale deep neural networks for the early diagnosis of Alzheimer's disease using structural MR and FDG-PET images	Lu et al.	2018	Scientific Reports	Multimodal deep learning combining MRI and PET imaging	Complex architecture and high hardware requirements

Table 2: Comparison of Existing CNN-Based Alzheimer's Disease Detection Methods

Author	Year	Dataset	Method	Reported Accuracy	Key Limitation
Basaia et al.	2019	ADNI	Deep Neural Network on MRI	86%	Limited generalization
Jain et al.	2019	OASIS	2D CNN	88.7%	Small dataset
Sarraf & Tofighi	2021	ADNI	DeepAD CNN	96%	High computational cost
Hosseini-Asl et al.	2016	ADNI	3D CNN	94%	Overfitting risk
Korolev et al.	2017	ADNI	Residual CNN	92%	Requires large data
Lu et al.	2018	ADNI + PET	Multimodal CNN	97%	Complex pipeline
Spasov et al.	2019	ADNI	Parameter-efficient CNN	90%	Limited interpretability
Wen et al.	2020	ADNI	CNN evaluation study	89%	Dataset bias

II] Background and Context : Alzheimer's disease (AD) is a chronic, progressive, and irreversible neurodegenerative disorder that primarily affects memory, cognitive functions, and behavior. It is the leading cause of dementia worldwide and represents a significant medical and social challenge due to its increasing prevalence among the elderly population. The disease gradually destroys brain cells, leading to severe cognitive decline, language impairment. Traditionally, the diagnosis of Alzheimer's disease has relied on clinical assessments, cognitive tests, and neuroimaging techniques such as Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET). Although these imaging modalities provide valuable insights into brain structure and function, manual interpretation by experts is time-consuming, subjective, and prone to inter-observer variability. Furthermore, subtle structural changes in the early stages of the disease often go unnoticed, leading to delayed diagnosis and limited treatment options. In recent years, advancements in Artificial Intelligence (AI) and Deep Learning (DL) have revolutionized the field of medical image analysis. Among various AI techniques, Convolutional Neural Networks (CNNs) have shown exceptional capability in learning spatial hierarchies and detecting complex patterns within imaging data. CNNs eliminate the need for handcrafted features, enabling automated and highly accurate classification of medical images. When applied to MRI scans, CNNs can learn discriminative features that distinguish between healthy subjects, individuals with Mild Cognitive.

III] Functional Features :

The proposed system for early prediction of Alzheimer's disease using Convolutional Neural Networks (CNNs) integrates several functional components that collectively enhance diagnostic automation, accuracy, and interpretability. The key features of this project are as follows:

1. **Automated MRI Preprocessing:** The system performs data preprocessing steps such as skull stripping, intensity normalization, and image resizing to ensure consistent image quality and effective deep learning
2. **Data Augmentation for Robustness:** The system applies augmentation techniques including image rotation, flipping, scaling, and shifting to improve model generalization and prevent overfitting.
3. **CNN-Based Feature Extraction:** The CNN architecture automatically learns hierarchical spatial features from MRI images, eliminating the need for manual feature engineering.
4. **Multi-Class Classification Capability:** The model classifies MRI scans into multiple categories — Normal, Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD).
5. **Explainable AI Visualization:** Using Gradient-weighted Class Activation Mapping (Grad-CAM), the model highlights critical brain regions influencing predictions .
6. **Performance Evaluation Metrics:** Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess model performance.
7. **Comparative Analysis with Traditional ML Models:** Results are compared against SVM and Random Forest models to demonstrate CNN superiority.

IV] Gap Identified :

Although significant advances have been made, several gaps persist in existing research and practical systems for automated Alzheimer's detection:

1. **Data Scarcity and Class Imbalance:** Many neuroimaging datasets have limited labeled examples for early-stage cases (e.g., MCI), leading to class imbalance and challenges in learning discriminative features for early detection.
2. **Domain Generalization and Multi-Center Validation:** Models trained on a single source dataset (e.g., ADNI) may not generalize well to images from different scanners, protocols, or populations. There is a need for multi-center validation to ensure clinical robustness.
3. **Explainability and Clinical Interpretability:** While Grad-CAM and saliency methods exist, integration of explainability into the model development cycle and rigorous validation against known biomarkers is still limited. Clinicians require transparent and reproducible explanations before adopting AI tools.
4. **Reproducibility and Standardized Pipelines:** Differences in preprocessing (skullstripping algorithms, intensity normalization, slice-selection) and evaluation protocols make fair comparison difficult. Standardized, well-documented pipelines are required for reproducible research.
5. **Focus on Deployment and Usability:** Most studies emphasize accuracy metrics but lack practical deployment considerations such as inference speed, resource constraints, user interface design, and integration with hospital workflows.

6. Early Conversion Prediction: A majority of works classify cross-sectional scans but do not effectively model longitudinal data to predict conversion from MCI to AD — a clinically valuable task that requires temporal modeling and longitudinal dataset usage.

V] Methodology

This study adopts a systematic literature review methodology to comprehensively analyze existing research on Convolutional Neural Network (CNN)-based approaches for the early prediction of Alzheimer's disease using MRI data. The review process follows structured guidelines to ensure transparency, reproducibility, and coverage of relevant studies.

- **Data Sources and Search Strategy:**

Relevant research articles were collected from major scientific databases including IEEE Xplore, ScienceDirect, SpringerLink, and PubMed. The literature search focused on publications from 2018 to 2025 to capture recent advancements in deep learning-based Alzheimer's detection.

A combination of keywords and Boolean operators was used, including: "Alzheimer's disease," "convolutional neural network," "deep learning," "MRI," "early diagnosis," and "medical image classification." The search was restricted to peer-reviewed journal articles and high-quality conference papers published in English.

- **Inclusion and Exclusion Criteria :**

- Studies using CNN or deep learning for Alzheimer's disease detection
- Research based on MRI or multimodal neuroimaging data
- Papers reporting quantitative performance metrics (e.g., accuracy, precision, recall)
- Peer-reviewed journal or reputed conference publications

The exclusion criteria included:

- Studies not related to Alzheimer's disease
- Papers using only traditional machine learning without CNN
- Review papers, editorials, and short communications
- Studies lacking sufficient experimental details

- **Study Selection Process:** The study selection process was conducted in multiple stages following PRISMA guidelines. Initially, all retrieved records were screened based on titles and abstracts to remove irrelevant studies. Duplicate records were eliminated. The remaining articles were then evaluated through full-text assessment to ensure compliance with the inclusion criteria. Finally, the most relevant studies were selected for qualitative comparative analysis.

- **Data Extraction and Analysis:** From each selected study, important information was systematically extracted, including dataset used (e.g., ADNI, OASIS), CNN architecture, preprocessing techniques, classification categories, performance metrics, and reported limitations. The extracted data were organized into comparative tables to facilitate trend analysis and performance evaluation across different approaches.
- **Quality Assessment:** To maintain the reliability of the review, the selected studies were evaluated based on methodological clarity, dataset adequacy, validation strategy, and reporting of performance metrics. Studies with incomplete experimental details or unclear validation procedures were carefully examined before inclusion.

VI] Discussion:

This review examined recent advancements in Convolutional Neural Network (CNN)-based approaches for the early prediction of Alzheimer's disease using brain MRI data. The analysis of the selected studies indicates that deep learning models have significantly improved automated neuroimaging-based diagnosis compared to traditional machine learning techniques. Most reported works demonstrate that CNN architectures can effectively learn hierarchical spatial features from MRI scans, enabling reliable classification of Normal, Mild Cognitive Impairment (MCI), and Alzheimer's disease (AD) stages. A clear trend observed across the literature is the increasing adoption of advanced CNN variants such as 3D CNNs, residual networks, and transfer learning-based models. Studies employing 3D CNN architectures generally achieve higher diagnostic performance because they capture volumetric brain information more effectively than 2D slice-based models. Similarly, transfer learning approaches have shown promise in scenarios with limited labeled medical data by leveraging knowledge from large-scale pretrained networks.

Reported classification accuracies in the reviewed studies typically range from approximately 85% to 97%, depending on dataset size, preprocessing strategy, and model complexity. Another important observation is the dominant use of the ADNI dataset in Alzheimer's disease research. While ADNI provides a well-curated benchmark dataset, heavy reliance on a single data source raises concerns regarding model generalization across different scanners, demographic groups, and clinical settings. Only a limited number of studies perform cross-dataset or multi-center validation, which remains a critical requirement for real-world clinical deployment. The review also highlights the growing interest in multimodal learning frameworks that combine MRI with PET imaging, clinical scores, or genetic information.

These hybrid approaches often demonstrate improved performance by capturing complementary disease biomarkers. Furthermore, explainable artificial intelligence (XAI) techniques such as Grad-CAM are increasingly being incorporated to visualize disease-relevant brain regions, thereby improving model transparency and clinical trust. However,

standardized validation of these explanations against neurological biomarkers is still limited. Overall, CNN-based approaches demonstrate strong potential for supporting early and automated Alzheimer's disease diagnosis. However, future research must emphasize large-scale multi-center validation, standardized evaluation frameworks, improved model interpretability, and lightweight architectures to enable reliable real-world clinical adoption.

VII]Results:

The systematic analysis of the selected studies indicates that Convolutional Neural Network (CNN)-based methods have demonstrated strong capability for the early detection and classification of Alzheimer's disease using brain MRI data. Across the reviewed literature, most models achieved high diagnostic performance, with reported classification accuracies generally ranging from approximately **85% to 97%**, depending on the dataset characteristics, preprocessing techniques, and network architecture employed. The comparative evaluation reveals that **3D CNN architectures** consistently outperform traditional 2D CNN models because they effectively capture volumetric spatial information from MRI scans. Similarly, **transfer learning-based approaches** have shown competitive performance, particularly in studies with limited labeled datasets, by leveraging pretrained deep networks.

In addition, **multimodal frameworks** that combine MRI with PET imaging or clinical features frequently report improved classification accuracy compared to single-modality systems. Another key observation is the dominant use of the **ADNI dataset**, which appears in the majority of the reviewed studies due to its standardized and publicly available neuroimaging data. However, only a limited number of works perform external validation on independent datasets, indicating that real-world generalization of many CNN models remains an open challenge.

The analysis also shows increasing adoption of **explainable AI techniques**, such as Grad-CAM, to highlight disease-relevant brain regions and improve model interpretability. Despite these advances, variability in preprocessing pipelines, class imbalance—especially for Mild Cognitive Impairment (MCI)—and high computational requirements continue to affect consistent performance across studies. Overall, the reviewed evidence confirms that CNN-based deep learning approaches provide a reliable and automated framework for early Alzheimer's disease detection. Nevertheless, further research is required to improve cross-dataset robustness, clinical interpretability, and deployment efficiency for practical healthcare applications.

From: Early prediction of Alzheimer's disease using convolutional neural network: a review

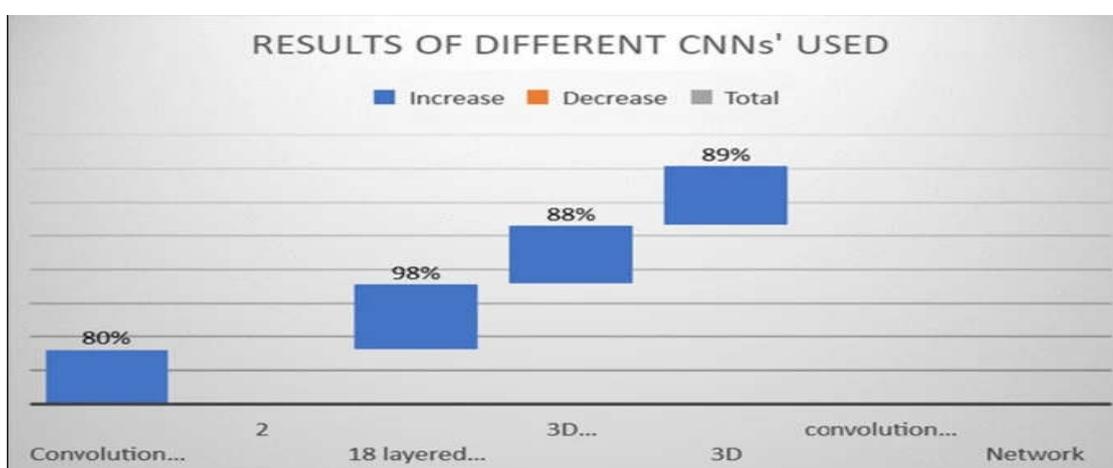
Research studies	Data set source	Data set description				
		Total samples	NC	EMCI	LMCI	AD
Atif Mehmood and colleagues (2021)	Data sets from ADNI	300	85	70	70	75
Modupe Odusami and colleagues (2021)	Data sets from ADNI	138	25	25	25	25
Janani Venugopalan and colleagues (2021)	Data sets from ADNI	503	132	104		266
Amnaya Pradhan and colleagues (2021)	Kaggle Data set	6000				
			80% train			
			20% test			
Aakash Shah and colleagues (2020)	Data collection is done yearwise	437	72			14
Huanhuan Ji and colleagues (2019)	Data sets from ADNI	615	3:1:1	182	254	179
Firouzeh Razavi and colleagues (2019)	Data sets from ADNI	99		52	43	56
Jyoti Islam and colleagues (2018)	Data sets from ADNI	416	4:1	73	75	62
Jyoti Islam and colleagues (2019)	Data sets from ADNI	988		400	661	169

LC: Normal Control; LMCI: Late Mild Cognitive Impairment; EMCI: Early Mild Cognitive Impairment; AD: Alzheimer's Disease

From: Early prediction of Alzheimer's disease using convolutional neural network: a review

Research studies	Model used	Accuracy obtained in %
Atif Mehmood and colleagues (2021)	The Convolutional Neural Network of multi-layer	80
Modupe Odusami and colleagues (2021)	18-layered Convolutional Neural Network	98
Janani Venugopalan and colleagues (2021)	3D Convolutional Neural Network	88
Amnaya Pradhan and colleagues (2021)	DenseNet169	87
	VGG19	88
Aakash Shah and colleagues (2020)	SVM	81
	86	86
	Decision tree	79
	Xboost	80
	Random forest classifier	81
Huanhuan Ji and colleagues (2019)	Convnet	97.65
Firouzeh Razavi and colleagues (2019)	Softmax regression	94.5
Jyoti Islam and colleagues (2018)	Deep CNN	82
Jyoti Islam and colleagues (2019)	3D Convolutional neural network	88.76
Priyanka Thakare and colleagues (2016)	SVM	95

SVM: Support Vector Machine; VGG: Visual Geometry Group

**VIII] Limitations:**

Despite the promising performance of Convolutional Neural Network (CNN)-based approaches for Alzheimer's disease detection, several limitations remain evident in the current body of research. One of the primary challenges is the **limited availability of large and balanced neuroimaging datasets**, particularly for early-stage conditions such as Mild Cognitive Impairment (MCI). Class imbalance can lead to biased model learning and may reduce the reliability of early diagnosis. Another important limitation is the **heavy reliance on single-source datasets**, most notably the ADNI database. Although widely used, models trained predominantly on one dataset may not generalize well to images acquired from different scanners, clinical settings, or demographic populations. The lack of extensive **multi-center and cross-dataset validation** raises concerns about the real-world clinical applicability of many proposed methods. High **computational complexity and resource requirements** of deep CNN architectures also present practical challenges.

Training 3D CNN and multimodal models often requires powerful GPU infrastructure, which may limit deployment in resource-constrained healthcare environments. In addition, although

explainable artificial intelligence techniques such as Grad-CAM are increasingly adopted, many models still function as **black-box systems**, and their clinical interpretability remains insufficiently validated against established neurological biomarkers. Furthermore, **variability in preprocessing pipelines and evaluation protocols** across studies makes direct comparison difficult and affects reproducibility. Differences in skull stripping methods, slice selection, data augmentation strategies, and performance reporting contribute to inconsistent benchmarking in the literature.

Finally, this review is limited to studies published in selected scientific databases and English-language peer-reviewed articles between 2018 and 2025. Relevant studies outside these sources or in other languages may not have been captured, which could introduce **selection bias**.

IX] Future Scope :

Future research on CNN-based early prediction of Alzheimer's disease should focus on improving the clinical robustness, generalizability, and interpretability of deep learning models. One of the most critical directions is the development and utilization of **large-scale, balanced, and multi-center neuroimaging datasets**. Expanding beyond single-source datasets will help models generalize across different scanners, demographic groups, and clinical environments, thereby enhancing real-world applicability. Another promising direction is the integration of **multimodal learning frameworks** that combine MRI with complementary biomarkers such as PET imaging, cognitive scores, genetic information, and electronic health records. Such fusion approaches can capture both structural and functional aspects of the disease and may significantly improve early-stage detection, particularly for Mild Cognitive Impairment (MCI) conversion prediction. Future work should also emphasize **longitudinal modeling** to predict disease progression over time rather than relying solely on cross-sectional classification. Incorporating temporal deep learning architectures, such as recurrent neural networks and transformer-based models, may enable more accurate prediction of conversion from MCI to Alzheimer's disease.

Improving **model interpretability and explainability** remains another important research priority. Although techniques such as Grad-CAM are increasingly used, further validation against clinically established biomarkers is required to build trust among healthcare professionals. Developing inherently interpretable or hybrid explainable frameworks will be essential for clinical adoption. In addition, there is a growing need for **lightweight and computationally efficient CNN architectures** that can support real-time inference and deployment in resource-constrained clinical settings. Model compression, pruning, and edge-AI implementations may play a significant role in translating research models into practical healthcare tools.

Finally, future studies should work toward **standardized preprocessing pipelines, evaluation protocols, and benchmarking frameworks** to enable fair comparison and reproducibility across studies. Collaborative efforts between AI researchers, neurologists, and healthcare institutions will be crucial for developing reliable, ethical, and clinically deployable Alzheimer's disease diagnostic systems.

X] Conclusion :

This paper presented a comprehensive systematic review of Convolutional Neural Network (CNN)-based approaches for the early prediction of Alzheimer's disease using brain MRI data. The analysis of recent studies demonstrates that deep learning models, particularly advanced CNN architectures, have significantly improved the accuracy and automation of Alzheimer's disease diagnosis compared to traditional machine learning techniques. Approaches such as 3D CNNs, transfer learning frameworks, and multimodal fusion models have shown promising performance in distinguishing Normal, Mild Cognitive Impairment (MCI), and Alzheimer's disease stages. Despite these advancements, several challenges remain. The majority of existing studies rely heavily on limited and single-source datasets, which raises concerns about model generalization in real-world clinical environments. Issues related to class imbalance, lack of standardized preprocessing pipelines, high computational requirements, and limited clinical interpretability continue to hinder widespread deployment of CNN-based systems. Overall, CNN-driven methodologies demonstrate strong potential to support clinicians in the early and automated detection of Alzheimer's disease. However, future research must prioritize multi-center validation, improved explainability, lightweight model design, and multimodal integration to achieve clinically reliable and scalable solutions. With continued progress in deep learning and medical imaging, AI-based diagnostic systems are expected to play an increasingly important role in enhancing early Alzheimer's disease diagnosis and patient care.

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