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Advanced YOLOv8 architecture for multi-class brain tumor detection

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ABSTRACT

Background: Accurate brain tumor detection is critical for early diagnosis and effective treatment planning in neuro-oncology. Magnetic resonance imaging (MRI) is a cornerstone for identifying and localizing brain tumors, guiding clinical interventions, and enhancing patient outcome. Advanced deep learning models, such as YOLOv8, offer promising solutions for automated and precise tumor detection in MRI.

Objectives: This study aimed to develop and evaluate a YOLOv8-based model for the accurate identification and localization of brain tumors, including pituitary tumors, meningiomas, and gliomas, using a publicly available Kaggle dataset of annotated MRI images.

Materials and methods: The YOLOv8 pretrained model was employed for brain tumor detection on a Kaggle dataset comprising annotated MRI images, including cases with pituitary, meningioma, and glioma, and no tumor. The dataset was pre-processed and split into training and validation sets for further analysis. The YOLOv8 model was fine-tuned to optimize the tumor detection and localization. Performance metrics, including precision, recall, F-1 score, and mean average precision (mAP), were calculated, and loss values were analyzed to evaluate the model's learning efficiency.

Results: The YOLOv8 model achieved a precision of 98.9%, recall of 98.9%, and accuracy of 99.5%. The mean average precision (mAP) reached 97.6%, indicating a high accuracy in detecting and localizing brain tumors. Loss value analysis demonstrated stable convergence during training, reflecting a robust model performance.

Conclusion: The YOLOv8-based approach provides a highly accurate and reliable method for detecting and localizing brain tumors in MRI. With exceptional precision, recall, and mAP, this model demonstrates significant potential for clinical applications, enabling faster and more precise neuro-oncological diagnosis and treatment planning.

Introduction

In the field of neurological disorders, brain tumors represent a significant and often life-threatening challenge. The prognosis of patients and assessment of treatment efficacy are critically dependent on early diagnosis and accurate localization.[1,2] Cancer has profoundly affected many lives, and most individuals have encountered someone who has suffered from its severe consequences.[3] Brain tumors are abnormal growths that develop within the brain or surrounding brain tissue. They can affect individuals of any age or sex, although certain risk factors may increase their likelihood. Brain tumor treatment typically involves a multidisciplinary approach, including chemotherapy,

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radiation therapy, or surgery, depending on the tumor type, location, and size. The effectiveness of treatment is contingent on early, accurate, and reliable detection, as it facilitates prompt intervention and significantly enhances the probability of a favorable prognosis.[4] Figure 1 shows a sample image of a brain tumor.

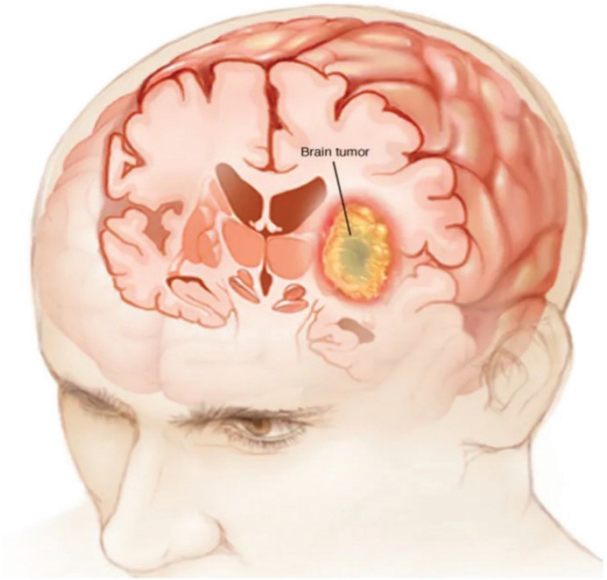

Figure 1. *Sample image of brain tumor.*

The anatomy of the human brain is highly complex, necessitating precise structural knowledge for the detection of anomalies. Various imaging techniques, such as computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), and magnetic resonance imaging (MRI), are employed by medical professionals to diagnose brain abnormalities.[5] Among these, MRI is the most prevalent technique because of its non-invasive nature and ability to produce high-resolution images that reveal the intricate anatomical details of the brain.[6]

The efficacy of treatment planning and improvement of patient outcomes is largely contingent upon early and accurate diagnosis. Medical imaging techniques play a crucial role in this process, particularly MRI, which is the most used because of its non-invasive nature and ability to generate high-resolution images of brain structures. Other imaging modalities include CT, PET, and SPECT.

This study focused on three primary types of brain tumors: gliomas, meningiomas, and pituitary tumors, in addition to a no-tumor category. Understanding the nature of these tumor types is essential for accurate detection and diagnosis.

Gliomas: Gliomas are tumors that originate from glial cells, which play a crucial role in supporting and protecting neurons in the brain. These tumors are often aggressive and present treatment challenges owing to their infiltrative nature. Gliomas represent the most prevalent type of primary brain tumor.

Meningioma: Meningiomas are tumors that develop in the meninges, the protective membranes covering the brain and spinal cord. Although typically benign and slow growing, meningiomas can exert significant neurological effects by exerting pressure on adjacent brain tissue.

Pituitary tumors: These tumors occur in the pituitary gland; a small but vital gland located at the base of the brain responsible for hormone regulation. Pituitary tumors can be benign or malignant and may produce a range of symptoms depending on their size and hormone secretion activity.

The state-of-the-art object detection method, You Only Look Once (YOLO),[7] is acclaimed for its ability to perform high-accuracy, real-time detection, particularly in complex scenarios. This capability makes YOLO a suitable choice for analyzing magnetic resonance imaging (MRI) scans. Moreover, YOLO and similar object detection techniques facilitate precise localization within images in addition to tumor diagnosis. In this study, we implemented YOLO v8 for brain tumor detection. The remainder of this paper is structured as follows: Section 2 presents a review of related state-of-the-artwork; Section 3 describes the proposed approach; Section 4 presents the experimental results; and Section 5 concludes with a discussion of future scope.

Literature Review

Author of this work employed YOLOv8, YOLOv11, and a custom convolutional neural network (CNN) model to accurately and efficiently identify brain malignancies, specifically pituitary, glioma, and meningioma, using artificial intelligence.[8] The models

leverage transfer learning and fine-tuning to classify magnetic resonance imaging (MRI) images into four categories, including "No Tumor." The models were trained using the publicly available CE-MRI Figshare Dataset. The custom CNN achieved an accuracy of 96.98%, whereas YOLOv11 and YOLOv8 attained remarkable accuracies of 99.56% and 99.49%, respectively. These results suggest that deep learning can substantially enhance brain tumor diagnosis and classification.

In this paper, further explored the efficacy of YOLOv8 in localizing brain tumors by analyzing the impact of model size and pretraining.[1] Experiments conducted on an NVIDIA Tesla T4 GPU using Google Colab revealed that pretrained models, particularly smaller ones, such as YOLOv8-XS, exhibited significantly higher accuracy than their non-pretrained counterparts. For example, YOLOv8-XS pretrained on the COCO dataset improved the Intersection over Union (IoU) and Dice scores by 15%. Additionally, the findings indicate that while pre-training enhances performance, its benefits diminish as the model size increases.

Work in this paper presents an enhanced YOLOv8 model for the precise identification of brain tumors in MRI data.[9] Key improvements include the integration of a vision transformer for deeper feature extraction, the use of ghost convolution to reduce computational demands, and the replacement of RT-DETR with NMS for a superior bounding box selection. When evaluated on a publicly available brain tumor dataset, the model outperformed other object detectors and standard YOLO versions, achieving a remarkable mean average precision (mAP@0.5) of 0.91, thereby demonstrating its high accuracy and efficiency.

The application of deep learning for rapid and precise malignant tumor diagnosis on mobile devices are emphasized in this work.[10] We assessed the performance of the ResNet12, DenseNet, YOLOv8, and MobileNet models using a brain tumor dataset comprising 4,489 images across 14 classes. The results indicated accuracy levels ranging from 88% to 97.3%. YOLOv8 emerged as the top performer owing to its minimal preprocessing time (0.1 ms), fastest inference time (1.8 ms), highest accuracy (97.3%), and compact size, making it ideal for real-time mobile applications.

Limitations of manual MRI analysis are addressed in this paper, by introducing an improved YOLOv8 model for brain tumor detection.[11] The model incorporates EMA for enhanced sensitivity to lesion features, CARAFE for broader contextual awareness, and C2f_DySnakeConv for improved tumor perception. The experimental results demonstrate that the revised model surpasses the original YOLOv8 and other open-source models, achieving improvements of 2.71%, 2.34%, 2.24%, and 3.73% in precision, recall, mAP@0.5, and mAP@0.5–0.95, respectively.

To enhance the detection and classification of brain tumors in challenging scenarios, this study proposes an innovative DC-YOLOv8FEN model. This model integrates advanced loss functions and dynamic attention mechanisms, along with vision transformers, self-shuffle attention, and a dual feature pyramid network, to facilitate enriched feature extraction. The model achieved an F1-score of 96.5%, accuracy of 99.5%, recall of 90.5%, and precision of 95.2%, demonstrating exceptional performance. This approach holds significant potential for assisting radiologists in real-time patient diagnosis, thereby improving precision and reducing delays.[12]

This paper also introduces a Gaussian Convolutional Neural Network (GCNN) method for multi-class brain tumor (BT) classification using MRI data. One dataset employed 3,064 images to classify tumors into pituitary, glioma, and meningioma categories, whereas another dataset utilized 516 images to classify gliomas into three grades (II, III, and IV). The proposed method achieved high accuracies of 99.8% and 97.14% on the two datasets, respectively, underscoring its efficacy in accurately identifying and categorizing various brain tumor types and grades.[13]

Furthermore, this study compares YOLOv5 and YOLOv7 for the detection and categorization of brain tumors using MRI scans of three distinct tumor types: meningiomas, gliomas, and pituitary tumors. Advanced mask alignment was employed during preprocessing to ensure the precise segmentation. Across a range of IoU thresholds, YOLOv7 exhibited slightly superior performance compared to YOLOv5 in terms of detection accuracy and mean Average Precision (mAP). Both models demonstrated their effectiveness and accuracy in medical imaging tasks, significantly outperforming traditional methods such as RCNN, Faster RCNN, and Mask RCNN.[14]

Materials and methods

Dataset

The brain tumor MRI dataset,[15] comprising 7,023 images from three sources—Figshare, SARTAJ, and Br35H—serves as an exceptional resource for classifying brain tumors into four categories: glioma, meningioma, no tumor, and pituitary. Notably, the 'no tumor' category was exclusively derived from the Br35H dataset. Additionally, the glioma class image, originally from the SARTAJ dataset, was replaced with an image from Figshare owing to misclassification errors identified in previous studies and training model results. This substitution aimed to enhance the reliability of the dataset. However, potential challenges, such as class imbalance or variations in imaging protocols across sources, may necessitate pre-processing techniques, such as normalization and augmentation, to ensure consistent model performance. Figure 2 shows sample images from the brain tumor dataset which includes glioma, meningioma, no tumor and pituitary images.

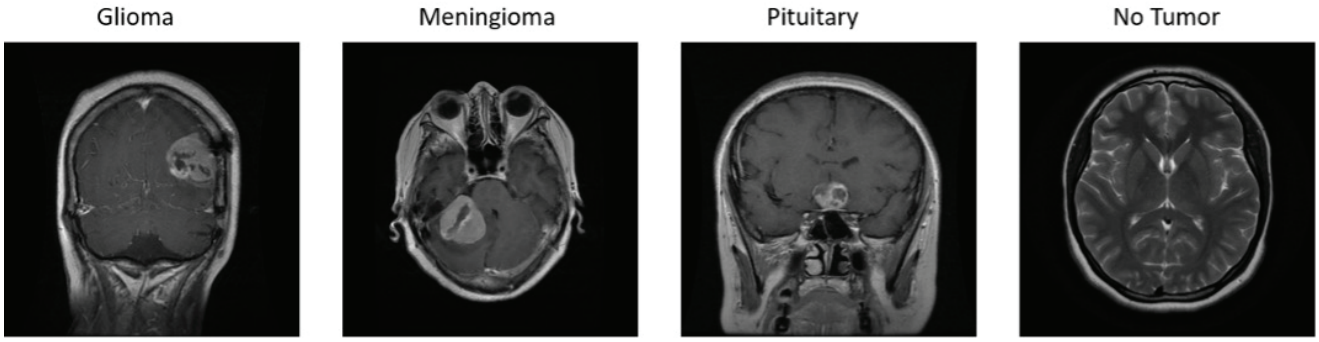

***Figure 2**. Sample images of brain tumor dataset.*

Methods

The proposed methodology for classifying brain MRI images into four categories—glioma, meningioma, no tumor, and pituitary, employs a structured pipeline based on the YOLOv8 model. As shown in Figure 3, this pipeline comprises seven stages, designed to ensure optimal model performance and rigorous scientific validation. Each stage is meticulously detailed, highlighting its technical implementation, underlying rationale, and integrative function within the overall process.

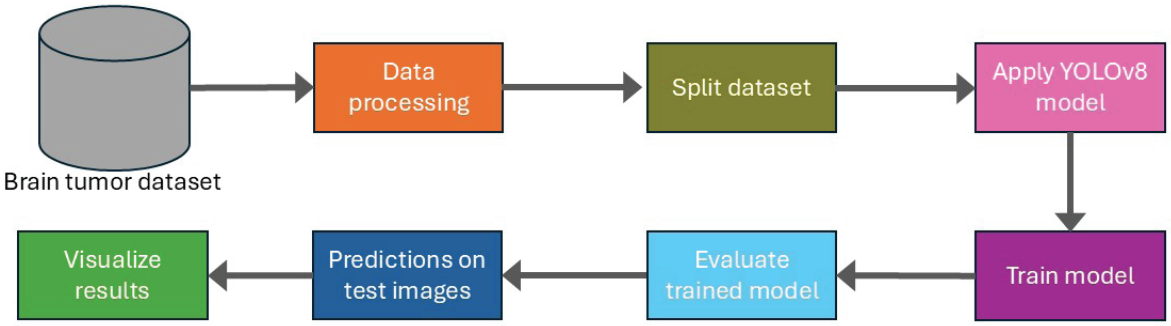

***Figure 3**. Proposed brain tumor detection framework.*

Data pre-processing

The initial phase of dataset preparation involved preprocessing, which encompassed 7,023 MRI images sourced from the Figshare, SARTAJ, and Br35H datasets. During this phase, variations in image resolution, intensity, and format are addressed using standardized transformations. The images were resized to a uniform resolution to comply with the input requirements of YOLOv8. Subsequently, the images were normalized to achieve a mean of 0 and unit variance, thereby enhancing the contrast and mitigating biases due to varying illumination. Gaussian filtering was employed to eliminate noise and other artifacts, whereas data augmentation techniques, such as horizontal flipping and brightness adjustment, were utilized to improve the model's generalization capabilities. This preprocessing is essential to ensure data reliability and coherence, which are crucial for extracting features with high fidelity in subsequent stages.

Dataset splitting

To facilitate supervised learning and ensure an unbiased evaluation of performance, the pre-processed data were partitioned into three distinct subsets: training, validation, and test data. A 70-15-15 stratified split was employed to maintain the same distribution of the four classes across the training, validation, and testing datasets. This stratification is essential, particularly given the potential imbalances in the 'no tumor' category, which is solely based on Br35H. The split was executed with a fixed seed (e.g., 42) during random sampling to ensure reproducibility. This approach allows for iterative improvement of the model and a separate assessment of its generalization performance on previously unseen observations, aligning with the best practices in machine learning evaluation.

YOLOv8 model application

To identify the most effective framework with a high success rate, we selected the state-of-the-art real-time object detection model YOLOv8 owing to its efficiency in testing speed and accuracy in medical image analysis. In this phase, the four-class classification task is fine-tuned using the pretrained YOLOv8 architecture, leveraging the weights from the ImageNet dataset. This model employs a convolutional neural network backbone to extract hierarchical

features, which are then used for bounding box regression and class prediction tasks in the detection head. The hyperparameters, including the learning rate (0.001), batch size (16) and anchor box sizes, were determined based on the image dimensions and tumor characteristics in the MRI. This step involves the application of transfer learning to expedite the convergence process and tailor the model specifically for brain MRI tumor detection.[16] Figure 4. illustrates the enhanced architecture of YOLOv8. The primary features of the YOLOv8 architecture are as follows:

Backbone: a deep convolutional neural network (CNN) that extracts hierarchical features from the input image, with CSPDarknet53 being a typical backbone.[17]

Neck: connects the backbone and head to facilitate feature flow across diverse scales. Unlike conventional feature pyramid networks (FPN), YOLOv8 employs a novel C2f module to integrate high-level features.

Head: responsible for predicting the bounding boxes and class probabilities. As an anchor-free network, YOLOv8 does not utilize predefined anchor boxes to predict the center of an object, thereby simplifying the detection process and potentially enhancing performance.

Loss function: the training of YOLOv8 involves a loss function comprising classification, localization, and abjectness losses. This multi-objective loss function aids in balancing the various components of detection tasks.

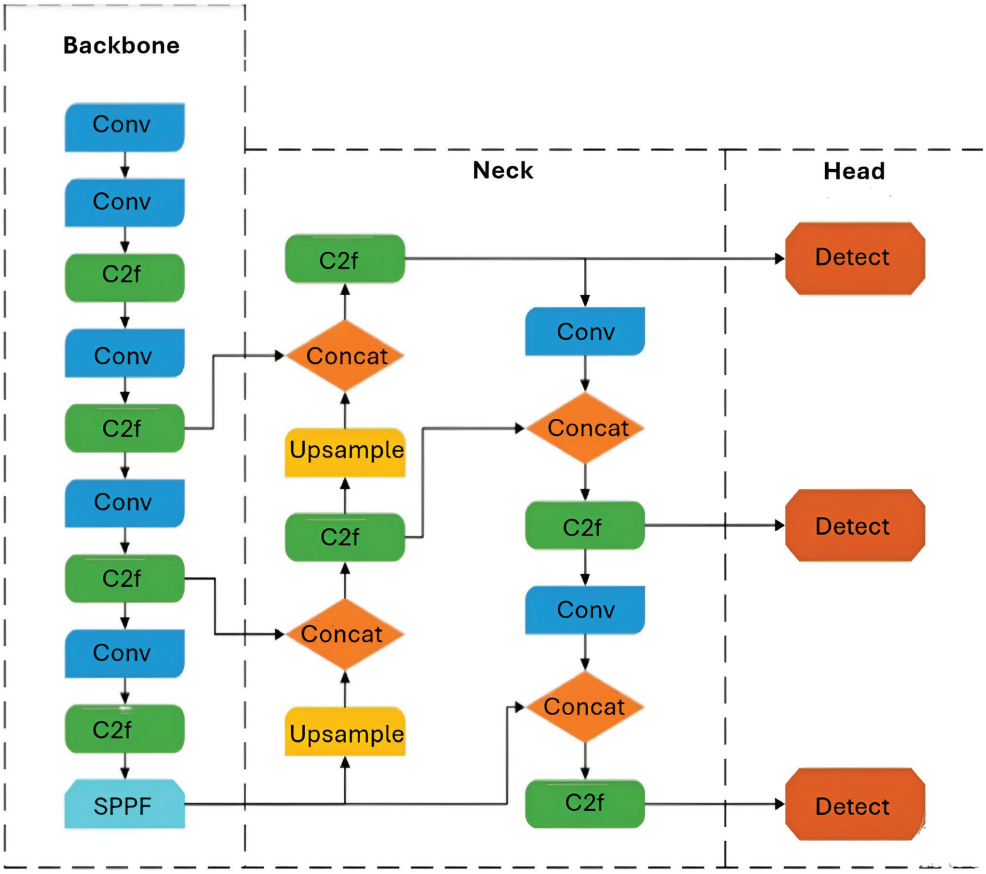

Figure 4*. The enhanced YOLOv8 architecture.*

Training model

The training subset was used to train the model, with YOLOv8 optimized through stochastic gradient descent (0.9) and a cosine-based annealing learning rate. This loss function incorporates classification loss (cross-entropy), localization loss (CIoU), and objectness loss, which are specifically designed to address the multi-class and multi-objective nature of the task to achieve equilibrium. Training was conducted until either 100 epochs were completed or convergence was achieved, with convergence being evaluated using the validation set to prevent overfitting through early stopping (patience=10 epochs). Performance metrics, including the mean Average Precision (mAP) at IoU=0.5, were monitored to assess progress. This rigorous training protocol ensures that the model effectively captures complex tumor patterns without incurring excessive computational costs.

Evaluation of the trained model

The model performance was critically evaluated after training on the independent test set. Evaluation metrics such as precision, recall, F1-score, and mean Average Precision (mAP) across all classes were considered to provide a comprehensive assessment of the accuracy and robustness of the classification.

To ascertain class-specific errors, a confusion matrix was constructed, with particular attention given to the glioma class owing to previous misclassification issues in the SARTAJ dataset. Comparisons with baseline models were conducted using statistical tests, such as the McNemar test, to ensure that the model's performance surpassed that of the baseline models. This approach serves to demonstrate the model's generalizability and clinical relevance, which are crucial for high-impact applications.

Prediction of test images

The trained YOLOv8 model was deployed on the test subset to generate predictions that included bounding boxes and class probabilities. This phase involves a forward pass through the network, followed by post-processing using non-maximum suppression (NMS) to eliminate overlapping detections, with an NMS threshold of 0.45. Ground truth labels and confidence scores were used to assess the discrepancies between the predicted labels and scores. Qualitative evaluation can be conducted by visualizing the predicted bounding boxes on the test images to identify false-positive or false-negative results. This process aims to enhance the practical applicability of the model in actual diagnostic practice.

Visualization

Visualization involves the superimposition of bounding boxes on test images to delineate the tumor regions. This process is executed through the visualize detection routine, wherein OpenCV is employed to draw rectangles and affix labels with confidence scores (e.g., the visualize routine utilizes OpenCV to render rectangles and labels with values indicating tumor detection, such as tumor: 0.97). Performance metrics were plotted using Matplotlib, with a code snippet illustrating box loss, mean Average Precision (mAP), precision, and recall on the x-axis, alongside the epoch on the y-axis, arranged in a 2×2 subplot configuration.

Evaluation metrics

Evaluation metrics are quantitative measures used to evaluate the performance of a model, algorithm, or system. We used accuracy described in Equation (1), precision represented by Equation (2), recall calculated using Equation (3), Mean Average Precision (mAP) represented by Equation (4) as performance metrics.[18]

Accuracy

This is a performance measure that indicates the percentage of correctly predicted instances (i.e., true positives and true negatives) against the total number of predictions.

$$Accuracy = \frac{TN + TP}{TP + FP + TN + FN} \quad (1)$$

Precision (P)

The percentage of accurately identified positive predictions among all positive predictions.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall (R)

The percentage of correctly predicted positive predictions among all actual positives.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

Mean average precision (mAP)

The average of the Average Precision (AP) of all classes. The part of the precision-recall curve is called AP.

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \quad (4)$$

Where N is the number of classes.

Results

In this study, the performance of the YOLOv8 model in identifying brain MRI tumors was evaluated using a dataset comprising 7,023 images categorized into four classes: glioma, meningioma, no tumor, and pituitary tumors. The YOLOv8 model employed pretrained weights through transfer learning, with training conducted at an initial learning rate of 0.001, a batch size of 16, and over 60 epochs. During test inference on 400 images with dimensions (1, 3, 640, 640), the model demonstrated processing times of 4.3, 12.8, and 3.3ms per image for preprocessing, inference, and postprocessing, respectively. Comparative performance metrics highlight the proposed model's superiority over existing approaches, as summarized in Table 1.

Table 1. Comparison of proposed model with existing models.

Author	Precision (%)	Recall (%)	Accuracy (%)
Remzan *et al.* [19]	97.71	97.71	97.71
Kaur *et al.* [20]	97.8	97.2	98.02
Rajput *et al.* [21]	99	98	99
Proposed	98.9	98.9	99.5

Notably, as shown in Figure 5, the model correctly identified a glioma in the image Tr-glTr_0006.jpg with a confidence score of 0.97. The resilience of the modified YOLOv8 architecture and its potent ability to accurately locate the glioma location inside the MRI scan are demonstrated by this detection output.

The Box Loss graph, shown in Figure 6, indicates efficient optimization and little overfitting, provides additional evidence for these findings by displaying a consistent drop in training and validation losses.

The mean average precision (mAP50-95) development over training epochs is seen in this graph shown in Figure 7. Early optimization changes are reflected in the initial oscillations. Strong convergence and high detection accuracy are then indicated by the curve stabilizing around 1.0. The trained YOLOv8 model's resilience and capacity for generalization are validated by the consistently high mAP values in subsequent epochs.

The variation in precision and recall for the different epochs is shown in Figure 8. After about 15 epochs, the precision-recall curve quickly stabilizes, and both metrics surpass 0.95, suggesting robust and steady classification accuracy throughout training.

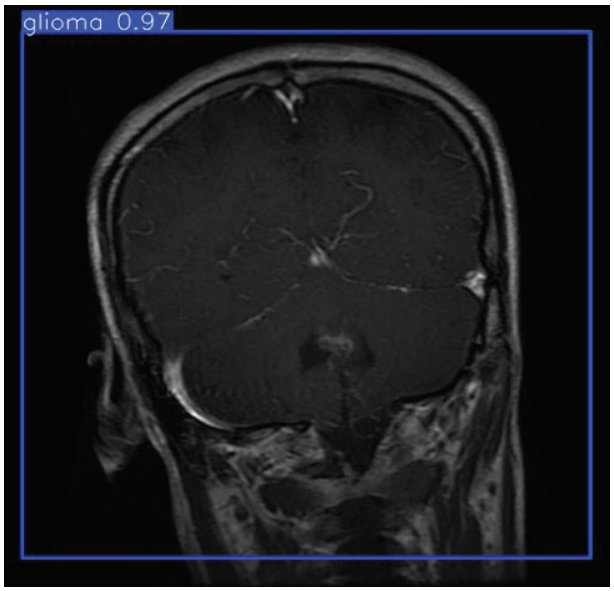

***Figure 5**. Predicted results.*

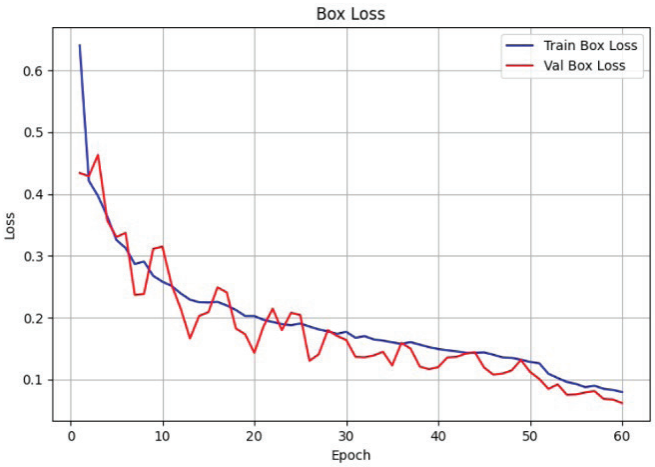

***Figure 6**. Variation in between loss and epoch.*

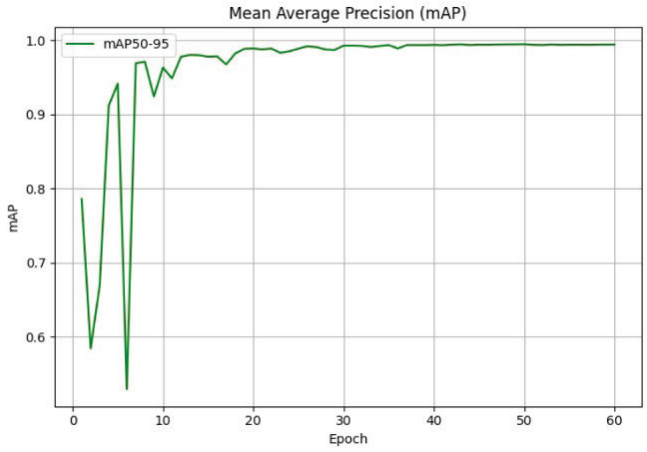

***Figure 7**. Graph plot between mean average precision and epoch.*

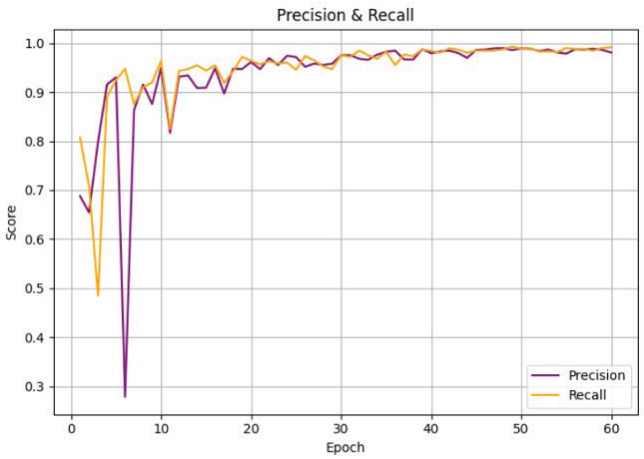

***Figure 8**. Variation of Precision and Recall between epochs.*

Discussion

By implementing and optimizing YOLOv8 for precise glioma, meningioma, and pituitary tumor detection and localization in MRI scans, this study achieves state-of-the-art performance while improving reproducibility by using a publicly available dataset. Inference testing on a subset of 400 images, each resized to a shape of (1, 3, 640, 640), revealed efficient processing times: an average of 4.3ms per image for preprocessing, 12.8ms for inference, and 3.3ms for postprocessing, resulting in a total processing time of approximately 20.4ms per image. This computational efficiency underscores the model's potential for real-time clinical applications, balancing speed with diagnostic reliability.

The model achieved a precision of 98.9%, recall of 98.9%, and overall accuracy of 99.5%, outperforming benchmarks such as Remzan *et al*. (97.71% across all metrics), Kaur *et al*. (precision 97.8%, recall 97.2%, accuracy 98.02%), and Rajput *et al*. (precision 99%, recall 98%, accuracy 99%).[19-21] These results indicate enhanced robustness in minimizing false positives and negatives, particularly in multi-class tumor classification, thereby advancing the state-of-the-art in AI-assisted brain MRI analysis. data processing and error correction.

The suggested YOLOv8-based model shows great promise as a quick and accurate method for automatically detecting brain tumors in MRI images. It can help radiologists identify and plan treatments for pituitary tumors, meningioma, and gliomas early on by increasing diagnostic efficiency and accuracy. While expert appraisal and multi-center validation are still necessary for clinical adoption, integration into clinical workflows may expedite screening and aid in decision-making.

Overall, the results suggest the model is performing well and could be useful for tumor detection, though it still requires some refinement.

Limitations

A publicly accessible Kaggle dataset was used to train and evaluate the model, which might not accurately reflect the variability of actual clinical MRI data. Furthermore, the identification performance for less-represented tumor types might have been impacted by possible class imbalance and a small sample size. The precise tumor segmentation that is essential for clinical decision-making is not addressed by the suggested YOLOv8 model, which instead concentrates on detection and localization. Additionally, the evaluation of clinical application was limited because no expert radiologist validation or comparison with established diagnostic procedures was carried out. Lastly, because no explainability techniques were used to illustrate or support the model's predictions, its interpretability is still restricted. These constraints should be addressed in future research by incorporating segmentation modules, external validation, and interpretability strategies.

Conclusion

The primary objective of this study was to employ the YOLOv8 model for the detection of tumors in brain MRI images and to evaluate its effectiveness and efficiency in comparison to existing medical object detection models, utilizing the publicly available dataset, which comprises 7,023 images categorized into glioma, meningioma, no tumor, and pituitary classes. The pre-trained YOLOv8n model, trained for more than 60 epochs, achieved a confidence level of 0.97 in detecting gliomas, with processing times of 4.3, 12.8, and 3.3ms for pre-processing, inference, and post-processing, respectively. The visualization of boxes and performance metrics, such as box loss, mAP50-95, precision, and recall, confirmed the model's capability to accurately identify tumor regions and improve over time. The experimental results indicate that the precision, recall, and accuracy values are 98.9%, 98.9%, and 99.5%, respectively. Additionally, the model provides a mean average precision (mAP) of 97.6% after comprehensive evaluations.

Future work will focus on enhancing the efficiency of the YOLOv8 model for deployment in edge devices and real-time clinical applications, as well as expanding the dataset and incorporating multimodal data to achieve improved generalization and tumor characterization.

Ethical approval

There are no humans or animals used for experimentation purpose.

Fundings

This research did not receive any specific grants from any funding agency in the public, commercial, or not-for-profit sectors.

Conflict of Interest

There are no conflicts of interest to declare.

Data availability statement

These datasets are publicly available on the Kaggle website under the names: figshare, SARTAJ, and Br35H**.**

CRediT authorship contribution statement

Kavita Singh: developed and implemented the proposed methodology, conceptualized the study and prepared the manuscript; **Rajesh Kumar**: supervisor of this work, contributed to the conceptualization, methodological design and manuscript drafting; **Satyendra Singh**: assisted with manuscript in writing, editing and revision.

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