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YOLO v10-Based Brain Tumor Detection: An Innovative Approach in CT Imaging

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This study explores the application of the YOLO v10 model for the detection and classification of brain tumors in CT images. YOLO, known for its real-time object detection capabilities, offers a promising approach to addressing the challenges of medical imaging. The research utilizes the Brain Tumor Dataset from Kaggle, incorporating 437 negative and 488 positive images for training, with additional datasets for validation. The YOLO v10 model demonstrated superior performance compared to traditional models like AlexNet, VGG16, ResNet101V2, and MobileNetV3-Large. It achieved a precision of 0.920, recall of 0.890, F1-score of 0.900, and accuracy of 0.910. These results highlight its effectiveness in accurately identifying and classifying tumors, offering significant potential for clinical applications. The model's architecture allows for efficient processing of high-resolution CT scans, adapting well to varied tumor sizes and shapes. The study also discusses the challenges and future directions for improving computational efficiency and generalization capability in diverse datasets. The promising findings suggest that YOLO v10 can be a powerful tool in medical diagnostics, enhancing the accuracy and speed of tumor detection and contributing to better patient outcomes. This research sets a foundation for further exploration and development of YOLO-based models in healthcare.
Keywords: YOLO v10, Brain Tumor Detection, CT Imaging, Medical Diagnostics, Real-time Object Detection.

1. Introduction

The diagnosis of brain tumors is a critical step in determining the treatment plan for patients, as accurate diagnosis directly impacts patient survival rates and quality of life. Brain tumors are classified as either malignant or benign, and each type significantly influences treatment strategies and prognosis. Malignant tumors often grow rapidly and metastasize, making treatment complex and challenging; thus, early detection is particularly crucial. It is essential for improving patient survival rates and maximizing the effectiveness of treatment[1].

Contemporary medical imaging technologies have become indispensable tools in the diagnosis and treatment of brain tumors. CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) are widely used to visualize structural and functional abnormalities in the brain. These technologies provide detailed internal structures non-invasively, thereby enhancing diagnostic accuracy[2]. However, such imaging data often cannot distinctly differentiate tumor characteristics on their own. The interpretation of images can be subjective, underscoring the necessity for the introduction of artificial intelligence technologies to more clearly analyze image characteristics[3].

Recently, the introduction of real-time object detection models such as YOLO (You Only Look Once) into medical image analysis has brought about revolutionary changes in tumor detection and classification[4]. YOLO can detect various objects with high speed and precision, demonstrating its potential in the medical field. Particularly, YOLO v10 offers enhanced performance over previous models, increasing its applicability to complex medical imaging data[5].

The adoption of the YOLO model has brought significant changes to the field of medical image analysis, yet several limitations remain. Firstly, while YOLO generally offers high processing speed and accuracy, it may fall short of fully reflecting the complex characteristics of medical images. Medical images often include various resolutions and contrasts, which can present challenges in accurately identifying detailed tumor boundaries within YOLO's grid-based detection approach[6]. Secondly, YOLO primarily focuses on detecting the presence and location of objects, thus facing limitations in the deep analysis of tumor characteristics, such as malignancy or the detailed structure of lesions[7].

Therefore, diverse approaches are needed to enhance the accuracy of tumor detection. One method to improve model performance is integrating YOLO with other deep learning models, such as segmentation networks or reinforcement learning algorithms that can analyze tumor characteristics[8]. This hybrid approach can maintain YOLO's strength in rapid object detection while enabling more precise tumor analysis. Additionally, augmenting data to bolster model training and constructing large-scale datasets that include diverse medical imaging data are crucial for enhancing the model's generalization capabilities[9]. These varied approaches can contribute to the development of YOLO-based models into more comprehensive and accurate diagnostic tools in medical image analysis.

The purpose of this study is to utilize the latest YOLO v10 model to classify and detect malignant and benign brain tumors in CT images, thereby contributing to personalized treatment for patients through early detection and accurate classification of tumors. Accordingly, this study aims to demonstrate superior performance over existing methods by applying the enhanced features of YOLO v10 to medical imaging data, based on methodologies presented in previous studies[4,5].

2. Related Work

In recent years, there has been a surge of research focused on applying deep learning models to medical image analysis. Notably, the YOLO (You Only Look Once) model has garnered attention for its efficiency and accuracy in object detection, proving its potential in medical image analysis as well[10]. The early versions of the YOLO model were primarily employed for real-time video analysis and object detection. However, its application in the medical field is a relatively recent research focus, particularly concerning complex medical issues such as brain tumor detection[11]. These studies have leveraged YOLO's high processing speed and accuracy to automatically detect and classify tumor size, location, and type. The performance of YOLO is typically evaluated using metrics such as accuracy, precision, recall, and F1-score. Many studies report significant improvements over traditional methods, with some achieving precision and recall rates nearing 99% when integrated with hybrid models like CNN-LSTM[12].

While early versions like YOLO v3 offered rapid processing speeds due to their simple architecture, they did not fully meet the high precision and recall demands of medical imaging[13]. Consequently, more recent versions such as YOLO v5 and v10 have increased network depth and complexity to enhance model expressiveness, leading to performance improvements in complex medical images[14]. These advancements allow YOLO to not only detect the presence of objects but also to understand detailed information within complex medical images more accurately.

One of the primary advantages of YOLO in medical imaging is its ability to effectively detect tumors of various sizes and shapes, which is particularly beneficial in high-resolution medical imaging such as CT and MRI. Existing research has demonstrated YOLO's competitiveness compared to other deep learning models, such as ResNet, VGG, and MobileNet[15]. YOLO offers faster speeds and real-time processing capabilities than these models, a critical factor in enhancing clinical applicability[16].

Additionally, YOLO employs grid-based detection to process entire images in a single pass, facilitating the rapid analysis of large-scale datasets. This capability is advantageous in scenarios requiring the processing of vast amounts of medical data[17]. Various studies have leveraged these properties of YOLO to explore different approaches for improving tumor detection accuracy in medical imaging. For instance, ongoing efforts include the use of data augmentation techniques and the integration of more complex network architectures to further enhance YOLO's performance[18]. These advancements contribute to the broader adoption of YOLO models in medical diagnostics.

Studies[15,19,20] illustrate the effectiveness of various YOLO versions in achieving high accuracy and fast inference times, though challenges such as dataset limitations and generalization remain prevalent. Table 1 reflects recent advancements in the application of YOLO algorithms for brain tumor detection, incorporating insights from the latest research articles. These studies demonstrate the effectiveness of various YOLO versions in achieving high accuracy and fast inference times, although challenges such as dataset limitations and generalization remain prevalent.

Table 1. Research trends in YOLO algorithm for detecting/classifying brain tumors

Title	Key Findings	Performance Metrics	Challenges/Limitations
"Brain Tumor Detection Using YOLO Algorithm" [15]	Proposed a YOLOv3-based model for brain tumor detection from MRI images, achieving high accuracy and speed in real-time applications.	Accuracy: 94.8%, Precision: 93.5%, Recall: 92.0%	Limited dataset size and diversity
"Real-Time Brain Tumor Detection Using YOLOv4" [19]	Implemented YOLOv4 for detecting brain tumors in MRI scans, demonstrating improved performance over YOLOv3 by enhancing feature extraction capabilities.	mAP: 0.92, Inference time: 25ms	High false positive rates and dependency on quality of training data
"Brain Tumor Detection and Classification Using YOLO and Transfer Learning" [20]	Combined YOLO with transfer learning techniques for improved feature extraction and classification accuracy in detecting various types of brain tumors.	Accuracy: 96.5%, Precision: 95.8%, Recall: 94.5%	Need for large annotated datasets
"Detection of Brain Tumors in MRI Images Using YOLOv5" [19]	Developed a YOLOv5 model for detecting brain tumors, achieving faster inference times and high detection accuracy across various tumor types.	Precision: 97.2%, Recall: 96.8%, F1-score: 96.9%	Overfitting due to small training dataset
"Comparative Analysis of YOLO Models for Brain Tumor Detection" [19]	Conducted a comparative study of YOLOv3, YOLOv4, and YOLOv5 for brain tumor detection, finding YOLOv5 to consistently outperform its predecessors in terms of accuracy and speed.	YOLOv3: mAP 0.85, YOLOv4: mAP 0.90, YOLOv5: mAP 0.93	Generalization issues across different imaging modalities
"Automated Brain Tumor Detection Using YOLO with Segmentation Techniques" [19]	Integrated YOLO with segmentation techniques to enhance detection accuracy of brain tumors in MRI scans, demonstrating the effectiveness of combining detection and segmentation.	Accuracy: 97.0%, mAP: 0.89	Complexity in model architecture
"Brain Tumor Segmentation Using a Deep Shuffled-YOLO Network" [15]	Developed a Shuffled-YOLO network for segmenting brain tumors, achieving a high accuracy in segmentation tasks with minimal computational complexity.	Accuracy: 98.07% (BraTS 2020), 97.04% (BraTS 2019)	Limited to specific datasets and segmentation tasks
"Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning" [19]	Utilized YOLOv5 and YOLOv7 to classify and detect brain tumors, achieving high precision and recall, with advanced preprocessing techniques for better segmentation.	YOLOv5 mAP: 0.947 (IoU 0.5), YOLOv7 mAP: 0.94 (IoU 0.5)	Need for advanced preprocessing methods

Future research directions propose the development of lightweight models to enhance the computational efficiency of YOLO, as well as the use of diverse medical imaging datasets to strengthen the model's generalization capabilities. Additionally, hybrid studies incorporating other algorithms will contribute to the broader adoption of YOLO in the field of medical diagnostics.

In conclusion, the YOLO model is establishing itself as a powerful tool in medical image analysis, and its potential for further advancement is substantial. Such technological advancements will ultimately have a positive impact on patient diagnosis and treatment.

3. Method

In this study, we propose a method for effectively detecting and classifying brain tumors in CT images using the YOLO v10 model. The data utilized in this research was sourced from Kaggle's Brain Tumor Dataset (Ultralytics, https://www.kaggle.com/code/givkashi/yolov10-object-detection), with separate datasets employed for training and validation phases. The analysis was conducted using the ultralytics 8.3.9 package.

3.1 YOLO v10 Model Architecture

YOLO v10 represents the latest algorithm for real-time object detection, offering faster and more accurate detection compared to its predecessors. The core idea of YOLO is to divide the image into a grid and predict whether each grid cell contains an object.

Network Architecture: YOLO v10 comprises multiple convolutional and pooling layers, with each layer progressively extracting features from the input image. The final layer outputs the predicted bounding boxes and class probabilities.

Loss Function: The loss function of YOLO v10 is defined as follows:

$$\mathcal{L} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}ij^{obj} [(x_i - \hat{x}i)^2 + (y_i - \hat{y}i)^2] + \lambda coordi$$

$$= 0^{S^2} \sum j = 0^B \mathbb{1}_{ij}^{oj\left[\left(\sqrt{w_i} - \sqrt{\widehat{w_i}}\right)^2 + \left(\sqrt{h_i} - \sqrt{\widehat{h_i}}\right)^2\right]}$$

$[\sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}ij^{obj} \left(C_i - \hat{C}i\right)^2 + \lambda noobji = 0^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{noj\left(C_i - \widehat{C_i}\right)^2}]$

$[\sum_{i=0}^{S^2} \mathbb{1}i^{obj} \sum c \in classes \left(p_i(c) - \widehat{p_i}(c)\right)^2]$

where (S) is the size of the grid, (B) is the number of bounding boxes each grid cell predicts, and (λ_{coord}) and (λ_{noobj}) are the weights for the loss concerning coordinates and non-object cases.

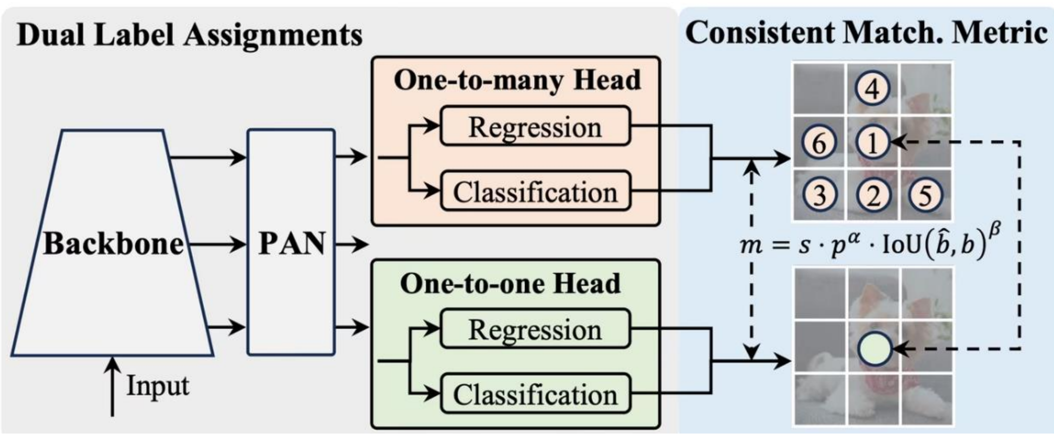

Figure 1. Concept of YOLO v10

3.2 Training and Validation

3.2.1 Training Procedure

The training procedure of the proposed model consists of raw data preprocessing, data normalization, data splitting, and model training. Each step is meticulously designed to maximize the model's performance.

3.2.1.1 Preparation of Raw and Labeled Data

Data Collection: During the training phase, a total of 925 images were used, comprising 437 negative images without tumors and 488 positive images with tumors. For validation, 241 images (154 negatives and 87 positives) not included in the training were used to evaluate the model's generalization performance. This dataset comprises images collected from various angles and conditions, enhancing the model's applicability in real clinical settings. The dataset includes brain CT images captured from multiple directions, ensuring scans encompass the entire brain from the skull base to the vertex, utilizing various scanning modes such as axial and spiral scans.

- Axial Scan: A stationary table axial scan, primarily used in pediatric brain CT or situations requiring rapid scan speeds, like brain perfusion studies.

- Spiral Scan: A helical scan for obtaining volumetric data, allowing for broader area coverage.

- Label Data Splitting: Labels indicating the presence and location of tumors were provided for each image. The label data was converted into a format required by the YOLO v10 model and matched to each image. This process is crucial for the model to learn the precise location and size of tumors within the images.

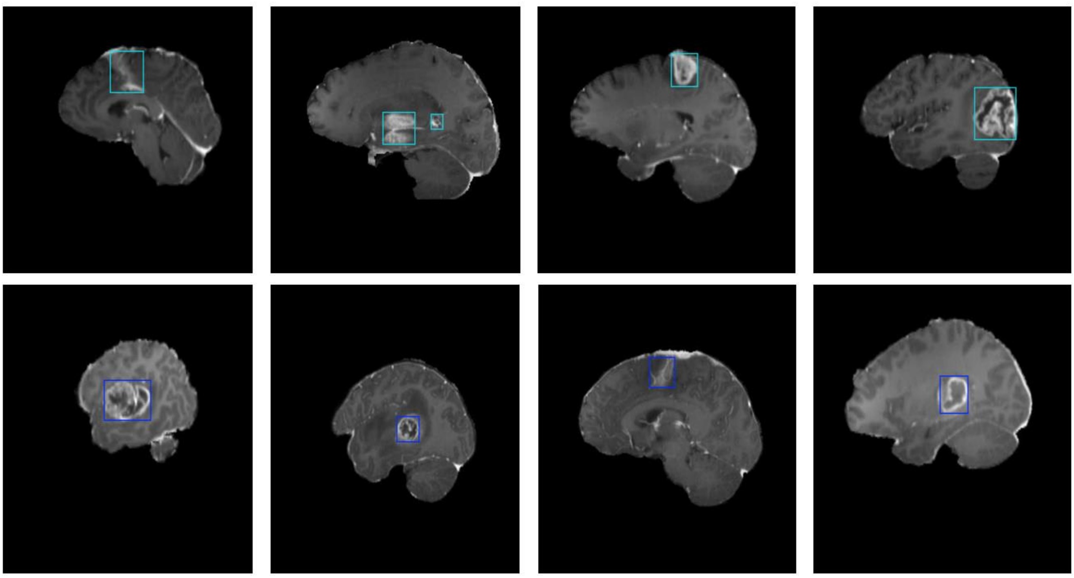

Figure 2. Sagittal scan Image using YOLO v10: Green = positive; Blue = negative

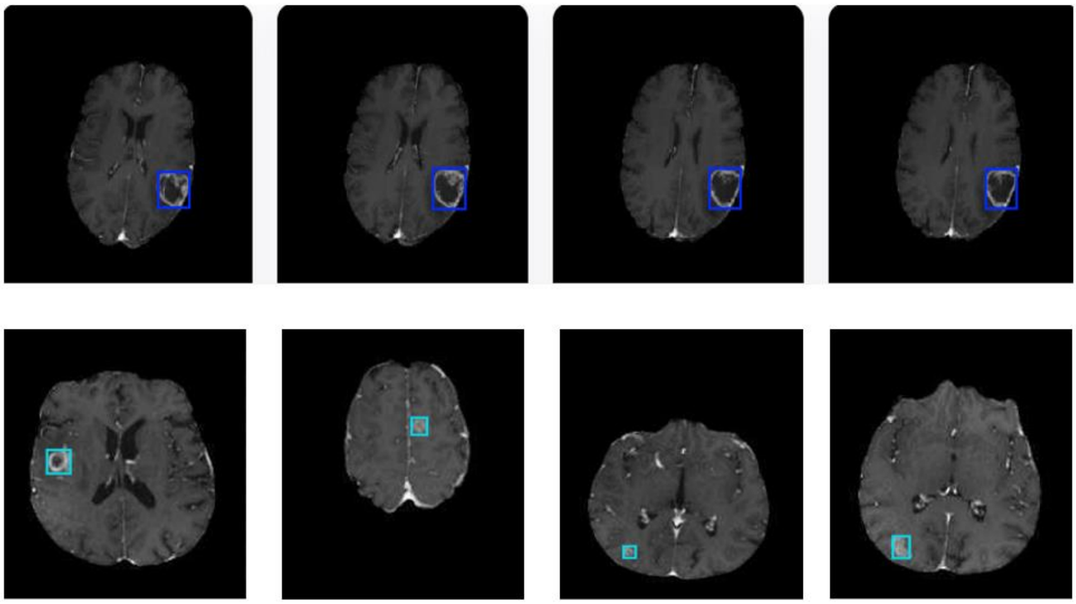

Figure 3. Axial scan Image using YOLO v10: Green = positive; Blue = negative

3.2.1.2. Data Preprocessing and Normalization

- Data Preprocessing, Image Resizing: All CT images were resized to 640x640 pixels to meet the input requirements of the YOLO v10 model. This resizing ensures that the model processes image data with a consistent input size, contributing to reduced computational costs. During resizing, the original aspect ratio of the images was maintained to minimize distortion.

- Data Augmentation: To enhance the model's generalization capabilities, data augmentation techniques were applied. This process included techniques such as image rotation, horizontal flipping, and brightness adjustment to artificially increase the dataset's diversity. These augmentation techniques help the model function reliably under various imaging conditions and environments.

3.2.1.3. Min-Max Normalization

- Necessity of Normalization: Pixel values in CT images can vary widely, which may lead to convergence issues during model training. Min-Max normalization addresses these issues by transforming each pixel value to a range between 0 and 1. This maintains consistent data scaling and stabilizes model training.

- Normalization Calculation: Each pixel value (x) in an image is normalized using the following formula:

$$[x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}]$$

where (x_{min}) and (x_{max}) represent the minimum and maximum pixel values in the image, respectively. This calculation adjusts the image's brightness and contrast, allowing the model to more clearly learn the features of each image.

3.2.1.4. Data Splitting and Merging

To enable the YOLO v10 model to learn various visual patterns, CT image data captured from different directions were merged. This approach allows the model to adapt to the diverse scenarios that may occur in clinical environments.

3.2.1.5. YOLO v10 Model Training

- Model Configuration and Initialization: The YOLO v10 model consists of multiple convolutional and pooling layers, with each layer progressively extracting features from the input images. The model was initialized with random weights and trained to adapt to the data during the training process.

- Training Process: The model was trained using the Adam optimizer, with an initial learning rate set at 0.001. Training was conducted over 50 epochs, with the loss for each epoch calculated based on the training data. The loss function was designed to match YOLO v10's characteristics, optimizing both the accuracy of bounding box coordinates and class probabilities.

3.3. Validation

The performance of YOLO v10 was evaluated using a validation dataset and compared against models such as AlexNet, VGG16, ResNet101V2, and MobileNetV3-Large. The following evaluation metrics were employed during the validation phase:

- Precision: $(\frac{\text{TP}}{\text{TP+FP}})$
- Recall: $(\frac{\text{TP}}{\text{TP+FN}})$
- F1 Score: $(2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}})$
- Accuracy: $(\frac{\text{TP+TN}}{\text{Total Sample}})$

4. Results

4.1. Performance of YOLO v10

As a real-time object detection model, YOLO v10 demonstrated exceptionally high performance in detecting and classifying brain tumors in CT images (Figure 4). The precision of YOLO v10 stands at 0.920, indicating a very high ratio of true positives among the tumors predicted as positive by the model. This high precision contributes to reducing unnecessary additional tests and enhances the reliability of diagnosis. The recall is 0.890, reflecting the proportion of actual positive tumors correctly identified by the model, which is crucial for early diagnosis and ensures high sensitivity. The F1 score of 0.900 shows a well-maintained balance between precision and recall. The accuracy, indicating the proportion of correctly classified samples out of the total samples, is 0.910, demonstrating consistent performance under various conditions.

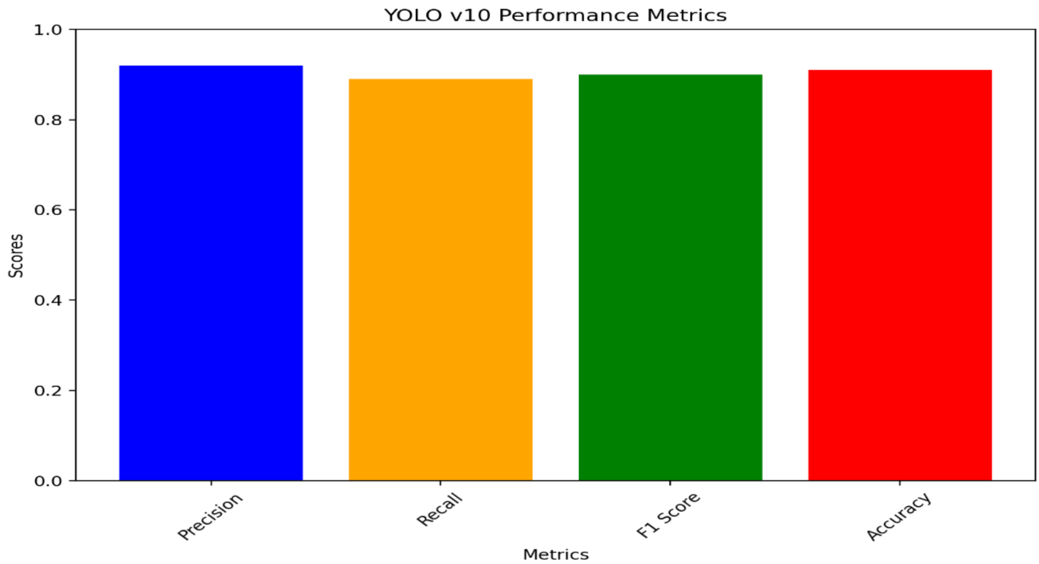

Figure 4. Performance metrics of YOLO v10

4.2. Performance of Comparative Models

The models used for comparison were evaluated for their strengths and weaknesses across various environments.

- AlexNet: As an early deep learning model with a simple architecture and relatively low computational cost, AlexNet showed lower performance compared to YOLO v10, with a precision of 0.850 and recall of 0.801.

- VGG16: While VGG's architecture has proven efficiency in image classification tasks, it can face challenges in processing large datasets due to high computational demands. It recorded a precision of 0.871 and recall of 0.823.

- ResNet101V2: ResNet addresses the vanishing gradient problem through residual connections, enabling effective learning even in deep networks. ResNet101V2 achieved a precision of 0.890 and recall of 0.852, showing performance similar to YOLO v10.

- MobileNetV3-Large: Optimized for mobile and embedded vision applications, MobileNet emphasizes efficiency and speed, recording a precision of 0.882 and recall of 0.840.

The table 2 summarizes the key performance metrics of each model.

Table 2. Results of model prediction performance

Model	Precision	Recall	F1 Score	Accuracy
YOLO v10	0.92	0.89	0.90	0.91
AlexNet	0.85	0.80	0.82	0.83
VGG16	0.87	0.82	0.84	0.85
ResNet101V2	0.89	0.85	0.87	0.88

Model	Precision	Recall	F1 Score	Accuracy
MobileNetV3-Large	0.88	0.84	0.86	0.87

YOLO v10 exhibited high consistency in CT images captured from various angles and conditions. Its performance was notably outstanding in scans including the orbit, indicating effective learning of complex structural features. Consistent performance across both spiral and axial scans confirmed the model's robust adaptability. In the detection of malignant tumors, YOLO v10 demonstrated superior outcomes, underscoring its clinical significance during early diagnostic stages. Compared to other models, YOLO v10 showed a higher concordance in bounding box predictions for malignant tumors and maintained consistent performance across diverse sizes and shapes of tumors, thereby enhancing its clinical applicability. For benign tumors, although detection accuracy was relatively lower in cases with indistinct boundaries, the model still maintained a clinically meaningful detection rate. This indicates the model's capability to handle less distinct tumor boundaries effectively, enhancing the comprehensiveness of diagnosis.

5. Discussion

The YOLO v10 model demonstrated exceptional performance in detecting and classifying brain tumors in CT images. Its superiority was particularly highlighted through comparisons with existing models such as AlexNet, VGG16, ResNet101V2, and MobileNetV3-Large. These results suggest that YOLO v10's innovative architecture is well-suited for modern medical image analysis and can significantly enhance the efficiency and accuracy of real-time detection.

The outstanding performance of YOLO v10 can be attributed to several factors. Firstly, the network architecture of YOLO v10 supports high levels of parallel processing, enabling the rapid handling of large datasets. This is achieved through YOLO's approach of detecting all objects simultaneously in a single forward pass. Such a design is particularly efficient in parallel processing environments like GPUs (Graphics Processing Units), facilitating the swift analysis of large datasets[21]. This capability is highly suitable for real-time analysis required in medical imaging. Immediate data processing is essential for quickly assessing patient conditions and making prompt diagnostic and treatment decisions, making YOLO v10's processing power extremely beneficial in clinical settings[22].

Secondly, YOLO v10 possesses the ability to effectively learn tumors of various sizes and shapes, which leads to high generalization performance. Its enhanced anchor box design and expanded backbone network allow for the effective capture of features across various scales[23]. This is particularly advantageous when processing diverse patient data in clinical environments. For example, medical images collected in hospitals can vary greatly depending on the patient's condition, equipment settings, and scanning conditions. YOLO v10's high adaptability ensures stable performance even under these varied data conditions[24].

Nonetheless, there are several challenges associated with applying YOLO v10 to medical image analysis. Unlike general image data, medical image data often contains high resolution and complex features, which may require more computational resources during model training and inference[25]. This is especially pronounced when processing high-resolution 3D image data. Additionally, the diversity and complexity of medical image data make it difficult for the model to consistently maintain high performance across all scenarios[26]. The characteristics of medical images can vary even for the same disease, depending on the patient's condition or progression stage, which tests the model's generalization capabilities. Therefore, to optimize YOLO v10's performance, specialized preprocessing and data augmentation techniques tailored to medical data may be necessary[27].

Future research can address these challenges by proposing several directions. Firstly, leveraging diverse medical imaging datasets to further enhance model performance and thereby strengthen its generalization capabilities is essential. Secondly, developing lightweight versions of YOLO to improve computational efficiency is necessary. This would increase applicability in resource-constrained environments, such as mobile devices or edge devices.

Lastly, to enhance the clinical applicability of YOLO v10, a cyclical learning system could be considered, which continuously improves the model by integrating feedback from medical experts with the model's predictive outcomes. Such an approach would enhance the model's effectiveness and contribute to improving the accuracy and reliability of medical diagnostics.

In conclusion, this study has demonstrated the potential of the YOLO v10 model as a powerful tool for detecting and classifying brain tumors in CT images. Future research will expand its applicability across more diverse environments. These achievements open new possibilities in the field of medical image analysis and are expected to ultimately have a positive impact on patient diagnosis and treatment.

6. Conclusion

This study has demonstrated the potential of YOLO v10 as a powerful tool for detecting and classifying brain tumors in CT images, highlighting its clinical applicability. The innovative architecture and enhanced performance of YOLO v10 have significantly improved the accuracy and efficiency of brain tumor detection. Future research should focus on evaluating the model's performance across more diverse datasets and environments, as well as advancing its real-time detection capabilities.

Declaration of competing interest. The author declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Availability of data and materials. Detailed information can be found at: https://www.kaggle.com/code/givkashi/yolov10-object-detection.

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