Brain Tumor Analysis in MRI Using Hybrid Transfer Learning and YOLO-Based Detection for Improved Diagnostic Accuracy

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Abstract: The correct detection of brain tumors in MRI images is required to deliver quick detection and efficient treatment, whereas various imaging characteristics complicate the functionality of automated practices. Clinical choices to be supported need to be supported by classification and localization techniques. The dataset is constituted by MRI scans which are labeled by tumor classification labels and bounding box labels. It has a great variety of tumor types and imaging characteristics, which makes it a good point of entry when it comes to the testing of automatic detection and classification systems. The proposed method uses transfer learning-based architectures such as VGG16, ResNet, Inception and DenseNet in classifying brain tumors. The models are evaluated using accuracy, precision, recall and F1-score which offer a strict method of comparative performance. To further improve things, we may resort to Xception, a collection of DenseNet and Xception, variants of YOLO such as YOLOv5, YOLOv8, YOLOv9, and YOLOv11 in order to locate and identify tumors, Grad-CAM to simplify the heatmap interpretation, and an interface based on Flask that allows interactive clinical usage. The ensemble model performs better than all the other classification models with 99.3 across all the metrics. The YOLOv8 has the highest detection mAP of 89.6 and a good Precision Recall balance. This demonstrates that the framework is robust and sound enough to be used in clinical practice on the precise classification and localization of brain tumors.
"Index Terms: *Brain tumor detection, transformative transfer learning, MRI, deep learning, transfer learning, medical imaging."*

1. INTRODUCTION

Human brains are extremely complex and in control of numerous various functions, including thinking to feeling. They also have a high tendency to numerous diseases. These disorders are severe, and brain tumors are particularly fatal since they can be quite terrible and are difficult to detect and cure. Brain tumor is a disease that develops in the brain or the central spinal canal due to the abnormal development of the cells. Depending on the place of origin and behaviors, they are categorized as benign (non-cancerous) and malignant (cancerous). The WHO has established a system of grading since I to IV. The least dangerous growth is referred to as Grade I, and the most dangerous is referred to as Grade IV [1]. Pituitary adenoma, glioma, and meningiomas are examples of primary brain tumors that begin at the brain itself. Secondary tumors or metastatic tumors on the other hand are caused by other organs of the body, typically the lungs or the breast [2]. The precise cause is yet to be established, although genetic mutations, which are transmitted through families, radiation exposures, and family history have been cited as the likely risk factors [3]. The symptoms of brain tumor vary depending on the size, the type and where the tumor is located. Headaches, nausea, mood swings, seizures and difficulty in seeing are some of the most frequent symptoms [4]. The most appropriate way of making a medical diagnosis is through MRI which provides a clear image of the structure of brain cells and enables a precise location and measurement of the tumors [5]. MRI is not similar to other forms of imaging processes such as

X-rays since it involves a process known as nuclear magnetic resonance and does not involve the use of harmful radiations [6]. It is more contrasted with soft tissues and hence easier to distinguish the healthy and unhealthy parts which is very vital in locating the borders of tumors [7]. In addition to conventional MRI, recent techniques such as fMRI and DTI assist us to know more about the functions of the brain, white matter pathways, and issues created by tumors [8]. They are highly important techniques of high-resolution imaging that can be used in surgery preparation and monitoring patients during the post-treatment period because they provide a method to measure the success of the treatment and locate a return [9]. Still, MRI has some problems, such as taking a long time to acquire, creating motion artifacts, and not being able to be used on people with metal devices [10].
Due to these complications with diagnosis, there is increased use of transfer learning and deep learning techniques in medical imaging. The approaches to the problem of the inadequate availability of annotated datasets in clinical practice are to apply large-scale models that are trained and modify them to identify brain tumors by the results of MRI scans. This paper is a continuation of these past ones, as it investigates the effectiveness of the various transfer learning models at identifying tumors more precisely and faster.

2. LITERATURE REVIEW

The presence of brain tumors are now detectable, classified, and even separated with high precision due to the ongoing enhancement of the medical imaging and machine learning. Researchers have developed many new techniques that have made imaging better, computer models better, and issues related to accuracy, lack of data, and privacy issues solved. As an example, the concept of SAD-NMR with the introduction of the singlet NMR principles into DTI and its practicalization was suggested by Melchiorre et al. [11]. Their work developed a new approach to examine molecular diffusion and tissue microstructures that can render the standard MRI more practical in a wider range of cases. The discovery of how to capture the higher features of diffusion is a major leap in brain imaging as it will aid us in the process of knowing how tumors modify the micro environments in the brain.
Ullah et al. [12] proposed a federated learning system that is scalable to assist in one of the increasing issues in the brain tumor segmentation. They have done this through concentrating on computational modeling and group learning. Their research emphasized the significance of the preservation and privacy data as well as enhancing the classification accuracy. Through the federated learning, they ensured that private medical information remained centralized and at the same time allowed other schools to collaborate to learn. This approach not only ensured the security of patient data, but it also made the work of segmentation more productive, which formed the foundation of privacy-sensitive joint healthcare systems. In another study, Ullah et al. [13] investigated the possibility of using a patch-based CNN to distinguish between brain tumors. They were able to find tumors easier because their approach was founded on big data which involves breaking down MR images into smaller and easier-to-process pieces. This enabled the computer work to be faster and the model to be better. The authors demonstrated that patch-based learning was in a better position to locate certain characteristics of the tumors and this is a viable alternative to whole image-based techniques. At the same time, Chen et al. [14] gave a complete outline of how deep learning can be used to improve and fix MRI images. Their study discussed the present condition of image enhancement methods, problems and opportunities that are present. They discussed how deep neural networks can address such typical issues with MRIs as reducing noise, addressing motion artifact, and increasing resolution, resulting in high-quality diagnostic images. Another important issue that was discussed by the authors concerns the necessity to strike a balance between performance and computational costs. As an illustration, they have indicated that deep learning enhances the quality of pictures significantly, yet they consume a lot of resources to be trained and utilized.
Transfer learning has also played a very significant role in medical imaging along with the advancement of MRIs. One of the studies by Singh and Pillay [15] investigated the concept of transfer learning within the context of an ant-based generation construction hyper-heuristic. They demonstrated in their work that the concepts of transfer learning could be applied to solve optimization problems to find improved solutions in cases where traditional learning methods did not succeed. Although they did not strictly work with brain tumors, the data that they collected regarding transfer learning strategies proved helpful in such fields as medical imaging where the data is scarce. Liu et al. [16] looked at the role of deep learning and medical picture analysis in diagnosing and predicting COVID-19, which adds to this view. They discussed how strong deep learning models can be in the medical context, particularly in a situation where the healthcare conditions are evolving rapidly. Their study revealed that deep learning procedures are applicable to a

range of imaging procedures and disease conditions. This further renders these techniques more helpful in detection and categorization of tumors.

The texture analysis is not a recent discovery that has helped in the study of brain tumors. In this area, Kunimatsu et al. [17] went a step further to describe MRI brain tumors using texture methods. They studied the use of texture features extracted out of MRI scans to guide physicians to make more appropriate diagnoses by exhibiting subtle variations in tissue structure that are not seen under normal imaging. The authors demonstrated that non-invasive, quantitative biomarkers may be utilized to assess tumors and assist doctors distinguish the difference between various types and grades of tumors through planned examination of MRI based textural data.

Islam et al. [18] developed a hybrid method of locating brain tumors in MR images in terms of algorithms. They applied the principal component analysis (PCA), template-based K-means grouping, and super pixel segmentation. The efficiency of this technique was increased through the application of superpixels and PCA in simplifying the images followed by the clustering in an attempt to locate the tumor regions. They found that their approach was more accurate than regular clustering approaches. This shows how important it could be to combine dimensionality reduction with unsupervised techniques in medical imaging.

The presence of datasets has been one of the major contributors to study advancement. A large contribution was made by Nickparvar [19] who posted an MRI catalog of brain tumors to Kaggle. This dataset has been utilized extensively by researchers, and it has been possible to compare and experiment on various segmentation and classification procedures. Such public datasets have not just facilitated the ease with which an experiment can be recreated, but have also expedited the creation of transfer learning-based practices that require fine-tuning on a specific domain in order to perform well.

Lastly, a more suitable region-growing method was proposed by Biratu et al. [20] to separate brain tumors in MR pictures. Their approach was superior to the common region-growing since it included additional limitations and adaptability. This reduced the chances of errors such as over-segmentation and spill over to regions that are not tumours. The study revealed that more effective approaches to region-growing can be used to better define the boundaries of tumors, which is significant in treatment planning as well as detection.

3. MATERIALS AND METHODS

The proposed system makes use of MRI data such as the Kaggle Brain Tumor MRI dataset [27] to have a complete architecture to classify and locate brain tumors. To sort, VGG16, resnet, inception, densenet121, Xception and a hybrid of Xception and DenseNet121 are employed with transfer learning in order to extract complex spatial and hierarchies tumor features. In order to clearly see the tumor, the YOLO family of models (YOLOv5, YOLOv8, YOLOv9, and YOLOv11) is used in conjunction with recognition and localization. Visual heatmaps made using Grad-CAM are simple to interpret since they indicate the areas of focus of an important decision [28]. The system is configured with Flask that provides an interactive, real-time interface with which MRI images can be viewed.

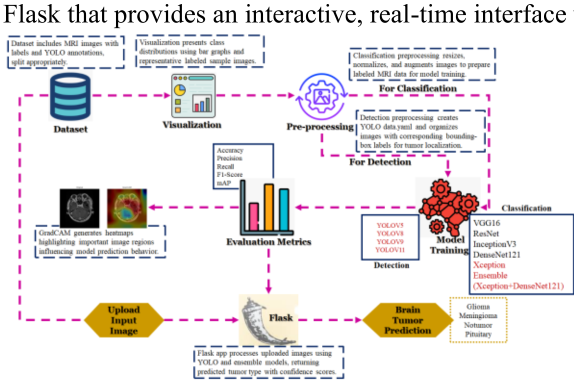

Fig.1 Proposed Architecture

The system design presents a full-fledged scheme of the analysis of MRI brain tumors. This begins by preparing the dataset, which involves labeling images in order to classify them, and placing bounding boxes in order to detect them [29]. Sample image visualization and class distribution make the data clean. The pictures are resized, normalized and enhanced before the commencing classification process. Meanwhile, the data on the detection is organized with the help of YOLO annotations. Models are then trained to classify and locate things and then they are evaluated on metrics like accuracy and mAP. Grad-CAM simplifies the process of understanding things as it highlights the critical areas [30]. Lastly, the Flask web application allows one to share photos and receive predictions concerning tumors and confidence ratings.

a) Dataset Collection:

The set that will be used in the classification exercise comprises 7,023 MRI images that have been divided into four categories: glioma, meningioma, pituitary and no tumor. In a more precise manner, the training set contains 4,914 images and the testing one contains 2,109 images. This will ensure fairness of the review. The pictures of gliomas, meningiomas, no tumors, and pituitary gland amount to 1,621, 1,645, 2,000 and 1,757, respectively. This is sufficient diversity to have deep learning models developed to learn to discriminate between tumor features.

To be detected, another dataset is utilized with 412 images being put aside (testing) and 1,646 images being put aside (training). This subset was selected very carefully to assist the object recognition algorithms that enable one to specifically find tumors and depict boundaries on the MRI scans. All these datasets are used to ensure that classification and detection tests are robust.

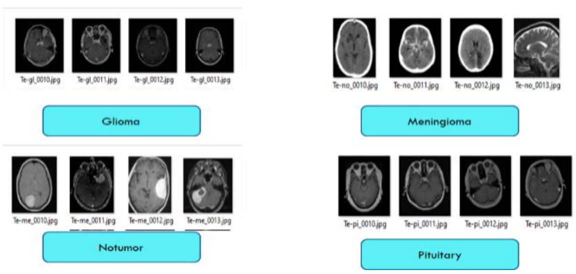

Fig.2 MRI Dataset

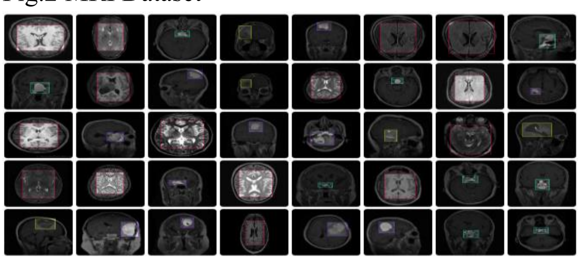

Fig.3

b) Visualization: To balance and represent the data, the bar graphs were applied to indicate the class distributions and the representative MRI images of each of the classes were displayed. These images demonstrated the prevalence of various forms of tumors and the difference in their structure. They aided in discovering any mistakes and decisions on editing. Researchers ensured fairness of learning by considering the counts of pictures and sample changes. This also assisted in preparing inputs towards activities such as classification and detection more.

c) Preprocessing: The preprocesses of MRI images were done systematically by resizing to a constant size, normalizing to maintain the pixel intensities constant and enhancing the image by flipping, rotating, zooming and adjusting the brightness. One of the data sets of YOLO identification.The paths of the datasets and the type of tumors were configured in a YAML file. Making the model more resistant to changes in MRI scans by augmentation and ensuring that the model can be optimized to each task and generalized was done by having different datasets to classify and detect.

d) Algorithms:

VGG16: VGG16 has small convolutional filters that capture spatial hierarchies and serve as a backbone in transfer learning in MRI images. It provides a strong initial foundation that allows one to accurately detect various types of brain tumors [21] and is compatible with a variety of medical image samples.

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

ResNet: ResNet involves the use of residual links to simplify the training of the deep networks to avoid the disappearance of gradients. It enhances the capability to draw out characteristics of MRI images of intricate tumors [22], which allows the classification to be more robust and precise besides guaranteeing robust learning of various, high-dimensional representations of medical data.

Inception: Inception employs parallel convolutions of varying filter size in order to extract multi-scale spatial features. It is well performing in the detection of tumors of various sizes and shapes in MRI images [23], learns very fast, has low computational costs and maintains a high accuracy of classification among all the classes of tumors.

DenseNet: DenseNet also forms numerous connections between the layers, and thus it is simpler to reuse features and contour the flow of the gradient. Such a design gets complex tumor architecture, generalizes more effectively, converges faster, and classifies more accurately [24], particularly when using small MRI datasets which are likely to face an overfitting issue.

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

Xception: Xception is a neural network that reduces the number of parameters required to capture significant tumor features but takes shorter durations to analyse MRI images as it deploys depth-separable convolutions to reduce the time taken [25]. It is also easy to design and classify as well as predicts better chances of coming true when used alone or with other models.

$$O_{i,j,k} = \sum_{m,n} X_{i+m,j+n,c} W_{m,n,k} \quad (3)$$

Ensemble (Xception + DenseNet121): This grouping is a combination of the fast separable convolutions of Xception and DenseNet121 dense connectedness which forms synergistic feature representations. The combination reduces error of both models, generalizes the model and enhances accuracy in the classification of brain tumors [26], which favors the accurate diagnosis results and better trust on the prediction results.

YOLOv5: YOLOv5 allows simultaneously predicting bounding boxes and classes, which enables brain tumors to be detected fast and precisely in an MRI scan. Due to its lightweight nature, it is able to make inferences fast and precisely hence it is well suited to real time applications that require identification of tumors in a short time and with minimum additional effort.

$$x = \sigma(t_x) + C_x, \qquad y = \sigma(t_y) + C_y \quad (4)$$

YOLOv8: YOLOv8 eases the process of locating the tumors with enhanced feature extraction and optimized anchor. It is very accurate and balanced in recalling in MRI analysis leading to more accurate localization and quicker inference. This renders it dependable in the provision of real-time diagnostic assistance as well as clinical interpretation.

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

YOLOv9: YOLOv9 enhances the detection of tumors by strengthening the spatial feature learning and multi-scale modeling. It ensures that the areas of tumor are well detected and at the same time opens the computer speed. This enables regular and dependable localization, which assists in medical picture examination and making a diagnostic choice.

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

YOLOv11: YOLOv11 can be used in advanced modules that identify tumors in MRI images, which are fine-grained, and this is highly accurate and fast. It is able to localize and classify simultaneously, which permits real-time examination, which can be comprehended and intended to be incorporated into clinical workflows and also large-scale diagnostic operations.

e) Integration of XAI and Flask Framework:

Xplainable Artificial Intelligence (XAI) can be added to the framework to simplify deep learning predictions and simplify the process of classifying and locating brain tumors. Heartraps are created using grad-CAM and other methods that indicate the most significant areas of an MRI that influence model decisions. This ensures that the accuracy of the predictions can be checked by the doctors and researchers and this improves the confidence and understanding of the model behavior in sensitive medical imaging processes.

The framework is launched using Flask which is a lightweight web application environment to allow the framework to be used in real time interaction. The deployment allows users to share MRI images via the convenient interface. The system will then process the images and will provide results of classification, detection, and XAI visualization. Such a seamless bridge between developed AI models and convenient, user-friendly healthcare applications.

4. EXPERIMENTAL RESULTS

Accuracy: The ability of a test to distinguish between unhealthy and healthy individuals is referred to as accuracy. To have a clue about the accuracy of a test, we are supposed to calculate the percentage of true positives and true negatives. Mathematically this can be expressed as.

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

Precision: Precision is the proportion of the cases or samples that have been classified correctly to the cases that were correctly classified as positives. Thus, it is the way to determine the accuracy:

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

Recall: Recall has been used in machine learning as a measure of how effective a model can be in locating all the significant examples of a given class. It depicts the extent to which a model is able to capture cases of a particular class. Calculation is done by the number of correctly predicted positives divided by the total number of real positives.

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

F1-Score: F1 score is the method of scoring the accuracy of a ML model. It sums the accuracy and the recall scores of a model. The measure of accuracy records the number of occasions in the entire dataset that a model gave a right guess.

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

mAP: MAP is a method of ranking things and quality measurement. It examines the number of related suggestions and their position in the list. Computing MAP at K is done by multiplying the AP at K of all searches or users by 100.

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

Table.1 Performance Evaluation Table – Classification

ML Model	Accuracy	Precision	Recall	F1 Score
VGG16	0.864	0.863	0.864	0.863
ResNet	0.611	0.634	0.611	0.606
Inception	0.924	0.924	0.924	0.924
DenseNet	0.991	0.991	0.991	0.991
Xception	0.991	0.991	0.991	0.991
Ensemble	**0.993**	**0.993**	**0.993**	**0.993**

Table.1 demonstrates that Ensemble is most reliable in classification of MRI and then DenseNet and Xception.

Table.2 Performance Evaluation Table – Detection

ML Model	Precision	Recall	mAP
Yolo v5	0.919	0.843	0.890
Yolo v8	**0.893**	**0.862**	**0.896**
Yolo v9	0.891	0.826	0.893
Yolo v11	0.837	0.805	0.856

YOLOv8 is the best in the overall performance as it performs better than other variants of the YOLO in several significant measures of evaluation in Table.2.

Fig.4 Accuracy Comparison Graph – Classification

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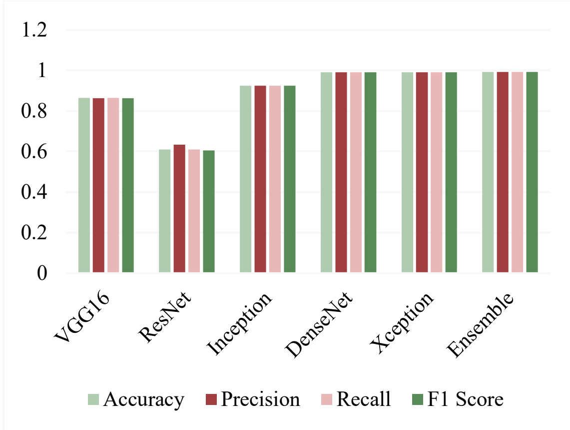
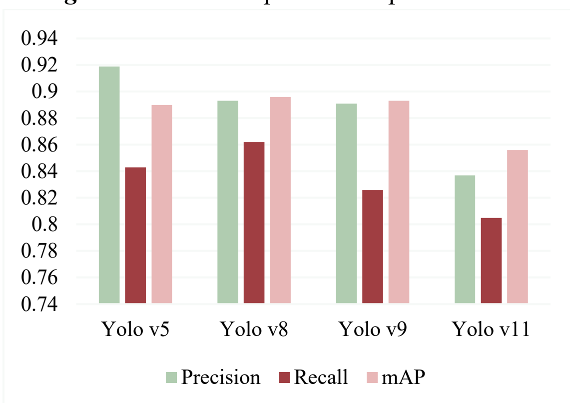


Figure 4 shows measures. The accuracy, precision, recall, and F1-score are displayed in light green, dark red, light pink, and green respectively. Ensemble model performs best in terms of overall outcome since it performs better than other models.

Fig.5 Precision Comparison Graph – Detection



Preciseness is shown in light green in Fig. 5, memory in dark red, and mAP in light pink. YOLOv8 has the best general performance of all the YOLO variants.

Fig.6 Upload Input Image

Figure 6 demonstrates the input interface whereby users are able to post MRI images to receive very precise results in order to automatically classify brain tumors.

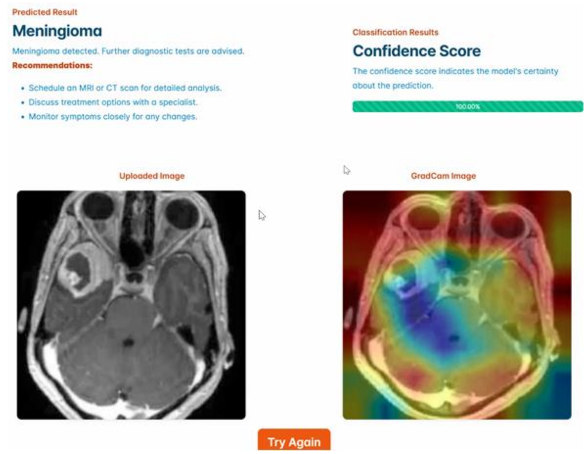


Fig.7 Predicted Results

Fig.7 output screen displays that the predicted tumor type is a meningioma and there is 100% certainty of the result, with a visualization of the heatmap by Grad-Cam.

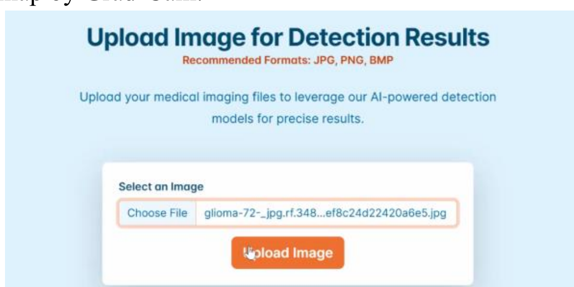


Fig.8 Upload Input Image

Figure 8 represents the detection interface, in which users can post pictures and see and identify brain tumor areas immediately.

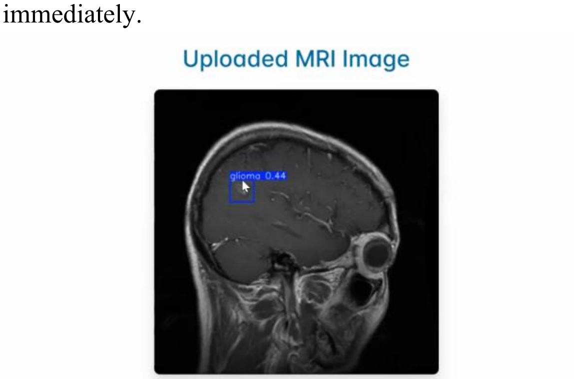


Fig.9 Predicted Results

Fig.9 output interface reveals that the type of tumor depicted in the MRI picture is glioma with a confidence score equal to 0.44.

5. CONCLUSION

Lastly, brain tumors can be correctly located and categorized using MRI scans with sophisticated machine learning and deep learning algorithms using good-annotated datasets that include names of the tumor types and bounding boxes to localize them. Combined with transfer learning-based models, such as VGG16, ResNet, Inception, and DenseNet, they also provide decent baseline performance on classification tasks in terms of F1-score, accuracy, precision, and recall. To enhance the frame further, additional layers, such as Xception, collective of DenseNet and Xception, and versions of the YOLO-based detection, such as YOLOv5, YOLOv8, YOLOv9, and YOLOv11, allow locating tumors with high accuracy besides classifying them. Grad-CAM and other explainable AI systems are easier to interpret by generating visual heatmaps of discriminative regions. A Flask-based interface can be deployed interactively to be used in clinical settings. It is evident in the test results that the ensemble model is more effective in classifying things with a success rate of 99.3% in all the measures of performance. Moreover, YoloV8 works more effectively in locating objects and has a mean precision of 0.896 and a trade-off of accuracy and recall. This entire system demonstrates how deep learning classification and detection models can be provided and utilized using easy to understand and implementable tools to assist doctors in making effective choices.

The structure can be extended to take into consideration data of various imaging techniques, including CT and PET scans, to aid in better describing and diagnosing tumors. The system can be made more accurate and fast by adding more complex ensemble tactics and real-time YOLO detection versions. Improved development in explainable AI methods such as SHAP or LIME can contribute to doctors making more appropriate decisions by simplifying clinical decisions. Remote diagnosis and telemedicine help can be made possible by putting the software on cloud-based platforms or mobile apps. Models can also be modified with time by adding continuous learning based on new patient data that ensures models remain functional and can be applied in additional clinical scenarios.

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