Research Article

Explainable Transfer Learning Framework for Multi-Class Brain Tumor Classification from MRI Images

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Abstract

Brain tumor detection is a critical task in medical imaging, where accurate classification and localization of tumor regions in MRI scans directly influence diagnostic precision and treatment planning. In this work, the Brain Tumor MRI dataset is utilized for multi-class classification and detection tasks. For classification, advanced transfer learning architectures including EfficientNetV2, Vision Transformer (ViT-B16), DenseNet121, and Xception were employed, along with ensemble techniques based on average, weighted average, and geometric mean to enhance predictive reliability. For tumor localization and detection, multiple YOLO variants (YOLOv5, YOLOv8, YOLOv9, and YOLOv11) were implemented with bounding box annotations in YOLO format. Additionally, explainable AI techniques such as Grad-CAM were incorporated to generate heatmaps highlighting discriminative tumor regions that influence model predictions. Experimental results demonstrate that DenseNet121 and Xception models achieved the highest classification accuracy of 99.54%, outperforming other classifiers. For detection, YOLOv8 delivered superior performance with a mean average precision (mAP) of 95.1%. These findings validate the effectiveness of integrating classification and detection frameworks with interpretability methods for robust and reliable brain tumor diagnosis. Furthermore, a Flask-based web application was developed to deploy the trained models, enabling users to upload MRI images and visualize tumor localization, predicted class, and confidence scores through an interactive interface.

Keywords—*Efficientnetv2, Convolutional Neural Network (CNN), Brain Tumor Vision Transformers (ViT), Magnetic Resonance Imaging (MRI), Multilayer Perceptron (MLP).*

1. **Introduction**

Brain tumors (BTs) encompass a diverse spectrum of nearly 200 abnormal tissue growths, posing significant challenges to human health. Among these, gliomas, originating from glial cells, are the most common malignant type, accounting for approximately 80% of cases [1]. The World Health Organization classifies gliomas into four grades, ranging from benign to highly malignant, and accurate grading is critical for determining treatment strategies. However, this grading process is often time-consuming and requires precision. Magnetic Resonance Imaging (MRI) serves as a non-invasive diagnostic tool, providing detailed insights into brain anatomy, yet its interpretation is labor-intensive and demands expert knowledge [2]. The complexity of brain tumor identification is compounded by other subtypes, such as meningiomas and pituitary tumors. Pituitary tumors, arising from the hormone-regulating pituitary gland, can be benign, affecting bone growth, or malignant, leading to hormone imbalances and vision impairment [3]. Early detection and precise classification are thus essential, as delays can adversely affect patient survival [4].

Recent advances in biomedical engineering and computational methods offer promising solutions. Xu et al. [5] proposed a 3D-stacked inertial microfluidic device for circulating tumor cell (CTC) separation, achieving high purity and efficiency in isolating tumor cells, demonstrating the potential of integrated microfluidic analysis. In parallel, emerging machine learning techniques, including deep learning (DL) and Vision Language Models (VLLMs), provide opportunities for improved brain tumor detection. VLLMs integrate visual and textual data, enabling nuanced interpretation of MRI scans alongside clinical documentation and patient histories [6]. Self-supervised learning and attention mechanisms further enhance model performance, particularly for rare tumor subtypes [7]. Deep learning frameworks, especially Convolutional Neural Networks (CNNs) and autoencoders, have been widely applied in medical imaging for classification, segmentation, and prediction tasks [8]. However, performance inconsistencies across datasets highlight the need for more robust architectures [9]. Vision Transformers (ViTs) have emerged as a powerful approach, capable of capturing complex spatial patterns in medical images while supporting scalability and generalization across diverse datasets and imaging modalities [10].

This study proposes a ViT-based framework for automatic multi-class brain tumor classification into pituitary, glioma, malignant glioma, and no-tumor categories. Leveraging hierarchical representations and attention mechanisms, the model extracts critical features from MRI scans, enabling precise identification of tumor types. The approach aims to reduce reliance on manual expert grading, enhance early detection, and facilitate

personalized treatment planning, ultimately improving patient outcomes while offering a scalable and adaptable solution for clinical deployment.

Related Work

Recent research in brain-computer interfaces (BCIs) and brain tumor classification has demonstrated significant advancements in leveraging deep learning, transformers, and hybrid architectures to improve diagnostic accuracy and patient care. Li et al. [11] proposed a CVT-based asynchronous BCI framework for brain-controlled robot navigation. Their study focuses on utilizing a cyclic vision transformer (CVT) to enhance asynchronous signal interpretation, enabling precise navigation tasks by translating neural signals into robotic commands. This approach emphasizes the importance of integrating advanced neural network architectures with BCIs, highlighting the potential of transformer-based models to process complex neural data effectively. Complementing this work, Si et al. [12] developed a cross-subject emotion recognition BCI using functional near-infrared spectroscopy (fNIRS) and a deep brain joint network (DBJNet). Their approach addresses the challenge of inter-subject variability in brain signal interpretation, demonstrating that multi-modal deep learning architectures can capture subtle neural patterns, improving the accuracy of emotion recognition across diverse subjects.

In the field of brain tumor classification, Kumar et al. [13] explored multi-class classification using residual networks combined with global average pooling. Their framework enhances feature extraction while reducing computational complexity, providing a scalable solution for accurately classifying multiple tumor types in MRI images. Similarly, Meshram et al. [14] investigated the use of Swin transformers for brain tumor detection. The Swin transformer architecture leverages hierarchical feature extraction and self-attention mechanisms to capture both local and global contextual information, resulting in improved performance over conventional convolutional approaches, particularly in multi-class classification scenarios. Ramakrishnan et al. [15] proposed a hybrid CNN architecture optimized with oneAPI to balance accuracy and computational efficiency for brain tumor classification. Their method demonstrates that hardware-aware optimization strategies, when combined with sophisticated network architectures, can significantly accelerate inference times without compromising predictive performance, making the model suitable for clinical applications.

Rastogi et al. [16] presented a multi-branch deep learning framework incorporating inception blocks and five-fold cross-validation for multi-class brain tumor MRI classification. By utilizing multiple network branches to capture diverse feature representations, their approach improves generalization and robustness across various tumor types, illustrating the effectiveness of modular network designs in medical image analysis. In parallel, Liu et al. [17] proposed a stimulated Raman CycleGAN model to generate virtual formalin-fixed and paraffin-embedded (FFPE) staining of fresh brain tissue. This technique enables accurate visualization and analysis of brain tumor histopathology without traditional staining procedures, reducing preparation time and providing high-fidelity tissue representation for downstream diagnostic applications.

Tandel et al. [18] employed an artificial intelligence paradigm for multi-class MRI brain tumor classification, focusing on integrating AI-driven feature extraction and classification strategies to enhance diagnostic precision. Their study underscores the utility of AI in differentiating between tumor subtypes, facilitating early detection and personalized treatment planning. Zhou et al. [19] introduced a vector quantization generative adversarial network (VQ-GAN) to generate three-dimensional brain tumor regions in MRI scans. By modeling spatial tumor structures in 3D, their approach aids in improving segmentation and visualization, which are critical for preoperative planning and treatment monitoring. Finally, Parshapa and Rani [20] conducted a comprehensive survey on machine learning techniques for brain tumor diagnosis. They reviewed a range of methodologies, emphasizing the importance of feature selection, model optimization, and cross-validation strategies to enhance predictive performance, particularly in scenarios with limited annotated data.

Materials And Methods

The proposed system presents a deep learning-based framework for automated multi-class brain tumor classification using MRI images, aiming to enhance diagnostic accuracy and streamline clinical workflows. The framework integrates EfficientNetV2 [26] for scalable and efficient feature extraction, complemented by Vision Transformer (ViT-B16) [27] to capture long-range dependencies and global contextual information. Additional architectures, including Xception and DenseNet121, provide enriched feature representations for diverse tumor types. Tumor localization is achieved using YOLO models (YOLOv5, YOLOv8, YOLOv9, and YOLOv11), enabling precise identification of abnormal regions. An ensemble strategy combining average, weighted average, and geometric mean improves prediction reliability, while Grad-CAM facilitates explainable AI visualizations. The

system is built on a structured workflow encompassing dataset preprocessing, model training, evaluation, and inference, with a Flask-based web interface for real-time MRI image analysis [28].

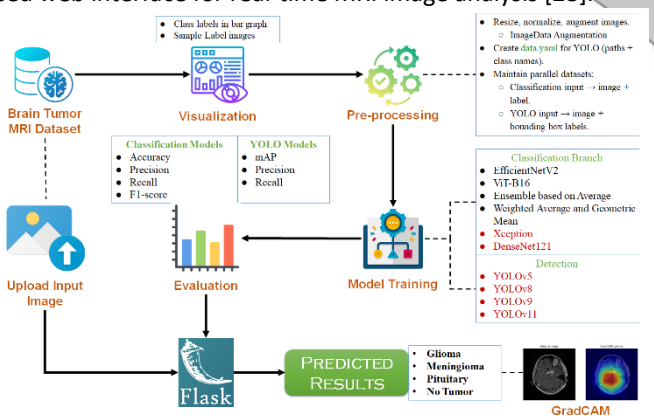


Fig. 1. System Architecture

The system architecture integrates multiple deep learning models for automated brain tumor classification using MRI images. It begins with dataset preprocessing, followed by feature extraction through EfficientNetV2, Xception, and DenseNet121, while Vision Transformer (ViT-B16) captures global context [29]. Tumor localization is performed using YOLO models (YOLOv5, YOLOv8, YOLOv9, YOLOv11), and predictions are combined via ensemble strategies to enhance reliability. Grad-CAM provides explainable visualizations, and a Flask-based web interface enables real-time image upload, classification, and tumor visualization, ensuring a comprehensive, end-to-end diagnostic framework [30].

A) Dataset Collection

The dataset comprises 2,197 MRI images, with 1,695 allocated for training and 502 for testing. For the classification branch, each image includes a corresponding class label indicating the tumor type. For the YOLO-based localization branch, bounding box annotations are provided in YOLO format (.txt) to identify and localize tumor regions within the scans. The dataset is carefully split into training, validation, and testing subsets, ensuring balanced representation across classes and enabling robust model training, evaluation, and accurate multi-class tumor detection.

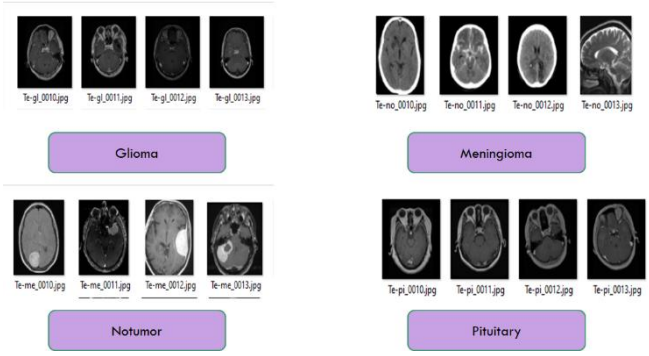


Fig.2 MRI Dataset

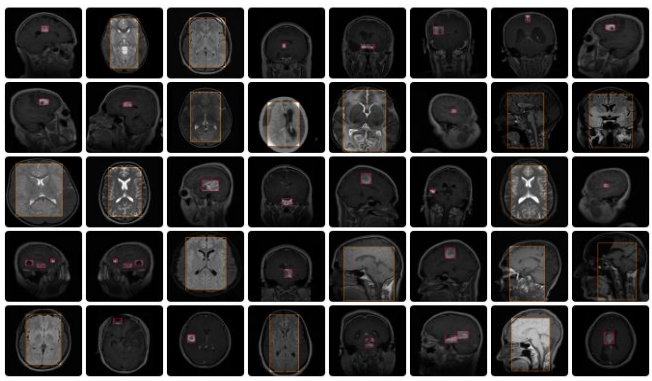


Fig.3 MRI Data

B) Image Processing

All MRI images are resized and normalized to ensure consistent dimensions and pixel value distribution, facilitating efficient model training. Images are also converted into formats compatible with the deep learning pipelines for both classification and YOLO-based detection tasks. This preprocessing step standardizes the input data, reduces computational overhead, and ensures that the models can effectively learn relevant features from tumor regions while maintaining high accuracy and reliability across diverse MRI scans.

C) Data Augmentation

To improve model generalization and robustness, the dataset undergoes augmentation techniques including rotation, horizontal and vertical flipping, zooming, and brightness adjustments. These transformations artificially expand the dataset, allowing the models to handle variations in MRI orientations, scales, and lighting conditions. By exposing the network to diverse scenarios during training, augmentation reduces overfitting, enhances feature learning, and ensures that the classification and detection branches can reliably identify tumors across varied imaging conditions.

D) Algorithms

EfficientNetV2: EfficientNetV2 extracts discriminative features from MRI images through compound scaling of depth, width, and resolution, enabling accurate multi-class brain tumor [21] classification while maintaining high efficiency and rapid convergence with pre-trained weights and fine-tuning.

Vision Transformer (ViT-B16): ViT-B16 captures long-range dependencies in MRI scans using patch-based embeddings and multi-head self-attention, learning global contextual relationships between image regions to improve classification [22] of subtle tumor patterns and enhance robustness across diverse scans.

Ensemble Methods: Combining outputs from multiple models through averaging, weighted averaging, or geometric mean reduces variance, mitigates individual model biases, and integrates complementary features, resulting in more consistent and accurate multi-class tumor [23] predictions from MRI data.

Xception: Xception leverages depthwise separable convolutions to extract spatial and semantic features from MRI images [24], improving representation learning, accelerating convergence, and enhancing multi-class tumor differentiation while minimizing computational overhead.

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

DenseNet121: DenseNet121 connects layers densely to promote feature reuse and gradient flow, capturing both low- and high-level MRI features, enabling precise tumor type identification [25] and improving classification stability and interpretability.

$$x_l = H_l\left(\left[x_0, x_1 \ldots, x_{l-1}\right]\right) \quad (2)$$

YOLOv5: YOLOv5 detects and localizes tumor regions in MRI scans efficiently by dividing images into grids, predicting bounding boxes and class probabilities simultaneously, balancing speed and accuracy for real-time tumor identification.

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

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

YOLOv8: YOLOv8 improves detection accuracy using enhanced backbone and multi-scale feature fusion, capturing detailed tumor boundaries and variations for precise localization across diverse MRI tumor sizes.

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

YOLOv9: YOLOv9 enhances bounding box precision and feature representation, identifying small and complex tumor structures while maintaining high accuracy, supporting spatially accurate tumor localization for clinical assessment.

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

YOLOv11: YOLOv11 emphasizes real-time detection and optimized performance, handling irregular tumor shapes and sizes with anchor-free prediction and robust backbone networks, delivering accurate and interpretable localization for MRI-based tumor evaluation.

E) Integration of XAI and Flask Framework

The integration of Explainable Artificial Intelligence (XAI) with the Flask framework provides a transparent and interactive approach for brain tumor analysis. XAI techniques, such as Gradient-weighted Class Activation Mapping (Grad-CAM), generate heatmaps that highlight regions of MRI scans most influential in model predictions. This interpretability allows clinicians to understand how models make decisions, enhancing trust

and supporting more informed diagnostic insights while ensuring the system's outputs are explainable and clinically meaningful.

The Flask framework enables a user-friendly web interface that allows easy interaction with the model. Users can upload MRI scans, receive tumor classification results, view bounding box localization, and access Grad-CAM visualizations in real time. This integration combines interpretability, accessibility, and practicality, facilitating effective AI-assisted diagnostic workflows.

Experimental Results

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

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

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

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

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

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

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

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

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

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

Table.1 Performance Evaluation - 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

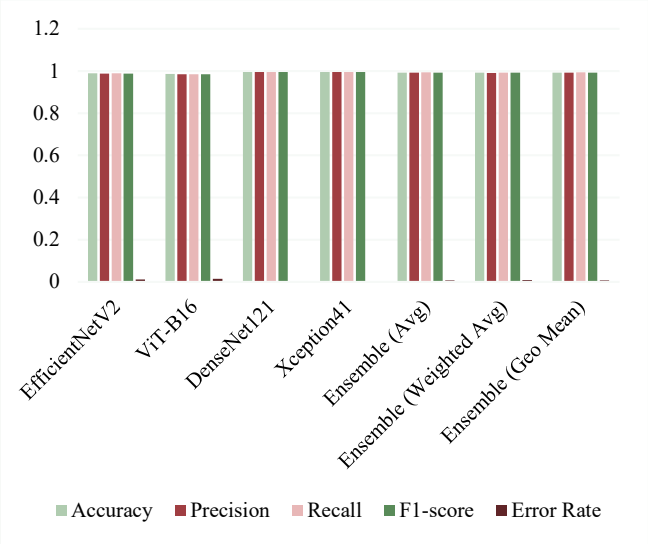
In Table.1, model performance comparison highlights DenseNet121 and Xception41 achieving the highest accuracy, with ensembles providing consistent, reliable results.

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

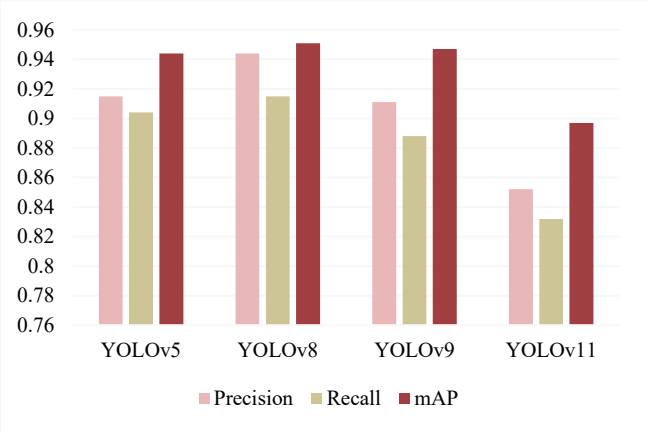
In Table.2, YOLOv8 achieves the highest overall performance, demonstrating superior detection accuracy and reliability compared to other YOLO variants.

Fig.4 Comparison Graph - Classification



In the fig.4, DenseNet121 and Xception41 clearly lead in performance, with their bars towering above others, while ensemble methods show balanced, consistent results across all metrics, highlighting reliability and overall robustness visually.

Fig.5 Comparison Graph – detection



In the fig.5, YOLOv8 clearly achieves the highest performance, with its bar prominently indicating superior detection accuracy and reliability compared to other YOLO variants.

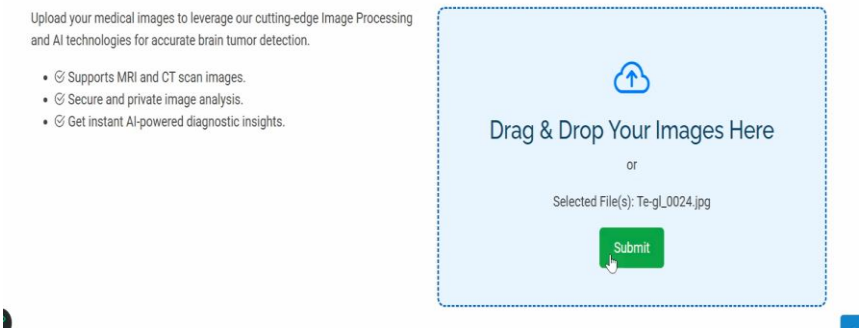


Fig.6 Upload Input Image

Fig.6 illustrates the input interface where users can upload brain scan images to obtain automated multi-class brain tumor classification results.

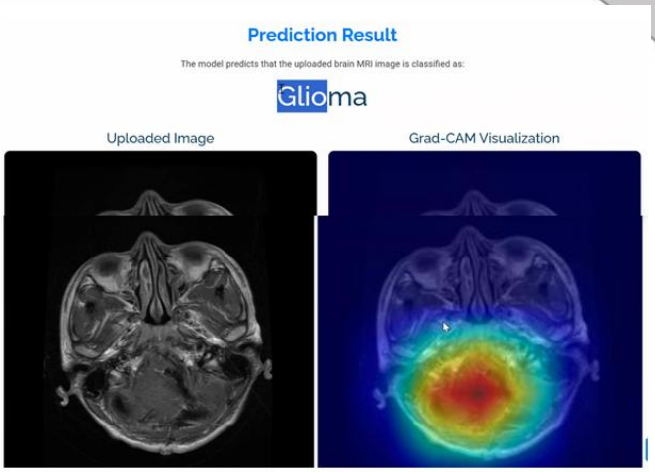


Fig.7 Predicted Results

Fig.7 displays the output interface showing the predicted tumor type as glioma, along with Grad-CAM visualization highlighting discriminative tumor regions.



Fig.8 Upload Input Image

Fig.8 illustrates the detection interface where users can upload brain scan images to automatically detect and visualize tumor regions accurately.

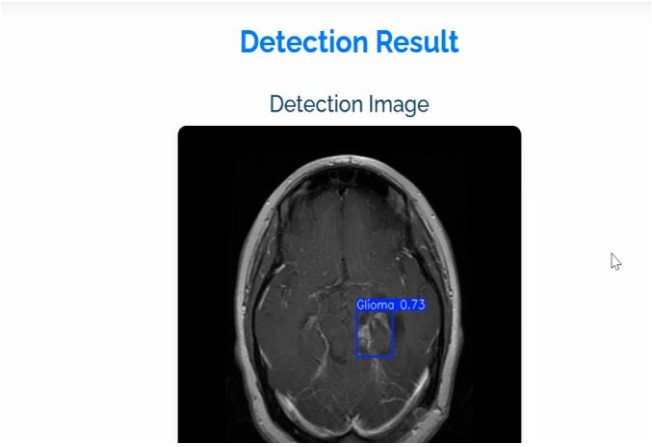


Fig.9 Predicted Results

Fig.9 displays the output interface showing the detected tumor type as glioma with a confidence score of 0.73 on the image.

Conclusion

The outcomes of this study highlight the effectiveness of integrating state-of-the-art deep learning models for reliable brain tumor classification and detection from MRI scans. Among the classification models, DenseNet121 and Xception demonstrated superior performance with an accuracy of 99.54%, precision of 99.51%, recall of

99.50%, and F1-score of 99.50%, establishing them as the most robust architectures for multi-class tumor classification. For detection, YOLOv8 achieved the best results, attaining a mean average precision (mAP) of 95.1%, precision of 94.4%, and recall of 91.5%, making it the most effective model for localizing tumor regions within MRI images. The integration of explainable AI using Grad-CAM further provided transparency by generating heatmaps that emphasized critical tumor regions, thereby enhancing clinical trust in automated predictions. These results indicate that combining classification and detection frameworks with interpretability techniques ensures accurate, efficient, and interpretable diagnostic support. Overall, the developed framework demonstrates the potential of deep learning-driven methodologies to advance brain tumor analysis, supporting radiologists with rapid, precise, and interpretable outcomes for improved treatment planning.

Future work will focus on expanding the dataset with larger and more diverse MRI collections to enhance the generalizability and robustness of classification models. Incorporating multimodal imaging data, such as CT and PET scans, can provide complementary diagnostic information and improve classification accuracy across varying tumor types. Further exploration of advanced deep learning architectures, including newer transformer-based models and hybrid fusion techniques, may yield enhanced performance. Optimization for computational efficiency and deployment on resource-constrained environments such as edge devices will also be considered to facilitate real-time clinical use. Additionally, integration with electronic health records can support personalized predictions by combining imaging data with patient demographics and clinical history for holistic decision-making.

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