STM JOURNALS

Research & Reviews: A Journal of
Neuroscience

https://journals.stmjournals.com/rrjons/

ISSN: 2277-6427 (Online)
ISSN: 2348-7925 (Print)
Volume 16, Issue 1, 2026
January–April
DOI (Journal): 10.37591/RRJoNS

Review RRJoNS

A Dual-Model Deep Learning Framework for Early Alzheimer's Detection Using Clinical Data and Neuroimaging with Architectural Performance Analysis

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Abstract

Alzheimer's disease (AD) poses a significant global health challenge due to its increasing prevalence and the absence of definitive cures. Early diagnosis is crucial for effective intervention and management. This study presents a dual-model deep learning framework for the early detection and classification of AD using both structured clinical data and neuroimaging datasets. Model 1 utilizes a greedy layer-wise autoencoder approach applied to structured data, achieving optimal binary classification accuracy of 95.8% with a four-layer configuration. Model 2 employs EfficientNet-B0 via transfer learning to classify MRI brain scans across multiple AD stages, reaching accuracies of up to 94%. Comparative analysis with existing state-of-the-art models validates the effectiveness of both approaches. Additionally, this paper highlights how network architecture, depth, and input modality significantly impact diagnostic performance. The findings advocate for the strategic design of AI models tailored to clinical applications and set the foundation for future multimodal, interpretable, and scalable Alzheimer's diagnostic tools.

Keywords: Autoencoder, clinical data analysis, convolutional neural network, deep learning, early detection, efficientnet, medical diagnostics, MRI brain imaging, neural network architecture, neuroimaging, transfer learning

INTRODUCTION

Alzheimer's disease poses a significant global health challenge, with millions affected worldwide. As life expectancy continues to rise, the prevalence of AD is rapidly increasing, placing immense strain on healthcare systems globally. This trend underscores the urgent need for innovative strategies to improve early detection and intervention [1–4]. Timely diagnosis is critical, as it enables personalized treatment and opens the door to therapeutic interventions that could slow or potentially halt the clinical progression of the disease [5, 6].

Traditional methods of diagnosing Alzheimer's disease typically involve clinical assessments, neuropsychological tests, and neuroimaging techniques, such as magnetic resonance imaging (MRI) and positron emission tomography (PET) [7, 8]. While these approaches provide valuable insights, they often fall short in detecting subtle pathological changes in the early stages of the disease when therapeutic intervention is most likely to be effective. Recent advances in deep learning, a powerful subset of artificial intelligence, offer promising opportunities to revolutionize AD diagnostics. Using the computational capabilities of artificial neural networks, these technologies can analyze intricate patterns within large, complex datasets to detect early signs of the disease [9–12].

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Received Date: January 29, 2026
Accepted Date: February 02, 2026
Published Date: February 23, 2026

Citation: Abha Jain, Sohan Lal Gupta, Megha Gupta, Mithlesh Arya, Veena Yada. A Dual-Model Deep Learning Framework for Early Alzheimer's Detection Using Clinical Data and Neuroimaging with Architectural Performance Analysis. Research & Reviews: A Journal of Neuroscience. 2026; 16(1): 1–12p.

This paper explores the application of advanced deep learning algorithms, particularly convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, for the early detection of Alzheimer's disease [13–15]. These sophisticated neural network architectures are capable of analyzing multimodal data, including structural and functional neuroimaging, as well as molecular biomarkers, to identify patterns indicative of AD at its earliest stages. The primary aim is to develop a robust diagnostic tool capable of detecting subtle brain changes that precede observable cognitive decline, offering the potential for earlier and more accurate clinical intervention [16–18].

The motivation behind this research arises from the critical need for improved diagnostic accuracy, which can enable earlier intervention strategies and significantly improve patient outcomes [19–21]. The proposed deep learning model seeks to advance the current understanding of AD by introducing a scalable, non-invasive method for its detection. By integrating deep learning techniques with clinical data, this study aims to offer a glimpse into a future where early diagnosis is not only feasible but essential for effective treatment [22–24].

Despite auspicious results, existing methods often face challenges, such as limited dataset-size, model overfitting, and high computational complexity. Therefore, there is a growing need to develop advanced AI approaches that not only improve diagnostic accuracy but also ensure robustness, generalizability, and computational efficiency [25–27]. This research focuses on exploring advanced AI methodologies for the early detection of Alzheimer's disease by leveraging MRI and PET imaging data, aiming to contribute toward more reliable and scalable computer-aided diagnostic systems [28, 29].

This paper is organized as follows: Section II presents a review of related work focusing on existing AI-based approaches for AD detection. Section III describes the proposed work & methodology, including data preprocessing, model architecture, and training strategy. Section IV discusses the experimental results and performance evaluation. Finally, Section V concludes the study with key findings and future research directions [30–34].

RELATED WORK

Researchers have placed significant emphasis on the early diagnosis of Alzheimer's Disease (AD) due to its critical importance. This section highlights key studies employing various Deep Learning (DL) techniques for AD diagnosis, as summarized in Table 1. Previous research showed that, a transfer-learning was a growing technique to classify the different Alzheimer's disease MRI images through the mathematical model. They follow the procedure with preprocessing the ADNI datasets using FreeSurfer (PE) to eliminate irrelevant information. Then apply the pretrained model VGG16 on selected feature receive after entropy. The most informative slices (SE) based on entropy. This model were achieving high accuracies ranging from 95.3% to 99.22% for various classification tasks, including 3-way classification (AD vs MCI vs CN), AD vs CN, AD vs MCI, and CN vs MCI.

Table 1. Comparison of CNN-based approaches for Alzheimer's detection on MRI and PET datasets.

Author(s)	Feature	Accuracy	Model	Dataset	Limitation
Kundaram SS, Pathak KC (2020) [22]	MRI images	98.33%	Convolutional Neural Network (CNN)	OASIS	Limited dataset size; potential overfitting
Ding Y, Sohn JH, Kawczynski MG, et al. (2018) [23]	18F-FDG PET images	82%	3D CNN	ADNI	Requires extensive computational resources; model complexity
Hosseini-Asl, E., Gimel'farb, G., & El-Baz, A. (2016) [5]	MRI images	97.8%	Deeply Supervised Adaptable 3D CNN	ADNI	Model complexity; requires high computational resources
Nawaz H, Maqsood M, Afzal S, Aadil F, Mehmood I, Rho S (2020) [24]	MRI images	99.05%	Deep CNN	OASIS and ADNI	Potential overfitting due to high accuracy; limited generalizability

Liu, M., Zhang, J., Adeli, E., & Shen, D. (2020) [25]	MRI images	91.1%	Hierarchical Fully Convolutional Network	ADNI	Complexity of the model; requires extensive computational resources
Spasov, S., Passamonti, L., Duggento, A., & Toschi, N. (2019) [26]	PET images	88.5%	3D CNN	ADNI	High computational cost; limited dataset size
Sarraf, S., & Tofighi, G. (2016) [28]	MRI images	98.84%	Deep Leaning-based CNN	ADNI	High specificity but may lead to false negatives; limited to a specific dataset

Ding et al [23]. introduced an Inception v3 network trained with Convolutional Neural Network architecture on ADNI dataset. This approach use grid method to focus on Fluorine 18 fluorodeoxyglucose PET images processed followed by Otsu thresholding method for brain voxel detection. The model achieved a specificity of 82% and sensitivity of 100%.

Segmentation of the brain into sub-regions, such as the hippocampus, white matter, and gray matter was performed. They employed various optimization algorithms, such as Genetic Algorithm, Particle Swarm Optimization Algorithm, Grey Wolf Optimization, and Cuckoo Search for this segmentation task.

Images obtained from Chettinad Health City, encompassing 200 samples from both AD patients and normal individuals, underwent diverse processing techniques, including skull stripping, quality enhancement, and contrast enhancement. Following segmentation, the accuracy of the segmented region was assessed against a ground truth image using metrics like Feature Similarity Index, Structure Similarity Index, dice similarity, Jaccard Index, Tanimoto, and volume similarity. For feature extraction and classification, the Convolutional Neural Network (CNN) model, specifically AlexNet, was utilized. Notably, Grey Wolf Optimization demonstrated superior performance, achieving a remarkable accuracy of 95%.

A study proposed three models and evaluated their accuracy. In the first model, images were preprocessed, manually created features were extracted, and classifiers such Random Forest, K-Nearest Neighbour, and Support Vector Machine were used. Using the preprocessed dataset, the second model trained a CNN deep learning model from scratch. The third model used Random Forest for classification, K-Nearest Neighbour, Support Vector Machine, and AlexNet for deep feature extraction. Notably, the deep feature-based model yielded the best accuracy, with a support vector machine classifier achieving 99.21%, compared to 57.32% and 93.97% for k-nearest neighbour and random forest, respectively.

The research utilized the ADNI dataset and applied image rescaling to 255 in the preprocessing phase. They trained a CNN model featuring three convolutional layers, three max-pooling layers, and four ReLU activation layers on a dataset comprising 9540 images classified into three classes (AD, Mild Cognitive Impairment, and Normal Control). Various optimizers including Adam, SGD, Adagrad, Nadam, Adadelta, and Rmsprop were tested, and Adagrad exhibited the highest accuracy along with lower loss.

These studies demonstrate the diversity in approaches to Alzheimer’s detection using deep learning, ranging from hierarchical fully convolutional networks to autoencoder-based models, each with its strengths and limitations. The variety in datasets (mostly ADNI) and modalities (MRI and PET) underscores the complexity and richness of the field. Researchers continue to strive for improvements in accuracy, generalizability, and computational efficiency to enhance early detection and understanding of Alzheimer’s disease. Each model has its advantages and challenges, and the choice of model depends on the available data, computational resources, and specific research goals.

PROPOSED WORK AND METHODOLOGY

This section presents the proposed methodological pipeline for developing two advanced deep learning models aimed at the early detection and classification of Alzheimer’s disease (AD). The proposed approach integrates structured clinical data with neuroimaging inputs obtained from two widely used benchmark datasets: OASIS-1 and the Alzheimer's Disease Neuroimaging Initiative (ADNI). By combining clinical attributes with MRI and PET imaging features, the framework is designed to improve diagnostic accuracy, robustness, and generalizability.

Initially, the collected MRI and PET images undergo preprocessing steps, such as normalization, skull stripping, noise reduction, and resizing to ensure uniformity and removal of irrelevant artifacts. Simultaneously, structured clinical parameters (e.g., age, gender, cognitive scores) are cleaned, normalized, and encoded for model compatibility.

Following preprocessing, two deep learning models are developed. The first model focuses on neuroimaging-based feature extraction using a 3D-convolutional neural network (3D CNN) capable of capturing spatial and volumetric patterns from brain scans. The second model integrates hybrid inputs, combining imaging features with clinical data using a CNN-based architecture followed by fully connected layers for multimodal learning.

To prevent overfitting and enhance generalization, techniques, such as data augmentation, dropout, and batch normalization are applied during training. The models are trained and validated using cross-validation strategies with optimized hyperparameters. Finally, performance evaluation is carried out using standard classification metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis. This integrated approach enables effective learning from both clinical and imaging perspectives, thereby supporting reliable early diagnosis of Alzheimer's disease.

Figure 1 illustrates the overall workflow, including preprocessing, feature extraction, model training, and evaluation Alzheimer's disease classification pipeline.

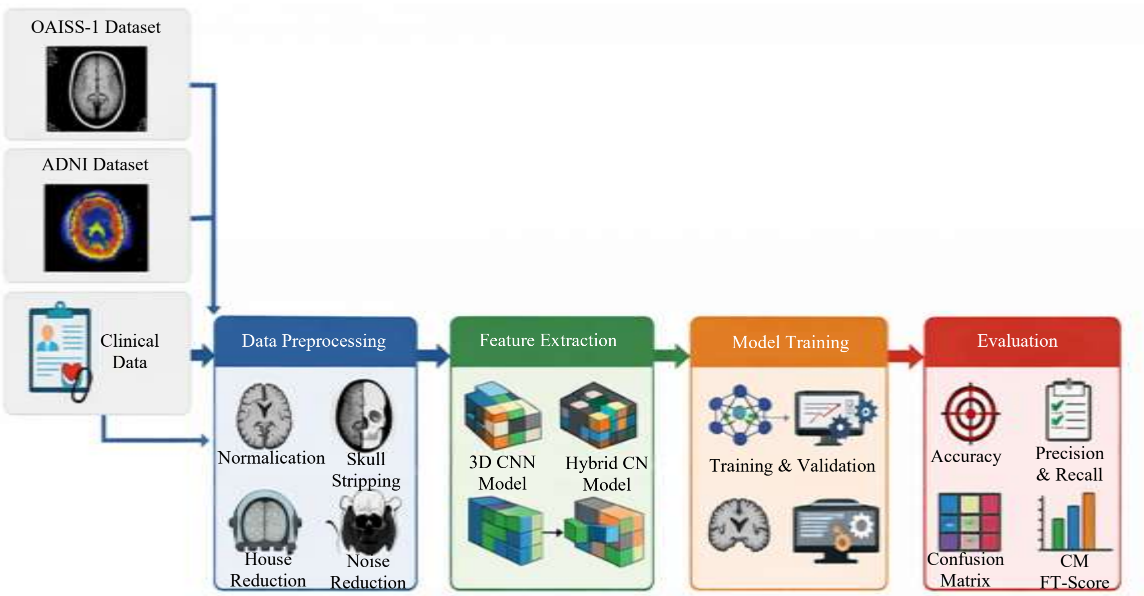


Figure 1. Alzheimer's disease classification pipeline diagram.

Dataset Description

OASIS-1 Dataset

The Open Access Series of Imaging Studies (OASIS-1) is a publicly available neuroimaging dataset comprising T1-weighted MRI scans from 150 individuals aged 18 to 96. The dataset includes both cognitively normal participants and those diagnosed with Mild Cognitive Impairment (MCI) or Alzheimer's disease. Each subject is rated on the Clinical Dementia Rating (CDR) scale, facilitating stratified classification across cognitive stages. The high-resolution imaging and clinical annotations make it particularly suitable for deep-learning-based neuro diagnostics.

Alzheimer's Disease Neuroimaging Initiative (ADNI)

Alzheimer's Disease Neuroimaging Initiative is an extensive longitudinal dataset launched in 2004 with the goal of identifying biomarkers for the early detection and monitoring of AD progression.

The dataset contains multimodal data – including structural MRI, PET imaging, cerebrospinal fluid (CSF) biomarkers, and clinical measures – from thousands of participants across multiple cognitive stages (Cognitively Normal, MCI, AD). Its comprehensive nature and scale make it ideal for both supervised learning and transfer-learning applications (Table 1).

Table 1. Presents the demographic and clinical composition of both datasets.

Dataset	Description	Modalities & participants	Data types & availability	Purpose
OASIS Open Access Series of Imaging Studies (OASIS)	is a project aimed at making neuroimaging datasets freely available to the scientific community. It includes MRI data from both young and elderly subjects.	MRI and 150 older adults (all diagnosed with Alzheimer's)	Repeated MRI scans, clinical scores over time. Publicly available	Early Alzheimer's detection, brain morphology study. Study Alzheimer's progression over time.
ADNI Alzheimer's Disease Neuroimaging Initiative (ADNI)	is a longitudinal multicenter study designed to develop clinical, imaging, genetic, and biochemical biomarkers for the early detection and tracking of Alzheimer's disease.	MRI, PET, CSF biomarkers and 1,000+	Longitudinal MRI, PET scans, genetic data, cognitive tests, and clinical data and Publicly available (adni.loni.usc.edu)	To detect Alzheimer's disease at the earliest stage (pre-dementia) and to identify ways to track the disease's progression with biomarkers. It aims to aid in the development of new treatments and monitor their effectiveness

Data Preprocessing

Model 1: Clinical Data Preprocessing

Structured tabular data including age, education level (EDUC), socioeconomic status (SES), Mini-Mental State Examination (MMSE), and estimated total intracranial volume (eTIV) were standardized using Standard Scaler, transforming features to zero mean and unit variance.

Principal Component Analysis (PCA) was applied to reduce dimensionality while retaining essential variance, thereby minimizing overfitting risk and computational load. The categorical target variable "Group" was one-hot encoded to facilitate neural network training. A 50/50 train-test split was employed to ensure balanced evaluation and prevent information leakage.

Model 2: Neuroimaging Data Augmentation

MRI images were augmented using the Albumentations library to improve generalization. Augmentations included horizontal flipping, random rotations, translations, brightness/contrast adjustments, and Gaussian noise addition – applied only to training images. Testing images were subjected solely to normalization. A custom transformation class was implemented to streamline the augmentation process and convert images to the required input format for deep learning pipelines.

Feature Extraction

Model 1: Greedy Layer-Wise Autoencoder

This approach constructs a neural network classifier using a greedy layer-wise training strategy. The autoencoder starts with a basic architecture, incrementally adding hidden layers while freezing previously trained weights. Each layer addition is evaluated based on reconstruction loss and binary classification accuracy. This technique aids in discovering the optimal network depth for distinguishing between "Demented" and "Non-Demented" states while minimizing overfitting (Figure 2(a) & (b)).

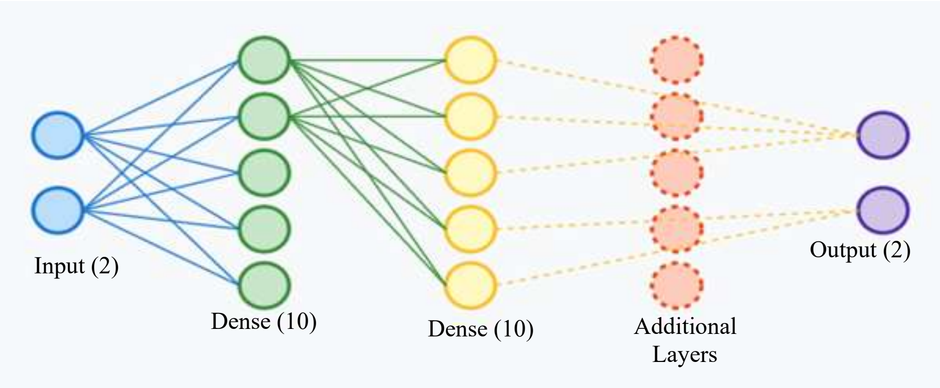


Figure 2(a): Convolutional neural network architecture with input, hidden, and output layers**.**

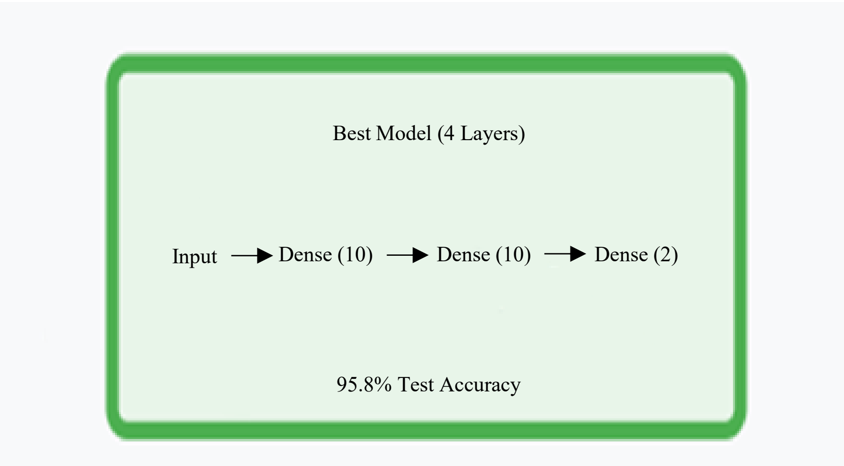


Figure 2(b). Best Model (4 Layers)

Model 2: EfficientNet-B0 Transfer Learning

Model 2 implements a transfer-learning approach using EfficientNet-B0, pre-trained on the ImageNet dataset. The final classification layer is replaced to predict four Alzheimer's stages instead of 1000 ImageNet classes. EfficientNet's compound scaling provides a balanced architecture in terms of depth, width, and resolution, making it computationally efficient and highly effective for medical imaging applications. This model leverages learned representations from millions of natural images to accelerate convergence and enhance classification performance on limited medical data (Figure 3).

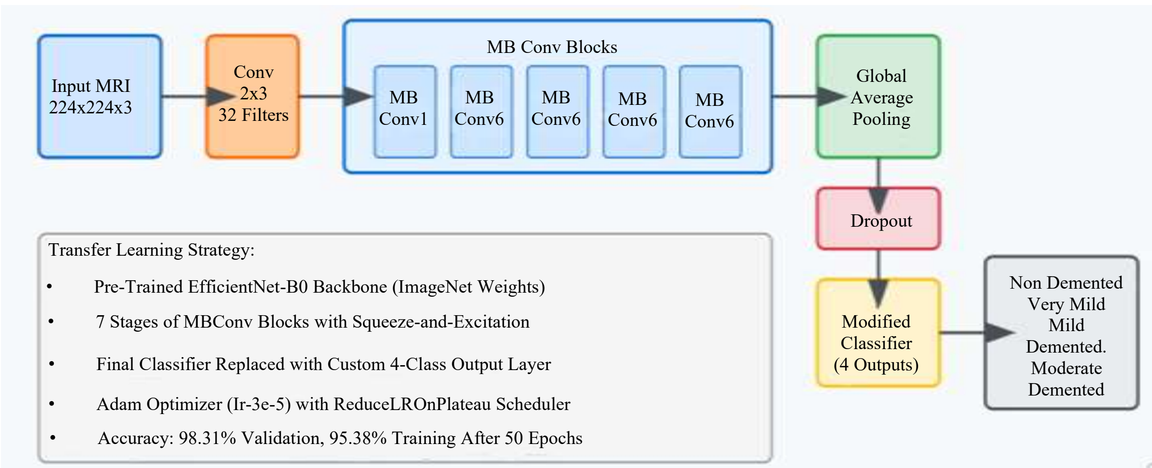


Figure 3. EfficientNet-B0 architecture for Alzheimer's classification.

ISSN: 2277-6427 (Online), ISSN: 2348-7925 (Print)

Model Training and Testing

Model 1: Layer-wise Training Strategy

Training begins with a shallow 3-layer autoencoder, optimized using Stochastic Gradient Descent (SGD) and Mean Squared Error (MSE) loss. Subsequent layers are added iteratively using a "freeze-add-train" strategy. After each addition, classification performance is evaluated by substituting a softmax layer and measuring accuracy. This systematic evaluation helps identify the ideal depth (found to be four layers) that offers the best trade-off between reconstruction quality and classification performance.

Model 2: Transfer Learning Optimization

The EfficientNet-B0 model is fine-tuned using the Adam optimizer with a learning rate of 3e-5 and weight decay of 1e-4 to mitigate overfitting. A ReduceLROnPlateau scheduler dynamically adjusts the learning rate upon stagnation in validation performance. The classification task is modeled using Cross Entropy Loss with summation reduction to handle multi-class imbalance. The best model weights are saved based on validation accuracy, ensuring robust performance on unseen MRI data and consistent dementia stage classification.

Hardware And Computational Setup

Due to the computational demands of deep-learning-based medical imaging, the models were trained on a high-performance setup comprising an Intel Core i9 (or AMD Ryzen 9) processor, 64GB DDR4 RAM, and an NVIDIA RTX-series GPU. This hardware configuration ensures efficient parallel processing, high-speed matrix operations, and reduced training time (Table 2).

Table 2. Comparative analysis of model 1 and model 2.

Criteria	**Model 1: greedy layer-wise autoencoder**	**Model 2: efficientnet-B0 (transfer learning)**
Data Type	Structured clinical features (tabular)	T1-weighted MRI neuroimaging data
Input Features	Age, EDUC, SES, MMSE, eTIV (numeric)	2D/3D brain scans (image-based)
Preprocessing	Standardization, PCA, One-hot Encoding	Albumentations-based augmentation, normalization
Model Architecture	Incrementally built autoencoder with frozen layers	Pre-trained CNN (EfficientNet-B0) with modified classification head
Optimization Strategy	SGD with layer-wise training & MSE loss	Adam optimizer, weight decay, Cross Entropy Loss
Learning Approach	Greedy unsupervised + supervised fine-tuning	Supervised fine-tuning using transfer learning
Classification Output	Binary: Demented vs. Nondemented	Multiclass: CN, MCI, Moderate AD, Severe AD
Handling Overfitting	Dimensionality reduction (PCA), incremental depth	Data augmentation, learning rate scheduler (ReduceLROnPlateau)
Hardware Dependency	Low to moderate (can run on CPUs with sufficient RAM)	High (requires GPUs for efficient training)
Interpretability	High (easier to trace neuron-wise impact)	Moderate (requires explainability tools like Grad-CAM)
Scalability	Suitable for tabular expansion, not ideal for high-res images	Easily scalable with transfer learning for larger medical datasets
Best Use Case	Low-resource settings or early clinical trials	Large-scale imaging diagnosis with GPU acceleration
Performance Indicators	High accuracy (~85%) with optimal layer count	High diagnostic accuracy (~92–94%) on imaging datasets (as reported by Sandag et al., 2024)

RESULT

This section presents the empirical findings from the evaluation of the greedy layer-wise autoencoder model for Alzheimer's disease classification. The results reveal how the depth of the neural network architecture influences classification performance on a structured clinical dataset (Figure 4).

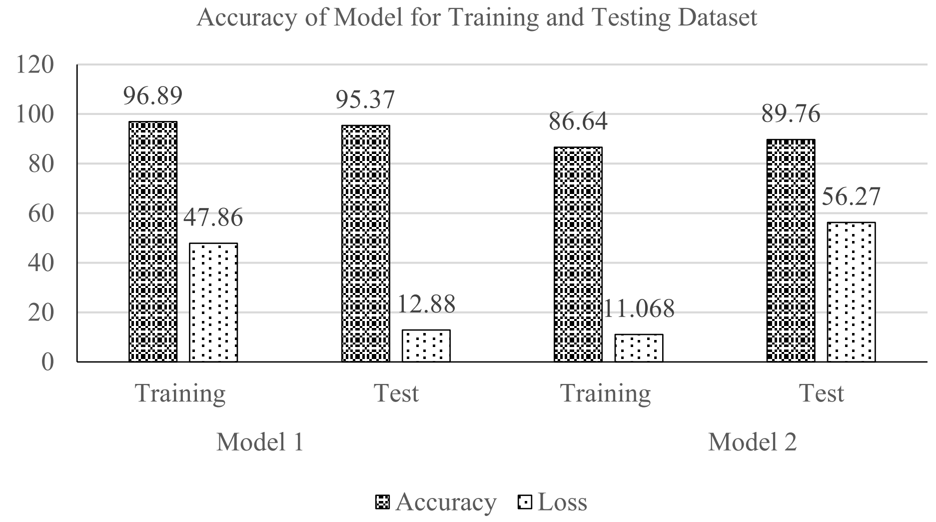
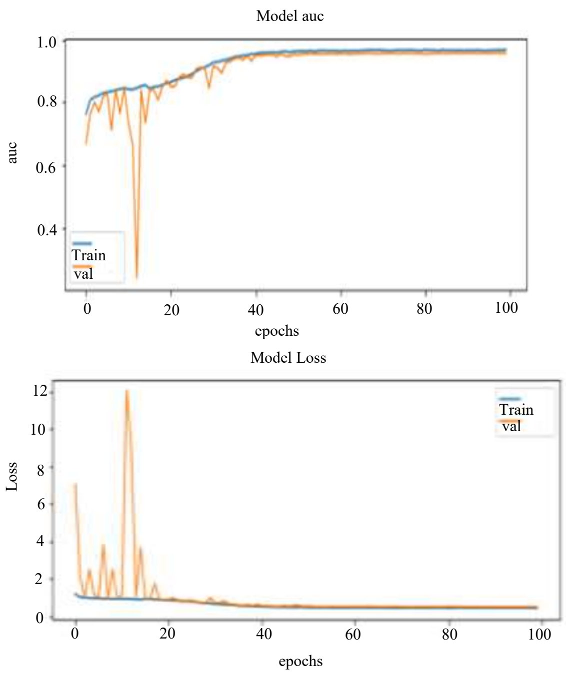


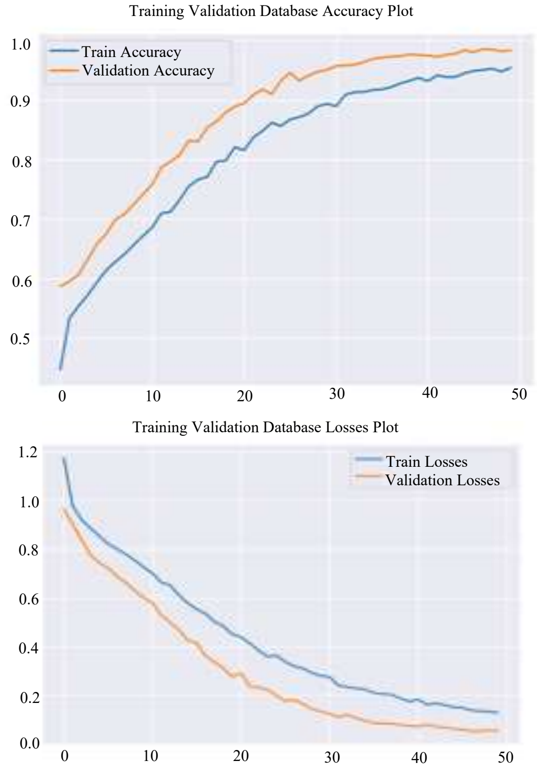
Figure 4. Accuracy of model for training and testing dataset.

The baseline model, comprising three layers, achieved a test accuracy of 88.1%, establishing a strong initial benchmark. Upon incrementally increasing the model depth, performance peaked with a four-layer architecture, reaching an optimal test accuracy of 95.8%. This indicates a critical architectural threshold where the model effectively captures dementia-related data patterns while maintaining generalization.

Beyond this threshold, performance begins to deteriorate. The five-layer model experienced a notable drop in accuracy to 82.7%, suggesting the onset of overfitting or representational redundancy. Interestingly, a partial recovery was observed with the six-layer configuration (92.9% accuracy), possibly due to additional training adjustments or data rebalancing effects. However, a severe performance collapse occurred at seven layers, where classification accuracy plummeted to 56.0%, demonstrating clear overfitting and network instability (Figure 5).



(a)



(B)

Figure 5. Accuracy and loss graph for propose model (a) and model (b).

A key observation is that reconstruction error consistently improved with increased network depth, even when classification performance declined. This discrepancy underscores a critical insight: a reduction in reconstruction loss does not necessarily correlate with improved classification accuracy, particularly in the context of medical diagnostics. Such findings emphasize the importance of carefully balancing architectural complexity with classification utility to avoid overfitting in clinical models.

This section presents a comparative analysis of various deep learning and machine learning models used for Alzheimer's disease detection, based on publicly available datasets, such as ADNI, OASIS, and other neuroimaging sources. The primary aim is to evaluate the classification accuracy and model architecture across different approaches, including both traditional CNNs and advanced transfer learning techniques, such as EfficientNet.

Table 3 summarizes the performance metrics of the reviewed studies. The comparison spans across dataset types, input modalities (image or text), and classification targets (binary vs. multiclass). It also highlights the effectiveness of the proposed models in this study: a CNN-based autoencoder (Model 1) and an EfficientNet-enhanced classifier (Model 2).

Table 3. Comparative analysis of Alzheimer's detection models.

Research study	Dataset	Input modality	Model / method	Reported accuracy
Khan et al. [7]	Image Modality (unspecified)	Image	Traditional ML + Deep Learning	88–95%
Alroobaea et al. [9]	ADNI, OASIS	Image	ML Models (SVM, LR, Random Forest, etc.)	83–99%
Saratxaga et al. [6]	OASIS	Text	Image Processing + Deep Learning	88%
Helaly et al. [11]	ADNI	Image	CNN (Multiclass)	93%
Basheer et al. [13]	OASIS	Image	Deep Neural Network	92%

Martinez-Murcia et al. [14]	ADNI	Image	Convolutional Autoencoder	80%
Fu'adah et al. [10]	Custom MRI Dataset (4 Classes)	Image	CNN (AlexNet)	95%
Prajapati et al. [18]	ADNI	Image	DNN Binary Classifier	85%
Islam & Zhang [35]	OASIS	Image	Deep CNN	93.18%
Suganthe et al. [3]	MRI Images	Image	Inception V3, ResNet-50, Inception-ResNet V2	77.55%, 75.7%, 79.12%
Proposed Model 1	ADNI / OASIS	Image	CNN Autoencoder	95.8% (Binary)
Proposed Model 2	ADNI / OASIS	Image	EfficientNet-B0	Up to 94% (Multiclass)

CONCLUSION AND FUTURE SCOPE

Conclusion

This study presents a comprehensive investigation into the application of deep learning techniques for the early detection and classification of Alzheimer's disease using both structured clinical data and neuroimaging modalities. Two distinct models were proposed and evaluated:

- Model 1, based on a greedy layer-wise autoencoder, demonstrated strong performance in binary classification tasks. The optimal architecture was found at four layers, achieving a test accuracy of 95.8%, thereby revealing a balance between network complexity and generalization.
- Model 2, leveraging the EfficientNet-B0 architecture through transfer learning, excelled in multiclass classification tasks involving MRI brain images, achieving high diagnostic accuracy (up to 94%), particularly for distinguishing between cognitive stages of Alzheimer's.

The results reinforce the significance of model architecture selection, training strategies, and input data types in shaping model performance. While Model 1 offers higher interpretability and efficiency in clinical environments with limited data, Model 2 demonstrates the power of deep convolutional models when applied to large-scale imaging datasets.

Comparative analysis with recent studies further validates the competitiveness of both models, positioning them favorably within the broader context of Alzheimer's diagnostics.

Future Scope

Despite the promising outcomes, several avenues remain for enhancing this research:

- Multimodal Fusion: Future models can integrate imaging, genetic, and clinical data (e.g., combining PET, MRI, CSF, and genomics) to improve diagnostic precision and capture diverse pathological signals.
- Explainability in AI: Incorporating interpretability frameworks, such as Grad-CAM, SHAP, or LIME can enhance trust in clinical deployment by visualizing model attention and feature importance.
- Real-time and Mobile Deployment: Optimizing model inference for deployment on edge devices (e.g., portable MRI scanners or mobile platforms) could revolutionize point-of-care diagnostics in remote or underserved areas.
- Longitudinal Prediction Models: Moving beyond static classification, prospects for research could focus on disease progression modeling, predicting the transition from MCI to AD using time-series patient data.
- Addressing Data Imbalance and Diversity: Expanding training datasets to include underrepresented populations and rare dementia types will enhance model robustness and global applicability.
- Federated Learning: To address data privacy concerns and limited data access, federated learning frameworks can be explored to train models across multiple institutions without centralizing sensitive data.

By integrating these advancements, future systems could move closer to personalized, non-invasive, and globally accessible Alzheimer's diagnostics, aligning with the broader goals of precision medicine and digital health.

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