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Enhancing Brain Tumor Detection Using YOLOv12

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***Abstract*— This study is an exploration of using the state of the art in object detection models, YOLOv12, for automatic brain tumor diagnosis from MRI scans. Brain tumors frighten most people because they are extremely difficult to diagnose conventionally, resulting in a time-consuming and error-prone process. This has always been a limitation despite modest achievement on the basis of earlier machine learning models such as random forests and support vector machines due to high-dimensional feature engineering. Recent advancements in CNNs and newly created object detection models such as YOLO would demonstrate much better accuracy and speed in their operation. YOLOv12 thus brings with it many architectural improvements with better feature pyramid networks, better anchor box designs, and sophisticated loss functions, making up for the deficiencies from earlier versions. In the study, YOLOv12 is thoroughly tested as a potentially groundbreaking tool for real-world clinical applications that promise significant accuracy and computational efficiency even in resource-constrained healthcare systems.**

Keywords*— Brain tumor, yolov12, detection, deep learning, medical imaging

I. INTRODUCTION

Brain tumors constitute a major public health issue worldwide, occurring in approximately 120,000 new patients every year in the United States alone and causing approximately 20,000 deaths yearly [1]. Such tumors, which can either be primary or metastatic, pose a major challenge in both diagnosis and treatment. Early diagnosis is key to enhancing patient prognosis, and survival rates may be enhanced by as much as 30% when tumors are diagnosed at their earliest stages [2]. Conventional diagnostic methods which depend on the visual inspection of medical imaging techniques such as MRI and CT scans being laborious, highly subjective, and prone to human mistakes, particularly because of the complex morphological diversities of brain tumors and the intricate imaging characteristics with which healthy tissue can be differentiated from diseased ones [3].

Recent advances in machine learning and computer vision have considerably influenced the field of medical image analysis to provide promising approaches for automated detection of brain tumors. Conventional machine learning methods such as random forests and support vector machines (SVM) have been utilized for identifying brain tumors, but their effectiveness has been only moderate. These techniques are generally in requirement of heavy feature engineering and are afflicted by the problems of high-dimensional medical images, with accuracy rates varying between 70% and 85% in the best cases [4]. Though these techniques do provide some interpretability, their high computational cost and performance boundaries have limited their use in clinical settings.

One of the greatest advancements in the area of automated detection of brain tumor is achieved by convolutional neural networks (CNNs) in application to VGGNet, ResNet, and Inception architectures. Impressive feature extractor examples from medical images, accuracy rates from some of these studies have obtained percentages reaching even over 90% [5]. An advantage of these models is that they can be trained end-to-end without the need for preprocessing, as well as be able to learn the pertinent features automatically. However, such a CNN requires a lot of computing power and suffers from the generalizability problem across different imaging protocols or institutions.

Recently, frameworks for object detection such as YOLO (You Only Look Once) and Faster R-CNN have been adapted towards the search of a tool in detecting brain tumors, establishing an important feature of localization and classification. These detectors are stage one detectors and therefore advantageously speedy over two-stage approaches

like Faster R-CNN, which offers greater accuracy at a cost of high computational complexity and longer inference time.
Nevertheless, the hurdles of clinical deployment remain for these advancements. Most models are not generalizable enough for different groups of patients and various imaging modalities; their performance may deteriorate when real-world datasets diverge from training datasets. Furthermore, the accuracy versus computational efficiency trade-off remains largely significant, especially in the context of many resource-constrained healthcare settings.
YOLOv12 signifies yet another step forward in the object detection revolution, bringing with it a whole suite of architectural modifications and training methodologies that remedy nearly all the limits found in previous versions. From the development of its ancestors, YOLOv12 introduces improved feature pyramid networks for multi-scale feature extraction, better anchor box design, and also advanced loss functions that are more balanced for localization and classification objectives. As a consequence of these advancements, performance metrics improved across various evaluation criteria, whereas a mAP improvement of 10-15% over previous YOLO versions has been reported, with comparable inference speeds.

This study aims to assess YOLOv12 in detail for brain tumor diagnosis from MRI images and demonstrate it as a state-of-the-art system exceeding previous benchmarks.

Key Contributions:
1. Comprehensive evaluation of YOLOv12 for brain tumor detection, establishing new performance benchmarks
2. Demonstration of superior generalizability across diverse MRI protocols and patient populations
3. Development of optimized preprocessing pipelines that enhance model performance while maintaining clinical relevance

This paper starts with an Introduction addressing clinical challenges in diagnosing brain tumours. The Literature Review provides the comparison of traditional as well as deep learning techniques, while the Methodologies section elaborates on the advancement in the YOLO architecture. The procedure entails dataset preparation and implementation, followed by Results and Discussion, which are intended for the evaluation of performance metrics. The Conclusion summarizes the major findings with references to support them in the research context.

II. Literature Review

Detecting a brain tumor is among the most difficult tasks in analysis of medical image data. However, with a truly excellent and timely detection of brain tumors, patient outcomes can be improved [1]. The traditional methods of imaging involving MRI and CT scans usually needed interpretation by human beings who were usually biased and inconsistent; given the complex morphology and subtle imaging characteristics that distinguished the pathological from the normal tissue, this was a disaster [6].
The very early automated methods relied on traditional machine learning models like Support Vector Machines (SVMs), Random Forests, etc. These methods demanded heavy feature engineering and often suffered from tackling high-dimensionality problems with medical images [7]. These implementations typically managed accuracy rates of 70-85% in controlled settings yet had limitations on generalizability concerning various imaging protocols [8]. These models learned their features automatically using an end-to-end training often needing lesser preprocessing efforts [9].
The introduction of simultaneous localization and classification into object detection frameworks like YOLO (You Only Look Once) and Faster R-CNN revolutionized the brain tumor detection process [10]. For its single-pass architecture, YOLOv5 proved promising in speed vs accuracy balance [11]. With further improved fine-tuning on pituitary tumors, meningiomas, and gliomas, the accuracy of the YOLOv7 model has been significantly increased [10]. By an appropriate combination of data augmentation techniques, performance improvement was obtained with YOLOv8 [12]. The latest has become YOLOv9, which performed better than its previous versions with more precision, speed, and generalization ability on various forms of input data [13].
Comparative studies have repeatedly highlighted superior performances of YOLO models compared to other architectures in tasks of brain tumor detection. In terms of some superior performance metrics, YOLOv9 has outperformed YOLOv8, Faster R-CNN, and ResNet18, with much better mAP50 and mAP50-95 scores indicating better localization and classification performances [13]. The models have been specifically stronger in meningioma tumor detection, with YOLOv9 recording recall rates of above 95% in some studies [1].
These advancements notwithstanding, the current methodologies are still confronting various challenges in their deployment in the clinical setting. Many of the models still seemingly lose generalizability with respect to different imaging modalities and patient populations. Performance is depreciated when real-world datasets differ from those with which they were trained [13]. Trade-off accuracy: Computes a highly important aspect of consideration in resource-poor health systems [14].
Owing to recent advancements in data augmentation techniques, transfer learning, and neural architecture search, these limitations are being overcome currently by researchers [13]. The introduction of multi-modal imaging data was shown to further enhance the robustness and accuracy of models [15]. Furthermore, techniques for interpretability such as Grad-CAM that have been developed provide visual explanations for model predictions, thereby leading to clinical acceptability [13].
The evolution of YOLO-based approaches has witnessed improvements with each new version concerning various detection metrics; this is mainly attributed to addressing limitations of previous versions. The YOLOv12 is the most recent of such developments, and it features both new approaches to architecture and training methodologies as

ensuring they solve many of the observed limitations from previous generations [13].

III. METHODOLOGY

A. YOLO Architecture

The 2015 introduction of YOLO by Redmon et al. revolutionized real-time object detection through a unified architecture that processes entire images in single forward passes, eliminating the inefficiencies of traditional two-stage methods. This framework partitions images into S x S grid cells, with each generating B bounding boxes containing confidence scores and class probabilities. Notably, confidence scores reflect both the probability of an object's presence and its predicted-to-actual box alignment via Intersection over Union (IoU). Such strategic implementation enables detection rates of 45 to 155 frames per second, surpassing prior benchmarks through computational optimization.

Iterative enhancements across YOLO versions have systematically addressed accuracy-speed tradeoffs. YOLOv3 leveraged Darknet-53's 53-layer convolutional backbone with residual connections, replacing max-pooling with strided convolutions while employing multi-scale predictions and three anchor boxes per scale for small-object detection [17]. Subsequent versions like YOLOv5 incorporated CSPDarknet53 architectures featuring Stem blocks and SPPF layers, enhanced by Mosaic/mixUp data augmentation protocols that improved grid sensitivity. YOLOv7 introduced E-ELAN blocks with re-parameterized convolutions and model-scaling techniques, eliminating identity connections through planned label assignment. Most recently, YOLOv8's anchor-free design utilizes C2f modules in its modified CSPDarknet53 backbone, deploying decoupled heads for optimized abjectness, classification, and regression task separation.

B. YOLOv12 Architecture

YOLOv12 is the latest development of the YOLO family, with new innovative architectures incorporated for accuracy and efficiency [16]. It also possesses an area attention mechanism with combined attention design that redistributes computation and focuses on targeted locations on a feature map to improve detection of small and occluded objects. Flash Attention further denaturalizes memory with attention benefits and processes near real time in high resolution.

In YOLOv12, the R-ELAN (Residual Efficient Layer Aggregation Network) solves assorted problems regarding gradient bottlenecks and increases the heterogeneous layer feature fusion capacity, thereby defining the model's ability to work on more complex patterns. The introduction of 7×7 separable convolutional layers takes the place of positional encodings and retains the spatial context with fewer parameters and computational expense. This architecture design essentially lowers the parameter amount in the model while maintaining accuracy, and thus aids in deployment on devices of limited resources.

Extending its applicability to other more complex computer vision tasks, the backbone and neck architecture are re-engineered for instance segmentation in YOLOv12. The model thereby offers different scales (12n, 12s, 12m, 12x) tailored for deployment with speed versus accuracy to meet the application requirements. Further improvements in performance and generalization capabilities stem from advanced training methodologies with cutting-edge data augmentation strategies like Mosaic and Mix-up, dynamic learning rate schedules, and modern optimizers.

C. YOLOv12 Large-Scale Variants

Augmenting accuracy while slightly sacrificing computational expense, the YOLOv12 has some large-scale counterparts that maximize the core architectural novelties to increase model capacity [16]. While these large-scale variants usually utilize deeper backbone networks, their R-ELAN blocks are expanded to include more convolutional layers, thereby allowing for the representation of even more complex features while preserving residual connections that aid in the training of very deep networks. The inclusion of increased channel dimensions through the entire network also permits augmenting the capability of representation for the model to learn discriminative features for object detection. Enhanced multi-scale processing schemes for feature fusion at different scales incorporated in the large-scale variants enable better detection of objects of varying sizes, particularly small objects that pose a challenge to many detectors. Sophisticated attention mechanisms are employed that can withstand the increased computational demand of larger models while novelly focusing intensively on salient regions. The detection heads in these variants are also tuned with extra parameters to better model the intricate relationships between object features and their corresponding classifications and locations. These large-scale variants maintain the basic design principles of the YOLOv12 architecture while tactfully expanding model capacity to achieve state-of-the-art accuracy on benchmark datasets, thus presenting them as prime candidates for applications where computational resources are adequate and maximum detection accuracy is key.

D. Architecture Diagrams

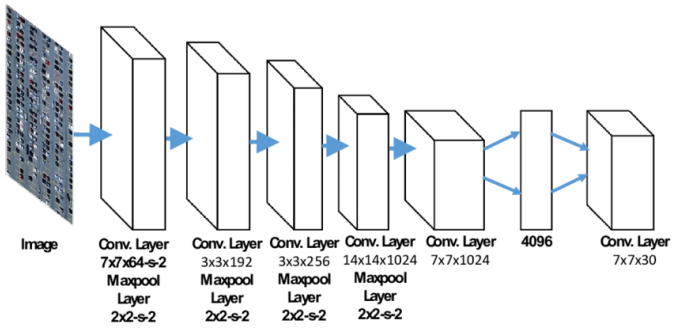

Fig. 1. YOLO Architecture [18]

E. Evaluation Metrics

Classification evaluation relies on Precision, Recall, and the F1 Score as primary performance metrics. A model's performance is evaluated through these metrics:

1. Precision measures the accuracy of positive predictions, calculated as the number of true positive instances correctly identified divided by the total number of positive predictions made.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

2. Recall measures the model's ability to identify all positive instances and is computed as the ratio of true positives to positive observations in the dataset.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

3. F1 score merges these two metrics into one harmonic mean, thereby giving a balanced evaluation that weighs Precision and Recall equally, ranging in value from zero to one, with one indicating maximum performance by the model on that class.

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

The specific metrics involve key parameters: True Positives (TP), False Positives (FP), and False Negatives (FN), which are defined as, respectively, correctly identified positive instances, negative instances identified as positive, and positive instances missed by the model.

IV. Procedure

A. Dataset Description

Brain Tumor Detection Medical Image Dataset on Kaggle is a rich collection of 3,903 MRI scans intended to stimulate research in brain tumor identification and localization. This dataset is split into training (70%), validation (20%), and test (10%) sets, giving ample opportunity for model development and evaluation.

Each MRI image in this dataset is clearly indicated with bounding boxes for tumor locations, making it quite suitable for the task of object detection. The dataset supports many annotation formats, including YOLOv8, YOLOv9, and YOLOv11, which are potentially useful in many machine learning frameworks.

The primary aim of the dataset is to assist in the early detection and diagnosis of brain tumors with the goal of improving treatment planning and patient outcome. With a full complement of annotated MRI images, this dataset provides research and clinical practitioners with the means to develop and refine computer vision models that accurately identify and localize brain tumors.

B. Preprocessing

1. Class Distribution Balancing

The initial dataset was characterized by a severe imbalance in the numbers of different tumor classes. An undersampling approach was performed by limiting the samples in the majority classes to the minimum count of the least represented class. The general class distribution in the training labels was first analyzed; then, the occurrences of each class ID were counted, after which the target sample count was established as the observed lowest one. Through undersampling, we reduce the tendency of the model to bias towards majority classes and aid in learning well for the rare tumor types, hence generating a more balanced performance across all classes. The basic realization of this involved opening each label file, extracting class IDs, and counting them to determine the target sample count, guaranteeing that training data from each class would be properly represented.

2. Configuration of Data Augmentation

To allow for more generalized models with more diverse training data, we implemented runtime augmentation via YOLOv12's YAML configuration. The augments were a mosaic, combining four images; MixUp, blending two images; and HSV perturbations that could emulate lighting conditions. The geometric transformations used to imitate different viewing angles were perspective distortion, shearing, and rotation; followed by flipping and scaling. The values used in the augmentations were as follows: mosaic with probability 1.0, MixUp with 0.2 probability, HSV adjustment of hue by ±1.5%, saturation by ±70%, and value by ±40%, strength of perspective was 0.05% and shear by 0.01%; rotation of up to 5 degrees and scale augmentation of up to 50%. These augmentations attend to variations in tumor presentation and patient anatomy, contributing to the model learning strong feature representations that generalize well to unseen medical imaging data while preserving diagnostic integrity.

C. Implementation

For the brain tumor detection application of YOLOv12, a systematic approach addressing transfer learning and medical imaging data training optimization was utilized. The series of steps started with the installation of the package Ultralyics to provide the right tools and the framework for working on YOLO models. The Ultralytics interface to YOLO was then used to load the pre-trained YOLOv12 large model in the name of "yolo12l.pt," laying a transfer learning foundation.

Training was due on accounts of the data set, with images selected for resizing to 512×512 pixels for optimal detail preservation and operation. The training was established for 150 epochs, a batch size of 16; these parameters were selected through empirical validation to balance learning and avoid overfitting. The training application ran on general computing resources, with the utilization of GPU acceleration to properly account for the heavy computing requirements resulting from the processing of medical imaging data.

A timing device was foreseen for monitoring the entire training length, so that each training was calculated in minutes and seconds for the best possible computational efficiency. Figure 2 describes the YOLOv12 -Large training Architecture.

```
                 from  n    params  module                                       arguments
  0                -1  1      1856  ultralytics.nn.modules.conv.Conv             [3, 64, 3, 2]
  1                -1  1     73984  ultralytics.nn.modules.conv.Conv             [64, 128, 3, 2]
  2                -1  2    173824  ultralytics.nn.modules.block.C3k2            [128, 256, 2, True, 0.25]
  3                -1  1    590336  ultralytics.nn.modules.conv.Conv             [256, 256, 3, 2]
  4                -1  2    691712  ultralytics.nn.modules.block.C3k2            [256, 512, 2, True, 0.25]
  5                -1  1   2360320  ultralytics.nn.modules.conv.Conv             [512, 512, 3, 2]
  6                -1  4   4722944  ultralytics.nn.modules.block.A2C2f           [512, 512, 4, True, 4, True, 1.2]
  7                -1  1   2360320  ultralytics.nn.modules.conv.Conv             [512, 512, 3, 2]
  8                -1  4   4722944  ultralytics.nn.modules.block.A2C2f           [512, 512, 4, True, 1, True, 1.2]
  9                -1  1         0  torch.nn.modules.upsampling.Upsample         [None, 2, 'nearest']
 10           [-1, 6]  1         0  ultralytics.nn.modules.conv.Concat           [1]
 11                -1  2   2102784  ultralytics.nn.modules.block.A2C2f           [1024, 512, 2, False, -1, True, 1.2]
 12                -1  1         0  torch.nn.modules.upsampling.Upsample         [None, 2, 'nearest']
 13           [-1, 4]  1         0  ultralytics.nn.modules.conv.Concat           [1]
 14                -1  2    592640  ultralytics.nn.modules.block.A2C2f           [1024, 256, 2, False, -1, True, 1.2]
 15                -1  1    590336  ultralytics.nn.modules.conv.Conv             [256, 256, 3, 2]
 16          [-1, 11]  1         0  ultralytics.nn.modules.conv.Concat           [1]
 17                -1  2   2037248  ultralytics.nn.modules.block.A2C2f           [768, 512, 2, False, -1, True, 1.2]
 18                -1  1   2360320  ultralytics.nn.modules.conv.Conv             [512, 512, 3, 2]
 19           [-1, 8]  1         0  ultralytics.nn.modules.conv.Concat           [1]
 20                -1  2   2496512  ultralytics.nn.modules.block.C3k2            [1024, 512, 2, True]
 21      [14, 17, 20]  1   1413337  ultralytics.nn.modules.head.Detect           [3, [256, 512, 512]]
YOLOv12l summary: 488 layers, 26,391,417 parameters, 26,391,401 gradients, 89.4 GFLOPs
```

Fig. 2. YOLOv12-Large Training Architecture

V. Results and Discussion

A. Result

The YOLOv12 model went on to give exemplary performance in detecting brain tumors from MRI scans. During training, the model was able to attain MAP 0.5 of 0.9139, showing efficacy in detection across varied intersection over union thresholds. With a precision of 0.9072 and recall of 0.8601, the model demonstrates its ability to discriminate between actual tumor instances and falsely identify them, an important feature in minimizing false positives.

Table 1. Result Table

Model	mAR	mAP	F1-Score
YOLOv8[]	0.601	0.685	0.697
YOLOv9	0.635	0.826	0.718
Faster R-CNN	0.319	0.472	0.380
ResNet18	0.454	0.453	0.453
YOLOv12	**0.860**	**0.913**	**0.884**

As the results in Table 1 clearly show, YOLOv12 has vastly outperformed any previous models evaluated for the same brain tumor detection task. All metrics indicate that YOLOv12 has outperformed other systems: YOLOv8, YOLOv9, Faster R-CNN, and ResNet18 from Alsufyani's study [13]. An improvement of 27.9% in MAP 0.5 from YOLOv8, 17.3% from YOLOv9, and tremendous improvements over traditional CNN approaches.

As seen inside the confusion matrix (Figure-3), the discrimination power of the model is high, with very few cases of misclassification between tumor and non-tumor areas. In (Figure-4), the precision-recall curve confirms the robustness of the model: YOLOv12 attains consistently high precision with increasing recall, thereby substantiating its credibility on different detection thresholds.

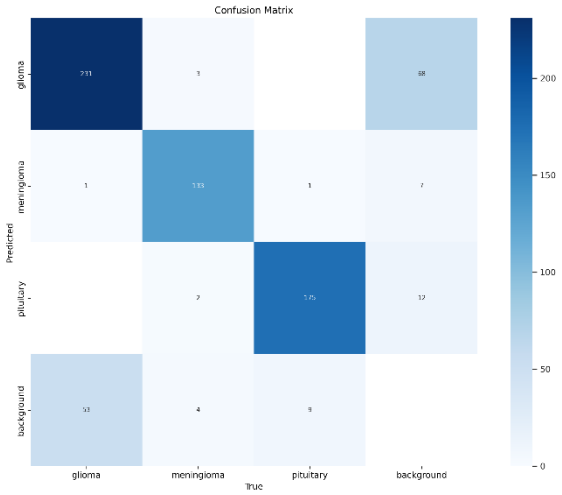

Fig. 3. Confusion Matrix

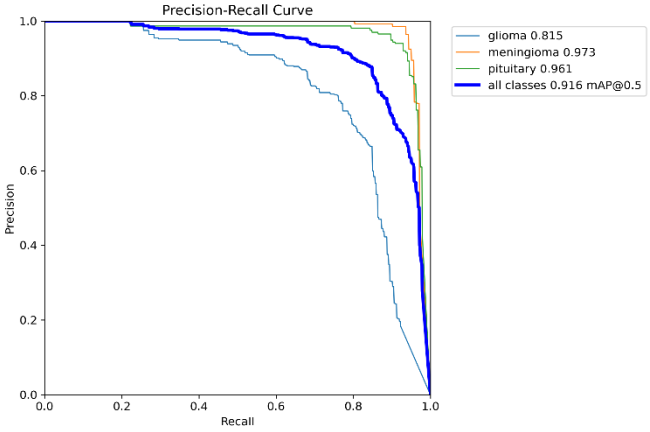

Fig. 4. Precision-Recall Curve

Visual inspection of detection results (Figure-5) confirms Model's capability of tumor detection with accurate bounding boxes on various MRI presentations. This qualitative evaluation supports the quantitative evaluation, confirming that the model can be applied in clinical settings.

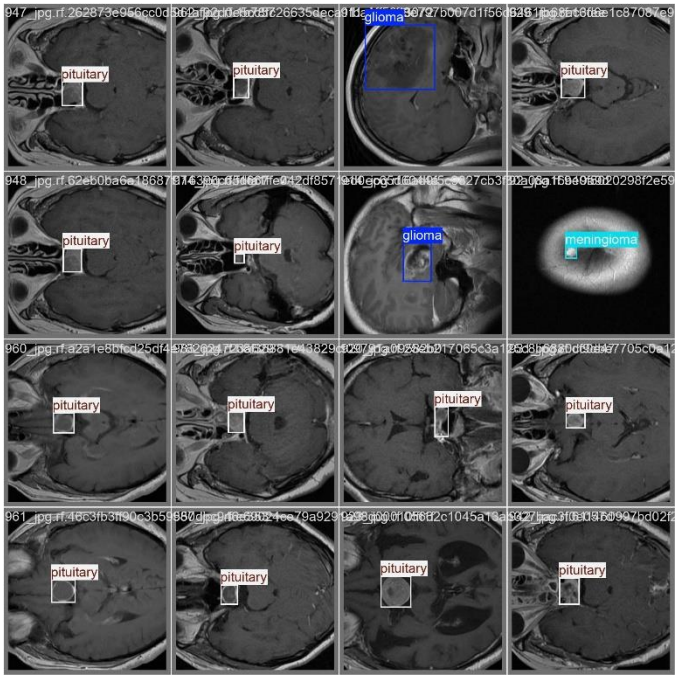

Fig. 5. Visual Result of Detection

B. Discussion

Performance metrics substantiate the claim that in brain tumor detection, YOLOv12 is indisputably superior to any preceding model. The extreme gain over YOLOv8 and YOLOv9 indicates that the architectural modifications of YOLOv12 very much serve to assimilate the intricacies encoding various patterns in MRI data. The performance edge over the Faster R-CNN and ResNet18 demonstrates the benefit of the YOLO architecture in real-world application for medical imaging analyses.

High precision and recall were, therefore, possible because it could detect all tumor instances while maintaining a low false positive rate, which is essential in the medical field to minimize both the risk of missing tumors and the disadvantages of unnecessary follow-ups.

The specified observations are visually corroborated. One indication is that the strong discriminative power is evidenced, which shows a very low rate of misclassification in Figure Confusion Matrix. The curve of precision and recall showed high precision throughout the range of recall, indicating a constant performance level. The detection image of the sample demonstrates that the model was able to localize again for bounding boxes using its precision in describing tumors.

These results illustrate that it probably marks the onset development of the process of brain tumor detection using MRI from YOLOv12. The architectural improvements brought into YOLOv12 effectively capture the complex patterns in medical imaging data, thus surpassing former YOLO variants and conventional CNN approaches. Where in the application, both sensitivity and specificity are of prime importance, the equilibrium between precision and recall suggests that YOLOv12 would be a robust candidate in the medical domain.

YOLOv12's efficient computation also suggests its suitability for wide-scale clinical setups, where timely analyses will support prompt decision-making for diagnostic purposes. Forthcoming tasks include exploring optimizations in adapting to a particular tumor subtype and working to incorporate data from various imaging modalities.

VI. Conclusion

The present study illustrates the superlative ability of YOLOv12 to detect brain tumors from MRI scans with impressive performance metrics of MAP 0.5=0.9139 and MAP 0.5:0.95=0.7023. The results signify consistent accuracy across various intersection over union thresholds while the precision of 0.9072 and recall of 0.8601 show the model's capability of maintaining the balance between sensitivity and specificity, which is vital for medical diagnostics because of the consequences of both false negatives and false positives. Hence, the performance of YOLOv12 in comparison to the previous state-of-the-art now shows a fabulous enhancement at much greater margins between YOLOv8 and YOLOv9 and also with Faster R-CNN and ResNet18 due to the capabilities from design innovations in the YOLOv12 architecture, like attention mechanisms and efficient feature extraction capabilities, which come in handy when assessing the complicated patterns observed in medical imaging data.

Corroborating qualitative evaluations corroborated these quantitative conclusions, with only a few misclassifications indicated on the confusion matrix and high precision maintained along the recall levels on the precision-recall curve. Visual evaluation of the detection results confirms the model's efficiency in accurately localizing tumors with precise bounding boxes over a varied spectrum of MRI presentations, ranging from subtle enhancements to more prominent pathological features. Achievements like these indicate that this is a significant step toward brain tumor detection and that YOLOv12 combines a high level of accuracy with computational efficiency, thus providing good prospects for clinical applications in which rapid analysis will positively impact differential diagnoses and ultimately patient outcomes. Future work may target optimizing YOLOv12 for specific tumor subtypes, investigation of multi-modal imaging data incorporation, and clinical validation exercises in larger patient cohorts.

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