Attention-Enhanced EfficientNet Framework for Multi-Class Brain Tumor Classification: A Deep Learning Approach

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Abstract:

Accurate brain tumor classification based on Magnetic Resonance Imaging (MRI) is of significant importance for the diagnosis and prognosis of brain tumors; however, it is a tedious and complex task due to the involvement of a large number of classes and the need for accurate and precise classification results, as existing deep learning models are only able to perform binary and three-class classification tasks, and are lacking in providing interpretable results. Therefore, in order to address the aforementioned challenges, a novel classification framework, i.e., attention-enhanced EfficientNetB4 with a Convolutional Block Attention Module, is proposed for brain tumor classification, where the proposed model is able to perform a 14-class classification task with improved accuracy and better interpretability of results, as it is based on the transfer learning of a pre-trained EfficientNetB4 model on ImageNet, and the use of a focal loss function for handling the problem of class imbalance, as well as a two-phase fine-tuning strategy for better adaptation of features. Grad-CAM is used for providing better interpretability of results, and the proposed model is validated through the calculation of accuracy, precision, recall, F1 score, and confusion matrix, where improved results are obtained compared to existing CNN models.

Keywords: Brain Tumor Classification; MRI; EfficientNetB4; CBAM; Explainable AI

Introduction

The classification of brain tumors through Magnetic Resonance Imaging (MRI) is of significant importance for the determination of the appropriate treatment, prognosis, and surgical interventions. The precise identification of the type of brain tumor is of utmost importance as it is known that various types of brain tumors need specific types of treatment and have varying prognosis. MRI is considered the best modality for brain tumor classification due to the better soft tissue contrast, non-invasive nature of the procedure, and the availability of multiple sequence images like T1, T2, and FLAIR.

However, these advantages come with a disadvantage, where interpretation of the images is a tedious and highly dependent process on the radiologist's level of expertise. As the volume of data in images increases, so does the workload, and this may result in variability and delayed decision-making. In addition, some tumors may have minor visual distinctions, and classification may be difficult.

Deep learning architectures, especially Convolutional Neural Networks (CNNs), have shown promising results in the automatic analysis of medical images. Models such as VGG, ResNet, DenseNet, and EfficientNet have improved the quality of feature representation and classification. However, most of the research has been focused on the classification of three classes, mainly for tumor classification. This is a significant limitation, considering the practical scenario where multiple types of tumors may be simultaneously present.

Another limitation is the class imbalance in medical images, where the model tends to learn from the majority class and perform poorly on the minority class. Lastly, deep learning models, such as CNNs, are often considered "black boxes" and cannot be easily interpreted. This is a significant limitation, considering the practical scenario where a model must be interpretable. Therefore, a scalable, multi-class, and interpretable deep learning framework is required, which can handle class imbalance and achieve high classification accuracy.

Related work

In recent research on brain tumor classification using MRI scans and various deep learning architectures, the accuracy of the models was impressive. A study conducted in 2019 on TL-DCNN using the VGG architecture and GAP achieved an accuracy of 98.93% on the Figshare dataset for three classes of brain tumors. The use of the TL concept was also advantageous. Another study conducted in 2021 on brain tumor classification using ResNet-50 and GAP achieved an accuracy of 97.48% on 3,064 MRI images. The training was stable, and the use of GAP minimized the occurrence of overfitting. A study conducted in 2022 on brain tumor classification using the Enhanced DenseNet architecture and fine-tuning and regularization achieved an accuracy of 97.1%. However, the study did not address the interpretability of the model. A study conducted in the same year on brain tumor classification using the G-ResNet architecture and feature fusion achieved an accuracy of 95%. The study also did not use attention mechanisms. A study conducted in 2023 on brain tumor classification using the Res-BRNet architecture and residual and region-based CNNs achieved an accuracy of 98.22% on four classes. The study also had the disadvantage of using high computational power. A CNN architecture using the WIAP pooling method was also effective in the classification of four medical datasets. The architecture classified eight classes and improved the accuracy, F1-score, and sensitivity while maintaining contextual information. However, the architecture was limited to three classes. Most of the architectures were also unable to validate the accuracy of the brain tumor classification on different datasets. Most of the architectures also failed to address the interpretability and explainability of the brain tumor classification.

Table 1. Compares this work with the related work or previous research by other researchers

Citation (Year)	Dataset	Model / Method	NO. of Classes	Results	Advantages	Limitations
[1] 2021	MRI (3,064 images)	ResNet-50 + GAP	3	97.48% Acc	GAP reduces overfitting;	Only 3 classes; no explainability

					stable train-ing	
[2] 2019	Figshare (3 tumor types)	TL-DCNN (VGG + GAP)	3	98.93% Acc	Transfer learning boosts ac-curacy	No cross -dataset validation
[3] 2023	Kaggle + Br35H + Figshare	Res-BRNet (Resid-ual + Region CNN)	4	98.22% Acc	Captures boundary + texture info	Complex; high compu-tation
[4] 2022	Figshare (3,064 im - ages)	Enhanced DenseNet (FT + Reg.)	3	97.1% Acc	Regularizatio n reduces overfitting	No inter-pretability analysis
[5] 2023	Four medical datasets	CNNs + WIAP pool-ing	8	↑ Acc, F1, Sensitivity	Reduces overfitting ; preserves context	High cost; not tumor-specific
[6] 2022	MRI tu mor dataset	G-ResNet (GAP + Feature Fusion)	3	95.0% Acc	Combines low/high-level fea-tures	No atten-tion; small dataset

Key Contribution

Developing a CBAM-integrated EfficientNetB4 model for 14-class MRI tumor classification.

• Comparison of the proposed model's performance against pre-trained CNNs (VGG16, ResNet50, DenseNet121, InceptionV3, MobileNetV2, EfficientNetV2S).

• Use of focal loss and data augmentation to handle the imbalanced nature of the dataset.

• Use of Grad-CAM for visualization of the outputs of the proposed model.

Methodology

Figure 1 presents the architecture of the proposed model. The details of the proposed architecture are as follows:

Dataset Preparation: The dataset contains MRI images of 14 types of tumors. The dataset is preprocessed to a uniform resolution of 224x224 pixels. The dataset is divided into training, validation, and testing sets using two ratios of 80-10-10 and 70-15-15. Exhaustive data augmentation techniques of rotation, translation, flipping, and zooming are applied.

Model Architecture:

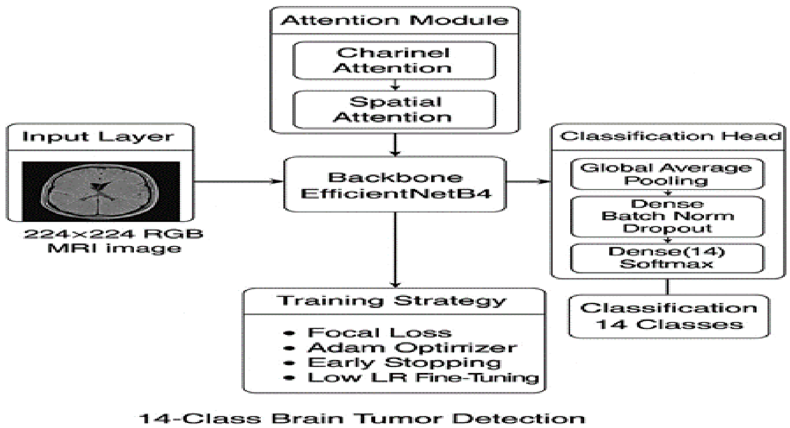

Figure 1. Model Architecture

The proposed framework utilizes EfficientNetB4 as the base model. It uses transfer learning from the ImageNet-pretrained weights. A Convolutional Block Attention Module (CBAM) is employed after the selected convolutional layers. It helps in the acquisition of channel-wise attention and spatial attention on the critical features related to the tumor. The classifier uses dense layers along with batch normalization and dropout regularization. It uses focal loss for the balancing of classes and the Adam optimizer along with early stopping.

Training Strategy: The training of the proposed framework is performed in two stages. In the first stage, the classifier is trained. This helps in the stability of the training. In the second stage, the last 100 layers are unfrozen. This helps in the adaptation of the features. The performance of the proposed framework is evaluated by using metrics such as accuracy, precision, recall, F1-score, and confusion matrix. Grad-CAM is employed for the explanation of the proposed framework. It helps in the explanation of the results.

Conclusions

In this study, a comprehensive and interpretable framework for multi-class brain tumor classification is proposed, utilizing the attention-enhanced efficient net B4 architecture. The proposed model overcomes the existing brain tumor classification models' drawbacks by utilizing the CBAM, Focal Loss, and structured training methods. The proposed framework has tremendous potential for brain tumor diagnosis with accuracy, robustness, and clinical applicability.

References

[1] R. L. Kumar, J. Kakarla, B. V. Isunuri, and M. Singh, "Multi-class brain tumor classification using residual network and global average pooling," Multimedia Tools and Applications, vol. 80, no. 9, pp. 13 429–13 438, 2021.

[2] P. P. Malla, S. Sahu, and A. I. Alutaibi, “Classification of tumor in brain mr images using deep convolutional neural network and global average pooling,” Processes, vol. 11, no. 3, p. 679, 2023.

[3] M. M. Zahoor et al., “Brain tumor mri classification using a novel deep residual and regional cnn,” Biomedicines, vol. 12, no. 7, p. 1395, 2024.

[4] N. Aziz, N. Minallah, J. Frnda, M. Sher, M. Zeeshan, and A. H. Durrani, “Precision meets generalization: Enhancing brain tumor classification via pretrained densenet with global average pooling and hyperparameter tuning,” PloS one, vol. 19, no. 9, e0307825, 2024.

[5] M. Karaaltun, “Whole image average pooling-based convolution neural network approach for brain tumour classification,” Neural Computing and Applications, vol. 36, no. 3, pp. 1351–1367, 2024.

[6] D. Liu, Y. Liu, and L. Dong, “G-resnet: Improved resnet for brain tumor classification,” in International Conference on Neural Information Processing, Springer, 2019, pp. 535–545.