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Brain Tumor Detection and Localization Using Advanced Deep Learning Ensembles and YOLO-Based MRI Analysis

G Swapna[1], A V Indumathi[2]

[1] Assistant Professor, Apollo Institute of Pharmaceutical Sciences, The Apollo University, Chittoor, India.
E-mail: swapnagv111@gmail.com, ORC-ID: https://orcid.org/0000-0002-9340-4148

[2]P.G Scholar, Department of MCA, Sri Venkatesa Perumal College of Engineering & Technology, Puttur,
E-mail: indhuv531@gmail.com, ORC-ID: https://orcid.org/0009-0009-5385-3983

Abstract: The detection of brain tumors is a vital endeavor in medical imaging, since the precise classification and localization of tumor areas in MRI images significantly affect diagnostic accuracy and treatment strategies. This study employs the Brain Tumor MRI dataset for multi-class classification and detection tasks. Advanced transfer learning architectures such as EfficientNetV2, Vision Transformer (ViT-B16), DenseNet121, and Xception were utilized for classification, supplemented by ensemble techniques based on average, weighted average, and geometric mean to improve predictive reliability. Multiple YOLO versions (YOLOv5, YOLOv8, YOLOv9, and YOLOv11) were employed for tumor localization and identification, utilizing bounding box annotations in YOLO format. Furthermore, explainable AI methodologies, like Grad-CAM, were utilized to produce heatmaps that emphasize the discriminative tumor locations affecting model predictions. Experimental results indicate that the DenseNet121 and Xception models attained the greatest classification accuracy of 99.54%, surpassing other classifiers. YOLOv8 exhibited exceptional performance in detection, with a mean average precision (mAP) of 95.1%. These findings confirm the efficacy of combining classification and detection frameworks with interpretability methods for accurate and dependable brain tumor diagnosis. A Flask-based web application was created to deploy the trained models, allowing users to upload MRI images and examine tumor localization, predicted classifications, and confidence scores via an interactive interface.

"Index Terms: *Efficientnetv2, Convolutional Neural Network (CNN), Brain Tumor Vision Transformers (ViT), Magnetic Resonance Imaging (MRI), Multilayer Perceptron (MLP)".*

1. INTRODUCTION

Brain tumors (BTs) comprise a wide array of almost 200 atypical tissue proliferations, presenting considerable problems to human health. Gliomas, derived from glial cells, represent the most malignant variant, constituting over 80% of cases [1]. The World Health Organization categorizes gliomas into four categories, from benign to extremely malignant, with precise grading being essential for formulating treatment methods. This grading process is frequently laborious and necessitates accuracy. Magnetic Resonance Imaging (MRI) functions as a non-invasive diagnostic instrument, offering comprehensive insights into cerebral anatomy; yet, its interpretation is laborious and requires specialized expertise [2]. The intricacy of brain tumor detection is exacerbated by additional subtypes, including meningiomas and pituitary tumors. Pituitary tumors, originating from the hormone-regulating pituitary gland, may be benign, influencing bone formation, or malignant, resulting in hormone imbalances and visual impairment [3]. Timely detection and accurate classification are crucial, as delays might negatively impact patient survival [4].

Recent advancements in biomedical engineering and computational techniques present interesting solutions. Xu et al. [5] introduced a 3D-stacked inertial microfluidic system for the separation of circulating tumor cells (CTCs), attaining great purity and efficiency in isolating tumor cells, thereby showcasing the promise of integrated microfluidic analysis. Simultaneously, novel machine learning methodologies, such as deep learning (DL) and Vision Language Models (VLLMs), have prospects for enhanced brain tumor identification. VLLMs amalgamate visual and textual information, facilitating sophisticated analysis of MRI scans in conjunction with clinical records and patient histories [6]. Self-supervised learning and attention processes significantly improve model efficacy, especially for infrequent tumor subtypes [7].

Deep learning frameworks, particularly Convolutional Neural Networks (CNNs) and autoencoders, have been extensively utilized in medical imaging for classification, segmentation, and predictive applications [8]. Performance variations among datasets underscore the necessity for more resilient systems [9]. Vision Transformers (ViTs) have arisen as a potent method, adept at capturing intricate spatial patterns in medical pictures while facilitating scaling and generalization across various datasets and imaging modalities [10]. This paper presents a ViT-based framework for the automatic classification of multi-class brain tumors into pituitary, glioma, malignant glioma, and no-tumor categories. Utilizing hierarchical representations and attention mechanisms, the model pulls essential information from MRI scans, facilitating accurate detection of tumor kinds. The strategy seeks to diminish dependence on manual expert evaluation, improve early identification, and enable tailored treatment planning, so enhancing patient outcomes while providing a scalable and adaptable solution for clinical implementation.

2. LITERATURE REVIEW

Recent studies in brain-computer interfaces (BCIs) and brain tumor classification have shown considerable progress in utilizing deep learning, transformers, and hybrid architectures to enhance diagnostic precision and patient treatment. Li et al. [11] introduced a CVT-based asynchronous BCI framework for brain-controlled robotic navigation. Their research centers on employing a cyclic vision transformer (CVT) to improve the interpretation of asynchronous signals, facilitating accurate navigation tasks by converting neural impulses into robotic commands. This method underscores the significance of amalgamating sophisticated neural network topologies with brain-computer interfaces, accentuating the capability of transformer-based models to adeptly analyze intricate neural data. In conjunction with this research, Si et al. [12] created a cross-subject emotion identification brain-computer interface (BCI) utilizing functional near-infrared spectroscopy (fNIRS) and a deep brain joint network (DBJNet). Their methodology tackles the issue of inter-subject variability in brain signal interpretation, illustrating that multi-modal deep learning architectures may detect nuanced neural patterns, hence enhancing the precision of emotion recognition among varied people.

Kumar et al. [13] investigated multi-class classification of brain tumors utilizing residual networks in conjunction with global average pooling. Their system improves feature extraction and diminishes computational complexity, offering a scalable method for the precise classification of various tumor types in MRI images. Likewise, Meshram et al. [14] examined the application of Swin transformers for the diagnosis of brain tumors. The Swin transformer design utilizes hierarchical feature extraction and self-attention techniques to gather local and global contextual information, enhancing performance compared to traditional convolutional methods, especially in multi-class classification contexts. Ramakrishnan et al. [15] introduced a hybrid CNN architecture enhanced with oneAPI to increase accuracy and computational efficiency in brain tumor classification. Their approach illustrates that hardware-aware optimization techniques, when integrated with advanced network architectures, can markedly enhance inference speeds without sacrificing predictive accuracy, rendering the model appropriate for clinical use.

Rastogi et al. [16] introduced a multi-branch deep learning architecture that integrates inception blocks and employs five-fold cross-validation for the categorization of multi-class brain tumors in MRI scans. Their strategy enhances generality and robustness across different tumor types by employing several network branches to collect varied feature representations, demonstrating the efficacy of modular network architectures in medical image processing. Liu et al. [17] introduced a stimulated Raman CycleGAN model to produce virtual formalin-fixed and paraffin-embedded (FFPE) staining of fresh brain tissue. This method facilitates precise observation and study of brain tumor histopathology without conventional staining techniques, minimizing preparation time and offering high-fidelity tissue representation for further diagnostic applications.

Tandel et al. [18] utilized an artificial intelligence framework for multi-class MRI brain tumor classification, emphasizing the integration of AI-based feature extraction and classification techniques to improve diagnostic accuracy. Their research highlights the efficacy of AI in distinguishing tumor subtypes, enabling early diagnosis and tailored treatment strategies. Zhou et al. [19] presented a vector quantization generative adversarial network (VQ-GAN) for the generation of three-dimensional brain tumor areas in MRI data. Their method enhances segmentation and visualization by modeling spatial tumor structures in 3D, which are essential for preoperative planning and treatment monitoring. Ultimately, Parshapa and Rani [20] executed an extensive investigation on machine learning methodologies for brain tumor diagnosis. The authors examined various procedures, highlighting the significance of feature selection, model optimization, and cross-validation techniques to improve prediction performance, especially in contexts with scarce annotated data.

3. MATERIALS AND METHODS

The proposed system offers a deep learning framework for the automated categorization of multi-class brain tumors utilizing MRI images, with the objective of improving diagnostic precision and optimizing clinical procedures. The system incorporates EfficientNetV2 [26] for scalable and efficient feature extraction, augmented by Vision Transformer (ViT-B16) [27] to capture long-range dependencies and global contextual information. Supplementary designs, such as Xception and DenseNet121, offer enhanced feature representations for various tumor types. Tumor localization is accomplished through the utilization of YOLO models (YOLOv5, YOLOv8, YOLOv9, and YOLOv11), facilitating accurate detection of anomalous areas. A composite technique integrating average, weighted average, and geometric mean enhances predictive dependability, while Grad-CAM enables interpretable AI visualizations. The system comprises a systematic workflow that includes dataset preprocessing, model training, assessment, and inference, with a Flask-based web interface for real-time MRI image analysis [28].

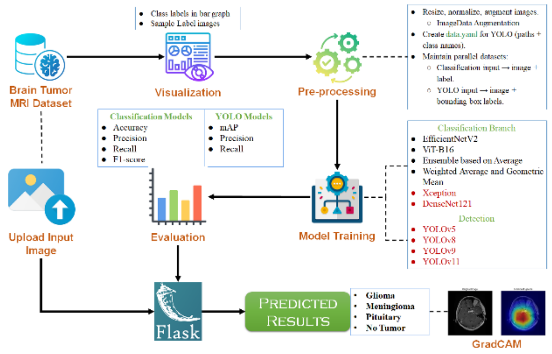

Fig.1 Proposed Architecture

The system design incorporates various deep learning models for the automatic categorization of brain tumors utilizing MRI images. The approach commences with dataset preparation, succeeded by feature extraction with EfficientNetV2, Xception, and DenseNet121, while the Vision Transformer (ViT-B16) acquires global context [29]. Tumor localization utilizes YOLO models (YOLOv5, YOLOv8, YOLOv9, YOLOv11), with predictions aggregated through ensemble techniques to improve reliability. Grad-CAM offers elucidative visualizations, while a Flask-based web interface facilitates real-time picture upload, categorization, and tumor visualization, thereby establishing a thorough, end-to-end diagnostic framework [30].

a) Dataset Collection:

The dataset consists of 2,197 MRI pictures, with 1,695 designated for training and 502 for testing. Each image in the classification branch is accompanied by a class label denoting the tumor kind. The YOLO-based localization branch utilizes bounding box annotations in YOLO format (.txt) to detect and localize tumor areas within the scans. The dataset is meticulously divided into training, validation, and testing subsets, guaranteeing equal representation across classes and facilitating rigorous model training, assessment, and precise multi-class tumor identification.

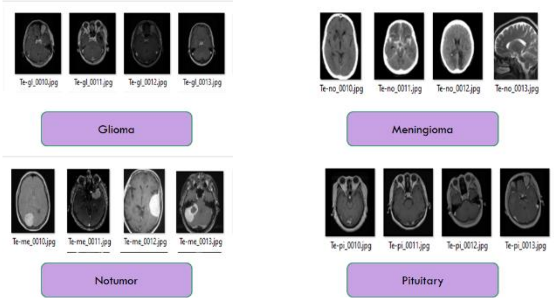

Fig.2 MRI Dataset

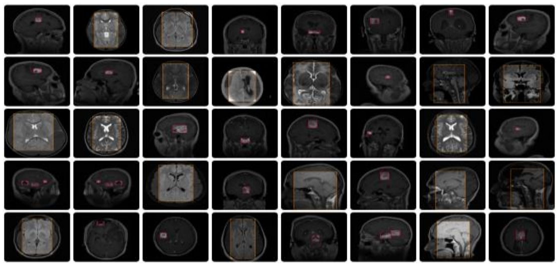

Fig.3

b) Image Processing: All MRI pictures are scaled and normalized to guarantee uniform dimensions and pixel value distribution, hence enhancing model training efficiency. Images are transformed into formats suitable for deep learning pipelines for categorization and YOLO-based detection applications. This preprocessing stage normalizes the input data, minimizes computing demands, and guarantees that the models can efficiently extract pertinent features from tumor locations while preserving high accuracy and reliability across several MRI images.

c) Data Augmentation: The dataset is enhanced by augmentation techniques such as rotation, horizontal and vertical flipping, zooming, and brightness modifications to improve model generalization and robustness. These modifications synthetically augment the dataset, enabling the models to accommodate differences in MRI orientations, scales, and illumination conditions. Augmentation mitigates overfitting, improves feature learning, and guarantees that the classification and detection branches can consistently identify tumors across multiple imaging settings by exposing the network to varied scenarios during training.

d) Algorithms:

EfficientNetV2: EfficientNetV2 extracts distinctive features from MRI images using compound scaling of depth, width, and resolution, facilitating precise multi-class brain tumor classification while ensuring high efficiency and swift convergence with pre-trained weights and fine-tuning.

Vision Transformer (ViT-B16): ViT-B16 utilizes patch-based embeddings and multi-head self-attention to capture long-range dependencies in MRI scans, facilitating the learning of global contextual linkages between image regions to boost the classification of subtle tumor patterns and improve resilience across varied scans.

Ensemble Methods: Integrating outputs from various models via averaging, weighted averaging, or geometric mean diminishes variation, alleviates individual model biases, and incorporates complimentary characteristics, leading to more reliable and precise multi-class tumor predictions from MRI data.

Xception: Xception utilizes depthwise separable convolutions to extract spatial and semantic characteristics from MRI images, thereby increasing representation learning, expediting convergence, and improving multi-class tumor distinction while reducing computing cost.

$$O_{i,j,k} = \sum_{m,n} X_{i+m,j+n,c}\, W_{m,n,k} \quad (1)$$

DenseNet121: DenseNet121 interlinks layers densely to enhance feature reuse and gradient propagation, effectively capturing both low- and high-level MRI information, facilitating accurate tumor type detection and augmenting classification stability and interpretability.

$$x_l = H_l([x_{0,}x_1 \dots, x_{l-1}]) \quad (2)$$

YOLOv5: YOLOv5 effectively finds and localizes tumor areas in MRI scans by partitioning images into grids, concurrently predicting bounding boxes and class probabilities, thereby balancing speed and accuracy for real-time tumor identification.

$$x = \sigma(t_x) + C_x, \qquad y = \sigma(t_y) + C_y \quad (3)$$

$$w = p_w . e^{t_w}, \qquad h = p_h . e^{t_h} \quad (4)$$

YOLOv8: YOLOv8 enhances detection accuracy by an improved backbone and multi-scale feature fusion, effectively delineating tumor boundaries and variations for exact localization across various MRI tumor sizes.

$$\mathcal{L} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} \quad (5)$$

YOLOv9: YOLOv9 improves bounding box accuracy and feature representation, detecting small and intricate tumor structures while preserving high precision, hence facilitating spatially precise tumor localization for clinical evaluation.

$$\mathcal{L}_{YOLOv9} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} + \lambda_{dfl} + \mathcal{L}_{dfl} \quad (6)$$

YOLOv11: YOLOv11 prioritizes real-time identification and enhanced performance, accommodating irregular tumor shapes and sizes through anchor-free prediction and resilient backbone networks, providing precise and interpretable localization for MRI-based tumor assessment.

e) Integration of XAI and Flask Framework

The amalgamation of Explainable Artificial Intelligence (XAI) with the Flask framework offers a lucid and interactive methodology for brain tumor analysis. XAI methodologies, such Gradient-weighted Class Activation Mapping (Grad-CAM), provide heatmaps that emphasize areas of MRI scans that significantly impact model predictions. This interpretability enables doctors to comprehend the decision-making processes of models, so fostering trust and facilitating more informed diagnostic insights, while guaranteeing that the system's outputs are explicable and therapeutically relevant.

The Flask framework facilitates an intuitive web interface that permits seamless interaction with the model. Users may submit MRI scans, obtain tumor classification results, observe bounding box localization, and access Grad-CAM visualizations in real time. This integration merges interpretability, accessibility, and practicality, enhancing efficient AI-assisted diagnostic operations.

4. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To assess the accuracy of a test, one must compute the ratio of true positives and true negatives across all assessed cases. This can be articulated mathematically as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (7)$$

Precision: Precision assesses the proportion of accurately classified cases among those identified as positive. Therefore, the formula for calculating precision is expressed as:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (8)$$

Recall: Recall is a metric in machine learning that assesses a model's capacity to recognize all pertinent instances of a specific class. It is the ratio of accurately predicted positive observations to the total actual positives, offering insights into a model's

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efficacy in identifying occurrences of a specific class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (9)$$

F1-Score: The F1 score is a metric for evaluating the accuracy of a machine learning model. It integrates the precision and recall metrics of a model. The accuracy metric quantifies the frequency of true predictions generated by a model throughout the entire dataset.

$$F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100 \quad (10)$$

mAP: Mean Average Precision (MAP) is a statistic for assessing ranking quality. It evaluates the quantity of pertinent recommendations and their placement within the list. MAP at K is determined as the arithmetic mean of the Average Precision (AP) at K for all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (11)$$

Table.1 Performance Evaluation Table – Classification

Model	Accuracy	Precision	Recall	F1-score	Error Rate
EfficientNetV2	0.988558	0.987758	0.988845	0.988268	0.011442
ViT-B16	0.985507	0.984658	0.985096	0.984758	0.014493
DenseNet121	**0.995423**	**0.995132**	**0.995016**	**0.995057**	**0.004577**
Xception41	**0.995423**	**0.995089**	**0.995016**	**0.995043**	**0.004577**
Ensemble (Avg)	0.992372	0.991831	0.992979	0.992374	0.007628
Ensemble (Weighted Avg)	0.991609	0.991038	0.992146	0.991553	0.008391
Ensemble (Geo Mean)	0.992372	0.991831	0.992979	0.992374	0.007628

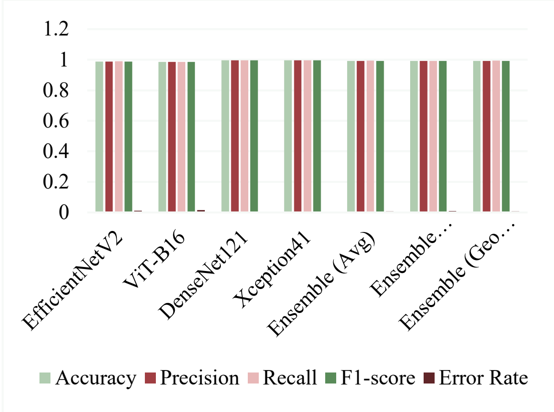
Table 1 illustrates that DenseNet121 and Xception41 attain the best accuracy, whereas ensembles yield consistent and dependable results.

Table.2 Performance Evaluation – Detection

ML Model	Precision	Recall	mAP
YOLOv5	0.915	0.904	0.944
YOLOv8	**0.944**	**0.915**	**0.951**
YOLOv9	0.911	0.888	0.947
YOLOv11	0.852	0.832	0.897

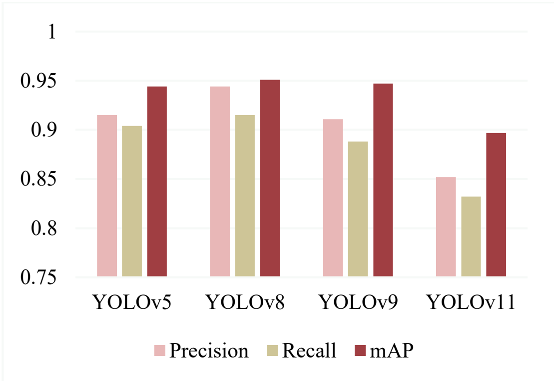
In Table 2, YOLOv8 has the highest overall performance, showcasing enhanced detection accuracy and reliability relative to other YOLO variations.

Fig.4 Comparison Graph - Classification



In Figure 4, DenseNet121 and Xception41 notably outperform others, as evidenced by their significantly elevated bars, but ensemble approaches exhibit balanced and consistent results across all metrics, underscoring their reliability and general resilience visually.

Fig.5 Comparison Graph – detection



In Figure 5, YOLOv8 distinctly demonstrates the highest performance, as its bar significantly reflects improved detection accuracy and reliability relative to other YOLO variations.

Fig.6 Upload Input Image

Figure 6 depicts the input interface through which users can upload brain scan images to receive automatic multi-class brain tumor categorization outcomes.

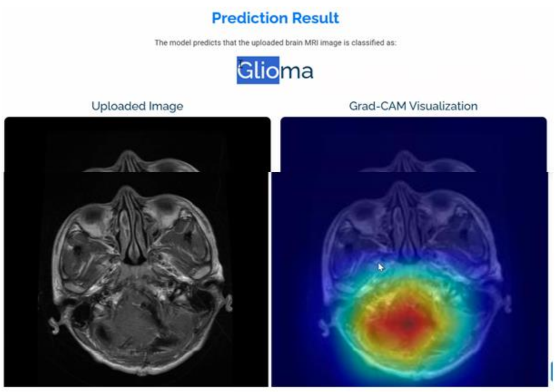


Fig.7 Predicted Results

Figure 7 illustrates the output interface, indicating the projected tumor type as glioma, accompanied by Grad-CAM imagery that emphasizes the distinguishing tumor locations.

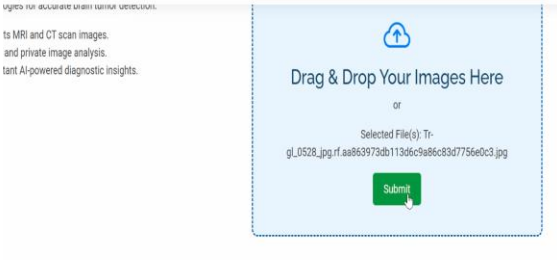


Fig.8 Upload Input Image

Figure 8 depicts the detection interface that enables users to upload brain scan pictures for the precise automatic detection and visualization of tumor locations.

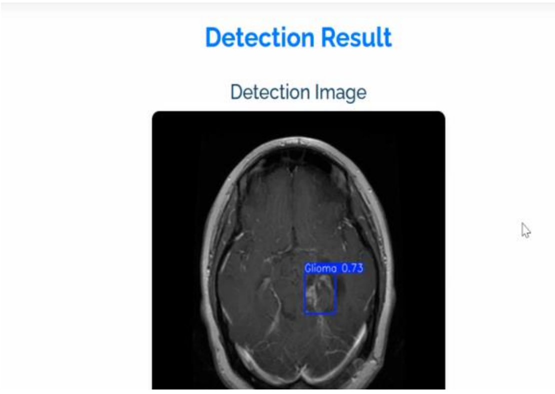


Fig.9 Predicted Results

Figure 9 illustrates the output interface indicating the identified tumor type as glioma, accompanied by a confidence score of 0.73 for the image.

5. CONCLUSION

Precise categorization and location of brain tumors using MRI scans are crucial for enhancing diagnosis accuracy and facilitating appropriate treatment planning. This system fulfills these requirements by incorporating multi-class classification, tumor identification, and interpretability into a cohesive medical imaging framework utilizing the Brain Tumor MRI dataset. Classification performance is attained with transfer learning models like EfficientNetV2, Vision Transformer (ViT-B16), DenseNet121, and Xception, augmented by ensemble techniques utilizing average, weighted average, and geometric mean fusion to improve predictive reliability. Tumor localization and identification are conducted with several YOLO variations, such as YOLOv5, YOLOv8, YOLOv9, and YOLOv11, which are trained with bounding box annotations in YOLO format. The integration of Grad-CAM enhances model transparency by providing visual explanations of the tumor regions that affect predictions. The deployment is facilitated by a Flask-based web application that enables users to upload MRI images and receive visualized detection outcomes, predicted tumor classifications, and confidence metrics. Quantitative assessment validates the system's efficacy, with DenseNet121 and Xception achieving a classification accuracy of 99.54%, while YOLOv8 reaches a mean average precision of 95.1% for detection. The system provides a dependable, automated, and interpretable diagnostic solution that improves clinical decision-making, diminishes human workload, and facilitates practical neuro-oncological analysis.

Future endeavors will concentrate on augmenting the dataset with larger and more heterogeneous MRI collections to improve the generalizability and robustness of classification models. Integrating multimodal imaging data, including CT and PET scans, can yield supplementary diagnostic insights and enhance classification precision across diverse tumor types. Further investigation into sophisticated deep learning architectures, encompassing novel transformer-based models and hybrid fusion techniques, may result in improved performance. Consideration will also be given to optimizing for computing efficiency and deployment in resource-constrained areas, such as edge devices, to enable real-time clinical application. Moreover, the integration of electronic health records can enhance tailored predictions by amalgamating imaging data with patient demographics and clinical history for comprehensive decision-making.

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