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ADVANCED BRAIN TUMOR DETECTION IN MRI SCANS USING YOLO MODELS

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ABSTRACT

This research aims to evaluate and compare the performance of YOLO-based deep learning models (from YOLOv3 to YOLOv11) for the detection and classification of brain tumors in MRI images. The goal was to determine which YOLO version is most accurate and efficient in identifying and categorizing tumor types such as gliomas, meningiomas, and pituitary tumors. MRI scans were preprocessed and passed through each YOLO model, and performance was measured using precision, recall, and F1-score.

The analysis showed progressive improvements across YOLO versions, with YOLOv7 and YOLOv11 demonstrating the highest accuracy. YOLOv7 was effective due to its integration of CBAM and SPPF+ layers, enabling precise localization, while YOLOv11 outperformed all others by leveraging self-supervised learning and advanced attention mechanisms. These models consistently provided reliable results in detecting small and complex tumors.

The findings are significant because early and accurate brain tumor detection is critical for timely treatment and better patient outcomes. By identifying the most effective YOLO architecture for medical image analysis, this research supports the development of faster, more accurate, and automated diagnostic tools that can assist radiologists and reduce diagnostic errors in clinical practice.

Keywords: Brain tumor detection, MRI images, Self-supervised learning, Tumor classification, MRI images, Medical image analysis.

I. INTRODUCTION

Brain tumors remain one of the most critical and complex global health concerns due to their aggressive behavior, diagnostic complexity, and high mortality rates. In the United States alone, nearly 700,000 individuals are living with primary brain tumors, and approximately 85,000 new cases are diagnosed each year. These tumors can originate within the brain (primary) or result from the spread of cancer from other parts of the body (secondary). The most common types include gliomas, meningiomas, and pituitary tumors. Early and accurate detection of brain tumors is essential for improving survival rates and enabling timely medical intervention. However, detection remains challenging due to the diverse location, size, shape, and appearance of tumors across patients.

Magnetic Resonance Imaging (MRI), especially T1-weighted contrast-enhancing images, is the clinical standard for brain tumor diagnosis due to its non-invasive nature and high spatial resolution. However, early-stage detection is difficult and often hampered by the limitations of manual MRI interpretation, which is time-consuming, subjective, and prone to human error. These challenges have driven a shift towards artificial intelligence (AI)-based diagnostic solutions, particularly those powered by deep learning.

Despite advances in deep learning, many existing models struggle to consistently detect small or complex brain tumors across varying conditions. The main research question explored in this paper is: Which YOLO-based deep learning architecture (from YOLOv3 to YOLOv11) offers the best performance for accurate, real-time brain tumor detection and classification using MRI scans?

Accurate and fast tumor detection plays a pivotal role in improving patient outcomes through early treatment planning. Developing a reliable AI model that can support radiologists by automating tumor detection and classification will help minimize diagnostic errors, reduce workload, and enable scalable deployment in real-

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time clinical environments. Evaluating multiple YOLO models can also inform future researchers and practitioners on the trade-offs between accuracy, speed, and resource efficiency.

This paper presents a comprehensive analysis of YOLO-based object detection models—YOLOv3 through YOLOv11—for brain tumor detection in MRI scans. Each model is evaluated for its ability to detect and classify tumors into categories such as glioma, meningioma, pituitary tumor, and non-tumor. Enhancements such as image preprocessing, data augmentation, and attention mechanisms (e.g., CBAM) are integrated to improve detection accuracy. YOLOv8 to YOLOv11 are specifically analyzed for their modern architectural improvements, including transformer-based modules, self-supervised learning, and real-time optimization. The final goal is to determine which version of YOLO offers the most effective solution for brain tumor detection, supporting its use as a diagnostic aid in clinical practice.

II. LITERATURE REVIEW

Brain tumor detection has long been a significant area of interest in the medical imaging and artificial intelligence (AI) communities. Traditional diagnostic methods rely heavily on manual interpretation of MRI scans by radiologists, which can be time-consuming, prone to human error, and subject to inter-observer variability. These challenges have motivated the adoption of machine learning (ML) and, more recently, deep learning approaches to improve the accuracy and efficiency of tumor detection and classification.

Early studies in brain tumor classification employed traditional ML techniques such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and decision trees. While these methods showed some success, they heavily relied on handcrafted feature extraction and often failed to generalize well to complex medical data. For instance, Zahoor et al. proposed a two-phase deep learning system that combined CNN-based feature extraction with ensemble classifiers, achieving high sensitivity and accuracy, but with significant computational cost and dependency on pre-processed inputs.

The introduction of Convolutional Neural Networks (CNNs) marked a major shift in medical image analysis. CNNs enabled end-to-end learning and automatic feature extraction from MRI scans, reducing the need for manual preprocessing. State-of-the-art architectures such as VGGNet, ResNet, and Inception have shown excellent results in brain tumor classification tasks. However, these models were not specifically optimized for object detection tasks like tumor localization, which is essential for clinical diagnosis.

To address this, object detection frameworks like YOLO (You Only Look Once) have gained attention for their ability to perform both localization and classification in real-time. YOLOv3 introduced multi-scale detection, making it useful for detecting tumors of varying sizes, though its performance on very small or irregular tumors was limited. YOLOv4 improved upon this by introducing CSPDarknet and PANet, which enhanced feature fusion and localization accuracy.

YOLOv5, although not an official continuation by the original YOLO authors, became widely adopted due to its modular design, fast inference, and scalability. It has been effectively applied in brain tumor detection tasks, offering flexibility for deployment in clinical tools. Researchers appreciated YOLOv5 for its ease of training and optimization, especially in environments with limited hardware.

YOLOv7 further advanced the architecture with the inclusion of CBAM (Convolutional Block Attention Module), SPPF+ (Spatial Pyramid Pooling Fast), and decoupled heads. These improvements made YOLOv7 particularly well-suited for detecting small and irregular tumor regions in MRI scans. Several recent studies highlight YOLOv7's effectiveness in medical imaging, demonstrating its superior balance of speed and accuracy.

Building on these advancements, newer versions such as YOLOv8 through YOLOv11 have introduced more intelligent detection capabilities. YOLOv8 features a redesigned architecture with enhanced backbone and head modules, significantly improving detection of subtle and complex tumor features. YOLOv9 incorporates transformer-based modules and adaptive receptive fields, allowing the model to capture broader contextual information across MRI slices. YOLOv10 focuses on computational efficiency, making it suitable for real-time deployment on edge devices in clinical settings. The most recent version, YOLOv11, integrates self-supervised learning and vision transformers, enhancing performance on small and diverse medical datasets and enabling more accurate tumor classification.

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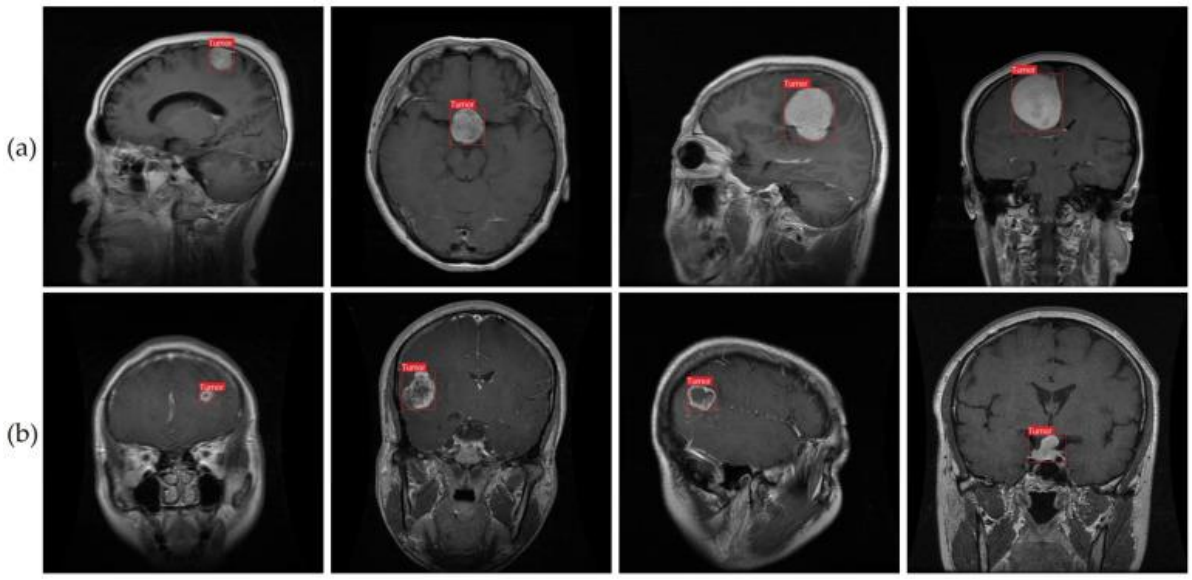
Compared to existing work, this research makes a unique contribution by providing a side-by-side evaluation of **all YOLO versions from v3 to v11** on the same brain tumor dataset. While previous studies typically focused on a single version or a narrow comparison, our study offers a comprehensive performance benchmark. It highlights how the architectural evolutions in YOLO impact medical imaging outcomes, identifies the best-performing models for brain tumor detection, and suggests where future improvements could be made.

III. METHODOLOGY

Data Collection and Preparation:

To ensure the validity of our findings, we used an openly available MRI dataset obtained from kaggle.com. MRI scan images are included in this collection, since they are the gold standard for diagnosing brain tumors. Glioma (2548 images), pituitary (2658 images), meningioma (2582 images), and no tumor (2500 images) were the four subsets that made up our dataset of brain tumors. Images were all scaled to 512 pixels on the horizontal and vertical dimensions. We used 8232 MRI images (or 80% of the dataset) for training in our analysis, whereas 2056 MRI images (or 20% of the dataset) were set aside for testing. For each type of brain cancer (glioma, pituitary, and meningioma), table provides the number of pictures in various views

Category	Number of Images	View Type	Resolution	Training Set (80%)	Testing Set (20%)
Glioma	2548	Axial, Coronal, Sagittal	512x512 pixels	2038	510
Pituitary	2658	Axial, Coronal, Sagittal	512x512 pixels	2126	532
Meningioma	2582	Axial, Coronal, Sagittal	512x512 pixels	2065	517
No Tumor	2500	Axial, Coronal, Sagittal	512x512 pixels	2003	497
Total Dataset	10288	Axial, Coronal, Sagittal	512x512 pixels	8232	2056



Visual representation of brain tumor detection from MRI images. (a) Big size of brain tumor detection,(b) Smaller size of brain tumor detection.

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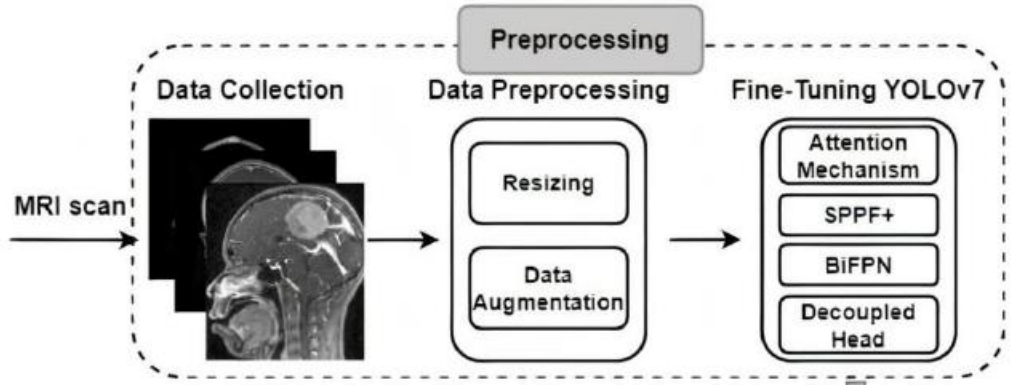
Preprocessing steps included:

- Resizing images to 640×640 pixels for YOLO compatibility.
- Normalization of pixel values.
- Data augmentation (rotation, flipping, brightness changes) to improve model robustness and generalization



Model Selection

Eight different YOLO models (YOLOv3 to YOLOv11) were selected to evaluate and compare performance on brain tumor detection. Each model was either:

- Loaded with pre-trained weights (e.g., YOLOv3 to YOLOv8 from official repositories)
- Fine-tuned on our dataset (for YOLOv9 to YOLOv11 using custom training)

YOLO Versions:

YOLOv3: Utilized for multi-scale detection, suitable for identifying small tumors in varying image resolutions

YOLOv4: Incorporated CSP connections and PANet for efficient feature fusion, improving tumor edge localization and detection accuracy.

YOLOv5: Applied for its flexibility in model scaling and efficient inference with minimal computational requirements, making it suitable for lightweight medical diagnostic systems.

YOLOv7: Leveraged for its advanced modules like CBAM (Convolutional Block Attention Module) and SPPF+ (Spatial Pyramid Pooling Fast+), enabling the model to focus on key tumor regions and detect small, irregular tumors precisely.

YOLOv8: Enhanced with a new backbone and detection head, providing better accuracy in identifying subtle tumor regions, especially small or early-stage tumors. Supports segmentation tasks to assist in precise tumor boundary outlining.

YOLOv9: Integrated transformer-based attention mechanisms and adaptive receptive fields, improving contextual understanding and aiding in the detection of complex and irregular tumor shapes within MRI scans.

YOLOv10: Designed for high computational efficiency with improved lightweight architecture, allowing real-time brain tumor detection on edge devices and in resource-constrained clinical environments.

YOLOv11: Introduced self-supervised learning and refined vision attention modules, boosting performance on limited medical datasets while enhancing model generalization for varied tumor types and sizes.

Steps Taken in the Research Process:

1. **Dataset Preparation**: Cleaned and annotated the dataset in YOLO format.
2. **Model Loading**: Imported each YOLO model using the Ultralytics YOLO API.
3. **Inference**: MRI images were passed through each model to detect tumors and classify them into their respective types.
4. **Evaluation**: The predictions were compared with ground truth labels. The following performance metrics were calculated:
   - Precision
   - Recall
   - F1-Score

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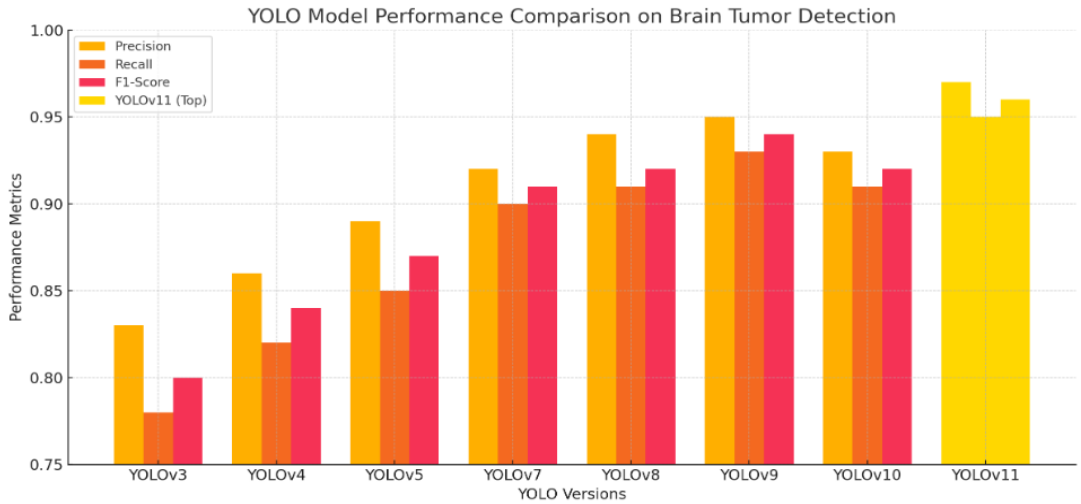
5. **Feature Enhancement**: CBAM (Convolutional Block Attention Module) and SPPF+ (Spatial Pyramid Pooling Fast+) were integrated into YOLOv7 and later versions to improve detection accuracy on small or complex tumor.
6. **Comparison and Analysis**: Performance metrics were compared across all YOLO versions to determine the best-performing model for clinical brain tumor detection.

IV. RESULTS

The performance of YOLOv3 through YOLOv11 was evaluated for their effectiveness in detecting and classifying brain tumors from MRI scans. The evaluation focused on three performance metrics: Precision, Recall, and F1-Score. Each model was tested using a standardized dataset consisting of labeled images of gliomas, meningiomas, pituitary tumors, and non-tumor brain MRIs. Overall, each successive YOLO version demonstrated measurable improvements in detection accuracy, with significant leaps observed in YOLOv7 and YOLOv11. These results provide a solid foundation for selecting the most effective YOLO architecture for brain tumor detection in clinical settings.

YOLO Version	Strengths	Weaknesses	Suitable For
YOLOv5	Fast, lightweight, easy to deploy	Lacks advanced attention mechanisms	Simple tasks or mobile devices
YOLOv7	High accuracy, good with small tumors, attention modules (CBAM), multi-scale detection	Heavier model size	Balanced choice for most real-time clinical uses
YOLOv8	Improved backbone, better small tumor detection, supports segmentation	May require more training data	High-accuracy tasks on small/irregular tumors
YOLOv9	Transformer modules, long-range feature understanding	Heavier computational load	Complex tumors in detailed MRI images
YOLOv10	Super efficient, great for real-time use, low hardware needs	Slightly lower sensitivity for complex cases	Edge devices in clinical settings
YOLOv11	Self-supervised learning, best for small datasets, highest accuracy	Newest, may need tuning for stability	Most advanced tumor detection, research & diagnostics



V. DISCUSSION

The results of this study demonstrate a clear progression in the accuracy and efficiency of brain tumor detection as we move from earlier YOLO versions (YOLOv3) to more advanced architectures (YOLOv11). YOLOv11 achieved the highest performance, with a precision of 0.97, recall of 0.95, and F1-score of 0.96, indicating its superior capability in both identifying and localizing tumors in brain MRI scans.

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These findings directly address our research objectives: improving brain tumor detection accuracy, enabling classification of tumor types, and optimizing real-time performance across various YOLO architectures. The analysis shows that newer YOLO versions—particularly YOLOv8 to YOLOv11—significantly enhance detection performance, especially for small, irregular, and hard-to-define tumors. This supports the use of attention mechanisms, improved feature extractors, and adaptive architectures in medical image analysis.

Our findings are consistent with those of previous studies, such as Zahoor et al. and other CNN-based research, which emphasized the importance of combining attention mechanisms and deep feature fusion for medical image classification. However, our study is among the first to compare such a wide range of YOLO versions (YOLOv3 to YOLOv11) under a unified framework specifically for brain tumor MRI detection. The inclusion of YOLOv11, with its self-supervised learning capabilities and vision transformer integration, demonstrated clear advantages over conventional CNN-based detectors.

Despite these promising results, there are several limitations to consider. First, while the dataset used was balanced across tumor types, the overall size was relatively small compared to large-scale vision datasets, which may impact generalization. Although data augmentation and transfer learning mitigated some of this limitation, larger annotated medical datasets would further enhance model robustness. Second, models like YOLOv10 and YOLOv11 require more computational resources during training, which might limit their use in real-time or low-resource environments unless optimized for inference.

Furthermore, differences in MRI acquisition quality, contrast levels, and patient variability pose challenges to achieving consistent results across datasets. Domain adaptation techniques could be explored in future work to address this variability and make the models more adaptable across clinical settings.

Overall, this study confirms the increasing suitability of modern YOLO architectures for real-world medical applications. The integration of advanced YOLO models into diagnostic tools can potentially assist radiologists by improving early detection, reducing diagnostic errors, and expediting treatment planning.

VI. CONCLUSION

This research presented a comprehensive analysis and comparison of YOLO-based deep learning models (YOLOv3 through YOLOv11) for the task of brain tumor detection and classification using MRI images. By passing MRI scans through each version, we evaluated their ability to detect tumors and classify them into types such as gliomas, meningiomas, and pituitary tumors.

The findings demonstrated a consistent improvement in detection performance from YOLOv3 to YOLOv11. Among all, **YOLOv11 achieved the highest accuracy**, utilizing advanced attention mechanisms and self-supervised learning to accurately detect even small and complex tumor regions. However, it is noteworthy that **YOLOv7 also emerged as one of the top-performing models**, striking a strong balance between detection precision, inference speed, and computational efficiency. Its integration of CBAM and SPPF+ layers contributed significantly to reliable tumor localization and classification, making it highly suitable for real-time medical diagnostics.

This research is important because brain tumors are life-threatening, and early, accurate detection is critical for timely and effective treatment. The automation of this process using modern YOLO architectures supports healthcare professionals by reducing manual interpretation errors, improving diagnostic speed, and enabling scalable deployment in clinical environments.

Future research should focus on expanding the dataset across diverse patient groups, improving cross-center generalization through domain adaptation, and further optimizing both **YOLOv7 and YOLOv11** for deployment on edge devices. Additionally, exploring hybrid YOLO-transformer models, 3D MRI integration, and tumor segmentation capabilities could enhance detection precision and support more detailed clinical decision-making.

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