International Journal of Innovative Engineering Applications

Journal homepage: https://dergipark.org.tr/ijiea

A COMPARATIVE ANALYSIS OF EFFICIENTNETB0 AND EFFICIENTNETV2 VARIANTS FOR BRAIN TUMOR CLASSIFICATION USING MRI IMAGES

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Abstract

Original scientific paper

Accurate and early diagnosis of brain tumors is critical for effective treatment planning, yet traditional methods of analyzing Magnetic Resonance Imaging (MRI) scans are labor-intensive and prone to variability among experts. Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a transformative tool in medical imaging by automating feature extraction and enhancing classification accuracy. This study provides a comparative analysis of EfficientNetB0 and three EfficientNetV2 variants (S, M, and L) for brain tumor classification using the Figshare Brain Tumor Dataset, which includes glioma, meningioma, and pituitary tumors. Each model was evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The results reveal that EfficientNetV2-S outperformed other models, achieving the highest accuracy of 98.20% and delivering balanced performance across all classes. EfficientNetV2-M and EfficientNetV2-L also demonstrated strong classification capabilities, with minor trade-offs in computational efficiency. These findings highlight the potential of EfficientNetV2 architectures for automated and reliable brain tumor classification, offering significant advantages for clinical applications. Future work could focus on integrating multi-modal imaging data and optimizing models for deployment in real-time diagnostic settings.

Keywords: *Brain tumor classification, deep learning, efficientNet, EfficientNetV2, medical imaging, MRI.*

MRI GÖRÜNTÜLERİNİ KULLANARAK BEYİN TÜMÖRÜ SINIFLANDIRMASI İÇİN EFFİCİENTNETB0 VE EFFİCİENTNETV2 VARYANTLARININ KARŞILAŞTIRMALI ANALİZİ

Özet

Orijinal bilimsel makale

Beyin tümörlerinin doğru ve erken teşhisi etkili tedavi planlaması için kritik öneme sahiptir, ancak Manyetik Rezonans Görüntüleme (MRI) taramalarını analiz etmenin geleneksel yöntemleri emek yoğun olup uzmanlar arasında değişkenliğe eğilimlidir. Derin öğrenme, özellikle Evrişimsel Sinir Ağları (CNN'ler), özellik çıkarmayı otomatikleştirerek ve sınıflandırma doğruluğunu artırarak tıbbi görüntülemede dönüştürücü bir araç olarak ortaya çıkmıştır. Bu çalışma, glioma, menenjiyoma ve hipofiz tümörlerini içeren Figshare Beyin Tümörü Veri Setini kullanarak beyin tümörü sınıflandırması için EfficientNetB0 ve üç EfficientNetV2 varyantının (S, M ve L) karşılaştırmalı bir analizini sağlar. Her model doğruluk, kesinlik, geri çağırma, F1 puanı ve ROC-AUC gibi ölçütler kullanılarak değerlendirildi. Sonuçlar, EfficientNetV2-S'nin diğer modellerden daha iyi performans gösterdiğini, %98,20'lik en yüksek doğruluğu elde ettiğini ve tüm sınıflarda dengeli bir performans sağladığını ortaya koymaktadır. EfficientNetV2-M ve EfficientNetV2-L ayrıca hesaplama verimliliğinde küçük ödünlerle güçlü sınıflandırma yetenekleri gösterdi. Bu bulgular, EfficientNetV2 mimarilerinin otomatik ve güvenilir beyin tümörü sınıflandırması için potansiyelini vurgulayarak klinik uygulamalar için önemli avantajlar sunuyor. Gelecekteki çalışmalar, çok modlu görüntüleme verilerini entegre etmeye ve gerçek zamanlı tanılama ortamlarında dağıtım için modelleri optimize etmeye odaklanabilir.

Anahtar Kelimeler: *Beyin tümörü sınıflandırması, derin öğrenme, EfficientNet, EfficientNetV2, tıbbi görüntüleme, MRI.*

1 Introduction

Brain tumors represent one of the most severe and complex medical conditions, necessitating accurate and early diagnosis to ensure effective treatment planning. Magnetic Resonance Imaging (MRI) is a critical tool in diagnosing brain tumors due to its ability to provide detailed images of soft tissues [1, 2]. However, manual analysis of MRI scans is labor-intensive and prone to variability among experts, which has driven the demand for automated and reliable classification methods.

Deep learning, particularly Convolutional Neural Networks (CNNs), has become a transformative technology in medical imaging, enabling automatic

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Received 28 June 2024; Received in revised form 22 November 2024; Accepted 30 April 2025

 Doi: https://doi.org/10.46460/ijiea.1523782

feature extraction and improved classification accuracy [3, 4]. EfficientNetB0, introduced as a baseline architecture, employed a novel compound scaling method to balance depth, width, and resolution, achieving state-of-the-art performance in image classification tasks [5]. The subsequent development of EfficientNetV2 models further improved computational efficiency and accuracy by introducing advanced training techniques and optimized architectural designs [6].

Deep learning approaches, particularly CNNs, have revolutionized brain tumor classification, leveraging their ability to extract high-level features from medical imaging datasets and significantly enhancing diagnostic accuracy [7]. Emerging techniques, such as data augmentation and transfer learning, have further improved the generalization and efficiency of CNN-based models in medical image classification [8, 9].

Existing research has demonstrated the effectiveness of both EfficientNetB0 and EfficientNetV2 architectures in medical imaging applications, including brain tumor classification [10, 11]. However, comparative studies evaluating their performance on the same dataset using consistent evaluation metrics remain limited.

In recent years, advanced approaches have made significant progress in the classification of brain tumors. For example, studies on accurate brain tumor classification with optimized EfficientNet architecture have presented innovative methods to improve model performance [12]. Gencer and Gencer (2024) introduced a hybrid model that combines EfficientNetB0 with a Quantum Genetic Algorithm (QGA), achieving remarkable accuracy in brain tumor classification. Their approach demonstrated significant advantages in feature selection and computational efficiency compared to traditional methods [13]. Furthermore, a comprehensive review on transfer learning techniques and model efficiency using MRI datasets has offered potential solutions to make existing deep learning approaches more efficient [14]. Such studies contribute to the development of more reliable and generally applicable models for brain tumor classification.

This study addresses this gap by conducting a comprehensive analysis of EfficientNetB0 and EfficientNetV2 variants (S, M, and L) for the classification of brain tumors using MRI images.

- This study aims to address critical gaps in brain tumor classification research by focusing on the following key objectives:
- To systematically evaluate the performance of EfficientNetB0 and EfficientNetV2 variants (S, M, and L) in brain tumor classification.
- To investigate how advanced architectures, particularly EfficientNetV2 models, impact model generalization and computational efficiency in handling high-dimensional MRI datasets.

To compare the strengths and weaknesses of EfficientNetB0 and EfficientNetV2 variants on a consistent dataset to determine the most effective model for practical clinical applications. The Figshare Brain Tumor Dataset [15] was selected for this study due to its comprehensive MRI image collection, enabling a robust evaluation of the proposed models. The results provide insights into the trade-offs between computational complexity and classification accuracy, offering practical implications for deploying these models in clinical settings. This paper is structured as follows: Section 2 outlines the dataset, preprocessing steps, and training processes for EfficientNetB0 and EfficientNetV2 variants, with Section 2.1 focusing on the evolution and features of EfficientNet architectures. Section 3 presents the comparative performance analysis of the models using evaluation metrics such as accuracy, precision, recall, and ROC-AUC. Section 4 summarizes the study findings and highlights the clinical potential of EfficientNetV2 models for brain tumor diagnosis.

2 Materials and Methods

The Figshare Brain Tumor Dataset [15] was used in this study, consisting of MRI scans categorized into three classes: glioma, meningioma, and pituitary tumor in Table 1. The dataset, downloaded from the Figshare platform, comprises MATLAB (.mat) files containing tumor images and their corresponding labels. All images were resized to 128x128 pixels for uniformity, and grayscale images were converted into RGB format to meet the input requirements of the EfficientNet models.

Data preprocessing involved resizing images, duplicating grayscale images across three channels to simulate RGB format, and shuffling the dataset. The dataset was split into 80% training and 20% testing subsets using a stratified random split to preserve class balance.

The study utilized four EfficientNet variants: EfficientNetB0, EfficientNetV2-S, EfficientNetV2-M, and EfficientNetV2-L. EfficientNetB0 served as the baseline model, leveraging compound scaling to balance depth, width, and resolution. The EfficientNetV2 variants introduced enhancements for faster training and higher accuracy. All models used pre-trained ImageNet weights for feature extraction, followed by a classification head comprising a dense layer with 128 units and ReLU activation, a dropout layer with a 0.5 rate, and a softmax output layer for multi-class classification.

Model training employed the Adam optimizer with a learning rate of 0.001 and sparse categorical cross-entropy loss. Each model was trained for 30 epochs with a batch size of 32. Early stopping with a patience of 10 epochs was applied to mitigate overfitting, and the learning rate was reduced by a factor of 0.2 when validation loss plateaued for five consecutive epochs.

The models' performance was evaluated using several metrics, including overall accuracy, precision, recall, F1-score, and confusion matrices. The area under the Receiver Operating Characteristic curve (ROC-AUC) was calculated for each class to assess classification performance further. Additionally, training and validation loss and accuracy plots were generated to visualize model convergence.

The experimental workflow consisted of data loading and preprocessing, independent training of each EfficientNet variant, feature extraction using the trained models, and performance evaluation. Python, TensorFlow, and Keras were the primary tools for model implementation, while OpenCV was used for image preprocessing. Scikit-learn facilitated evaluation metric calculations, and visualizations were created using Seaborn and Matplotlib.

Table 1. Dataset Details.

Collection Period	Not specified
Published By	Jun Cheng (2015)
Platform	Figshare
Total Images	3064
Image Modality	T1-weighted contrast-enhanced MRI
Tumor Types	Glioma, Meningioma, Pituitary Tumors
Number of Patients	233
Image Planes	Axial, Coronal, Sagittal
Image Size	512 × 512 pixels

2.1 EfficientNet Variants: Evolution and Comparative Features for Brain Tumor Classification

EfficientNet models represent a significant leap in the design of convolutional neural networks (CNNs) by introducing compound scaling, which balances the network's depth, width, and resolution [6]. The successes of deep architectures in deep learning have laid important groundwork, especially with the work of Simonyan and Zisserman on large-scale image recognition with deep networks [16]. The EfficientNet family has evolved to include variants such as EfficientNetB0 and its successors in the EfficientNetV2 series (S, M, and L), which offer improved accuracy and computational efficiency.

EfficientNetB0 was introduced as the baseline model, leveraging a novel scaling method to achieve state-of-the-art performance with fewer parameters and FLOPS compared to traditional architectures. It employs depthwise separable convolutions and compound scaling, which optimally scales depth, width, and resolution [6, 17]. This architecture demonstrated significant improvements in image classification tasks while maintaining computational efficiency.

EfficientNetV2-S is a smaller variant of the EfficientNetV2 family, optimized for faster training and better performance. This model incorporates several enhancements, such as Fused-MBConv layers, which reduce the complexity of mobile inverted bottleneck layers used in EfficientNetB0, and progressive learning for improved convergence [6]. EfficientNetV2-S is particularly suitable for scenarios requiring faster inference and lower memory usage.

EfficientNetV2-M strikes a balance between model size and performance. It extends the capabilities of EfficientNetV2-S by increasing the network's depth and width while maintaining the efficiency improvements introduced in the V2 architecture [6, 18]. This variant is well-suited for tasks requiring high accuracy with moderate computational resources.

EfficientNetV2-L, the largest variant in the EfficientNetV2 family, offers superior performance by scaling up the network's dimensions while incorporating the architectural optimizations of the V2 series. This model is designed for high-accuracy applications where computational resources are less constrained, such as advanced medical imaging tasks [6, 18].

The EfficientNet variants demonstrate a progressive improvement in terms of computational efficiency and accuracy. EfficientNetB0 provides a strong baseline for image classification, while the EfficientNetV2 models enhance performance through architectural optimizations and training techniques. In this study, these variants were evaluated on the Figshare Brain Tumor Dataset, comparing their accuracy, ROC-AUC scores, and confusion matrices to determine the most effective model for brain tumor classification.

3 Experimental Results and Discussions Conclusion

Table 2 evaluates the performance of EfficientNet models (EfficientNetB0 and EfficientNetV2 variants: S, M, and L) in brain tumor classification. Performance metrics include Precision, Recall, F1-Score, and overall Accuracy.It is seen that EfficientNetB0 model provides high accuracy especially on Class2 and Class3, but shows lower performance in Precision and Recall values for Class1.EfficientNetV2-S model shows a very balanced and high performance for all classes. Especially for Class3, both Precision and Recall values are 1.00, indicating that it provides perfect classification in this class. The overall accuracy of the model (98.20%) is one of the highest compared to other EfficientNetV2 variants.EfficientNetV2-M model shows similar accuracy for Class2 and Class3, while slightly lower Precision and Recall values are encountered on Class1. However, the model performs quite well in terms of overall accuracy (97.87%).The EfficientNetV2-L model has shown consistent performance in Class1 and Class2 classes, while maintaining Precision, Recall and F1-Score values at 99% levels for Class3. However, the overall accuracy of this model (97.71%) is slightly lower than the V2-S model.Overall, the EfficientNetV2-S model has the highest accuracy and stability for all classes, providing a clear superiority compared to Ef ficientNetB0.

In Figure 1, EfficientNetB0 performed less effectively compared to other models, with a low correct classification rate, especially for Class1. EfficientNetV2-S outperformed other models by showing high accuracy rates for all classes. EfficientNetV2-M showed a balanced performance in Class1 and Class3, while its false positive rates were slightly higher than EfficientNetV2-S. EfficientNetV2-L showed the best classification performance for Class2, but lagged behind other EfficientNetV2 variants in Class1. Overall, EfficientNetV2 models showed better overall performance compared to EfficientNetB0 and produced more balanced results across classes.

Table 1. Performance Comparison of EfficientNet Variants in Brain Tumor Classification.

Model	Class	Precision	Recall	F1-Score	Accuracy
	Class1	0.98	0.68	0.80	
EfficientNetB0	Class2	0.85	0.99	0.92	0.9021
	Class3	0.95	0.95	0.95	
	Class1	0.95	0.99	0.97	
EfficientNet V2-S	Class2	0.99	0.97	0.98	0.9820
	Class3	1.00	0.99	1.00	
	Class1	0.95	0.97	0.96	
EfficientNet V2-M	Class2	0.99	0.97	0.98	0.9787
	Class3	0.99	0.99	0.99	
	Class1	0.96	0.95	0.96	
EfficientNet V2-L	Class2	0.98	0.98	0.98	0.9771
	Class3	0.99	0.99	0.99	

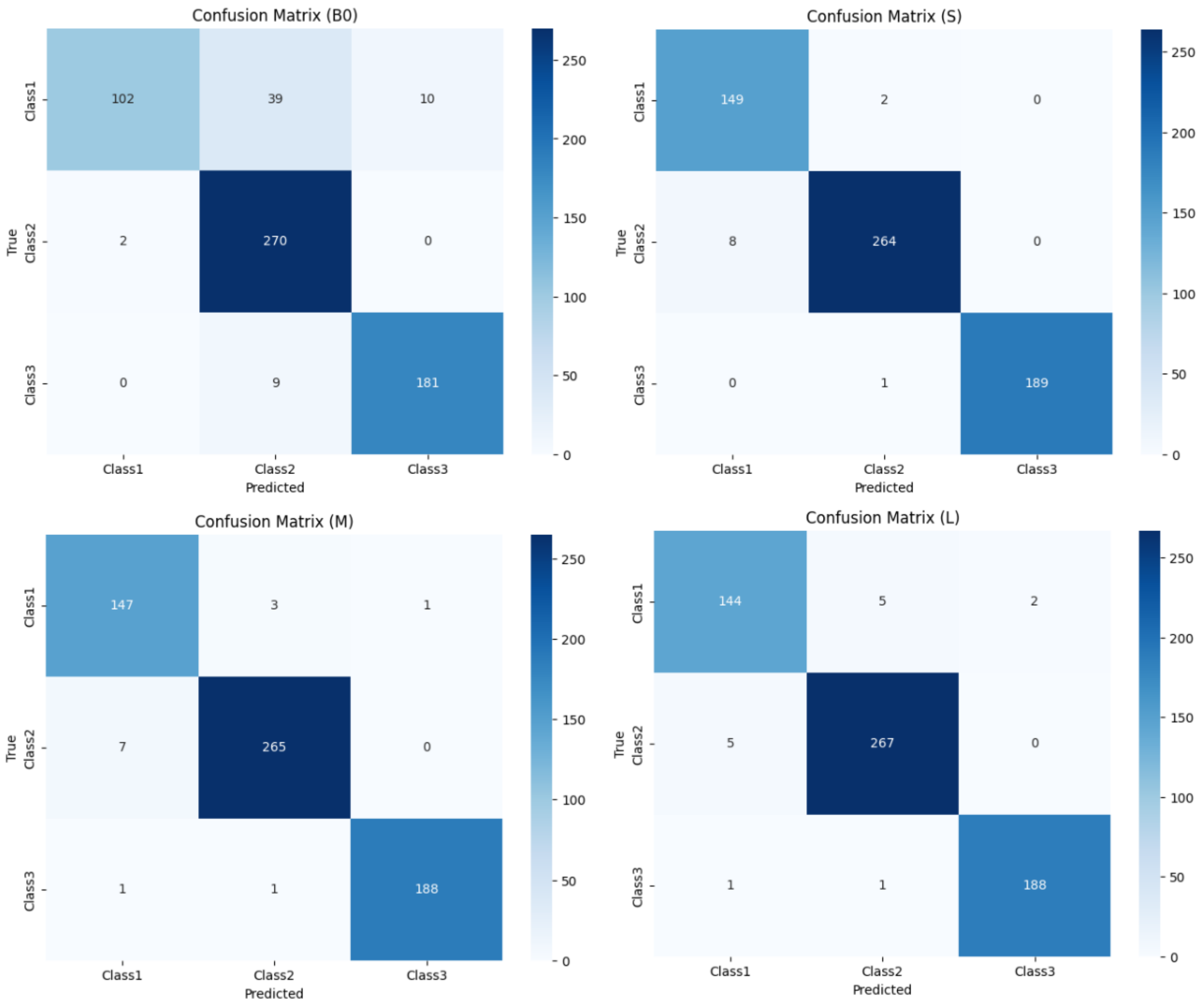

Figure 1. Confusion Matrices of EfficientNet Variants for Brain Tumor Classification.

In Figure 2, significant fluctuations were observed in the validation loss graph of the EfficientNetB0 model, indicating that the model experienced a less stable learning process.The EfficientNetV2-S model exhibited a more stable learning curve in terms of validation loss and reached high accuracy levels quickly.The EfficientNetV2-M model showed that validation loss decreased steadily and the model provided a rapid increase in validation accuracy.The validation loss graph of the EfficientNetV2-L model contained more fluctuations compared to the other EfficientNetV2 variants, but the overall accuracy level remained high.In general, the EfficientNetV2 variants showed more stable and high-performance learning compared to the EfficientNetB0 model in both loss and accuracy graphs

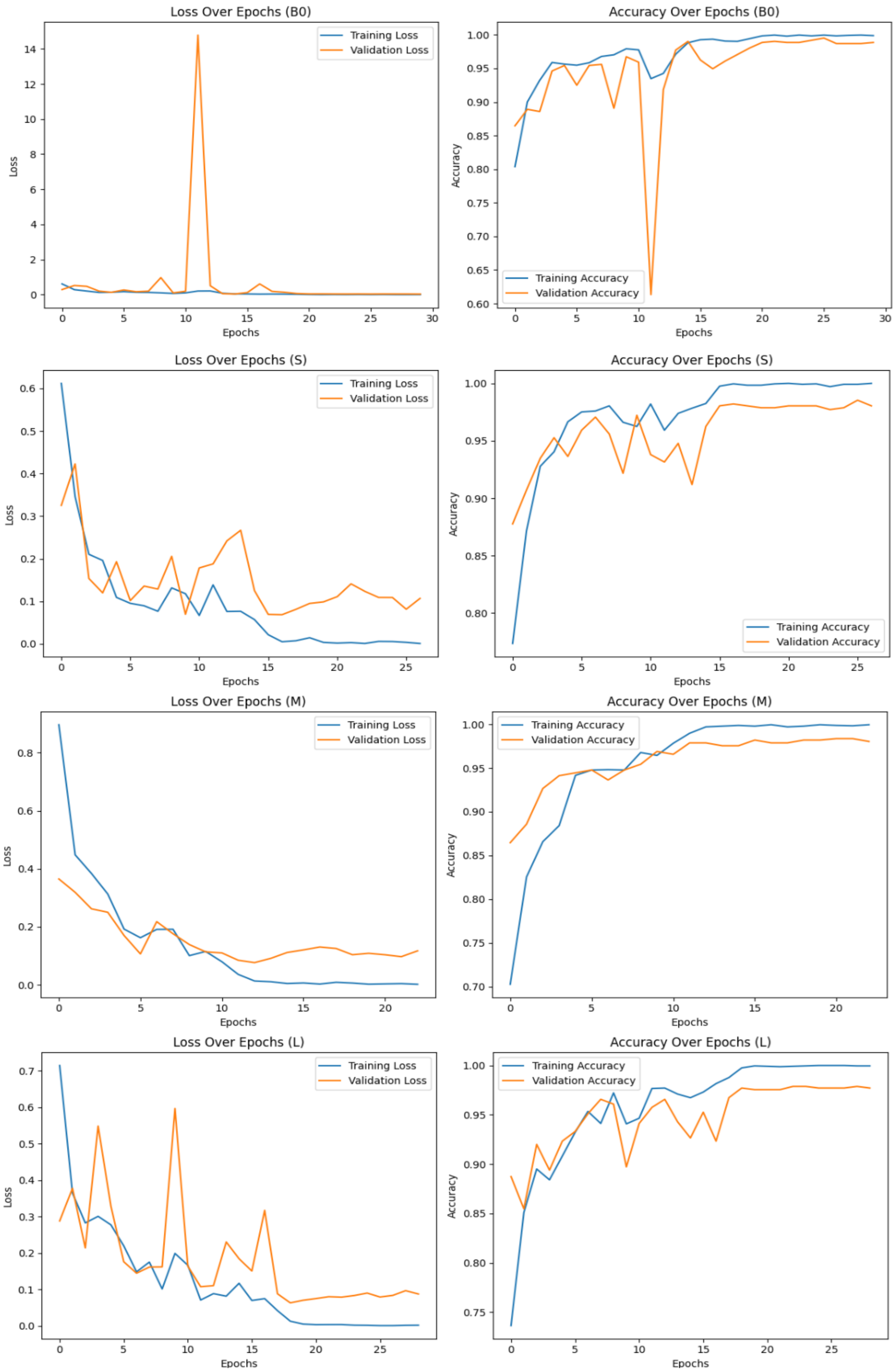

Figure 2. Loss and Accuracy Trends Across EfficientNet Variants During Training.

In Figure 3, the EfficientNetB0 model showed a slightly higher performance with AUC scores of 0.97 for Class1 and Class2 and 0.99 for Class3. EfficientNetV2-S showed excellent classification capacity by increasing the AUC values to 1.00 for all classes. EfficientNetV2-M model also showed a very strong performance with an AUC score of 1.00 for all classes. EfficientNetV2-L, like other EfficientNetV2 variants, showed a successful overall performance with an AUC value of 1.00 for each class. ROC curves clearly show that EfficientNetV2 models have a higher generalization capacity compared to EfficientNetB0 and provide superior performance in brain tumor classification.

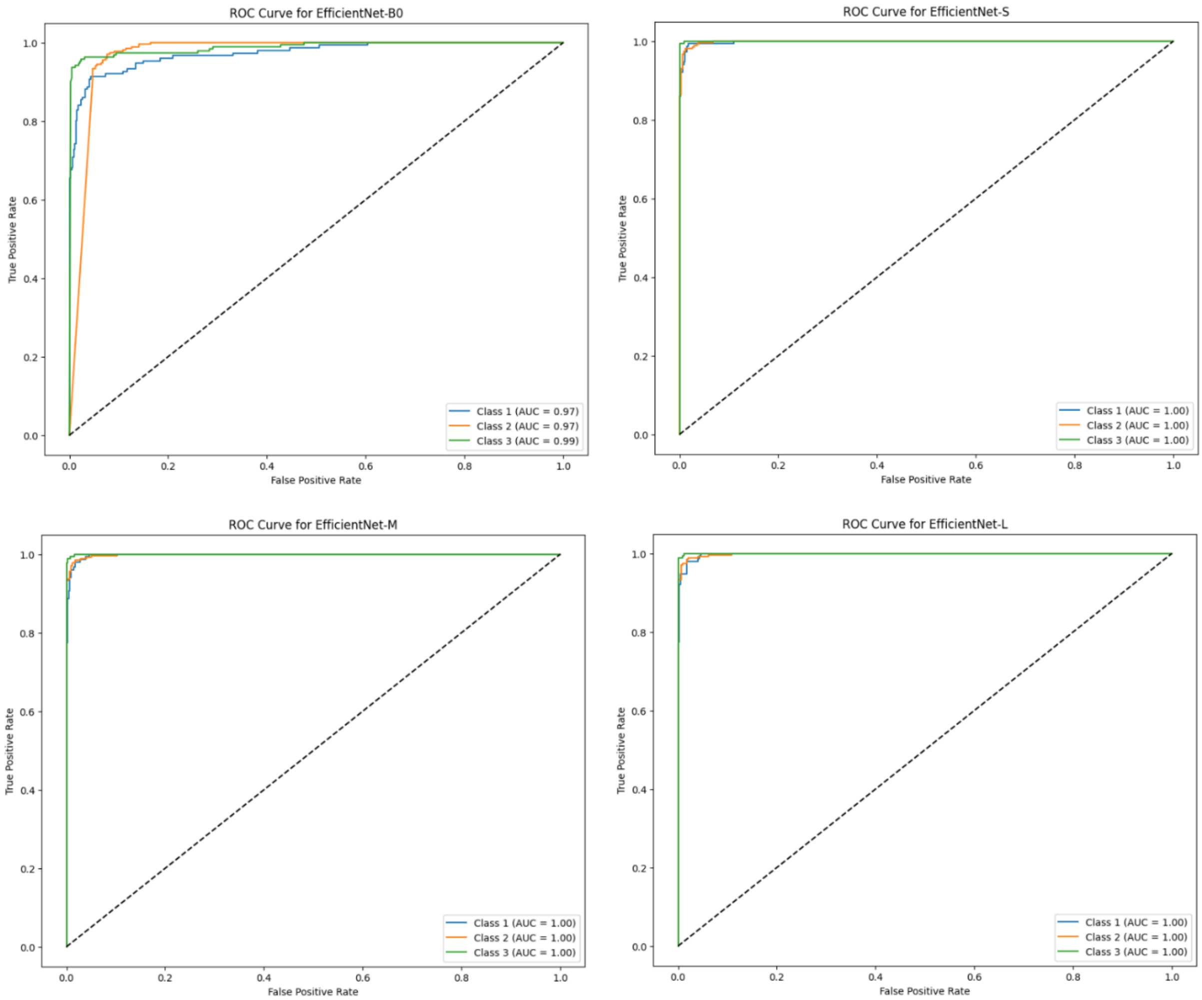

Figure 3. ROC Curves and AUC Scores for EfficientNet Variants in Brain Tumor Classification.

4 Conclusion and Future Work

Brain tumor classification using MRI images remains a critical challenge in medical imaging, demanding high accuracy and computational efficiency for practical applications. This study provides a comparative analysis of EfficientNetB0 and the EfficientNetV2 variants (S, M, and L) to address this challenge. Results indicate that while EfficientNetB0 serves as a strong baseline model, the EfficientNetV2 variants significantly outperform it in terms of accuracy, precision, recall, and AUC scores across all classes. Specifically, the EfficientNetV2-S variant emerged as the most effective model, achieving the highest accuracy (98.20%) and balanced performance across all tumor classes. EfficientNetV2-M and EfficientNetV2-L also demonstrated excellent classification capabilities, with minor trade-offs between computational complexity and performance. EfficientNetV2-S, with its advanced architectural enhancements and efficient training techniques, provides a promising solution for real-world clinical applications, offering high accuracy while minimizing computational costs. EfficientNetV2-S, with its advanced architectural enhancements and efficient training techniques, provides a promising solution for real-world clinical applications, offering high accuracy while minimizing computational costs. Overall, the results highlight the potential of EfficientNetV2 architectures for reliable and automated brain tumor classification, paving the way for their integration into diagnostic workflows. Future studies can focus on several key directions to build upon the findings of this research. Expanding the dataset to include larger and more diverse samples can improve the generalizability of the models, ensuring robust performance across different patient populations and imaging conditions. Incorporating multi-modal imaging data, such as CT scans or PET images, can enhance classification accuracy and provide a more comprehensive diagnostic approach by leveraging complementary information from various imaging techniques. Developing explainable AI methods to interpret model predictions would enable clinicians to understand and trust the decision-making process of the models, fostering their adoption in clinical workflows. Optimizing the models for deployment on edge devices, such as portable medical imaging equipment, can facilitate real-time diagnosis in resource-constrained settings, making advanced diagnostic tools accessible in remote or underserved regions. Integrating classification models with tumor segmentation techniques could create a complete diagnostic pipeline, including tumor localization and grading, thereby offering a more holistic approach to brain tumor diagnosis and treatment planning. These advancements have the potential to significantly enhance the practical utility and impact of AI-driven diagnostic systems in medical imaging.

Declaration

Ethics committee approval is not required.

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