

Brain Tumor Detection and Classification using YOLOv10 and AI Chatbot Using LLMs

Sanket Satpute¹, Jagruti Khairnar², Kunal Shinde³ Rohini Sangle⁴

Prof. Jyoti Thakur⁵

Department of AIML (Artificial Intelligence & Machine Learning)¹²³⁴⁵

Lokneta Gopinathji Munde Institute of Engineering Education & Research (LOGMIEER)s, Nashik, India

Abstract: The integration of advanced medical imaging techniques and artificial intelligence (AI) has greatly improved the early detection and diagnosis of brain tumors. This paper introduces a novel system for brain tumor detection and classification using the YOLOv10 (You Only Look Once) model, enhanced by an AI chatbot powered by Large Language Models (LLMs). Leveraging the real-time object detection capabilities of YOLOv10, the system accurately classifies brain tumors from MRI images into four categories: Glioma, Meningioma, Pituitary, and No Tumor. This deep learning-based approach ensures swift and precise analysis of complex medical images.

In addition, an AI chatbot is integrated to provide seamless interaction and information retrieval for both patients and healthcare professionals. Utilizing LLMs, the chatbot offers advanced conversational abilities, delivering detailed explanations about tumor types, potential treatments, and further medical advice based on the detected tumor characteristics.

This dual-system approach aims to enhance diagnostic accuracy while providing real-time, accessible support, ultimately improving decision-making for medical practitioners and enhancing patient outcomes. The proposed system exemplifies the synergy between cutting-edge AI technologies and medical diagnostics, showcasing the potential to revolutionize patient care.

Keywords: YOLOv10, LLMs, Chatbot, Brain Tumor, Pinecone

I. INTRODUCTION

Brain tumors are among the most complex and life-threatening medical conditions, often requiring timely and accurate diagnosis to improve patient prognosis. Magnetic Resonance Imaging (MRI) has become a critical tool for identifying and evaluating brain tumors. However, traditional methods of diagnosing tumors through manual analysis by radiologists are time-consuming and prone to human error, which can delay treatment and affect outcomes.

In recent years, artificial intelligence (AI) has emerged as a powerful tool in the field of medical imaging, providing automated solutions that can analyse complex medical images with high precision and speed. Specifically, deep learning models such as convolutional neural networks (CNNs) have demonstrated remarkable success in detecting and classifying tumors. Object detection models, particularly the YOLO (You Only Look Once) series, have gained popularity due to their ability to perform real-time analysis while maintaining high accuracy. The YOLOv10 model, a state-of-the-art advancement in this series, offers significant improvements in both speed and detection accuracy, making it an ideal candidate for medical image analysis.

Despite the advancements in AI-based diagnostic tools, patients and healthcare professionals often lack access to comprehensive and interactive systems that not only classify tumors but also provide detailed information about the diagnosis and possible treatments. The introduction of AI chatbots, powered by Large Language Models (LLMs), has the potential to bridge this gap. These chatbots can facilitate enhanced interaction, providing users with in-depth explanations and medical advice based on the diagnostic outcomes.

Method	Speed	Accuracy
Traditional MRI Analysis	Slow	Moderate

Method	Speed	Accuracy
CNN-based Models	Fast	High
YOLOv10-based System	Real-Time	Very High
AI Chatbot (LLMs)	Instantaneous	Detailed Explanations, Medical Advice

Table 1: Comparison of Traditional and AI-based Methods for Brain Tumor Detection

The objective of this study is to develop a dual-system approach that combines the real-time brain tumor detection and classification capabilities of the YOLOv10 model with an AI-powered chatbot for delivering personalized medical insights. This system aims to improve diagnostic accuracy, reduce the time required for tumor classification, and provide accessible support to both healthcare professionals and patients. By leveraging advanced deep learning techniques and conversational AI, this paper presents a novel solution that enhances the overall diagnostic process and contributes to better patient care.

II. LITERATURE SURVEY

Paper-1: Building Customized Chatbots for Document Summarization and Question Answering using Large Language Models (LLMs). Pokhrel et al. (2023) developed a system that uses Large Language Models (LLMs) to create customized chatbots for document summarization and question answering. This project focuses on leveraging the capabilities of OpenAI's LLMs, alongside LangChain, which manages tasks like document retrieval, summarization, and query answering. Streamlit is used to create an interactive web interface for users. The system finds applications in both academic and industrial settings by providing automated knowledge management and research assistance. This chatbot-based framework aligns with our use of AI chatbots in healthcare, particularly for patient-doctor communication in brain tumor detection scenarios. The chatbot's ability to process and summarize large volumes of medical information offers a unique application for aiding medical professionals in quicker, more accurate decision-making, which resonates with the objectives of our brain tumor detection system.

Paper-2: Automated Brain Tumor Segmentation and Classification in MRI Using YOLO-Based Deep Learning. Almufareh et al. (2023) presented a method that automates the segmentation and classification of brain tumors using the YOLO (You Only Look Once) framework, adapted specifically for medical imaging. Their work aims to improve diagnostic accuracy by speeding up the classification process in MRI scans of the brain. The research involves detecting various tumor types, such as Glioma, Meningioma, and Pituitary, using real-time object detection. The system is designed to support healthcare professionals by providing quicker and more accurate diagnoses through automated detection, reducing human error and time consumption. This project strongly correlates with our work, where we utilize similar deep learning approaches to segment and classify tumors, further enhancing our model's ability to aid doctors in precise diagnosis.

Paper-3: Brain Tumor Detection using Deep Learning. Shivedikar et al. (2023) discuss the critical issue of brain tumor detection, highlighting the growing need for fast, automated, and reliable methods for identifying tumors. Their work utilizes Convolutional Neural Networks (CNN) and transfer learning techniques such as VGG16 to predict whether a tumor is present in MRI images. The use of CNNs helps to automate the detection process, allowing for the identification of brain tumors without the need for manual analysis, which can be time-consuming and prone to inaccuracies. This research demonstrates the efficacy of using deep learning models to improve detection rates, which is a foundational aspect of our project. By combining CNN-based architectures with transfer learning, we aim to develop a robust system for identifying brain tumors, contributing to more reliable and faster diagnostic processes in the medical field.

III. PROPOSED SYSTEM

The proposed system for brain tumor detection and classification, combined with an AI-powered chatbot, is designed to enhance the diagnostic workflow. The system is divided into three major sections in the user interface:

Image Upload Section:

- **Functionality:** In this section, users (either healthcare professionals or patients) can upload an MRI image of the brain. The system accepts the image in standard formats like JPEG, PNG, or DICOM.
- **Backend:** Once the image is uploaded, the system sends it to the YOLOv10 model for tumor detection.

Result Display Section:

- **Functionality:** After the YOLOv10 model processes the MRI, this section displays the classification result. It identifies whether a tumor is present or not, and if detected, classifies it into one of the predefined categories: Glioma, Meningioma, Pituitary, or No Tumor.
- **Backend:** The YOLOv10 model, trained on a dataset of brain MRI scans, performs real-time object detection to classify the tumor. The result is displayed with a confidence score, helping users assess the likelihood of the diagnosis.

Chatbot Interaction Section:

- **Functionality:** This section includes an AI chatbot that allows users to ask questions related to brain tumors, treatments, or diagnosis procedures. The chatbot leverages an LLM (in this case, the Llama model) to provide responses based on the tumor classification result or any other medical information relevant to the user's query.
- **Backend:** The chatbot is connected to a pre-trained LLM which has been fine-tuned for medical conversations. It pulls relevant information from medical databases or responds based on previously trained data, ensuring that users receive accurate and reliable information.

IV. SYSTEM Architecture

The architecture of the system can be explained in the following modules:

Front-End:

- **User Interface (UI):** The UI is designed for ease of use, with three clear sections for image upload, results, and chatbot interaction.
- **Technologies:** HTML, CSS, and JavaScript are used to develop the front end, with frameworks like React or Vue.js ensuring smooth interaction. The front end communicates with the back end through APIs.

Back-End:

YOLOv10 Model:

- **Purpose:** The YOLOv10 model is employed for object detection and tumor classification.
- **Pipeline:** When an MRI image is uploaded, the YOLOv10 model processes it using its convolutional layers to detect and classify the tumor into one of the categories.
- **Data Input/Output:** The input is a brain MRI scan, and the output is a classified tumor (or absence of it) with a probability score.

LLM (Llama Model):

- **Purpose:** The LLM is responsible for chatbot conversations, allowing users to ask questions about tumor detection, types, treatments, and more.
- **Integration:** The chatbot is tightly integrated with the detection results, meaning that it can provide explanations based on the detected tumor type. For example, it can give specific information about Glioma if that was the detected result.
- **Technologies:** The chatbot uses API calls to communicate with the Llama-based model for real-time responses.

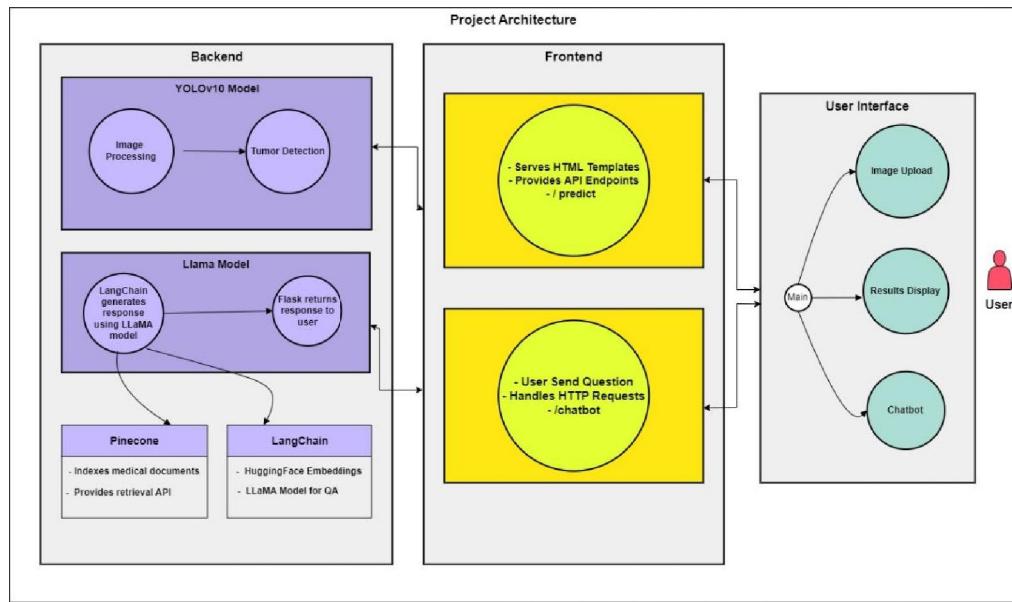


Fig. 1. Project Architecture Diagram

Data Flow:

The user uploads an MRI image.

The image is processed by the YOLOv10 model for tumor detection and classification.

The classification result is displayed in the middle section.

The chatbot uses the LLM to answer user queries, considering the tumor classification (if any).

The system ensures that user input, including image data, is processed securely, adhering to data privacy standards such as HIPAA for medical data handling.

Training Datasets:

The YOLOv10 model has been trained on a labeled dataset of brain MRI images categorized into Glioma, Meningioma, Pituitary, and No Tumor. The accuracy of the model is continually improved through model retraining with larger datasets.

The Llama model has been fine-tuned with medical literature and data relevant to brain tumors, treatments, and patient care to ensure reliable chatbot responses.

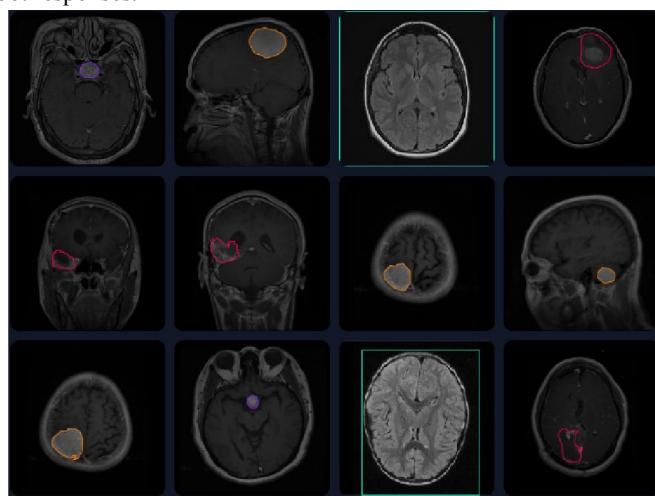


Fig. 2. Dataset of MRI Images

Evaluation Metrics:

YOLOv10: Accuracy, precision, recall, F1 score, and intersection-over-union (IoU) for model evaluation on test data.

Chatbot:

The LLM is evaluated based on response accuracy, relevancy, and user satisfaction.

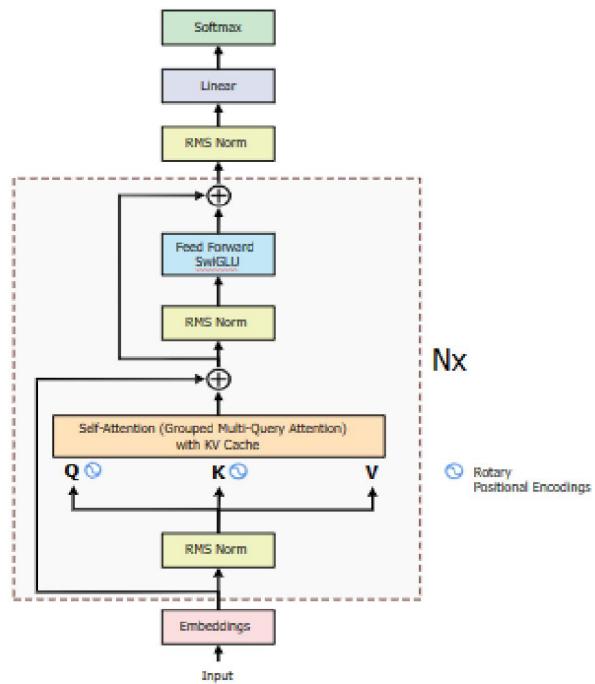


Fig. 3. Llama Model Architecture

Security & Privacy:

Data encryption is used for MRI images and chat conversations. Anonymization techniques are applied to protect user identities.

Scalability:

The system is built with scalability in mind, allowing it to handle increasing user traffic as it becomes more widely adopted by healthcare professionals.

V. CONCLUSION

In this research, we have successfully developed an integrated system that combines advanced deep learning models and conversational AI to detect and classify brain tumors. Using the YOLOv10 architecture, the system is able to accurately identify and classify tumors from brain MRI images, distinguishing between Glioma, Meningioma, Pituitary, and the absence of tumors. The addition of an AI chatbot powered by the Llama model ensures that both patients and healthcare professionals can access timely and reliable information regarding tumor types and potential treatments, enhancing user experience and decision-making.

This dual approach, which combines state-of-the-art object detection with a natural language processing interface, demonstrates significant potential for improving the diagnostic process in medical settings. The system not only facilitates early detection, but also empowers users by providing accessible and clear information, ultimately contributing to better healthcare outcomes. Future work may include expanding the system's capabilities by incorporating more types of tumors, refining the chatbot's medical knowledge, and improving real-time interaction speed and accuracy.

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