ISSN 2616-5775 Vol. 8, Issue 4: 98-105, DOI: 10.25236/AJCIS.2025.080412

Research on Medical Imaging Detection of Brain Tumors Based on YOLOv8m Algorithm

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Abstract: *Brain tumors are a deadly form of malignant neoplasms that pose a significant danger to patients' health and life. This study aims to improve the diagnostic efficiency and precision of brain tumors by utilizing the YOLOv8m deep learning model for automatic detection of medical imaging. High-quality datasets from the Kaggle platform are employed in this study, comprising axial, coronal, and sagittal MRI images for brain tumor detection. The model undergoes 200 epochs of training and testing, with performance enhancement achieved via hyperparameter optimization and data augmentation techniques. During the experiments, the YOLOv8m model shows remarkable detection performance, achieving mAP@0.5 of 95% and mAP@0.5:0.95 of 64.6%. The precision achieved is 95%, with recall at 89%. Additionally, the bounding box regression loss decreases from 3.0 to 0.5 throughout the training process, and the validation loss stabilizes at 1.4, suggesting substantial optimization in object localization and classification tasks, with no overfitting observed. The results of this study show that the YOLOv8m model can efficiently and accurately perform automatic detection of brain tumor regions, providing reliable technical support for clinical diagnosis.*

Keywords: *YOLOv8m, Brain tumors, Medical Imaging Detection*

1. Introduction

Brain tumors are one of the deadly malignant tumors, posing significant threats to the life and health of patients, with a high incidence rate. According to the 2020 Global Cancer Epidemiology Database, approximately 308,000 new cases of brain tumors were diagnosed globally, with 251,000 deaths attributed to the disease [1]. In recent years, researchers have employed various methods for brain tumor detection, including traditional image processing and electromagnetism-based imaging techniques. For instance, one study combined similarity models with active contour methods for brain tumor boundary extraction and preliminary localization [2], while another designed a confocal imaging algorithm based on electromagnetic theory to achieve early localization of brain tumors by calculating scattering parameters[3]. However, these methods still face limitations in detection accuracy, automation, and handling complex medical images, highlighting the need for more advanced and efficient technologies.

The swift progress of artificial intelligence, especially deep learning, is revolutionizing medical imaging analysis [4]. As one of the core technologies of deep learning, Convolutional Neural Networks (CNNs) have demonstrated exceptional capabilities in image recognition and object detection. [5]. The YOLO (You Only Look Once) algorithm series, known for its exceptional real-time processing ability and high accuracy, has been extensively applied in object detection, with the latest YOLOv8m demonstrating significant improvements in model architecture and algorithm optimization, enhancing both detection accuracy and computational efficiency[6].

Over the past few years, an increasing amount of research has been employing YOLO-based models for medical image analysis, such as using YOLO for lung CT image analysis to significantly improve lung nodule detection efficiency[7]. However, research on brain tumor detection, especially exploring the use of YOLOv8 for this purpose, is still in its infancy. The complexity and diversity of brain tumor imaging data pose higher demands on object detection algorithms. YOLOv8, with its deeper feature extraction mechanism and optimized loss function, shows great potential in handling complex medical imaging data, offering new possibilities for the automated detection of brain tumors[8].

This study explores the application of the YOLOv8m model in brain tumor medical image detection. The research uses the brain tumor detection dataset from Kaggle, which includes labeled MRI (Magnetic

ISSN 2616-5775 Vol. 8, Issue 4: 98-105, DOI: 10.25236/AJCIS.2025.080412

Resonance Imaging) images from multiple imaging planes. Through hyperparameter optimization and data augmentation techniques, the YOLOv8m model is applied for automatic brain tumor detection. An experimental framework has been developed to assess the effectiveness and robustness of the model. The research methodology includes model training, parameter tuning, and performance evaluation to ensure efficient detection in complex medical images.

2. Methods and Dataset

2.1 Methods

YOLO Series Algorithms have emerged as a major breakthrough in object detection, thanks to their instantaneous processing capabilities and exceptional precision. YOLOv8m, as the cutting-edge version of this series, has undergone comprehensive upgrades and optimizations based on its predecessors. This version retains the effectiveness of the YOLO series while incorporating cutting-edge technologies in network architecture and algorithm design, greatly improving performance in complex situations and multi-scale object detection tasks. [9-11]. At present, YOLOv8m is extensively used in a wide range of object detection applications, such as traffic monitoring, industrial inspection, and medical image analysis, providing efficient solutions across different fields.

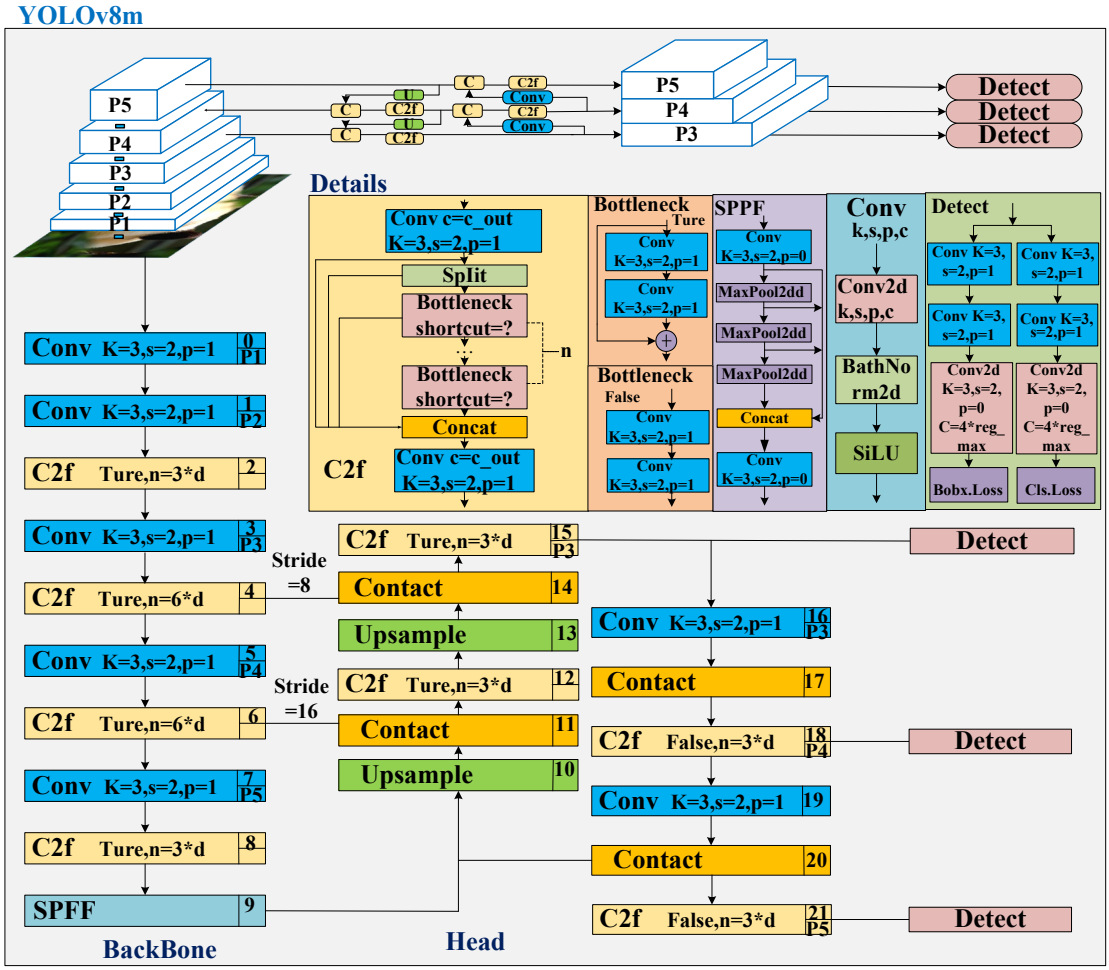

Figure 1. YOLOv8m Architecture Diagram

YOLOv8m is an efficient and precise object detection model, with its network structure shown in Figure 1. It is mainly composed of three parts: Backbone, Neck, and Head. The Backbone plays a key role in extracting features at multiple scales from the input image, using an improved convolutional neural network structure. It introduces the C2f (Cross Stage Partial with Faster Version) module, which optimizes feature extraction efficiency through deep residual connections, significantly reducing computational complexity. Simultaneously, the SPPF (Spatial Pyramid Pooling-Fast) module is employed to enhance the model's contextual awareness by applying multi-scale pooling, enabling the

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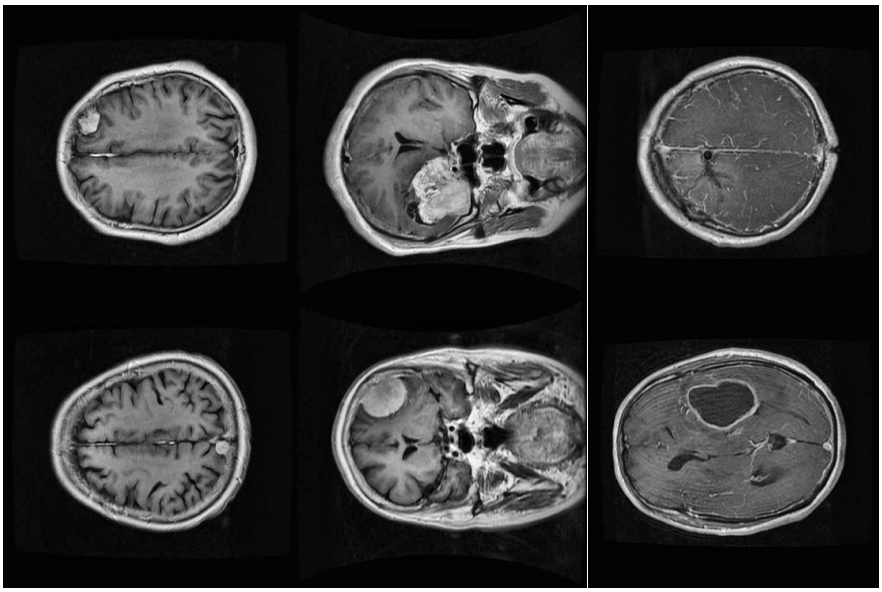
network to capture global information. The Neck component fuses multi-scale features effectively using FPN (Feature Pyramid Network) and PAN (Path Aggregation Network). Its upsampling and downsampling operations combine high-resolution and low-resolution features, while the C2f module and feature concatenation (Concat) enhance feature representation. The Head component is responsible for object classification prediction and bounding box regression, using a multi-scale detection strategy. Detection is performed at different levels of the feature pyramid (P3, P4, and P5) to meet the detection needs for both small and large objects, and the model outputs classification (cls) and bounding box (bbox) predictions. Through modular design, YOLOv8m significantly improves detection performance, with the C2f module reducing the number of parameters, achieving a lightweight design, the SPPF module enhancing global awareness through pooling, and the combination of FPN and PAN strengthening the fusion of multi-scale features. This allows the model to maintain high efficiency while achieving higher detection accuracy.

The main advantage of YOLOv8m lies in its excellent balance between detection accuracy and speed[12-14]. Through optimized loss functions, such as CIoU(Complete Intersection over Union) and Focal Loss(Focal Loss for Dense Object Detection), as well as an adaptive anchor mechanism, the model excels in multi-scale object detection and adapting to complex backgrounds. Furthermore, YOLOv8m introduces deeper feature extraction modules, enabling more accurate localization of objects when processing images with rich details. Additionally, the model supports flexible parameter adjustments, making it suitable for devices with varying computational capacities, thus ensuring both efficiency and practicality. These advantages make YOLOv8m one of the important tools for automated detection in medical image analysis.

2.2 Dataset

This study uses the Brain Tumor Object Detection Dataset from the Kaggle open-source platform[15], which was labeled and released by David Roberts and other researchers. The dataset consists of manually annotated brain MRI images, as shown in Figure 2, covering three imaging planes: Axial, Coronal, and Sagittal. Tumor regions are accurately annotated using the MakeSense labeling tool and include bounding box information for subsequent analysis. The data primarily originates from the RSNA-MICCAI competition's T1wCE sequence and includes MGMT-positive labels, specifically for brain tumor detection.

The whole dataset is split into 803 images for training, 132 images for validation, and 111 images for testing, maintaining an 8:1:1 ratio for balanced distribution. This high-quality open dataset provides rich sample resources for the study, ensuring the credibility of the experimental results and enhancing the practical application value of YOLOv8m-based brain tumor detection research.



(a) Axial Image (b) Coronal Image (c) Sagittal Image

Figure 2. The dataset of brain MRI images

ISSN 2616-5775 Vol. 8, Issue 4: 98-105, DOI: 10.25236/AJCIS.2025.080412

3. Experiment and Testing

3.1 Experimental Environment

The study was conducted in a high-performance environment with a 64-bit Windows 11 Professional system, ensuring stability and compatibility. The hardware includes a 12th Gen Intel Core i5-12500H processor, an NVIDIA GeForce RTX 3050 GPU (4GB memory), and 16GB DDR4 RAM, all supporting CUDA for efficient deep learning. The system also features an Intel Iris Xe Graphics auxiliary display for improved efficiency. Python 3.8.10 and PyCharm were used as the primary development tools, along with PyTorch 1.12.1, CUDA 11.6, and CUDNN 8.4.0 for model development. Libraries like NumPy and OpenCV supported data processing and visualization. This setup provided the necessary technical foundation for training and optimizing the YOLOv8m brain tumor detection model, ensuring reliable and reproducible results.

3.2 Assessment Criteria

This research employed four key performance indicators to thoroughly evaluate the effectiveness of the YOLOv8m-based brain tumor image object detection model: Box Loss, Precision, Recall, and mean Average Precision (mAP@0.5:0.95). These indicators demonstrate the system's detection performance and localization effectiveness from various aspects. The following is a detailed description:

3.2.1 Box Loss

Box Regression Loss quantifies the discrepancy between the predicted bounding box and the actual ground truth, reflecting the model's performance in the object localization task. YOLOv8 commonly uses CIoU loss to optimize the matching between the predicted boxes and the actual ground truth boxes.

The specific formula is as follows:

$$\mathcal{L}_{\text{CIoU}} = 1 - \text{IoU}\frac{\rho^2(\mathbf{b},\mathbf{b^g})}{c^2}\alpha v \tag{1}$$

Where:

(1) **IoU** represents the intersection over union (IoU) between the predicted box and the ground truth box, indicating the ratio of the overlapping area between the two boxes.

(2) $\boldsymbol{\rho^2(b, b^g)}$ is the Euclidean distance between the center points of the predicted and ground truth boxes.

(3) $\boldsymbol{c}$ is the diagonal length of the smallest enclosing box that contains both the predicted and ground truth boxes.

(4) $\boldsymbol{v}$ is used to measure the aspect ratio consistency between the predicted and ground truth boxes.

(5) $\boldsymbol{\alpha}$ is the adjustment coefficient.

During training, as the number of epochs increases, Box Loss typically decreases and stabilizes, indicating improved target localization. A lower loss value signifies that the predicted box is closer to the ground truth, reflecting better accuracy in localization.

3.2.2 Precision

Precision measures the accuracy of the model's prediction of positive samples, reflecting the rate of false positives. The formula is as follows:

$$\text{Prectsion} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

Where:

(1) **TP (True Positive)**: The number of correctly detected positive samples;

(2) **FP (False Positive)**: The number of false positives detected as positive samples.

A higher precision indicates that most of the targets predicted as positive samples are accurate. For example, in brain tumor detection tasks, a higher precision reduces the likelihood of false positive tumor detections, which is crucial for ensuring the reliability of detection results. This is particularly significant in tasks that aim to minimize false positives.

ISSN 2616-5775 Vol. 8, Issue 4: 98-105, DOI: 10.25236/AJCIS.2025.080412

3.2.3 Recall

Recall measures the model's ability to cover all positive samples, reflecting the rate of false negatives. The formula is as follows:

$$\text{Recal} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

Where:

FN (False Negative): The number of true positive samples that were not detected.

A higher recall indicates that the model is able to detect more positive samples, reducing the occurrence of missed detections. In medical image analysis, such as brain tumor detection tasks, missed detections can directly lead to misdiagnosis or delayed treatment, making recall a crucial metric. To ensure the comprehensiveness of detection, recall should be maximized.

3.2.4 mAP@0.5:0.95

Mean Average Precision (mAP) serves as the primary overall assessment measure in object detection, used to assess the overall performance of a model across different detection difficulties. The core of mAP is Average Precision (AP), and its calculation formula is as follows:

$$\boldsymbol{AP} = \int_0^1 p(r)dr \tag{4}$$

Where:

$\boldsymbol{p(r)}$ represents the Precision-Recall (PR) curve.

mAP is the mean of the AP across all categories, and the formula is as follows:

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} \text{AP}_i \tag{5}$$

For mAP@0.5:0.95, it denotes the mean of Average Precision (AP) values computed at varying Intersection over Union (IoU) thresholds, from 0.5 to 0.95, with increments of 0.05. A higher mAP value indicates stronger detection capabilities of the model in complex scenarios, particularly in multi-scale and small object detection tasks. For example, in brain tumor detection, mAP offers an effective measure of the model's overall ability to detect tumor areas with diverse sizes and shapes.

By combining these formulas with practical application scenarios, a comprehensive analysis of the model's performance in target localization, positive sample prediction, coverage, and overall detection performance can be conducted, thus providing clear directions for model optimization.

3.3 Experimental Results and Analysis

This experiment provides a comprehensive evaluation of the YOLOv8 model's performance during the training and validation processes. The results demonstrate the variation trends of key evaluation metrics (Figures 3 and 4). The detailed analysis is as follows:

The **Box Regression Loss (train/box_loss and val/box_loss)** shows that as the training iterations increase, the loss value decreases rapidly from an initial value of approximately 3.0 to nearly 0.5, eventually stabilizing. The validation set loss follows a similar trend and stabilizes at around 1.4. This indicates significant optimization in the model's boundary box prediction errors, with no evident overfitting.

Precision (metrics/precision) rises quickly from the initial value and stabilizes, eventually reaching 0.95, indicating that the model exhibits high accuracy in brain tumor detection with a low false detection rate. This suggests that YOLOv8 performs excellently in recognizing positive samples, with the majority of predictions being correct.

Recall (metrics/recall) rapidly increases and stabilizes, ultimately reaching around 0.89, indicating that the model effectively covers most positive samples with a low false negative rate. A high recall reflects the model's sensitivity to positive samples, which is particularly important for medical image analysis tasks that require reducing missed detections.

The **Mean Average Precision (mAP@0.5 and mAP@0.5:0.95)** also demonstrates excellent performance. mAP@0.5 stabilizes at 0.95, suggesting the model's exceptional detection capability under a relatively loose IoU threshold. mAP@0.5:0.95 ultimately reaches around 0.646, which

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comprehensively reflects the model's detection precision in multi-scale targets and complex scenarios, demonstrating strong generalization ability.

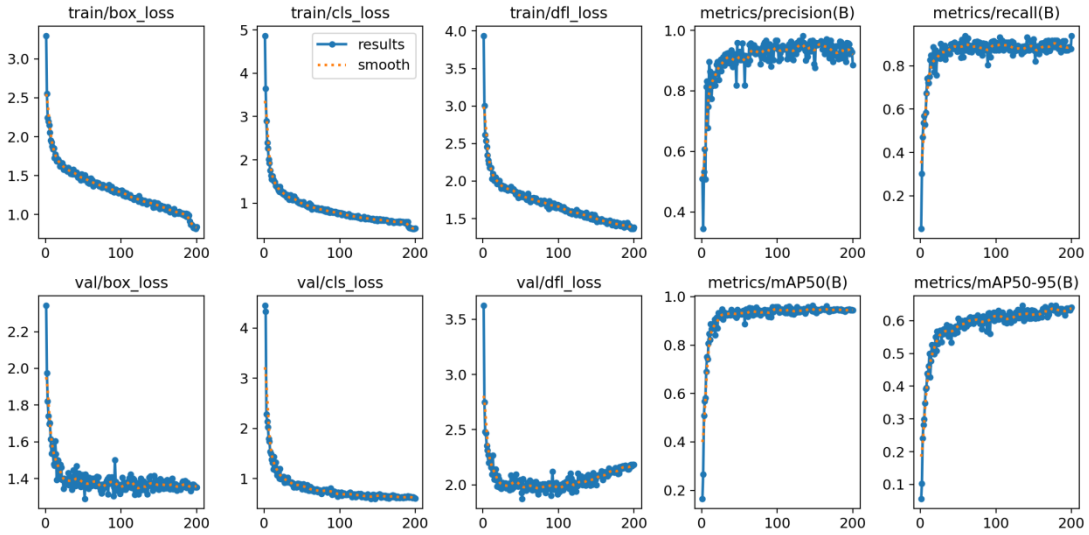

Figure 3. Experimental Results

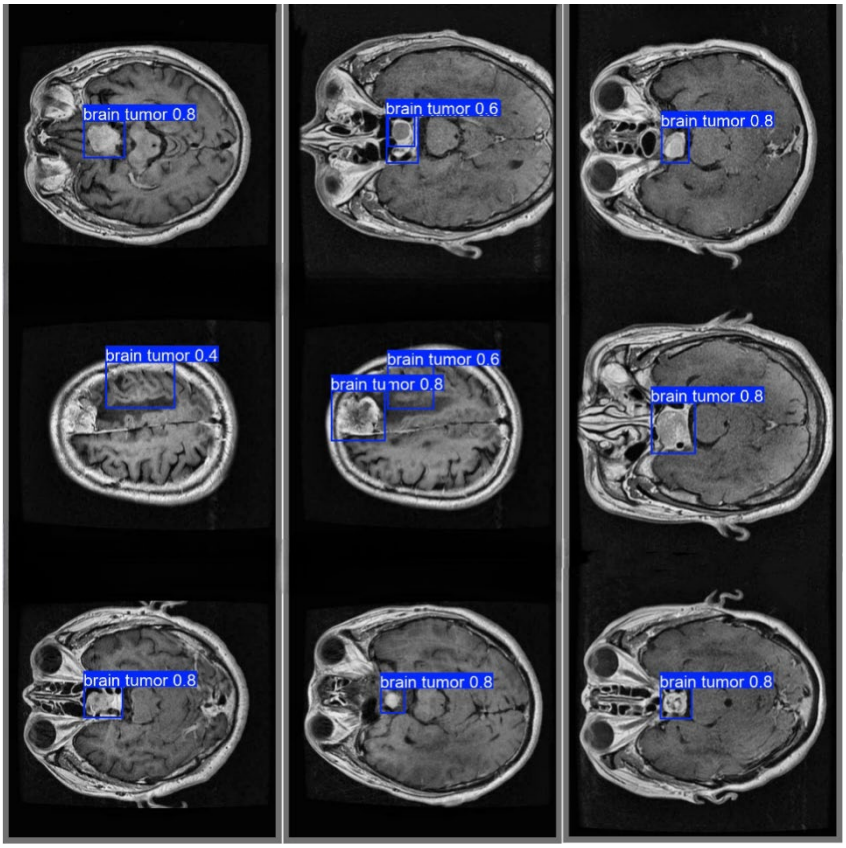

Figure 4. YOLOv8 Validation Set Brain Tumor Detection Results

4. Conclusion and Outlook

4.1 Conclusion

Brain tumors are a high-mortality malignancy that poses a significant threat to patient health. Traditional diagnostic methods, primarily relying on medical imaging (e.g., MRI and CT) and physicians' judgments, are time-consuming and prone to subjectivity, increasing the risk of misdiagnosis and missed

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diagnoses. With the rapid development of AI and deep learning, particularly in object detection algorithms, new solutions for medical image analysis have emerged. This study explores automated brain tumor detection using the YOLOv8m model, aiming to improve detection efficiency and accuracy to support clinical diagnosis.

The research employs YOLOv8m due to its enhanced network structure and advanced algorithm features, targeting complex brain tumor imaging data. Using a high-quality labeled dataset from Kaggle and various data augmentation techniques, the model showed excellent performance in precision, recall, and mAP@0.5:0.95, validating YOLOv8m's application in brain tumor detection. The results demonstrate its high accuracy and low false-negative rate, offering effective technical support for automated brain tumor detection.

This study also emphasizes the vast potential of deep learning techniques in analyzing medical images, offering new perspectives and practical foundations for future research in brain tumor detection and other medical imaging fields.

4.2 Outlook

Although this study has shown promising results in brain tumor detection, there are some limitations. The dataset is relatively small and lacks diversity, which may affect the model's generalization, particularly in complex clinical scenarios. Additionally, the use of general data augmentation and basic optimization methods, without specific fine-tuning for brain tumor images, may impact the detection of small or complex lesions. The model's inference speed and computational resource requirements also need optimization for real-time clinical use.

Future efforts should prioritize increasing the dataset size, integrating multimodal imaging data, and refining feature extraction methods. Additionally, improving the model's efficiency and exploring multitask or transfer learning could enhance performance in small-sample scenarios. These advancements will contribute to more efficient and accurate solutions for automated brain tumor detection, aiding clinical applications.

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