



Application of Deep Learning for the Classification of Brain Tumor Magnetic Resonance Imaging Images

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Abstract

Accurate and timely classification of brain tumors from Magnetic Resonance Imaging (MRI) is essential for supporting clinical diagnosis and treatment planning. This study presents a comparative evaluation of transfer learning-based Convolutional Neural Network (CNN) architectures, including ResNet-50, DenseNet121, and EfficientNet-B2, for binary brain tumor MRI classification (Glioma and Meningioma). The dataset was augmented to improve model generalization, and the data were split into training and test sets using an 80:20 hold-out split. The models were trained using Adam and RMSProp optimizers with different learning rates, and their performance was evaluated using accuracy, precision, recall, and F1-score. Experimental results demonstrate that data augmentation significantly enhances classification performance across all evaluated architectures. Among the tested models, ResNet-50 with the RMSProp optimizer and a learning rate of 0.001 achieved the best performance, yielding the lowest training and validation losses and perfect classification results on the test set, with accuracy, precision, recall, and F1-score approaching 100%. DenseNet121 and EfficientNet-B2 also achieved excellent performance but were slightly inferior to ResNet-50. These findings indicate that transfer learning with ResNet-50 and RMSProp provides an effective and reliable solution for automated brain tumor MRI image classification.

Keywords: Brain Tumor, Convolutional Neural Network, DenseNet121, EfficientNet-B2, MRI, ResNet-50

1. INTRODUCTION

Cancer remains one of the leading causes of death worldwide and is recognized by the World Health Organization (WHO) as the second leading cause of mortality, representing a major global public health challenge [1]. In Indonesia, the Global Burden of Cancer Study (GLOBOCAN) 2020 reported 396,914 new cancer cases and 234,511 cancer-related deaths, highlighting the increasing burden of cancer on the national healthcare system [2]. Among the various cancer types, brain tumors are associated with particularly high morbidity and mortality due to their complex diagnosis and treatment. In Indonesia, brain tumors account for approximately 1.5% of all cancer cases, with an estimated 300 new cases reported annually [3]. Moreover, brain tumors are among the most common cancers affecting both children and adults, emphasizing the importance of early and accurate diagnosis to improve treatment outcomes and patient survival [4].

Brain tumors can be classified into several major types, including glioma, meningioma, and pituitary tumors, each with distinct characteristics, malignancy levels, and treatment approaches [1]. Therefore, accurate identification of tumor types is essential for supporting early diagnosis and determining appropriate therapeutic strategies. Accurate brain tumor classification can improve treatment effectiveness and increase patients' chances of recovery.

Advances in medical imaging technology have significantly improved the diagnosis and management of brain tumors. Among the available imaging modalities, Magnetic Resonance Imaging (MRI) is the most widely used because it provides high-resolution images with excellent soft-tissue contrast without exposing patients to ionizing radiation [1]. MRI enables detailed visualization of brain tissue structures, making it highly effective for detecting abnormalities and supporting clinical decision-making. However, MRI interpretation still depends heavily on radiologists' expertise, which may introduce subjectivity into the diagnostic process. Furthermore, the large volume of MRI data makes manual analysis time-consuming and susceptible to interpretation errors [1]. These challenges have encouraged the adoption of deep learning techniques,

particularly transfer learning, to improve classification accuracy while reducing the need for large annotated medical imaging datasets.

With the rapid development of artificial intelligence, Machine Learning (ML) and Deep Learning (DL) techniques have been increasingly applied to medical image analysis as computer-aided diagnostic tools for healthcare professionals [5]. Compared with conventional classification methods such as Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), deep learning models can automatically learn complex image representations without requiring manual feature extraction [6]. Among these models, Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in various image classification tasks, particularly in medical imaging applications[7]. Baranwal et al. (2020) also reported that CNN outperformed SVM in terms of accuracy, precision, recall, and Area Under the Curve (AUC).

Several previous studies have demonstrated the effectiveness of CNN-based approaches for brain tumor classification using MRI images. Badža et al. (2020) proposed a CNN architecture that achieved an accuracy of 96.56% using 10-fold cross-validation [1]. Subsequently, Çınar and Yildirim (2020) introduced a modified ResNet-50 hybrid model that achieved an accuracy of 97.01% [8]. Irmak (2021) further compared several CNN architectures and reported the highest classification accuracy of 99.33% [9]. Although these studies confirm the strong potential of CNN-based architectures for improving brain tumor classification, most investigations focused on evaluating a single architecture or employed different experimental settings, making direct performance comparisons difficult. Consequently, a systematic comparative evaluation using consistent datasets, preprocessing methods, and training configurations remains necessary to identify the most effective CNN architecture for brain tumor MRI classification.

Despite these promising results, most previous studies have focused on a single CNN architecture or modifications of a specific model. Comparative evaluations of multiple state-of-the-art CNN architectures on the same dataset remain limited, particularly in determining the most effective model for brain tumor classification from MRI images.

Therefore, this study aims to implement and compare the performance of three transfer learning-based deep learning architectures, namely ResNet-50, DenseNet121, and EfficientNet-B2, for brain tumor MRI image classification. To ensure a fair comparison, all models are evaluated using the same dataset, preprocessing pipeline, data augmentation strategy, training configuration, and optimization settings. Model performance is comprehensively assessed using accuracy, precision, recall, and F1-score to identify the most effective architecture for automated brain tumor diagnosis. The findings are expected to provide practical insights into selecting robust transfer learning models for computer-aided diagnosis and to contribute to the development of reliable artificial intelligence applications in medical image analysis.

2. MATERIAL AND METHOD

This study was conducted through a series of systematic stages to develop an optimal brain tumor MRI image classification model. The research began with data collection, during which brain tumor MRI images were acquired and subsequently preprocessed to improve image quality and ensure data suitability before model training. The pre-processed data were then used for the training and testing phases employing three Convolutional Neural Network (CNN) architectures, namely ResNet-50, DenseNet121, and EfficientNet-B2. During training, optimization algorithms were used to efficiently update model parameters, thereby improving classification performance. Finally, the models were evaluated and analyzed using a confusion matrix and performance metrics, including accuracy, precision, recall, and F1-score, to compare the performance of each architecture. The overall research workflow in Figure 1.

2.1. Collecting Data

The dataset used in this study consisted of brain tumor MRI images obtained from XYZ Hospital. The dataset contained two classes, namely glioma and meningioma, with a total of 2,875 MRI images. Before being used for model training, all images underwent cropping and resizing during the pre-processing stage to remove irrelevant regions and standardize the input image size. The distribution of the dataset used in this study is presented in Table 1.

Table 1. Class Distribution

No	Class	Data
1	Glioma	840
2	Meningioma	2035
		2875

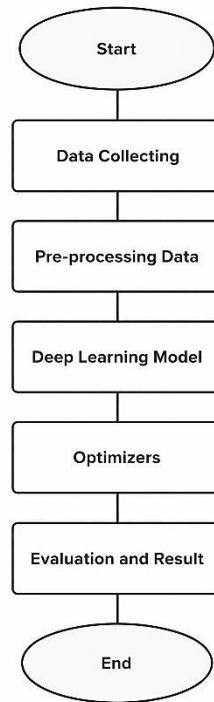


Figure 1. Research Methodology

2.2. Splitting Data

A total of 1,311 brain tumor MRI images, consisting of two classes, namely glioma and meningioma, were used in this study. The dataset was split using an 80:20 hold-out split, with 80% allocated to the training set and 20% to the test set. Furthermore, the training set was further split into training and validation subsets using the same 80:20 ratio. This data partitioning enabled the models to be trained, validated, and evaluated on separate datasets, ensuring reliable performance assessment. The dataset distribution is presented in Table 2.

Table 2. Data Distribution After Hold-out

Class	Data Training		Data Testing
	Train	Validation	
Glioma	537	135	168
Meningioma	1302	326	470

2.3. Augmentation Data

After the dataset was partitioned, data augmentation was applied to the training set to increase sample diversity and reduce the risk of overfitting. The augmentation techniques included random rotation, width and height shifting, zooming, horizontal flipping, vertical flipping, and the nearest fill mode to fill empty pixels generated during image transformations. These augmentation operations were intended to improve the model's generalization capability by exposing it to a wider variety of brain tumor MRI image variations, thereby enhancing its robustness in the classification task.

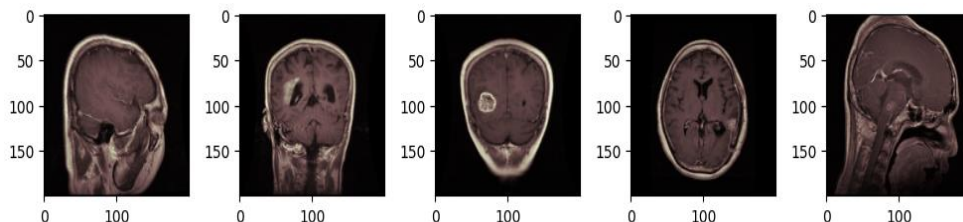


Figure 2. MRI Data After Augmentation

2.4. ResNet-50

ResNet-50 is a widely used Convolutional Neural Network (CNN) architecture introduced by He et al. based on the concept of residual learning to address the performance degradation problem in very deep neural networks [10]. The architecture employs skip connections, also known as identity shortcuts, which allow

information to bypass one or more layers, thereby facilitating more stable and efficient training [11]. With a depth of 50 layers, ResNet-50 achieves a good balance between classification accuracy and computational efficiency, making it one of the most widely adopted architectures for various image classification tasks, including medical image analysis.

2.5. DenseNet121

DenseNet121 is a Convolutional Neural Network (CNN) architecture developed to overcome the vanishing gradient problem in deep neural networks. Unlike ResNet, which employs residual connections through additive operations, DenseNet connects each layer to all preceding layers using a dense connection mechanism, allowing every layer to access and reuse feature maps learned by previous layers [12]. This architecture enhances feature propagation, encourages feature reuse, reduces the number of trainable parameters, and improves training efficiency [13]. Consequently, DenseNet121 has been widely applied to a variety of image classification tasks, particularly in medical image analysis.

2.6. EfficientNet-B2

EfficientNet-B2 is one of the variants of the EfficientNet family of Convolutional Neural Network (CNN) architectures that employs the compound scaling method, which uniformly scales network depth, width, and input resolution to improve both model accuracy and computational efficiency [14]. The EfficientNet architecture was developed using Neural Architecture Search (NAS) to achieve optimal performance while minimizing computational cost. The EfficientNet family consists of eight variants, ranging from EfficientNet-B0 to EfficientNet-B7, each offering different levels of model complexity and computational requirements [15].

2.7. Optimizers

The optimization process was performed iteratively by updating the model parameters based on the computed gradients to achieve optimal convergence [16]. In this study, two optimization algorithms, RMSProp and Adam, were employed. RMSProp (Root Mean Square Propagation) is an adaptive optimization algorithm that adjusts the learning rate using the exponentially weighted moving average of squared gradients, enabling faster convergence and overcoming the diminishing learning rate problem associated with Adagrad [17].

Adam (Adaptive Moment Estimation), on the other hand, combines the advantages of Momentum and RMSProp by utilizing estimates of the first and second moments of the gradients to compute an adaptive learning rate for each model parameter. This approach improves the stability and efficiency of the training process while accelerating convergence [17].

Both optimization algorithms were applied to each of the three CNN architectures, namely ResNet-50, DenseNet121, and EfficientNet-B2, to evaluate their effects on brain tumor MRI image classification performance. The comparison was conducted based on the resulting loss values and evaluation metrics, including accuracy, precision, recall, and F1-score.

3. RESULTS AND DISCUSSION

The Deep Learning models developed in this study were based on three Convolutional Neural Network (CNN) architectures, namely ResNet-50, DenseNet121, and EfficientNet-B2. All models were trained using an augmented brain tumor MRI image dataset. The experiments were conducted with a batch size of 64, 10 epochs, and a learning rate of 0.0001, using two optimization algorithms, Adam and RMSProp. Model performance was evaluated using training and validation learning curves, confusion matrices, and several performance metrics, including accuracy, precision, recall, F1-score, and loss.

3.1. Deep Learning Models

The Deep Learning models in this study were developed using three Convolutional Neural Network (CNN) architectures: ResNet-50, DenseNet121, and EfficientNet-B2. All models were trained on an augmented dataset of brain tumor MRI images. The experiments were conducted with a batch size of 64, 10 training epochs, and a learning rate of 0.0001, using Adam and RMSProp as the optimization algorithms. Model performance was evaluated using training and validation learning curves, confusion matrices, and standard performance metrics, including accuracy, precision, recall, F1-score, and loss. Training and Validation Loss Curves for ResNet50, DenseNet121, and EfficientNet-B2 are shown in Figures 3-5.

Figure 3 presents the training and validation loss curves of the ResNet-50 architecture. During training, both the training and validation losses decreased progressively, reaching their minimum values at epoch 9. The model achieved a training accuracy of 99.73% and a validation accuracy of 100%. Figure 4 illustrates the training performance of the DenseNet121 architecture. The model achieved a training accuracy of 99.34% and a validation accuracy of 99.47%. The corresponding training and validation curves indicate stable convergence throughout training. Figure 5 shows the training and validation curves of the EfficientNet-B2 architecture. The

model achieved a training accuracy of 99.65% and a validation accuracy of 99.56%. Both the training and validation losses exhibited a consistent downward trend throughout the training process.

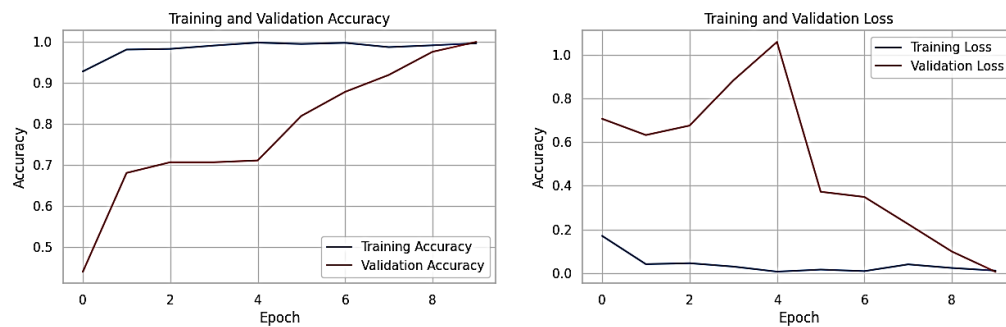


Figure 3. Training and Validation Loss ResNet50

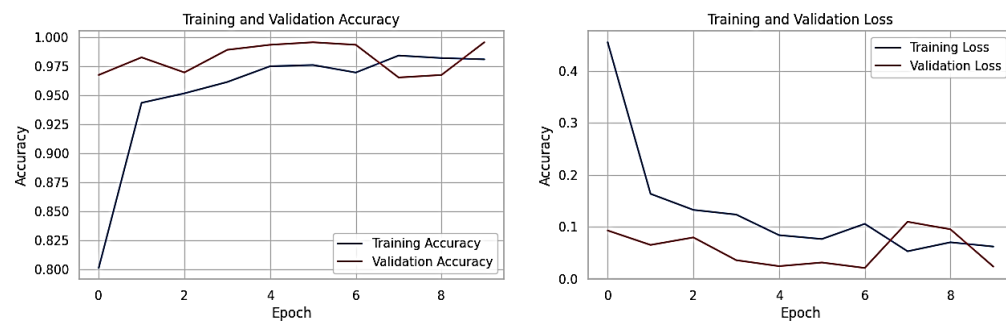


Figure 4. Training and Validation Loss DenseNet121

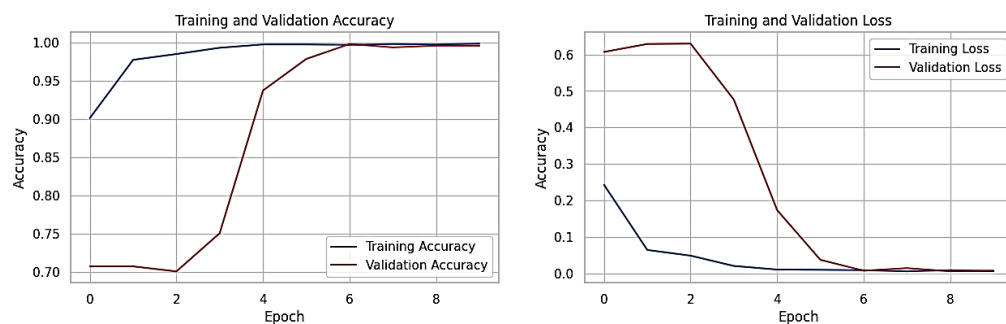


Figure 5. Training and Validation Loss EfficientNet-B2

The classification performance of the ResNet-50 architecture, evaluated using the confusion matrix, is presented in Figure 6.

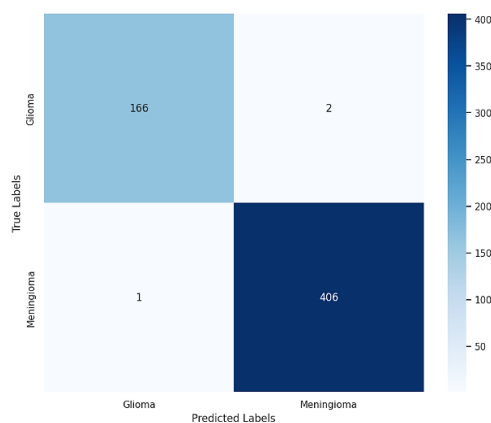


Figure 6. Confusion Matrix ResNet50

The model achieved an accuracy of 99.06%, precision of 98.00%, recall of 99.00%, and an F1-score of 99.00%. Figure 7 presents the confusion matrix obtained from the DenseNet121 architecture. The classification results demonstrate performance comparable to that of ResNet-50, with a high classification rate for both brain tumor classes. The confusion matrix of the EfficientNet-B2 architecture is shown in Figure 8. The model achieved an accuracy of 99.56%, precision of 99.25%, recall of 99.25%, and an F1-score of 99.25%.

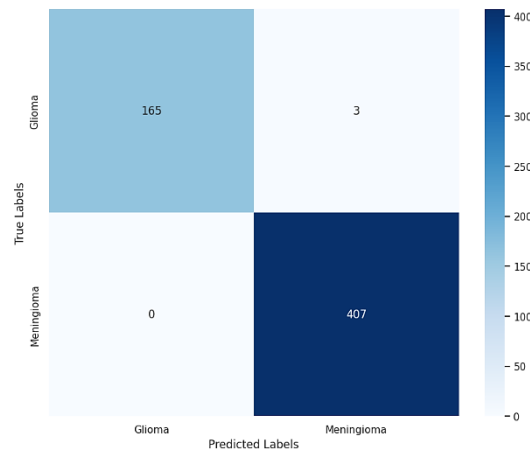


Figure 7. Confusion Matrix DenseNet121

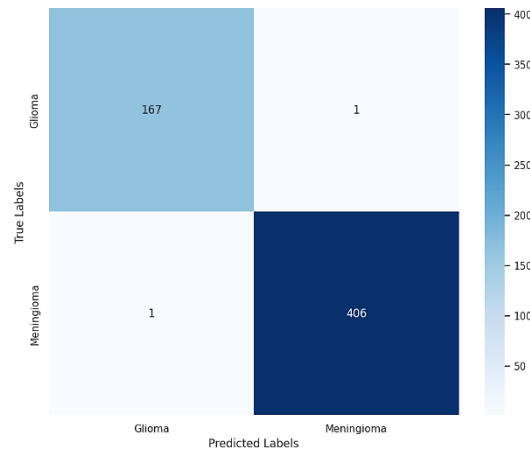


Figure 8. Confusion Matrix EfficientNet-B2

A summary of the experimental results is presented in Table 3, which compares the performance of the three CNN architectures using the Adam and RMSProp optimizers. The comparison includes training loss, validation loss, training accuracy, validation accuracy, and testing accuracy for each experimental configuration.

Table 3. Result Model Performance

No	Architecture	Optimizers	Training Loss	Validation Loss	...	Validation Accuracy	Testing Accuracy
1	ResNet-50	Adam	0,010317	0,005469	...	1	0,994783
2	ResNet-50	RMSProp	0,000171	0,000396	...	1	1
3	DenseNet121	Adam	0.012589	0.020465	...	0.993492	0.994783
4	DenseNet121	RMSProp	0,000094	0,000951	...	1	0,998261
5	EfficientNet-B2	Adam	0,000117	0,006303	...	0,995662	0,996522
6	EfficientNet-B2	RMSProp	0,000048	0,001528	...	1	0,996522

Table 3 summarizes the performance of all evaluated transfer learning-based CNN architectures under different optimizer settings. Overall, all models achieved excellent classification performance, with testing accuracies exceeding 99%, indicating that the selected architectures effectively learned discriminative features from brain tumor MRI images. Among the evaluated models, ResNet-50 combined with the RMSProp optimizer achieved the best overall performance, recording the lowest validation loss (0.000396) and perfect

validation and testing accuracies of 100%. DenseNet121 and EfficientNet-B2 also achieved highly competitive results, though their test accuracies were slightly lower. These findings indicate that all evaluated architectures are suitable for brain tumor classification, while ResNet-50 provides the most robust and stable performance under the adopted experimental configuration.

The superior performance of ResNet-50 can be attributed to its residual learning mechanism, which facilitates efficient gradient propagation through skip connections and enables the extraction of more discriminative hierarchical features. Furthermore, the consistent superiority of RMSProp over Adam across all evaluated architectures suggests that its adaptive learning strategy effectively stabilizes parameter updates, resulting in lower training and validation losses and improved model convergence on the MRI classification task.

These findings are consistent with previous studies reporting the effectiveness of ResNet-based transfer learning models for medical image classification, where residual connections improve feature representation while mitigating the degradation problem in deep neural networks [8], [9]. Likewise, several studies have shown that RMSProp performs particularly well on image classification tasks because it adaptively adjusts the learning rate according to the magnitude of recent gradients, enabling faster convergence and reducing oscillations during optimization. The combination of ResNet-50 and RMSProp therefore provides an effective balance between feature extraction capability and optimization efficiency, which explains its superior performance compared with DenseNet121 and EfficientNet-B2 in this study. The consistently high performance across all three architectures also confirms the effectiveness of transfer learning for brain tumor MRI classification with relatively limited medical imaging datasets.

3.2. Discussion

The experimental results demonstrate that all evaluated transfer-learning-based CNN architectures achieved excellent classification performance, with test accuracies exceeding 99%. These findings indicate that transfer learning effectively enables pre-trained CNN models to extract representative features from brain MRI images despite the relatively limited size of medical imaging datasets. Among the evaluated architectures, ResNet-50 consistently achieved the highest test accuracy and the lowest validation loss, indicating superior generalization [5]. The residual learning mechanism implemented through skip connections allows ResNet-50 to alleviate the degradation problem encountered in deeper neural networks while preserving discriminative feature representations. Similar observations have been reported in previous studies, where ResNet-based transfer learning achieved highly competitive performance in medical image classification tasks, particularly for brain tumor detection and diagnosis [8], [11].

Another important finding is the consistent superiority of the RMSProp optimizer over Adam across all evaluated architectures. RMSProp produced lower training and validation losses while maintaining stable convergence throughout training. This behavior can be attributed to its adaptive learning rate mechanism, which normalizes parameter updates based on the magnitude of recent gradients, thereby reducing oscillations during optimization and improving convergence stability. Such characteristics are particularly beneficial for transfer learning, where only a portion of the network parameters is fine-tuned. Recent optimization studies have likewise demonstrated that adaptive gradient optimization strategies significantly improve convergence efficiency and classification performance in deep neural networks [16], [18].

Although DenseNet121 and EfficientNet-B2 achieved slightly lower accuracies than ResNet-50, both architectures still demonstrated excellent performance and reliable generalization capability. DenseNet121 benefits from dense connectivity that encourages feature reuse and improves gradient flow, making it computationally efficient while maintaining competitive classification accuracy. EfficientNet-B2, on the other hand, employs compound scaling to balance network depth, width, and input resolution, resulting in efficient feature extraction with relatively fewer parameters [9]. Nevertheless, the superior performance of ResNet-50 observed in this study suggests that residual feature learning remains more suitable for the characteristics of the employed brain MRI dataset. Similar comparative findings have also been reported in previous medical image classification studies, where different CNN architectures exhibit varying performance depending on dataset characteristics, feature complexity, and optimization strategy [6], [15].

Overall, the results confirm that transfer learning represents an effective solution for automated brain tumor MRI classification, especially when annotated medical datasets are limited. The use of identical preprocessing procedures, data augmentation, training configurations, and evaluation metrics across all evaluated architectures ensures that the observed performance differences primarily reflect the intrinsic capabilities of each CNN architecture rather than differences in experimental settings [10]. Consequently, the superior performance of ResNet-50 with the RMSProp optimizer provides practical evidence for its application in computer-aided diagnosis systems for brain tumor detection. Future research may extend this work by evaluating larger multi-center MRI datasets, investigating transformer-based architectures and hybrid CNN-transformer models, and incorporating explainable artificial intelligence techniques to improve model transparency and clinical interpretability [5], [19].

4. CONCLUSION

This study successfully implemented a transfer-learning-based deep learning approach using the ResNet-50, DenseNet121, and EfficientNet-B2 architectures to classify brain tumor MRI images. The dataset was split into training and test sets using an 80:20 hold-out split. Model performance was evaluated using a confusion matrix based on accuracy, precision, recall, and F1-score. The experimental results demonstrated that all three architectures achieved excellent classification performance, with accuracy exceeding 99%.

Among the evaluated models, the combination of ResNet-50 and the RMSProp optimizer achieved the best overall performance, yielding the lowest training and validation losses and 100% testing accuracy. Meanwhile, DenseNet121 and EfficientNet-B2 also exhibited high classification performance, although their results were slightly inferior to those of ResNet-50. In addition, the RMSProp optimizer consistently outperformed Adam by producing lower loss values and higher classification accuracy across all evaluated architectures. These findings indicate that the combination of the ResNet-50 architecture and the RMSProp optimizer is the most effective approach for brain tumor MRI image classification on the dataset used in this study.

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