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Neuroai: An Intelligent Framework For Brain Tumor Anomaly Detection In MRI Using Yolov8

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Abstract: A detailed and accurate evaluation of brain tumors from medical images is a requirement in modern medical care because early detection has a powerful impact on treatment outcomes. Magnetic Resonance Imaging (MRI) is common for the investigation of brain disorders, but it is labour intensive and reliant on interpretive experience to read scans with expert observers. This paper develops NeuroAI, an automated system for detecting brain tumor anomalies that makes use of deep learning-based object detection to analyse MRI scans. The proposed model utilizes YOLOv8 to localize tumor sites and subcategorize tumor types such as meningioma, glioma, pituitary tumors and non-tumor cases. ARG, or Retrieval Augmented Generation, provides contextual medical explanations for the types of tumors that were observed and makes the system more readable. The model is trained and assessed using MRI scans from The Cancer Imaging Archive (TCIA). It also includes confidence levels and IoU values to balance the sensitivity and detection accuracy. Observations have shown that the system reliably detects and classifies brain tumors, which indicates that this system can function as a conduit for clinical decision-making and medical education.

Keywords — Brain Tumor Detection, MRI Analysis, YOLOv8, Deep Learning, Object Detection, Anomaly Detection, Medical Artificial Intelligence

I. INTRODUCTION

It is suggested that brain tumors occur due to uncontrolled cell growth in the brain and can be broadly classified as malignant. Brain tumors pose risks as they may interfere with essential neurological functions as a: cognition, vision, speech, and motor control. Early and accurate detection plays a critical role in determining appropriate treatment strategies and improving patient outcomes. Magnetic Resonance Imaging (MRI)is the most preferred procedure for brain tumor diagnostic because it provides high resolution images and excellent soft tissue contrast without exposure to ionizing radiation. MRI scans allow clinicians to visualize tumor size, location, and structure. The diagnosis but remains significantly dependent on the manual inspection performed by radiologists and therefore processing is time-consuming and subjective. The ever-larger quantity of medical imaging data combined with the growing number of qualified radiologists in the entire world calls for the development of automated diagnostic systems. Improvements in AI, particularly deep learning, have demonstrated remarkably successful image analysis tasks. The added benefit of localizing regions of interest, which is vital for clinical interpretation, is provided by object detection models, in contrast to simple classifiers. This research introduces NeuroAI and has an end-to-end deep learning framework for detecting and defining tumours in MRIs. By merging YOLOv8-basedobjectdetection with explainable AI via a RAG module and a user-friendly interface, the system hopes to assist physicians, improve diagnostic efficacy, and make available to advanced medical imaging analysis.

II. BACKGROUND AND MOTIVATION

A. Challenges in Manual Brain Tumor Diagnosis

Manual MRI interpretation requires extensive training and experience. Radiologists must analyze multiple slices across different imaging planes, making the process cognitively demanding. Subtle variations in tumor appearance, overlapping intensity patterns, and irregular tumor boundaries often complicate diagnosis. In resource-limited or rural healthcare settings, the lack of specialized radiologists can lead to delayed diagnosis and treatment.

B. Need for Automated and Explainable Systems

Automated systems have a potential for detection, but clinical use requires trust and interpretation. The medical community is skeptical of black-box models without explanations. This is why it is important to incorporate automated detection with easily observable results to increase acceptance and usability in practice in healthcare.

III. RELATED WORK

Traditional imaging protocols, such as thresholding, edge detection, and region-based segmentation, were employed in the early brain tumor detection models. These techniques required hand-crafted features and were sensitive to noise and imaging conditions. Machine learning increased, and classifiers like Support Vector Machines and Random Forests were developed. But their performance relied largely on manual feature engineering. Deep learning, and particularly CNNs, revolutionized medical imaging in that they extract feature automatically from raw images. CNNs were also effective in MRI-based brain tumor classification in several studies. A few more recent studies focus on object detection models, which enable precise localization of tumor regions. The popularity of YOLO-based architectures was due to the detectability in real time. But many of the existing systems rely on detection accuracy and lack of understanding or user interaction. The proposed NeuroAI system addresses these deficiencies by combining object detection, multi-class classification, threshold tuning, and medical explanation generation into a single system.

IV. SYSTEM OVERVIEW

The NeuroAI framework is designed as a modular and scalable system consisting of four major components:

- **MRI Image Acquisition and Preprocessing**
- **YOLOv8-Based Tumor Detection and Classification**
- **RAG-Based Medical Explanation Module**
- **Web-Based User Interface and Deployment**

The overall workflow begins with MRI image upload, followed by tumor detection and classification, explanation generation, and result visualization.

Fig. 1. NeuroAI system interface

Figure 1 shows a user facing version of the proposed Neuro AI system. The design enables users to load MRI brain scans directly to a web-based interface, making it fast and easy to use. Adjustable confidence and IoU threshold sliders are provided for clinicians or users to further adjust detection sensitivity depending on diagnostic needs. The class confidence scores and bounding boxes indicate the tumor area that are detected in the visualization panel. Also, there is a text explanation module in the interface that displays medically relevant information based on the tumor type. This collaborative design brings the automated detection a step further into human understanding, making it appropriate for both clinical decision making and educational applications.

V. DATASET DESCRIPTION

The MRI dataset used in this study was obtained from **The Cancer Imaging Archive (TCIA)**, a publicly available repository maintained by the National Cancer Institute. TCIA provides de-identified, ethically usable medical imaging data suitable for academic research.
The dataset includes MRI scans representing:

- Meningioma
- Glioma
- Pituitary tumors
- Non-tumor cases

The data was divided into training, validation, and testing subsets to ensure unbiased evaluation. Preprocessing steps included image resizing, normalization, and quality filtering. Data augmentation techniques such as rotation, flipping, and scaling were applied to enhance generalization and mitigate overfitting.

Fig. 2. Sample MRI image selection

Fig. 2 shows the selection of images for the dataset during the evaluation phase of the proposed system. MRI scans are classified into classes categorized according to a tumor type, including meningioma, glioma, pituitary tumor and non-tumor cases. This system of organization facilitates data collection and experimentation during training and testing. Tests are conducted manually by selecting images to test for real-world performance of the model on unseen samples. Such class-wise organization is essential to ensure accurate evaluation and a level of class-specific detection behavior, particularly in medical imaging where visual similarities among classes can impact model performance.

Tumor Class	Description
Meningioma	Tumors originating from the meninges
Glioma	Tumors arising from glial cells
Pituitary	Tumors affecting the pituitary gland
No Tumor	Normal brain MRI scans

Fig. 3. Table of Dataset Composition

Fig. 3 describes the tumor categories used for the study and their clinical description. The inclusion of several tumor types allows the proposed system to perform multi-class classification, rather than binary detection, which also increases its clinical utility. A specific anatomical and visual patterning within the tumor category is evident in MRI images, suggesting this particular challenge to automated detection. A non-tumor class also allows the model to function as anomaly detection system, distinguishing pathological cases from healthy brain scans. This multi-class setup improves the robustness of the framework and makes it more applicable for diagnostic purposes.

VI. METHODOLOGY

A. YOLOv8 Architecture

YOLOv8 is a single-stage object detection model that performs localization and classification in a single forward pass. This architecture enables real-time inference while maintaining high detection accuracy. The model predicts bounding boxes along with class probabilities for each detected object.

B. Detection Threshold Selection

To minimize false negatives, a confidence threshold of **0.25** was selected. This choice prioritizes sensitivity, which is critical in medical diagnosis where missing a tumor can have severe consequences. An IoU threshold of **0.45** was chosen to handle irregular tumor boundaries commonly observed in MRI scans.

C. Multi-Class Tumor Detection

The model outputs predictions for four classes: meningioma, glioma, pituitary tumor, and no tumor. This multi-class setup allows the system to function both as an anomaly detector and a tumor classification tool.

VII. MATHEMATICAL MODELING AND ALGORITHM DESIGN

YOLOv8 predicts bounding boxes and class probabilities using the following formulation:

a. Bounding Box Prediction:

$$B_x = \sigma(t_x) + c_x, B_y = \sigma(t_y) + c_y$$
$$B_w = p_w e^{t_w}, B_h = p_h e^{t_h}$$

where $\sigma(\cdot)$denotes the sigmoid function.

b. Intersection over Union (IoU):

IoU = Area of Overlap/Area of Union

An IoU threshold of 0.45 was selected to accommodate irregular tumor boundaries.

c. Confidence Score:

$$\boldsymbol{Confidence = P(object) \times IoU}$$

A confidence threshold of 0.25 was used to prioritize sensitivity.

d. Softmax Classification:

$$\boldsymbol{Softmax(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}}}$$

e. Overall Loss Function

$$\boldsymbol{L = L_{cls} + L_{box} + L_{obj}}$$

VIII. MODEL TRAINING AND IMPLEMENTATION DETAILS

The YOLOv8 model was implemented using the Ultralytics framework. Training was conducted using GPU-accelerated hardware to ensure efficient convergence. Hyperparameters such as learning rate, batch size, and number of epochs were tuned empirically.

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	16
Image Size	640 x 640
Epochs	Multiple iterations

Fig. 4. Table of Training Configuration

The Illustration presents the key training parameters used to develop the YOLOv8-based detection model. The choice of optimizer, learning rate, and batch size plays a crucial role in achieving stable convergence and optimal performance. A fixed image resolution was selected to balance detection accuracy and computational efficiency. These hyperparameters were empirically tuned to ensure reliable learning while minimizing overfitting. Providing detailed training configuration enhances the reproducibility of the study and allows other researchers to replicate or extend the proposed framework.

IX. EXPERIMENTAL SETUP AND EVALUATION METRICS

Performance was evaluated using standard metrics:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Recall was prioritized due to its importance in minimizing false negatives.

X. RESULTS AND DISCUSSION

The proposed NeuroAI framework performance was assessed through qualitative and analytical analysis of MRI brain scans taken from the TCIA. The analysis focused on how the system could detect, localize, and classify brain tumors in real-world conditions with high sensitivity, which is an essential consideration for clinical diagnostics. The proposed system does simultaneous localization as well as multiclass classification as they do with the traditional technique of predicting only a tumor to provide a more complex view of MRI scans. But, the most striking finding of this experimental study is that the system is extremely versatile in identifying tumor sites from normal brain tissue in numerous tumor types such as meningioma, glioma and pituitary tumors. YOLOv8-based detection model consistently produced abnormal regions that had well defined boundaries, even in cases where tumor boundaries were irregular or completely blended with surrounding tissues. This feature also highlights the value of the acquired spatial features and demonstrates the utility of spatial approaches for object detection in clinical imaging applications that require accurate localization to make clinical decisions. The model's scores of classification confidence also show high discriminative performance. On properly identified tumor regions, the model predicted high confidence values for corresponding tumor class and low confidence values for non-relevant classes. This behaviour indicates that the model has learned class specific visual characteristics despite the high prevalence of similarities between classes in brain MRI scans. In particular, there was reliable differentiation between tumor and non-tumor cases indicating that the system can be used as an anomaly detection strategy. This is of clinical importance, because the assumption that healthy tissue is pathologic is susceptible to unnecessary follow-up and increased patient anxiety. In this model the use of a relatively low confidence threshold of 0.25 is a design choice. In their experimental studies, the presence of this threshold allows for sensitivity to be prioritized and therefore possible tumor locations are not overlooked. False negatives are much more critical in medical diagnosis than false positives because missed tumors can inhibit treatment and lead to worse patient outcomes. This lower confidence threshold allows the system to identify subtle or early-stage tumors that would otherwise have been overlooked by more conservative models. While this could increase the number of low confidence detections, these can be analysed by clinicians and thus the system is an effective decision support tool rather than a fully autonomous diagnostic system. The IoU threshold of 0.45 also plays an important role in balancing detection accuracy with localization precision. Brain tumors have irregular patterns and diffuse boundaries which can lead to some overlap between predicted and ground truth regions. But, where the localization is clinically appropriate, they may be penalized by a stricter IoU limit. This threshold allows for the model to account for anatomical variability without compromising spatial consistency. It has been found that this threshold aids in the accurate determination of specialized tumors with complex morphology, including gliomas, which exhibit an infiltrative growth pattern. A stable performance across several MRI scans from a qualitative perspective suggests a good generalization capability for the system. This robustness was also maintained by the use of data augmentation during training, where models were exposed to a wider range of orientations, scales and intensity variability. This is particularly important in medical imaging applications, where acquisition conditions and patient factors can have a dramatic influence on image quality. The model's ability to cope with such variability suggests that it may also be applied in actual clinical practice outside of controlled experimentation. One of the highlights of the findings is that the RAG module integrates well with the AR program to improve interpretability. While the detection model outputs quantitative data in the form of bounding boxes and confidence scores, the RAG module converts these results into medical context. This combination of visual and text information encourages user-centered understanding and trust in the forecasts that are made by the system. Such interpretability is essential in clinical practice because health professionals need not only predictions, but context in order to develop diagnostic reasoning. While it has strengths, experimental testing was also able to reveal weaknesses that warrant discussion. While visual similarity between tumor types did occasionally result in minor classification ambiguities, such as between meningioma and glioma with overlapped intensity characteristics. These misclassifications show the complexity of brain tumor imaging and call for more contextual or multimodal data in future improvements. On top of that, the use of 2D MRI slices may affect the model's ability to accurately represent 3D tumor structure, suggesting that future research could benefit from 3D volumetric analysis. Overall, these results suggest that this NeuroAI framework effectively addresses important problems of automatic brain tumor detection and classification. Using object detection with sensitivity focused thresholding as well as the outputs which are explicable in order to obtain accurate tumor identification and to remain clinically relevant. The performance of the system is consistent with its function as an additional diagnostic tool for aiding clinicians in the analysis of MRI scans more efficiently and consistently. This data supports the role of deep learning based object detection models in medical imaging applications and diagnostic workflows for healthcare patients.

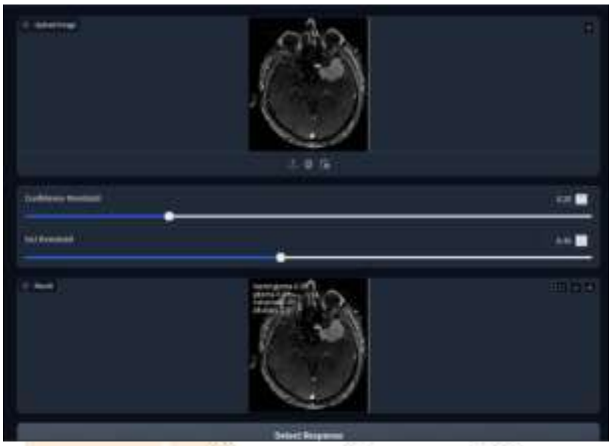

Fig. 5. Brain tumor detection by the system

The figure illustrates a complete detection cycle performed by the proposed NeuroAI framework, starting from the MRI brain scan and culminating in the final tumor detection output. The upper portion of the interface displays the uploaded MRI image, representing real-world clinical input data. The middle section highlights the adjustable confidence and Intersection-over-Union (IoU) threshold controls, which allow users to fine-tune detection sensitivity and spatial overlap requirements. In the presented example, a confidence threshold of 0.25 and an IoU threshold of 0.45 were used to prioritize sensitivity and accommodate irregular tumor boundaries commonly observed in brain MRI scans. The lower portion of the figure shows the detection result generated by the YOLOv8 model, where the tumor region is localized and classified with corresponding confidence scores. The high confidence value assigned to the meningioma class demonstrates the model's ability to accurately distinguish tumor types while suppressing non-relevant classes. This end-to-end visualization reinforces the practical effectiveness of the system by clearly linking input data, parameter selection, and detection outcomes within a single integrated interface.

XI. CONCLUSION

This paper presented NeuroAI, a multi-objective deep learning model that automates the identification, localization, and multiclass classification of brain tumors using MRI scans. The proposed system sought to address key limitations of conventional MRI based diagnosis, such as manual interpretation, variability in diagnostic outcome, and increasing radiology workload. The YOLOv8 object detection architecture allows for tumor localization and classification in one inference step and produces spatial and semantic information relevant for clinical interpretation. One of the biggest contributions of this work is the design of brain tumor detection as a anomaly detection and object localization problem rather than as a simple image classification task. This method allows for the system to identify abnormal regions in MRI scans, and distinguishes among several types of tumors, including meningioma, glioma, pituitary tumor, and non-tumor cancer. The use of sensitivity focused detection thresholds reflects the clinical priority to minimize false negatives, so that more subtle or early onset tumors will not be overlooked. Plus, the results from experiments revealed that this design choice achieves a satisfactory balance between detection robustness and clinical relevance, demonstrating that model objects may be appropriate for medical imaging applications. Another of the important aspects of the proposed framework is the use of explainability as a module of Retrieval Augmented Generation (RAG). Although deep learning models are generally criticized as a black box model, contextual medical explanations and detection outputs make transparency and user trust more important. It provides medically related informed decision making and allows for the sharing of information with clinicians, students, and researchers, through the conversion of the raw model predictions into interpretive medical knowledge. This preoccupation with interpretability is consistent with the existing best practices in medical artificial intelligence, where explainability is increasingly identified as a requirement of real-world use. NeuroAI's practical impact is further enhanced by its web application usage. The system is available in a normal web browser, which eliminates specialized hardware or programs, and is suitable for a variety of applications, including resources limited environments. This framework is intended to serve as a decision support tool, rather than replace clinical knowledge of radiologists by highlighting areas of interest and providing pre-tests that can improve diagnostic accuracy and consistency. Its performance is good but also it identifies important areas for improvement. This reliance on 2-dimensional MRI slices leaves the system unable to fully capture three-dimensional tumor morphology; further validation through larger multi-institutional datasets will allow generalizability across populations of patients. On top of that, clinical application would require strict review and regulation as well as ethical and legal considerations. Finally, the proposed NeuroAI framework demonstrates the potential of deep learning-based object detection models to increase the accuracy of brain tumor diagnosis by combining detection automaton, multi-class classification, interpretability, and real-time deployment into one single unit. The results from this study suggest that medical imaging platforms that are embedded in AI and designed for ethical and clinical purposes can be useful to healthcare professionals and improve diagnostic processes and the progression of artificial intelligence into modern medicine.

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