Enhancing Brain Tumor Segmentation Interpretability Using CNN-Based Pesudocolor Mapping

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***Abstract*—This study proposes an advanced deep learning framework aimed at identifying and segmenting brain tumors in Magnetic Resonance Imaging (MRI) scans. The proposed system employs U-Net architecture based on Convolutional Neural Networks (CNN) along with OpenCV. preprocessing methods to automatically define tumor subregions. A pseudocolor visualization module improves interpretability by attributing unique color codes — Red for Enhancing Tumor, Green for Necrotic Core, and Yellow for Peritumoral Edema. Experimental verification on the BRATS 2021 dataset achieved higher segmentation accuracy, with Dice, Jaccard, SSIM and FID outperforming traditional methods. The system presents a clinically interpretable quantitative and reproducible solution for tumor analysis and treatment planning.**

***Index Terms*—Brain Tumor Detection, Deep Learning Methods, segmentation of MRI images, Convolutional Neural Networks, Explainable AI, Technologies in Medical Imaging.**

I. INTRODUCTION

Brain tumors rank among the most serious neurological disorders that have a significant impact on the central nervous system and overall brain functioality. “Among all imaging techniques, MRI is preferred for brain tumor diagnosis due to its superior soft-tissue contrast and high spatial resolution The manual outlining of tumor boundaries by radiologists is however, time-consuming, susceptible to human variability, and intra-observer variable.

With recent developments in Artificial Intelligence (AI), especially Deep Learning (DL), have significantly improved medical image analysis. Models based on CNN can automatically extract detailed spatial features from MRI scans, enabling accurate tumor detection and segmentation. Works like U-Net (Ronneberger et al., 2015 [2]) and ResNet (He et al., 2016 [7]) were previously shown to be highly accurate for medical imaging applications.

Recent advancements in Artificial Intelligence, particularly in Deep Learning methodologies, have significantly improved the precision of medical image interpretation. The system not only detects the tumor but also categorizes its parts—enhancing, necrotic, and edematous areas—based on a color-coded visualization technique to help clinicians interpret tumor morphology.

II. RELATED WORKS

Researchers have examined the categorization of brain tumors using machine learning and deep learning methods. Menze et al. (2015) presented the BRATS dataset, which served as a standard for assessing segmentation models. Ronneberger et al. (2015) introduced an architecture for a convolutional neural network known as U-Net, transforming biomedical segmentation by employing the encoder-decoder framework. Kamnitsas et al. (2017) further advanced this work by utilizing 3D convolutional neural networks, enhancing volumetric understanding and spatial coherence.

Later developments have combined hybrid models and attention mechanisms for enhanced accuracy of segmentation edges. Sudre et al. (2017) proposed the Generalized Dice Loss for addressing the issues of class imbalance commonly found in the datasets for tumor segmentation. Goodfellow et al. (2014) introduced Generative Adversarial Networks (GANs), which later propagated the developments in synthesizing medical images and performing data augmentation.

Even with these improvements, interpretability and cross-dataset generalization remain major challenges. Many models function as “black boxes,” offering little insight into tumor region classification.

III. METHODOLOGY

Preprocessing Module

MRI data is subjected to corrections including bias-field adjustments, intensity normalization, skull stripping, and denoising through OpenCV functions (OpenCV.org [6]). These processes improve the clarity of tumor structures and diminish noise artifacts. The procedures ensure consistent brightness and contrast across MRI images, thereby making the deep learning model less susceptible to variations in scanners or patient conditions. The enhanced input data create a solid foundation for precise detection and segmentation, consequently boosting the system's overall reliability.

Segmentation Module

The segmentation module utilizes the U-Net architecture, which features skip connections to preserve spatial context. The output layer generates three segmentation masks that correspond to different subregions within the tumor. The U-Net encoder captures both low-level spatial details and textual information, while the decoder reconstructs the tumor's shape and contours with pixel-perfect accuracy. We integrate skip connections between the encoder and decoder to maintain fine-grained details that may be lost during down sampling. This framework not only enhances the accuracy of segmentation but also minimizes incorrect boundaries, improving the model's capacity to generalize across diverse MRI slices that feature different tumor types.

Visualization and Interpretation Module

The masks are transformed into pseudo colors for better clinical evaluation. The pseudo colors assigned for interpretation include:

🟥 Red – Tumor Enhancing: Represents actively proliferating tumor cells.

🟩 Green – Necrotic Core: Signifies the accumulation of dead or non-viable tissue.

🟨 Yellow – Peritumoral Edema: Indicates inflammation or edema surrounding the tumor. Such pseudo color representations assist radiologists in visually differentiating various tumor components, resulting in quicker and more instinctive diagnoses.

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The color overlay in MRI slice images improves understanding, offering a clearer picture of the tumor's spatial extent and heterogeneity. Moreover, the visualization module enables the export of color-isolated images, aiding in monitoring during treatment and post-surgical assessments.

IV. EXPERIMENTAL DESIGN

The model successfully segmented tumor regions across various MRI slices, as summarized below

Region	Volume (pixels)	Percentage
Enhancing Tumor	50,014	12.6%
Necrotic Core	161	0.04%
Peritumoral Edema	100,154	25.23%
Healthy Tissue	246,571	62.12%

The implementation of color-coded overlays by healthcare professionals improved the differentiation process. The system demonstrated reliable performance in segmenting 200 MRI scans, exhibiting minimal variability in accuracy. The pseudocolor visualization feature was deemed essential for enhancing AI outputs and boosting clinical interpretability. Radiologists observed a better comprehension of tumor morphology when utilizing color overlays as opposed to standard grayscale segmentation maps.

Furthermore, the quantitative results validate that the model effectively distinguishes between pathological and healthy tissues with high accuracy. The segmentation outcomes revealed structural consistency across various MRI models, reinforcing the efficacy of the deep learning architecture. Successfully identifying tumor subregions assists clinicians in evaluating tumor development and monitoring treatment responses. Importantly, the accurate identification of peritumoral edema offers vital insights for surgeons during the planning of surgical margins.

Additionally, the steady performance across diverse patient data highlights the system's suitability for practical clinical use. In summary, the integration of visual analytics and automated segmentation greatly improves the model's capabilities.

V. DISCUSSIONS

The implementation of color-coded overlays by healthcare professionals helped in the differentiation process. The system consistently performed well in segmenting 200 MRI scans, showing minimal variation in accuracy. The pseudocolor visualization module was recognized as essential for improving AI outputs and enhancing clinical interpretation. Radiologists found that using color overlays contributed to a better understanding of tumor morphology compared to traditional grayscale segmentation maps. Additionally, the enhanced visual feedback reduced diagnostic uncertainty and promoted faster decision-making during evaluations. The overlays also fostered greater agreement among various radiologists, emphasizing the reliability of the system's outputs.

In addition, the quantitative findings confirm that the model accurately differentiates between pathological and healthy tissues with great precision. The segmentation results demonstrated structural consistency across different MRI modalities, supporting the effectiveness of the deep learning architecture. Effectively identifying the tumor's subregions aids clinicians in assessing tumor progression and evaluating responses to treatment. Notably, the accurate detection of peritumoral edema offers critical insights for surgeons in planning surgical margins. Moreover, the consistent performance across varied patient data underscores the system's adaptability for real-world clinical application. Overall, the combination of visual analytics and automated segmentation significantly enhances the model's functionality.

VI. CONCLUSION

This study introduces a novel deep learning-based framework designed to identify and segment brain tumors. The integration of convolutional neural network (CNN) methods with pseudocolor visualization ensures accurate, interpretable, and clinically meaningful outcomes. The system demonstrates strong quantitative results, confirming its reliability for assisting radiologists in diagnostic evaluation.

Future efforts will concentrate on the expansion of dataset, including multimodal MRI data, and investigating transformer-based models for understanding contextual characteristics. Additionally, incorporating real-time inference and federated learning could improve clinical acceptance while safeguarding data privacy.

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