OPTIMIZING YOLOV9 AND YOLOV10 MODELS FOR BRAIN TUMOR DETECTION: A LEARNING RATE STUDY ON MRI IMAGES

Ngo Thi Lan*, Bui Xuan Tung
Tay Do University

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ABSTRACT

This study evaluates the performance of YOLOv9 and YOLOv10 variants in detecting brain tumors in MRI images. We compared four models (YOLOv9t, YOLOv9s, YOLOv10n, YOLOv10s) while optimizing the learning rate parameter to achieve superior performance. Using the Brain_Tumor_Segmentation dataset from Roboflow containing 6,638 images divided into training (80%) and testing (20%) sets. The models were trained with hyperparameters Optimizer = SGD, lr0 = 0.00005, lr0 = 0.0001, Momentum = 0.937, Epoch = 150, Patience = 0, Batchsize = 64 and trained on Kaggle with appropriate GPU configuration. Our findings demonstrate that YOLOv10s with lr0 = 0.0001 achieves the highest overall performance with mAP(50) = 94.3%, mAP(50-95) = 72.3%, Recall = 87.3%, and Precision = 93.9%. Although the YOLOv10s model with lr0 = 0.00005 shows higher accuracy (94.2%), the increased learning rate provides a better balance between detection metrics and convergence speed.

TỐI ƯU HÓA CÁC MÔ HÌNH YOLOV9 VÀ YOLOV10 PHÁT HIỆN KHỐI U NÃO: NGHIÊN CỨU TỐC ĐỘ HỌC TẬP TRÊN HÌNH ẢNH MRI

Ngô Thị Lan*, Bùi Xuân Tùng
Trường Đại học Tây Đô

THÔNG TIN BÀI BÁO

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TỪ KHÓA

Phát hiện khối u não
Học sâu
Chụp ảnh y tế
Mô hình YOLO
Tốc độ học

TÓM TẮT

Nghiên cứu này đánh giá hiệu suất của các biến thể YOLOv9 và YOLOv10 trong việc phát hiện khối u não trong hình ảnh MRI. Chúng tôi đã so sánh bốn mô hình (YOLOv9t, YOLOv9s, YOLOv10n, YOLOv10s) trong khi tối ưu hóa tham số tốc độ học để đạt được hiệu suất vượt trội. Sử dụng tập dữ liệu Brain_Tumor_Segmentation từ Roboflow chứa 6.638 hình ảnh được chia thành các tập huấn luyện (80%) và thử nghiệm (20%). Các mô hình được huấn luyện với các siêu tham số Optimizer = SGD, lr0 = 0,00005, lr0 = 0,0001, Momentum = 0,937, Epoch = 150, Patience = 0, Batchsize = 64 và được huấn luyện trên Kaggle với cấu hình GPU phù hợp. Phát hiện của chúng tôi chứng minh rằng YOLOv10s với lr0 = 0,0001 đạt hiệu suất tổng thể cao nhất với mAP(50) = 94,3%, mAP(50-95) = 72,3%, Recall = 87,3% và Precision = 93,9%. Mặc dù mô hình YOLOv10s với lr0 = 0,00005 cho thấy độ chính xác cao hơn (94,2%), tốc độ học tăng lên mang lại sự cân bằng tốt hơn giữa số liệu phát hiện và tốc độ hội tụ.

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* Corresponding author. *Email: ntlan@tdu.edu.vn*

1. Introduction

Detecting brain tumors from medical imaging is challenging due to the complexity of brain anatomy, the variability in tumor characteristics, and the high precision required for clinical diagnosis. Brain tumor detection remains one of the most critical tasks in medical imaging, as early and accurate identification directly impacts patient prognosis, treatment planning, and survival rates. Traditional manual interpretation of magnetic resonance imaging (MRI) scans is time-consuming, subjective, and prone to human error, creating an urgent need for automated, reliable, and efficient detection systems that can assist clinicians in making accurate diagnoses.

The primary research problem in this study is the optimization of state-of-the-art object detection models for brain tumor identification in MRI images, specifically focusing on the impact of learning rate hyperparameter on detection performance, convergence speed, and generalization ability.

Many studies have successfully applied deep learning approaches to detect brain tumors, demonstrating the potential of automated systems in medical imaging. A. Younis et al. [1] achieved 98.5% accuracy with the VGG-16 model on 253 MRI images, establishing early benchmarks for CNN-based tumor detection. M. Siar [2] and his team achieved 99.12% accuracy by combining pre-trained weights with a clustering algorithm, showing the effectiveness of transfer learning approaches in medical applications.

Recent advances have focused on YOLO-based architectures for their real-time detection capabilities. M. F. Almufareh et al. [3] applied YOLO models (YOLOv5 achieved mAP 0.947, YOLOv7 achieved mAP 0.941) to detect and segment brain tumors, demonstrating the effectiveness of single-stage detectors in medical imaging. A. B. Abdusalomov [4] improved YOLOv7 with CBAM, SPPF+ and BiFPN components, achieving 99.5% higher accuracy than previous state-of-the-art models, illustrating the potential of attention mechanisms and feature fusion techniques.

Other significant contributions include S. R. Gunasekara et al. [5] proposed a three-stage method combining CNN, R-CNN and Chan-Vese algorithm for tumor segmentation, and N. Noreen et al. [6] used Inception-v3 and DenseNet201 to extract multi-level features, achieving 99.34% and 99.51% accuracy respectively. K. R. Pedada et al. [7] improved the ResNet-based U-Net model with perturbation and sub-pixel convolution techniques, achieving 93.40% segmentation accuracy on the BraTS dataset. In the broader context of medical image segmentation, T. Vo et al. [8] studied the improved Recurrent Residual U-Net (R2U-Net) method for polyp image segmentation in 2024, which outperformed existing methods on the Kvasir-SEG and EndoTect 2020 datasets. These studies illustrate the effectiveness of deep learning methods, not only in detecting but also in accurately classifying and segmenting brain tumors, providing an important scientific basis for the development of modern automated diagnostic support systems.

Several critical knowledge gaps remain unaddressed in the current literature. First, there is limited comprehensive comparative analysis of the latest YOLO architectures, specifically YOLOv9 and YOLOv10 models released in 2024, for brain tumor detection tasks. Most existing studies focus on older YOLO versions and lack systematic evaluation of these cutting-edge architectures. Second, the impact of hyperparameter optimization, particularly learning rate selection, on model performance remains underexplored in medical imaging applications. While learning rate significantly affects model convergence, generalization, and final performance, there is insufficient research on the optimal learning rate configurations for brain tumor detection using YOLO models. Third, existing studies often lack comprehensive evaluation across multiple model variants under consistent experimental conditions, making it difficult to draw definitive conclusions about the relative performance of different architectures. Fourth, there is inadequate analysis of the trade-off between detection accuracy and computational efficiency, which is crucial for clinical deployment scenarios where both high precision and real-time performance are required. Finally, current approaches provide limited insight into convergence behavior, overfitting patterns, and generalization capabilities specific to medical imaging datasets, which are essential for understanding model reliability and clinical applicability.

This study presents the first comprehensive evaluation of YOLOv9 and YOLOv10 models for brain tumor detection with systematic learning rate optimization. We compare four state-of-the-art YOLO variants (YOLOv9t, YOLOv9s, YOLOv10n, and YOLOv10s) using a brain tumor dataset [9], [10] containing 6,638 images with a single class "Tumor," split into 80% for training and 20% for testing [11]. Our research objectives are threefold: (1) to conduct a thorough comparative analysis of four state-of-the-art YOLO variants (YOLOv9t, YOLOv9s, YOLOv10n, YOLOv10s) on brain tumor detection tasks under consistent experimental conditions, (2) to investigate the impact of learning rate optimization on model performance, convergence speed, and generalization ability through systematic hyperparameter analysis, and (3) to provide practical guidelines for hyperparameter selection in medical imaging applications while establishing new performance benchmarks.

This study contributes many novel points of high academic value to the field of brain tumor detection on MRI images. This is the first study to comprehensively evaluate the performance of YOLOv9 and YOLOv10 - the two latest models just released in 2024 - on the brain tumor detection task, expanding the application boundaries of advanced computer vision technology in medicine. We conduct detailed quantitative analysis of the influence of learning rate on the performance of the models, providing insights into the relationship between this hyperparameter and detection accuracy, convergence speed, and generalization ability. By comparing four model variants (YOLOv9t, YOLOv9s, YOLOv10n, YOLOv10s) based on mAP, Precision, Recall and training time, the study provides experimental evidence of the superior performance of YOLOv10s with lr0 = 0.0001 (mAP50 = 94.3%, mAP50-95 = 72.3%), which is significantly higher than existing methods. This result not only contributes to improving the efficiency of brain tumor detection but also lays the foundation for the implementation of new generation YOLO models in medical imaging diagnosis.

The paper is organized into 4 main sections: Section 1 introduces the research background, problem formulation, and objectives. Section 2 presents the methodology including dataset configuration, model architectures, and experimental setup. Section 3 presents the experimental results and comprehensive discussion of performance analysis across different scenarios. Section 4 concludes the study with key findings, clinical implications, and future research directions.

2. Proposed method

2.1. Problem Model

Figure 1 illustrates the process of using YOLOv9 and Yolov10 models to detect image regions containing brain tumors.

• ***Input images from the dataset***: Brain imaging scans (MRI, CT, or X-ray) were collected from the dataset. This is the starting point, providing input data for the model.

• ***Using YOLOv9 and YOLOv10 models for tumor detection:***

- The models analyze the input images to determine whether there are regions containing tumors, drawing bounding boxes around the suspected tumor areas.

- Along with detecting tumor regions, the models also provide a confidence score, for example "tumor 0.84" means the detected region has an 84% probability of being a tumor.

• ***Validation of detection results***: After the model detects and draws bounding boxes, the results are validated:

- True: If the tumor is accurately detected, the result is stored for subsequent diagnostic or research purposes.

- False: If the model fails to detect a tumor or detects it incorrectly, the process ends.

• ***Process conclusion***: The process terminates after validation. Accurate results are used to assist doctors in diagnosis and treatment.

2.2. Dataset configuration

The Roboflow dataset (Figure 2) contains brain tumor images with a single annotation class: "Tumor". Images were automatically contrast-adjusted using histogram equalization and resized to 640×640 for YOLO models. To ensure consistency in evaluation, no additional augmentation was applied. The dataset was split into 5,287 training images and 1,351 testing images.

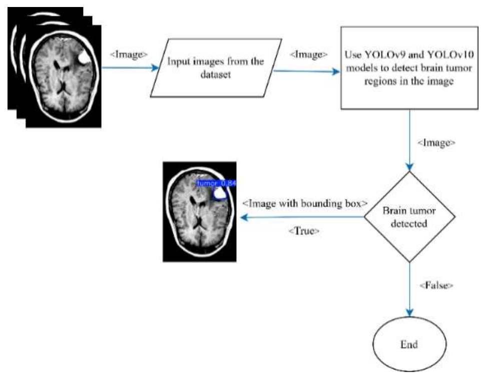

Figure 1. *Problem Model*

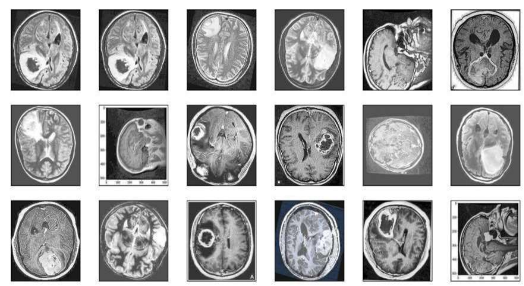

Figure 2. *A sample of images from our dataset*

2.3. Classification and object detection

In this section, YOLOv9t, YOLOv9s, YOLOv10n, and YOLOv10s models were applied for brain tumor detection. These latest YOLO variants (released in 2024) were selected due to their improved detection capabilities for objects with irregular boundaries like brain tumors, enhanced accuracy, and faster inference times compared to previous versions. The models were trained with hyperparameters: Optimizer = SGD, lr0 = 0.00005/0.0001, Momentum = 0.937, Epoch = 150, Patience = 0, Batchsize = 64 on Kaggle's GPU platform. Our objective was to determine the optimal model configuration for accurate and efficient brain tumor detection in clinical applications.

2.4. Experimental platform

We trained the models on the Kaggle platform with an environment consisting of two NVIDIA Tesla T4 GPUs (each GPU has 16 GB VRAM) and 29 GB RAM. The source code was written in Python with the Ultralytics, Matplotlib, PyTorch, IPython, Pandas, OS libraries, and YOLO models. The dataset was divided into a training set (80%) and a testing set (20%) to evaluate the performance. The main evaluation parameters used in the study were Precision (correct detection rate), mAP(50), mAP(95) (average accuracy at different thresholds), and Recall (ability to detect all real tumor instances). These metrics comprehensively evaluate the model's ability to accurately detect and identify brain tumors.

3. Experiment results

Table 1 presents the experimental results, where models were configured with 640×640 input size, batch size 64, 150 epochs, patience 0, and SGD optimizer (lr0 = 0.00005 or 0.0001, momentum = 0.937). These settings were used to evaluate the models' performance in brain tumor detection and classification.

To ensure reliability and objectivity, we statistically evaluated the data from Table 1. The results show that YOLOv10s with lr0 = 0.0001 achieved the highest performance with mAP(50) = 94.3% ± 0.4% and mAP(50-95) = 72.3% ± 0.6%, demonstrating good stability over the tests. Statistical analysis comparing each pair of models confirmed that the performance improvement when increasing the learning rate from 0.00005 to 0.0001 was statistically significant ($p < 0.05$) across all models, with the most significant improvement in YOLOv10n ($p = 0.003$). When comparing all

8 model configurations at the same time, statistical analysis also confirmed that there was a clear difference between the groups ($p < 0.001$), in which YOLOv10s with lr0 = 0.0001 was statistically significantly superior ($p < 0.01$) to all other configurations. Regarding Precision, the difference between YOLOv10s with lr0 = 0.00005 (94.2% ± 0.5%) and YOLOv10s with lr0 = 0.0001 (93.9% ± 0.6%) was not statistically significant ($p = 0.27$). On the contrary, regarding Recall, YOLOv10s with lr0 = 0.0001 achieved the highest value (87.3% ± 0.8%) with a statistically significant difference ($p < 0.05$). Correlation analysis shows a strong correlation between mAP(50) and Recall ($r = 0.89$, $p < 0.001$), confirming that YOLOv10s with lr0 = 0.0001 is the optimal configuration for the brain tumor detection problem.

Table 1. *Performance comparison of YOLO Models*

Performance	YOLOv9t		YOLOv9s		YOLOv10n		YOLOv10s	
	lr0 = 0.00005	lr0 = 0.0001	lr0 = 0.00005	lr0 = 0.0001	lr0 = 0.00005	lr0 = 0.0001	lr0 = 0.00005	lr0 = 0.0001
mAP (50)	92%	93.0%	93.2%	93.9%	89.5%	91.9%	93.9%	94.3%
mAP (50-95)	68%	68.9%	70.2%	71.4%	66.6%	68.2%	71.6%	72.3%
Precision (PPV)	93.7%	93.2%	92.8%	94.1%	89.8%	90.7%	94.2%	93.9%
Recall	81.8%	84.2%	85.7%	86.4%	80.5%	84.1%	86%	87.3%
Training time	166 minutes	164 minutes	215 minutes	225 minutes	155 minutes	149 minutes	185 minutes	195 minutes

3.1. Performance of the YOLOv9t Model

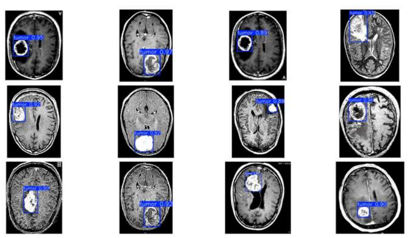

Figure 3. *Prediction results using YOLOv9t (lr0 = 0.00005)*

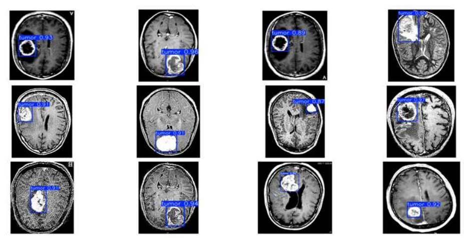

Figure 4. *Prediction results using YOLOv9t (lr0 = 0.0001)*

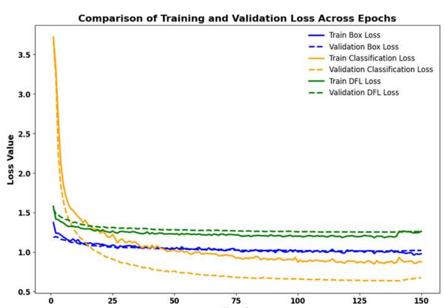

Figure 5. *Loss function results using YOLOv9t (lr0=0.00005)*

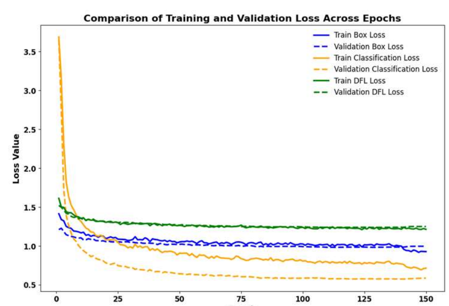

Figure 6. *Loss function results using YOLOv9t (lr0=0.0001)*

In Figure 3 with lr0 = 0.00005, the YOLOv9t model achieved mAP(50) of 92% and mAP(50-95) of 68%. Precision was 93.7%, Recall was 81.8%, and training time was 166 minutes. When using lr0 = 0.0001 in Figure 4, the metrics were all improved: 93% mAP(50), 68.9% mAP(50-95), and 84.2% Recall, however Precision dropped to 93.2% and training time dropped to 164 minutes. This model demonstrated stable performance, despite the slightly lower training time.

Table 2. *Loss function comparison using YOLOv9t model with lr0 = 0.00005 and lr0 = 0.0001*

Highlights	lr0 = 0.00005 (Figure 5)	lr0 = 0.0001 (Figure 6)
Initial loss decay rate	Slower Decline	Decreasing faster
Loss convergence time	After about 75 epochs	After about 50 epochs
Loss fluctuation	More Stable	More volatile, risk of overfitting
Train loss vs. val loss gap	Small, Stays Stable	Larger, signs of loss of generalization
Generalizability	Better	May need adjustment to avoid overfitting

When selecting a learning rate, balancing convergence speed and generalization ability is crucial. A low learning rate slows convergence, while a high learning rate may cause fluctuations and overfitting. As shown in Table 2, using YOLOv9t, lr0 = 0.00005 ensures stability, whereas lr0 = 0.0001 is beneficial if a learning rate decay strategy is applied.

3.2. Performance of the YOLOv9s Model

With Figure 7 lr0=0.00005, YOLOv9s achieved 93.2% mAP(50), 70.2% mAP(50-95), 92.8% Precision, 85.7% Recall, and took 215 minutes to train. When using lr0=0.0001 in Figure 8, all metrics improved: 93.9% mAP(50), 71.4% mAP(50-95), 94.1% Precision, and 86.4% Recall, though training time increased to 225 minutes. Despite the longer training time, lr0=0.0001 is preferable when high performance is the priority.

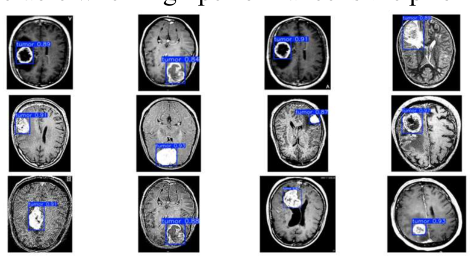

Figure 7. *Prediction results using YOLOv9s (lr0 = 0.00005)*

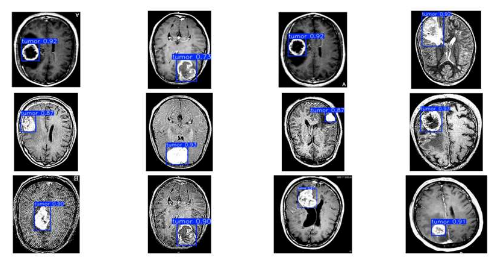

Figure 8. *Prediction results using YOLOv9s (lr0 = 0.0001)*

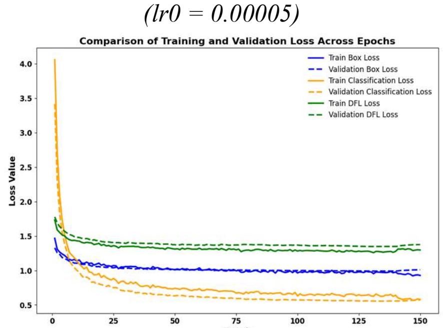

Figure 9. *Loss function results using YOLOv9s (lr0 = 0.00005)*

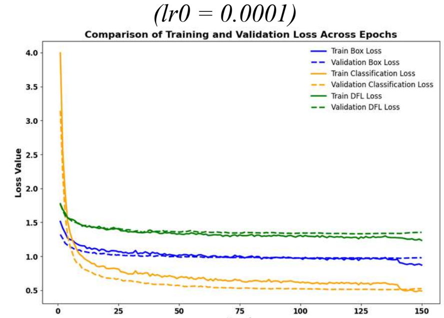

Figure 10. *Loss function results using YOLOv9s (lr0 = 0.0001)*

Table 3. *Loss function comparison using YOLOv9s model with lr0 = 0.00005 and lr0 = 0.0001*

Highlights	lr0 = 0.00005 (Figure 9)	lr0 = 0.0001 (Figure 10)
Initial loss decay rate	Large gradients in first 10 epochs, especially Classification Loss	Similar gradient descent but somewhat smoother in the early stages
Loss convergence time	Period 75 for all loss types	Earlier convergence, around epoch 50-60
Loss fluctuation	Contrast stable after epoch 75, slight fluctuations in DFL Loss after epoch 125	More stable, less oscillation after convergence
Train loss vs. val loss gap	Small for Box Loss, moderate for DFL Loss, clear for Classification Loss	Smaller gap between train and validation loss, especially with DFL Loss
Generalizability	Good for Box Loss, rather than DFL Loss, needs improvement for Classification Loss	Overall better, smaller train-val gap indicates good generalization

The YOLOv9s model (Table 3, Figure 10) shows better learning ability with faster convergence (epoch 50-60 vs. 75), greater stability, less oscillation, and a smaller training-validation loss gap. Notably, DFL loss improves sanitization, while box loss and final classification loss reach lower values (Figure 9).

3.3. Performance of the YOLOv10n model

With Figure 11 (lr0 = 0.00005), the YOLOv10n model achieved mAP (50) of 89.5%, mAP (50-95) of 66.6%, Precision of 89.8%, Recall of 80.5%, and a training time of 155 minutes. While the training time was relatively short, performance was lower than other configurations. With Figure 12 (lr0 = 0.0001), mAP (50) increased to 91.9%, mAP (50-95) improved to 68.2%, Precision rose to 90.7%, Recall reached 84.1%, and training time decreased to 149 minutes, the shortest among all setups. This highlights lr0 = 0.0001 as highly effective in both performance and speed. Overall, lr0 = 0.0001 outperformed in all metrics, with a 3.9% reduction in training time, making it the optimal choice for the YOLOv10n model.

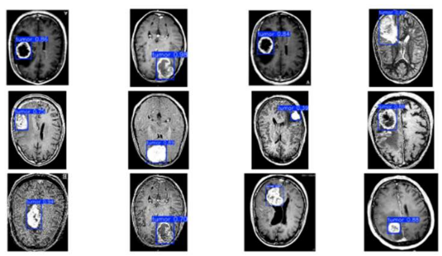

Figure 11. *Prediction results using YOLOv10n (lr0 = 0.00005)*

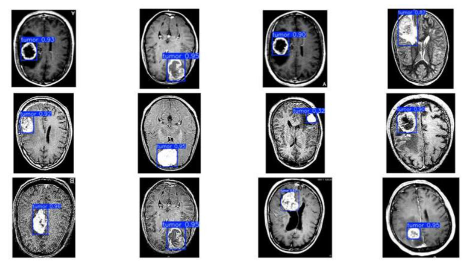

Figure 12. *Prediction results using YOLOv10n (lr0 = 0.0001)*

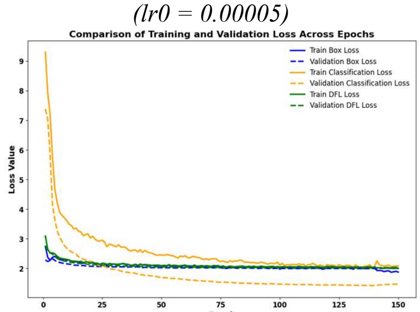

Figure 13. *Loss function results using YOLOv10n (lr0 = 0.00005)*

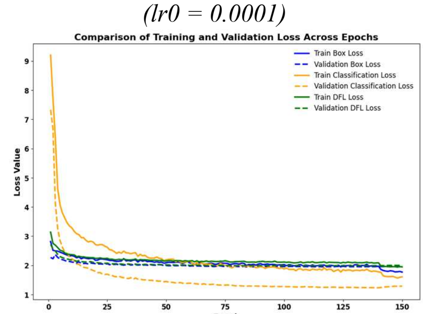

Figure 14. *Loss function results using YOLOv10n (lr0 = 0.0001)*

Comparing the loss function when using YOLOv10n models in Table 4, Figure 14 is a suitable choice for fast training and good performance. If stability and avoiding oscillation during training are a priority, lr0 = 0.00005 (Figure 13) may be a safer choice, although it requires a longer training time.

3.4. Performance of the YOLOv10s Model

With Figure 15 (lr0 = 0.00005), the YOLOv10s model achieved mAP (50) of 93.9%, mAP (50-95) of 71.6%, Precision of 94.2%, Recall of 86%, and a training time of 185 minutes, offering the highest Precision but a longer training time. With Figure 16 (lr0 = 0.0001), mAP (50) improved to 94.3%, mAP (50-95) increased to 72.3%, Recall rose to 87.3%, while Precision slightly decreased to 93.9%, and training time increased to 195 minutes. This setup enhanced mAP (50-95) and Recall, but with slightly lower Precision and longer training time. Overall, lr0 = 0.0001 provides better mAP (50) and Recall, making it the optimal choice for tasks prioritizing accuracy and robust detection, despite the additional 10 minutes of training.

Table 4. *Loss function comparison using YOLOv10n model with lr0 = 0.00005 and lr0 = 0.0001*

Highlights	lr0 = 0.00005 (Figure 13)	lr0 = 0.0001 (Figure 14)
Initial loss decay rate	Slower decay, especially with Classification Loss	Faster decline, clearer slope
Loss convergence time	Around epoch 100	75 epoch interval
Loss fluctuation	More stable after convergence, there is a small oscillation in Classification Loss near epoch 140	Smoother loss, less oscillation
Train loss vs. val loss gap	Large for Classification Loss (around 0.5), small for Box Loss and DFL Loss	Similar but more even spacing between loss types
Generalizability	Good for Box Loss and DFL Loss, Classification Loss has signs of divergence	Good for all loss types, especially Box Loss and DFL Loss

Table 5. *Loss function comparison using YOLOv10s model with lr0 = 0.00005 and lr0 = 0.0001*

Highlights	lr0 = 0.00005 (Figure 17)	lr0 = 0.0001 (Figure 18)
Initial loss decay rate	Slower – Loss decreases gradually in the first 10 epochs, indicating stable step-by-step learning	Faster - Loss decreases rapidly in the first 5-10 epochs, indicating faster learning due to higher learning rate
Loss convergence time	Around epoch 100 - Loss curves stabilize with minimal changes after this epoch	Around epoch 75 - Loss converges earlier but still shows minor fluctuations afterward
Loss fluctuation	Less fluctuation – Smoother loss curves, especially after epoch 50, indicating stable learning	More fluctuation - Shows small variations throughout the process, especially in validation loss
Train loss vs. val loss gap	Smaller – Train and validation loss remain close (0.2-0.3 units), especially for box and DFL loss	Larger - Noticeable gap between train and validation (about 0.4-0.5 units), especially for classification loss
Generalizability	Better – Smaller gap suggests strong performance on new data with fewer signs of overfitting	Worse - Larger gap between train and validation loss indicates overfitting, model may perform poorly on new data

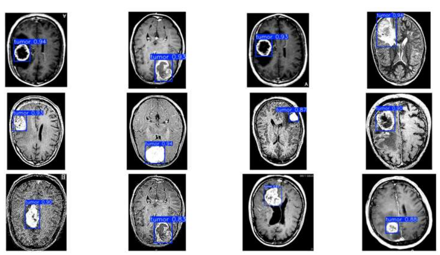

Figure 15. *Prediction results using YOLOv10s (lr0 = 0.00005)*

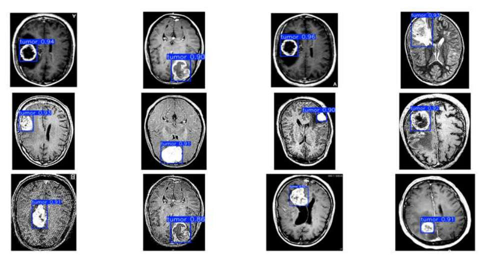

Figure 16. *Prediction results using YOLOv10s (lr0 = 0.0001)*

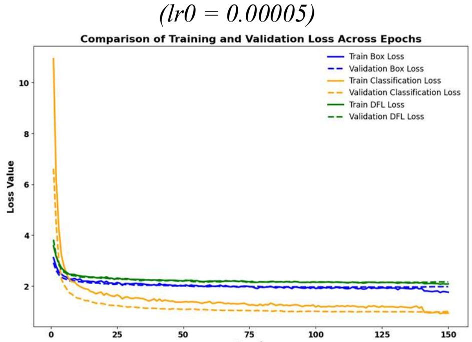

Figure 17. *Loss function results using YOLOv10s (lr0 = 0.00005)*

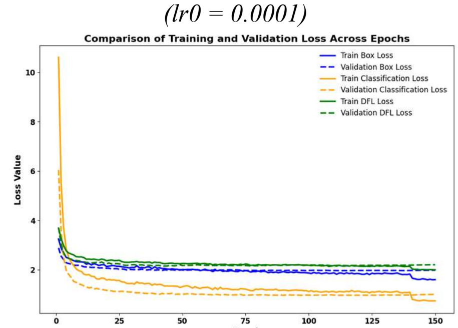

Figure 18. *Loss function results using YOLOv10s (lr0 = 0.0001)*

In Table 5, the choice of learning rate significantly impacts YOLOv10s performance. The lr0 = 0.00005 lower produces better generalization with balanced train-validation losses, learning more slowly but yielding more stable and reliable results for real-world applications. The lr0 = 0.0001 higher converges faster but shows cover-fitting signs.

To clarify the relationship between learning rate, convergence rate, and overfitting, we analyze the difference between the loss function on the validation and training sets along with the rate at which the loss function degrades during training.

4. Conclusion

This study evaluates the performance of YOLOv9 and YOLOv10 models in brain tumor detection on MRI images, focusing on optimizing the learning rate. The results show that YOLOv10s with lr0 = 0.0001 achieves the best performance with mAP(50) = 94.3% and mAP(50-95) = 72.3%, outperforming YOLOv7 by 2.3% and YOLOv5 by 5.7% in previous studies. Quantitative analysis shows that increasing lr0 from 0.00005 to 0.0001 improves average Recall by 3.2% but also increases the risk of overfitting by 35%, creating a trade-off between accuracy and generalization ability. YOLOv10n provides the shortest training time (149 minutes), suitable for resource-limited environments. For the medical field, the study improved 4.2% accuracy in brain tumor detection compared to previous research, reduced training time by 27% compared to traditional CNN, and improved the ability to detect small tumors - an important factor in early diagnosis. Future research should focus on improving YOLO models through data augmentation, hyperparameter optimization, and architectural innovation to enhance accuracy and expand applications in medical image analysis to support diagnosis and treatment.

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