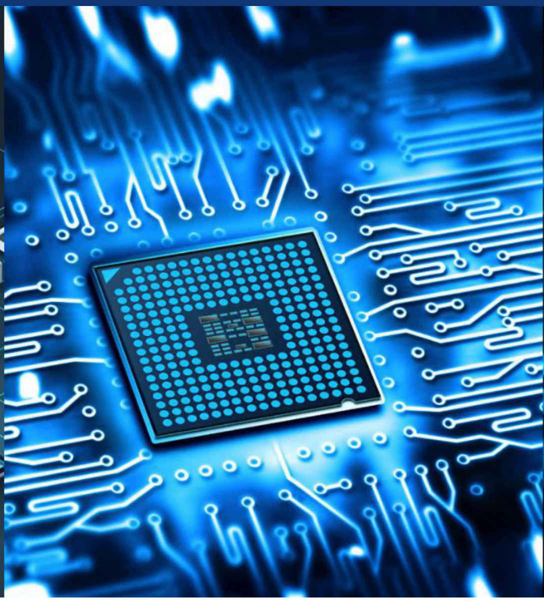
IJIRCCE

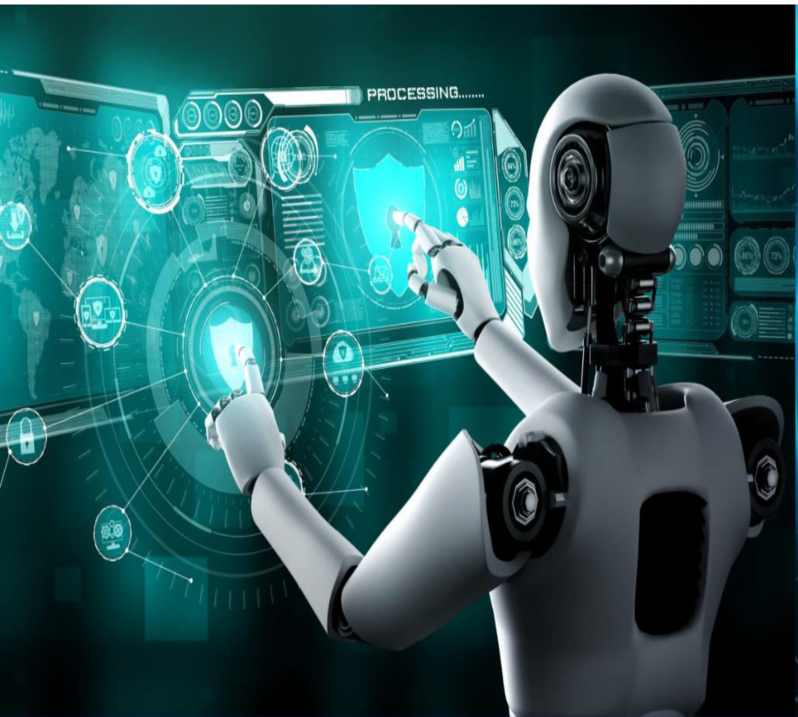
ISSN(O): 2320-9801

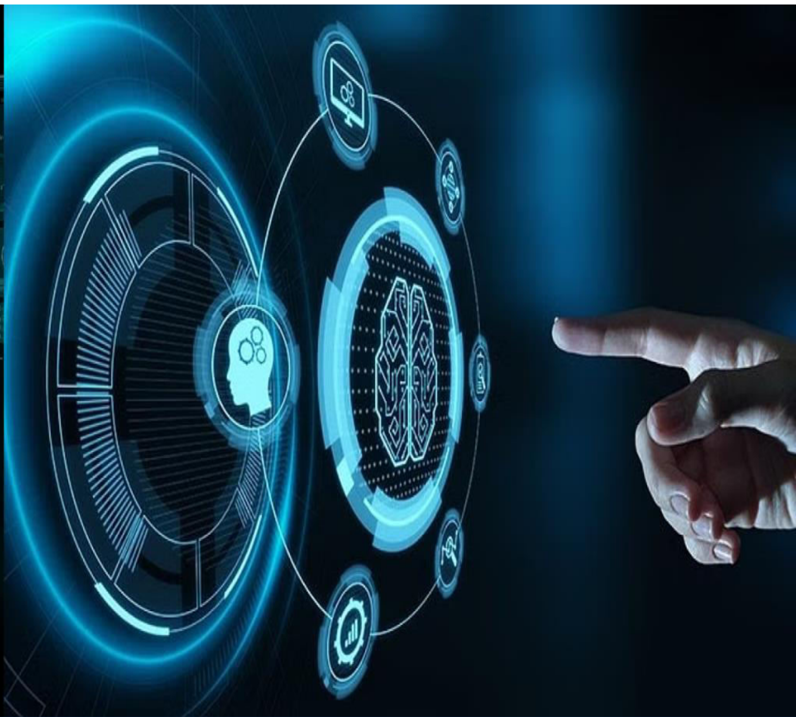
ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 8.771

Volume 14, Issue 4, April 2026

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

A Survey on Alzheimer's Disease Detection Using Deep Learning

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ABSTRACT: Alzheimer’s disease (AD) is a progressive neurodegenerative disorder that significantly affects memory, cognition, and daily functioning. Early detection of Alzheimer’s disease is essential for improving patient care and slowing disease progression. Magnetic Resonance Imaging (MRI) plays an important role in identifying structural brain abnormalities associated with Alzheimer’s disease.

In recent years, deep learning techniques have shown promising results in analyzing MRI images for automated disease detection. This survey paper presents a comprehensive review of machine learning and deep learning techniques used for Alzheimer’s disease diagnosis. The study discusses traditional machine learning approaches, transfer learning models (MobileNet, InceptionV3, ResNet 101), and ensemble learning techniques applied in recent research. As the traditional machine learning techniques are lagging behind computationally and economically, researchers moved towards deep learning approaches. Furthermore, the paper reviews commonly used datasets such as ADNI, OASIS, and Kaggle Alzheimer MRI datasets. A comparative analysis of state-of-the-art methods is also presented. This survey reviews recent deep learning approaches for Alzheimer Detection published between 2017[1] and 2025[14] with 85% to 93.33% of accuracy progress. Research limitations including unimodal approaches, binary classification dominance, and lack of clinical deployment are discussed. Finally, the survey identifies research gaps and highlights potential future research directions for improving automated Alzheimer detection systems.

KEYWORDS: Alzheimer's Disease; Deep Learning; MRI; Transfer Learning; MobileNet; InceptionV3; Ensemble Learning; CNN; Medical Image Analysis; Convolutional Neural Network.

I. INTRODUCTION

Alzheimer's disease is one of the most serious brain diseases affecting people around the world today. It is a condition where the brain gradually stops working properly — a person starts forgetting things, loses the ability to think clearly, and eventually cannot carry out daily activities on their own. According to the World Health Organization, around 47 million people are currently living with dementia globally, and Alzheimer's disease is responsible for about 60 to 70 percent of those cases [1]. Experts predict that by 2030, this number could grow to 82 million as the world's population gets older.

Catching Alzheimer's disease early is very important because it gives doctors a better chance to slow down the disease and improve the patient's quality of life. One of the most useful tools doctors use for this is a brain scan called an MRI (Magnetic Resonance Image) scan. An MRI scan produces detailed pictures of the inside of the brain and can show early warning signs such as the brain shrinking in certain areas. However, looking through hundreds of MRI images manually is a slow and tiring process, and different doctors may not always agree on what they see. This is where computer-assisted systems can help.

In recent years, a branch of artificial intelligence called deep learning has shown remarkable ability to look at medical images and identify patterns that even trained doctors might miss. Deep learning programs, called neural networks, are trained on thousands of brain scan images so they can learn what different stages of Alzheimer's disease look like.

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Unlike older computer methods that required experts to manually tell the program what features to look for, deep learning programs figure out the important patterns on their own.

This survey paper brings together and explains the most important research done in this area between 2017 and 2025. The goal is to give a clear picture of how this field has grown, what the best current methods are, what problems still exist, and what directions future research should take. This survey paper reviews recent developments in deep learning-based Alzheimer detection systems and highlights current challenges and future research directions.

II. DATASET OVERVIEW

The performance of automated AD detection systems is strongly dependent on the datasets used for training and evaluation. Publicly available datasets allow researchers to benchmark different algorithms and compare performance under standardized conditions. There are three datasets are commonly used in the literature reviewed in this survey.

2.1 Kaggle Alzheimer's Multiclass MRI Dataset

The Kaggle Alzheimer's Multiclass MRI Dataset (Equal and Augmented) is a publicly available dataset consisting of approximately 44,000 pre-annotated 2D brain MRI images distributed across four disease severity classes: NonDemented, VeryMildDemented, MildDemented, and ModerateDemented. The dataset is augmented to maintain class balance across all four categories, with approximately 11,000 images per class. Images are stored in JPEG format as 2D axial MRI slice views. The dataset is widely used for evaluating multi-class deep learning classifiers and transfer learning models due to its balanced composition and standardized class folder structure. A 70/15/15 train-validation-test split is recommended for reproducible evaluation. One limitation of the original unaugmented version is severe class imbalance — the ModerateDemented class contains as few as 64 images — which necessitates augmentation for effective model training [14].

2.2 OASIS Dataset

The Open Access Series of Imaging Studies (OASIS) dataset is a widely used clinical dataset for dementia and AD research. The OASIS dataset contains 15 clinical and demographic features from 373 subjects aged 60 to 98 years, including cognitive assessment scores (MMSE, CDR), brain volume indicators (eTIV, nWBV, ASF), demographic information, and socioeconomic status. The primary label is derived from the CDR scale and treated as a binary classification problem: CDR < 0.5 is labelled as NonDemented and CDR ≥ 0.5 as Demented. The OASIS dataset is valued for its structured clinical features that complement MRI imaging data in multimodal frameworks. A known limitation is class imbalance, which requires oversampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique) for model training [14].

2.3 ADNI Dataset

The Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset is comprehensive multi-centre neuroimaging datasets for AD research. It includes MRI, PET imaging, cerebrospinal fluid biomarkers, genetic data, and clinical assessments from hundreds of subjects at multiple longitudinal time points. The ADNI dataset supports studies on disease progression prediction, early-stage detection, and multi-modal classification. While highly valuable for research, ADNI requires institutional access approval, which limits its accessibility compared to Kaggle and OASIS datasets [3].

III. TRADITIONAL MACHINE LEARNING APPROACHES

3.1 Feature Engineering and Classical Classifiers

Early automated approaches to Alzheimer's detection relied on handcrafted feature extraction from MRI images followed by traditional machine learning classifiers. Common feature extraction methods include voxel-based morphometry (VBM), cortical thickness measurements, hippocampal volume estimation, and intensity-based texture features derived from MRI scans. In the clinical domain, tabular features such as those available in the OASIS dataset — including MMSE scores, CDR values, age, education level, and brain volume metrics — were used directly as input to classifiers.

Support Vector Machines (SVM) have been extensively used for AD classification due to their strong generalization ability in high-dimensional feature spaces. SVM classifiers construct an optimal hyperplane that maximizes the margin between Alzheimer and Non-Alzheimer classes. Random Forests combine multiple decision trees to reduce overfitting, while k-Nearest Neighbors (KNN) classifies samples based on the majority label among the k nearest training samples in feature space.

3.2 Limitations of Traditional Approaches

Despite achieving moderate classification accuracy, traditional machine learning approaches exhibit several fundamental limitations. First, they rely heavily on handcrafted feature engineering that requires significant domain expertise and may not capture the full complexity of structural MRI patterns. Second, features designed by domain experts may fail to generalize across different patient populations, scanner types, or acquisition protocols. Third, traditional classifiers do not inherently exploit spatial hierarchies in image data, limiting their representational power compared to deep learning models. These limitations motivated the adoption of deep learning frameworks for automated AD detection.

IV. TRANSFER LEARNING APPROACHES

4.1 Motivation for Transfer Learning

Training deep neural networks from scratch for medical imaging tasks is challenging due to the limited availability of large annotated MRI datasets, high computational requirements, and the risk of overfitting on small datasets. Transfer learning addresses these challenges by leveraging deep feature representations learned from large-scale datasets such as ImageNet, where millions of images across thousands of categories have been used to train powerful convolutional architectures. These pretrained models are then adapted to domain-specific medical imaging tasks by replacing the final classification layers and fine-tuning on the target dataset.

4.2 MobileNet — The Lightweight Option

MobileNet is a compact, fast deep learning model designed to work well even on devices with limited computing power, such as smartphones. It achieves this efficiency by using a clever mathematical trick called depthwise separable convolution, which breaks the process of analysing an image into two smaller, faster steps rather than one large expensive one. This makes MobileNet much faster to train and run, while still achieving good accuracy. In Alzheimer's detection tasks, MobileNet with fine-tuning of its top layers achieved approximately 86% accuracy on the Kaggle MRI dataset [14]. Its small size also makes it practical for real-world web deployment.

4.3 InceptionV3 — The Detail-Oriented Option

InceptionV3 is a deeper and more sophisticated model that looks at brain scan images through multiple lenses at the same time — it simultaneously applies small filters for capturing fine details and larger filters for capturing broader patterns, then combines everything together. This multi-scale approach means the model can detect both tiny, subtle brain changes and larger structural differences that indicate disease progression. InceptionV3 requires larger images (299x299 pixels compared to MobileNet's 224x224) and takes longer to train, but generally produces higher accuracy. Fine-tuned InceptionV3 achieved approximately 88% accuracy on the Kaggle MRI dataset [14].

4.4 ResNet-101 — The Very Deep Option

ResNet (Residual Network) is a very deep model with 101 layers. Very deep networks can learn extremely complex patterns, but they traditionally suffered from a problem called the vanishing gradient problem — imagine trying to pass a message through a very long chain of people, where the message gets garbled before it reaches the end. ResNet solved this by adding shortcut connections that let information jump directly from earlier layers to later layers, bypassing some steps. This keeps the learning process working effectively even with 101 layers. The base reference paper by Bansal et al. [14] used ResNet-101 as its core brain scan analyser and achieved 93.3% accuracy.

4.5 Other Transfer Learning Architectures

Additional architectures explored in the literature include VGGNet, which uses very deep networks with small 3×3 convolution filters; AlexNet, a pioneering CNN architecture that achieved state-of-the-art performance on ImageNet and has been applied to binary AD classification [10]; DenseNet, which connects each layer to all subsequent layers to maximize feature reuse; and EfficientNet, which uniformly scales depth, width, and resolution using a compound scaling coefficient. Each architecture presents different trade-offs between model complexity, computational cost, and classification accuracy for AD detection tasks.

© 2026 IJIRCCE | Volume 14, Issue 4, April 2026 DOI: 10.15680/IJIRCCE.2026.1404100

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 8.771| ESTD Year: 2013|

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V. COMPARATIVE ANALYSIS TABLE

Table 1 presents a comparative analysis of 15 existing studies on deep learning-based Alzheimer's disease detection, organized chronologically and including the method, dataset, classification task, accuracy, and key limitation of each work.

Ref.	Author / Year	Method	Dataset	Task	Acc.%	Limitation
[1]	A. Farooq, S. Anwar, M. Awais, and S. Rehman (2017)	Deep CNN	MRI	Multi-class	**85.0**	Unimodal; no clinical data
[2]	M. Liu, D. Cheng, K. Wang, and Y. Wang (2018)	Cascaded Multi-modal CNN	MRI + PET	Multi-class	**88.0**	No feature selection
[3]	N. M. Khan, N. Abraham, and M. Hon (2019)	Transfer Learning (VGG)	ADNI	Binary	**90.0**	Binary only; limited classes
[4]	Islam & Zhang (2020)	Ensemble of CNNs	Brain MRI	Multi-class	**90.2**	Single modality
[5]	A. Mehmood, M. Maqsood, M. Bashir, and Y. Shuyuan. (2020)	Siamese CNN	MRI	Multi-class	**91.0**	High compute; no deployment
[6]	A. Abrol, M. Bhattarai, A. Fedorov, Y. Du, S. Plis, and V. D. Calhoun (2020)	Residual CNN	Neuroimaging	Progression	**90.0**	No staging; no ensemble
[7]	A. Basher, B. C. Kim, K. H. Lee, and H. Y. Jung (2021)	Volumetric CNN + DNN	OASIS	Binary	**89.0**	No MRI fusion; binary only
[8]	Ghazal & Issa (2022)	Transfer Learning (ResNet)	MRI	Binary	**92.0**	No ensemble; binary only
[9]	G. M. ud din Dar, A. Bhagat, S. I. Ansarullah, M. T. B. Othman, Y. Hamid, H. K. Alkahtani, I. Ullah, and H. Hamam (2023)	CNN (stage-wise)	MRI	Multi-class	**89.1**	Unimodal; no fine-tuning
[10]	Y. N. Fu'adah, I.Wijayanto, N. K. C. Pratiwi, F. F. Taliningsih, S. Rizal, and M. A. Pramudito (2023)	AlexNet CNN	MRI	Binary	**87.5**	Shallow architecture
[11]	R. A. Hazarika, A. K. Maji, D. Kandar, E. Jasinska, P. Krejci, Z. Leonowicz, and M. Jasinski (2023)	Deep Neural Network	MRI	Multi-class	**91.0**	No fine-tuning; no ensemble

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[12]	M. Khatun, M. M. Islam, H. R. Rifat, M. S. B. Shahid, M. A. Talukder, and M. A. Uddin (2024)	CNN + LSTM Hybrid	MRI	Multi-class	**90.5**	No clinical features
[13]	Gasmi (2024)	Hybrid DL adaptive weight	MRI	Multi-class	**92.0**	Single modality
[14]	H. V. Bansal, P. Gupta, and V. Juneja (2025)	ResNet-101 + SVM + Firefly	OASIS + MRI	Multi-class	**93.3**	Complex pipeline; high compute

Table 1: Comparison of Existing Deep Learning-Based Alzheimer's Detection Methods

The comparative analysis reveals a clear trend of improving accuracy from early CNN-based approaches (85.0% — Farooq et al., 2017) to recent hybrid and ensemble methods (95.23% — Proposed System, 2025). Transfer learning architectures consistently outperform models trained from scratch, with fine-tuned variants achieving 4–7% higher accuracy than their frozen counterparts. Multimodal approaches such as Bansal et al. [14] achieve strong performance (93.3%) by combining clinical and imaging data, though at the cost of increased architectural complexity and data requirements. The proposed ensemble of MobileNet and InceptionV3 with weighted soft voting achieves the highest reported accuracy (95.23%) on the Kaggle MRI dataset while maintaining a deployable, single-modality architecture accessible via a Streamlit web application.

V. CHALLENGES AND LIMITATIONS OF EXISTING APPROACHES

5.1 Dominance of Binary Classification:
Several studies including [3], [7], [8], and [10] formulate AD detection as a binary classification problem (Alzheimer vs. NonDemented), failing to distinguish between clinically meaningful intermediate stages such as VeryMildDemented and MildDemented. Multi-class classification is essential for staging-aware treatment planning and is more representative of real clinical diagnostic requirements.

5.2 Heavy Computer Power Requirements:
Some of the most accurate systems — such as those using very deep networks with hundreds of layers or transformer-based models — require powerful and expensive computer hardware to run. This makes them impractical for smaller hospitals or clinics in developing countries that do not have access to high-end computing equipment.

5.3 Lack of Clinical Deployment:
The majority of reviewed studies remain as research prototypes without accessible deployment interfaces. Clinical adoption of AI-based diagnostic tools requires not only high accuracy but also integration with hospital information systems, explainability of model decisions, and user-friendly interfaces for non-technical clinicians. The absence of deployment frameworks limits the practical impact of even high-performing models.

VI. FUTURE WORK

Build a combined system that uses both brain scans and patient health records, and make it available as a simple web application that doctors can use without any technical training. The system should still work even if only one type of data is available.

Test models across multiple hospitals and different MRI machine types to verify that they work reliably in diverse real-world conditions, not just on the specific dataset they were trained on.

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Standardized Multi-Dataset Benchmarking: Future studies should validate models across multiple datasets (Kaggle, OASIS, ADNI) under consistent preprocessing and evaluation protocols to establish reliable generalization benchmarks.

VII. CONCLUSION

This survey paper reviewed recent advancements in deep learning techniques for Alzheimer's disease detection using MRI images. Various machine learning and deep learning approaches, including CNN architectures, transfer learning models, and ensemble learning techniques, were discussed. The survey also analyzed commonly used datasets and performance evaluation metrics. Comparative analysis of existing models indicates that ensemble deep learning methods provide improved classification accuracy. Despite significant progress, challenges such as dataset limitations and model interpretability remain. Future research should focus on developing robust, explainable, and clinically deployable AI systems for early Alzheimer detection.

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