Journal of Soft Computing Paradigm (ISSN: 2582-2640)
www.irojournals.com/jscp/

Deep Learning-Driven Alzheimer’s Disease Classification: Custom CNN and Pretrained Architectures for Accurate MRI Analysis

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Abstract

Millions of people worldwide suffer from Alzheimer's Disease (AD), a progressive neurological disorder. An early and accurate diagnosis is necessary to treat the disease more effectively. This study investigates the application of deep learning methods in classifying the Alzheimer's disease using medical imaging data. A Custom Convolutional Neural Network (CNN) was developed, and it outperformed the performance of the several state-of-the-art pre-trained models, including DenseNet121, VGG16, InceptionV3, and ResNet50, with an exceptional accuracy of 98.18%. The research demonstrates the potential of deep learning algorithms in improving the medical diagnoses by using both transfer learning techniques and custom designed architectures.

Keywords: Alzheimer's Disease, Deep Learning, Custom Convolutional Neural Networks (CNN), Dementia, Hybrid Model, Pretrained Models.

1. Introduction

Alzheimer's disease (AD), the most prevalent cause of dementia worldwide, is a progressive neurological disorder predominantly affecting the elderly. Characterized by the gradual deterioration of cognitive functions, including reasoning, memory, and problem-solving abilities, early diagnosis and treatment are essential for managing the symptom, and mitigating the disease progression, as well as improve the patient health. However, the early detection of AD presents challenges due to the overlap of its symptoms with those of other

DOI: https://doi.org/10.36548/jscp.2025.1.003
Received: 18.02.2025, received in revised form: 23.03.2025, accepted: 08.04.2025, published: 19.04.2025

neurological conditions and normal aging. Magnetic resonance imaging (MRI) is frequently employed in clinical settings to identify structural brain alterations indicative of AD, such as cortical thinning and hippocampal atrophy. Despite its utility, manual analysis of MRI scans is a time consuming and a labor-intensive process, susceptible to inter-radiologist variability.

To address these limitations, deep learning has emerged as a potential method for automating and improving the processing of medical imaging data. Convolutional Neural Networks (CNNs), with their demonstrated efficacy in extracting features from complex visual information, are particularly well-suited for AD classification. While conventional approaches often rely on individual CNN architectures, the integration and optimization of advanced models like DenseNet121, VGG16, InceptionV3, and ResNet50 enhances the diagnostic accuracy. This research investigates the classification of AD based on MRI scans through the combination of these established architectures with a custom-designed CNN. The results obtained are highly promising, with the custom CNN model achieving an accuracy of 98.18%.

This study explores the classification of Alzheimer's disease utilizing a multi-model deep learning strategy encompassing a custom CNN, DenseNet121, VGG16, InceptionV3, and ResNet50 architectures. The investigation demonstrates the strengths of each architecture and their applicability to medical imaging analysis. The proposed models aim to improve the potential of AI-driven diagnostics by achieving high accuracy on MRI data, thereby enabling timely and precise AD diagnosis. Furthermore, this work delineates the challenges encountered and explores avenues for future advancements to augment the impact of artificial intelligence in clinical diagnostics. The proposed research emphasis the transformative potential of deep learning in neurological diagnostics, paving the way for accurate, scalable, and efficient methodologies for the detection of Alzheimer's disease.

2. Related Work

Recent advancements in artificial intelligence (AI) have unlocked significant potential for addressing challenges in medical imaging, particularly in the detection and classification of Alzheimer's disease (AD). Numerous studies have explored the application of machine learning, especially deep learning, to improve early diagnosis, enhance diagnostic accuracy, and analyze structural alterations associated with AD.

A notable contribution [1] introduced a multi-scale CNN for AD classification using MRI data. Their model achieved high accuracy by integrating both global and local features extracted from brain images. The study emphasized the importance of pre-processing techniques, such as normalization and augmentation, in mitigating class imbalance and improving model generalizability. Similarly, a study [2] investigated transfer learning methods, demonstrating the utility of pre-trained models in medical imaging tasks by achieving higher accuracy in distinguishing cognitively normal individuals from Alzheimer's patients. Their approach involved freezing the initial layers of a model pre-trained on ImageNet to retain features relevant to MRI data. However, the research highlighted limitations related to dataset variability and suggested the need for more diverse training samples.

A study [3] proposed a novel deep learning pipeline combining CNNs and Long Short-Term Memory (LSTM) networks. This approach focused on extracting temporal information from longitudinal MRI images to better track disease progression over time. By addressing a key challenge in AD diagnosis, this hybrid model significantly improved classification sensitivity for individuals in the Mild Cognitive Impairment (MCI) stage. In another study [4], DenseNet121 was employed, achieving a high accuracy in diagnosing Alzheimer’s. Their work demonstrated the effectiveness of densely connected networks in enhancing feature propagation and reducing redundancy, emphasing the importance of deeper network architectures for handling the intricate variations observed in Alzheimer's MRI datasets.

A study [5] presented an autoencoder-based transfer learning method for AD diagnosis. Their approach effectively reduced overfitting on smaller datasets by pre-training on a large natural image dataset and subsequently fine-tuning using MRI data. This study validated the efficacy of utilizing knowledge from larger image datasets for specific medical imaging tasks. Similarly, a study [6] utilized VGG16 for AD classification, highlighting its straightforward yet deep feature extraction architecture. Despite noting computational complexity as a potential drawback compared to lighter models, VGG16 achieved comparable performance due to its depth.

In contrast, research [7] focused on hybrid machine learning techniques, combining CNN-derived features with Random Forest (RF) classifiers. This approach proved particularly effective in scenarios with limited datasets, as RF classifiers provided robust decision boundaries to complement CNN-based feature extraction, achieving accuracy above 90%. However, the study did not explore scalability to larger datasets. A study [8] investigated capsule networks for Alzheimer's classification in an innovative study. Capsule networks, with their superior preservation of spatial hierarchies compared to conventional CNNs, enabled better performance on MRI data, achieving better accuracy, albeit with significant computational demands.

Research [9] explored lightweight CNN architectures customized for mobile healthcare applications, achieving real-time Alzheimer's diagnosis with a slight trade-off in accuracy compared to larger architectures.

Finally, research [10] explored generative adversarial networks (GANs) as a method to augment Alzheimer's MRI datasets. By synthesizing realistic yet diverse MRI images, they addressed the issue of limited data availability, resulting in an average performance improvement of 3% in model accuracy. GAN-based augmentation was found to be most beneficial for under-represented classes in datasets, such as mild cognitive impairment.

Collectively, the reviewed research demonstrates the significant progress in the application of deep learning techniques for Alzheimer's classification. While architectures like DenseNet121, VGG16, and ResNet50 remain reliable, emerging approaches such as transformers, hybrid models, and GAN-based data augmentation are opening new avenues. Further research is necessary to optimize these systems for clinical translation, addressing challenges related to explainability, computational efficiency, and dataset diversity.

3. Proposed Work

3.1 Dataset Collection and Preprocessing

This study utilizes the publicly available Alzheimer MRI 4 classes dataset from Kaggle[11], comprising 6,400 magnetic resonance imaging (MRI) scans across four diagnostic categories: very mild, mild, moderate, and non-demented. For training the models, the researchers selected a subset of 6,336 images from the very mild, mild, and non-demented classes. To ensure consistent quality, enhance learning, and mitigate biases during model training, appropriate preprocessing techniques were applied. Figure 1 displays sample images from the dataset.

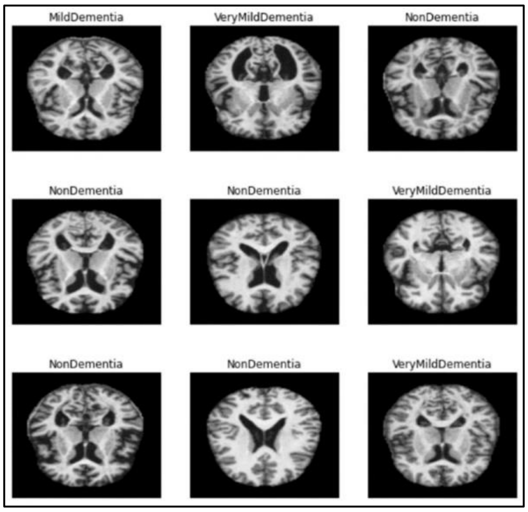

Figure 1. Sample Data from the Alzheimer's Dataset

The Alzheimer's disease classification using deep learning, include the preparation of MRI image datasets which, involves important preprocessing steps to ensure optimal model performance. This includes resizing all images to a uniform resolution for consistent input dimensions, normalizing pixel intensities to a standard range (typically 0-1) to address variations in contrast and brightness, and applying skull-stripping techniques to isolate brain regions by removing non-brain tissue. Additionally, denoising and smoothing filters are used to minimize artifacts and enhance the visibility of key anatomical features relevant to the disease. These preprocessing methodologies standardizing the data, improves the image quality, and enable deep learning models to effectively learn and identify subtle disease-related patterns within the brain scans.

3.2 Custom CNN Architecture for Classifying Alzheimer's Disease

A custom-built Convolutional Neural Network (CNN) was developed specifically for Alzheimer's disease classification using MRI scans, in contrast to employing pre-trained models. This custom architecture was designed to optimize feature extraction, computational efficiency, and classification accuracy for the specific medical imaging data. The CNN's layered structure was engineered to learn hierarchical features from the input images. It incorporated convolutional layers for extracting spatial features, pooling layers to reduce the dimensionality of feature maps, and fully connected layers to perform the final classification of brain images into Alzheimer's disease categories. This customized design aimed to enhance the model's ability to discern subtle, disease-specific patterns within the MRI data.

Table 1. Custom CNN model Summary

Layer	Type	Parameters/Shape	Activation	Pooling	Trainable Parameters	Non-Trainable Parameters
Input	Input	(Image Height, Image Width, Number of Channels) - determined by pre-processed MRI slice size (128x128x1)	None	None	0	0
Conv1	Convolutional	Filters: 32, Kernel: 3x3, Stride: 1, Padding: 'same', Input Channels: 1	ReLU	MaxPool 2x2	(32 * 3 * 3 * 1) + 32 = 320	0
Conv2	Convolutional	Filters: 64, Kernel: 3x3, Stride: 1, Padding: 'same', Input Channels: 32	ReLU	MaxPool 2x2	(64 * 3 * 3 * 32) + 64 = 18496	0
Conv3	Convolutional	Filters: 128, Kernel: 3x3, Stride: 1, Padding: 'same', Input Channels: 64	ReLU	MaxPool 2x2	(128 * 3 * 3 * 64) + 128 = 73856	0
Conv4 (Larger Kernel)	Convolutional	Filters: 512, Kernel: 14x14, Stride: 1, Padding: 'same', Input Channels: 128	ReLU	MaxPool 2x2	(512 * 14 * 14 * 128) + 512 = 10276352	0
Conv5 (Smaller Kernel)	Convolutional	Filters: 512, Kernel: 7x7, Stride: 1, Padding: 'same', Input Channels: 512	ReLU	MaxPool 2x2	(512 * 7 * 7 * 512) + 512 = 12845568	0
Flatten	Flatten	Output: (Variable) (e.g., after several MaxPool layers, the spatial dimensions reduce)	None	None	0	0

ISSN: 2582-2640

FC1 (Hidden)	Fully Connected	Units: 512, Input Units: 8192	ReLU	Dropout (0.5)	(8192 * 512) + 512 = 4194816	0
FC2 (Hidden)	Fully Connected	Units: 128, Input Units: 512	ReLU	Dropout (0.5)	(512 * 128) + 128 = 65664	0
Output	Fully Connected	Units: 4 (for four classes), Input Units: 128	Softmax	None	(128 * 4) + 4 = 516	0
Optimizer	Optimizer	Adam (Learning Rate: 0.001, with decay)				
Loss Function	Loss	Cross-entropy				
Epochs	Training Parameter	60				
Batch Size	Training Parameter	32				
Total Trainable Parameters					27,301,632	
Total Non-Trainable Parameters						0

The custom Convolutional Neural Network (CNN) model summary, as illustrated I Table 1, begins with an input layer for MRI images. It features a series of five convolutional layers with ReLU activation, employing varying kernel sizes (3x3 and larger 14x14, smaller 7x7) and increasing filter counts (32 to 512) to extract hierarchical features. Max-pooling layers follow each convolutional block for downsampling. The feature maps are then flattened and fed into two fully connected hidden layers (512 and 128 units with ReLU activation and dropout). Finally, a four-unit output layer with Softmax activation performs the classification into four brain disease categories. The model, trained with Adam optimizer and cross-entropy loss over 60 epochs with a batch size of 32 has an estimated total of 27.3 million trainable parameters and zero non-trainable parameters**.** The first step in optimizing the model was to carefully choose hyperparameters in order to balance computing performance with model complexity. Adam optimizer was used to optimise the learning rate, guaranteeing that the model converged efficiently during training without going above the ideal weights. The number of epochs was selected to be 60 to avoid underfitting or overfitting, and the batch size was modified to satisfy GPU memory limitations while preserving steady gradient updates. Table 2 illustrates the hyperparameters used.

Table 2. Hyperparameter Values used for Training the Custom CNN Model

Hyperparameter	Configuration Value	Optimization Method
Learning Rate	0.0001	Manually tuned; reduced on plateau during training
Optimizer	Adam	Chosen for fast convergence and adaptive learning
Batch Size	32	Selected after experimentation for stability
Epochs	60	Early stopping used after no improvement in val loss
Dropout Rate	0.5 after dense layers	Tuned to reduce overfitting

The fine-tuning methods seen in the Table above were used to optimise the custom CNN architecture, which demonstrated its capacity to accurately diagnose Alzheimer's disease from MRI scans with an accuracy of 98.18%. The model's ability to extract significant and disease-relevant characteristics was made possible by the careful fine-tuning procedure, which eventually helped to outperform pretrained architectures and conventional techniques.

3.3 DenseNet121 for Alzheimer's Disease Classification

One notable feature of DenseNet121 is its "dense connectivity" technique. DenseNet121 ensures maximum information flow and feature reuse by providing feature maps from all previous levels to each layer. As is often the case in medical imaging, this connection architecture improves performance on very limited datasets by enabling the network to learn a variety of characteristics without redundancy as seen in Figure 2.

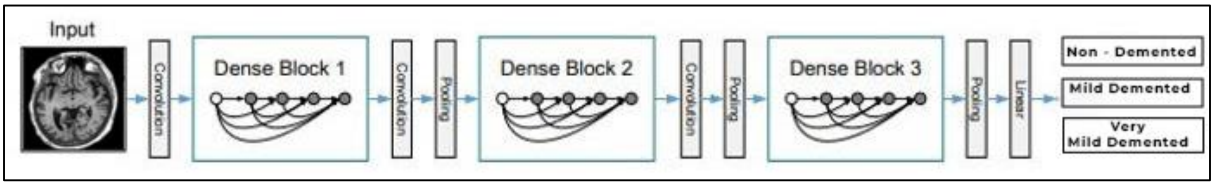

Figure 2. DenseNet121 Architecture for Classifying Alzheimer's Disease [4]

DenseNet121's architecture centers on dense blocks with stacked convolutional layers (1x1 and 3x3), Batch Normalisation, and ReLU. Its key innovation is dense connectivity, where each layer receives input from and connects to all preceding layers, enabling feature reuse and parameter efficiency. Fine-tuning prioritized hyperparameter optimization using a cyclical learning rate scheduler, an adaptive Adam optimizer, and a decaying learning rate to enhance convergence and accuracy. The DenseNet121 achieved 96.85% accuracy in Alzheimer's disease classification, with its dense connections proving effective for extracting subtle, early-stage structural brain anomalies.

3.4 VGG16 for Alzheimer's Disease Classification

VGG16 features a uniform architecture with 13 convolutional layers utilizing small 3x3 kernels for effective spatial feature extraction, followed by three fully connected layers. Convolutional blocks are succeeded by max-pooling for spatial down sampling and maintaining key features while ensuring computational efficiency. The convolutional layers increase in depth from 64 to 512 filters. The final classification is performed by three fully connected layers, the last employing a softmax activation. Fine-tuning involved a modest learning rate and the Adam optimizer with a learning rate scheduler for stable and accurate weight updates. Achieving an accuracy of 95.42% in the specific task, VGG16, despite being slightly less accurate than other models, remains a reliable and interpretable choice for medical imaging applications.

3.5 ResNet50 for Alzheimer's Disease Classification

ResNet50, a 50-layer network, utilizes residual blocks with shortcut connections, enabling the learning of residual functions by skipping layers. Each block consists of convolutional layers, Batch Normalisation, and ReLU, with 1x1 convolutions for dimension matching and a bottleneck design for computational efficiency. After convolutional blocks, global average pooling reduces spatial dimensions, followed by a classification-specific fully connected layer that is modified in this study to three output neurons with Softmax for MCI, Alzheimer's, and normal classification. This modified ResNet50, employing global average pooling before the final layer to mitigate overfitting and enhance performance, achieved 97.14% accuracy in differentiating brain scans, demonstrating its strong ability to capture both detailed and abstract features for effective classification.

3.6 Building InceptionV3 for Alzheimer's Disease Classification

InceptionV3, a 48-layer CNN, utilizes inception modules that parallelly apply multi-sized filters (1x1, 3x3, 5x5) for multi-scale feature extraction, enhancing both local and global information capture. It employs auxiliary classifiers and factorized convolutions for efficiency and performance. 1x1 convolutions precede larger convolutions to reduce computational cost. Trained on an Alzheimer's dataset with a batch size of 32, the model's performance was monitored using accuracy and loss through TensorBoard visulaizations. The original output layer was replaced with a three-neuron dense layer (Softmax activation) for three diagnostic categories, preceded by global average pooling to reduce parameters and overfitting. The optimized InceptionV3 achieved 96.72% accuracy in detecting Alzheimer's-specific features, showcasing a balance between classification effectiveness and computational efficiency, particularly beneficial for identifying hidden brain scan variations.

4. Results and Discussion

The study evaluated several deep learning models for Alzheimer's disease classification using MRI data. The Custom CNN achieved the highest test accuracy of 98.18%, indicating the effectiveness of a task-specific architecture. ResNet50 and InceptionV3 also demonstrated strong performance with competitive accuracies. In training, VGG16 achieved 95.42% accuracy (Figure 3 (d)), and DenseNet121 achieved 96.85% accuracy (Figure 4). The accuracy metric was calculated using equation (1). The results suggest that while pre-trained architectures like ResNet50, InceptionV3, VGG16, and DenseNet121 show robust feature extraction, a custom-designed CNN can potentially offer superior performance by being customed to the specific characteristics of the Alzheimer's MRI dataset.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FP} + \text{FN} + \text{TN}) \tag{1}$$

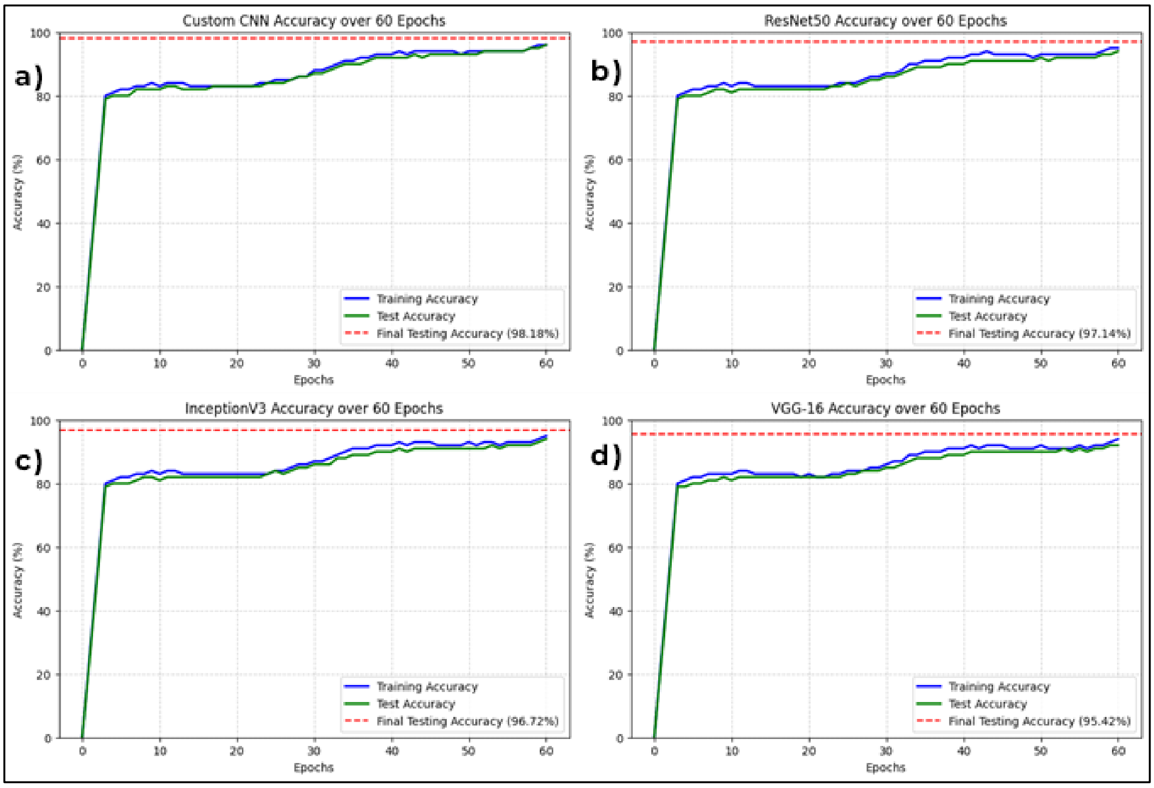

Figure 3. Training and Validation Accuracy and Losses of Custom CNN (a), ResNet50 (b), InceptionV3 (c), and VGG-16 (d)

The study highlights the significance of preprocessing in enhancing generalization and ensuring reliable results for MRI-based Alzheimer's classification, particularly essential for small datasets prone to overfitting. Model evaluation was conducted using TensorFlow and Keras in Python, with 20% of the data held out for validation. A key discussion point is the trade-off between model performance and interpretability. While deep, complex models like DenseNet121 and InceptionV3 achieve high accuracy, the Custom CNN offers better accuracy due to its simpler design, making it potentially more suitable for clinical applications where transparency is important.

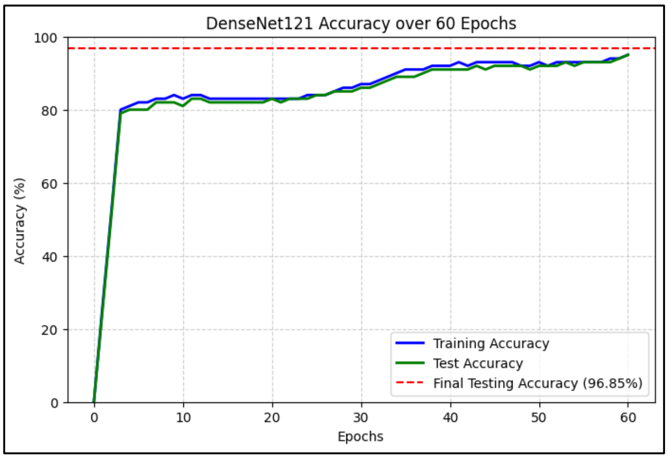

Figure 4. Training and Validation Accuracy of DenseNet121

This research demonstrates potential of deep learning models in enhancing Alzheimer's disease diagnosis. It emphasizes the importance of balanced approaches that consider not only accuracy but also interpretability and computational efficiency. The study's findings suggest promising avenues for future research into the practical application of deep learning models within medical settings, positioning them as valuable assets for early disease detection and better treatment.

5. Conclusion

This study demonstrates the significant potential of deep learning for Alzheimer's disease classification using MRI data, emphasizing the importance of custom CNN architecture and thorough dataset preparation for achieving high accuracy. The custom CNN achieved the an accuracy of 98.18%, outperforming pre-trained models like DenseNet121 and InceptionV3. The future improvements will include larger and more diverse datasets, multi-modal data integration such as, PET, CT, clinical records, genetics, and biomarkers to enhance model generalizability and diagnostic precision in Alzheimer's disease.

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