

An Explainable AI System for Efficient Brain Tumor Diagnosis on Edge Devices using Transfer Learning

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Abstract –

Brain tumors remain one of the severe neurological disorders, requiring early and accurate detection to enhance patient survival rates and treatment effectiveness. Conventional manual evaluation of Magnetic Resonance Imaging (MRI) images often requires significant time and is vulnerable to inaccuracies, particularly in resource-constrained medical settings. This project introduces an “Explainable Artificial Intelligence (XAI)”-driven system that utilizes “transfer learning” along with “lightweight deep learning architectures” to provide accurate, interpretable, and real-time brain tumor diagnosis on “edge devices”. The proposed system incorporates a “hybrid image enhancement pipeline”—integrating Independent Component Analysis (ICA), adaptive filtering operations combined with Contrast Limited Adaptive Histogram Equalization (CLAHE) are employed to refine MRI images by enhancing contrast and reducing noise artifacts. The processed images are then evaluated using optimized “MobileNet/EfficientNet” and “Tiny Vision Transformer (Tiny-ViT)” models, trained through transfer learning based approach is employed to classify multiple tumor types, namely glioma, meningioma, pituitary, and notumor.

To improve interpretability and ensure clinical reliability, the system integrates “Grad-CAM”, “SHAP”, and “LIME”-based explainability techniques that visually emphasize the regions influencing model predictions. Additional modules are designed to perform “tumor segmentation, size estimation”, and “growth pattern analysis” across sequential MRI scans. Furthermore, model methods such as quantization and pruning are applied to optimize the model for efficient operation on resource-constrained edge devices (e.g., Raspberry Pi, mobile GPUs) with reduced latency and minimal memory usage. Experimental evaluation using standard benchmark datasets such as “BraTS, Figshare”, and “Kaggle Brain MRI” is expected to achieve classification accuracy exceeding 98% while maintaining high efficiency and real-time performance.

Keywords—Brain Tumor , Classification , Detection , Tumor Segmentation , Deep Learning

1. INTRODUCTION

Brain tumors, characterized by abnormal and uncontrolled proliferation of cells within the brain, pose a significant global health challenge due to their potential to cause severe neurological damage and increased mortality when not detected at an early stage [1], [5]. Since these tumors can expand rapidly, often doubling in size within nearly 25 days, timely and accurate diagnosis is crucial for effective treatment and enhanced patient survival outcomes [13]. Magnetic Resonance Imaging (MRI) continues to serve as a primary diagnostic modality for identifying brain tumors; however, manual evaluation by medical professionals is frequently time-consuming and susceptible to diagnostic errors [17]. According to the World Health Organization (WHO), more than 120 different types of brain tumors have been identified, varying from benign to malignant forms, which underscores the necessity for precise classification to support prompt and suitable medical treatment [15].

Brain tumors continue to pose a critical risk to human life due to their aggressive growth patterns and their potential to disrupt vital brain functions [16]. Conventional diagnostic approaches, which rely heavily on manual MRI interpretation, are not only time-consuming but also dependent on the expertise of radiologists, often resulting in subjective and inconsistent outcomes [14]. In addition, in developing regions and rural healthcare settings, the lack of access to skilled professionals and advanced computational infrastructure further delays diagnosis, thereby contributing to increased mortality rates [9].

The rapid growth of medical imaging data has created a strong need for automated, reliable, and interpretable diagnostic systems that support clinicians in the early detection and classification of brain tumors [2],[24]. Although existing deep learning models achieve high levels of accuracy, they often operate as "black-box" systems, providing minimal insight into how decisions are made—an important drawback in medical contexts where transparency and trust are crucial [6], [19]. Furthermore, many high-performing models require substantial computational resources, which limits their practical deployment in edge devices or resource-constrained environments [7], [12].

As a result, there is a pressing need to develop a lightweight, interpretable, and edge-compatible AI framework capable of accurately detecting and classifying brain tumors while maintaining transparency, data privacy, and real-time applicability [3], [8]. This research seeks to overcome these limitations through the application of transfer learning techniques, explainable AI (XAI) methods, and model optimization techniques to achieve high diagnostic performance even on low-power hardware platforms [10], [11].

The evolution of artificial intelligence, especially deep learning technologies, has led to significant improvements in brain tumor detection and classification tasks [18], [20]. Modern frameworks, including Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and transfer learning-based ensemble models such as VGG-16, ResNet-50, and Inception-v3—have achieved outstanding performance in differentiating normal and abnormal brain tissues in MRI scans, outperforming conventional methods by removing the dependency on handcrafted feature extraction [4], [21]. Methods such as eight-direction Sobel edge detection and enhanced K-means clustering combined with The use of Gray-Level Co-occurrence Matrix (GLCM) features contributes to improved precision in edge detection and classification results[22]. Furthermore, statistical and machine learning methods, such as Support Vector Machines (SVM) and fuzzy logic-based classifiers, enhance tumor segmentation performance by mitigating challenges like image noise and poor contrast[23].

Integrating artificial intelligence (AI) with emerging technologies like digital twins and IoT-based smart platforms enhances the development of efficient and connected healthcare systemshealthcare systems is significantly transforming personalized diagnosis and clinical decision-making processes [2]. Digital twins, which serve as virtual models of brain conditions generated from MRI data, facilitate the design of precise and individualized treatment strategies, while secure frameworks incorporating encryption mechanisms ensure the protection of sensitive patient information during tumor detection procedures [7]. In addition, Explainable Artificial Intelligence (XAI) addresses the limitations associated with black-box models by providing interpretable and transparent outputs, thereby enhancing reliability and trust in clinical applications [6]. By combining advanced AI methodologies with medical imaging techniques, automated diagnostic systems deliver faster, more accurate, and non-invasive solutions, reducing the chances of diagnostic errors while also bridging gaps in clinical expertise and data management challenges [24].

2. LITERATURE REVIEW

Significant improvements in brain tumor detection and classification have been achieved through the combination of machine learning (ML) and deep learning (DL) algorithms with medical imaging modalities, notably Magnetic Resonance Imaging (MRI). Early surveys in this domain have played a pivotal role in laying the groundwork, emphasizing the transformative potential of ML in identifying brain tumors through MRI scans. These surveys delve into foundational elements such as brain anatomy, which is crucial for understanding the spatial context of tumors within structures like the cerebrum, cerebellum, and brainstem. They also explore the importance of high-quality datasets, including publicly available ones like the Brain Tumor Segmentation (BraTS) challenge dataset, which provide annotated MRI images for training models. Key processes covered include tumor segmentation, where

algorithms delineate tumor boundaries from healthy tissue; feature extraction, involving the identification of relevant characteristics like texture, intensity, and shape; and classification, which categorizes tumors into benign or malignant types. However, these surveys candidly address persistent challenges, such as the inherent variability in tumor morphology—tumors can differ vastly in size, shape, location, and contrast enhancement—making it difficult to develop universally robust models. Additionally, issues like data scarcity, class imbalance, and the need for computational efficiency are highlighted as barriers to clinical adoption [1]. check the plagiarism and remove it and dont reduce the sententance and dont remove the numbers which are written in the square bracket

The integration of privacy-preserving approaches within AI-driven healthcare systems has significantly improved the security and trustworthiness of medical data handling in modern smart healthcare environments [2]. In addition, advanced optimization methods that emphasize MRI image enhancement and preprocessing have contributed greatly to refining the quality of input data, which in turn leads to better overall model performance [3]. Furthermore, deep learning models, especially those based on ResNet architectures, have shown remarkable effectiveness in accurately classifying brain tumors across multiple categories [4].

Conventional machine learning methods have played an important role by introducing well-structured approaches for feature extraction, feature selection, and classification, thereby establishing the foundation for contemporary intelligent diagnostic systems [5]. The development of Explainable Artificial Intelligence (XAI) has helped overcome the shortcomings of black-box models by enabling greater transparency and interpretability, which are critical for effective clinical decision-making [6]. In addition, secure hybrid deep learning frameworks have been proposed to achieve both high diagnostic precision and the safeguarding of sensitive patient information through the use of encryption and secure computation techniques [7]. Moreover, hybrid optimization-driven models that integrate deep learning with clustering algorithms have enhanced segmentation accuracy by efficiently managing complex tumor boundaries in MRI scans [8].

The growth of telemedicine has facilitated remote diagnosis and consultation, significantly improving the accessibility of healthcare services in rural and underserved areas where skilled radiologists may not be easily available [9]. Machine learning approaches have also been effectively utilized in solving optimization problems across various domains, highlighting their ability to improve efficiency and predictive accuracy in complex environments [10]. Furthermore, advanced predictive models enhance decision-making capabilities by utilizing large-scale datasets along with sophisticated learning techniques [11]. Additionally, cloud-based data management strategies, such as data de-duplication, support efficient storage and retrieval of extensive medical imaging datasets [12].

Deep convolutional neural networks (CNNs) have shown remarkable effectiveness in identifying brain tumors directly from MRI scans by automatically learning hierarchical feature representations, eliminating the need for manual feature engineering [13]. The combination of CNN-based feature extraction with conventional machine learning classifiers has further improved the accuracy and robustness of tumor classification systems [14]. Bibliometric analyses and review studies offer a broad perspective on research developments, emphasizing the rapid advancement of automated tumor detection methods while also identifying significant challenges within the field [15]. Deep learning-based techniques consistently outperform traditional approaches by achieving higher accuracy, faster computation, and better generalization performance [16].

The integration of machine learning and deep learning approaches has led to the creation of hybrid systems that enhance the efficiency of MRI-based tumor detection and classification processes [17]. Intelligent diagnostic systems built on deep CNN architectures enable automated and efficient analysis, thereby reducing reliance on manual interpretation by medical professionals [18]. Explainable and cost-sensitive neural network models have been introduced to tackle challenges such as class imbalance, ensuring more dependable predictions in real-world scenarios [19]. Furthermore, advanced object detection frameworks, including YOLO-based models, have improved tumor localization by accurately detecting affected regions within MRI images [20].

Recent developments in deep learning include self-distillation strategies, where models enhance their performance by learning from their own predictions, particularly in complex tasks like 3D tumor segmentation [21]. Federated learning-based methods support collaborative model training across different institutions without requiring the sharing of raw data, thereby maintaining data privacy and security [22]. Hybrid architectures that combine multiple neural network models, such as CNNs and BiLSTM networks, have demonstrated superior performance in managing complex and high-dimensional medical imaging datasets [23]. Comprehensive survey studies suggest that despite notable progress, issues such as high computational requirements, limited interpretability, and challenges in real-time implementation continue to be critical areas for future research in brain tumor detection systems [24].

3. PROPOSED WORK

3.1 Formalization of Problem

Timely and precise identification of brain tumors plays a vital role in enhancing patient outcomes and increasing survival chances. Conventional MRI-based diagnosis depends heavily on radiologist expertise, which may lead to inter-observer variability, diagnostic delays, and subjective interpretation errors. Additionally, deep learning-based automated systems, although capable of delivering high accuracy, often suffer from two major limitations — the lack of interpretability and the requirement for high-end computational resources that make them impractical for deployment in real-time or remote healthcare settings. Hence, the formal problem can be stated as follows:

To create an XAI-based, low-complexity, and efficient model that enables automated detection and classification of brain tumors in MRI data., while providing visual explanations of model predictions for enhanced clinical trust and deploying it efficiently on edge devices.

Formally, the problem can be expressed as:

Given a dataset of MRI brain images $D = \{I_1, I_2, \dots, I_n\}$,

where each image I_i belongs to one of the classes $C = \{\text{Glioma, Meningioma, Pituitary, Normal}\}$, the goal is to learn a function

$$f: I_i \rightarrow C$$

therefore

f accurately predict the correct tumor class C for unseen images,

provides a corresponding explainability map $E_i = \text{Explain}(f(I_i))$ to visualize important features, and executes efficiently on edge hardware with constraints such as limited RAM (<1 GB), low latency (<100 ms), and low power consumption.

3.2 System Architecture

The workflow of the proposed brain tumor detection system commences with obtaining MRI images of the brain., which act as the main input for the analysis process. Magnetic Resonance Imaging is commonly preferred because it provides detailed visualization of soft tissues inside the brain. However, the raw MRI data often contains issues such as noise, poor contrast, motion distortions, and inconsistent intensity levels. To overcome these limitations, an initial preprocessing phase is applied to improve and standardize the input data. During this phase, pixel values are normalized to achieve consistent intensity levels, images are resized or cropped according to the input specifications of deep learning models, and skull stripping may be applied to remove unwanted non-brain areas.. These steps help in

reducing unwanted variations and enhance the quality of the images, enabling more accurate tumor detection.

After preprocessing, the images are passed through a separate stage focused on noise reduction and quality enhancement, which is essential for improving detection performance, especially when tumors are small, irregular, or not clearly visible. Various denoising techniques, including Gaussian smoothing, non-local means filtering, and wavelet-based approaches, are applied to eliminate unwanted noise while preserving important structural information.

Simultaneously, image enhancement methods such as Contrast Limited Adaptive Histogram Equalization (CLAHE) are applied to enhance image contrast, allowing tumor boundaries to appear more defined and subtle irregularities to become easier to detect. By improving the overall visual clarity of MRI scans, this step enables deep learning models to receive higher-quality input data, which ultimately contributes to improved performance in both tumor detection and classification tasks.

Following the enhancement phase, the refined images are supplied as input to a lightweight and efficient deep learning model specifically developed for brain tumor detection. Models such as MobileNet, EfficientNet, and Tiny Vision Transformers are often preferred due to their ability to maintain a balance between high accuracy and low computational requirements, making them appropriate for real-time deployment in clinical environments with limited hardware capabilities. During the training process, techniques including data augmentation, dynamic learning rate adjustment, and regularization methods are implemented to enhance model generalization and ensure consistent performance across various MRI modalities and diverse imaging conditions.

At the prediction stage, the trained system delivers three primary outputs that together provide a complete diagnostic assessment. Initially, the classification unit evaluates the MRI scan to detect the presence of a tumor and assigns it to specific categories such as glioma, meningioma, or pituitary tumor, facilitating precise diagnosis. Next, the tumor measurement module employs segmentation strategies, including threshold-based methods or deep learning models like U-Net, to outline tumor boundaries and calculate an estimated size or volume. This information is valuable for clinical decision-making, including therapy planning and outcome evaluation. Finally, the explainability module applies Grad-CAM to generate heatmaps that visualize the regions influencing the model's decisions, enhancing system transparency and clinician confidence.

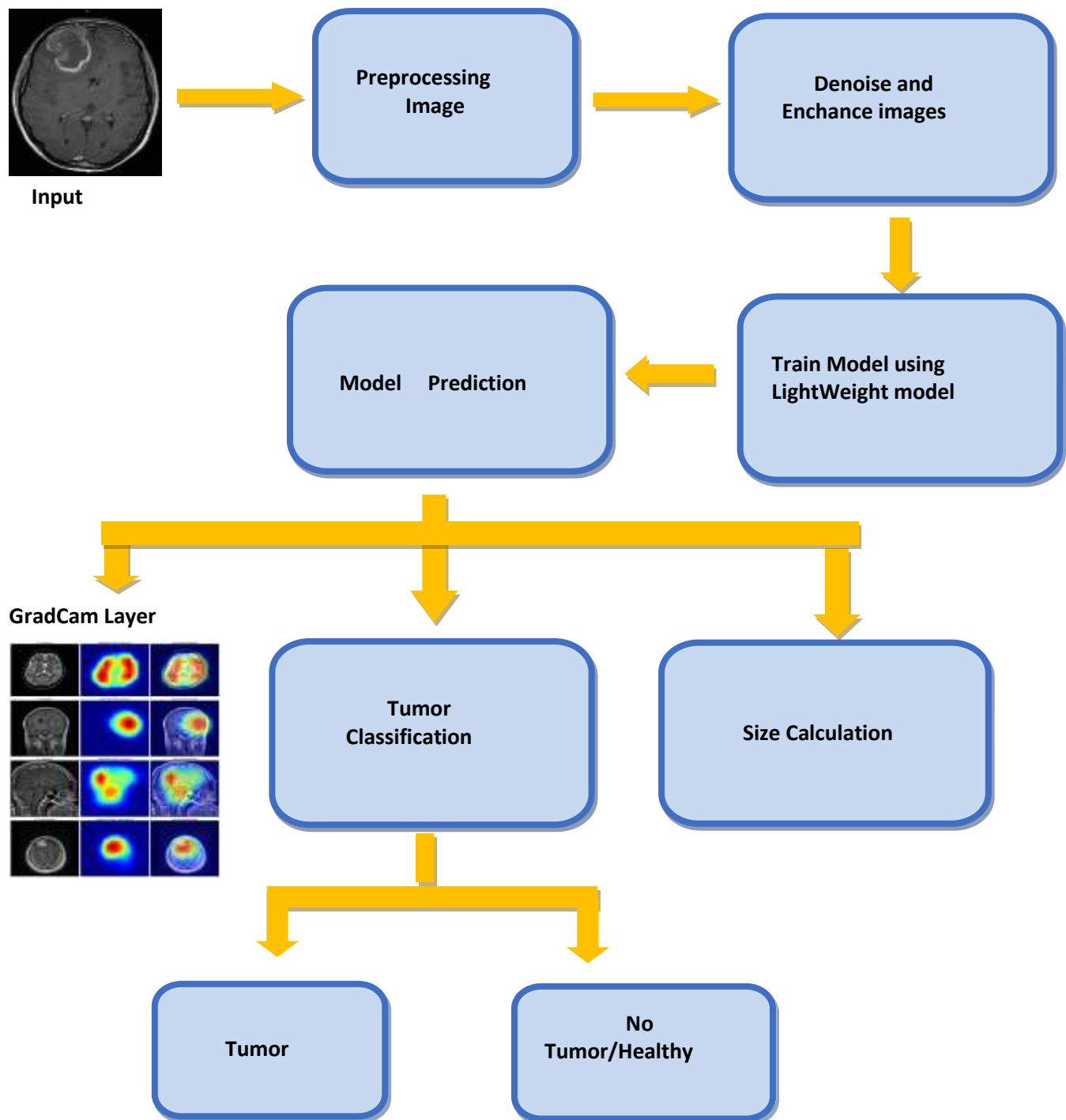


Fig -1: system Architecture

3.3 Data Flow Diagram

The DFD provides a visual representation of data movement within the system and outlines the processing steps that convert input data into final results.

Level 0: Context Diagram

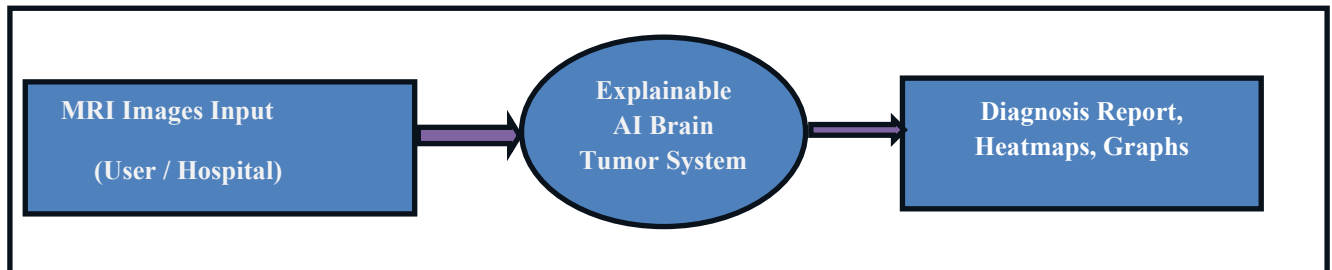


Fig. 2 Context Diagram

Description:

- The user uploads MRI images to the system.
- The system processes them through AI models and returns a diagnostic report and explainable heatmaps.

Level 1: Data Flow Diagram

Flow Explanation:

1. The user provides the MRI image.
2. The preprocessing module cleans and enhances the image.
3. The deep learning classifier identifies tumor presence and type.
4. The explainability module highlights critical image regions for transparency.
5. The segmentation and size module outlines tumor boundaries.

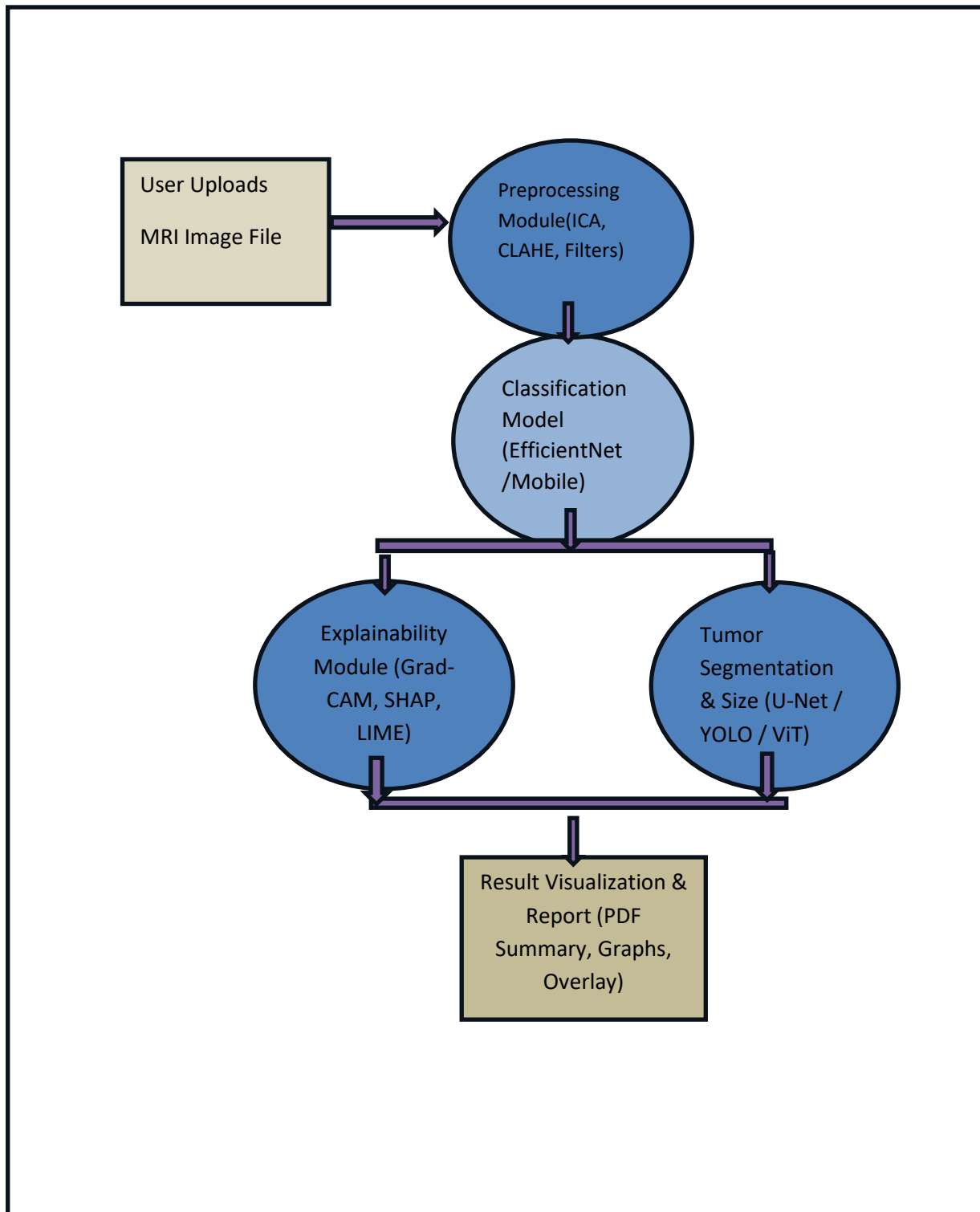


Fig. 3. DFD of Software

3.4 Class Diagram

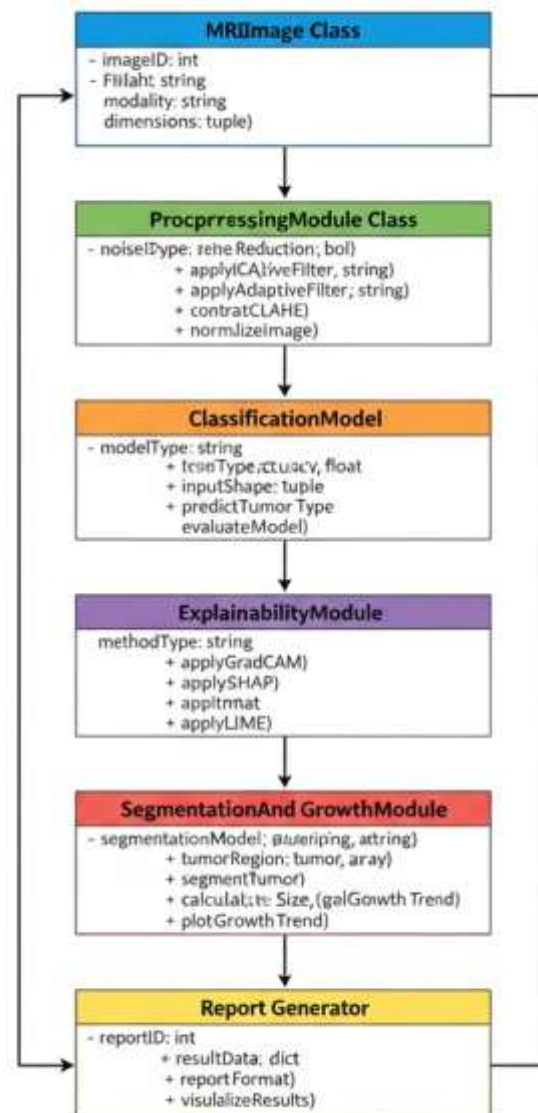


Fig. 4. Class Diagram of Software

3.5 Control Flow Diagram

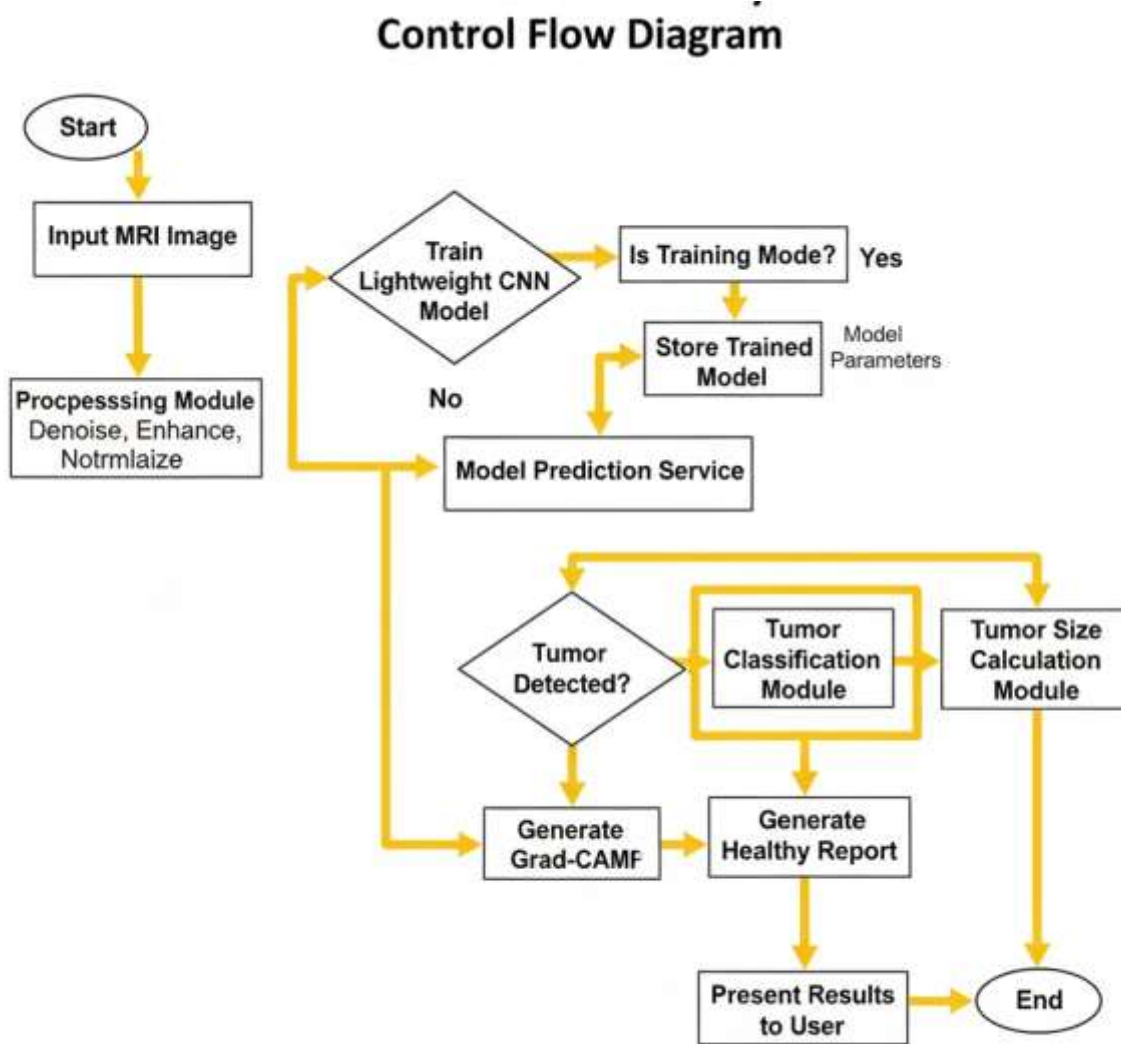


Fig. 5. Control Flow Diagram of Software

4. CONCLUSIONS

The proposed Explainable Artificial Intelligence (XAI)-based Brain Tumor Diagnosis System effectively combines deep learning, image enhancement techniques, and explainable methods to deliver accurate, transparent, and efficient tumor detection from MRI scans. This framework addresses key challenges in modern neuro-diagnostic practices, including limited availability of expert clinicians, computational limitations in resource-constrained settings, and the lack of interpretability associated with conventional deep learning models. By employing advanced preprocessing approaches such as Independent Component Analysis (ICA), Adaptive Filtering, and Contrast Limited Adaptive Histogram Equalization (CLAHE), the system improves MRI image quality and enhances tumor visibility. Lightweight transfer learning architectures, including MobileNet, EfficientNet, and Tiny Vision Transformers (ViT), achieve strong diagnostic accuracy while maintaining computational efficiency suitable for real-time implementation. A significant contribution of this study is the integration of explainability techniques such as Grad-CAM, SHAP, and LIME, which provide both visual and quantitative explanations for model predictions, thereby increasing clinical reliability and enabling radiologists to validate the decision-making process. Additionally, the incorporation of tumor segmentation, size estimation, and growth monitoring supports effective treatment planning and patient management.

In summary, the developed system fulfills its core objectives by delivering an accurate, interpretable, and resource-efficient solution for brain tumor detection and analysis. It narrows the gap between artificial intelligence technologies and clinical practice by offering a transparent and deployable model suitable for real-world healthcare applications. Future developments may include integrating multimodal medical datasets such as CT, PET, and genomic information, adopting federated learning techniques for secure data sharing, and implementing cloud-edge hybrid frameworks to enable large-scale clinical deployment. These enhancements are expected to expand the system's role in personalized medicine and intelligent healthcare systems.

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