

An Explainable NeuroAI-Based Framework for Brain Tumor Detection and Classification Using YOLO, CNN, and Radiomic Features

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Abstract - Brain tumor detection and classification are critical tasks in medical diagnostics that require high accuracy, reliability, and interpretability. Traditional methods rely on manual analysis of Magnetic Resonance Imaging (MRI) scans, which can be time-consuming and prone to human error. To address these challenges, this paper proposes an Explainable Artificial Intelligence (AI)-based framework for automated brain tumor detection, classification, and clinical support. The proposed system integrates a You Only Look Once (YOLO) model for precise tumor localization, followed by region-of-interest (ROI) extraction to enhance classification performance. A Convolutional Neural Network (CNN) is then used to classify tumor types and generate confidence scores. To improve interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is employed to visualize the regions influencing the model's decision. In addition, radiomic feature extraction is performed to obtain intensity, texture, shape, and spatial characteristics of the tumor. An uncertainty estimation module is incorporated to evaluate the reliability of predictions, enabling risk-aware decision support. Furthermore, the system is deployed through a user-friendly web interface that supports multilingual interaction, allowing patients and healthcare professionals to access diagnostic results, doctor-oriented insights, and detailed reports in their preferred language. The final output includes tumor classification, explainable insights, uncertainty assessment, and personalized reports, making the system suitable for real-world clinical applications. Overall, the proposed approach enhances transparency, accuracy, reliability, and accessibility in AI-driven healthcare solutions.

Key Words: Brain Tumor Detection, Convolutional Neural Network (CNN), YOLO, Explainable AI, Grad-CAM, Radiomics, Uncertainty Estimation, Medical Image Analysis.

1. INTRODUCTION

Brain tumors are among the most critical neurological disorders, requiring early and accurate diagnosis for effective treatment planning. Magnetic Resonance Imaging (MRI) is widely used for detecting brain abnormalities due to its high-resolution imaging capability. However, traditional diagnosis relies heavily on manual analysis by radiologists,

which can be time-consuming, subjective, and prone to human error.

In recent years, Artificial Intelligence (AI) and deep learning techniques have shown significant potential in medical image analysis. Convolutional Neural Networks (CNNs) are widely used for image classification tasks due to their ability to automatically extract hierarchical features from images [3]. Similarly, object detection models such as You Only Look Once (YOLO) enable efficient and real-time localization of regions of interest within images [1]. These advancements have paved the way for automated and accurate brain tumor detection systems.

Despite these developments, many existing approaches focus primarily on detection and classification while lacking interpretability and clinical insight. The "black-box" nature of deep learning models makes it difficult for healthcare professionals to trust the predictions. To address this issue, Explainable Artificial Intelligence (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) have been introduced to visualize the regions influencing model decisions [5]. Additionally, radiomics enables the extraction of quantitative features from medical images, providing deeper insights into tumor characteristics and supporting clinical decision-making [7].

This paper proposes an Explainable AI-based framework for brain tumor detection and classification using MRI images. The system integrates YOLO for tumor localization, followed by region-of-interest (ROI) extraction to improve classification performance. A CNN model is used to classify tumor types, while Grad-CAM is employed to enhance interpretability. Furthermore, radiomic feature extraction and uncertainty estimation are incorporated to provide clinically relevant insights and assess prediction reliability. The system is deployed through a user-friendly web interface with multilingual support, enabling accessible and efficient interaction for both patients and healthcare professionals.

The proposed approach aims to improve accuracy, transparency, and usability in AI-driven medical diagnostics, thereby contributing to more reliable and accessible healthcare solutions.

2. LITERATURE REVIEW

Several research works have been carried out in the field of brain tumor detection and medical image analysis using deep learning techniques. Joseph Redmon et al. (2016) introduced the YOLO framework for real-time object detection, enabling fast and efficient localization of objects within images [1]. Later, Redmon et al. (2018) improved this model with YOLOv3, enhancing detection accuracy and performance for objects of varying sizes [2]. Alex Krizhevsky et al. (2012) demonstrated the effectiveness of Convolutional Neural Networks (CNNs) for image classification tasks, establishing a foundation for modern deep learning approaches in medical imaging [3]. Similarly, Karen Simonyan and Andrew Zisserman (2014) proposed a deeper CNN architecture that significantly improved classification accuracy [4].

Ramprasaath R. Selvaraju et al. (2017) introduced Grad-CAM, an explainable AI technique that provides visual interpretations of deep learning model decisions, improving transparency in critical applications such as healthcare [5]. Geert Litjens et al. (2017) presented a comprehensive survey on deep learning in medical image analysis, highlighting the effectiveness of CNN-based models in disease detection [6]. Philippe Lambin et al. (2012) introduced the concept of radiomics, which involves extracting quantitative features from medical images to support clinical decision-making [7]. Sergio Pereira et al. (2016) applied CNNs for brain tumor segmentation in MRI images, demonstrating improved accuracy compared to traditional approaches [8].

Bjoern Menze et al. (2015) developed the BRATS dataset, which serves as a benchmark for brain tumor segmentation and analysis [9]. Dinggang Shen et al. (2017) provided an overview of deep learning techniques in medical imaging, emphasizing their role in improving diagnostic performance [10]. Although these approaches have shown promising results, most existing methods focus primarily on detection and classification, with limited emphasis on explainability, uncertainty estimation, and user accessibility. The proposed system addresses these limitations by integrating YOLO-based detection, CNN classification, explainable AI techniques, radiomic feature extraction, and a multilingual web-based interface.

3. PROPOSED METHODOLOGY

The proposed system presents an integrated framework for automated brain tumor detection, classification, and clinical analysis using MRI images. The methodology combines object detection, deep learning, explainable AI, radiomic feature extraction, and a user-friendly web interface to provide accurate and interpretable results. The overall workflow of the system consists of multiple stages, as described below.

3.1 System Architecture

The overall architecture of the proposed system consists of the following stages:

1. Input Acquisition:

- MRI brain image is uploaded by the user through the web interface.

2. Preprocessing:

- Image resizing and normalization are performed to prepare the input for the model.

3. Tumor Detection (YOLO):

- YOLO model detects tumor regions in the MRI image. [1]
- Bounding boxes are generated around suspected tumor areas.

4. Region of Interest (ROI) Extraction:

- The detected tumor region is cropped using bounding box coordinates.
- Removes irrelevant background information.

5. Tumor Classification (CNN):

- Cropped ROI is passed into a CNN model.
- The model classifies tumor type (e.g., glioma, meningioma, pituitary).
- Confidence scores are generated.

6. Explainability (Grad-CAM):

- Grad-CAM generates heatmaps highlighting important regions.
- Helps in understanding model decisions.

7. Radiomic Feature Extraction

- Intensity features: mean, standard deviation
- Texture features: GLCM-based features
- Shape features: area, perimeter, circularity
- Spatial features: tumor area percentage, bounding box size, tumor location

8. Uncertainty Estimation

- Evaluates reliability of model predictions.
- Identifies low-confidence or uncertain cases.

9. Report Generation

- Combines classification results, features, and explanations.
- Generates a clinical-style report for users.

10. Web Interface with Multilingual Support

- Displays results including images, heatmaps, and reports.
- Supports multiple languages for better accessibility.

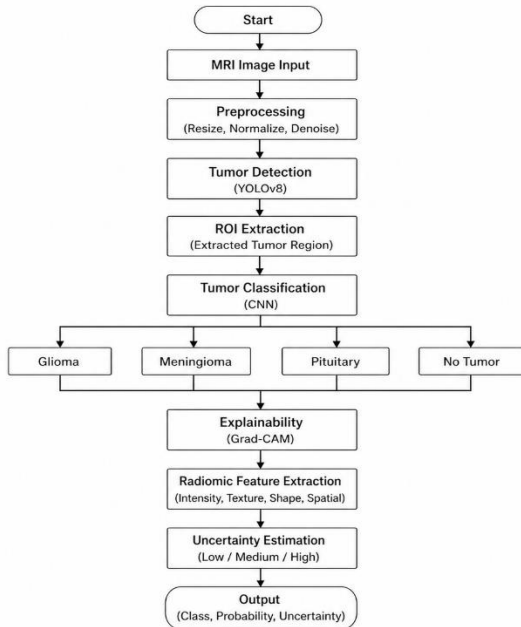


Fig -1: Project System Architecture

3.2 Tumor Detection using YOLO

In the proposed system, tumor detection is performed using the You Only Look Once (YOLO) model, which enables real-time object detection in MRI images [1]. The model processes the entire image in a single forward pass and predicts bounding boxes along with confidence scores for potential tumor regions. This approach allows efficient and accurate localization of tumors, even in complex medical images.

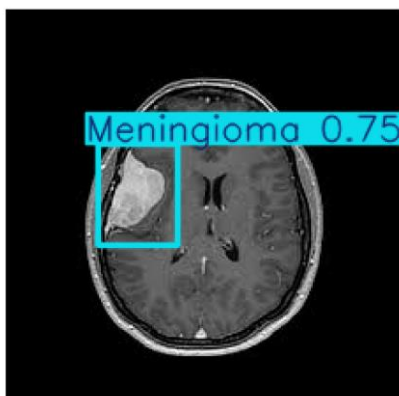


Fig -2: YOLO Detection

3.3 Region of Interest (ROI) Extraction

After tumor detection, the identified region is extracted using the bounding box coordinates provided by the YOLO model. This region of interest (ROI) focuses only on the tumor area, eliminating irrelevant background information. This improves the system improves classification accuracy.

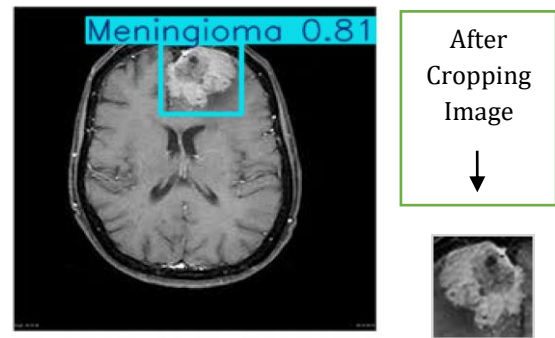


Fig -3: Cropped Image

3.4 Tumor Classification using CNN

The extracted ROI is provided as input to a Convolutional Neural Network (CNN) for tumor classification. The CNN model learns hierarchical features from the image and classifies it into different tumor types such as glioma, meningioma, and pituitary tumor [3]. The model also generates confidence scores indicating the probability of each predicted class.

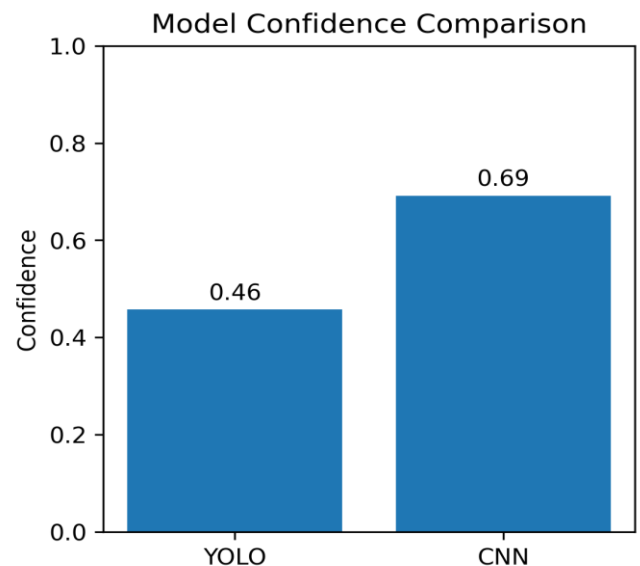


Fig -4: CNN Classified Image

3.5 Explainable AI using Grad-CAM

To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) is applied to visualize the regions influencing the model's prediction [5]. Grad-CAM generates heatmaps over the input image, highlighting important areas that contributed to the classification. This improves transparency and helps in understanding the decision-making process of the model.

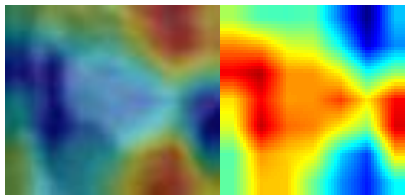


Fig -5: Heatmap by Grad-CAM

3.6 Radiomic Feature Extraction

Radiomic feature extraction is performed on the ROI to obtain clinically relevant information about the tumor. Intensity features such as mean and standard deviation are computed to analyze pixel distribution. Texture features are extracted using the Gray-Level Co-occurrence Matrix (GLCM), while shape features such as area, perimeter, and circularity describe tumor geometry. Additionally, spatial features including tumor area percentage, bounding box size, and tumor location are calculated to provide insights into tumor size and position.

3.7 Uncertainty Estimation

An uncertainty estimation module is incorporated to evaluate the reliability of model predictions. The system analyzes confidence scores and prediction behavior to identify cases with low certainty. This helps in distinguishing between reliable and uncertain predictions, enabling risk-aware decision-making in clinical applications.



Fig no 6: Uncertainty Core

3.8 Web Interface and Multilingual Support

The proposed system is deployed through a user-friendly web interface that allows users to upload MRI images and view results. The interface displays detection outputs, classification results, Grad-CAM visualizations, extracted features, and detailed reports. Additionally, multilingual support is integrated to provide outputs and medical insights in different languages, improving accessibility for both patients and healthcare professionals.

4. IMPLEMENTATION

The proposed system is implemented using deep learning and web development frameworks to perform brain tumor detection, classification, and analysis. The implementation details are summarized as follows:

4.1 Tools and Technologies

Python is used as the primary programming language (version 3.10). Deep learning models are developed using TensorFlow and Keras, while OpenCV is used for image processing. The web application is built using Flask, with HTML and CSS for the user interface.

Table -1: Tools Used in Project

Category	Tools / Technologies
Language	Python 3.10 version
Detection	YOLO (Ultralytics)
Classification	TensorFlow, Keras
Computer Vision	OpenCV
Feature Extraction	NumPy, scikit-image
Machine Learning	scikit-learn, joblib
Explainable AI	Grad-CAM, SHAP
Backend	Flask
Frontend	HTML, CSS, JavaScript
Translation	Google Translate API
Visualization	Matplotlib
Report Generation	FPDF

4.2. Dataset:

The dataset is sourced from Roboflow Universe [11], which provides annotated MRI images for object detection tasks. Such datasets typically include multiple tumor classes such as glioma, meningioma, and pituitary tumors, and are commonly used for training deep learning models in medical imaging applications.



Fig -7: Dataset

4.3 Training Details:

The YOLO model is used for tumor detection and is fine-tuned for MRI images. The CNN model is trained for tumor classification using labeled image data. The training process includes multiple epochs, optimization techniques, and validation to improve accuracy and reduce overfitting.

4.4 Preprocessing

Before training, MRI images are preprocessed to ensure consistency and improve model performance. The preprocessing steps include image resizing to a fixed input size, normalization of pixel values, and data augmentation techniques such as rotation, flipping, and zooming. These techniques help in increasing dataset diversity and reducing overfitting, thereby improving the generalization capability of the model.

4.5 Feature Extraction

In addition to deep learning-based predictions, radiomic feature extraction is performed on the detected tumor regions. Intensity features such as mean and standard deviation describe the distribution of pixel values. Texture features based on Gray Level Co-occurrence Matrix (GLCM) capture spatial relationships between pixels. Shape features such as area, perimeter, and circularity provide information about tumor geometry. Spatial features such as tumor area percentage, bounding box size, and tumor location are also extracted to provide clinically relevant insights.

4.6 System Deployment:

The trained models are integrated into a Flask-based web application that allows users to upload MRI images and view results. The system provides outputs including tumor classification, confidence scores, Grad-CAM visualizations, extracted features, and multilingual diagnostic reports.

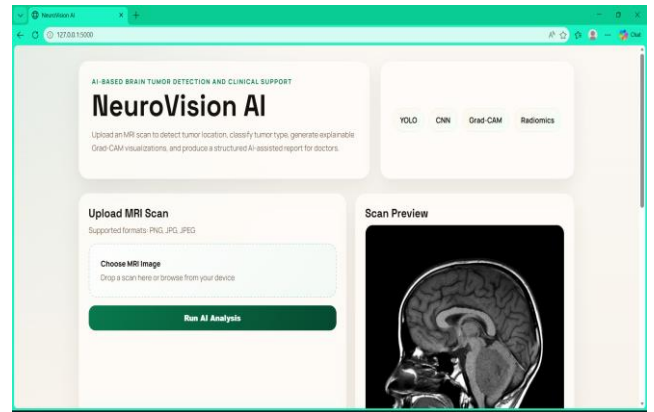


Fig -8: Web Interface

5. Model Performance:

5.1 YOLO Metrics -

The YOLO model demonstrates strong detection performance with a high mAP@0.5 of 95.63%, indicating accurate localization of tumor regions. The precision and recall values further confirm the model's effectiveness in identifying tumors across different classes.

Table -2: Yolo metrics

Metric	Values
Precision	0.93
Recall	0.93
mAP@0.5	95%
mAP@0.5:95	0.58

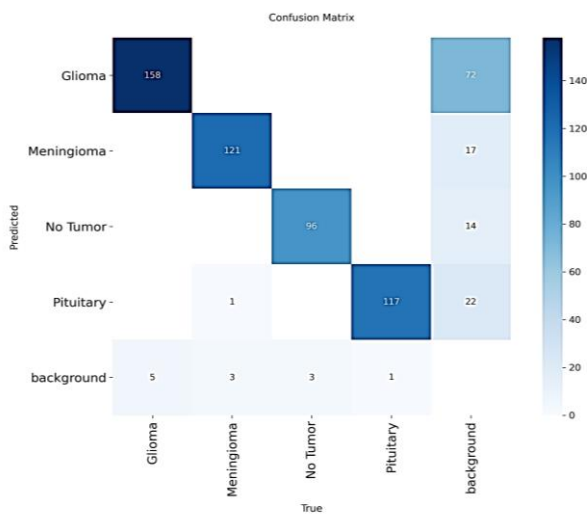


Fig -9: Confusion Matrix for YOLO

5.2 CNN Metrics

The CNN model achieved an overall accuracy of 90% in classifying brain tumor types. The model shows strong performance for glioma and pituitary tumors, while slightly lower recall is observed for meningioma cases.

Table -3: CNN Metrics

Class	Precision	Recall	F1Score
Glioma	0.95	0.95	0.95
Meningioma	0.94	0.80	0.86
Pituitary	0.83	0.95	0.88
Average	0.91	0.90	0.90

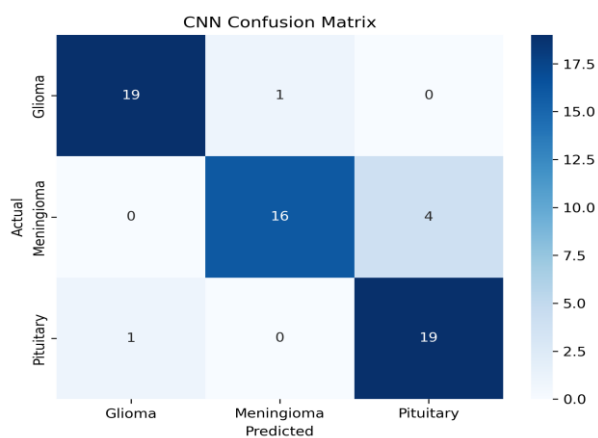


Fig -10: Confusion Matrix for CNN

5.3 Real-Time Performance

- YOLO Training: 4 – 5hrs
- Tumor detection (YOLO): 1.0 – 1.5 seconds per image
- CNN Training: 10min
- Classification (CNN): 2 – 3 seconds
- Total prediction time: 3 – 5 seconds per image
- Hardware tested: Intel Core i5 Processor, 4GB RAM

6. RELATED WORKS

Several research works have been carried out in the field of brain tumor detection using deep learning techniques. YOLO-based models have been widely used for real-time object detection due to their speed and accuracy [1][2]. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image classification tasks, particularly in medical imaging applications [3][4]. Explainable AI techniques such as Grad-CAM have been introduced to improve transparency by visualizing important regions influencing model predictions [5]. Additionally, radiomics-based approaches extract quantitative features from medical images to support clinical decision-making [7]. Benchmark datasets such as BRATS have played a significant role in evaluating model performance in brain tumor analysis [9].

7. CONCLUSION

In this paper, an Explainable Artificial Intelligence (XAI)-based framework for brain tumor detection and classification using MRI images has been successfully developed. The proposed system integrates YOLO for accurate tumor localization and a Convolutional Neural Network (CNN) for tumor classification, achieving reliable performance in medical image analysis.

The incorporation of region-of-interest (ROI) extraction enhances classification accuracy by focusing on relevant tumor regions. Additionally, Explainable AI techniques such as Grad-CAM improve model transparency by visualizing the regions influencing predictions, while radiomic feature extraction provides clinically meaningful insights into tumor characteristics.

An uncertainty estimation module is included to evaluate prediction reliability, enabling risk-aware decision-making. Furthermore, the deployment of the system through a web-based interface with multilingual support enhances accessibility for both patients and healthcare professionals.

Overall, the proposed system offers an accurate, interpretable, and user-friendly solution for brain tumor diagnosis, contributing to improved clinical decision support and advancing AI-based healthcare applications.

7.1 Applications

The proposed system can be used in hospitals and diagnostic centers to assist radiologists in early detection and classification of brain tumors. It can also be integrated into telemedicine platforms to enable remote diagnosis and consultation. Additionally, the system can serve as an educational tool for medical students and researchers in the field of medical imaging.

8. FUTURE WORK

The proposed system can be further enhanced by incorporating larger and more diverse datasets to improve model generalization and robustness. Future work can explore advanced deep learning architectures such as transformer-based models for improved feature extraction and classification accuracy. Integration of 3D MRI analysis can provide more comprehensive spatial information about tumors, leading to better diagnostic insights.

Additionally, the system can be extended for real-time clinical deployment by integrating it with hospital management systems. Mobile and cloud-based implementations can further improve accessibility for remote healthcare services. Enhancing uncertainty estimation techniques and incorporating patient history data can also improve the reliability and clinical usefulness of the system.

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