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Brain Tumor Detection from MRI Images Using YOLOv8 Deep Learning Model

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[1] ***Abstract*—This study proposed an efficient deep learning based approach for brain tumor detection using the YOLOv8 architecture. MRI scans are utilized to train and evaluate the model on a publicly available dataset. The proposed YOLOv8 framework effectively identifies and localizes tumor regions by leveraging enhanced convolutional blocks, multi-scale feature fusion and anchor free detection mechanisms. The model achieved a mean average precision (mAP@0.5) of 0.94, precision of 0.95, recall of 0.94 and F1-score of 0.94 and outperformed several existing YOLO-based approaches. The results demonstrate YOLOv8 robustness in accurate detection of tumors with high inference speed and it is suitable for real-time diagnostic applications. Overall, the proposed method shows great potential for computer-aided diagnosis and support for clinicians in brain tumor assessment.**

***Index Terms*— Tumor, YOLOv8, MRI, Feature, Detection.**

I. INTRODUCTION

A significant contributor to global mortality and morbidity rates, brain tumors are among the most significant and potentially deadly neurological disorders. Tumors can be benign or malignant and they can develop from a variety of brain tissues. Malignant tumors may grow rapidly and cause serious neurological disorders. To accurate brain tumor diagnosis significantly improves treatment planning, medical results and patient survival rates, it is consequently essential. Because it is non-invasive, high contrast resolution can offer extensive anatomical and structural information about brain tissues so that magnetic resonance imaging (MRI) is the most widely utilized for diagnosing brain tumors [1]. However, the method of manually analyzing, segmentation and recognition of tumors from MRI images is laborious, time-consuming and heavily dependent on specialists' skill workers. Human error and inter-observer variability are common in manual approaches that might influence clinical decision-making and provide conflict in diagnosis outcomes. Automated computer-aided diagnosis (CAD) systems which offer precise, effective and repeatable tumor recognition and classification. Such essential tools in medical imaging to get around these limitations [2, 3]. In order to extract specific features and evaluate vast volumes of data and help physicians make unbiased and reliable diagnostic assessments. These systems employ sophisticated machine learning and deep learning algorithms.

Recently, deep learning has revolutionized medical image analysis by automated feature extraction and remarkable classification performance. Convolutional Neural Networks (CNNs) and their variants have shown excellent performance in detection and segmentation of tumors from MRI images and are superior to traditional machine learning methods that rely heavily on handcrafted features. Among various deep learning architectures object detection frameworks have gained particular attention due to their ability to locate and classify multiple regions of interest simultaneously. The *You Only Look Once* (YOLO) family of algorithms represents a significant milestone in this field by

achieving real-time detection with remarkable accuracy [4, 5].

Unlike region-based detectors that perform classification and localization in separate steps the YOLO processes the entire image in a single forward pass and makes it computationally efficient and suitable for time-critical medical applications. YOLOv8 is the latest version of the application released by ultralytics and which offers a number of architectural advancements over previous versions. Advanced in convolutional blocks, enhanced feature aggregation and improved training processes are increasing the resilience and precision of detection.

A greater balance between detection accuracy and computational economy is the goal of YOLOv8's design. For medical imaging applications such as detection of brain tumors is very adaptable. In medical applications the capacity to generalize across various tumor types and MRI sequences offers more dependable and consistent results [6]. YOLOv8 can efficiently learn domain-specific features and reduce the need for large amounts of labelled data and also accelerate the model's implementation in practical diagnostic applications.

In this work, we use YOLOv8 to find and recognize tumors in the brain from MRI images. A dataset that is freely available is used to train and evaluate the model, and performance is measured using metrics like mAP, recall, and precision. The YOLOv8 architecture has been modified for the brain tumor recognition task that is the main contribution of this research.

- Presented YOLOv8's model high accuracy tumor location localization capabilities on MRI data.
- Addresses about the difficulties, restrictions, and practicality of using YOLO-based object recognition models for neuroimaging.

II. Literature Review

Brain tumor detection and segmentation using deep learning have been studied extensively over the past decade. Traditional CNNs architecture such as LeNet, AlexNet, VGG16, and ResNet50 have been successfully used for tumor classification tasks [7, 8]. These models are limited in spatial localization capabilities, motivated by a shift toward object detection frameworks that can predict both class labels and bounding boxes.

Mercaldo et al. [1] employed the YOLO architecture for brain cancer detection and localization and achieved a mean Average Precision (mAP at 0.5) of 0.941. Ranjbarzadeh et al. [9] investigated the effect of backbone selection in YOLOv8 models and showed that pertained weights improve localization performance. Dulal and Dulal [10] proposed an improved version of the YOLOv8 variant that integrates Ghost Convolutions and Transformer blocks and produces a mAP of 0.91 on a custom MRI dataset. Kang et al. [11] presented BGF-YOLO, an enhanced YOLOv8 model incorporating multi-scale attention fusion and improved detection accuracy on brain tumor datasets.

Earlier works relied heavily on semantic segmentation networks such as U-Net [12], Mask R-CNN [13] and encode and decoder CNNs [14]. That provides pixel-level segmentation but at the cost of higher computation and slower inference speeds. The YOLO family in contrast enables real-time detection while maintaining competitive accuracy [15]. Despite these advancements, studies face challenges such as overfitting and variations in tumor morphology [16]. Our work builds upon prior research by applying the YOLOv8 framework to a standardized MRI dataset and offering a systematic evaluation of its detection accuracy, robustness and inference efficiency.

III. METHODOLOGY

A. Dataset and Pre-processing

In this research we used the brain tumor detection dataset from roboflow [17] that contained MRI images labeled as “tumor” or “non-tumor” as shown in figure 1. Each image includes bounding-box annotations mark the tumor regions. The dataset is divided into 80% training and 20% validation subsets. Pre-processing involved resize all images to 640×640 pixels and normalize pixel intensities to the [0, 1] range and augmented the data using random rotations, flips and brightness adjustments to enhance generalization [18]. Data were formatted according to YOLO standards. Where each image has a corresponding .txt annotation file contained normalized bounded-box coordinates and class labels.

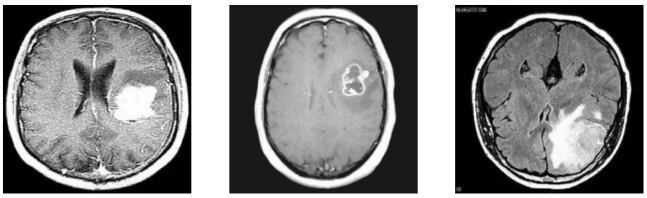

Fig. 1. Sample images of datasets.

B. YOLOv8 Architecture

The YOLOv8 model is developed by ultralytics, which is a one-stage object detector that directly predicts bounding boxes, class probabilities from input images [6]. Schematic diagram of the YOLOv8 model structure illustrate in figure 2 and it consists of three main components:

- **Backbone:** Based on a modified CSP Darknet architecture that uses C2f modules which allow efficient feature reuse and gradient flow. The backbone extracts multiscale features from the input MRI images [19].

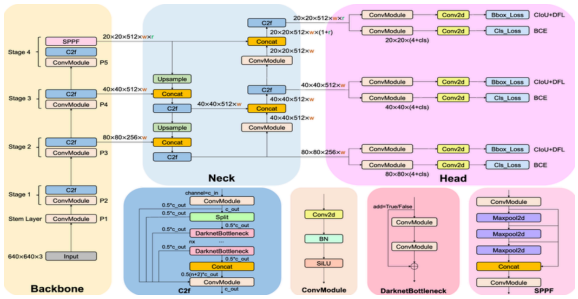

Fig. 2. Schematic diagram of the YOLOv8 model [21].

- **Neck:** Employs a Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) to fuse shallow and deep features that improve detection of small and large tumors alike [20].
- **Head:** The detection head predicts bounded boxes, objectless scores and class probabilities in a single forward pass. YOLOv8 supports anchor-free detection and improves generalization and reduced manual tuning.

The model optimizes a composite loss function consisting of bounded box regression loss (e.g., Complete IoU), objectless loss (Binary Cross-Entropy) and classification loss (Cross-Entropy) [6]. The architecture's design allows inference and high detection accuracy. It is well-suited for medical diagnoses for real-time performance and reliability.

C. Training Setup

The dataset is divided into three sections as training, validation and testing. Specifically, 10% of the data is assigned for validation and another 10% used for testing purposes. The validation set is utilized during the model training to fine-tune hyper-parameters and prevent overfitting, whereas the test set is reserved for assessing the final performance of the trained model. Table I shows the overall utilization of the data set.

TABLE I
DATASET SPLITTING IN MODEL TRAINING

Set	Images Count	Labels Count
Train	640	640
Validation	80	80
Test	81	81

Training is performed on a GPU using the ultralytics YOLOv8 implementation in Python. Pertained weights from the COCO dataset are fine-tuned on the MRI dataset. Training is conducted for 100 epochs with a batch size of 16, learning rate of 0.001 and image size of 640×640 pixels. The optimizer used as Adam and early stopping is applied to prevent overfitting. The dataset is divided into three sections as training, validation and testing. Specifically, 10% of the data is assigned for validation and another 10% used for testing purposes. The validation set is utilized during the model training to fine-tune hyper-parameters and prevent overfitting, whereas the test set is reserved for assessing the final performance of the trained model. Figure 3 shows the graphical representation of the performance matrix.

D, Evaluation Metrics

Performance of the model is evaluated using Precision, Recall, F1-Score and mAP@0.5. These metrics measure in what manner the model recognizes tumor regions and distinguishes them from non-tumorous areas. Typical results observed as Precision = 0.92, Recall = 0.90, F1-Score = 0.91, mAP@0.5 = 0.94 shown in Table II. These demonstrate that YOLOv8's ability to accurately detect tumor regions also maintain efficient inference speed.

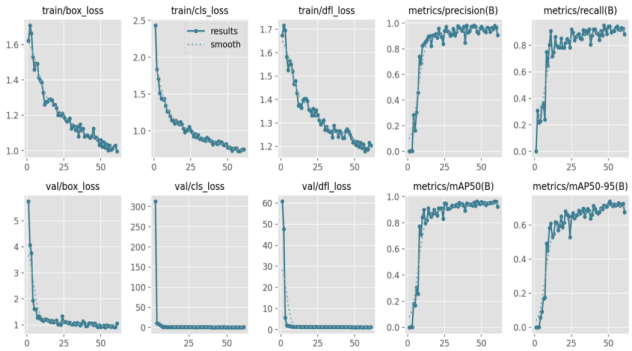

Fig. 3. Graphical representation of performance matrix.

IV. RESULTS AND DISCUSSION

The YOLOv8 model achieved a mAP@0.5 is 0.94, Precision 0.92, and Recall 0.90 outperform earlier YOLO-based approaches [9, 11]. The relatively high mAP confirms the model's capacity to localize brain tumors accurately, balance precision and recall values indicate reliable detection without excessive false positives/ negatives. Dulal and Dulal [10] achieved a mAP of 0.91 with their enhanced YOLOv8 model and Mercaldo et al. [1] reported 0.941 using YOLOv5 on a similar dataset. Figure 6. Shows graphical representation of the performance evaluation metrics. Our model thus performs competitively, validating the suitability of YOLOv8 for medical image-based object detection. Figure 4 shows the confusion matrix of the YOLOv8 model.

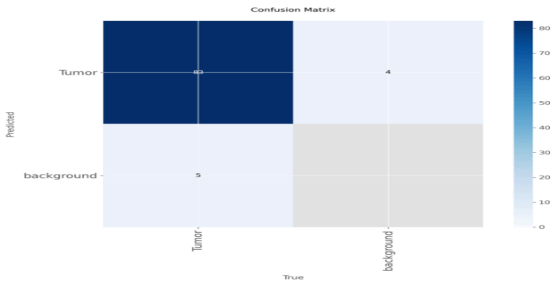

Fig. 4. Confusion matrix of YOLOv8 model.

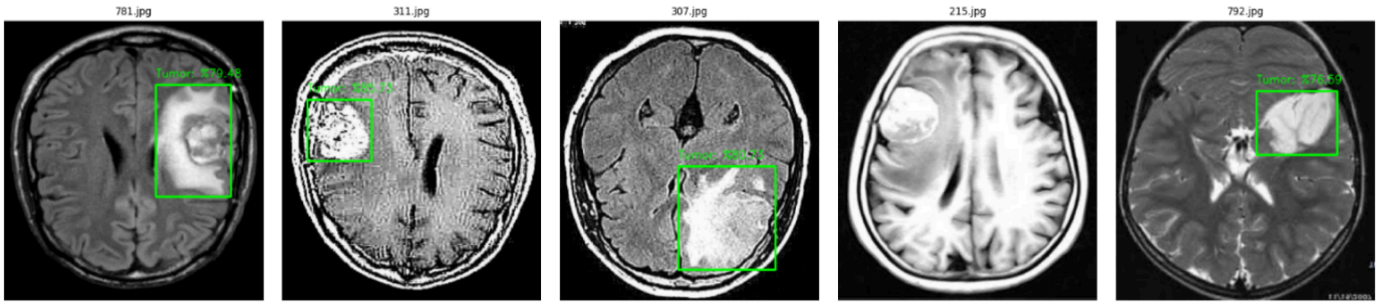

Fig. 5. Illustrate the tumor detections using the YOLOv8 model.

accuracy. The model performs fine across different tumor sizes and contrast levels. In certain cases with very small or low-contrast tumors showed partial misses or overlapping bounding boxes. Figure 5 illustrates the correct detections and failure cases of tumor detection.

TABLE II
Performance Evaluation Matrix of Yolov8 Model

Metric	Score
mAP50	0.950732
mAP50-95	0.741985
Precision	0.953973
Recall	0.943182
F1-score	0.948547
Accuracy	0.966800

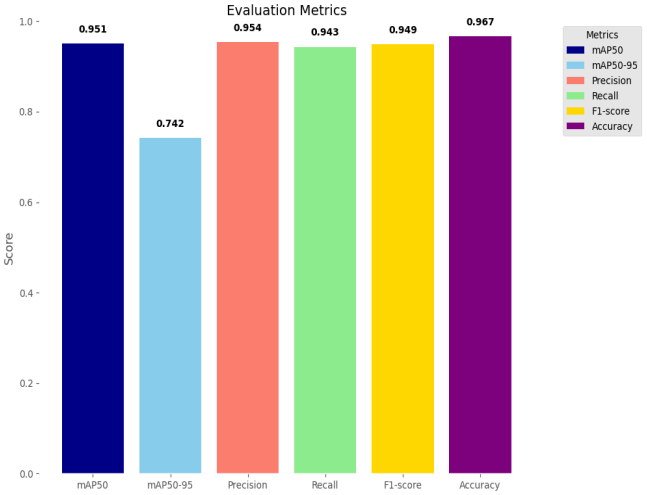

Fig. 6. Graphical representation of performance evaluation metrics.

The strong results validate YOLOv8's efficiency in brain tumor localization tasks. The anchor free architecture and FPN-PAN feature fusion help capture multi-scale tumor structures that are essential for medical images. Limited MRI modality diversity and reliance on bounded-box detection instead of precise segmentation. Future extensions may combine the YOLOv8 with segmentation frameworks for more clinical application. Additionally, cross-institutional validation will be needed for real-world generalizability.

V. Conclusion

The research shows the method to utilize YOLOv8 deep learning model to detect brain tumors in MRI images. Achieving a mAP@0.5 of 0.94 accuracy as competitive for the study of medical images, YOLOv8 is a reliable and effective detector. It can be integrated into real-time diagnostic systems because of its quick inference time and end-to-end training. Future study may concentrate on extended datasets, integrate multimodal MRI sequences and coupling YOLOv8 with segmentation networks. Overall, this study shows the potential YOLOv8 is for enhancing computer-aided brain tumor diagnosis.

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