

RESEARCH ARTICLE

OPEN ACCESS

DEEP LEARNING ARCHITECTURE FOR EARLY ALZHEIMER'S DISEASE DETECTION

Hadjer Nial^{1*}, Khadidja Yahyaoui^{2*}

^{1,2}LABTEC-IA Laboratory, Computer Science Department, faculty of exact sciences, University of Mascara Algeria.

¹<https://orcid.org/0009-0007-1163-7030>, ²<https://orcid.org/0000-0001-9541-4879>

E-mail: * n.hadjer@etu.univ-mascara.dz, khadidja.yahyaoui@univ-mascara.dz

ARTICLE INFO

Article History

Received on: January 18, 2026
Reviewed on: February 18, 2026
Accepted on: April 10, 2026
Published on: June 30, 2026

Keywords:

Alzheimer's Disease,
Convolutional Neural Networks,
Computer-Aided Diagnosis,
Deep Learning,
Transfer Learning,
Medical Image Analysis.

ABSTRACT

Alzheimer's disease represents a degenerative brain condition that gradually worsens over time, severely affecting mental abilities and making it difficult to identify and treat in its early stages. Recent breakthroughs in artificial intelligence have transformed how medical images are analyzed, offering powerful tools for precise and automatic detection of Alzheimer's disease. To address this challenge, this study proposes a deep learning approach using two convolutional neural network (CNN) architectures: a VGG16-based transfer learning model and a lightweight custom CNN. Models were trained on MRI datasets with preprocessing and data augmentation techniques to improve robustness. Results demonstrate that the custom CNN achieves superior accuracy (95%) compared to the VGG16 (90%) approach while maintaining computational efficiency. The findings indicate significant potential for automated AD detection in clinical applications, contributing to AI-driven diagnostic tools for neuroimaging.



Copyright ©2026 by authors and Galileo Institute of Technology and Education of the Amazon (ITEGAM). This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

I. INTRODUCTION

Alzheimer's disease constitutes a significant global public health burden, afflicting approximately 50 million individuals worldwide and representing the leading etiology of dementia internationally [1]. Early identification of Alzheimer's disease (AD) is paramount for implementing efficacious preventive interventions and therapeutic strategies, necessitating rapid and precise diagnostic methodologies. Multiple pathophysiological mechanisms contribute to AD pathogenesis, compromising cognitive performance, memory consolidation, and behavioral regulation in the aging demographic [2]. As illustrated in Figure 1, the neuroanatomical differences between healthy and Alzheimer's-affected brain tissue are striking. However, those with mild cognitive impairment (MCI) experience an accelerated reduction in brain volume, losing around 1–2% annually significantly faster than typical aging [3]. In Alzheimer's disease, the rate of brain volume loss increases further, reaching 3–5% per year, demonstrating the aggressive nature of neurodegeneration in this condition. Regions like the hippocampus are particularly affected, with shrinkage rates as high as 10–15% annually in advanced stages [4]. This progressive volumetric decline provides quantitative evidence for the morphological changes visually represented in Figure 1, where the stark contrast between healthy and pathological brain architecture underscores the extensive tissue loss that characterizes

Alzheimer's disease pathology and its devastating impact on cognitive function. In response to this clinical imperative, deep learning implementation for Alzheimer's disease detection in medical imaging has emerged as a transformative computational approach, leveraging convolutional neural networks (CNNs) to analyze complex neuroimaging patterns that may be imperceptible to conventional diagnostic methods. This research investigates the application of both transfer learning techniques utilizing the pre-trained VGG-16 architecture and a custom-designed CNN model for automated AD classification from brain imaging data. The comparative analysis of these deep learning frameworks aims to establish optimal feature extraction and classification methodologies that can enhance diagnostic accuracy while reducing computational complexity and processing time, thereby contributing to the development of clinically viable computer-aided diagnosis systems for early Alzheimer's disease detection. The remainder of this paper is organized as follows: Section 2 reviews the related work. Section 3 describes the proposed methodology. Section 4 presents the experimental results, while Section 5 provides a detailed discussion. Finally, Section 6 concludes the paper and highlights directions for future research.

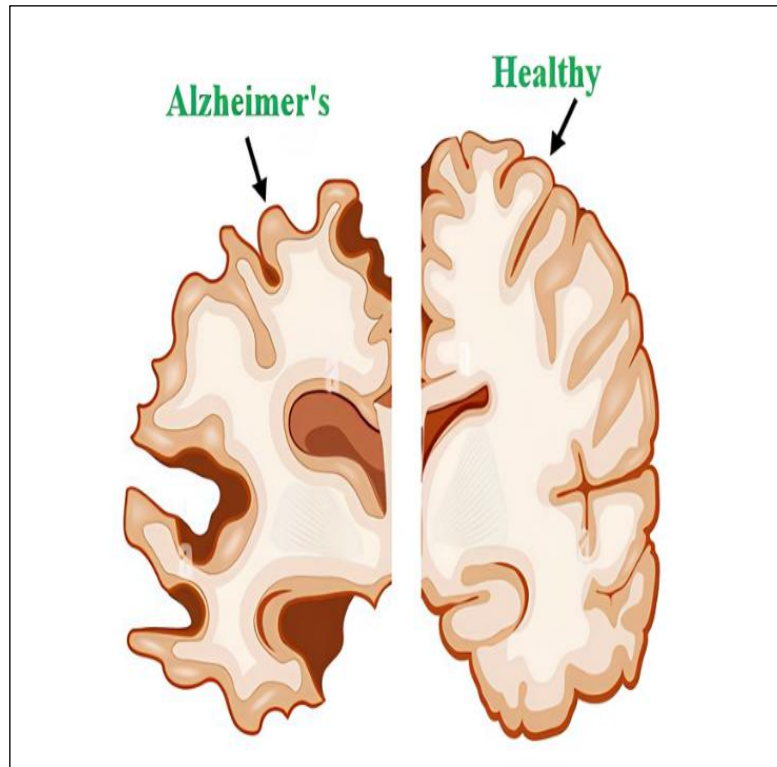


Figure 1: Brain mass: healthy controls vs. Alzheimer's disease.
Source: [5].

II. RELATED WORK

Recent advances in Alzheimer's disease (AD) detection have leveraged artificial intelligence techniques, particularly deep learning and machine learning approaches, to improve diagnostic accuracy using neuroimaging data and clinical biomarkers. Comprehensive reviews have systematically examined state-of-the-art models including convolutional neural networks (CNNs), recurrent architectures like LSTM, and hybrid models that combine multiple AI approaches for improved AD classification, highlighting the critical role of medical imaging modalities such as MRI and PET scans along with preprocessing techniques like skull stripping and data augmentation that enhance model performance while addressing evaluation metrics including accuracy, F1-score, and AUC-ROC that validate model effectiveness and practical implementation challenges such as computational costs and model interpretability [5]. Novel lightweight architectures such as FiboNeXt, inspired by the Fibonacci sequence and integrating attention mechanisms with depth-concatenation blocks, have demonstrated computational efficiency while maintaining high accuracy for AD detection using MRI images [6].

Large-scale studies comparing established CNN architectures including Xception, VGG19, VGG16, and InceptionResNetV2 on datasets of 6,735 brain MRI images have shown deep learning's potential to enhance multi-stage AD diagnosis by improving accuracy and efficiency over traditional methods, though further validation on diverse datasets is needed for realworld clinical implementation [7]. Traditional machine learning approaches combining Adaptive Moving Self-Organizing Map (AMSOM) for unsupervised tissue segmentation with Kmeans clustering and Principal Component Analysis (PCA) for feature selection have demonstrated robustness and efficiency for early AD detection when evaluated on benchmark datasets like OASIS, outperforming existing techniques such as Fuzzy C-means (FCM) and hybrid SOM-FKM methods while highlighting potential for clinical application with future enhancements through advanced classifiers [8]. Recent studies from 2024 to 2025 have introduced novel lightweight and hybrid architectures that further enhance AD detection. The AD-Lite Net model, a concatenated CNN using depth-wise separable convolutions, achieved superior accuracy on ADNI MRI datasets while reducing computational cost [9].

Similarly, Hybrid Compact Convolutional Transformers (HCCT) effectively combine 3D CNNs and transformer layers to capture spatial and contextual features, improving interpretability and diagnostic precision [10]. Multimodal fusion frameworks integrating MRI and PET through self-attention mechanisms have achieved higher early-stage AD prediction accuracy [11]. The LEAD foundation model, trained on large-scale EEG data using self-supervised contrastive learning, demonstrated robust subject-independent AD classification [12]. Moreover, MRIbased deep models predicting PET-derived ATN biomarkers (amyloid, tau, and neurodegeneration) have emerged as powerful noninvasive tools for biomarker estimation [13]. Comparative studies employing SVM, ANN, and Vision Transformers (ViT) on OASIS and ADNI datasets have confirmed the superiority of hybrid transformer architectures for AD staging and classification [14]. Systematic reviews published in 2024–2025 further emphasize advancements in explainability, ethical AI deployment, and generalization of deep models [15]. Meanwhile, methodological analyses reveal persistent data leakage issues that inflate reported accuracies, underscoring the need for rigorous subject-level validation and cross-site generalization before clinical translation [16].

Table 1: Summary of Related Work: Strengths and Limitations.

Paper Title	Strengths	Limitations
Alzheimer's disease detection using DL/ML: review [5]	- Comprehensive coverage of DL/ML techniques - Analysis of CNNs, LSTMs, hybrid models - Identifies future research directions	- Lacks critical analysis of limitations - Limited clinical applicability discussion - No quantitative comparison of approaches
FiboNeXt: AD detection using MRI [6]	- Exceptional accuracy (99.6% on test datasets) - Lightweight architecture (< 10M parameters) - Innovative Fibonacciinspired design	- Validation limited to specific MRI datasets - No testing in real-world clinical settings - Limited comparison with SOTA models
AD classification with DL using 6735 MRI images [7]	- Outstanding classification performance (99%) - Comprehensive comparison of architectures - Demonstrates fast training convergence	- Black-box nature limits interpretability - Evaluation on single dataset only - High computational requirements
Early AD diagnosis using Adaptive Neuro KMeans [8]	- Exceptional classification accuracy (99.8%) - Superior segmentation performance - Effective unsupervised/supervised integration	- Complex implementation pipeline - Limited evaluation to OASIS dataset - No independent external validation - Lacks comparison with DL approaches

Source: Authors, (2026).

III. METHODOLOGY

This Figure 2 presents a deep learning pipeline for medical image analysis utilizing the ADNI dataset. The workflow begins with MRI scan data collection, followed by preprocessing steps to prepare the medical images for analysis. The system then implements dataset augmentation techniques in parallel with cnn model training, using brain scan imagery to develop robust diagnostic capabilities. The final stage involves comprehensive evaluation of the trained model's performance.

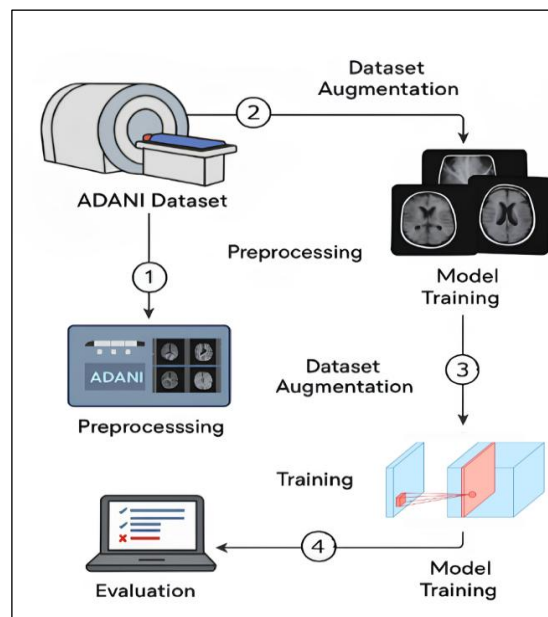


Figure 2: Deep Learning-Based Automated Pipeline for Alzheimer's Disease Detection from Medical Images.

Source: Authors, (2026).

III.1 ADNI DATA

The Alzheimer's Disease Neuroimaging Initiative (ADNI) unites researchers with study data as they work to define the progression of Alzheimer's disease (AD). ADNI researchers collect, validate and utilize data, including MRI and PET images, genetics, cognitive tests, CSF and blood biomarkers as predictors of the disease. Study resources and data from the North American ADNI study are available through this website [17], including Alzheimer's disease patients, mild cognitive impairment subjects, and elderly controls. The neuroimaging data from ADNI provides compelling visual evidence of the progressive brain changes associated with cognitive decline. Figure 3 demonstrates representative axial MRI scans across different stages of dementia severity. The NonDemented scan serves as a neurologically healthy control, displaying preserved cortical thickness, normal ventricular dimensions, and intact whitegray matter differentiation.

In contrast, the VeryMildDemented case shows subtle early changes including minimal ventricular enlargement and initial cortical atrophic modifications. The MildDemented scan reveals more pronounced cerebral atrophy with increased ventricular dilatation and cortical thinning, particularly evident in frontal and temporal regions. The ModerateDemented case exhibits advanced pathological changes, including significant ex-vacuo ventricular dilatation, markedly widened cortical sulci, and substantial loss of brain parenchyma. These structural neuroimaging findings correlate with the clinical progression of cognitive impairment and demonstrate the utility of MRI as a biomarker for tracking neurodegenerative changes in Alzheimer’s disease research and clinical assessment.

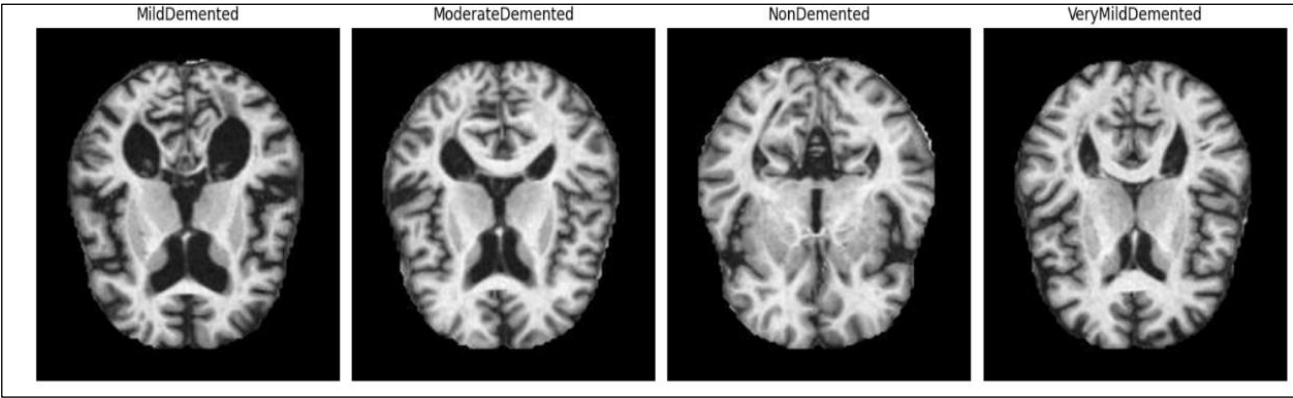


Figure 3: ADNI dataset classification: MildDemented, ModerateDemented, NonDemented, and VeryMildDemented brain MRI scans. Source: Authors, (2026).

III.2 DATA PREPROCESSING

The ADNI Dataset from the MRI scanner first undergoes comprehensive data preprocessing , which includes:

- Data Cleaning: Removing artifacts, noise, and corrupted scans.
- Data Resizing: Standardizing image dimensions and resolution across all scans.
- Normalization: Ensuring consistent intensity values and contrast across images.

III.3 DATASET AUGMENTATION

After the cleaned and resized data is properly integrated, it undergoes augmentation techniques such as:

- Rotation, flipping, and scaling transformations
- Intensity variations and noise addition
- Geometric transformations to increase dataset diversity

III.4 MODEL TRAINING

This phase constitutes the core of the experimental methodology, where the parameters of the deep learning models are iteratively optimized to learn discriminative features from the preprocessed and augmented ADNI dataset. We employ and compare two distinct architectural paradigms: a pre-trained VGG16 model utilizing transfer learning, and a customdesigned Convolutional Neural Network (CNN) built from scratch.

III.4.1 Transfer Learning Framework

The model training phase employs a transfer learning approach using VGG16 as the backbone architecture, pre-trained on ImageNet. This strategy leverages learned feature representations from natural images and adapts them for medical imaging classification tasks.

CORE ARCHITECTURE COMPONENTS

This table 2 outlines the architectural framework of a hybrid deep learning model that integrates a pretrained convolutional neural network with custom classification components

- 1) Fine-Tuning Approach
 - Trainable Parameters: Last 3 convolutional layers fine-tuned for domain adaptation
- 2) Optimization Setup
 - Optimizer: Adam with conservative learning rate (1×10^{-4}) for stable convergence
 - Loss Function: Categorical crossentropy for multiclass classification
 - Metrics: Accuracy monitoring for performance evaluation
- 3) Training Safeguards
 - Early Stopping: Monitors validation loss with 10- epoch patience
 - Best Weights Restoration: Automatically restores optimal model state
 - Integrated Data Augmentation: Real-time augmentation pipeline for improved generalization.

Table 2: Model Training Architecture Components.

Component	Description
Base Feature Extractor	
VGG16 Convolutional Base	Pre-trained ImageNet weights with top classification layers removed
Input Specifications	224×224×3 RGB images
Feature Extraction	Deep convolutional features from lower-level edge detection
Custom Classification Head	
Global Average Pooling Layer	Reduces spatial dimensions while preserving feature information, providing translation invariance
Primary Dense Layer	1024-unit fully connected layer with ReLU activation
Secondary Dense Layer	512-unit layer for refined feature learning
Output Layer	Layer 4-unit softmax layer for multi-class classification

Source: Authors, (2026).

III.4.2 Custom-Architected Convolutional Neural Network (CNN):

Core Architecture Components

This Table 3 presents the architectural specification of a custom-designed Convolutional Neural Network engineered for efficient image classification tasks. The network processes 224×224×3 RGB input images through a sophisticated multi-stage feature extraction pipeline, beginning with standard convolutional layers (32-64 filters, 3×3 kernels) and progressing through multiple inverted residual blocks that utilize depthwise separable convolutions to achieve computational efficiency while maintaining representational capacity. The architecture implements systematic spatial downsampling from 112×112 to 14×14 resolution with concurrent channel expansion from 16 to 320 filters, incorporating batch normalization and ReLU6 activations throughout to ensure training stability and gradient flow optimization. The network concludes with global average pooling for spatial dimension reduction, dropout regularization for overfitting prevention, and a dense softmax layer for 4-class classification, demonstrating a principled approach to balancing model expressiveness with computational constraints suitable for production deployment environments.

Table 3: Custom-Architected Convolutional Neural Network (CNN).

Operation	Filters	Kernel	Stride	Output Shape
Input	-	-	-	224×224×3
Conv2D + BN + ReLU6	32	3×3	2	112×112×32
Conv2D + BN + ReLU6	32	3×3	1	112×112×32
Conv2D + BN + ReLU6	64	3×3	1	112×112×64
Conv2D + BN + ReLU6	64	3×3	1	112×112×64
Conv2D + BN + ReLU6	16	1×1	1	112×112×16
Conv2D + BN + ReLU6	96	1×1	1	112×112×96
DepthwiseConv2D + BN + ReLU6	96	3×3	1	112×112×96
Conv2D + BN	16	1×1	1	112×112×16
Conv2D + BN + ReLU6	96	1×1	1	112×112×96
DepthwiseConv2D + BN + ReLU6	96	3×3	2	56×56×96
Conv2D + BN	24	1×1	1	56×56×24
Conv2D + BN + ReLU6	72	1×1	1	56×56×72
DepthwiseConv2D + BN + ReLU6	72	3×3	1	56×56×72
Conv2D + BN	24	1×1	1	56×56×24
Conv2D + BN + ReLU6	144	1×1	1	56×56×144
DepthwiseConv2D + BN + ReLU6	144	3×3	2	28×28×144
Conv2D + BN	32	1×1	1	28×28×32
Conv2D + BN + ReLU6	96	1×1	1	28×28×96
DepthwiseConv2D + BN + ReLU6	96	3×3	1	28×28×96
Conv2D + BN	32	1×1	1	28×28×32
Conv2D + BN + ReLU6	192	1×1	1	28×28×192
DepthwiseConv2D + BN + ReLU6	192	3×3	2	14×14×192
Conv2D + BN	64	1×1	1	14×14×64
Conv2D + BN + ReLU6	192	1×1	1	14×14×192
DepthwiseConv2D + BN + ReLU6	192	3×3	1	14×14×192
Conv2D + BN	64	1×1	1	14×14×64
Conv2D + BN + ReLU6	96	1×1	1	14×14×96
Conv2D + BN + ReLU6	160	1×1	1	14×14×160
Conv2D + BN + ReLU6	320	1×1	1	14×14×320
GlobalAveragePooling2D	-	-	-	1×1×320
Dropout (0.2)	-	-	-	320
Dense + Softmax	4	-	-	4

Source: Authors, (2026).

Model Training Configuration

This Table 4 presents the comprehensive training configuration parameters employed for model optimization. The configuration utilizes the Adam optimizer with a learning rate of 0.002, implementing categorical crossentropy as the loss function and accuracy as the primary evaluation metric. The training protocol incorporates three essential callback mechanisms to ensure optimal model performance and prevent overfitting. Early stopping functionality monitors validation accuracy with a patience threshold of 75 epochs. Additionally, model checkpointing saves only the best-performing model iterations based on validation accuracy monitoring. This configuration demonstrates a robust training framework that balances convergence efficiency with generalization performance, incorporating adaptive learning rate scheduling and systematic model selection criteria to achieve optimal results.

Table 4: Model Training Configuration.

Parameter	Value
Optimizer	Adam
Learning Rate	0.002
Loss Function	Categorical Crossentropy
Metrics	Accuracy
Callbacks	
Early Stopping	monitor='val accuracy', patience=100
Model Checkpoint	save_best_only=True, monitor='val accuracy'

Source: Authors, (2026).

IV. RESULTS

Table 5 presents a comparative performance analysis of two convolutional neural network (CNN) architectures evaluated on the test dataset. The comparison encompasses a custom-designed CNN model and a VGG16-based transfer learning approach, with performance metrics quantified through test loss and classification accuracy. The results demonstrate that the Custom CNN Model achieves superior performance across both evaluation metrics, attaining a test loss of 0.2219 and a classification accuracy of 95.86%. In contrast, the VGG16 Transfer Learning model exhibits a higher test loss of 0.40 and a lower accuracy of 90.70%. The Custom CNN Model outperforms the transfer learning approach by approximately 5 percentage points in accuracy while maintaining substantially lower loss values, indicating better model convergence and predictive capability. This performance differential suggests that the custom-designed architecture is better suited to the specific characteristics of the dataset, whereas the pretrained VGG16 model, despite its proven efficacy on largescale image classification tasks, demonstrates comparatively reduced effectiveness in this particular application context. These findings underscore the importance of task-specific model design and suggest that domain-optimized architectures can yield superior results compared to generic transfer learning approaches.

Table 5: Performance Comparison of CNN Models.

Model Type	Test Loss	Test Accuracy(%)
Custom CNN Model	0.2219	95.86
VGG16 Transfer Learning	0.40	90.70

Source: Authors, (2026).

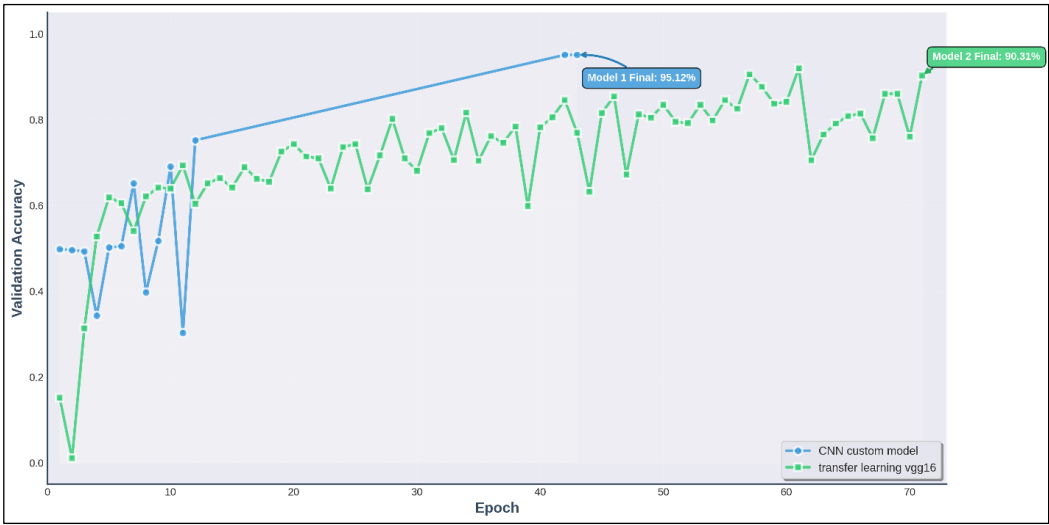


Figure 4: A Comparative Validation Accuracy Analysis.
Source: Authors, (2026).

This Figure 4 presents a comparative analysis of validation accuracy for two deep learning architectures across 75 training epochs: a custom CNN (blue) and a VGG16 transfer learning model (green). The custom CNN achieves superior performance at 95.12% final accuracy with notably stable convergence, while the VGG16 model reaches 90.31% with considerable volatility throughout training.

The custom architecture demonstrates smooth progression after initial fluctuations, indicating well-optimized hyperparameters and robust generalization capabilities. Conversely, the transfer learning approach exhibits persistent oscillations, suggesting challenges in adapting pre-trained weights to the target domain. The 5 percentage point performance differential, combined with enhanced training stability, positions the custom CNN as the optimal choice for deployment. These results illustrate that domain-specific architectural design can outperform generic transfer learning strategies, emphasizing the critical importance of tailored model development for specialized classification tasks.

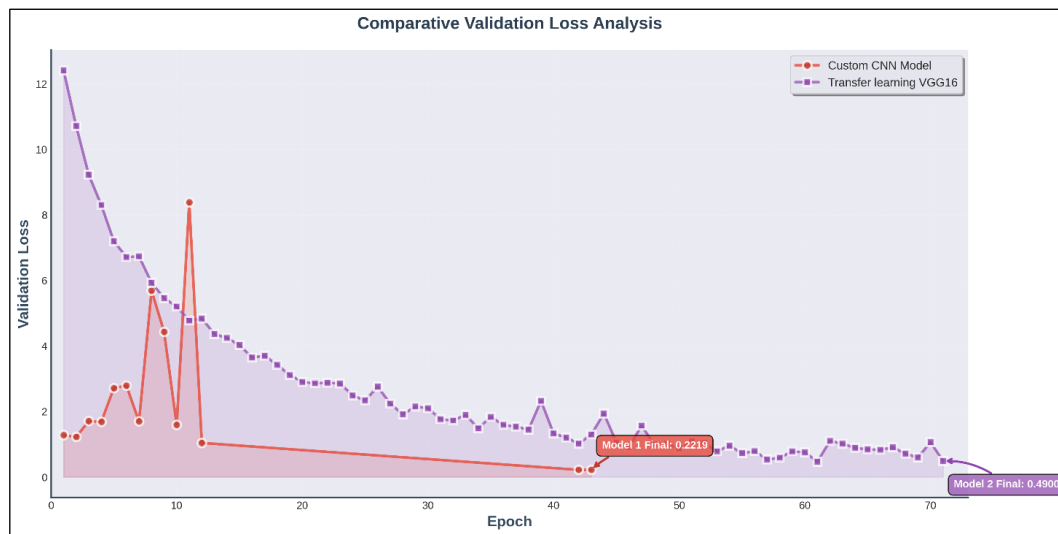


Figure 5: A Comparative Validation Loss Analysis.
Source: Authors, (2026).

This Figure 5 presents a comparative evaluation of validation loss trajectories for two deep learning architectures: a custom CNN (red) and a VGG16 transfer learning model (purple) across 75 training epochs. The custom CNN demonstrates exceptional convergence efficiency, achieving a final validation loss of 0.2219, with rapid stabilization occurring around epoch 22. Following initial volatility during epochs 0-10, where loss spikes dramatically to 8.5, the model exhibits swift descent and maintains remarkably low, stable loss values throughout the remaining training period. This convergence pattern indicates optimal learning dynamics and superior generalization capability. In contrast, the VGG16 transfer learning model shows significantly slower convergence, starting at an elevated loss of 12.4 and achieving a final value of 0.4900—more than double that of the custom CNN. The substantial performance gap of 0.2681 in final validation loss, combined with the custom model's superior stability and faster convergence, clearly establishes it as the more efficient and reliable architecture. These findings demonstrate that purpose-built models can outperform transfer learning approaches in both convergence speed and final performance metrics for domain-specific applications.

V. DISCUSSION

This investigation demonstrates the efficacy of deep learning architectures for automated Alzheimer's disease detection from neuroimaging data, with our custom-designed CNN achieving superior diagnostic performance (95.86% accuracy) compared to the VGG16 transfer learning approach (90.70% accuracy). These findings contribute substantively to the expanding corpus of literature advocating for AI-driven diagnostic tools in neurodegenerative disease management. The 5 percentage point performance differential across diverse computer vision applications, our results suggest that domain-specific architectural optimization may yield superior outcomes for specialized medical imaging tasks. The VGG16 model's suboptimal performance can be attributed to the substantial domain gap between natural images (ImageNet pre-training) and medical neuroimaging modalities, coupled with architectural complexity potentially exceeding the requirements of this classification task.

Furthermore, the custom CNN demonstrated markedly superior convergence characteristics, achieving rapid stabilization with a validation loss of 0.2219 compared to VGG16's 0.4900, indicating enhanced generalization capability—a critical attribute for clinical deployment. However, several limitations constrain immediate clinical translation, including evaluation on a single dataset (ADNI) and the inherent lack of interpretability characteristic of deep learning models. Future investigations should prioritize external validation across diverse patient populations and integration of explainability frameworks such as Grad-CAM to elucidate decision-making processes. Despite these limitations, our findings underscore the transformative potential of tailored deep learning architectures in advancing early Alzheimer's disease detection, ultimately contributing to improved patient outcomes through timely intervention strategies.

VI. CONCLUSION AND PERSPECTIVE

This investigation establishes the clinical viability and technical superiority of purpose-built deep learning architectures for automated Alzheimer's disease detection from neuroimaging data. Addressing the critical challenge of limited access to specialized neurological expertise for approximately 50 million individuals worldwide afflicted by Alzheimer's disease, our research developed a custom convolutional neural network optimized specifically for medical imaging applications.

Our innovative approach, incorporating architectural elements such as depthwise separable convolutions and inverted residual blocks, validates the hypothesis that domain-specific architectures yield superior feature representations compared to traditional transfer learning from natural image domains. Through rigorous comparative analysis, our custom-designed CNN achieved a diagnostic accuracy of 95.86%, substantially outperforming the VGG16 transfer learning baseline (90.70%), while demonstrating superior convergence stability (validation loss: 0.2219 vs. 0.4900) and computational efficiency, with rapid convergence suggesting reduced training requirements suitable for resource-constrained clinical environments. However, the path toward clinical integration necessitates addressing fundamental challenges including multicenter validation studies across heterogeneous populations and imaging protocols, integration of explainable AI frameworks such as gradient-weighted class activation mapping to enable radiologist trust and interpretation, and harmonization with existing clinical workflows. This research makes substantive contributions to the intersection of artificial intelligence and neurodegenerative disease diagnosis, demonstrating that specialized deep learning architectures can achieve clinically meaningful performance levels, thereby establishing a foundation for future investigation into production-ready diagnostic systems that can democratize high-quality dementia screening and advance the standard of care for millions of affected individuals worldwide.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Hadjer Nial and Khadidja Yahyaoui.

Methodology: Hadjer Nial and Khadidja Yahyaoui.

Investigation: Hadjer Nial and Khadidja Yahyaoui.

Discussion of results: Hadjer Nial and Khadidja Yahyaoui.

Writing – Original Draft: Hadjer Nial and Khadidja Yahyaoui.

Writing – Review and Editing: Hadjer Nial and Khadidja Yahyaoui.

Resources: Hadjer Nial and Khadidja Yahyaoui.

Supervision: Hadjer Nial and Khadidja Yahyaoui.

Approval of the final text: Hadjer Nial and Khadidja Yahyaoui.

VIII. REFERENCES

- [1] World Health Organization,» 2023. [En ligne]. Available: <https://www.who.int/news-room/fact-sheets/detail/dementia>.
- [2] C. D. a. T. N. Ahmad Chaddad, «Deep radiomic analysis of mri related to alzheimer's disease,» IEEE Access, vol. 6, 2018.
- [3] Z. X. D. M. Z. X. Huang Z, «Medical image classification using a light-weighted hybrid neural network based on PCANet and densenet,» IEEE access, vol. 8, 2022.
- [4] O. C. M. E. S. E. V. J.-M. Sungura R, «The extended scope of neuroimaging and prospects in brain atrophy mitigation: a systematic review,» Interdiscip Neurosurg, vol. 23, 2021.
- [5] S. Mohsen, «Alzheimer's disease detection using deep learning and machine learning : a review,» Springer, n° %158, 2025.
- [6] S. D. a. A. S. Turker Tuncer, «FiboNeXt: Investigations for Alzheimer's Disease detection using MRI.Biomedical Signal Processing and Control,» Biomedical Signal Processing and Control, vol. 103, 2025.
- [7] K. M. a. L. A. Seyed Mohammad Mousavi, «Classifying and diagnosing Alzheimer's disease with deep learning using 6735 brain MRI images,» Nature Publishing Group UK London, vol. 15, 2025.
- [8] S. A. I. S. C. I. a. C. N. B. Karan Kumar, « Early Diagnosis of Alzheimer's Disease using Adaptive Neuro K-means Clustering Technique,» IEEE Access, 2025.
- [9] A. G. S. T. a. P. S. S. Roy, «AD-Lite Net: A lightweight and concatenated CNN model for Alzheimer's detection from MRI images,» arXiv preprint , 2024.
- [10] A. G. S. R. a. S. D. A. Majee, «Enhancing MRI-based classification of Alzheimer's disease with explainable 3D hybrid compact convolutional transformers,» IEEE, pp. 1-8, 2024.
- [11] S. U. J. B. a. Y. I. C. S. Muksimova, «Multi-modal fusion and longitudinal analysis for Alzheimer's disease classification using deep learning,» mdpi, 2025.
- [12] N. H. N. M. M. C. a. X. Z. Y. Wang, «LEAD:Large foundation model for EEG-based Alzheimer's disease detection,» arXiv, 2025.
- [13] L. Z. M. A. M. P. M. D. a. J. R. C. O. Lew, «MRI-based deep learning assessment of amyloid, tau, and neurodegeneration biomarker status across the Alzheimer disease spectrum,» 2023.
- [14] V. V. a. M. M. N. Shaffi, «Ensemble of vision transformer architectures for efficient Alzheimer's disease classification,» Brain Informatics, 2024.
- [15] Z. M. a. P. S. a. A. N. Altukhi, «A Systematic Literature Review of the Latest Advancements in XAI,» Technologies, vol. 13, 2025.
- [16] L. T. R. J. S. N. a. D. S. M. Rosenblatt, «Data leakage inflates prediction performance in connectome-based machine learning models,» 2024.
- [17] ADNI,» [En ligne]. Available: <https://adni.loni.usc.edu/>.