AI-based System for Brain Tumor Segmentation and 3D Visualization

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***Abstract*—Computer vision is a branch of artificial intelligence that enables computers to learn patterns and extract useful information from various visual content. In healthcare, advances in computer vision models have been employed to provide accurate analysis of medical images, aiding tasks such as disease detection, human organ segmentation, and medical image classification. Such systems have the potential to enhance healthcare by improving patient outcomes and enabling early and accurate detection of diseases. The 3D CATBraTS is a novel deep learning architecture designed for three-dimensional segmentation of brain tumors on various magnetic resonance imaging (MRI) acquisitions. This paper presents a real-world web application capable of automatically detecting and accurately locating brain tumors on medical images. The proposed tool integrates the 3D CATBraTS as the backend deep learning model to improve its applicability and usability. The web application empowers medical professionals to perform segmentations seamlessly, even without coding skills, resulting in an improved user experience.**

***Index Terms*—AI web application, brain tumor, medical imaging, deep learning**

I. Introduction

Diagnostic medical imaging is an evolving field in healthcare, with advanced technologies continually emerging to improve healthcare services. In recent years, artificial intelligence (AI) has been dominantly adopted in medical imaging to facilitate the transition to AI-based computer-aided diagnosis (CADx) or computer-aided detection (CADe) systems [1] [2] [3]. A CAD system serves as a tool to assist specialist doctors or radiologists in interpreting medical images more efficiently. These CAD systems find numerous applications, including the diagnosis and segmentation of breast masses [1], anatomical structure [4], Alzheimer's disease [5] and more.

Convolutional neural networks (CNNs) are deep learning (DL) models that have emerged as dominant players in medical imaging, demonstrating high accuracy and low loss rates [6]. More recently, Vision Transformer (ViT) [7] received significant interest for their self-attention mechanism, allowing models to capture long-range dependencies and improve efficiency. Despite these advancements, the integration of AI models into current medical image viewers remains limited. Many systems primarily focus on the 3D visualization of medical images in formats like DICOM, which is a standard for exchanging medical images and data. While these systems offer useful features such as annotation, they often lack advanced AI-driven image processing capabilities. For instance, a tool developed in previous research [8] provides 2D and 3D visualization, zooming, windowing, and manual labeling, but it does not incorporate AI for automated high-quality processing.

The goal of this research is to provide healthcare experts with an easy-to-use, AI-supported web application that can automatically detect and segment brain tumors from MRI scans. The proposed interactive web application is accessible through a web interface, enabling medical professionals to perform tumor segmentation on any device without needing high-specification devices. Hosted on a cloud-based server, the application enables the uploading and analysis of medical scans, helping professionals make more informed decisions while reducing diagnostic errors. Furthermore, this research work may have a significant impact on the scientific community by introducing a novel open-source framework for brain tumor segmentation utilizing the latest advancements in CNN and ViT technologies.

The rest of the article is structured as follows: the proposed web application, 3D visualization and the AI model are presented in Section II. Section III discusses the usage and the limitations of the framework. Finally, section IV includes a summary and future directions.

II. Methodology

Our study aims to introduce a web-based application that uses AI technology to detect and extract tumor areas from brain MRI scans. The application is designed to be easy to use and accessible to all users. We developed the application using the Flask framework, incorporating both front-end and back-end components. To begin using the application, users upload 3D MRI scans containing four modalities: Flair, T1-weighted, T1-weighted with contrast enhancement, and T2-weighted. Our advanced deep learning technique is then applied to the images to identify and extract tumors from the brain MRI modalities if detected. Once the computations are complete, the segmentation results are displayed as 3D plots of the brain and the tumor, including its sub-regions. Figure 1 presents an overview of the proposed web application.

A. 3D CATBraTS

The web application integrates a CNN-ViT model named 3D Channel Attention Transformer for Brain tumor Segmen-

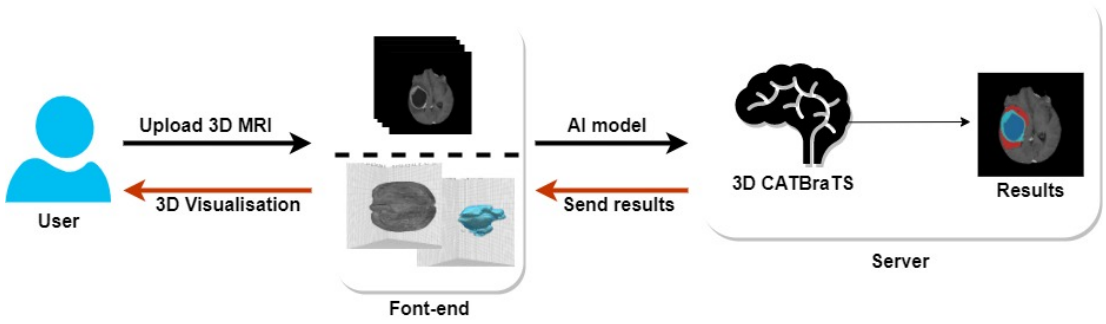

Fig. 1. Web application framework. The user uploads 3D MRI scans with four modalities through the web application: Flair, T1-weighted, T1-weighted with contrast enhancement, and T2-weighted. Later, the medical images are processed using an AI-enabled framework called 3D CATBraTS that locates brain tumors from the MRI scans. Finally, the segmentation results are sent back to the user for 3D visualization.

tation (3D CATBraTS), which performs volumetric segmentation of brain tumors from magnetic resonance imaging (MRI) scans. This model has been presented and evaluated in [9]. As depicted in Figure 2, 3D CATBraTS consists of two phases. Phase one is the vision transformer part, while phase two is CNN encoding and decoding blocks. In phase one, the input, a multi-modality MRI scan of the patient's brain, is converted into a flattened sequence of patches followed by a low-dimensional linear embedding. Positional embedding is then added to the patches, which are fed into a CNN encoder comprising five CATBraTS residual (res) blocks. CATBraTS res blocks downsamples the size of the embedded patches and consists of several 3x3x3 convolution layers, followed by 3D batch normalization and LeakyReLU activation function. These layers are added to a projection of the input using a skip connection and are fed into a channel attention layer and activated by another layer of LeakyReLU. Each channel of a feature map has a different contribution to the model's training. With the channel attention layer, each channel is weighed based on its importance and significance. The model was trained on the BraTS 2021 dataset [10] [11] [12], and compared to Swin UNetR [13] and SegResNet [14]. SegResNet won first place in the BraTS 2018 challenge, while the Swin UNeTR is one of the top-ranked models in the BraTS 2021 challenge, and it is the first transformer to achieve high accuracy. The results obtained from the study showed that the 3D CATBraTS outperformed both the Swin UNetR and the SegResNet in the validation phase of the BraTS 2021 challenge, surpassing the nearest competing model by 5.8% on the mean dice coefficient of the three sub-regions of brain tumor: enhancing tumor, tumor core, and whole tumor.

B. 3D Visualization

The 3D CATBraTS software is capable of performing 3D segmentation of brain tumors in three sub-regions, namely the whole tumor, enhancing tumor, and tumor core. The automatic segmentation framework generates a volumetric representation in three dimensions, resulting in a binary volume. To refine this representation, a Gaussian smoothing algorithm is applied during the reconstruction process, followed by a 3D interpolation to remove noise. This method, commonly utilized in pre-processing tasks within computer vision, aims to enhance the structural details of images across various visualization scales [15]. Subsequently, the smoothed data is transformed into an isosurface, consisting of points where the data function reaches a uniform value known as the isovalue. The isosurface reconstruction is performed using the marching cube algorithm [16], which converts the data into a polygonal mesh. To further refine the mesh, Laplacian smoothing is applied, resulting in a more precise representation of the organ in three dimensions. The resulting 3D model is then superimposed onto a single 2D slice from the original medical image volume for visualization. This interactive 3D representation allows users to load the binary mask from the segmentation process and visualize the resulting mesh. Additionally, users can manipulate the representation using functionalities such as zooming, rotation, and panning. Figure 3 shows the interactive 3D representations of the brain tumor in the proposed system. Furthermore, the proposed application includes features for visualizing brain and tumors in single 2D slices. Upon loading the medical image volume, users have access to three primary views: axial, sagittal, and coronal. The segmented brain and the three sub-regions of the tumor are then superimposed onto the original medical slice (2D), as depicted in Figure 4.

C. Open-source imaging framework

Numerous deep learning models have been developed for medical imaging, showcasing high accuracy across various tasks. However, their implementation in real-life healthcare settings remains limited. One of the reasons for this is the complexity associated with installing these models and the demand for high computing resources. To overcome this challenge, we present a web-based deep learning model designed to simplify adoption within healthcare settings. The proposed framework is openly accessible and freely available on GitHub at the link (provided after acceptance). Comprehensive deployment instructions and documentation are also provided on the GitHub repository. Making the framework open-source empowers researchers to adopt or customize it without restrictions, encouraging the development of innovative, tailored algorithms.

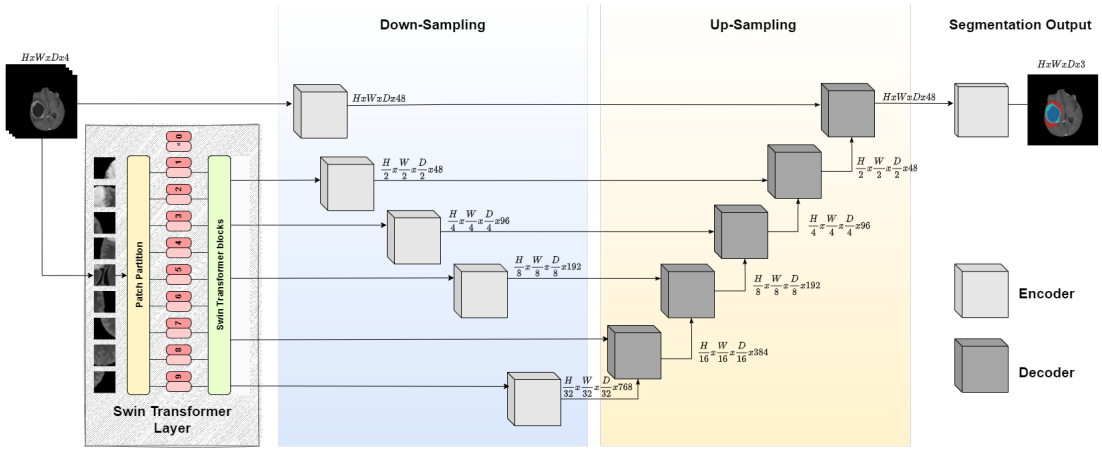

Fig. 2. Architecture of 3D CATBraTS consisting of vision transform and convolutional neural network [9].

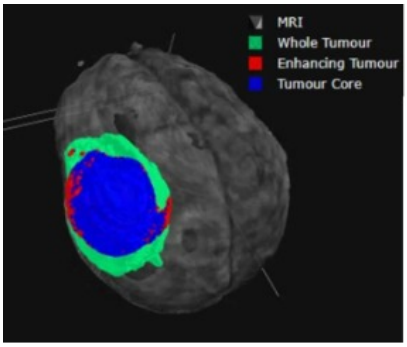

Fig. 3. 3D visualization of the brain and the segmentation output from the proposed web application. Whole tumor (green), enhancing tumor (red), and tumor core (blue).

D. Web application

The web application integrates a trained 3D CATBraTS to help medical professionals perform segmentation using a refined and trained model. Deep learning models were commonly deployed on the client's own servers, but this approach presented several limitations. These limitations include: 1. Clients, typically clinical experts, are required to install the model on their systems and train it using their data. This process can take several days to complete. And, 2. Training the model on the client's side requires access to GPU-enabled and powerful computing resources and the installation of various libraries. Therefore, we introduce the 3D CATBraTS web-based application. Figure 5 provides a snapshot of the web application, and Figure 6 displays an overview of the network architecture. The proposed web application was implemented using the Flask framework (https://flask.palletsprojects.com/). The Flask framework is a lightweight web framework written in Python, simplifying the development of the user interface and the integration with the back-end server. Flask provides essential modules such as routing and templating, facilitating the creation of the user interface Hypertext Markup Language (HTML) and Cascading Style Sheets (CSS).

The web application consists of two components: the front-end (client-side) and the back-end (server-side). The server side employs the 3D CATBraTS deep learning model for automatic brain tumor segmentation in MRI scans, while the client side offers a user-friendly interface for interaction. The user workflow includes:

- Accessing the web-based application at the link (provided after acceptance)
- Uploading a volume MRI scan of the brain in NIFTI format for a single patient, containing Flair, T1-weighted, T1-weighted with contrast enhancement, and T2-weighted acquisitions; each of the MRI acquisitions is taken at various contrasts. NIFTI is a format for storing medical images that makes it easier and quicker to process a whole-volume image instead of a sequence of slices [17].
- Initiating the processing functionality after selecting and uploading each MRI modality and clicking the start button. This will send the scans to the AI-enabled CAD system for processing them and receiving the segmentation results.
- Visualizing the segmented brain regions, including the whole tumor (green), tumor core (blue), and enhancing tumor (red), in axial, coronal, and sagittal views.
- Visualizing three plots (on the bottom of each view) where each slice appears one after the other as an animation.
- Visualizing an interactive 3D shape of the three regions of the brain tumor.
- Exploring additional functionalities such as changing scan types, rotating, zooming in, and zooming out.

III. Results and Discussion

The proposed web-based AI-enabled CAD system is accessible from various devices and offers real-time brain tumor segmentation from MRI scans in NIFTI format. It serves as

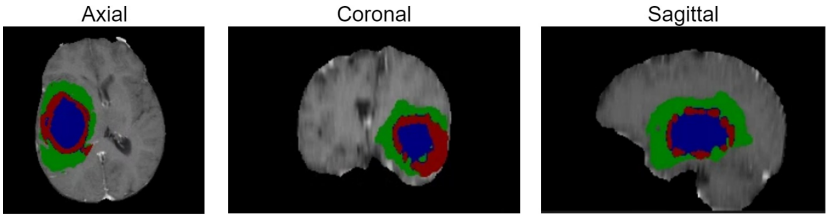

Fig. 4. A 2D slice of a whole brain overlaid with the segmentation results of 3D CATBraTS show in axial, coronal and sagittal planes.

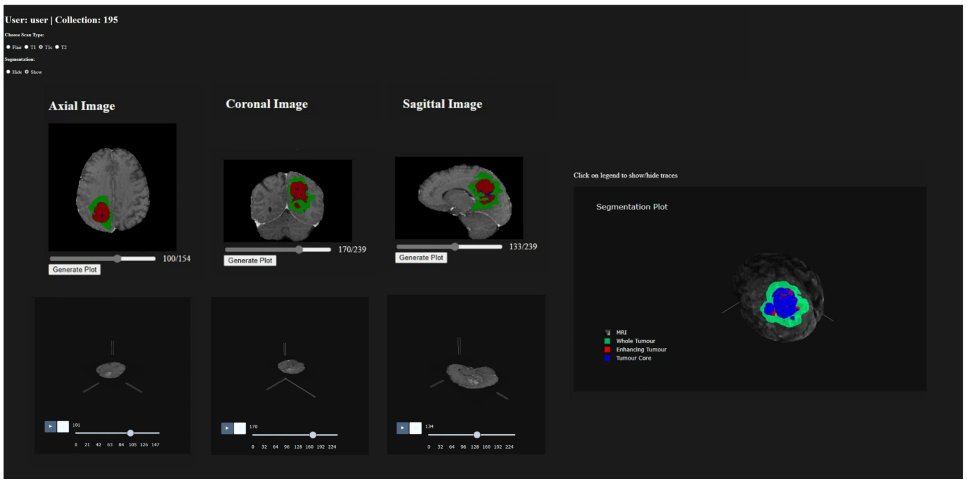

Fig. 5. screenshot of the web interface. user can view and interact with a 3-dimensional visualization of the segmented brain tumor. There are three views: Axial, Coronal, and Sagittal plane. The user can choose between four MRI modalities, including Flair, T1-weighted, T1-weighted with contrast enhancement, and T2-weighted.

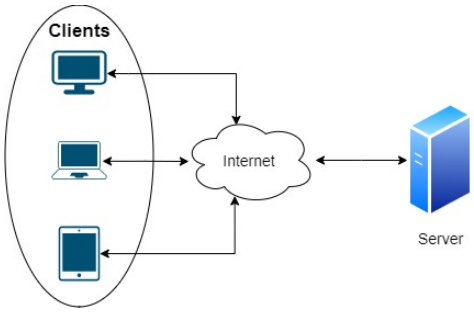

Fig. 6. client-server computer network where the server provides services to multiple clients.

an open-access platform for clinical experts and researchers, allowing unrestricted usage and modification. Updates to the deep learning model can be seamlessly implemented without user intervention, given the platform's web-based nature.

While this study offers considerable benefits to the medical and research community, several important limitations must be considered. Firstly, medical images are large in size, which affects processing time. When a user uploads images to the server, segmentation results can take up to two minutes to be returned. Future improvements will focus on optimizing processing speed. Secondly, the current user interface design and functionalities are basic. Planned enhancements include aligning the UI with modern design standards, incorporating accessibility features, and refining user interaction based on ongoing tests with medical professionals. Another key objective is to integrate human feedback into the segmentation process, allowing users to manually adjust the segmented mask, which is expected to enhance model quality and improve segmentation accuracy. Future upgrades aim to introduce features such as exporting the segmented tumor mesh for visualization in a virtual reality environment. Finally, while the proposed web-based CAD system has demonstrated potential as a scalable tool for brain tumor segmentation, with minor modifications, it could be extended to other medical imaging tasks, such as organ segmentation, visualization, and fetal body extraction.

IV. Conclusion

AI models for medical imaging can significantly assist healthcare professionals in diagnosing and localizing brain tumors. We presented a web-based deep learning model for automating the process of tumor segmentation from 3D MRI scans. Healthcare experts can seamlessly adopt the proposed web application for the early diagnosis of the disease, which will play a vital role in improving patient outcomes. A possible area for future research would be to enable collaborative learning in order to optimize the accuracy of the model and share it with all web application users.

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