

Brain Tumor Classification Based on a Dual-Backbone ECA Fusion Network Model

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Abstract

In recent years, with the gradual maturation of deep learning technologies and the steady improvement in computational power, computer-aided diagnostic techniques have been increasingly applied in clinical disease diagnosis. To effectively localize lesions, determine their categories, and provide reliable diagnostic support for clinicians, this paper proposes a dual-backbone ECA fusion network, which mainly consists of three components: a dual-backbone deep feature extraction module, an attention module, and a feature fusion and classification module. The research method of this paper employs two backbone networks, ResNet50 and EfficientNetB0, as two branches. After the feature extraction process, the ECA attention mechanism is adopted to enhance the feature extraction ability of the lesion area. Finally, through feature fusion, the classification of glioma, meningioma, pituitary tumor and normal control is achieved. Through comparative experiments, it was found that the proposed dual convolutional branch model structure can identify different types of brain tumors. On the test set, it achieved an accuracy of 93.28%, an AUC of 98.28%, and a precision of 94.12%, achieving good results. At the same time, in order to improve the interpretability of the model, Grad-CAM++ was used to show the regions of interest of the network, which coincided with the lesion area, further verifying the effectiveness of our dual-branch model.

Keywords brain tumor; neural network; attention mechanism; lesion classification

1 Introduction

World Health Organization Classification of Central Nervous System Tumors, 2021 (Newly 5). Brain tumors represent heterogeneous tumors originating from different cell populations within the central nervous system (CNS), including glial cells, neurons, meninges, embryonic tissue, germ cells and other tissues. Such a global heterogeneous diagnostic and classification system combines morphological, immunohistochemical and molecular genetic features to provide better determination of tumor types, subtypes, and malignancy levels. Brain tumors vary substantially in biology, clinical outcomes, and response, ranging from slowly growing benign lesions to highly invasive malignant tumors that severely impair neural functions and threaten patient survival. The 2021 classification is a more comprehensive system focusing on molecular typing, as it clearly divides diffuse gliomas into adult and pediatric tumors, and demonstrates the high heterogeneity and clinical complexity of central nervous system tumors^[1]. According to the 2021 global statistical report of Ostrom et al.^[2] from the Central Brain Tumor Registry of the United States, primary brain and central nervous system tumors are highly heterogeneous tumor groups that grow from

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neural and central system tissues, including malignant and benign tumors with differing incidence, pathological features, clinical histories and patient survival as primary chronic diseases that severely threaten human health.

The field of smart classification of brain tumor MRI images has received considerable attention. Das et al.^[3] developed a brain tumor classification model using convolutional neural networks (CNN). They preprocessed the images using size normalization, Gaussian filtering, and histogram equalization and used multi-layer convolution, pooling and Dropout regularization to perform end-to-end classification of gliomas, meningiomas and pituitary tumors. They found that convolutional neural networks can automatically learn and diagnose brain tumor image features. Khan et al.^[4] proposed a lightweight convolutional neural network detection scheme for binary brain tumor categorization. They extracted effective brain regions using Canny edge detection and region cropping, and used data augmentation to reduce the small sample size and to effectively distinguish benign and malignant tumors. The authors showed that the lightweight network could still achieve high recognition accuracy with low computational cost which helps in rapid clinical screening. Ari et al.^[5] proposed a brain tumor detection system based on deep learning and traditional image processing. They adopted non-local mean filtering and local smoothing denoising preprocessing, utilized local receptive field based extreme learning machine (ELM-LRF) for tumor classification, and performed watershed segmentation and morphological operation to find lesion areas. They outperformed traditional convolutional neural networks such as CNN, AlexNet, and manual feature methods in recognition accuracy and time, which provides an effective reference in computer-assisted clinical diagnosis.

In conclusion, although the existing methods have achieved certain results in the classification task of brain tumors, there is still room for improvement in aspects such as multi-scale lesion information fusion, enhancement of key region features, and model interpretability. Therefore, based on four groups of data including glioma, meningioma, pituitary tumor, and normal brain tissue, this paper introduces the ECA channel attention mechanism into a dual-branch deep learning network. It adopts a multi-scale parallel input and feature fusion strategy to enhance the acquisition ability of lesion features at different scales, improve the accuracy and robustness of brain tumor classification, and use the Grad-CAM++ heatmap to display the decision regions of the model, thereby enhancing the interpretability and credibility of the diagnostic results.

2 Dataset

2.1 Data Source

The experimental data are sourced from two publicly available datasets on Kaggle: Brain Tumor Classification^[6] and Brain Tumor MRI Dataset^[7]. These two datasets contain four types of tumors: glioma, meningioma, pituitary tumor, and brain MRI images without tumors. The data are stored in JPG format. The Brain Tumor Classification dataset contains 3,264 image files, while the Brain Tumor MRI Dataset contains 7,200 image files, totaling 10,464 MRI images. This experiment sets the training set, validation set, and test set in a 4:1:1 ratio.

2.2 Data Augmentation Strategies

To enhance the generalization ability of the model, some data augmentation strategies were adopted during the training phase: random horizontal and vertical flipping, random translation, and adjustment of the brightness and contrast of different image pictures, to increase the interference information and improve the robustness of the model. During the validation and testing phases, only central scaling and standardization were performed.

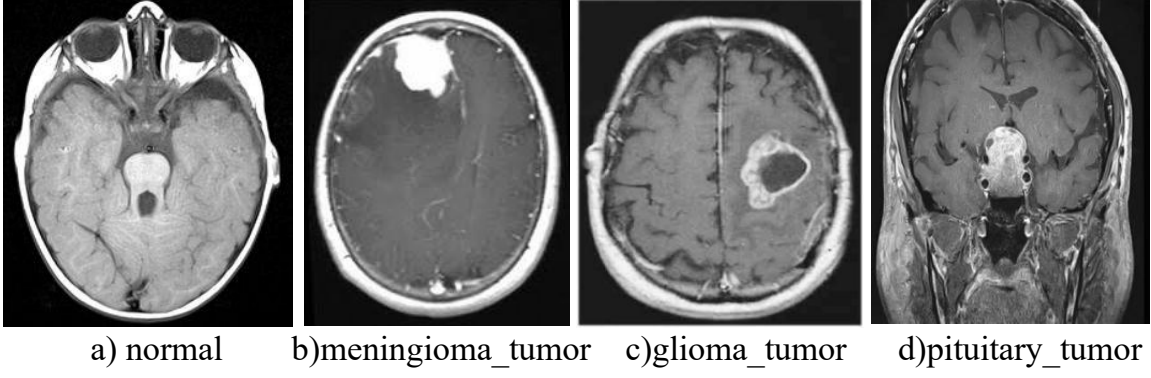


Figure 1: Images of different types of brain tumors.

3 Method

3.1 Attention Mechanism

The attention mechanism is widely used in various visual tasks due to its plug-and-play and lightweight characteristics, such as image segmentation, image detection, image classification, and medical image analysis. In the field of deep learning, the channel attention mechanism has become a key technology for improving the performance of convolutional neural networks. The classic channel attention mechanisms include SENet^[8] (Squeeze-and-Excitation Network) and the improved ECA^[9] attention mechanism based on SENet. The core idea of the channel attention mechanism is to enable the network to automatically learn the importance of different feature channels and enhance useful features while suppressing irrelevant information by dynamically adjusting the channel weights. SENet achieves this goal through the “compression-excitation” (Squeeze-and-Excitation) operation and won the championship in the ImageNet competition. However, as the model depth and complexity increase, the computational issue of SENet gradually becomes prominent. In response to this, ECA attention proposes an improvement method for the shortcomings of SENet’s attention mechanism. It replaces the fully connected layer with a one-dimensional convolution with an adaptive kernel size to achieve efficient cross-channel interaction while avoiding dimension reduction. This design enables ECA-Net to achieve the best performance-efficiency ratio in many visual tasks. For the classification of MRI images of brain tumors, gliomas, meningiomas and pituitary tumors have different textures, shapes and edges. Therefore, by using the ECA attention mechanism, it can focus more on the more challenging areas in the classification.

3.2 Model Architecture

After the original image undergoes data augmentation, it is input into the network model. Through the dual-branch ECA attention network fusion model, using the pre-trained weight models of ResNet50 and EfficientNetB0 on ImageNet, the ECA attention module is connected, feature extraction is carried out, and the final result is obtained through classification. The final network’s focus on the lesion area is displayed through a heatmap. The fused features sequentially pass through two fully connected layers (the first outputting 256 dimensions and the second outputting 4 dimensions), each followed by a Dropout layer (rate 0.4) to prevent overfitting. Finally, a Softmax layer outputs the four-class probabilities (glioma, meningioma, pituitary tumor, no tumor).

4 Results

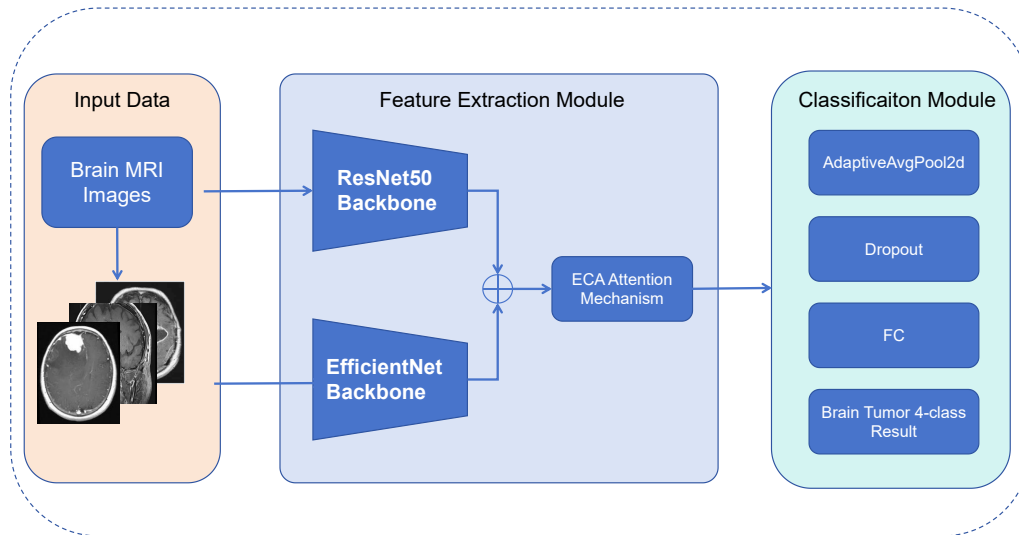


Figure 2: Diagram of the dual-branch network model.

4.1 Experimental Results

During the experiment, the original training set was randomly divided into training and validation sets at a ratio of 8:2, while an independent test set directory was used to ensure objectivity of the evaluation. The model employed a cross-entropy loss function with label smoothing (smoothing coefficient set to 0.05). This paper employs the cross-entropy loss function, and the optimizer is AdamW. The initial learning rate is set at 1×10^{-4} , and the weight decay coefficient is 1×10^{-5} . The epoch is set to 15, and the early stopping strategy is adopted. That is, if the model's performance does not improve for more than 6 epochs, the training process will be terminated. Finally, the performance of the model proposed in this paper was verified on the test set using accuracy, precision, recall, F1-score and AUC. These indicators were calculated using the macro parameter in the scikit-learn library.

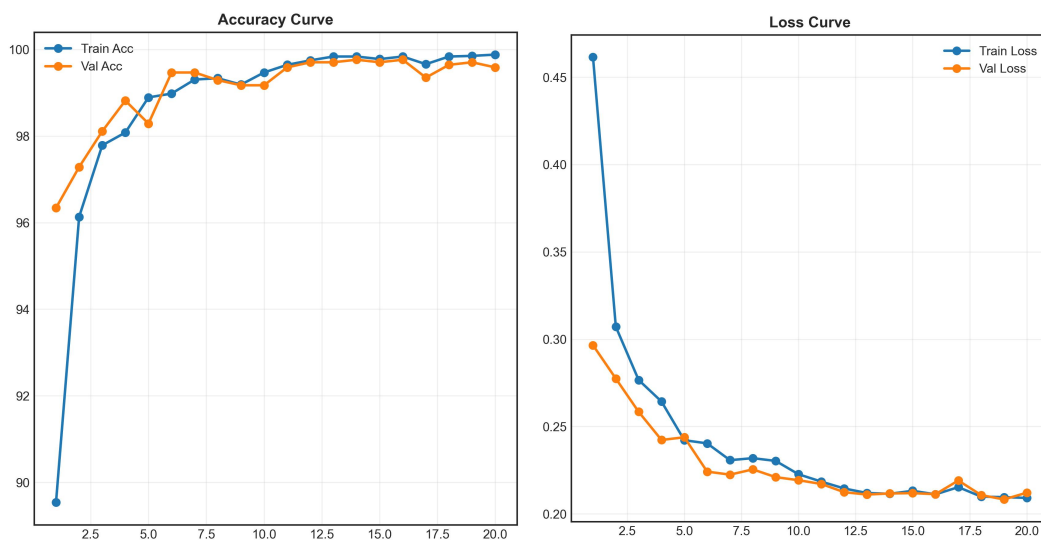


Figure 3: Accuracy and loss curves.

The loss curves and validation curves for model training are shown in Figure 3. Both the training loss and validation loss decreased slowly. During this stage, the training accuracy and validation accuracy both increased significantly, indicating that the model quickly learned the basic feature patterns of the data.

When the number of training iterations reached 20, the training loss dropped from approximately 0.46 to approximately 0.22, and the validation loss dropped to approximately 0.21. The accuracy rates of the training set and validation set also reached a relatively high level, and the loss and accuracy curves of the training set and validation set showed the same trend with a small difference. These curves indicate that during the training process, the model did not experience overfitting or underfitting, and the convergence process was stable, with good generalization performance. Finally, the model reached a stable state.

4.2 Ablation Study

In this paper, we present the transfer learning methods. As can be seen from the experimental results in Table 1, the model using pre-trained weights from ImageNet performs better on all the metrics. The performance of the pre-training model in accuracy, precision, recall, and AUC, compared to the non-pre-trained model, increases by 0.95%, precision by 1.23%, recall by 0.93% and AUC by 1.22%. It is possible that the pre-trained model is more useful in medical classification tasks where the model converges faster and learns more discriminative features which can improve performance.

Table 1: Experimental Results of Transfer Learning

Pretrained	Acc	Precision	Recall	AUC
True	93.28%	94.12%	93.29%	98.28%
False	92.33%	92.89%	92.36%	97.06%

Table 2 presents the classification performance of the single-branch network and the dual-branch fusion network in the tasks of this study. From the results in the table, it can be seen that the dual-branch ResNet50 + EfficientNetB0 model performs very well in most indicators, with an accuracy rate of 93.28%, a precision rate of 94.12%, a recall rate of 93.29%, and an AUC value of 98.28%. Compared to the ResNet50 model, the accuracy rate has increased by 0.80%, and the AUC has increased by 1.19%; compared to the EfficientNetB0 model, the accuracy rate has increased by 0.15%, and the AUC has increased by 1.23%. This indicates that the multi-branch feature fusion strategy can effectively integrate the advantages of different network features, leveraging the extraction ability of ResNet50 for anatomical structure features and the capturing advantage of EfficientNetB0 for fine-grained pathological features, thereby significantly improving the overall classification performance and clinical generalization ability of the model.

Table 2: Experimental Results of Single-Branch and Dual-Branch Networks

Model	Acc	Precision	Recall	AUC
ResNet50	92.48%	93.62%	92.50%	97.09%
EfficientNetB0	93.13%	94.18%	93.14%	97.05%
ResNet50 + EfficientNetB0	93.28%	94.12%	93.29%	98.28%

4.3 Heatmap

Figure 4 shows the Grad-CAM++ heatmap generated by the dual-branch model on the MRI images of brain tumors. From the picture, we can observe that the high attention areas of the model (the warm-colored parts) closely overlap with the lesion areas. The attention is mainly focused on the core lesion area and the characteristic enhanced edge of the tumor, while the attention to the surrounding normal brain tissue is relatively low. This indicates that in the classification decision-making process of the model,

it mainly pays attention to the key lesion areas related to the tumor rather than background noise or irrelevant areas, verifying the rationality and clinical interpretability of the model's decision logic.

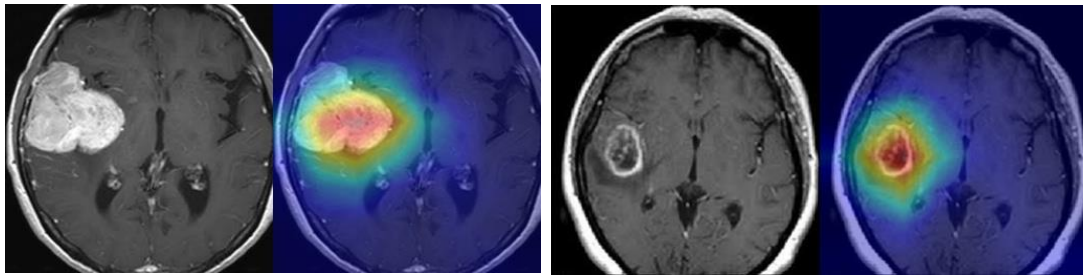


Figure 4: Grad-CAM++ Heatmap Visualization of Lesion Regions.

5 Conclusion

This paper focuses on the MRI medical imaging classification task of brain tumors. It mainly conducts research from three aspects: the selection of the dataset, the dual-branch network, and the attention mechanism fusion. It also analyzes the deep learning classification methods suitable for this study. Based on the brain tumor classification task using MRI images, a dual-branch channel attention network integrating ResNet50 and EfficientNetB0 is constructed. Firstly, by introducing pre-trained weights through the transfer learning strategy, the generalization ability of the model is effectively provided; secondly, through multi-branch feature fusion and the ECA channel attention mechanism, the model's ability to extract lesion features is enhanced, achieving significant improvements in key indicators such as accuracy, precision, recall, and AUC. Experimental results show that the proposed model exhibits excellent performance in the brain tumor classification task, and the rationality and interpretability of the model's decision-making process are verified through Grad-CAM++ visualization. Future research will further expand the dataset size, combine multimodal imaging data, and explore more lightweight and robust models to promote the practical application of deep learning technology in clinical brain tumor auxiliary diagnosis.

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