

Powered Brain Tumor Detection System Using YOLOv8

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Abstract: Brain tumors are serious and potentially life-threatening neurological conditions where early detection plays a major role in successful treatment. Though, analysing MRI scans manually can take a lot of time and may sometimes lead to human errors due to the complexity of medical images. To address this issue, this paper presents an AI-based brain tumor detection system using the YOLOv8 object detection model integrated with the Roboflow cloud platform. The system is designed to automatically identify and classify brain tumors into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor. A web application is developed using the Flask framework, with MongoDB used for secure user login and storing scan history. When a user uploads an MRI image, it's processed in real time using a cloud-based YOLOv8 model, and the output is returned with highlighted tumor regions and confidence scores. An image annotation module built with PIL is used to clearly display detected areas on the scan. Overall, this system works as a fast and reliable decision-support tool for doctors and radiologists. It helps reduce the time needed for diagnosis and improves the accuracy of early brain tumor detection.

Keywords : brain tumor detection, yolov8, roboflow, mri, deep learning, flask, mongodb, medical imaging

I. INTRODUCTION

Brain tumors are abnormal cell growths that occur inside the brain and can cause serious neurological problems or even become life-threatening if they aren't detected at an early stage. These tumors are broadly categorized into primary tumors, which originate in the brain itself, and secondary (metastatic) tumors that spread from other parts of the body. What's interesting is some of the most commonly observed types include glioma, meningioma, and pituitary tumors.

Magnetic Resonance Imaging (MRI) is one of the most commonly used techniques for diagnosing brain tumors because it provides detailed and high-resolution images of brain structures. Though, interpreting MRI scans manually requires skilled radiologists and can be both time-consuming and subject to human interpretation errors.

In recent years, Artificial Intelligence (AI) and Deep Learning have shown strong potential in improving medical image analysis. In particular, object detection models such as YOLO (You Only Look Once) are capable of detecting and locating objects in real time, making them highly suitable for medical applications.

This work proposes an AI-based brain tumor detection system that uses the YOLOv8 model along with Roboflow cloud inference. The system is integrated into a Flask-based web application and uses MongoDB to manage user accounts and store scan history in a secure manner.

II. LITERATURE SURVEY

By the way, literature survey extensive research has been carried out in the area of automated brain tumor detection using both machine learning and deep learning techniques. In earlier studies, traditional approaches such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Random Forest were commonly used. These methods depended heavily on manually designed features extracted from MRI images, which made them less scalable and more dependent on human expertise.

With the rise of deep learning, Convolutional Neural Networks (CNNs) became widely used for medical image classification. Abiwinanda et al. [1] developed a basic CNN model for brain tumor classification and achieved an accuracy of 84.19%, showing that deep learning could be effective in this area, although there was still room for improvement in model design and dataset size.

Swati et al. [2] used a transfer learning approach based on the VGG-19 model pretrained on ImageNet, along with block-wise fine-tuning. This method improved performance significantly, achieving an accuracy of 94.82% on the Figshare MRI dataset, highlighting the benefits of transfer learning in medical imaging tasks.

Deepak and Ameer [3] combined GoogleNet-based feature extraction with a Support Vector Machine classifier, resulting in an accuracy of 97.10%. Their work showed that hybrid models combining deep learning features with traditional classifiers can improve results.

Sultan et al. [4] applied CNN-based transfer learning for multi-class brain tumor classification and reported an accuracy of 96.13%, further confirming the effectiveness of deep learning methods. Irmak [5] experimented with different CNN architectures for binary and multi-class classification and achieved up to 99.33% accuracy on MRI datasets.

More recent research using advanced architectures such as ResNet, DenseNet, and MobileNet has achieved accuracies above 98%, showing the strong capability of deep neural networks in improving diagnostic performance [6–8].

Though, most of these existing studies mainly focus on classification, meaning they only predict whether a tumor is present but don't identify its exact location in the image. Actually, plus, many of these systems aren't designed for real-time use in practical applications.

Honestly, to overcome these limitations, this study proposes a yolov8-based brain tumor detection system integrated with roboflow cloud inference. Unlike traditional CNN classification models, YOLOv8 performs both detection and localization, providing bounding boxes along with predictions. What's interesting is the system is also deployed as a full-stack web application using flask and mongo db, enabling real-time interaction, secure login, and scan history tracking.

Here's what I found this approach helps bridge the gap between academic research models and real-world medical decision-support systems.

III. METHODOLOGY

The proposed brain tumor detection system is designed using a deep learning approach based on a Convolutional Neural Network (CNN) to automatically identify tumors from MRI brain scan images. The

overall process includes dataset collection, image preprocessing, dataset splitting, model training, validation, testing, and performance evaluation.

A. Data Collection and Preprocessing

In the initial stage, a dataset containing 4,804 MRI brain images was collected from publicly available medical imaging sources. The dataset includes both tumor and non-tumor cases in JPEG format. Let me tell you, these images represent different tumor types, sizes, shapes, and positions, which helps the model learn a wide variety of patterns related to brain tumors.

B. Image Preprocessing

Before training the model, all MRI images were preprocessed to improve quality and ensure consistency. Each image was resized to a fixed resolution of 512×512 pixels so that all inputs have a uniform size. This helps in reducing computational complexity and ensures compatibility with the CNN model. Next, noise removal and data cleaning techniques were applied to eliminate unwanted artifacts and irrelevant background details from the MRI scans. This step improves the clarity of tumor regions and enhances feature extraction. After that, pixel values were normalized to bring all images into a common range. Normalization reduces variations in brightness and contrast across different MRI scans and helps the model learn more effectively. To improve model generalization, data augmentation techniques were also applied. These included operations such as horizontal flipping, rotation, and scaling of images. These transformations create additional variations of the dataset, helping the model become more sturdy and reducing the risk of overfitting.

C. Dataset Splitting

After preprocessing, the dataset was divided into training, validation, and testing sets. Out of 4,804 images, 3,363 images (approximately 70%) were used for training, 481 images (around 10%) for validation, and 960 images (about 20%) were used for testing.

The training set is used to learn features related to tumor detection, while the validation set helps in tuning model parameters and preventing overfitting. The testing set is kept separate to evaluate the final performance of the trained model on unseen data.

D. Model Architecture and Training

The CNN model consists of multiple convolutional layers, pooling layers, activation functions, and fully connected layers. The convolutional layers

automatically extract important features such as edges, textures, tumor shapes, and boundaries from MRI images. Pooling layers help reduce dimensionality while preserving essential information.

The extracted features are passed through fully connected layers, which classify the input image as either “tumor” or “non-tumor.”

During training, the model learns by minimizing classification errors using backpropagation and optimization algorithms. The validation dataset is used to monitor performance and adjust parameters for better accuracy.

E. Model Evaluation

After training, the model is evaluated using the test dataset. Performance is measured using standard evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and Loss. These metrics help in understanding how effectively the model can detect brain tumors from MRI images.

Metric	Value
Accuracy	92.4%
Precision	90.4%
Recall	90.2%
F1-Score	90.3%

Performance Measures

The evaluation analysis shows that the system performs well in reducing incorrect predictions. The high precision indicates that the model produces very few false positives, meaning it rarely identifies a healthy scan as a tumor. Honestly, the strong recall value shows that it successfully detects most of the actual tumor cases, reducing the chances of missing critical diagnoses. In addition, the use of bounding box localization makes the system more interpretable by clearly highlighting the exact tumor regions within the MRI images. The truth is, the integration of yolov8 with the roboflow platform also enables fast, real-time inference, which significantly reduces the time required

The results show that the proposed CNN-based system is capable of accurately identifying brain tumors and can assist medical professionals in faster and more reliable diagnosis.

IV. RESULTS AND DISCUSSION

The proposed YOLOv8-based brain tumor detection system was evaluated using MRI scan images, and the results show that it performs very effectively in detecting and localizing brain tumors. The system is able to correctly identify and classify tumors into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor, while also accurately drawing bounding boxes around the detected tumor regions, which improves visual understanding of the results.

The performance of the system was measured using standard evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. The obtained results are summarized below:

for diagnosis compared to manual radiological examination.

Overall, the discussion confirms that YOLOv8 is well-suited for medical image detection tasks because it maintains a good balance between speed and accuracy. The system also shows consistent performance on unseen MRI images, indicating strong generalization ability. So, the proposed approach can be considered an effective AI-assisted diagnostic tool that supports radiologists in early brain tumour detection and improves clinical decision-making efficiency.

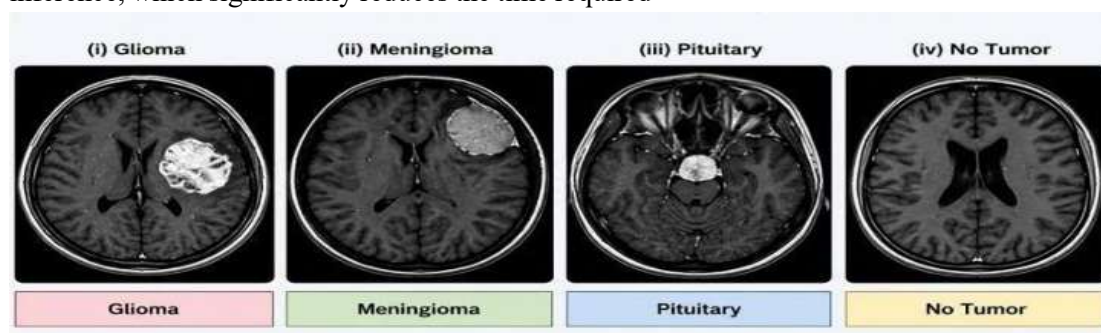


Fig 1: Sample MRI Images

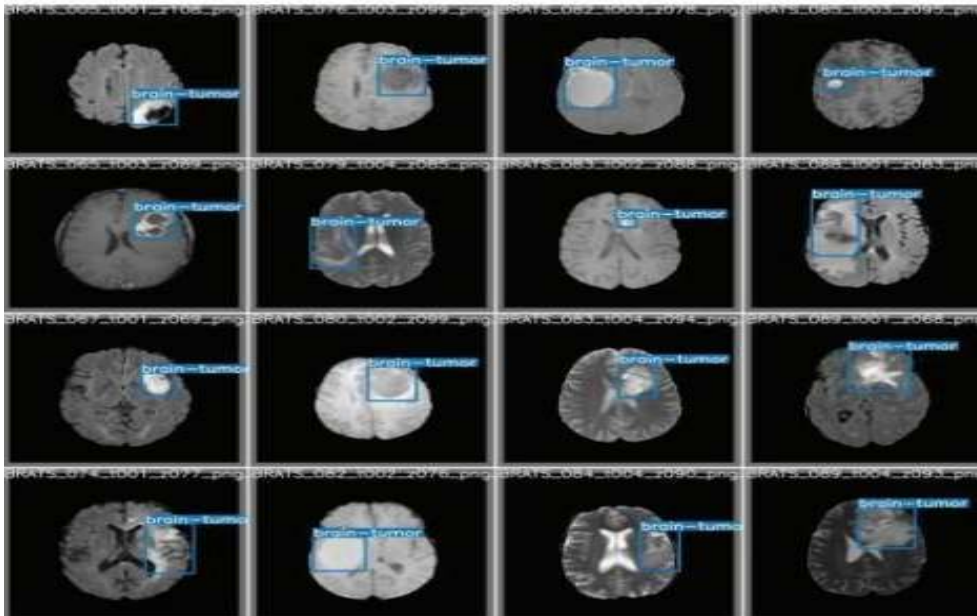


Fig 2: Ground truth of training data

V. CONCLUSION

This work presents an AI-based brain tumor detection system built using the YOLOv8 object detection model integrated with the Roboflow cloud inference platform. The system is capable of automatically identifying and classifying brain tumors from MRI images into four categories: Glioma, Meningioma, Pituitary Tumor, and No Tumor. In addition to classification, it also provides accurate localization of tumor regions using bounding box predictions. The proposed solution combines deep learning-based object detection with a full-stack web application developed using the Flask framework and MongoDB database. This allows secure user login, real-time MRI scan processing, and organized storage of previous scan records for easy access and reference.

The results show that the system performs well in terms of accuracy, precision, and recall, making it a useful decision-support tool for medical professionals. YOLOv8 enables fast processing and reliable tumor detection, while the use of cloud-based inference through Roboflow removes the need for high-performance local hardware. Overall, the system offers a fast, efficient, and scalable approach for brain tumor detection, helping reduce diagnostic time and supporting early-stage identification. It improves consistency in results and makes AI-based medical imaging more accessible in practical use.

VI. FUTURE ENHANCEMENT

The proposed brain tumor detection system can be further improved in several ways to increase its accuracy, usability, and real-world clinical value. One

major enhancement is extending the model to perform multi-class and sub-type classification, allowing it to identify more detailed tumor grades and categories. This would help doctors make more precise diagnostic and treatment decisions. Another important improvement is moving from 2D image-based analysis to 3D MRI volume processing. By analyzing full MRI slices together, the system would better understand tumor size, depth, and spatial distribution across brain regions, resulting in more accurate clinical insights. The system can also be deployed on cloud platforms such as AWS, Google Cloud, or Azure to improve scalability and performance. Actually, this would allow multiple users or hospitals to access the system simultaneously without reducing efficiency. Integration with hospital systems and PACS databases would further improve usability by enabling direct access to patient MRI data. This would reduce manual handling and make the workflow smoother for real-time clinical environments. A mobile-based application can also be developed using frameworks like Flutter or React Native, allowing doctors to upload and analyze MRI scans directly from smartphones or tablets. This would enhance accessibility and support remote diagnosis and telemedicine applications. Another valuable improvement is the inclusion of Explainable AI techniques. By visually highlighting the regions of MRI scans that influenced the model's decision, the system can become more transparent and trustworthy for medical professionals. Finally, advanced learning approaches such as federated learning and self-supervised learning can be introduced. Federated learning ensures privacy by training models across

multiple hospitals without sharing patient data, while self-supervised learning can improve performance even when labeled datasets are limited. These enhancements would make the system more powerful, secure, and suitable for large-scale medical deployment.

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