2025 IEEE 2nd International Conference on Computing, Applications and Systems (COMPAS) | 979-8-3315-5525-2/25/$31.00 ©2025 IEEE | DOI: 10.1109/COMPAS67506.2025.11381885

Brain Tumor Detection in MRI Images with YOLOv12

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***Abstract*—The precise identification of brain tumors via MRI imaging continues to pose a considerable challenge within the domain of medical diagnostics. Although conventional deep learning models have shown effectiveness, they often encounter difficulties in detecting accuracy and efficiency in various types of tumors. In this research, we introduce an enhanced approach for brain tumor detection that employs the latest YOLOv12 object detection framework. We assess and contrast the performance of YOLOv12 with several other leading models, illustrating its superior detection accuracy. The YOLOv12n model notably achieves the highest mAP@50 of 93.3%, outperforming previous YOLO versions and conventional techniques. The model is trained and evaluated using a comprehensive MRI dataset that includes various tumour types, thereby ensuring its generalisability and robustness. These findings highlight YOLOv12's potential as a reliable, quick, and accurate method for real-time brain tumor diagnosis and medical picture analysis.**

***Index Terms*—YOLOv12, Brain Tumor, Deep Learning, Machine Learning**

I. Introduction

Brain tumors can present themselves quite uniquelyand are accompanied by challenges ddue tovarious types and landf malignant potential. Their earEarly accurate identification is integral, for it caase the main determinant of treatment and prognosis [1]. Magnetic resonance imaging (MRI) continues to be one of the most preferred techniques for the identification of brain tumors because it offers detailed pictures of soft tissue including the brain [2]. However, analysis of complex magnetic resonance images poses challenges and the consequences of a misdiagnosis can be catastrophic [3]. Therefore, there is a dire need to improve the speed and accuracy of brain tumor identification. This is one of critical engineering and medical challenges [4]. Not even the most advanced machine learning systems, using sophisticated algorithms, have been able to automate the critical aspects of brain tumor detection [2],[5]. Performing the same task, even the most well-trained systems based deep learning [6], [7] have plenty of room for improvement. It has been difficult to obtain the diverse training data sets needed to train the model due to privacy issues and the infrequency of certain tumor types [8]. Furthermore, such models require considerable amounts of computation, which can be a challenge in poorly resourced environments. Another serious problem is the 'black box' feature of a deep learning model in which the model makes decisions that are not explained in any detail, making it very difficult to validate clinically and also undermines the trust that many professionals have in such systems. Furthermore, certain models are prone to overfitting, meaning that they perform very well on the training data, yet fail to do well to any new and even slightly different clinical situations [9]. Real-time object detection, which can be done using the You Only Look Once (YOLO) series, has gained considerable importance due to the relative ease of achieving a good trade-off between speed and accuracy [10]. The most current version, YOLOv12, has substantially improved architecture design and performance and is very applicable to the detection of brain tumors on MRI images [11]. Such improvements include the AAM (Area Attention Module), RELAN (Residual Efficient Layer Aggregation Network) , 7×7 depthwise separable convolutions that result in significant accuracy gain with substantially lower computational costs load. They build on the strong performance of the earlier YOLO frameworks in medical imaging, which, for instance, tumor detection, lesion localization, anatomical structure identification [12] , performed commendably. Next, attention-based attention mechanisms are gradually being incorporated into medical imaging research [7], demonstrating the clinical relevance of the YOLOv12 architecture in parallel with the dominant movements in AI-assisted analysis of histopathology radiology [13].

This is the first application of YOLOv12 for brain tumor detection from MRI images, with developments such as the AAM and RELAN added for improving detection speed and detection rate. In the context of real-time medical image processing, the model's performance as benchmarked with past epochs and contemporary models is also analyzed. YOLOv12 is shown to the best developed version, as it outperforms the rest of the models evaluated. Quantitative plus qualitative assessments also underscore the improvements this research

makes regarding accuracy and speed.

II. Related Work

A. MRI for Brain Tumor

Because MRI uses radio waves and powerful magnetic fields to produce comprehensive images of the brain and spinal cord without the use of ionising radiation, it is an essential tool for diagnosing and treating brain tumours [14]. The ability to distinguish between different types of brain tissue and tumours is improved by advanced MRI techniques such as diffusion-weighted imaging (DWI), fluid-attenuated inversion recovery (FLAIR), T1-weighted and T2-weighted imaging, and magnetic resonance spectroscopy (MRS) [15]. These features support accurate diagnosis, treatment strategy formulation, and ongoing assessment since MRI can identify subtle variations in tissue properties, aiding in tumor mapping in relation to vital brain structures for surgical preparations and assessing treatment efficacy during follow-up after treatment [16]. Nonetheless, interpreting MRI results remains complex due to factors like artefacts, patient movement, and variations in tumor appearance, highlighting the need for expert radiological review and, often, histological verification through biopsy.

B. Machine Leaning

The field of brain tumor detection has been greatly transformed by machine learning (ML), which has facilitated the creation of algorithms that can analyse intricate medical imaging data with both speed and accuracy [2]. In the process of identifying brain tumours, ML models—especially deep learning frameworks like convolutional neural networks (CNNs)—are trained on extensive collections of brain scans to accurately recognise and categorise tumors [5] and [9]. These models are designed to learn and identify patterns and anomalies in images that may suggest whether a tumor is malignant or benign[17], thereby aiding radiologists in making more precise diagnoses and developing treatment plans [8]. Machine learning (ML) not only improves diagnostic capacity by providing an objective and data-driven perspective, but also improves the workflow in imaging departments, which shortens the time to diagnosis and may improve the overall accuracy of an evaluation of a brain tumor [9]. This technological development is of great importance in identifying an early diagnosis and optimising patient outcomes in neuro-oncology.

C. Deep Learning

In the field of brain tumor diagnosis, deep learning—a subset of machine learning characterized by networks that can learn from unstructured or unlabeled data without supervision—has made substantial strides. Complex picture data may be navigated by deep learning algorithms, which can also spot patterns that human observers would miss. They make use of CNN-style structures. These models are trained on large MRI image datasets to detect features associated with different kinds of brain tumors, improving diagnosis speed and accuracy [6]. By streamlining the identification process, deep learning gives radiologists powerful tools to evaluate tumor attributes like size, shape, and possible malignancy [6]. This not only facilitates a more precise and prompt diagnosis but also aids in customising treatment plans, which has a considerable effect on patient care strategies in neuro-oncology [18]. As deep learning develops further, its application in therapeutic settings may improve patient outcomes and diagnostic precision in the detection and treatment of brain cancers. Recently, deep learning advances have incorporated attention architecture and residual networks for tumor detection. Mahmud et al. (2020) stated that the attention mechanism could improve precision in detection and localization [19]. Tonni et al. (2025) reviewed the promise of transfer learning in diagnosis of tumors; transfer learning could help adapt even more complex network architectures for medical imaging and tumor detection applications [20].

Think of these advances as supporting the idea that attention mechanism, residual connections, and enhanced training processes could augment detection frameworks like YOLOv12 for timely and appropriate identification of brain tumors in medical images.

III. Methodology

A. Dataset

The Roboflow Universe puts together a large MRI dataset of brain tumors that is meant to be used with the newest computer vision techniques to find and classify brain cancers. It comprises 3903 MRI images categorised into four distinct classes:

- **Glioma:** Glioma is a tumor originating from glial cells in the brain
- **Meningioma:** Tumors arising from the meninges, the protective layers surrounding the brain and spinal cord.
- **Pituitary Tumor:** Tumors located in the pituitary gland, affecting hormonal balance.
- **No Tumor:** MRI scans that do not exhibit tumor presence.

Object detection is also made easy since the location of tumors is annotated through bounding boxes on each of the images within the data set. To organize the data, we will set the training, validation, and testing phases to 70%, 20%, and 10%, respectively. While this serves as a foundation for the model's development and assessment, this also as a model's functional parts division. We aim to provide data for the early detection and diagnosis in order to streamline the treatment initiation or enhance the outcomes of the treatment. Complete with beautifully labeled annotated MRI scans, this dataset enables researchers and experts to design and perfect computer vision models for improved precision and efficiency in brain tumor detection and localization. Leaving aside in detail the format of its annotations, which is varied and includes YOLOv8, YOLOv9, and YOLOv11, this dataset is quite universal and can be used to work through many machine-learning frameworks. Its compatibility with such formats presupposes real-time and effective object detection which is perfect when immediate and accurate outcomes are necessary. However,

through this dataset, researchers, and medical practitioners can develop an advanced AI solution to medical imaging and achieve effective and accurate results in clinical applications.

The bar chart shows the distribution of images across three medical categories: glioma, meningioma, and pituitary. Glioma has the highest number of images, while meningioma has the least. Fig. 2 shows the sample data from the brain tumor MRI dataset.

B. Data Acquisition

Kaggle is the source of the medical imaging collection used to detect brain tumors. It includes subsets of training, validation, and testing MRI images. The YOLO format is used in the collection, and each image's bounding box annotations are saved in a.txt file.

The dataset link is as follows: https://www.kaggle.com/datasets/pkdarabi/medical-image-dataset-brain-tumor-detectionKaggle Medical Image Dataset—Brain Tumor Detection

C. Data Preprocessing and Annotation

To satisfy the input specifications of the YOLOv12 model, each image is shrunk to 640 × 640 pixels. Normalized bounding box coordinates and the class label are included in the annotations. Among the other preprocessing procedures was data augmentation. methods to improve the training data's robustness and diversity, such as mixup and mosaic9.

D. Model Selection

The most recent version of the YOLO object recognition framework, YOLOv12, was selected for this purpose due to its high accuracy and real-time capability. Significant updates are provided by it, such as the 7 × 7 depthwise separable convolutions, residual efficient layer aggregation network, and area attention (A2) module. Each of these elements enables the model or models to more effectively target tumor regions, capture characteristics, and still retain a quick computation turnaround time.

E. Progress of YOLOv12

We have seen significant advancements made to the YOLO models throughout the years. Each time some new features were added to the existing models for the purpose of better performance and enhanced accuracy of detection and applicability in various computer vision applications. YOLOv10 and YOLOv11 added more features and improved performance further by powerful data augmentation and attention with more complex scenarios. New features added in YOLOv12 such as R-ELAN, flashattention, and augmented with 7x7 separable convolutions, improved feature extraction and computational efficiency, further improving performance [10]. These new models can, therefore, be seen as valuable additions to applications for object detection.

F. Training Procedure

The model was constructed from pretrained weights of YOLOv12n, YOLOv12m, and YOLOv12s, which offer an effective lightweight structure for object recognition. The model was trained over a total of 20 epochs. The optimizer used was SGD, and the learning rate schedule started at a value of 0.001 to encourage smooth learning and avoid local minima. The training configuration was defined in the data.yaml file, which indicated the directories for training, validation, and test datasets. This configuration ensures the proper separation of datasets and optimises the training workflow. All training activities took place on a Tesla T4 GPU equipped with 15095 MiB of memory, which provided enhanced computational speed and shortened training time. The training process lasted around 0.409 hours, showcasing the model's ability to handle high-dimensional image data with relatively low computational requirements.

TABLE I: Training hyperparameters

Epochs	20
Learning Rate	0.001
Layers	272
Parameters	2568633
Graphical Processing Unit (GPU)	Tesla T4, 15095 MiB
Training Time	0.409 hours

G. Evaluation and Inference

Post-training, the best-performing model weights are used to evaluate the detection performance on test images. Inferences are performed with a confidence threshold of 0.25. The model's output included class predictions and bounding boxes, which were visualised on the test images to verify accuracy. The visualisation confirmed that the model successfully identified tumor regions with precision.

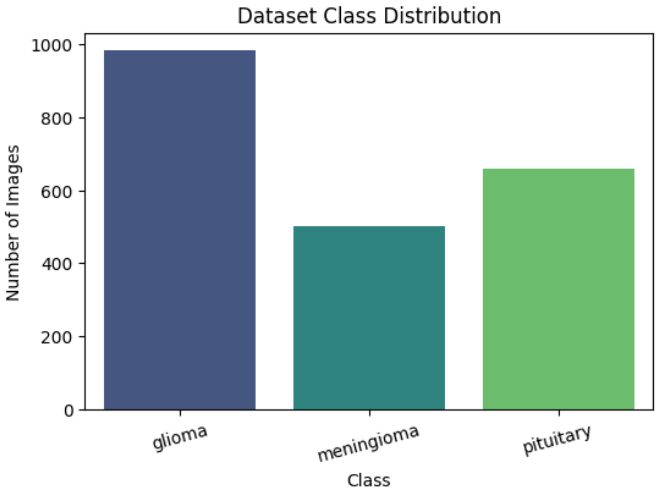

Fig. 1: Dataset class distribution

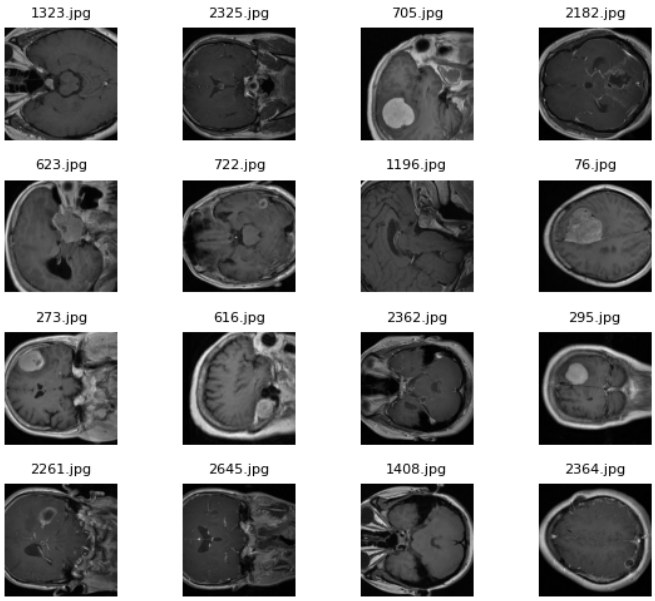

Fig. 2: Sample data

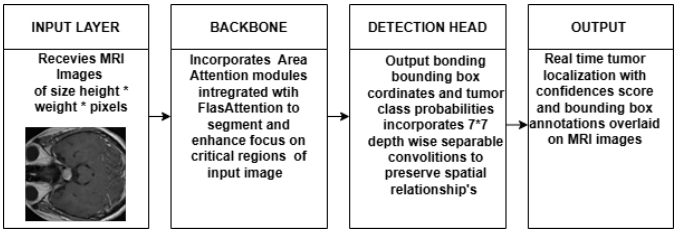

Fig. 3: Proposed model

IV. Results and Discussion

The YOLOv12 model is trained for 20 epochs using the pre-trained yolo12n.pt weights on the annotated MRI brain tumor dataset. Precision, recall, the F1 score, the confusion matrix, training and validation loss, and the training and evaluation process all exhibit consistent convergence. Effective learning was demonstrated by the final model's high mean average precision (mAP), low classification loss, and low localization loss. Fig. 4 shows the actual number of predictions. Diagonal values like 242 for glioma and 179 for pituitary indicate correct predictions. Off-diagonal values show errors; for instance, 84 background samples are misclassified as glioma, and 2 glioma cases are wrongly predicted as pituitary. This matrix gives a clear idea of the exact number of correct and incorrect predictions per class.

The training and validation curves for the improved YOLOv12 model are shown in Fig. 5. Trends for box loss, classification loss, and distribution focal loss (DFL) over the course of training are shown in the first three columns. It is evident that all loss values consistently decrease with time, signifying effective learning, robust model stability, and strong fitting capability. The fourth and fifth columns represent the precision and recall metrics, which exhibit an upward trend

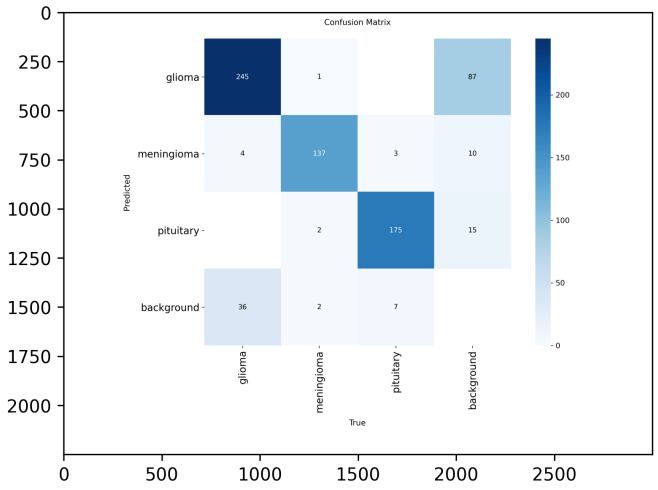

Fig. 4: Confusion matrix

as training progresses, with values near 0.8, indicating the increasing confidence and precision of the model in predicting infant brain tumors. The lower rows present the corresponding validation losses, which also show a steady decrease, further reinforcing the generalization of the model's performance.

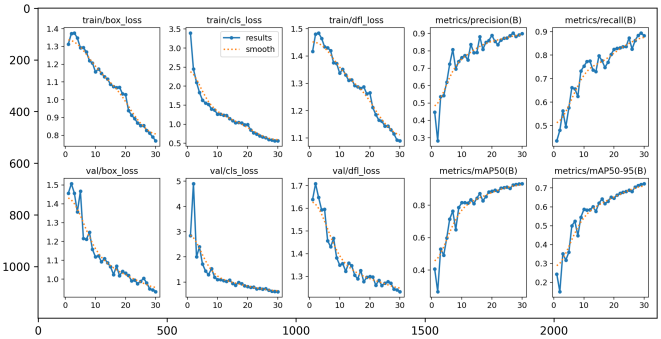

Fig. 5: Performance metrics curve

The evaluation of results is conducted through precision, recall, mAP and various performance metrics. Figs. 6 and 8 illustrate the accuracy and effectiveness of the model via precision recall and precision confidence curves. These curves depict the overall accuracy of the model for the categories glioma (85.5%), meningioma (97.5%), and pituitary (96.8%). The mPA at 0.5 (mAP50) for all classes is 93.3%, which means a high degree of precision and recall for the majority of brain tumor categories, although there is potential for improvement in the detection of neutral glioma. These findings underscore the effectiveness of YOLOv12 in the detection of brain tumors while also pinpointing areas that require further improvement, especially in the identification of brain tumors with lower accuracy rates.

The sensitivity of the model shows its ability to detect positive cases. Among tumor types, glioma had the lowest accuracy, followed by pituitary tumors, while meningiomas

had the highest. The suggests glioma are harder to classify, possibly due to unique features. Improving performance may require more glioma data, better feature extraction, or advanced model architecture..

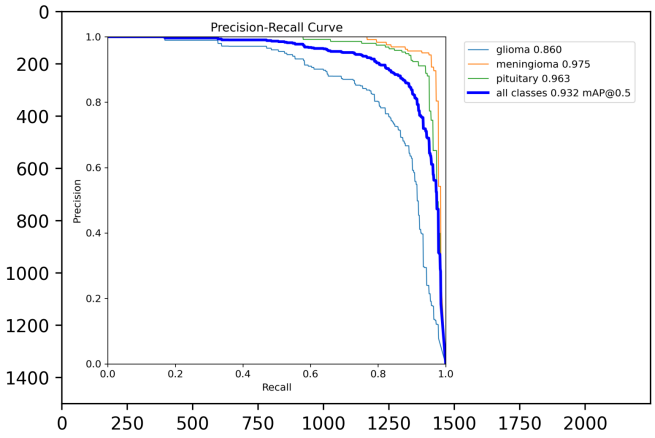

Fig. 6: Precision-recall curve

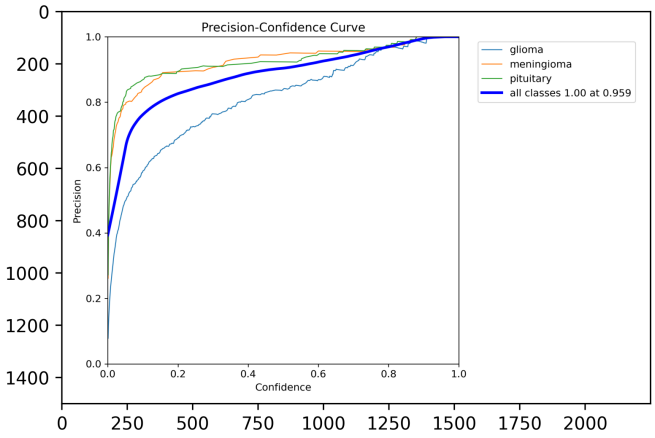

Fig. 7: Precision-confidence curv

Fig. 8 shows MRI brain scans with tumours detected by the YOLOv12 model. Colored boxes highlight the predicted tumor areas. The model successfully identifies tumors with 93.3% accuracy in different locations and sizes, proving its effectiveness in brain tumour detection.

TABLE II: Data description and classification for our proposed method

Class	Images	Box(p)	R	mAP50	mAP50-95
All	612	0.89	0.901	0.933	0.722
Glioma	285	0.788	0.793	0.855	0.585
Meningioma	142	0.95	0.951	0.975	0.83
Pituitary	185	0.932	0.96	0.968	0.75

The mean average precision at 50% junction over union (mAP @ 50), which is also popular in object detection, including medical imaging, can be applied to the assessment of accuracy of predicted tumor locations. It computes the overlap

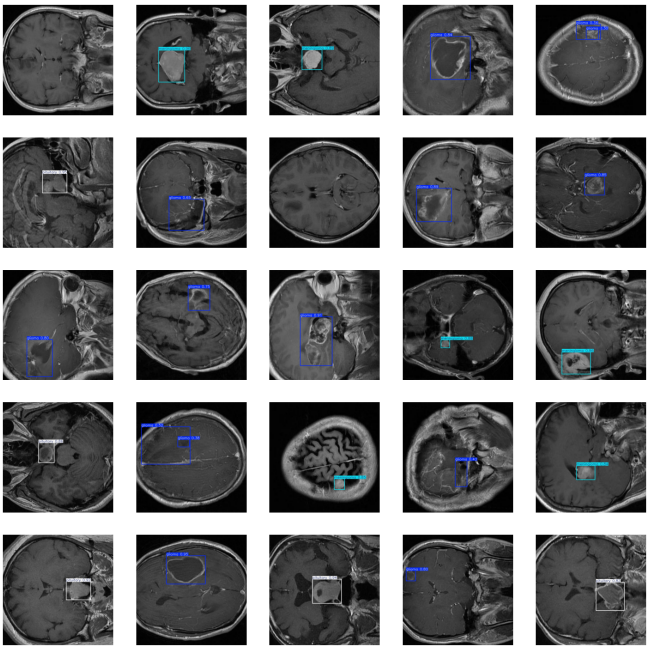

Fig. 8: Tumor detection with test image

between detected boxes and reference (or annotations), with at last 50% overlap needed to consider a detection. This measure is a good compromise between precision and recall, so it may be well suited for tasks - such as brain tumor detection - in which the exact localization of the tumors must be accurate for diagnosis and treatment.

The performance of YOLOv12 in processing MRI images supports its efficiency in clinical applications. The model achieves an inference latency of 0.1215 seconds per image, processing 30.04 images per second (FPS). The processing times break down as follows: 2.2 ms for preprocessing, 18.0 ms for inference, and 1.5 ms for postprocessing per image. These results demonstrate that YOLOv12 is capable of meeting the real-time processing requirements needed for accurate and efficient tumor detection in medical environments.

In table 3, evaluation of YOLOv12 variants (n, s, m) indicates the YOLOv12n variant achieves the best overall performance with an mAP@50 of 93.3%, recall 98%, and F1-Score 90%, while maintaining perfect precision. These results affirm that YOLOv12-n strikes a strong balance between accuracy, recall, and precision, making it a robust and reliable choice for real-time brain tumor detection from medical images.

TABLE III: Performance comparison of YOLOv12 variants

Variant.	**mAP@50**	**mAP@50-95**	**Rec.**	**Prec.**	**F1**
n	0.933	0.722	0.98	1.00	0.90
s	0.905	0.685	0.97	1.00	0.86
m	0.891	0.664	0.97	1.00	0.84

In Table 4: YOLOv12 is obtained a highest accuracy of 93.3%, outperforms over the state-of-the-art methods by [YOLOv11 (90.0%),YOLOv6-l, Faster-RCNN (91.66%). The

YOLOv12n variant has mAP@50 of 93.3%, recall of 98% and F1-Score of 90%, showing competitive speed as well as performance. These results demonstrate the effectiveness of YOLOv12 for brain tumor detection, and architectural modifications such as area attention modules and depth-wise separable convolutions, to increase accuracy.

TABLE IV: Comparison of methods for brain tumor detection

Model	Acc.(%)	Dataset
YOLOv11 [21]	90.0	Medical Image Dataset: Brain Tumor Detection
Faster R-CNN [22]	91.66	Medical Image Dataset: Brain Tumor Detection
YOLOv6-L [23]	92.9	Br35H: Brain Tumor Detection 2020
VGG-19 [24]	88.0	Brain Tumor Set
RF + ROI [24]	87.0	BRATS
CNN [25]	89.0	MRI Image Brain Tumor
YOLOv12n (Proposed)	**93.3**	Medical Image Dataset: Brain Tumor Detection

V. Conclusion

To conclude, the integration of advanced deep learning techniques, like YOLOv12, into tumor detection systems marks a substantial step forward in medical imaging diagnostics. Through comprehensive analysis and comparison, YOLOv12 demonstrated the highest performance over other models, particularly in terms of detection precision, recall and overall accuracy. Among YOLOv12's variants, YOLOv12n shows the most promising results, highlighting its ability to efficiently identify tumors across diverse MRI datasets. These advancements not only offer more accurate diagnostic tools but also promote real-time processing capabilities essential for clinical use. Future research may focus on expanding classification across complex tumour types while maintaining computational efficiency.

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