Efficient Residual-Based DCNN for Brain Tumor Classification Using MRI

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Abstract
Brain tumor diagnosis using magnetic resonance imaging (MRI) is a critical step in clinical decision-making. Manual analysis of MRI scans is time-consuming and highly dependent on expert radiologists, making automated solutions essential. This report presents an efficient residual-based Deep Convolutional Neural Network (DCNN) for multi-class brain tumor classification. The proposed model integrates residual learning with extensive data augmentation to enhance feature extraction and generalization. Experiments are conducted on a publicly available MRI dataset containing four classes: glioma, meningioma, pituitary tumor, and no tumor. Performance is evaluated against well-established transfer learning models, including InceptionV3, Xception, and a hybrid AlexNet–MobileNet architecture. The proposed residual DCNN achieves a classification accuracy of 98.02%, outperforming all benchmark models.

1. Introduction
Brain tumors are among the most complex and life-threatening neurological diseases due to their aggressive behavior and impact on essential brain functions. Global statistics indicate a steady rise in both incidence and mortality rates associated with brain and central nervous system cancers. Early detection and accurate diagnosis are therefore essential for improving survival rates and treatment outcomes. Magnetic Resonance Imaging (MRI) is widely used for brain tumor diagnosis because of its superior soft-tissue contrast. However, manual interpretation of MRI scans is labor-intensive and prone to inter-observer variability. These challenges have motivated the adoption of artificial intelligence (AI) techniques, particularly deep learning, to support automated and reliable brain tumor detection.

2. Literature Review

Recent advances in deep learning have significantly improved automated brain tumor classification. Transfer learning-based CNNs such as AlexNet, ResNet, InceptionV3, and Xception have achieved strong performance on MRI datasets. However, these models are typically trained on natural images and may not fully capture MRI-specific features. Residual learning has shown promise in enabling deeper and more stable networks, yet its application as a task-specific architecture for brain tumor classification remains limited.

3. Methodology

The experiments utilize a publicly available brain MRI dataset consisting of 7,023 images across four classes: glioma, meningioma, pituitary tumor, and no tumor. The dataset was split into 81.3% training data and 18.7% testing data. Extensive data augmentation techniques were applied, including rotation, flipping, zooming, shearing, width shifting, and height shifting, to improve generalization and reduce overfitting.

Three benchmark models (InceptionV3, Xception, and AlexNet–MobileNet) were compared against the proposed residual-based DCNN, which incorporates skip connections to facilitate deep feature learning specific to MRI images.

4. Results and Discussion

All models were trained for up to 50 epochs with a batch size of 32. The proposed residual-based DCNN achieved the highest classification accuracy of 98.02%, outperforming InceptionV3 (95.19%), Xception (95.35%), and AlexNet, MobileNet (97.56%).The improved performance is attributed to the task-specific architecture and residual connections, which enable effective learning of MRI-specific patterns.

5. Conclusion

This report presented an efficient residual-based DCNN for automated brain tumor classification using MRI images. The proposed model achieved superior performance compared to state-of-the-art transfer learning approaches. The findings highlight the importance of task-specific deep learning architectures in medical image analysis and their potential for real-world clinical deployment.