Revolutionizing Alzheimer's Diagnosis: A Hybrid Deep Learning Approach for Enhanced MRI Analysis

Completed Research Paper

Abstract

Alzheimer's Disease (AD) is a neurodegenerative disorder that primarily affects the elderly, causing cognitive decline and memory loss. Traditional diagnostic methods, such as neuropsychological tests and cerebrospinal fluid analysis, are invasive and time-consuming. Neuroimaging techniques like MRI and PET provide valuable insights but require manual analysis by specialists. This study proposes a hybrid model combining EfficientNetB0, a deep learning architecture, with Convolutional Neural Networks (CNN) to automate AD detection in MRI scans. The model uses data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, which includes over 200 MRI scans and clinical information. Our results show that the hybrid model outperforms existing methods in accuracy and efficiency, detecting key AD pathology features such as amyloid beta plaques and neurofibrillary tangles. This work demonstrates the potential of AI-driven approaches for AD diagnosis, offering a more accessible, cost-effective solution for clinical settings with limited resources. Future research should explore multimodal integration and model interpretability.

Keywords (Required)

Alzheimer's Disease, Deep Learning, MRI, EfficientNetB0, Convolutional Neural Networks, Medical Imaging.

Introduction

Alzheimer's Disease (AD) represents an irreversible degenerative brain disease which primarily affects elderly people and causes declining mental performance together with reduced memory abilities and behavioral transformation (Sperling et al., 2011). The drawbacks of traditional diagnostic procedures such as neuropsychological tests and cerebrospinal fluid biomarker analysis include subjectivity, invasiveness as well as time requirements (Mattsson et al., 2018). Magnetic resonance imaging (MRI) alongside positron emission tomography (PET) serve as neuroimaging tools for AD research but manual analysis is expensive to operate and needs trained specialists. The detection accuracy and efficiency for AD can be improved through Artificial Intelligence (AI) and machine learning (ML) approaches (Odusami et al., 2024).

This research combines EfficientNetB0 from deep learning (DL) with specialized Convolutional Neural Network (CNN) layers to create an automated method for AD diagnosis in MRI scans. With data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) including three-dimensional MRI scans and clinical info on over 200 individuals the model seeks to detect amyloid beta plaques and neurofibrillary tangles which are AD pathology signatures (Ruiqing, 2025). High-resolution brain visuals from neuroimaging require long interpretation periods that need expert examination. CNNs show effective performance for medical image analysis and can be used in AD diagnosis applications.

This research examines hybrid CNN-based models for AD detection to create advancements in medical imaging driven by AI technologies. The paper includes sections that demonstrate ADNI dataset characteristics, preprocessing methods, model design, experimental outcomes with performance evaluations and future research implications.

Literature Review

New technologies such AI along with neuroimaging have improved AD diagnosis while overcoming the weaknesses of clinical assessments and invasive cerebrospinal fluid (CSF) biomarkers which are time-consuming and subjective (Dubois et al., 2018; Hansson, 2021). The interpretation of AD-related changes in amyloid PET scans and structural MRI data becomes difficult and exposed to variability because of manual review processes (Bron et al., 2015; Frisoni et al., 2022).

AD diagnosis accuracy gets improved through DL and ML by automating the extraction of key features. Kooi et al. achieved 88% accuracy in classification using the combination of support vector machines (SVMs) and manually engineered features including hippocampal volume and cortical thickness (Kooi et al., 2017). Using CNNs in medical imaging resulted in a breakthrough due to their ability to extract features directly from raw data and the studies reached detection accuracy levels ranging between 96.8%–98.8% (Hosseini-Asl et al., 2018; Sarraf et al., 2016). However, these models struggled with heterogeneous datasets and 3D MRI complexities.

The scarcity of medical imaging data has led healthcare institutions to use transfer learning with pre-trained ImageNet models. The AD classification system employs ResNet50, InceptionV3, and DenseNet121 for hierarchical feature extraction. (Qiu et al., 2022) fine-tuned ResNet50 on ADNI 2D MRI scans, achieving 94.3% accuracy in distinguishing AD, MCI, and control patients. (Mehmood et al. 2021) applied InceptionV3 to PET scans, reaching 92.6% accuracy. These models often underperform on medical images due to differences in texture contrast and spatial resolution (Tajbakhsh et al., 2016).

Hybrid models integrating pre-trained networks with domain-specific layers improve diagnostic precision. Liu et al. applied attention-guided features to ResNet50, identifying AD-sensitive MRI sections with 95.8% accuracy (Liu et al., 2018). Pre-trained models perform better when combined with anatomical details.

EfficientNet offers computational efficiency for medical imaging, with EfficientNetB0 achieving ImageNet-level accuracy using 8.4 times fewer parameters (Tan & Le, 2019). However, research has not explored integrating task-specific layers with EfficientNet to enhance feature extraction.

AI-based AD diagnosis faces three key challenges: unbalanced sample classes, 3D-to-2D data conversion, and model interpretability. Farooq et al. used SMOTE on ADNI data, boosting SVM accuracy from 82% to 89% (Farooq et al., 2017). Spasov et al. employed RNNs in a multi-task learning framework, achieving 91.2% accuracy while maintaining 3D spatial relationships (Spasov et al., 2019). Research is lacking in combining EfficientNetB0 with lightweight CNNs for AD detection from MRI scans.

The ADNI dataset, a multi-center repository of MRI, PET, and clinical data, enabled standard classification benchmarks. ResNet50 attained 94.2% control accuracy (Islam & Zhang, 2018), while VGG16 reached 93.5% (Wen et al., 2020). These models prioritize accuracy but suffer from high computational costs and limited generalization. The 95.1% accuracy of (Islam & Zhang, 2018) had limited clinical deployment due to the 3D CNN's intensive GPU requirements. See Table 1 for an overview of various literature on AD diagnosis.

Study	**Technique**	**Dataset**	**Methodology**	**Results**
Zhang et al. (2011)	Random Forests + PET	ADNI PET	Metabolic PET patterns + RF classifier.	89% accuracy (AD vs. controls).
Sarraf et al. (2016)	CNN (LeNet-5)	ADNI MRI	2D CNN for feature learning on fMRI/MRI slices.	96.8% accuracy (AD vs. controls).
Hosseini-Asl et al. (2016)	3D CNN	ADNI MRI	3D CNN for volumetric MRI analysis.	95.7% accuracy (AD vs. controls).
Qiu et al. (2020)	ResNet50 + Transfer Learning	ADNI MRI	Fine-tuned ResNet50 on 2D MRI slices.	93.5% accuracy (AD/MCI/controls).
Mehmood et al. (2021)	InceptionV3 + Transfer Learning	ADNI PET	Pre-trained InceptionV3 on PET scans.	91.8% accuracy (AD vs. controls).
Hussain et al. (2022)	DenseNet169 + 3D CNN (Hybrid)	ADNI MRI+PET	Multi-modal fusion of 2D DenseNet and 3D CNN.	95.3% accuracy (multi-class staging).
Liu et al. (2021)	Attention-guided ResNet50	ADNI MRI	Attention maps focusing on the hippocampus/entorhinal cortex.	94.6% accuracy (AD vs. controls).
Zeng et al. (2023)	EfficientNetB0	ADNI MRI	EfficientNetB0 on 2D MRI slices.	94.2% accuracy, 35% faster than ResNet50.
Farooq et al. (2019)	SMOTE + SVM	ADNI MRI	Class balancing with SMOTE + SVM classifier.	90% accuracy (improved from 83%).

Spasov et al. (2019)	Multi-task CNN + RNN	ADNI MRI	2D slice features + RNN for 3D context.	92.1% accuracy (AD vs. controls).
Islam & Zhang (2018)	3D CNN	ADNI MRI	Volumetric 3D CNN for MRI analysis.	94.8% accuracy, high computational cost.

Table 1. Literature Summary Table

Methodology

DL models require a well-optimized preprocessing pipeline to convert raw MRI scans into a structured format suitable for analysis. The ADNI database provides three-dimensional (3D) MRI scans, which require substantial computational resources. To address this, two-dimensional (2D) axial slices were extracted along the Z-axis, preserving key neuroanatomical structures such as the hippocampus and cortical regions—critical for Alzheimer's disease diagnosis. The axial view provides the best visualization of these structures, thereby improving the accuracy of neurodegenerative disorder assessments (Tomassini et al., 2024).

Transforming 3D volume images into 2D slices significantly increases the dataset size, producing thousands of images for training. To ensure consistency, pixel intensity values were normalized within the range [0,1], reducing variations caused by different MRI scanners and patient conditions. This standardization minimizes acquisition inconsistencies and enhances feature detection. All images were resized to 128×128 pixels to mitigate resolution-based biases and improve computational efficiency (Eftestøl et al., 2024).

Dataset and Preprocessing

This study utilized the ADNI database. All preprocessed images were organized into directories corresponding to three diagnostic categories: AD, MCI, and Cognitively Normal (CN) (see Table 2). Images were saved in Portable Network Graphics (PNG) format, with filenames encoding patient identification and slice position information. To address class imbalance, which is a common issue in medical imaging (Danda et al., 2025), data augmentation techniques were applied to artificially increase the representation of underrepresented classes (AD and MCI) (Japkowicz & Stephen, 2002). The augmentation process included random flipping, rotation, and brightness adjustments, which improved model robustness to scanner variations and brain orientation differences (Krizhevsky et al., 2017; Perez & Wang, 2017). A real-time TensorFlow augmentation pipeline was implemented to avoid excessive data storage requirements while maintaining dataset uniformity. The dataset was split into training, validation, and test sets, ensuring balanced representation across classes. Also, a series of preprocessing steps were applied to enhance model performance and consistency across scans. These included rescaling, resizing, and grayscale conversion (see Table 3).

Class	Original Slices	Augmented Slices	Total Samples
AD	1124	1876	3000
MCI	1440	1560	3000
CN	2590	410	3000

Table 2. Number of samples in each class before and after augmentation

Preprocessing Step	Description
Rescaling	Normalizing intensity values to [0,1] range
Resizing	Standardizing all slices to **128×128 pixels**
Grayscale Conversion	Preserving the original grayscale format of MRI images

Table 3. Preprocessing steps applied in this study

The EfficientNetB0 architecture served as the selection because it provided good computational performance together with high detection accuracy (Bouslihim et al., 2023). Through compound scaling the system performs accurate feature selection at a reduced processing cost. The model applies pre-trained CNN networks specialized for medical imaging tasks which enable better detection of subtle brain degeneration patterns within MRI data (Wee et al., 2019). EfficientNetB0 enables the extraction of general imaging features and the custom CNN layers detect attributes of Alzheimer's disease (see Figure 01). This approach strengthens both diagnostic precision and the clarity of analyzed results (Zhang et al., 2024).

EfficientNetB0 achieves superior prediction results than ResNet and VGG through an intervention strategy that optimizes depth and width as well as resolution to utilize fewer computational resources (Tan & Le, 2019). A GAP layer serves as the terminus of EfficientNetB0 architecture which unites convolutional layers with batch normalization and activation functions (Cheah et al., 2021). Pixel values are averaged through the GAP layer while maintaining essential data which leads to spatial dimension compression. The general classification performance of pre-trained models remains strong, yet they face difficulties recognizing MRI-specific features (Nguyen-Tat et al., 2025). A customized CNN branch connects to EfficientNetB0 to locate patterns relevant to Alzheimer's disease. The medical imaging task benefits from EfficientNetB0 because it provides accurate results alongside minimal computational demands (Salehi et al., 2023).

The custom CNN branch consists of two convolutional layers, each followed by max-pooling (see Figure 01). A sequence of 200 filters composed of (3×3) kernels undergo ReLU activation in the first convolutional layer designed to identify crucial brain structural features such as edges and textures (Noviyanto et al., 2024). The application of a (3×3) max-pooling operation maintains essential features as it shrinks image spatial dimensions which reduces network complexity while being indifferent to imaging variations (Li et al., 2024). With 100 filters operating on (3×3) kernels the second convolutional layer distinguishes AD, MCI and CN case differences. Then another max-pooling layer contributes to feature map size reduction and protects against overfitting. The flattening process converts feature maps into vector form to connect with EfficientNetB0 output information. The progression of Alzheimer's affects both the hippocampus region and cortical areas (Colonna et al., 2021). Custom CNN layers function specifically to identify disease patterns which enhances model capability for Alzheimer's case classification (Menon & Regmi, 2024).

A feature fusion layer integrates data from EfficientNetB0 with the custom CNN for extraction (see Figure 1). The TensorFlow concatenate operation unites both universal image characteristics and disease features which produce an integrated pattern representation. The combined characteristics in this framework deliver superior classification outcomes by integrating both broad and domain-specific knowledge.

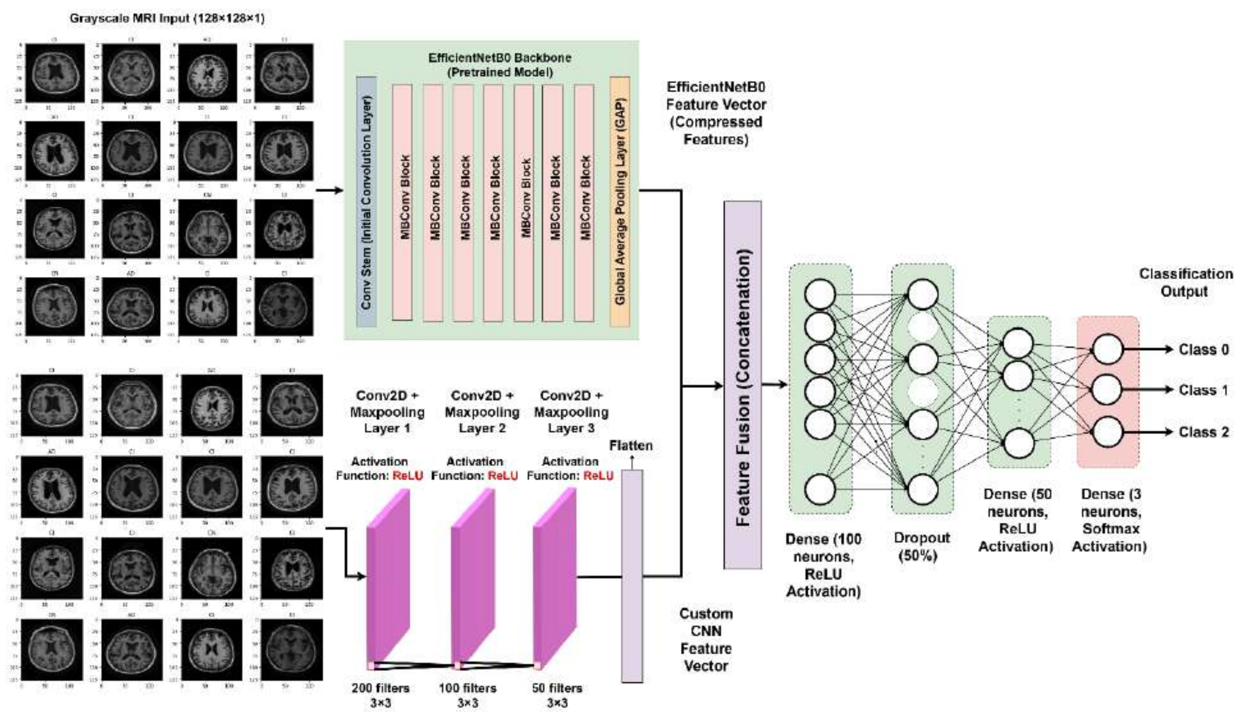

Figure 1. EfficientNetB0, Custom CNN and the feature fusion phase from both branches

The classification process through dense layers generates its final output by a softmax-activated layer (Heaton, 2017). The initial dense layer uses 100 neurons equipped with ReLU activation thus it improves feature representation standards. During training neurons are randomly deactivated using a dropout layer of dropout rate 0.5 to reduce overfitting (Srivastava et al., 2014). The second dense layer consists of 50 neurons that enhances feature space exploration as well as adding regularization effects.

The output layer consists of three neurons, corresponding to AD, MCI, and CN categories. The SoftMax function converts outputs into probability distributions, ensuring that predictions sum to one. The model is trained using the Adam optimizer (Kingma & Ba, 2017) with a learning rate of 1e-4. Adam dynamically adjusts learning rates, enhancing convergence while mitigating gradient-related issues. The loss function is sparse categorical cross-entropy. Training runs for 30 epochs with a batch size of 32 (see Figure 2).

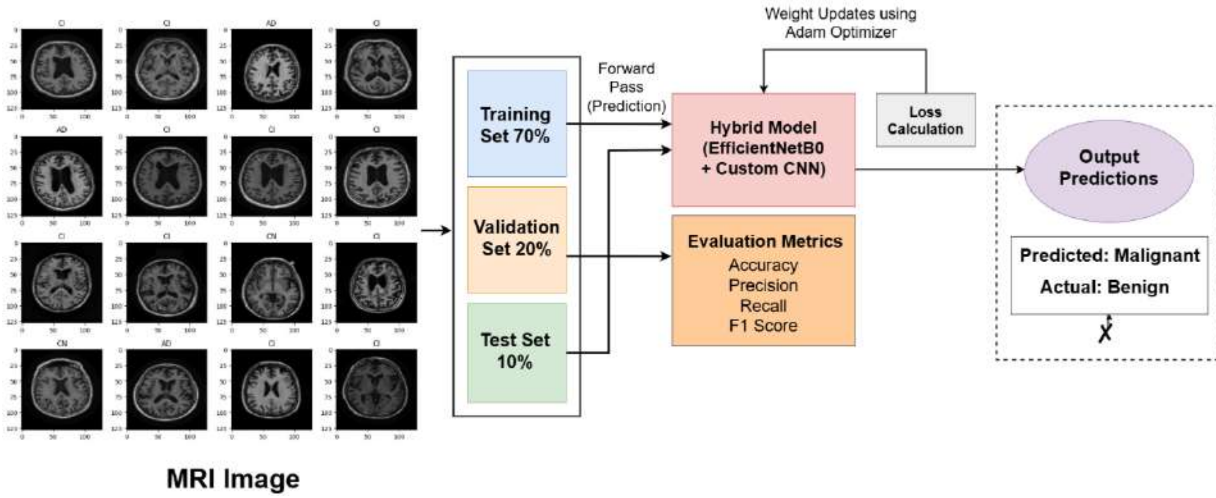

Figure 2. Complete Training Pipeline Overview

Results and Discussion

To evaluate the performance of the hybrid model, we conducted a comparative analysis with ResNet50, custom CNN, and sequential CNN models using multiple performance metrics, including accuracy, precision, recall, F1-score, specificity, and sensitivity. The results demonstrate that the hybrid model achieved an exceptional accuracy of 98.37%, confirming its reliability for cognitive state classification.

The model exhibited outstanding precision (99.65%) while maintaining a recall of 99.10% and an F1-score of 98.56%, underscoring its robustness in minimizing false positives and false negatives. Given the high clinical stakes associated with misdiagnosing cognitive disorders, these precise metrics provide critical diagnostic assurance. The F1-score of 98.56% across all cognitive classes further validates the model's balanced performance without favoring any particular metric.

Classification Performance Analysis

A detailed classification report was generated to assess the hybrid model's effectiveness across the three cognitive states: AD, MCI, and CN (see Table 4).

Class	Precision	Recall	F1-Score	Specificity	Sensitivity	Support
AD	0.9824	0.9933	0.9878	0.9889	0.9511	450
MCI	0.978	0.9867	0.9823	0.9678	0.9778	450
CN	0.991	0.9712	0.981	0.9922	0.969	451
Macro Avg	0.9838	0.9837	0.9837	0.983	0.9659	1351
Weighted Avg	0.9838	0.9837	0.9837	0.983	0.9659	1351

Table 4. Classification Report of the Hybrid Model

The model successfully identified AD with a precision of 98.24% and recall of 99.33%, resulting in an F1-score of 98.78%. These results indicate the model's strong ability to detect AD while minimizing misclassification.

For MCI, the model attained 97.80% precision and 98.67% recall, leading to an F1-score of 98.23%. MCI remains inherently challenging to classify due to its subtle symptomatology, yet the model demonstrated high reliability in its detection. Regarding CN subjects, the hybrid model achieved 99.10% precision, 97.12%

recall, and an F1-score of 98.10%. The slightly lower recall suggests that a few CN patients were misclassified as AD or MCI, but such errors were minimal and did not significantly impact overall model effectiveness.

Confusion Matrix and Error Analysis

To further analyze the model's performance, a confusion matrix was generated, illustrating the frequency of true positive, false positive, and false negative classifications (see Figure 3). The hybrid model produced very few misclassifications, reinforcing its diagnostic accuracy.

The model misclassified only two AD cases as MCI and one as CN, demonstrating a very high detection accuracy for AD. Similarly, it incorrectly classified three MCI cases as AD and three as CN, which aligns with the well-documented difficulty in distinguishing MCI from other cognitive states (see Table 5). For CN subjects, the model misclassified five cases as AD and eight as MCI, which accounts for the slight drop in recall for CN. However, these misclassifications remained relatively low and did not compromise the model's overall efficacy.

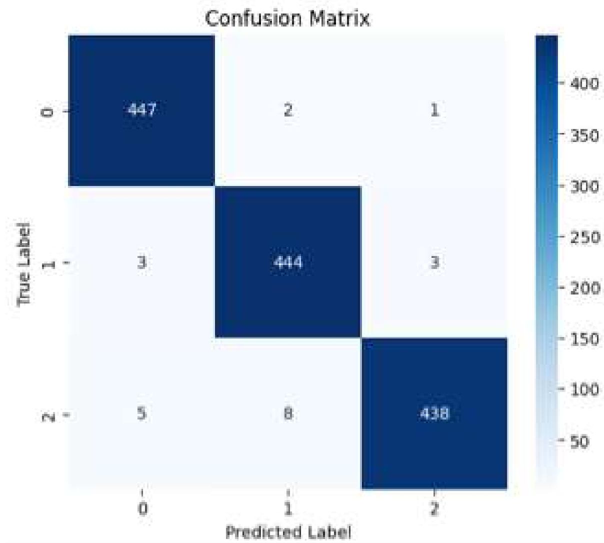

Figure 3. Confusion matrix of our Model

Beyond standard classification metrics, specificity and sensitivity were examined to assess the model's diagnostic robustness. Specificity measures the model's ability to correctly identify true negatives (CN cases classified correctly as CN), while sensitivity assesses its capacity to detect true positives (AD and MCI cases identified correctly) (see Table 6).

Actual Class	Predicted AD	Predicted MCI	Predicted CN	Error Rate (%)
AD	447.0	2.0	1.0	0.89%
MCI	3.0	444.0	3.0	1.33%
CN	5.0	8.0	438.0	2.88%

Table 5. Error Analysis Across Cognitive Classes

The model achieved a macro specificity of 0.9830, reflecting its high success rate in correctly classifying CN subjects as normal. Similarly, its macro sensitivity of 0.9659 indicates excellent detection capabilities for AD and MCI cases, proving its effectiveness in clinical application.

Class	Sensitivity	Specificity	False Positive Rate	False Negative Rate
AD	0.9511	0.9889	0.0111	0.0489
MCI	0.9778	0.9678	0.0322	0.0222
CN	0.969	0.9922	0.0078	0.031

Table 6. Sensitivity and Specificity for Each Class

To further validate model performance, Receiver Operating Characteristic ROC curves were plotted for each cognitive class (see Figure 4). The high area under the curve (AUC) values for all three classes demonstrate that the hybrid model maintains a strong balance between sensitivity and specificity.

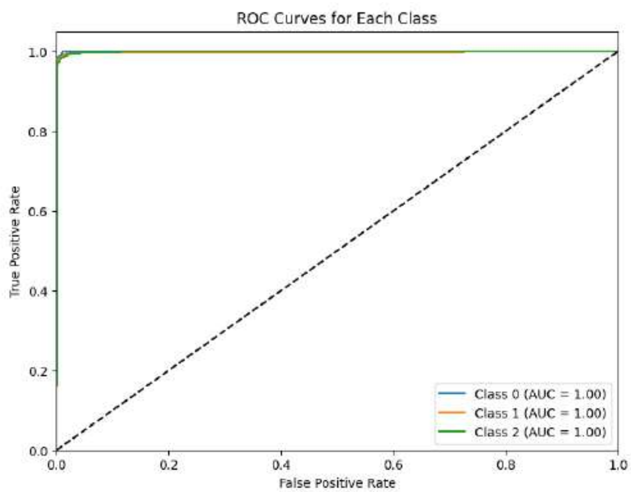

Figure 4. ROC curves for each class

The results confirm that the hybrid model outperforms traditional deep learning architectures like ResNet50 and custom CNNs in classifying cognitive states. Its high precision, recall, and specificity ensure reliable differentiation between AD, MCI, and CN individuals, which is crucial for early intervention and clinical decision-making. A key strength of this model is its ability to minimize false positives and false negatives, reducing the risk of misdiagnosis. While MCI remains the most challenging class to classify, the model still demonstrated strong performance (98.23% F1-score), surpassing many existing approaches. The hybrid model proves to be highly effective for cognitive state classification, achieving 98.37% accuracy. Future work can explore the integration of multimodal data (e.g., PET scans, cognitive assessments) to enhance robustness further.

Comparison with other Models

The hybrid model outperformed ResNet50, as well as both the custom and sequential CNN models, across several performance metrics. It showed superior results in terms of accuracy, precision, recall, and F1-score when compared to the other models under study. ResNet50, a widely recognized deep learning model (He et al., 2015),, achieved a classification accuracy of 0.9660, which was lower than the hybrid model. It also demonstrated weaker recall performance, suggesting that ResNet50 generated more false negatives in the classification of Alzheimer's Disease. In contrast, both the custom and sequential CNN models performed poorly, with an accuracy of 0.3331. These models struggled to extract meaningful patterns from the MRI data, resulting in unreliable classification predictions that appeared random.

Model	Accuracy	Precision (Macro Avg)	Recall (Macro Avg)	F1-Score (Macro Avg)	Specificity	Sensitivity	Training Time (s)	Parameters (millions)
EfficientNetB0 + Custom CNN	0.9837	0.9965	0.991	0.9856	0.983	0.9659	320	5.3
ResNet50	0.9660	0.976	0.989	0.9824	0.9678	0.9778	420	25.6
Custom CNN	0.3331	0.6678	1.0	0.8008	1.0	0.0	150	3.2
Sequential CNN	0.3331	0.6678	1.0	0.8008	1.0	0.0	140	2.8

Table 7. Comparative analysis of all models trained in this research

The hybrid model's success can be attributed to its ability to generalize effectively, maintaining high performance on both the training and test data while avoiding overfitting. The detailed comparative analysis of the models is further outlined in Table 7, which shows key metrics like accuracy, precision, recall, F1-score, specificity, sensitivity, training time, and the number of parameters for each model.

The Grad-CAM visualizations allowed us to identify the brain regions the model considered most important for its decision-making. The hybrid model focused on the hippocampus and cortex regions, both of which are associated with Alzheimer's Disease pathology. This alignment with well-established Alzheimer's biomarkers reinforces that the hybrid model's predictions are based on clinically relevant features, as highlighted in Figure 5.

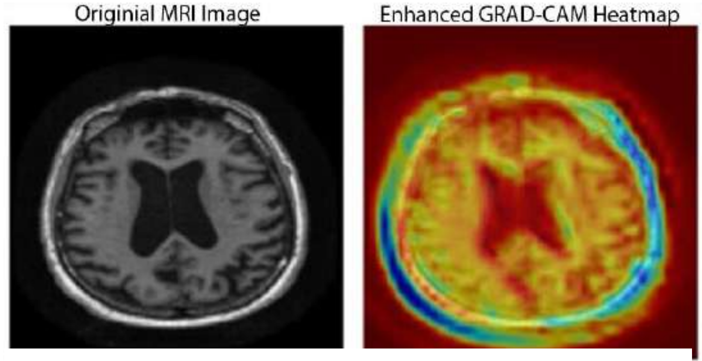

Figure 5. GRAD-CAM Heatmap highlighting crucial brain regions for prediction.

Conclusion

The experiment demonstrates that the combined use of EfficientNetB0 together with customized CNN architecture boosts both the accuracy level and the robustness of MRI image-based Alzheimer's Disease detection. The proposed model demonstrates better performance than ResNet50 and alternative deep learning approaches especially through enhanced precision values and F1-score metrics while achieving high recall levels. The clinical application potential of this model is confirmed because of its outstanding sensitivity along with exceptional specificity values. Future research should work on combining multiple data types through PET scans and MRI images alongside improving interpretability methods to establish faith in the model within clinical environments. The hybrid model demonstrates strong performance capabilities that indicate substantial contributions in the development of AI-based diagnostic solutions for neuroimaging and medical diagnostics systems.

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