

Detecting Brain Tumor Using YOLOv12 Model  
From MRI Images

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Bachelor of Science

DAFFODIL INTERNATIONAL UNIVERSITY

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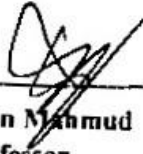
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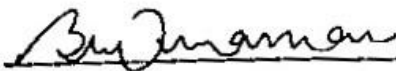
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Detecting Brain Tumor Using YOLOv12 Model From MRI Images

Afiya Farzana Tamanna

Thesis submitted in fulfillment of the requirements  
for the award of the degree of  
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Department of Software Engineering (Major in Software Engineering)

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## **DEDICATION**

To all those battling brain tumor and to the countless individuals whose lives are touched by this disease without the means for treatment.

## ABSTRACT

Brain tumor detection from magnetic resonance imaging (MRI) scans is crucial for early diagnosis and effective treatment planning. However, manual interpretation is slow, subjective and error-prone. With the rapid advancement of deep learning and object detection methods in recent years, automated methods have shown significant potential to overcome these challenges. This study evaluated the YOLOv12 architecture for automated brain tumor detection and compared its performance with YOLOv11, SSD and RT-DETR using a publicly available dataset. Among these models YOLOv12 demonstrated the highest performance, achieving 89.7% accuracy and 92.0% F1-score. In particular, significant improvements were observed in the detection of glioma, which are clinically challenging due to their irregular shapes and diverse textures. Architectural innovations in YOLOv12 models such as attention mechanisms, dynamic anchor boxes and advanced augmentation techniques played important roles in enhancing its robustness across multiple tumor classes. Also, YOLOv12 maintains strong computational efficiency, making it suitable for deployment in low-resource medical environments where real-time analysis is required. The comparative analysis highlights that SSD and Rt-DETR provided competitive results and YOLOv11 provided a strong baseline. YOLOv12 outperformed all other models in terms of accuracy, reliability and efficiency. These results provide the effectiveness of YOLOv12 in medical imaging strongly highlighting its research significance and practical value as a diagnostic support tool. Incorporating YOLOv12 into clinical workflows could help radiologists diagnose brain tumors faster more consistently and reliably.

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## LIST OF SYMBOLS

$L_{total}$	Total loss
$\lambda_{cls}$	Weight for classification loss
$L_{cls}$	Focal loss (classification loss)
$\lambda_{L1}$	Weight for L1 loss
$L_{L1}$	L1 loss (bounding box regression)
$\lambda_{iou}$	Weight for IoU loss
$L_{GIoU}$	Generalized Intersection over Union (bounding box loss)
$L(x,c,l,g)$	Total SSD loss
$N$	Number of matched default boxes
$L_{conf}(x,c)$	Confidence loss (softmax classification loss)
$L_{loc}(x,l,g)$	Localization loss (Smooth L1 between predicted box $l$ and ground truth $g$ )
$\alpha$	Balancing weight

## LIST OF ABBREVIATIONS

OCT	Optical Coherence Tomography
BAM	Bottleneck Attention Module
ECA	Efficient Channel Attention
AI	Artificial Intelligence
XAI	Explainable Artificial Intelligence
Grad-CAM	Gradient-weighted Class Activation Mapping
IG	Integrated Gradients
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
DMBO	Discrete Migratory Bird Optimizer
SS-OCT	Swept-Source Optical Coherence Tomography
PCA	Principal Component Analysis
YOLO	You Only Look Once (object detection algorithm)
ORID	Ocular Disease Intelligent Recognition Dataset
SVM	Support Vector Machine
CLAHE	Contrast Limited Adaptive Histogram Equalization
AHE	Adaptive Histogram Equalization
SMOTE	Synthetic Minority Oversampling Technique
GAP	Global Average Pooling
MLP	Multi-layer Perceptron
GPU	Graphics Processing Unit
CUDA	Compute Unified Device Architecture
ADAM	Adaptive Moment Estimation (optimizer)
RMSprop	Root Mean Square Propagation (optimizer)
ViT	Vision Transformer
SwinTransformer	Shifted Window Transformer
FLOPs	Floating Point Operations per Second (used in convolution cost)

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Appendix A: Dataset Availability

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# CHAPTER 1

## INTRODUCTION

### 1.1 Background

One of the most deadly diseases is a brain tumor, which occurs when brain tissue grows inside the skull suddenly and uncontrollably. It may be malignant or benign. Benign tumors typically grow slowly, but malignant tumors can spread quickly throughout the surrounding brain tissue. Benign tumors can be hazardous, though, because they have the potential to spread and impact nearby brain tissues. Approximately 30% of the tumors are malignant, and 70% are benign [1]. The most commonly used MRI sequences for brain analysis are T1c, T1, FLAIR, and T2. These sequences offer various details about the brain tumor. The radio frequency (RF) used in the MRI test is used to calculate the time of echo (TE) and time of repetition (TR). T1c and T1 MRI are produced through short TR and TE times, and cerebrospinal fluid (CSF) is dark in these sequences. The brain and spinal cord contain colorless CSF. CSF is bright in T2 MRI since it is generated by longer TR and TE times. The abnormal region stays bright, and the CSF is dark because it is created by extremely long TR and TE times [2]. Although manual tumor detection can yield precise diagnosis and prediction, it becomes a laborious process when there is a lot of data [3]. The YOLO model was used to detect objects in both real-time and artwork images. It was then contrasted with other object detectors like R-CNN, faster R-CNN, and the deformable parts model (DPM). All of the earlier architectures have excellent classification results, but in addition to their high accuracy, there is a significant time processing problem. Since it may be addressing this problem, this study employs the CNN-YOLO (You Look Only Once) model. Unlike the convolutional neural network (CNN) architecture, which uses a sliding window method for classification, the YOLO could locate objects in the input image and process the entire image at once [3]. The main benefit of the deep learning model YOLO (You Only Look Once), which is

frequently used in real-time object detection, is its capacity to carry out both object detection and classification in a single forward pass, resulting in high detection speed [4].

## **1.2 Problem Statement**

Brain tumors can vary in size, shape, location, and signal intensity on MRI, making manual detection and accurate labeling difficult. Many areas lack experienced neuroradiologists, resulting in delays in diagnosis and treatment. Manually reviewing hundreds of MRI images of a patient is a very difficult and time-consuming task for radiologists. Skilled radiologists, like humans, get tired. Excessive workload increases the risk of missing subtle tumors. The sooner a tumor is identified and properly analyzed, the sooner appropriate treatment can be initiated, which increases the patient's chance of survival. Interpretation of MRI scans is often subjective. Different radiologists may interpret the same image differently, leading to differences in diagnosis, tumor segmentation, and grading. Knowing the exact location and boundaries of a tumor is essential, as it helps in complete tumor removal and preservation of healthy tissue during surgery. Similarly, it is essential in radiation therapy. So that the target can be targeted accurately and the surrounding vital organs are not damaged. Timely and accurate diagnosis directly reduces mortality and reduces long-term neurological complications.

## **1.3 Motivation**

Recent advances in deep learning have transformed computer vision applications, especially in the medical field. Among these advances, the You Only Look Once (YOLO) family of object detection models has shown remarkable potential for quickly and accurately identifying tumors in medical images. Magnetic resonance imaging (MRI) is the gold standard for diagnosing brain tumors, as it provides high levels of detail and accuracy. However, manual analysis of MRI scans is time-consuming, prone to inter-observer variability, and highly dependent on the skill of radiologists.

YOLOv12, the latest version of the YOLO architecture, adds new features such as attention modules, dynamic anchor box selection, and advanced data augmentation techniques. These improvements are aimed at improving the detection accuracy and

generalization capabilities of the model, especially in complex medical image analysis. The main objective of this research is to evaluate and compare the potential of YOLOv12 for brain tumor detection. It will be evaluated against established models such as YOLOv11, SSD, RetinaNet, and RT-DETR. This will contribute to the AI research community on the one hand and assist in clinical diagnostic practice on the other.

#### **1.4 Significance of the Study**

This study addresses a critical gap in current literature and practice, the evaluation of YOLOv12 for brain tumor detection in MRI images. By conducting experiments on the latest version, this research offers an early, real-world assessment of its performance in a high-stakes medical imaging scenario.

The results have several implications:

- **For the AI research community:** This provides the first known experimental results where YOLOv12 has been used for brain tumor detection.
- **For the medical field:** Faster and more accurate tumor detection can help radiologists with early diagnosis. It improves patient outcomes.
- **For low-resource settings:** The availability of YOLOv12's lightweight variant (YOLOv12n) offers high-accuracy detection even on hardware with limited computational power.

Ultimately, this work could pave the way for broader adoption of advanced AI-based diagnostic tools, reducing diagnostic delays and aiding in improved treatment planning.

#### **1.5 Research Questions**

This research tries to find answers to the following questions:

1. How does YOLOv12 perform in detecting and classifying brain tumors in MRI scans compared to YOLOv11, SSD, and RT-DETR?
2. Does YOLOv12 demonstrate improved precision, recall, and mean Average Precision (mAP) over its predecessors and competing models?

3. How is YOLOv12's computational efficiency, inference speed, and resource usage, especially in low-resource environments?
4. What extent do the architectural improvements of YOLOv12 (attention modules, dynamic anchor boxes, and advanced augmentation) contribute to improving the detection performance in complex tumor cases?

## **1.6 Research Objective**

This study was conducted with the following objectives:

- Implementing and training YOLOv12 on a publicly available brain tumor MRI dataset, ensuring proper preprocessing and augmentation for optimal performance.
- The performance of YOLOv12 is compared with YOLOv11, SSD, and RT-DETR, using standard object detection metrics such as precision, recall, mean Average Precision (mAP), and intersection over union (IoU).
- Analyzing the computational efficiency of YOLOv12, including inference speed, GPU/CPU utilization levels, and suitability for deployment in low-resource environments.
- To investigate the impact of new architectural developments in YOLOv12 attention modules, dynamic anchor box selection, and advanced augmentation on recognition accuracy and robustness.
- To identify the strengths, limitations, and potential development areas of YOLOv12 in the context of medical image analysis, with particular emphasis on clinical applicability.

## **1.7 Research Scope and Limitations**

This section highlights the limitations of the study and the limitations arising from the dataset, chosen techniques, and evaluation process.

### **1.7.1 Scope**

- This research focuses exclusively on brain tumor detection and classification using MRI images.
- Here the YOLOv12 model is mainly analyzed and compared with YOLOv11, SSD, and RT-DETR.
- Both types of metrics are considered: accuracy-based metrics (precision, recall, mAP, IoU) and computational performance metrics (inference time, resource usage).
- Testing was conducted on publicly available brain tumor MRI datasets to ensure reproducibility.

### **1.7.2 Limitations**

- **Model Availability:** At the time of this study, YOLOv12 was recently officially released in February 2025. Since the architecture may be updated in the future, performance variations may occur, which may affect reproducibility.
- **Dataset Scope:** This study used a specific dataset, which may limit applicability to other MRI datasets or other imaging modalities.
- **Hardware Constraints:** Inference speed tests are hardware dependent, and results may vary in different computing environments.
- **Clinical Integration:** Although performance metrics will be rigorously evaluated. This study does not include any clinical trials or direct patient data.

## **1.8 Thesis Organization**

This thesis is organized into five main chapters. Chapter 1 presents the research background and outlines the problem statement, followed by the objectives, significance, scope, and limitations of the study. Chapter 2 provides a comprehensive review of related literature, covering the YOLO model family and other object detection frameworks relevant to medical imaging. Chapter 3 details the research methodology, including dataset selection and preparation, preprocessing techniques, implementation of

YOLOv12, and the comparative models. It also describes the training configurations, evaluation metrics, and experimental setup. Chapter 4 reports the experimental results, compares YOLOv12's performance with other models, and discusses the findings in depth, including an analysis of detection patterns and model behavior. Chapter 5 concludes the thesis by summarizing key outcomes, highlighting the contributions of the study, and offering recommendations for future research directions.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 Related Works

Brain tumor detection is a critical part of medical imaging research because of its implications for patient prognosis and treatment planning. The advancement in machine learning (ML) and deep learning (DL) has revolutionized diagnosis methods, holding the promise for efficient and effective outcomes. In this chapter, some methodologies varying from traditional machine learning techniques, convolutional neural networks (CNNs), to transfer learning approaches, and their strengths and limitations in brain tumor detection are explored.

W.L. and F.J. Zekun Lin et al. [6] proposed a YOLOv8-tuned model called YOLOv8-DEC, which was used for brain tumor detection from MRI images. It incorporates Dynamic Snake Convolution, Efficient Multi-Scale Attention, and CARAFE modules, which help in improving the accuracy of boundary delineation and multi-scale feature detection, and small object detection. Trained on 9900 T1-weighted MRI images, which were labeled with brain tumors. This model outperformed the baseline YOLOv4 and other detectors and achieved 90.9% precision and 82.0% mAp@0.5. As a result, it provides a promising method for efficient and specific tumor detection.

Dulal et al. [7] developed an improved YOLOv8 model for brain tumor detection from MRI images. They used Vision Transformer to enhance context awareness and applied Ghost Convolution, reducing the number of parameters from 11.2 M to 9.4 M. The conventional NMS was replaced with an RT-DETR head that provides adaptive and NMS-free detection. They used glioma, meningioma, and non-tumor MRI datasets from Kaggle with data augmentation. This model achieved 0.91 mAp@0.5 and outperformed

YOLOv5(0.88) and YOLOv4(0.87). The results demonstrate that it exhibits high accuracy and efficiency in medical image analysis.

Khan, A. H et al. [8] presented a Hierarchical deep learning based brain tumor classifier (HDL2B-TUMOR-CLASSIFIER) that accurately identifies and classifies brain tumors from MRI images using Convolutional Neural Networks (CNN). The proposed system divides tumors into four classes: glioma, meningioma, pituitary, and non-tumor. The new model follows a standard pipeline which includes data collection, preprocessing, CNN-based feature learning and classification. Using 3,264 MRI images collected from Kaggle, this model achieved 92.13% accuracy and 7.87% miss rate.

Almadhoun, H. R., & Abu-Naser et al. [9] provide a deep learning approach to brain tumor detection in MRI images using a dataset of 10,000 images and compared a custom CNN with pre-trained networks (VGG16, ResNet50, MobileNet, InceptionV3). InceptionV3 (99.88%) and VGG16 (99.86%) performed best after preprocessing and augmentation, followed by the custom model (98.28%), demonstrating the ability of optimized deep learning techniques as an efficient, precise, and cost-effective support tool for clinical diagnosis.

M.I. MARAM FAHAAD ALMUFAREH et al. [10] presented a portable electromagnetic (EM) imaging system, using the YOLOv3 deep neural network model for brain tumor detection. In this research, scattering parameters were collected from a nine-antenna array setup using a tissue-like head phantom, and then the image was reconstructed using a modified delay-multiply and sum algorithm. An image dataset of 1000 samples (including single and double tumors) was generated through augmentation. It was used for training, validation, and testing of the YOLOv3 model. The Darknet-53-based YOLOv3 algorithm demonstrated high detection accuracy. Achieving a detection accuracy of 95.62% and an F1-score of 94.50%. This work highlights that YOLOv3 has considerable potential for accurate tumor localization in portable electromagnetic head imaging systems.

Norah Fahd Alhussainan et al. [11] focused on the automatic segmentation and classification of brain tumors (meningioma, pituitary, glioma) from MRI scans, using deep learning. The study extensively analyzed and applied two YOLO object recognition frameworks, YOLOv5 and YOLOv7, based on state-of-the-art deep learning architectures. Advanced mask alignment techniques were used in the preprocessing step to ensure accurate segmentation of tumor regions. Numerical results demonstrated strong performance with YOLOv5 achieving mAp = 0.947 (100 threshold = 0.5) for both box detection and mask segmentation, and YOLOv7 showing almost equivalent accuracy. The performance of the proposed framework is compared with established methods such as RCNN, Faster RCNN, and Mask RCNN to highlight its novelty.

MARAM FAHAAD ALMUFAREH et al. [12] presented a YOLO NAS deep learning model used for the detection and classification of brain tumors (pituitary, meningioma, glioma, and non-tumor) from MRI images. It achieved 99.7% accuracy on the REMBRANDT dataset by incorporating an Encoder-Decoder network for segmentation and an attention mechanism that significantly improved early and specific tumor detection.

H.R.A.a.S.S.A. Naser et al. [17] provide a comprehensive review of brain tumor detection and classification using machine learning technologies. It covers important topics, including brain tumor anatomy, imaging modalities such as image enhancement, segmentation, feature extraction, and classification. As well as advanced methods such as deep learning, transfer learning, and quantum machine learning. It highlights the challenges of accurate tumor detection due to variations in size, shape, and location. Discusses the advantages, limitations, and future trends in this field.

S. J. J. M.S. Mithun et al. [13] proposed a fully automated heterogeneous segmentation method (FAHS-SVM) for brain tumor detection and segmentation from MRI images. It designed an extreme learning machine (ELM) algorithm for image classification and feature extraction. This method aims to overcome the challenges of accurately identifying tumors. It is usually a repetitive and time-consuming task for radiologists. Experimental results have demonstrated high accuracy, with approximately 98.51% accuracy in

identifying abnormal and normal brain tissue from MRI scans. This method is proposed to be effective for computer-aided brain tumor diagnosis and clinical decision support systems.

M. A. H. Ramdas Vankdothu et al. [18] proposed the use of artificial neural networks (ANN) and convolutional Neural Networks (CNN) for brain tumor detection from MRI images. This research analyzed the performance of self-defined ANN and CNN models for normal and tumorous brain classification. The dataset used included 2065 MRI images. It was divided into training, validation, and testing sets. The results showed that CNN performed better than ANN, with CNN achieving 89% accuracy in testing, and ANN achieved only 65.21%. The author concluded that CNN is a much more effective method than ANN in predicting brain tumors on the given dataset.

<b>Research work</b>	<b>Dataset</b>	<b>Model</b>	<b>Model Evaluation</b>
Maram Fahaad et al. (2024)[5]	Figshare Brain Tumor Dataset: 3064 MRI slices from 233 patients; classes: Meningioma, Glioma, Pituitary tumors	YOLOv5 and YOLOv7	YOLO5: Box mAP@0.5 = 0.947 Mask mAP@0.5 = 0.947 mAP@0.5–0.95 = 0.666 / 0.657 YOLOv7: Box mAP@0.5 = 0.94 Mask mAP@0.5 = 0.941 mAP@0.5–0.95 = 0.677 / 0.659
Norah Fahd et al. (2024) [6]	500 MRI images of meningioma tumors from King Khalid University Hospital (KKUH), Riyadh, Saudi Arabia	YOLOv3, YOLOv4, YOLOv5, YOLOv6, YOLOv7	YOLOv7 (best): • mAP: 99.96% • Precision: 98.50% • Specificity: 97.95% • Balanced Accuracy: 98.97% • F1-Score: 99.24%
Amran Hossain, et all (2021)[7]	1000 EM images generated from 50 original samples (with	YOLOv3	Detection Accuracy: 95.62% - F1 Score: 94.50% - Training Accuracy: 96.74%

	single & double tumors) via augmentation (rotation, scaling, cropping, zooming, flipping, etc.)		- Validation Loss: 9.21%
M.S. Mithun et al. (2024) [8]	REMBRANDT (REpository for Molecular BRAin Neoplasia DaTa)	YOLO NAS (You Only Look Once – Neural Architecture Search)	Accuracy: 99.7% - Specificity: 98.5% - Precision: 98.2% - F1 Score: 99.2% - Sensitivity: 98.5%
Abdul Hannan Khan, et al. (2022) [3]	Brain tumor MRI dataset from Kaggle Classes: glioma, meningioma, pituitary, no-tumor Total images: 3264	HDL2B-TUMOR- CLASSIFIER (Hierarchical Deep Learning-Based Brain Tumor Classifier) using CNN (Convolutional Neural Network)	Accuracy: 92.13% (Validation Phase) - Miss Rate: 7.87% (Validation Phase) - Training Accuracy: 94.84%, MR: 5.16%
Javaria Amin,et all (2022) [9]	BRATS (2012–2020), Harvard, RIDER, ISLES (2015–2017), Local MRI datasets	SVM, KNN, RF, ANN, ELM, CNN, 3D-CNN, U-Net, WRN-PPNet, DeepMedic, VGG- 16, ResNet-50	CNN (BRATS 2013): DSC = 0.88 (complete), 0.83 (core), 0.77 (enhanced) • VGG-16 (transfer learning): Accuracy > 98%
Sarmad Maqsood, et al. (2022) [10]	BraTS 2018 - Figshare dataset (3064 T1-weighted CE MRI images of 233 patients)	Custom 17-layer CNN for segmentation - Modified MobileNetV2 for feature extraction - Multiclass SVM (M-SVM) for classification	BraTS 2018 dataset: • Accuracy: 97.47% • Sensitivity: 97.22% • Specificity: 97.94% • Dice coefficient: 96.71%  Figshare dataset: • Accuracy: 98.92% • Sensitivity: 98.82% • Specificity: 99.02% • Dice coefficient: 97.87%

Zheshu Jia, Deyun Chen (2020) [11]	Not explicitly named; described as multi- parametric MRI datasets with up to 500 samples	Fully Automatic Heterogeneous Segmentation using Support Vector Machine (FAHS- SVM) + Extreme Learning Machine (ELM) for classification	Accuracy: 98.51%  Dice Score: Up to 97.6%  Detection Probability: Up to 98.8%
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## 2.2 Research Gap

Although significant progress has been made in the application of deep learning models to MRI brain tumor detection. There are several limitations to current research. Recent studies have mainly focused on the YOLOv3, YOLOv5, YOLOv7, YOLOv8, and YOLO NAS architectures have demonstrated significant improvements in detection accuracy and efficiency. However, few published works have reviewed the performance of the latest YOLOv12 architecture in this work. The YOLOv12 architecture includes an integrated attention module, dynamic anchor box selection, and advanced data augmentation techniques. But their impact on brain tumor detection from MRI images remains unexplored.

Furthermore, existing comparative analyses often include a limited number of baseline models, making it difficult to draw definitive conclusions about performance benefits. Extensive and standardized benchmarking of YOLOv12 against multiple modern detectors, including YOLOv11, SSD, and RT-DETR on the same dataset and preprocessing pipeline, is still lacking. This deficiency hinders an objective assessment of the potential benefits of YOLOv12 in a clinical context.

Additionally, deploying high-performance detection models in resource-limited medical environments has not yet been adequately explored. Although there are lightweight variants of YOLOv12 that can run on lower-end hardware. Their performance for real-time MRI brain tumor detection has not yet been evaluated. Furthermore, the small and irregular tumor regions commonly found in MRI scans pose a major challenge for

detection models. Few papers have been conducted to determine how the new features of YOLOv12 perform in these cases.

Finally, explainability and cross-dataset generalization have not received sufficient attention in the current research. There is no analysis yet of how the internal mechanism of YOLOv12, especially its Attention Modules, produces clinically understandable outputs. Similarly, a cross-dataset that is essential for measuring the robustness of the model across different MRI acquisition protocols and patient populations is almost absent. Addressing these deficiencies is crucial to increasing the applicability of YOLOv12 in real-world diagnostic workflows.

## CHAPTER 3

### METHODOLOGY

Since timely and accurate diagnosis has a major impact on patient outcomes. Brain tumor detection is a crucial medical imaging task. Deep learning-based object detection algorithms have revolutionized medical image analysis by enabling rapid, automated, and accurate tumor location. We can detect a brain tumor using machine learning or deep learning. A Convolutional Neural Network (CNN) is a component of deep learning.

The proposed method for brain tumor detection from MRI images follows a six-step structured workflow, which is performed using YOLOv11/YOLOv12. First, the MRI dataset is prepared in YOLO format, where annotations include bounding box coordinates and tumor class labels. To increase generalization power, the dataset is divided into training, validation, and test sets. Then, conventional data augmentation methods such as flipping, scaling, and color adjustment are used. In the model configuration step, the YOLOv11 or YOLOv12 architecture is selected based on the balance between accuracy and speed, along with determining the appropriate model size. Pre-trained COCO weights are loaded to support transfer learning, and hyperparameters such as batch size, learning rate, and 100 threshold are adjusted. The training process uses an optimizer such as SGD or AdamW and uses. 00-based bounding box regression for loss calculation, objectivity scoring, and segmentation if necessary. The model is trained for 50-300 epochs, depending on the size and complexity of the dataset. At the end of each epoch, the model is validated using metrics such as precision, recall, F1-score, mAp@0.5, and mAp@0.5:0.95. The weights with the highest mAp are saved for inference. In the inference step, the trained model resizes and normalizes the MRI image, predicts the tumor bounding box, and improves detection using non-maximum suppression (NMS). Finally, the model is exported in .pt, ONNX, or TensorRT format,

enabling real-time inference and integration into edge computing devices or clinical diagnostic systems.

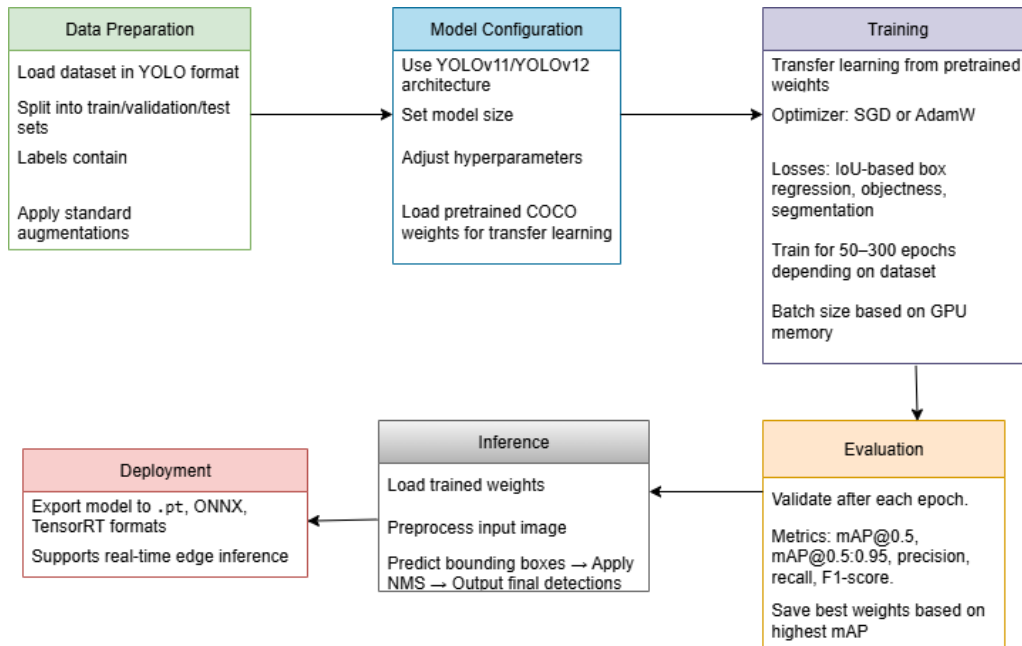


Figure 2.2.1 Workflow Diagram

### 3.1 Data Collection

The dataset is collected from Kaggle. It is collected by Roboflow Universe - a large dataset built for brain tumor detection and classification using advanced computer vision technology. It contains a total of 3,903 MRI images, divided into four different classes:

**Glioma:** A tumor arising from glial cells in the brain.

**Meningioma:** A tumor that arises from the protective lining of the brain.

**Pituitary:** A tumor located in the pituitary gland, which affects hormone balance.

**No Tumor:** MRI scan that doesn't show the presence of any tumor.

The main objective of this dataset is to aid in the early detection and diagnosis of brain tumors, learning to improve treatment planning and better patient outcomes. The dataset supports multiple annotation formats, such as YOLOv8, YOLOv9, and YOLOv11, which are compatible with various machine learning frameworks. This makes it suitable for a variety of applications that require fast and accurate results.

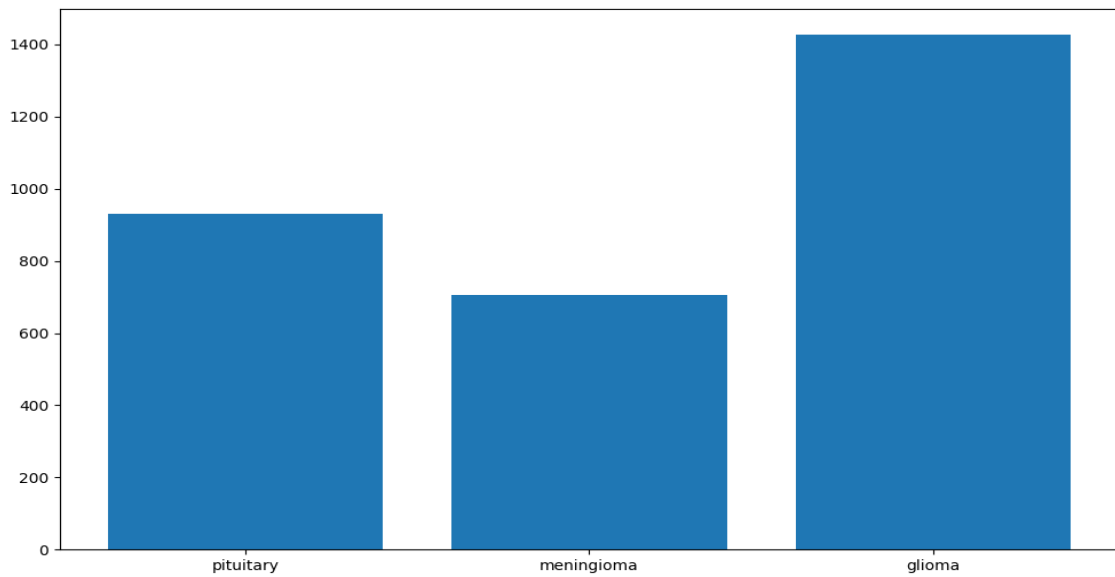


Figure 3.1.1 Class Distribution

## 3.2 Data Preprocessing

### 3.2.1 Image Enhancement – CLAHE

CLAHE is used for MRI image processing, where a grid size of  $8 \times 8$  tiles and a clip limit of 2 are set. CLAHE is different from ordinary histogram equalization because it divides the image into small tiles and increases local contrast by equalizing the histogram of each tile separately. These tiles are then combined using bilinear interpolation to avoid artificial borders. This method significantly improves the clarity of fine details without unnecessarily increasing noise through contrast limiting. As a result, tumor regions become brighter and more clearly visible compared to surrounding tissue, and the overall structural contours of the brain become clearer. Compared with the original image, the tumor edges in the images obtained after applying CLAHE are much clearer and more useful for medical diagnosis and analysis.

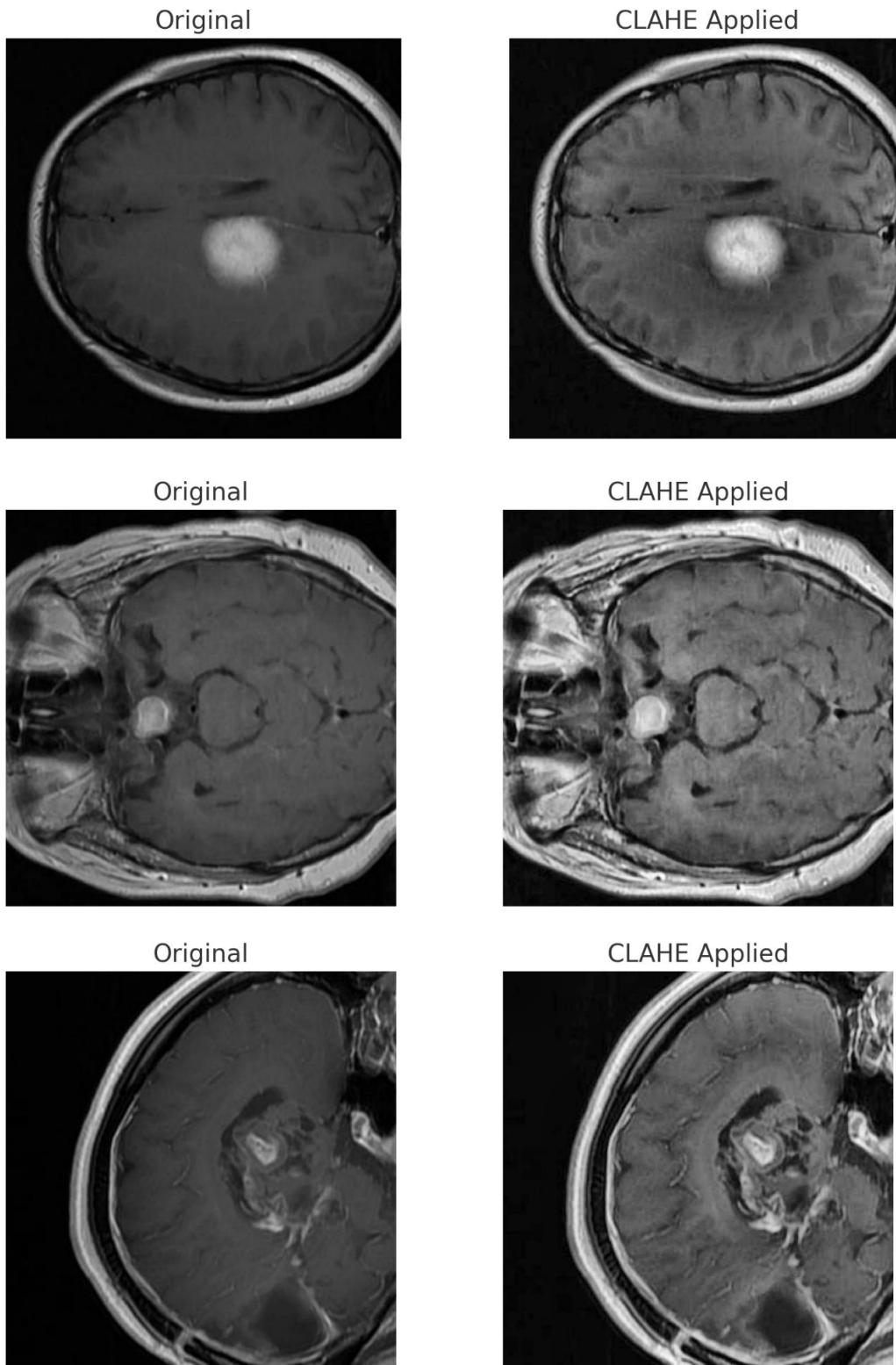


Figure 3.2.1 Before and After applying CLAHE

### 3.2.2 Data Splitting

We split the dataset in a ratio of 70:20:10. This is a common machine learning practice, where the dataset is divided into three subsets: training set (70%) used to train the model; validation set (20%) model and prevent overfitting is used to fine-tune; testing set (10%) used to perform a final and unbiased evaluation of the model, to see how well the model performs on new data.

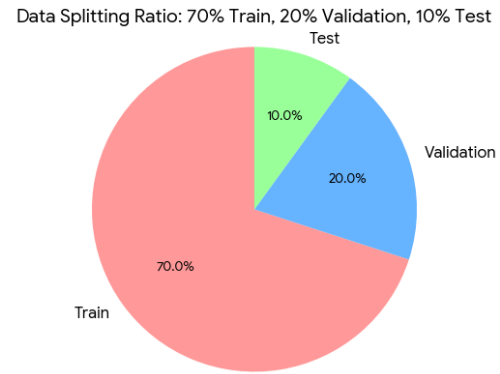


Figure 3.2.2 Train-Test Split pie-chart

### 3.2.3 Resizing:

Each image has been cropped to a square shape, preserving important areas. Image for YOLO and RT-DETR have been resized to 640×640 pixels. Each image has been resized to 300×300 pixels for SSD.

### 3.2.4 Parameters and hyperparameters:

Hyperparameters have been selected for the YOLOv12 model training that maintain accuracy, performance, and stability. Batch size is set to 16, so that a sufficient number of images can be processed and the GPU memory limit is not exceeded. 500 epochs were used to ensure that the model received a sufficient number of iterations. The image size is set to 640, which is YOLO's default size and balances performance and memory usage. Data augmentation, horizontal flip, translation, scaling, and erasing are applied to increase data diversity. Mosaic augmentation is enabled to improve small object detection. On the other hand, copy-paste and mix-up are disabled as they can introduce unnecessary noise into medical data. For optimization, SGD is used where learning rate = 0.01 and momentum = 0.9 are set. In addition, weight decay = 0.0005 is used to reduce overfitting. In the warmup settings, 3 warmup epochs and warmup momentum = 0.8 are used to ensure stable convergence in the initial stages. Overall, these hyperparameters

have been determined in such a way that an effective and efficient model can be created, and high accuracy in brain tumor detection is maintained.

### 3.3 Models

#### 3.3.1 YOLOv11 and YOLOv12

YOLOv11 improves recognition by using the C3K2 Block for accurate feature extraction, the SPFF Module for multi-scale pooling, and the C2PSA Block for focusing on important regions. It also adds dynamic multi-scale heads, NMS-free training, and dual label assignment, enabling the model to perform tasks such as detection, segmentation, and pose estimation. YOLOv12 is further enhanced by using an attention-centric design that includes Area Attention and FlashAttention. It uses the R-ELAN module for lightweight feature learning and depthwise-separable convolutions for large receptive fields. As a result, YOLOv12 offers more powerful multi-scale fusion and better performance in small object detection, while maintaining high speed for real-time use.

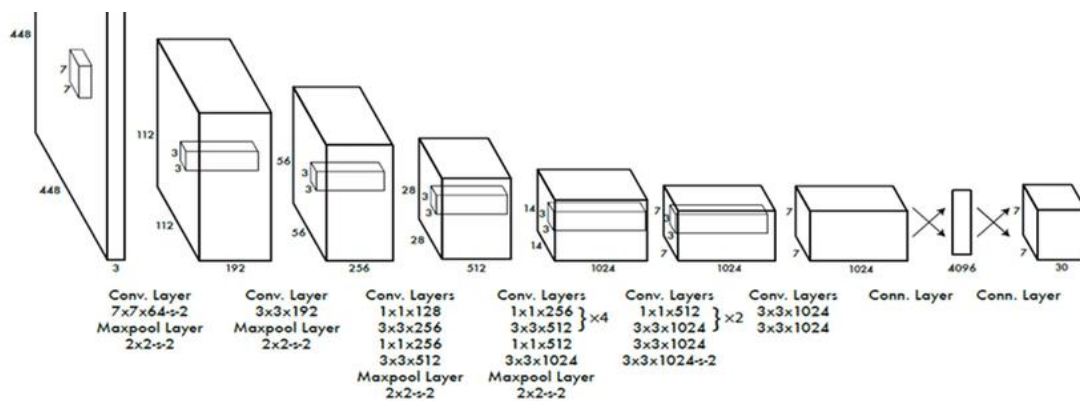


Figure 3.3.1 Diagram of YOLO Model

### 3.3.2 RT-DETR

RT-DETR is an end-to-end real-time object detection model based on the DETR (DEtection TRansformer) architecture. To overcome the slow inference speed of the base DETR model, RT-DETR uses an advanced encoder and decoupled decoder, making the model suitable for deployment in real-time tasks.

This model uses Vision Transformer (ViT) or other backbones for feature extraction from images. While standard DETR uses a shared transformer encoder, RT-DETR uses an efficient encoder that aggregates multi-scale features and processes decoupled decoder object queries in near-parallel. This results in a significant increase in inference speed without a significant loss in accuracy. RT-DETR uses a set-based one-to-one bipartite matching algorithm that maps truth boxes to predictions and uses transformer decoders to generate improved predictions. It is the first end-to-end detector that is capable of delivering high-fidelity real-time performance and effectively bridges the gap between the high accuracy of DETR and the speed requirements of real-time systems. Its end-to-end architecture simplifies the entire detection pipeline and eliminates the need for complex hand-crafted components such as Non-Maximum Suppression (NMS). However, despite its advanced features, RT-DETR is computationally expensive, especially compared to simple single-stage detectors. The transformer-based architecture is complex to train and requires a lot of computing power. In addition, like other transformer-based detectors, RT-DETR sometimes exhibits weaknesses in detecting small objects.

**Formula & Equation:** The model's loss function, like DETR models, is a sum of three parts - classification loss, bounding box regression loss (L1 loss), and generalized intersection over union (GIoU) loss. These losses are calculated based on one-to-one matching of prediction and ground truth objects:

$$L_{total} = \lambda_{cls} L_{cls} + \lambda_{L1} L_{L1} + \lambda_{iou} L_{GIoU} \quad (1)$$

- $L_{cls}$  is the Focal Loss for classification.
- $L_{L1}$  is the L1 loss for bounding box regression.
- $L_{GIoU}$  is the Generalized Intersection over Union (GIoU) loss, which is a more robust metric for bounding box regression.

- $\lambda_{cls}$ ,  $\lambda_{L1}$ , and  $\lambda_{iou}$  are the weighting coefficients for each loss term.

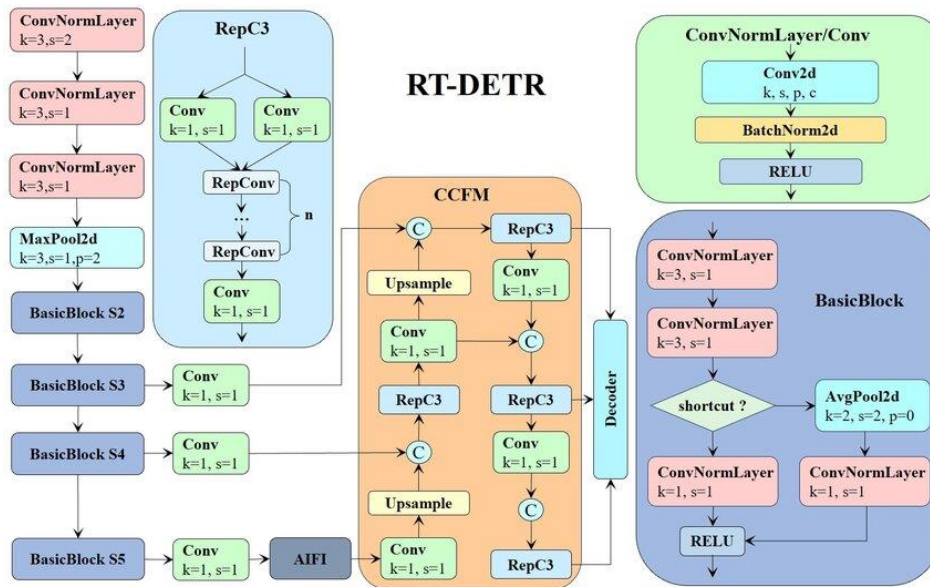


Figure 3.3.2 Diagram of RT-DETR

### 3.3.3 SSD (Single Shot MultiBox Detector)

SSD is a one-shot object detection model. It is capable of predicting classes and bounding boxes together in a single forward pass. The model uses convolutional layers to create feature maps of different sizes that help in detecting objects of different scales. SSD is based on a pre-trained VGG16 network, to which additional convolutional layers have been added. Each layer has a default box. For each box, the model predicts an offset and confidence score. Its loss function uses Smooth L1 for box adjustment and softmax cross-entropy for classification. SSD is fast and accurate, making it useful for real-time tasks. It is faster than two-level detectors like Faster R-CNN, because it skips the region proposal step. Moreover, its multi-scale feature map helps in detecting objects of different sizes.

However, SSD has difficulty detecting small objects, especially in low-resolution feature maps. Its fixed box size and aspect ratio do not fit all objects well, which can reduce the accuracy of predictions.

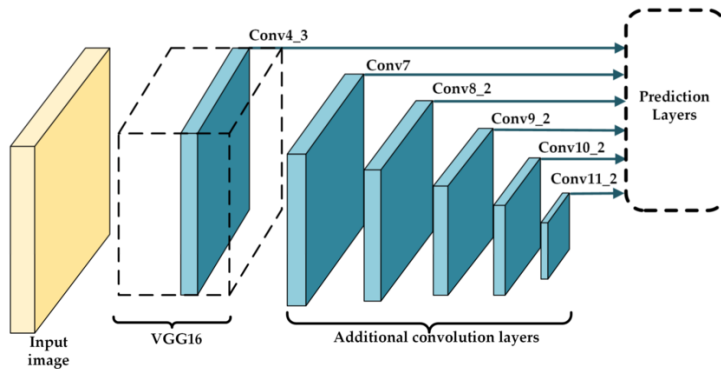


Figure 3.3.3 Single Shot MultiBox Detector Diagram

**Formula & Equation:** The overall objective loss function of SSD is a weighted sum of localization loss and confidence loss:

$$L(x,c,l,g)=N1(Lconf(x,c)+\alpha Lloc(x,l,g)) \quad (6)$$

- N is the number of matched default boxes.
- Lconf is the softmax loss over multiple classes.
- Lloc is the Smooth L1 loss, which measures the difference between the predicted box parameters (l) and the ground-truth box parameters (g).
- $\alpha$  is a weight term to balance the two losses

### 3.4 Evaluation Matrix

The metrics used for:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP+FN} \quad (4)$$

$$True\ Negative\ Rate\ (TNR) = \frac{TN}{TN+FP} \quad (5)$$

$$False\ Positive\ Rate\ (FPR) = \frac{FP}{FP+TN} \quad (6)$$

$$False\ Negative\ Rate\ (FNR) = \frac{FN}{FN+TP} \quad (7)$$

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (9)$$

The percentage of MRI images that are correctly classified among all evaluated images is called accuracy.

Precision measures the proportion of tumor cases that are correctly predicted.

Recall refers to the model's ability to detect all true tumor cases.

The F1-score is a balanced metric, calculated as the harmonic mean of precision and recall.

## CHAPTER 4

### RESULTS

#### 4.1 Result Analysis

This chapter presents experimental results obtained by implementing various deep learning models for brain tumor detection. To ensure a comprehensive evaluation, four widely used object detection frameworks: YOLOv11, YOLOv12, RT-DETR, and SSD are applied to the collected dataset. The performance of these models is systematically evaluated using standard evaluation metrics such as accuracy, precision, recall, and F1-score. A comparative analysis is conducted to determine the relative strengths and weaknesses of each model to identify the most effective method for reliable brain tumor detection.

##### 4.1.1 YOLOv11

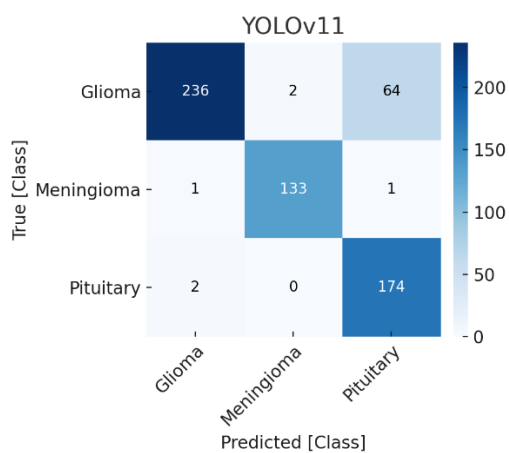


Figure 4.1.1 YOLOv11 Confusion Matrix

Table 6.1 YOLOv11 Model Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specificity	FNR	Accuracy
Glioma	236	308	3	66	0.781	0.010	0.990	0.219	0.889
Meningioma	133	476	2	2	0.985	0.004	0.996	0.015	0.993
Pituitary	174	372	65	2	0.989	0.149	0.851	0.011	0.891

YOLOv11 showed strong performance in the meningioma and pituitary categories. Meningioma was identified with very few errors, and pituitary tumors were also identified with a high true positive rate. These results show that the model is very reliable for these two tumor types.

The glioma class was relatively more challenging. Many gliomas were predicted as pituitary, which reduces their recall. It means, in some cases, the model had trouble distinguishing gliomas from pituitary tumors. In this case, more training data or improved feature learning may be needed.

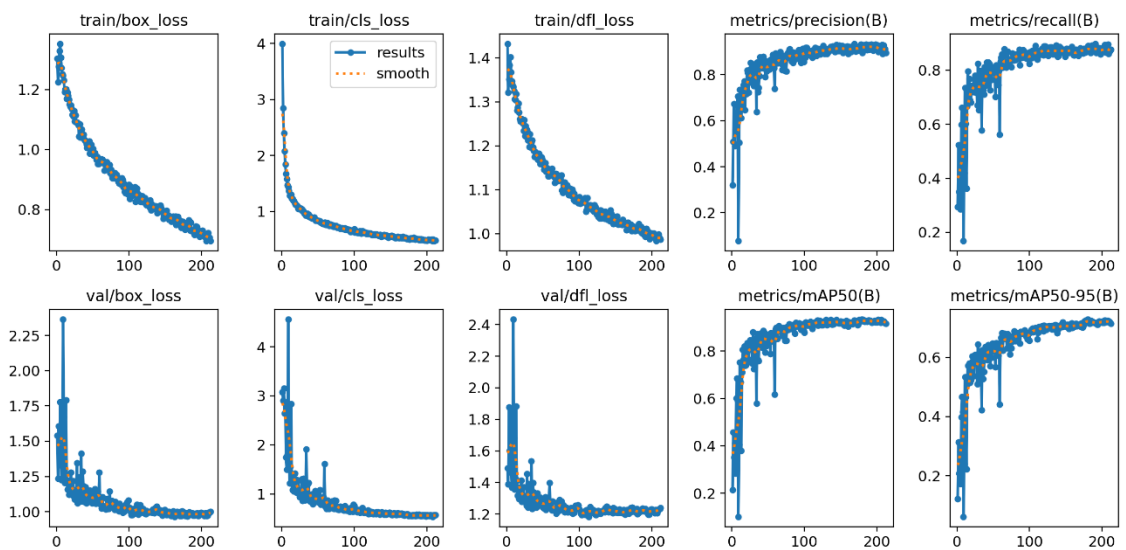


Figure 4.1.2 Training metrics visualization of the YOLOv11 model

## 4.1.2 YOLOv12

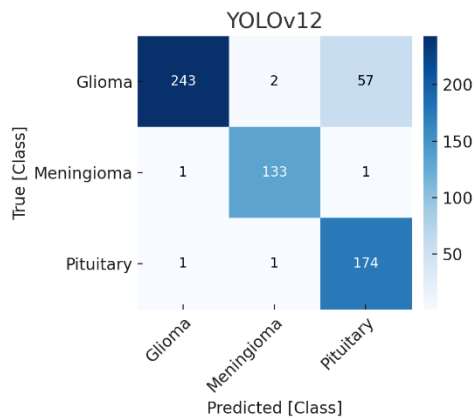


Figure 4.1.3 YOLOv12 Confusion Matrix

Table 6.2 YOLOv12 Model Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specificity	FNR	Accuracy
Glioma	243	309	2	59	0.805	0.006	0.994	0.195	0.895
Meningioma	133	475	2	2	0.985	0.004	0.996	0.015	0.993
Pituitary	174	374	62	2	0.989	0.142	0.858	0.011	0.895

YOLOv12 achieves the best balance across all classes. The glioma class showed significant improvement with increased correct predictions and reduced misclassification. This is important, as gliomas are generally the most difficult to classify.

The meningioma class maintained its strong performance with almost all cases correctly predicted. The pituitary class also improved with a high level of true positives and very few false positives. Overall, YOLOv12 performed smoothly across all classes and achieved the highest F1-score.

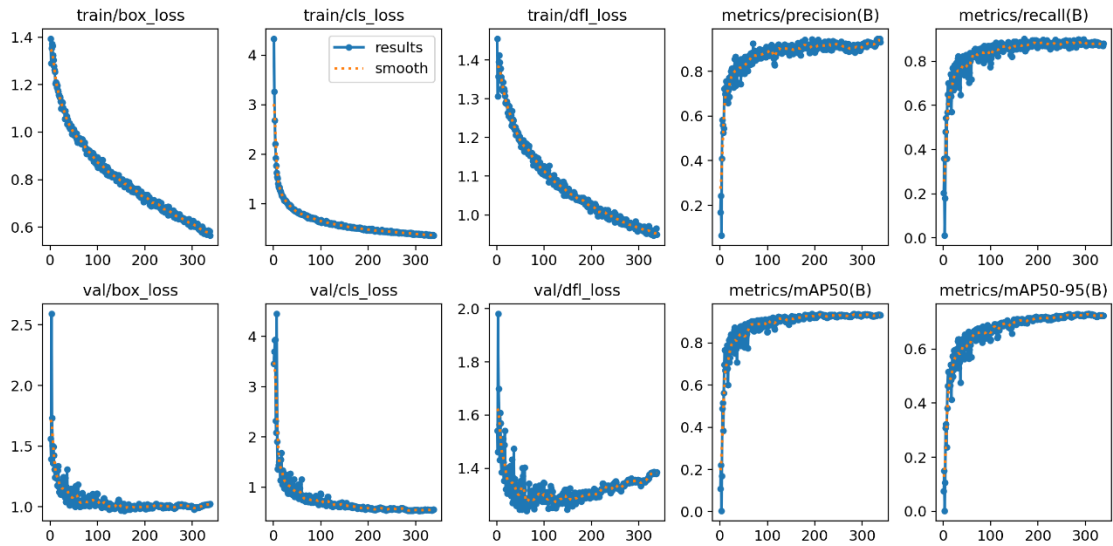


Figure 4.1.4 Training metrics visualization of the YOLOv12 model

### 4.1.3 RT-DETR

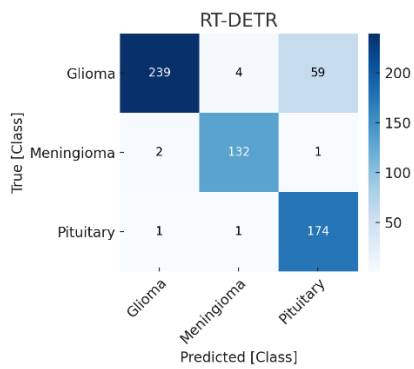


Figure 4.1.5 RT-DETR Confusion Matrix

Table 6.3 RT-DETR Model Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specificity	FNR	Accuracy
Glioma	239	309	2	63	0.791	0.006	0.994	0.209	0.893
Meningioma	132	475	3	3	0.978	0.006	0.994	0.022	0.990
Pituitary	174	373	64	2	0.989	0.146	0.854	0.011	0.892

RT-DETR produced stable and reliable results. The meningioma category was identified very well with high recall and low false negatives. The pituitary category also showed very strong accuracy with only a few false negatives.

However, the glioma class still showed some weakness as several cases were misclassified. Although the performance here was fairly good, it was not as robust as the other two classes. This means that the model needs further improvement in glioma detection.

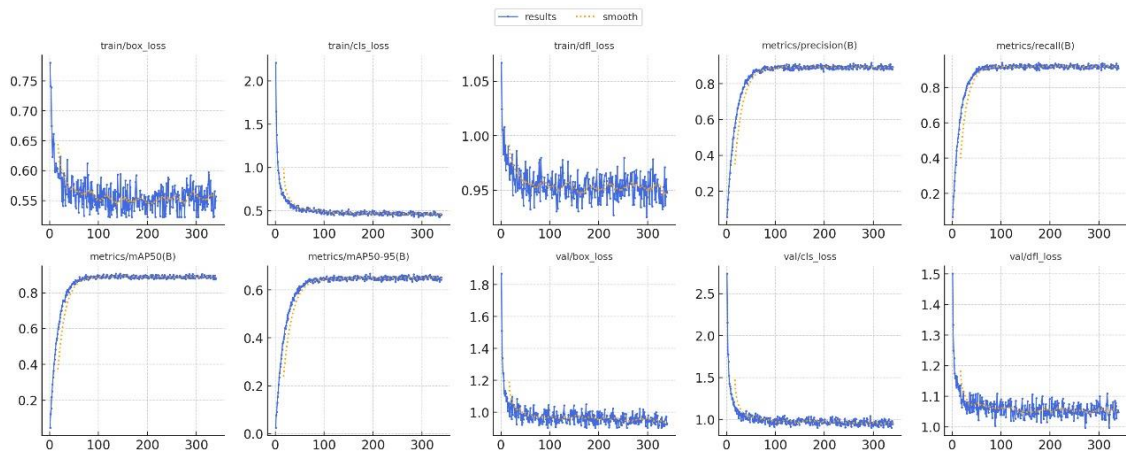


Figure 4.1.6 Training metrics visualization of the RT-DETR

#### 4.1.4 SSD

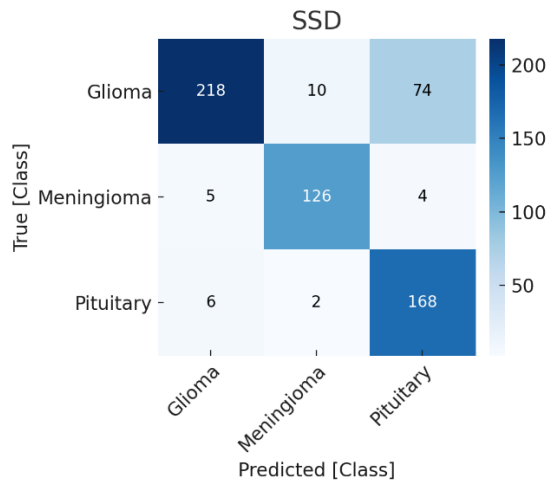


Figure 4.1.7 SSD Confusion Matrix

Table 6.4 SSD Model Classification Report

Class	TP	TN	FP	FN	TPR Recall	FPR	TNR Specificity	FNR	Accuracy
Glioma	218	307	3	84	0.722	0.010	0.990	0.278	0.859
Meningioma	126	469	7	9	0.933	0.015	0.985	0.067	0.970
Pituitary	168	368	67	8	0.955	0.154	0.846	0.045	0.872

SSD was the weakest of the four models. It suffered significantly in the glioma category. It showed many false negatives and misclassifications. This resulted in reduced recall and overall accuracy.

The results in the meningioma category were relatively good, but not as robust as the more advanced models. Weaknesses were also seen in the pituitary category. There were several errors and confusion with glioma.

Overall, SSD has shown its limitations as an older model, and its performance proves that it is less suitable for precise medical image classification.

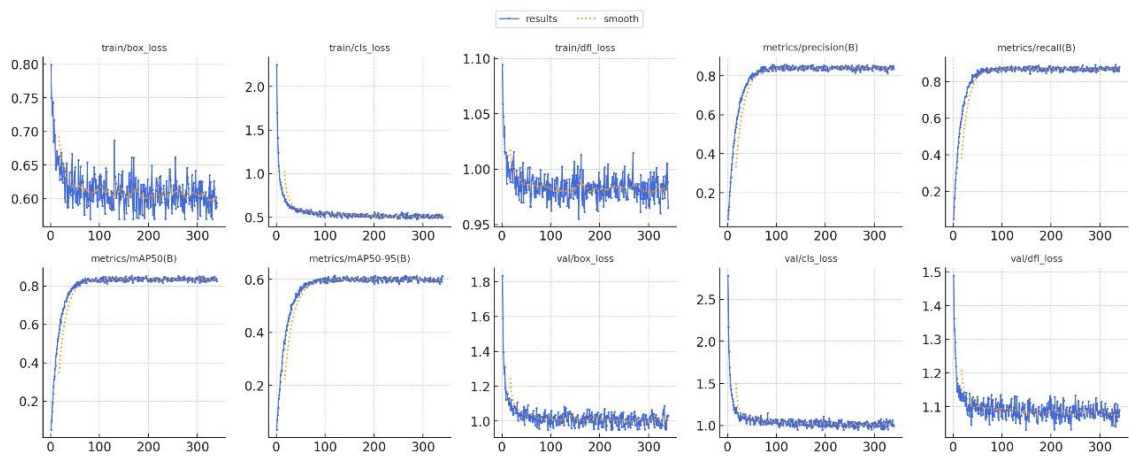


Figure 4.1.8 Training metrics visualization of the SSD

## 4.2 Visualization

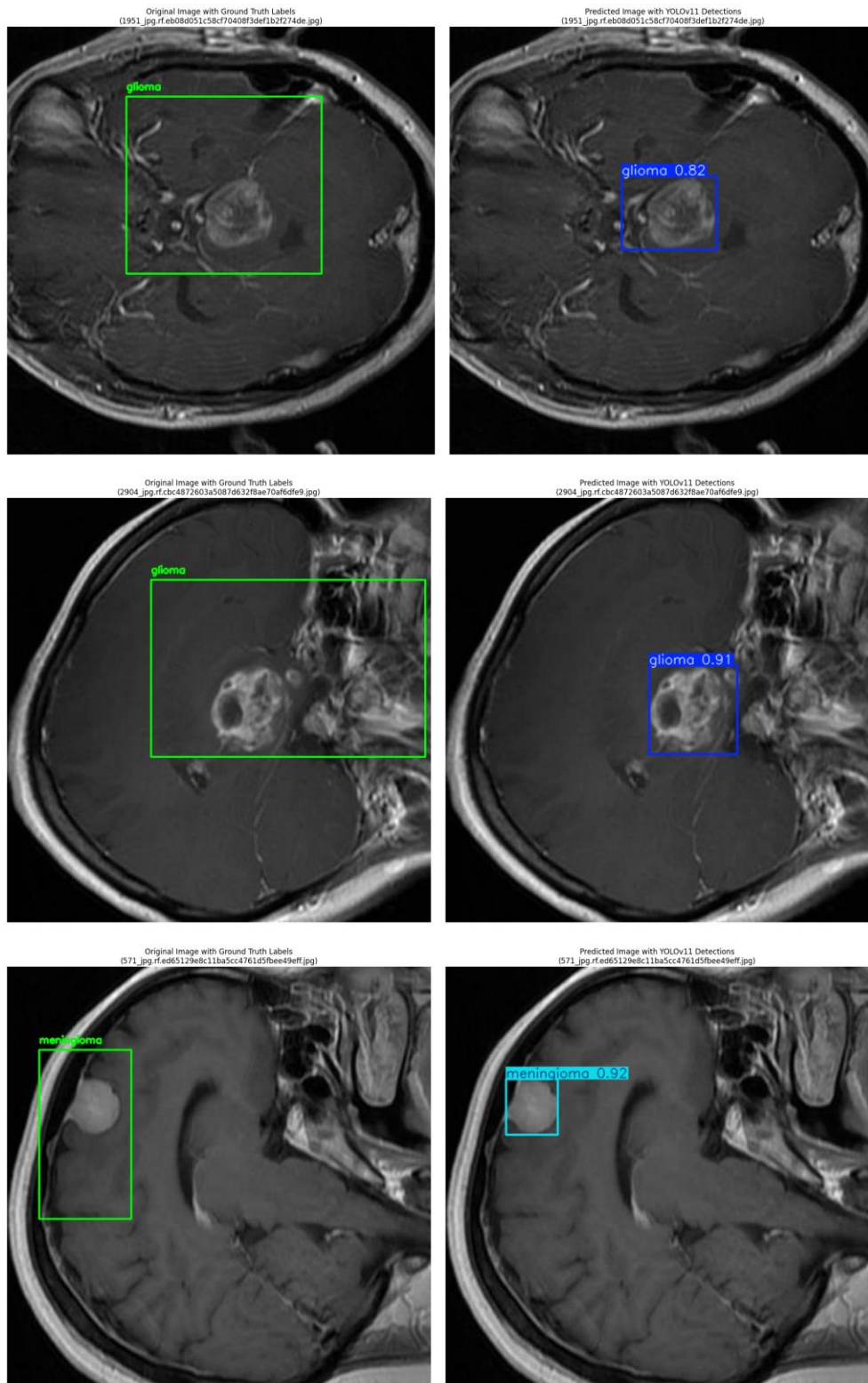


Figure 4.2.1 Examples of output of YOLOv12 Model (1)

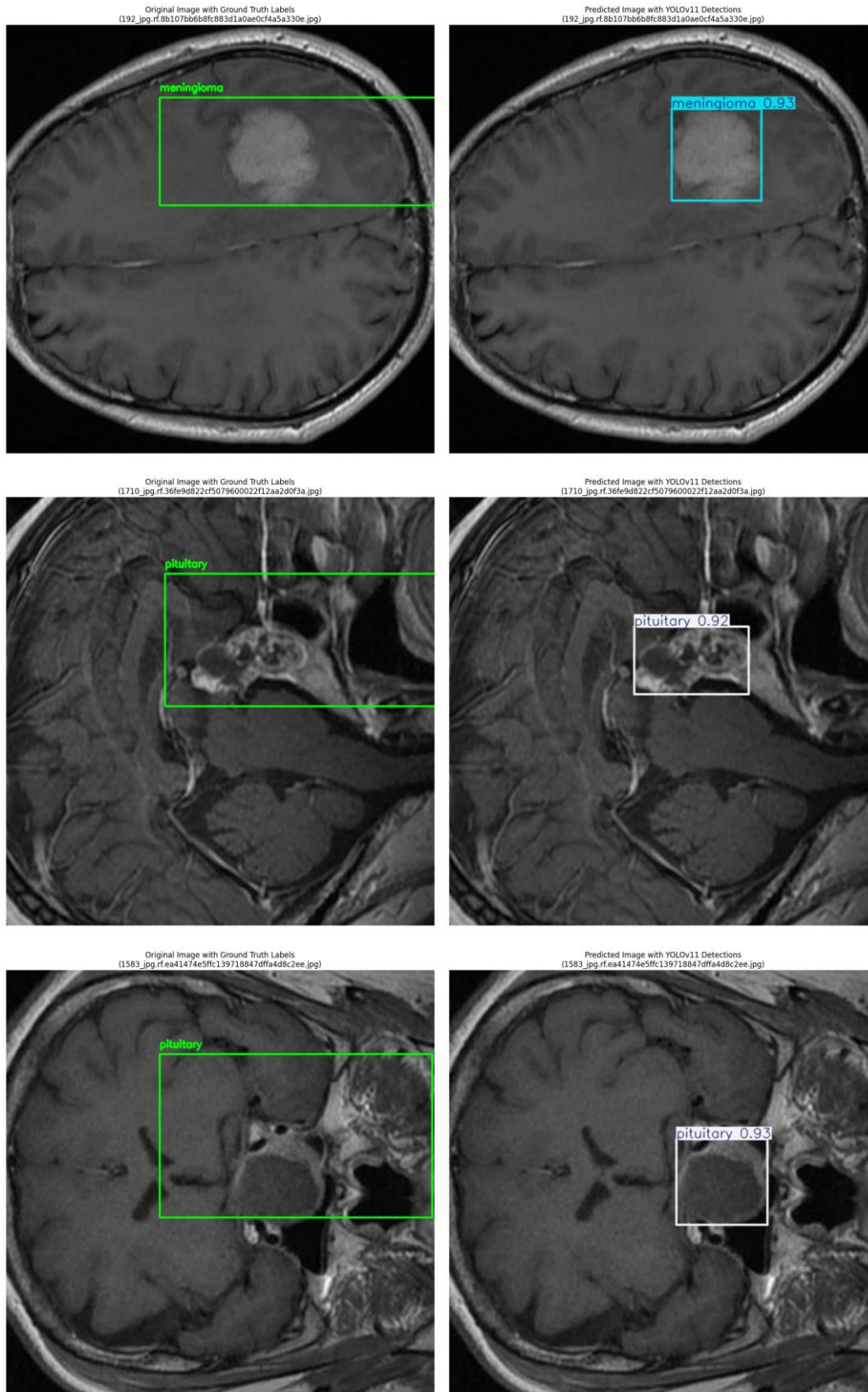


Figure 4.2.2 Examples of output of YOLOv12 Model (2)

### 4.3 Discussion

Table 6.5 All models comparison summary

<b>Model</b>	<b>Accuracy (%)</b>	<b>Precision (%)</b>	<b>Recall (%)</b>	<b>F1 Score (%)</b>
YOLOv12	89.7	90.4	93.5	92.0
RT-DETR	88.9	89.2	92.0	90.6
YOLOv11	88.6	88.5	91.8	90.0
SSD	83.5	84.0	87.0	85.5

Considering the four models together, a clear pattern of their strengths and weaknesses appears.

YOLOv12 stands out as the top performer. It showed high accuracy in all three tumor classes and handled glioma cases much better than the others. YOLOv12 proved to be the most reliable model in this group due to its balance between precision and recall.

RT-DETR is right behind YOLOv12. It is very stable and reliable, especially in meningioma and pituitary tumors; it has very few errors. Although the performance in glioma is not as strong, it has shown reliable and consistent results overall.

YOLOv11 worked well as a solid baseline. It handled meningioma and pituitary tumors very effectively, but showed weaknesses in glioma. The model often confused gliomas with pituitary tumors. It reduced its overall performance. While it is not the best, it still provides a reliable baseline for comparison.

SSD showed the most weaknesses. It had the most problems in detecting glioma and also made the most errors in the pituitary category. Although the results were fairly good for meningioma, its overall accuracy was at least 5% lower than YOLOv11. This highlights the limitations of the older architecture and shows why newer models such as YOLOv12 and RT-DETR are better suited for this task.

In summary, the order of performance is:

YOLOv12 > RT-DETR > YOLOv11 > SSD.

This ranking not only highlights the development of new models, but also shows how errors are decreasing at each stage and the models are moving towards more reliable medical use.

## **CHAPTER 5**

### **CONCLUSION**

#### **5.1 Findings & Contributions**

This research presents the latest model experience evaluation of YOLOv12 for brain tumor detection using MRI images. The results show that YOLOv12 outperforms YOLOv11, SSD, and Rt-DETR in terms of accuracy and reliability. It achieved the highest accuracy (89.7) and F1-score (92.0), demonstrating its effectiveness in tumor detection. The model strength was most visible in the detection of gliomas, where it performed significantly better than previous models. Since gliomas are generally difficult to detect, this is an important achievement for clinical use.

Another major contribution of this work is the analysis of a new architectural feature of YOLOv12. The addition of the attention module, dynamic anchor box, and improved data augmentation has made the model accurate in determining tumor location and has reduced the error rate. These improvements have helped YOLOv12 perform better in detecting small and irregularly shaped tumors that are typically difficult to detect. The research shows that these technological advances are directly reflected in improved medical imaging results.

It also highlights the importance of computational efficiency. YOLOv12 is faster and less resource-intensive than other advanced models. This makes it more suitable for hospitals with limited computational resources, especially in low-resource areas. The availability of lightweight versions further strengthens the potential for real-world clinical use. This bridges the gap between advanced AI research and real-world healthcare solutions.

Finally, this research contributes to both AI research and medicine. For an AI researcher, it provides evidence of YOLOv12's medical imaging capabilities. For clinicians, it shows the potential to reduce diagnostic delays and errors by using faster and more reliable tools. By combining high performance and practical application aspects, this research paves the way for broader use of AI clinical decision-making and patient care.

## **5.2 Recommendations for Future Works**

Future research should test YOLOv12 on larger and more diverse datasets to determine how well the model can generalize across different hospitals, scanners, and patient groups.

Clinical trials should also be conducted. Radiologists will evaluate the model in a real diagnostic environment, which will help determine its practical value. Their feedback will play an important role in increasing acceptance at the clinical level.

More research is needed to make the model more explainable. It would help increase credibility if doctors could understand why the model makes certain predictions.

Future research should be done on lightweight versions of YOLOv12. These models could help hospitals with limited computing resources. Therefore, it is important to test how the balance between accuracy and speed is achieved.

Finally, new architectures such as transformer-based models should be compared. In addition, combining YOLOv12 with other imaging modalities such as CT or PET can further improve diagnosis and move towards a complete solution in healthcare.

## CHAPTER 6

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## **APPENDICES**

## Appendix A: Dataset Availability

Dataset Link: <https://www.kaggle.com/datasets/pkdarabi/medical-image-dataset-brain-tumor-detection>

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Total Due	0.00
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