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Encephalon_DC: Classification of Brain Diseases Using Deep Learning Techniques †

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Abstract

The brain is the most complex organ in the human body, and neurological disorders pose significant diagnostic challenges. This study focuses on three prevalent conditions—Alzheimer's disease, brain tumors, and Parkinson's disease—collectively referred to as Encephalon Diseases. We propose a three-level deep learning-based framework, termed the Encephalon Diseases Classifier, for automated diagnosis from magnetic resonance imaging (MRI) scans. In Level 1, MRI images are classified as normal or diseased. Level 2 further categorizes diseased cases into one of the three targeted conditions. Level 3 performs stage or subtype classification for Alzheimer's disease and brain tumors. The framework employs four convolutional neural network (CNN) architectures, namely ResNet152-V2, EfficientNet-B0, DenseNet121, and VGG16, trained on a preprocessed dataset. Experimental results show that ResNet152-V2 achieves the highest accuracy of 100%, while EfficientNet-B0 and DenseNet121 yield comparable performance across all levels. The proposed method demonstrates the potential of multi-level deep learning strategies for precise and scalable Encephalon disease classification.

Keywords: brain disease; encephalon; Alzheimer's Disease; Parkinson's Disease; brain tumors; image classification; deep learning; MRI images

1. Introduction

The brain is responsible for cognition, sensory processing, motor control, and the regulation of vital physiological processes. It is a core component of the central nervous system (CNS), together with the spinal cord, and consists of billions of neurons and glial cells that transmit electrical and chemical signals to coordinate bodily functions [1,2]. Historically, its role has been interpreted through various metaphors, from mechanical devices to computational systems, reflecting shifts in scientific understanding [3]. The term encephalon, derived from the Greek enkephalos meaning "within the head", refers directly to the brain [4,5]. Early Greek scholars such as Alcmaeon of Croton and Plato recognized the brain's central role in perception and intelligence, although others, like Aristotle, attributed primary control to the heart [6–10].

In this work, we focus on three major neurological disorders—Alzheimer's disease (AD), Parkinson's disease (PD), and brain tumors—collectively referred to as Encephalon Diseases. These conditions cause structural and functional brain damage, severely impacting quality of life. AD is characterized by widespread neuronal death, particularly in the

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entorhinal cortex and hippocampus, leading to progressive memory loss and cognitive decline. PD results from the degeneration of dopamine-producing neurons in the basal ganglia, causing tremors, rigidity, and impaired motor coordination [11]. Brain tumors encompass benign and malignant growths such as meningiomas, gliomas, and pituitary tumors, each affecting distinct brain regions and cell types [12–14].

In our recent work [15], we demonstrated how artificial intelligence (AI) methods can be used to diagnose a number of prevalent diseases and conditions affecting the brain. These include brain tumors, epilepsy, Parkinson's disease, and dementia, particularly phases of Alzheimer's disease. The most widely used dataset sources for brain research, neuropsychological testing, and brain imaging methods are then examined and separated into categories for open-access and proprietary datasets. The most popular performance metrics are discussed in the article's conclusion.

Given the complexity of diagnosis, particularly from magnetic resonance imaging (MRI) scans, numerous studies have applied machine learning (ML) and deep learning (DL) techniques to automate classification tasks. Building upon this body of work, we propose the Encephalon Diseases Classifier, a multi-tier DL-based framework utilizing ResNet152-V2, EfficientNet-B0, DenseNet121, and VGG16 architectures. The framework performs hierarchical classification: first distinguishing normal from diseased MRI scans, then categorizing diseased cases into AD, PD, or brain tumors, and finally determining stage or subtype for AD and tumor cases. This approach aims to improve diagnostic accuracy, standardization, and scalability in medical image analysis.

2. Literature Review

Through our research, we focus on studying the use of AI techniques in the diagnosis of common brain diseases and disorders, such as dementia, especially the Alzheimer's stage, Parkinson's disease, and brain tumors.

2.1. Alzheimer's Disease (AD) Studies

The study in [16] evaluated the precision of machine learning in identifying dementia biomarkers in the Open Access Series of Imaging Studies (OASIS) database. Research on dementia is impacted by the correctness and imbalance of datasets. Unbalanced classes may be created and segmented by a neural network and reinforcement learning system. High-resolution sickness probability maps will be produced by accurately diagnosing dementia and taking into account its four stages. It expresses dementia illness risk precisely and understandably via deep reinforcement learning. To avoid imbalance, classes should be evenly represented in samples. The MRI image shows a class imbalance. Trial accuracy increased by 6%, precision by 9%, recall by 13%, and F-score by 9–10% with the Deep Reinforcement System. Diagnosis efficiency has also increased.

Effective machine learning algorithms were assessed for their capacity to diagnose dementia using OASIS, according to the authors in [17]. Two convolutional neural network (CNN) models (AlexNet and ResNet-50) and hybrid deep learning and machine learning techniques (AlexNet+SVM and ResNet-50+SVM) were also evaluated for the identification of Alzheimer's disease. After the OASIS dataset was balanced, the missing values were filled in, and the missing values were restored. All of the machine learning methods, including SVM, Decision Tree, Random Forest, and KNN, shown exceptional performance in diagnosing dementia. The precision, recall, and F1 scores for the Random Forest method were 93%, 98%, and 96%, respectively, with a total accuracy of 94%. The MRI image dataset, the second dataset, was examined using hybrid AlexNet+SVM and ResNet-50+SVM models, as well as AlexNet and ResNet-50 models. All models had excellent performance, but the hybrid approaches that combined deep learning and machine learning performed

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better overall. The hybrid AlexNet+SVM model scored 94.8%, 93%, 97.75%, and 99.70% for accuracy, recall, specificity, and AUC, respectively.

Researchers [18] suggested utilizing a deep neural network to predict AD using MRI. Results from contemporary image classification networks with transfer learning, such as ResNet, VGG, and others, are promising. Pretrained versions of these networks perform better through transfer learning. A ResNet-based approach with many layers has been shown to perform effectively when predicting the various stages of the disease. The trials are conducted using the Kaggle dataset.

2.2. Brain Tumor Studies

In order to identify a tumor, the authors of the study reported in [19] used brain MRI scans to build a CNN. The Softmax Fully Connected layer had a 98.67% classification accuracy. Additionally, the accuracy of the Radial Basis Function (RBF) classifier is 97.34%, whereas the Decision Tree (DT) classifier is 94.24%. Based on the data from the categorizers, the network accuracy on the picture testing showed that the Softmax classifier has the highest accuracy in CNN. This is a novel approach to brain imaging tumor identification that combines CNN with feature extraction techniques. The test's accuracy, according to the study, was 99.12%.

In [20], the authors proposed classifying tumors using multiple kernel-based probabilistic clustering and a deep learning classifier. The three parts of the proposed method are the segmentation, feature extraction, and classification modules. The median filter is employed in the de-noising process after the MRI image has been preprocessed to make it suitable for segmentation. Important characteristics will be selected for classification using Linear Discriminant Analysis (LDA) after feature extraction. With the highest values at 1, 0.85, and 0.94, respectively, the suggested approach yielded average recall, specificity, and accuracy values of 0.88, 0.80, and 0.83. Improved outcomes show the effectiveness of the recommended approach.

2.3. Parkinson's Disease (PD) Studies

The authors of [21] introduced a deep neural network-based model to classify Parkinson's disease. Their suggested approach has a 94.87% accuracy rate in classifying people with the disease. Parkinsonism can be identified using the patient's dataset. The following methods were also compared: Random Forest, K-Nearest Neighbor, Decision Tree, Classification and Regression Trees, Linear Discriminant Analysis, Support Vector Machine (SVM), Linear Regression, Logistic Regression, Multilayer Perceptron, and Naive Bayes.

The study by [22] examines and contrasts computational intelligence techniques for PD detection. Classification facilitates quicker PD diagnosis and better treatment outcomes. Finding the optimal classification algorithm is challenging when dealing with local datasets. In order to ascertain which classifier is the most effective and precise for PD classification, this study evaluates Multilayer Perceptron, SVM, and K-Nearest Neighbor classifiers on the benchmark (voice) dataset. These classifiers make use of speech input datasets from the UCI machine learning library. The Levenberg–Marquardt algorithm was used by artificial neural network (ANN), which was the best classifier (95.89%).

The authors of [23] shown that it is feasible to detect PD completely automatically from a single 1000 um area in sections that range from the frontal brain to the dorsal motor nucleus of the vagus nerve. Image processing and statistical methods are used to do this, with machine learning demonstrating improved accuracy. They demonstrated that it is feasible to do binary classification on high-resolution sections in a couple of minutes and to identify regions of interest for the pathologist to perform manual visual verification.

They also demonstrated state-of-the-art PD detection (> 90% accuracy on single 1000 um regions).

Table 1 summaries the classification methods of Parkinson's disease, brain tumors, and Alzheimer's disease in previous studies.

Table 1. Summary of classification methods of Parkinson's disease, brain tumors, and Alzheimer's disease in previous studies.

Ref	Disease	Method	Dataset	Metrics
[16]	Dementia	CNN Deep Reinforcement Learning BOOST DRL-XGBOOST	Alzheimer's Dataset (4 classes of Images)".	Acc = 90.23% Pre = 92.34% Sen = 95.45% F1 score = 96.12%
			OASIS-2.	Acc = 91.23% Pre = 92.3% Sen = 94.56% F1 score = 95%
			Balanced ADNI dataset	Acc = 93.23% Pre = 94.5% Sen = 96.34% F1 score = 92.12%
[17]	Dementia and Alzheimer's	Deep Learning + Hybrid Methods	OASIS	Acc = 94%, Pre = 98% Recall = 98%, F1 score = 96%,
		AlexNet	Alzheimer's Dataset (MRI dataset)	Acc = 92.20% Spe = 97.00% Sen = 94.50% AUC = 99.45%
		ResNet-50		Acc = 93.10% Spe = 97.25% Sen = 92.25% AUC = 98.82%
		Hybrid (AlexNet + ResNet-50).		Acc = 94.10% Spe = 97.50% Sen = 91.75% AUC = 99.31%
[18]	Alzheimer's Disease	VGG16, VGG19, ResNet18, ResNet34, ResNet50, ResNet101	Alzheimer's Dataset (4 classes of Images)	Acc = 99.51% Sen = 0.98% Pre = 0.99% F1 score = 98%
[21]	Parkinson's Disease	Deep Neural Networks model (PDCD)	Kaggle [NAN]	Acc = 94% Sen = 92% Pre = 93% F1 score = 92%
[22]	Parkinson's Disease	Artificial Neural Network (ANN)	Parkinson's dataset	Acc = 95.89% Sen = 93.75% Spe = 96.59%
[23]	Parkinson's Disease	PDNet (a variation of the EfficientNet-B7 model).	A private dataset (Parkinson's UK Brain Bank).	Acc = 90% Sen = 93% Spe = 88% Pre = 88% F1 score = 91%

3. Materials and Methods

3.1. Methodology: Encephalon Diseases Classifier

The proposed Encephalon Diseases Classifier, shown in Figure 1, consists of four stages: (1) Data Discovery, (2) Data Preprocessing, (3) Model Building, and (4) Results Evaluation.

This method relies on training and testing four deep learning models on the *Encephalon Dataset*. All models were trained using the Adam optimizer and a batch size of 64 for 10, 20, 50, and 100 epochs. Categorical cross-entropy was used as the loss function. The training, testing, and evaluation were performed on Google Colab.

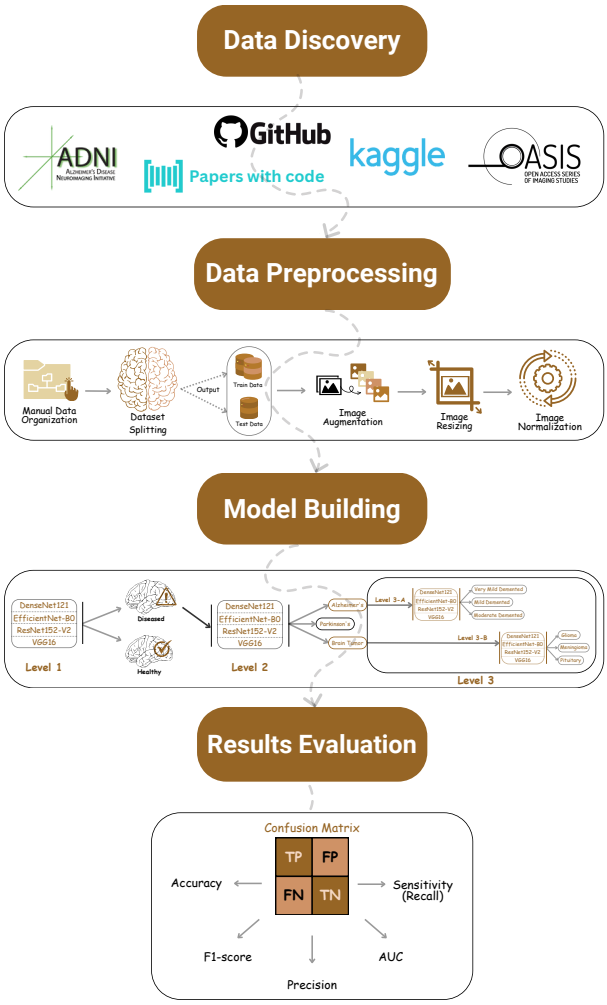


Figure 1. Encephalon Diseases Classifier framework.

3.2. The Dataset Chosen

The proposed *Encephalon Dataset* was constructed by merging three public MRI sources: the Augmented Alzheimer MRI Dataset [24], which is an augmented version of the Alzheimer's Dataset (4 classes of Images), Brain Tumor MRI Dataset [25], and (NTUA) Parkinson's Dataset [26], yielding 32,400 images split into training (83%) and testing (17%) sets. The hierarchical classification structure comprises Level 1—binary classification (healthy vs. diseased); Level 2—multi-class (Alzheimer's, Parkinson's, tumor); and Level 3—sub-class categorization for Alzheimer's (*Mild_Demented*, *Moderate_Demented*, *Very_Mild_Demented*) and tumors (*Glioma*, *Meningioma*, *Pituitary*). Preprocessing removed irrelevant or duplicate images and enhanced balance through manual augmentation (rotation, flipping, contrast adjustment), ensuring dataset quality and consistency for model

evaluation. Figure 2 shows the hierarchical organization of this dataset and how many images are included in each class.

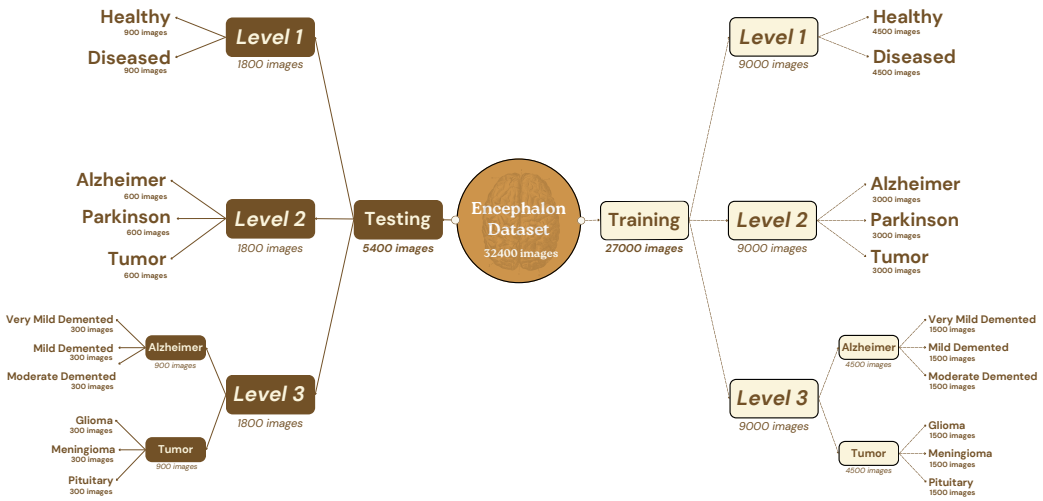


Figure 2. Encephalon Dataset composition.

3.3. The Models Chosen

3.3.1. DenseNet121

DenseNet121, characterized by dense connectivity and bottleneck layers, was modified by removing the fully connected layer and adding 2D global average pooling, batch normalization, and dense and dropout layers. The final softmax layer matched the classification classes [27]. The model was compiled with categorical cross-entropy and trained, totaling about 8.6 million parameters with 1.7 million trainable.

3.3.2. EfficientNet-B0

EfficientNet-B0, leveraging compound scaling for efficient and accurate classification, was adapted by adding global average pooling and a softmax dense output layer per classification level. Compiled with categorical cross-entropy, it was trained on the dataset, with roughly 4.2 million parameters and over 4.1 million trainable.

3.3.3. ResNet152-V2

ResNet152-V2, a deep residual network with pretrained weights, was extended by global average pooling and a softmax dense output layer matching class counts [28]. After compilation with categorical cross-entropy, it was trained, containing about 58.3 million parameters and over 58 million trainable.

3.3.4. VGG-16

VGG-16, a 16-layer CNN with 3 × 3 convolutions and ReLU activations [29], was customized by adding a flatten layer and a softmax dense output layer. The model was compiled with categorical cross-entropy and trained, with around 14.8 million parameters, mostly non-trainable.

3.4. Evaluation Metrics

In classification tasks, model performance is commonly evaluated using a confusion matrix, which summarizes correct and incorrect predictions for each class [30]. For binary classification, the matrix consists of four outcomes—True Positives (TPs), True Negatives (TNs), False Positives (FPs), and False Negatives (FNs). We will use the following performance metrics to evaluate our proposed model:

- Accuracy (Acc) represents the overall proportion of correctly classified samples and is computed as follows:

$$Accuracy(Acc) = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- Precision (Pre) measures the fraction of predicted positive samples that are actually positive:

$$Precision(Pre) = \frac{TP}{TP + FP} \quad (2)$$

- The Area Under the ROC Curve (AUC) quantifies the classifier's ability to distinguish between classes, ranging from 0 (completely incorrect) to 1 (perfect prediction) [31].
- Recall, or sensitivity/True Positive Rate (TPR), measures the proportion of actual positives correctly identified:

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- The F1 score is the harmonic mean of precision and recall, providing a balanced performance metric:

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

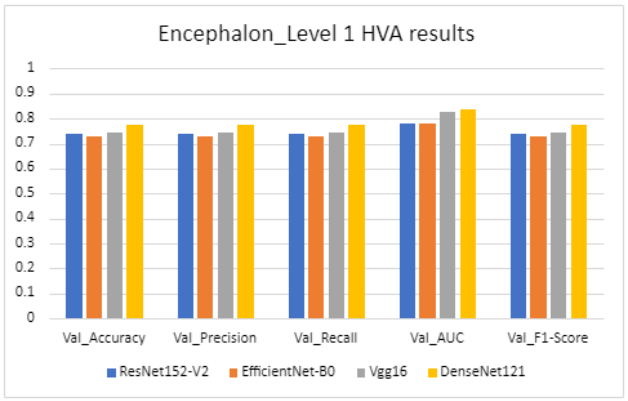
4. Results

We implemented four models for the proposed multilevel brain disease classification framework and evaluated them in two scenarios: the highest validation accuracy (HVA), representing the epoch with the highest validation accuracy throughout the entire model execution process, and the last validation accuracy (LVA), specifically representing the final epoch of that process. The results are analyzed by comparing the performance metrics of the four models across all classification levels in both scenarios. This comparison helps identify the most suitable model for the framework. Notably, some models achieved high accuracy in certain levels but underperformed in others; these variations are examined to highlight strengths and weaknesses at different classification stages.

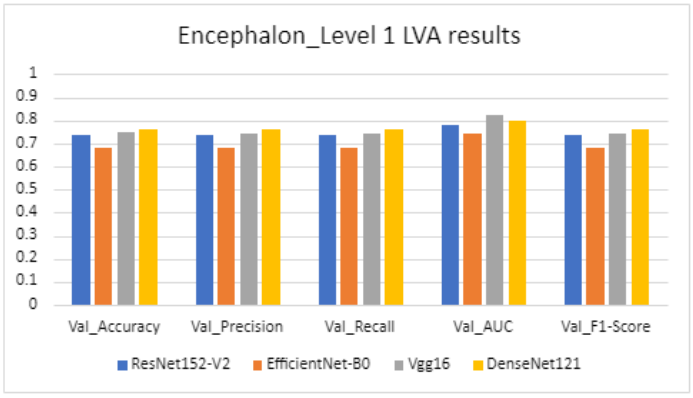
The Level 1 results are presented in Figure 3. The bar charts indicate that DenseNet121 and VGG16 achieved the highest performance across all metrics for both HVA and LVA cases. DenseNet121 obtained the best results, with Val_Accuracy values of 77.39% in the HVA case and 75.94% in the LVA case. VGG16 ranked second, reaching 74.70% Val_Accuracy in both cases. In contrast, EfficientNet-B0 recorded the lowest performance among all models for this classification level in both scenarios.

The Level 2 results are illustrated in Figure 4. The bar charts show that ResNet152-V2 and EfficientNet-B0 achieved the highest performance across all metrics in the HVA case, while in the LVA case, DenseNet121 followed ResNet152-V2. ResNet152-V2 attained the best results for both cases, with 100% Val_Accuracy in HVA and 99.89% in LVA. In the HVA case, EfficientNet-B0 ranked second with 99.89% Val_Accuracy, whereas in the LVA case, DenseNet121 achieved second place with 99.17% Val_Accuracy. Notably, in HVA, VGG16 recorded the lowest performance, while in LVA, EfficientNet-B0 had the weakest results.

Level 3 tumor is presented in Figure 5. For both HVA and LVA cases, ResNet152-V2 and EfficientNet-B0 achieved the highest performance across all metrics, with ResNet152-V2 obtaining 99.41% Val_Accuracy in both cases. VGG16 recorded the lowest performance at this classification level in both scenarios.

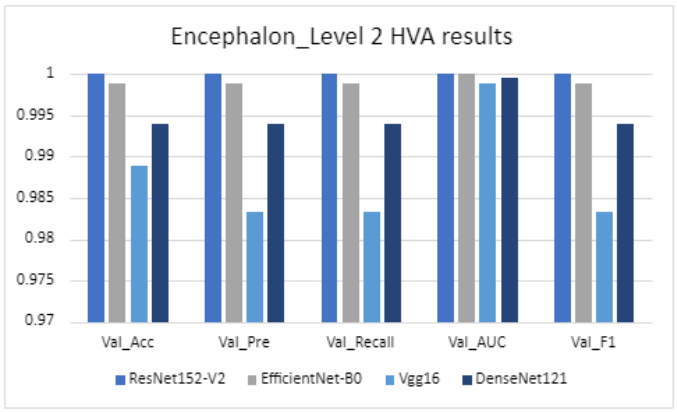


(**a**) Level 1 HVA values

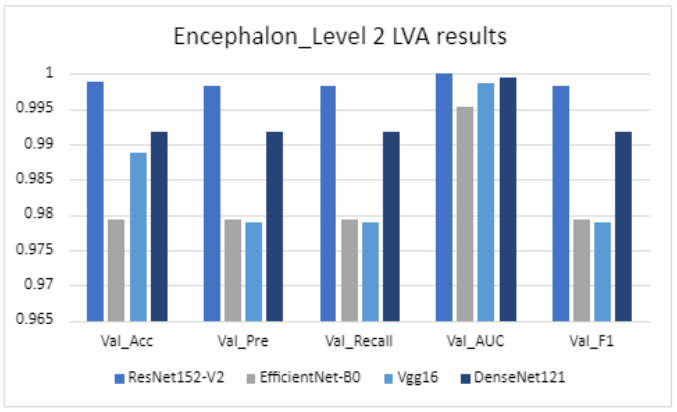


(**b**) Level 1 LVA values

Figure 3. Comparison of Encephalon_Level 1 testing results.

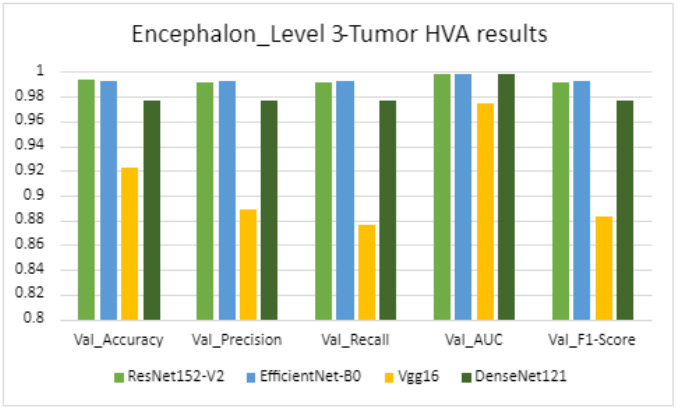


(**a**) Level 2 HVA values

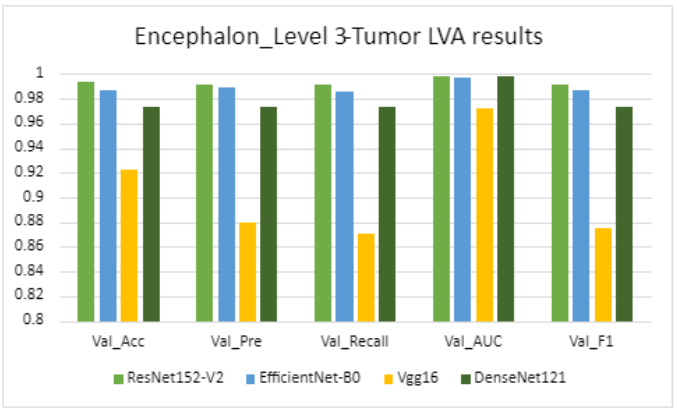


(**b**) Level 2 LVA values

Figure 4. Comparison of Encephalon_Level 2 testing results.



(**a**) Level 3 Tumor HVA values



(**b**) Level 3 Tumor LVA values

Figure 5. Comparison of Encephalon_Level 3 brain tumor testing results.

Figure 6 depicts Level 3 Alzheimer's disease. Here, EfficientNet-B0 and ResNet152-V2 achieved the best results for both HVA and LVA cases. EfficientNet-B0 led with 99.78% Val_Accuracy in HVA and 99.44% in LVA, while VGG16, again, showed the lowest performance in both scenarios.



(**a**) Level 3 Alzheimer's HVA values (**b**) Level 3 Alzheimer's LVA values

Figure 6. Comparison of Encephalon_Level 3 Alzheimer's testing results.

To highlight the variation in the performance among these models, Figure 7 presents a boxplot comparing the validation accuracy of all four models.

- ResNet152-V2: Highest Val_Accuracy of 100%, lowest of 75%, outlier at 63%, and a mean of approximately 89%.
- EfficientNet-B0: Highest Val_Accuracy of 100%, lowest of 67%, outlier at 34%, and a mean of 80%.
- VGG16: Highest Val_Accuracy of 98%, lowest of 79%, outlier at 74%, and a mean of approximately 89%.
- DenseNet121: Highest Val_Accuracy of 99%, lowest of 80%, outlier at 75%, and a mean of 91%.

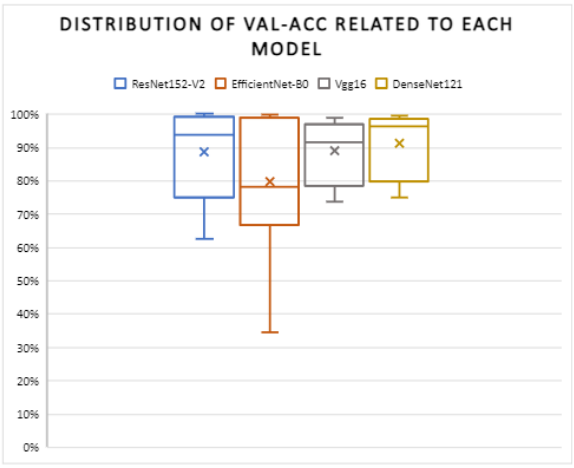


Figure 7. Distribution of validation accuracy of each model.

For misclassification rates, Figure 8 shows the distribution for each model, where lower values indicate better performance.

- **ResNet152-V2:** Lowest misclass of 0.00, highest of 0.29, outlier at 0.37, and a mean of 0.16.
- **EfficientNet-B0:** Lowest misclass of 0.01, highest of 0.35, outlier at 0.66, and a mean of 0.22.
- **VGG16:** Lowest misclass of 0.02, highest of 0.24, outlier at 0.27, and a mean of 0.14.
- **DenseNet121:** Lowest misclass of 0.01, highest of 0.22, outlier at 0.25, and a mean of 0.09.

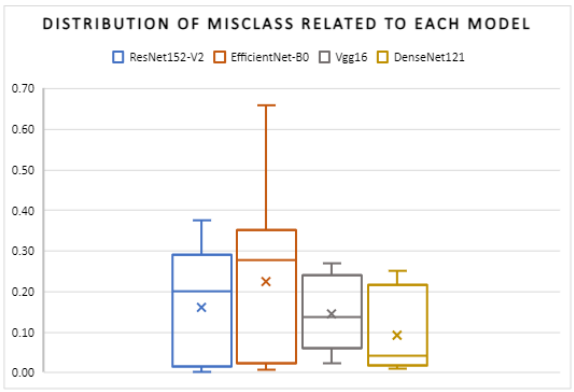


Figure 8. Distribution of misclassification of each model.

Overall, the findings indicate that **ResNet152-V2** achieved the best performance across accuracy, precision, recall, AUC, and F1 score. It was followed by **EfficientNet-B0**, and then **DenseNet121** with comparable results across the three classification levels. The **VGG16** model consistently recorded the lowest performance.

All source codes for the framework models implemented in this study are available in the referenced GitHub repository [32].

5. Discussion

In this section, a comparison is presented between the proposed work and previous studies related to the selected brain diseases, as discussed in the literature review. The comparison focuses on studies that employed the same datasets used in this work or that addressed diseases similar to those considered herein.

Table 2 summarizes the performance reported in several references for Alzheimer's disease classification, alongside the best results obtained by the proposed model, EfficientNet-B0, using the same dataset, *Alzheimer's Dataset (4 Classes of Images)*. Figure 9 illustrates a bar chart comparing the performance metrics of our model with those from the referenced studies. The results demonstrate that the proposed model outperformed all prior works, achieving 99.78% in validation accuracy, precision, recall, and F1 score, along with an AUC of 99.91%.

Table 2. Comparison between previous studies on Alzheimer's disease.

Model	Accuracy	Precision	Recall	F1 Score	AUC
RL [16]	83.23	82.13	81.23	81.23	-
DRL [16]	84.34	83.45	82.12	80.23	-
DRL-XGBOOST [16]	90.23	92.34	95.45	96.12	-
AlexNet [17]	92.2	-	94.5	-	99.45
ResNet-50 [17]	93.1	-	92.25	-	98.82
Hybrid AlexNet [17]	94.8	-	93	-	99.7
Hybrid ResNet-50 [17]	94.1	-	91.75	-	99.31
VGG16 [18]	97.95	96.25	97.25	96.75	-
Resnet 101 [18]	99.71	99.5	99.25	99.5	-
EfficientNet-B0 (Our)	99.78	99.78	99.78	99.78	99.91

For brain tumor classification, Table 3 presents a comparison between the results reported in previous studies and the best performance achieved by our model, ResNet152-

V2, using the same dataset, *Brain Tumor MRI Dataset*. Figure 10 provides a bar chart illustrating the performance metrics of our model alongside those from prior works listed in Table 3. The proposed model achieved superior accuracy (99.42%) and precision (99.11%) compared to all referenced studies. However, one prior work reported a perfect recall of 100%, which exceeded the recall obtained by our model. Since F1 score and AUC values were not reported in the earlier studies, these metrics were excluded from the comparison.

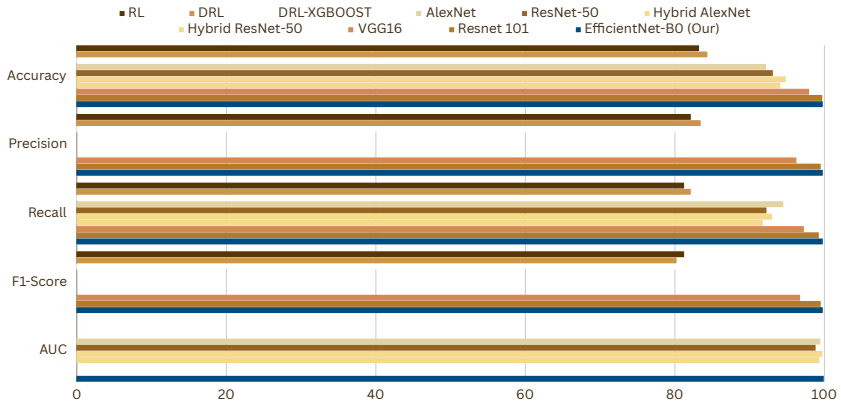


Figure 9. A visualization of the performance metrics of our study in comparison to previous ones on Alzheimer's disease.

Table 3. Comparison between previous studies on tumors.

Model	Accuracy	Precision	Recall
CNN + Softmax [19]	98.67	98.26	100
CNN + RBF [19]	97.34	96.59	100
CNN + DT [19]	94.24	95.37	100
Their model [19]	99.12	98.83	100
FFBN [20]	83	-	88
ResNet152V2 (Our)	99.41	99.11	99.11

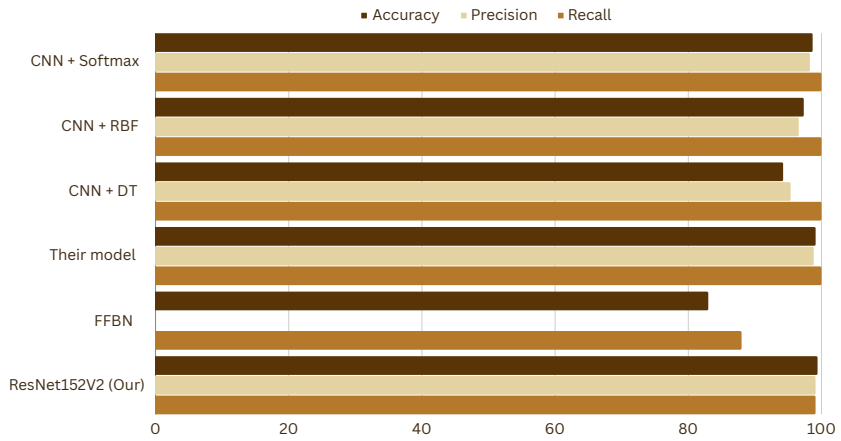


Figure 10. A visualization of the results of our study in comparison to previous ones on brain tumors.

Table 4 compares Parkinson's disease classification results from three previous studies with those obtained by our ResNet152-V2 model across multiple datasets. Figure 11 presents a bar chart contrasting the performance metrics of our model against the prior works listed in Table 4. The proposed model outperformed all others, achieving 100%

in accuracy, precision, recall, F1 score, and specificity. Since the previous studies did not report AUC, it was excluded from this comparison.

All source codes for the framework models implemented in this study are available in the referenced GitHub repository [32].

Table 4. Comparison between previous studies on Parkinson's disease.

Model	Accuracy	Precision	Recall	F1 Score	Specificity
PDCD [21]	94	93	92	92	-
ANN [22]	95.89	-	93.75	-	96.59
PDNet [23]	90	88	93	91	88
ResNet152V2 (Our)	100	100	100	100	100

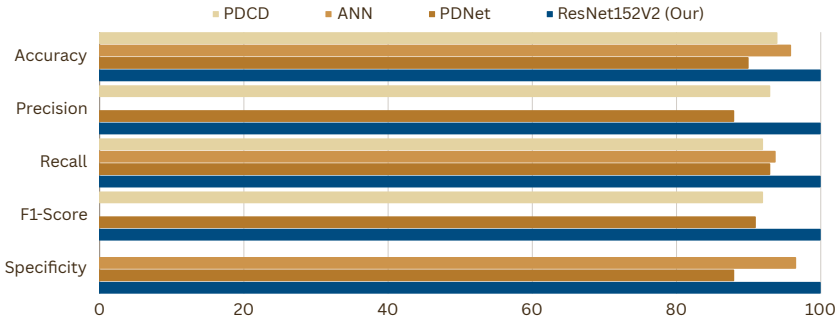


Figure 11. A visualization of the performance metrics of our study in comparison to previous ones on Parkinson's disease.

6. Conclusions

This study provided a comprehensive understanding of brain disorders and emphasized the importance of advanced diagnostic tools that support medical professionals in achieving accurate and early diagnoses. We proposed, implemented, and evaluated the Encephalon Diseases Classifier framework using the Encephalon Dataset, which includes cases of Alzheimer's disease, Parkinson's disease, and brain tumors. The framework incorporated four deep learning models—DenseNet121, EfficientNet-B0, ResNet152-V2, and VGG-16—trained and tested across multiple classification levels. In Level 2 classification, the ResNet152-V2 model achieved a 100% validation (testing) accuracy, while the EfficientNet-B0 model attained a 100% training accuracy. These results demonstrate that each model exhibits distinct strengths at different levels of disease classification, underscoring deep learning techniques' potential to improve the precision of brain disorder diagnosis.

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Abbreviations

The following abbreviations are used in this manuscript:

AD	Alzheimer's disease
AI	Artificial intelligence
ANN	Artificial neural network
CNN	Convolutional neural network
CNS	Central nervous system
DL	Deep learning
DT	Decision tree
HVA	Highest validation accuracy
LDA	Linear discriminant analysis
LVA	Last validation accuracy
ML	Machine learning
MRI	Magnetic resonance imaging
OASIS	Open Access Series of Imaging Studies
PD	Parkinson's disease
RBF	Radial basis function
SVM	Support vector machine

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