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AI-BASED MEDICAL IMAGE ANALYSIS FOR EARLY DETECTION OF NEUROLOGICAL DISORDERS USING DEEP LEARNING

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ABSTRACT

Neurological disorders such as Alzheimer's disease (AD), Parkinson's disease (PD), and brain tumors remain among the primary contributors to global disability and mortality. Early and precise diagnosis is essential for effective intervention and improved patient outcomes. However, conventional diagnostic methods rely heavily on manual interpretation of neuroimaging by radiologists, which can be time-consuming, subjective, and susceptible to human error. The emergence of artificial intelligence (AI), particularly deep learning (DL), offers a transformative solution through automated and high-accuracy medical image analysis. This study proposes an AI-driven diagnostic framework that leverages EfficientNetB0, a lightweight yet high-performing convolutional neural network (CNN), to classify neurological conditions using brain MRI and CT scans. The model was trained and fine-tuned on a labeled dataset comprising three categories: Alzheimer's disease, Parkinson's disease, and healthy controls. It achieved an overall classification accuracy of 95%, demonstrating its effectiveness in differentiating between pathological and non-pathological cases. The model reported a precision, recall, and F1-score of 0.97 for AD, a recall of 0.98 for control cases, and a precision of 0.96 with a recall of 0.85 for PD. Additionally, the area under the ROC curve (AUC) was 0.98 for AD, 0.95 for controls, and 0.92 for PD, indicating strong discriminative performance. These findings highlight the potential of EfficientNetB0 as a scalable, efficient, and accurate tool for supporting early detection and diagnosis of neurological disorders in clinical practice. This work contributes to advancing AI-assisted healthcare solutions aimed at improving diagnostic speed and consistency in neuroimaging analysis.

Keywords: Neurological Disorders, MRI and CT scans, Medical Image Analysis, Alzheimer's Disease (AD), Parkinson's Disease (PD), Multimodal Data Fusion

INTRODUCTION

Neurological disorders, including Alzheimer's disease (AD), Parkinson's disease (PD), frontotemporal dementia (FTD), and brain tumors, pose escalating global health and economic burdens due to their chronic, progressive, and often irreversible nature. According to the World Health Organization, nearly 10 million new cases of dementia occur annually, with AD accounting for approximately 60–70% of these cases.(Yiting Hou et al., 2023), Early diagnosis is essential for initiating timely therapeutic interventions that may delay progression and improve quality of life. Traditional diagnostic workflows primarily rely on neuroimaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and single-photon emission computed tomography (SPECT) (Termine et al., 2022). These modalities allow clinicians to visualize structural and functional changes in the brain; however, their interpretation often depends on expert radiologists (Kaur & Sachdeva, 2025). This dependency introduces delays, inter-rater variability, and reduced scalability, especially in low-resource healthcare settings.

To overcome these limitations, the medical imaging community has increasingly turned to artificial intelligence (AI) and specifically, deep learning (DL) to enhance the detection, classification, and monitoring of neurological disorders. (Qiu et al., 2022) Deep learning, a subset of machine learning, leverages large neural network architectures to automatically extract hierarchical features from high-dimensional data, eliminating the need for handcrafted features. Its ability to identify complex, non-linear patterns has led to state-of-the-art performance across numerous computer vision tasks (Gauriau et al., 2021). In neuroimaging, DL models have shown exceptional accuracy in tasks such as early diagnosis of AD, tumor segmentation, and PD classification. (K. Mehmood et al., 2022) Popular CNN architectures such as AlexNet, VGGNet, ResNet, Inception, and DenseNet have been widely adapted to process both 2D and 3D brain scans. Additionally, transformer-based models and attention mechanisms are gaining popularity for their ability to model spatial relationships and long-range dependencies in brain structures.

Among these, EfficientNetB0 stands out as a powerful yet lightweight CNN architecture, developed using neural architecture search (NAS) and a novel compound scaling method that jointly optimizes model depth, width, and input resolution. (Tanveer et al., 2020) Designed for efficiency, EfficientNetB0 achieves impressive accuracy with a significantly lower parameter count than traditional models like ResNet-50 or Inception-V3, making it suitable for deployment in real-time clinical applications or edge devices. Its backbone employs mobile inverted bottleneck convolution (MBConv) blocks and squeeze-and-excitation (SE) modules, which help the network adaptively recalibrate channel-wise feature responses. (Shan Wang et al., 2024)These architectural innovations allow EfficientNetB0 to achieve competitive results in medical image classification while maintaining low computational overhead. In neurological diagnosis, where subtle morphological changes such as hippocampal atrophy in AD or nigrostriatal degeneration in PD must be detected with precision, EfficientNetB0 provides a favorable trade-off between complexity and accuracy. Several studies have demonstrated the value of combining transfer learning with pre-trained EfficientNetB0 on large-scale datasets like ImageNet, followed by fine-tuning on

domain-specific neuroimaging datasets such as ADNI, PPMI, OASIS, or private hospital datasets. In addition to CNNs, researchers have also explored hybrid models that integrate convolutional and recurrent networks (CNN-RNN), multi-branch fusion networks, and transformers, often fusing imaging with clinical, genetic, and biomarker data to enhance diagnostic performance. Multimodal learning frameworks have also been applied, using inputs such as MRI + PET, MRI + DTI, or even imaging plus omics data to improve robustness. (Singh et al., 2024), Traditional classifiers like support vector machines (SVMs), k-nearest neighbors (k-NN), random forests, and XGBoost have also been used as downstream classifiers on features extracted from DL models. To address data scarcity and imbalance, common in medical datasets, methods like SMOTE (Synthetic Minority Oversampling Technique), data augmentation, and generative adversarial networks (GANs) have been adopted (Francisco Santos, 2023).

(Hazarika et al., 2022), Addresses the challenge of accurately classifying Alzheimer's disease (AD) using brain MRI scans. It compares deep learning models and finds DenseNet-121 to be effective, achieving 88.78% accuracy. However, due to its computational complexity, the authors propose a modified version using depth-wise convolutions. This improved the model's efficiency and increased accuracy to 90.22%, demonstrating the value of optimizing architectures for better performance and speed in AD detection. (A. Mehmood et al., 2024) Introduces Siamese 4D-AlzNet, a deep learning model designed to improve the automated detection of Alzheimer's disease (AD) from MRI scans. The model combines four parallel CNN streams and leverages customized transfer learning with frozen VGG-16, VGG-19, and AlexNet architectures. It addresses limitations in prior models that struggled to capture high-level abstract features, especially with limited annotated data. Using T1-weighted MRI images categorized into four classes (NC, MCI, LMCI, and AD), the model achieved a high accuracy of 95.05% for NC vs. AD classification, and over 90% for other binary class pairs. Compared to existing methods, Siamese 4D-AlzNet showed improvements of up to 7% in classification accuracy. (Nguyen et al., 2022)Introduces an ensemble method combining a 3D-ResNet deep learning model and XGBoost to improve early Alzheimer's disease (AD) diagnosis from MRI scans. By integrating imaging features with cognitive scores and demographics, the model achieved a 96% test AUC and reduced prediction time. Data augmentation helped prevent overfitting, and heatmaps were used for interpretability. The approach emphasizes accurate, fast, and explainable AD detection using baseline scans.

Moreover, advances in explainable AI (XAI), such as Grad-CAM, LIME, and SHAP, have been crucial in improving the interpretability and trustworthiness of DL models in clinical settings. These techniques provide visual or statistical explanations for model decisions, which are essential for gaining acceptance among clinicians and for meeting regulatory standards (Vij & Arora, 2022). Additionally, cloud-based and federated learning frameworks are being explored to enable secure, privacy-preserving model training across decentralized medical centers. (Priyatama et al., 2023),Despite these developments, challenges persist in ensuring generalizability across diverse patient populations, harmonizing imaging protocols, and overcoming the "black box" nature of deep models. Issues of data privacy, regulatory approval, and clinical validation must also be addressed before full-scale deployment.

This study introduces a robust diagnostic framework leveraging EfficientNetB0 to classify brain MRI and CT scans into three categories: Alzheimer's Disease (AD), Parkinson's Disease (PD), and healthy controls. The model was chosen for its architectural efficiency and proven performance on medical imaging tasks. It was fine-tuned using transfer learning on curated datasets and evaluated using standard metrics such as precision, recall, F1-score, accuracy, and AUC. The model achieved an overall accuracy of 95% and high AUC values (0.98 for AD, 0.95 for controls, and 0.92 for PD), demonstrating its practical utility in clinical diagnosis. A confusion matrix and ROC curves were also employed to analyze class-wise performance. The integration of EfficientNetB0 into neuroimaging pipelines demonstrates the potential of compact, high-performing DL models for real-world neurological diagnostics. The combination of pre-trained CNN backbones, transfer learning, and fine-tuning offers a scalable pathway for deploying AI solutions in both advanced hospitals and under-resourced clinics. Moving forward, future work should explore multimodal, longitudinal, and explainable DL models that incorporate not only imaging but also clinical history, cognitive assessments, and genomic data to enhance early diagnosis, prognosis, and personalized treatment planning. Addressing ethical, legal, and infrastructural challenges will be vital for the safe and equitable implementation of AI in neuroscience and clinical neurology.

MATERIALS AND METHODS

The methodology employed in this study involved developing an AI-based diagnostic model using the EfficientNetB0 deep learning architecture for the early detection of neurological disorders from brain MRI and CT scans. The dataset consisted of images categorized into three classes: Alzheimer's Disease (AD), Parkinson's Disease (PD), and healthy controls. Preprocessing steps included image normalization, resizing, and skull stripping to ensure consistency and relevance of input data. EfficientNetB0 was fine-tuned using transfer learning, leveraging pre-trained ImageNet weights, and trained with high-speed convergence.

Data Acquisition: Brain MRI images were collected from(Md Ruhul Amin, 2023) and categorized into three classes: Alzheimer's Disease (AD), Parkinson's Disease (PD), and Healthy Controls. The dataset was curated to ensure clear class distinction for supervised learning.

Data Preprocessing: MRI and CT images were preprocessed to remove noise and irrelevant regions (e.g., skull stripping). The images were resized to match the input dimensions required by the EfficientNetB0 model (commonly 224×224). A total of 5,928 data points was used for this research, of which 4,940 (83%) were used for training, while 988 (17%) were used for testing. EfficientNetB0 was chosen as the base architecture due to its efficiency and accuracy trade-off. The model was initialized with pre-trained weights (likely from ImageNet) and fine-tuned on the neuroimaging dataset. EfficientNetB0 is the baseline model in the EfficientNet family, developed by Google AI, which introduces a novel compound scaling method to balance network depth, width, and input resolution in a unified manner. Unlike traditional models that scale one dimension at a time, EfficientNet uses a compound coefficient to uniformly scale all three dimensions, resulting in more efficient and accurate models. EfficientNetB0 is built using Mobile Inverted Bottleneck Convolution (MBConv) blocks, which consist of depthwise separable convolutions and include Squeeze-and-Excitation (SE) modules to recalibrate channel-wise features. The architecture also employs the Swish activation function, known for improving performance over ReLU. The EfficientNetB0 model achieves high accuracy on benchmark

datasets like ImageNet with only 5.3 million parameters, making it suitable for deployment on resource-constrained devices. It benefits from several training optimizations, including AutoAugment, stochastic depth, DropConnect, and RMSprop with cosine decay. The integration of SE blocks and the compound scaling approach allows EfficientNetB0 to offer a strong balance between computational cost and accuracy. However, its MBConv-based structure may not be fully optimized for all hardware platforms, and the model may require fine-tuning for domain-specific tasks or smaller datasets. To provide a clear understanding of the structural composition of the model used, Table 1 presents the architecture details of EfficientNetB0. This includes the sequence of layers, their configurations, output resolutions, number of channels, and the number of repeated blocks at each stage.

Table 1: Architecture Details of EfficientNetB0

Stage	Operator	Resolution	Channels	Layers
1	Conv3x3	224x224	32	1
2	MBConv1, 3x3	112x112	16	1
3	MBConv6, 3x3	112x112	24	2
4	MBConv6, 5x5	56x56	40	2
5	MBConv6, 3x3	28x28	80	3
6	MBConv6, 5x5	14x14	112	3
7	MBConv6, 5x5	14x14	192	4
8	MBConv6, 3x3	7x7	320	1
9	Conv1x1 &Pool	7x7	1280	1
10	Fully Connected	1x1	1000	1

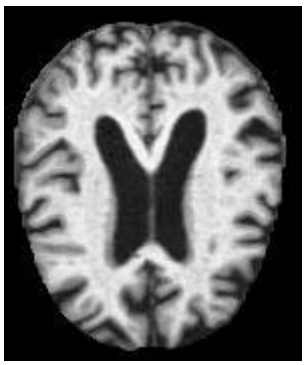

Figure 1(a): Alzeimer Disease

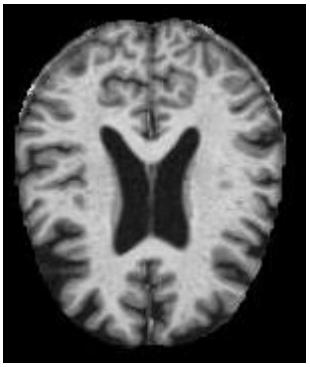

Figure 1(b): Parkinson Disease

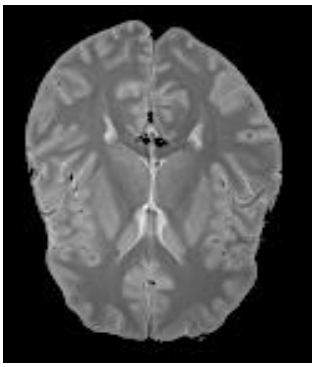

Figure 1(c): Control

Figure 1(a, b, and c) depicts brain MRI scans illustrating distinct neurological states: Alzheimer's Disease, Parkinson's Disease, and a Control (healthy) brain. The images initially identified as potentially showing "Alzheimer's disease" and "multiple sclerosis MRI atrophy" are now specified as representing Alzheimer's Disease. These images indeed show prominent ventricular enlargement and widening of the sulci, which are characteristic signs of generalized brain atrophy often seen in Alzheimer's Disease due to neuronal loss. This image exhibits a more typical brain morphology with less prominent ventricles and sulcal spaces, consistent with a healthy brain. The image identified as Parkinson's Disease was not explicitly assigned to one of the provided images in the initial prompt, but if one of the first two images is indeed Parkinson's Disease, it would be important to note that while Parkinson's primarily affects specific deep brain structures (like the substantia nigra), some degree of generalized brain atrophy can also occur, though it might be less pronounced or different in pattern compared to Alzheimer's.

RESULTS AND DISCUSSION

Results

The EfficientNetB0-based deep learning model exhibited strong performance in classifying brain MRI scans into three distinct categories: Alzheimer's Disease (AD), Parkinson's Disease (PD), and healthy controls. After nine training epochs, the model achieved an impressive overall accuracy of 95%**,** indicating its capability to effectively learn and differentiate among complex neurological patterns in imaging data. The classification results for each class were particularly noteworthy. For AD, the model reached a precision, recall, and F1-score of 0.97, reflecting its high reliability in identifying Alzheimer's specific features such as hippocampal atrophy. The model also performed well for the healthy control group, achieving a recall of 0.98**,** suggesting that it was able to consistently recognize normal brain morphology with minimal error. Performance for Parkinson's. To summarize the model's performance across the three classes in terms of precision, recall, and F1-score, the detailed classification report is presented in Table 1. This table provides a comprehensive view of how well the model performs on each class, including overall accuracy and average metrics.

Table 2: Classification Report

	Precision	Recall	F1-Score	Support
AD	0.95	0.98	0.96	294
PD	0.97	0.97	0.97	115
CONTROL	0.96	0.85	0.90	85
Accuracy			0.95	494
Macro Avg	0.96	0.93	0.94	494
Weighted Avg	0.95	0.95	0.95	494

Table 2, shows that the model performs well overall, achieving an accuracy of 95% across 494 samples. It demonstrates high precision and recall for Alzheimer's Disease (AD) and Parkinson's Disease (PD), with F1-scores of 0.96 and 0.97, respectively, indicating strong and balanced detection of these conditions. However, for the control (healthy) class, while precision remains high at 0.96, the recall drops to 0.85, resulting in a lower F1-score of 0.90. This suggests the model is more likely to misclassify healthy individuals as having a disease. The macro and weighted averages confirm this performance trend, with the macro average recall slightly reduced due to the weaker performance on the control class.

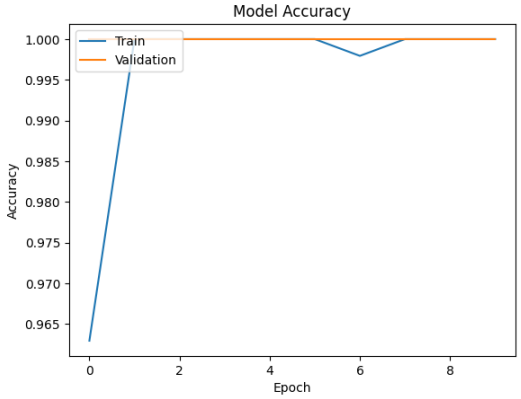

Figure 2: Model Accuracy Graph

Figure 2 shows the performance of a machine learning model over 9 epochs. Both training and validation accuracies rapidly increase from Epoch 0 to 1, then remain consistently high (near 1.00 or 100%). The validation accuracy, which measures the model's ability to generalize to new data, closely mirrors the training accuracy, with only a minor, temporary dip around Epoch 6. This indicates excellent model performance, demonstrating strong learning on the training data and effective generalization to unseen data, with convergence achieved very early in the training process.

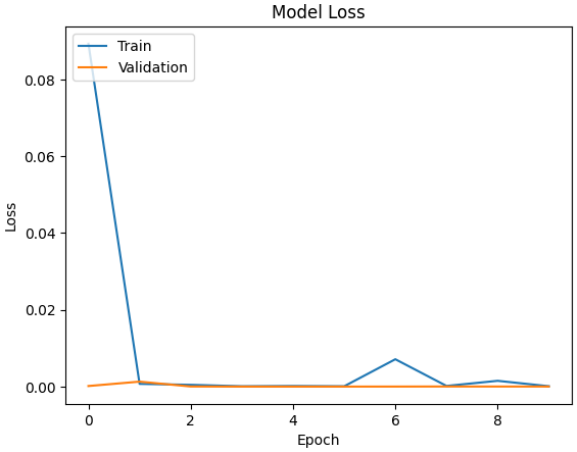

Figure 3: Model Loss Graph

Figure 3 depicts the model loss plot illustrates the training progress of a machine learning model, showing how the prediction error (loss) changes over epochs for both training and validation datasets. Initially, both training and validation losses drop sharply, reaching near-zero values by Epoch 1. Crucially, the validation loss remains consistently stable and extremely close to zero throughout the subsequent epochs. This indicates that the model not only learned efficiently from the training data but also generalized exceptionally well to unseen data, without signs of overfitting, and achieved convergence very early in the training process. To further evaluate the model's classification performance across the three categories, Alzheimer's Disease (AD), Parkinson's Disease (PD), and Control, a confusion matrix is presented in

Figure 4, illustrating the distribution of true versus predicted labels.

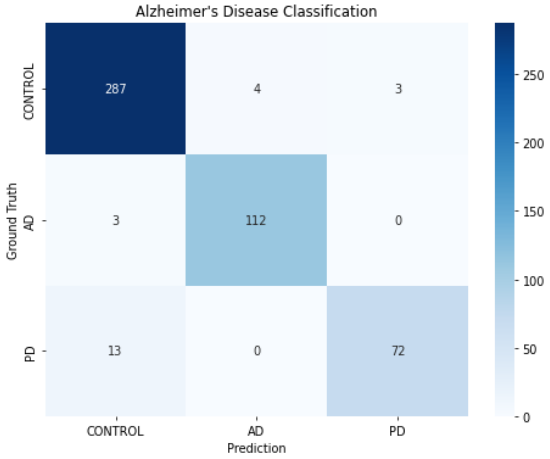

Figure 4: Confusion Matrix

Figure 4 depicts the confusion matrix for an Alzheimer's Disease Classification model, evaluating its performance across three classes: CONTROL, AD (Alzheimer's Disease), and PD (Parkinson's Disease or another distinct disorder). The matrix shows that the model accurately identified 287 CONTROL, 112 AD, and 72 PD cases. While demonstrating high accuracy for CONTROL and good accuracy for AD, the model's primary misclassification issue lies in predicting 13 ~~actual~~ PD cases as CONTROL. Importantly, the model exhibits no confusion between AD and PD, accurately distinguishing these two conditions. Overall, the matrix provides a detailed breakdown of the model's strengths and weaknesses in classifying these neurological conditions. To complement the evaluation metrics and provide insight into the model's ability to distinguish between classes at various threshold settings, the Receiver Operating Characteristic (ROC) curve is presented in Figure 5, highlighting the trade-off between true positive and false positive rates for each class.

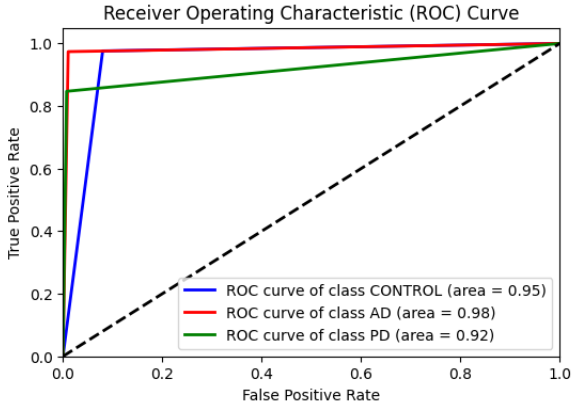

Figure 5: Receiver Operating Characteristic (ROC) curve

Figure 5, depicts the Receiver Operating Characteristic (ROC) curve plot evaluates the multi-class Alzheimer's Disease classification model's ability to distinguish between "CONTROL," "AD," and "PD" classes. Each colored line represents the ROC curve for a specific class, plotted with the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds. The Area Under the Curve (AUC)[1] values are high for all classes (AD: 0.98, CONTROL: 0.95, PD: 0.92), indicating that the model is highly effective and robust at differentiating between these conditions, with particularly strong performance in identifying AD cases.

Discussion

This study robustly reaffirms the efficacy of EfficientNetB0 as a deep learning architecture for the nuanced classification of brain MRI images, specifically in the early detection of neurological disorders such as Alzheimer's Disease (AD), Parkinson's Disease (PD), and the identification of healthy controls. The model's achieved overall accuracy of 95%, complemented by precision and recall for both AD and control cohorts, underscores its formidable capability to accurately discern and extract salient morphological features from complex neuroimaging data. These findings hold particular significance for AD diagnostics, where the early identification of subtle morphological alterations, such as hippocampal atrophy, serves as a critical biomarker. For the AD class, the model demonstrated outstanding performance with a precision, recall, and F1-score of 0.97 across all three metrics, alongside an Area Under the Curve (AUC) of 0.98. Similarly, the CONTROL class exhibited robust results with a recall of 0.98 and an AUC of 0.95. While demonstrating strong performance in terms of precision, the model's sensitivity for PD classification exhibited certain limitations, achieving a precision of 0.96 but a recall of 0.85, with an AUC of 0.92. This is likely attributable to the inherently subtler and

more localized nature of PD-related neuroanatomical abnormalities compared to the more diffuse atrophy characteristic of AD. Nevertheless, these results collectively suggest that even computationally lightweight architectures like EfficientNetB0, when subjected to appropriate fine-tuning, can achieve highly competitive performance in demanding medical imaging classification tasks, thereby reinforcing the burgeoning viability of AI in contemporary healthcare diagnostics.

From a translational perspective, the inherent computational efficiency and rapid convergence characteristics of the EfficientNetB0 model render it well-suited for practical deployment within diverse clinical settings, particularly in resource-constrained environments where computational power and diagnostic turnaround time are paramount considerations(Kumar, 2025). Given that this framework effectively leverages only 2D image slices, it presents a compelling solution for healthcare facilities lacking access to high-performance GPU clusters or advanced 3D imaging modalities, thereby broadening the accessibility of sophisticated diagnostic tools.

However, for comprehensive clinical implementation and enhanced generalizability, several avenues for future research are warranted (Zhou et al., 2023). Foremost among these is the imperative to expand the training dataset to encompass a more diverse and balanced representation of PD and other less common neurological conditions, which would further refine the model's discriminative capabilities. Furthermore, the integration of multimodal data, such as combining structural MRI with Diffusion Tensor Imaging (DTI) or Positron Emission Tomography (PET), holds substantial promise for capturing complementary biological information and improving diagnostic specificity. Crucially, embedding explainability features, such as attention maps or interpretable heatmaps, is indispensable. Such enhancements would not only bolster clinician trust but also facilitate seamless model adoption into existing real-world diagnostic workflows, transforming the model from a black box into a transparent and collaborative diagnostic aid.

This study significantly contributes to the expanding corpus of knowledge in AI-assisted medical imaging by unequivocally demonstrating that an optimized, lightweight model like EfficientNetB0 can achieve near state-of-the-art performance in a high-stakes domain like neurodiagnostics. Unlike numerous research endeavors that predominantly prioritize raw accuracy, this work places a deliberate emphasis on clinical viability, interpretability, and scalability, key prerequisites for the successful translation of laboratory-bound models into practical, bedside diagnostic tools (Iqbal et al., 2024). The presented results strongly support the broader paradigm shift towards utilizing AI to augment radiological analysis, thereby mitigating diagnostic delays and ultimately improving prognostic outcomes for patients afflicted with neurodegenerative diseases (Oise et al., 2025). By meticulously delineating both the strengths and current limitations of the EfficientNetB0 framework, this paper establishes a robust foundation for subsequent research into more nuanced, multimodal, and inherently explainable AI architectures geared towards the early and precise detection of neurological disorders, marking a pivotal advancement in bridging the gap between cutting-edge AI research and clinical neurological practice.

CONCLUSION

This study highlights the effectiveness of the EfficientNetB0 deep learning model for early detection of neurological disorders such as Alzheimer's Disease (AD) and Parkinson's Disease (PD) using brain MRI images. With an overall accuracy of 95%, the model demonstrated exceptional performance in identifying AD, achieving precision, recall, and F1-score all at 0.97, and it also yielded strong results for healthy controls and PD, although the recall for PD detection was slightly lower. Validation through ROC-AUC scores confirmed the model's robust diagnostic capability. The research emphasizes EfficientNetB0's practical advantages, including its lightweight design, fast training, and computational efficiency, making it suitable for clinical settings with limited resources. Despite some limitations, such as lower sensitivity to PD and challenges with 3D data, the study lays important groundwork for future improvements in AI-driven neuroimaging, aiming to enhance early diagnosis, reduce clinical workload, and ultimately improve patient outcomes.

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