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Addressing the complexities of postoperative brain MRI cavity segmentation–a comprehensive review

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ABSTRACT

Postoperative brain magnetic resonance images (MRI) is pivotal for evaluating tumor resection and monitoring post-surgical changes. The segmentation of surgical cavities in these images poses challenges due to artifacts, tissue reorganization, and heterogeneous appearances. This study explores challenges and advancements in postoperative brain MRI segmentation, examining publicly accessible datasets and the efficacy of various deep learning models. The analysis focuses on different U-Net models (U-Net, V-Net, ResU-Net, attention U-Net, dense U-Net, and dilated U-Net) using the EPISURG dataset. The training dice scores are as follows: U-Net 0.8150, attention U-Net 0.8534, V-Net 0.7602, ResU-Net 0.7945, dense U-Net 0.83, dilated U-Net 0.80. The study thoroughly assesses existing postoperative cavity segmentation models and proposes a fine-tuning approach to enhance the performance further, particularly for the best-performing model, attention U-Net. This fine-tuning involves introducing dilated convolutions and residual connections to the existing attention U-Net model, resulting in improved results. These improvements underscore the necessity for ongoing research to select and adapt efficient models, retrain specific layers with a comprehensive collection of post-operative images, and fine-tune model parameters to enhance feature extraction during the encoding phase.

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1. INTRODUCTION

The postoperative resection cavity of the brain refers to the void or space that remains in the brain after surgical resection or removal of a brain tumor or lesion [1]. During the surgical procedure, the surgeon removes the tumor or lesion along with some surrounding healthy tissue to ensure a complete resection. This removal creates a cavity or void within the brain where the tumor or lesion used to be. The size and shape of the resection cavity can vary depending on the characteristics of the tumor or lesion and the extent of the surgical resection [1]. The cavity may be irregularly shaped and can involve multiple lobes or regions of the brain. After the surgery, the postoperative resection cavity gradually fills with cerebrospinal fluid (CSF) and undergoes healing and remodeling [2]. The healing process involves the formation of scar tissue and the gradual reduction in cavity size over time. Comparing preoperative and postoperative images in brain surgery is essential for multiple reasons. It allows doctors to evaluate treatment effectiveness, monitor disease progression, detect complications, and aid in surgical planning [3], [4]. This comparison helps assess the success of the surgical intervention, track changes in the lesion or tumor, identify adverse effects, guide future treatments, and optimizing patient care.

Accurate segmentation of postoperative recurrent tumors and cavities in brain magnetic resonance images (MRI) is essential for the effective management of brain tumor treatment, particularly in patients with glioblastoma. The success of treatment relies on precise delineation of the tumor, enabling determination of its extent, volume, and location relative to functional areas of the brain [5], [6]. Adapting preoperative segmentation algorithms for postoperative images presents challenges due to tissue changes, artifacts, and the presence of resection cavities [7]. Therefore, the development of dedicated algorithms that consider postoperative features becomes essential for achieving effective segmentation [8]–[10]. This study underscores the significance of postoperative brain MRI in assessing tumor resection and monitoring surgical outcomes. It explores advanced U-Net models, with attention U-Net identified as the top performer. Through fine-tuning, the model achieves a dice coefficient of 0.87, indicating potential improvement. Challenges related to limited training data are addressed with recommended data augmentation techniques. The paper analyzes various U-Net models, highlighting improvements in the best-performing attention U-Net model. The findings emphasize the ongoing need for research to adapt efficient models, retrain specific layers with a more extensive image collection, and fine-tune parameters for improved feature extraction. The paper covers methodologies, data pre-processing, data augmentation, and deep learning techniques for improving segmentation accuracy in postoperative brain MRI analysis. It is divided into five sections:

a. Imaging modalities used for postoperative brain MRI, their advantages, and limitations.
b. Overview of the available post operative datasets.
c. General post-operative segmentation model pipeline: i) preprocessing methods; ii) data augmentation methods; and iii) state-of-the-art segmentation techniques.
d. Comparison of existing post operative cavity segmentation model.
e. Results and discussions.

2. IMAGING MODALITIES FOR POSTOPERATIVE BRAIN MRI

MRI is a non-invasive medical imaging technique that uses a powerful magnetic field, radio waves, and a computer to produce detailed images of the body. MRI scans of the brain can be used to diagnose a wide range of neurological conditions, including tumors, stroke, and degenerative diseases. Postoperative MRI is an effective imaging technique for monitoring the status of brain tumors after surgery. Different imaging modalities available for postoperative brain MRI includes T1-weighted, T2-weighted, fluid-attenuated inversion recovery (FLAIR) [11]–[13], diffusion-weighted imaging (DWI), and perfusion-weighted imaging (PWI) [12], [13]. T1-weighted MRI is used for assessing the postoperative cavity and the presence of any residual tumor tissue. T2-weighted MRI provides information on the edema surrounding the tumor and is useful in identifying areas of residual tumor tissue [14]–[16]. FLAIR imaging is a modification of T2-weighted imaging that suppresses the signal from cerebrospinal fluid, making it easier to detect small areas of edema and residual tumor tissue. DWI provides information on the mobility of water molecules in the brain tissue, which can be used to identify areas of cellular damage and necrosis. PWI provides information on the blood flow in the brain tissue, which can be used to assess tumor vascularity and detect areas of tumor recurrence [17]–[19].

3. DATASET

The mini bite [20], [21] and EPISURG [22] datasets are publicly available resources utilized in postoperative brain MRI segmentation research, specifically focusing on cases of brain tumors and postoperative MRI scans of epilepsy patients. Widely employed in segmentation studies, these datasets play a crucial role in evaluating deep learning algorithms for cavity segmentation. The EPISURG dataset, abbreviated from the epilepsy surgery dataset, is in neuroimaging informatics technology initiative (NIfTI) format and serves as a valuable asset for postoperative cavity segmentation. It comprises T1-weighted MRI from a significant cohort of 430 patients who underwent resective brain surgery for epilepsy treatment, including both preoperative and postoperative MRI scans. This study applies existing postoperative cavity segmentation models to the dataset and assesses their performance. Software tools such as MRIcroGL, 3D slicer, ITK-SNAP, and FSL view enable the visualization of NIfTI format MRI data. These tools offer features like slice-based viewing, volume rendering, and segmentation. Users can overlay various image types, including segmentation masks, to better understand the brain's structure. "SliceDrop", a tool for visualizing and sharing medical imaging data, is utilized for displaying MRI data in NIfTI format.

The datasets mentioned have certain limitations and challenges for post-operative brain MRI segmentation research. Some of these difficulties are: lack of ground truth, heterogeneity in image structure, variability in tumor shape and size and class imbalance. To tackle these challenges, researchers have put forth various techniques, including data augmentation, transfer learning, ensemble modeling with multiple models, and the incorporation of additional modalities such as diffusion tensor imaging (DTI) and magnetic resonance spectroscopy (MRS) to enhance segmentation accuracy. Furthermore, some researchers have delved into semi-supervised and weakly supervised learning methods, wherein the model is trained using a combination of limited labeled images and unlabeled data. These approaches prove beneficial in mitigating the constraints posed by limited datasets, ultimately contributing to the improved accuracy of post-operative brain MRI segmentation.

4. METHODS

The postoperative brain MRI segmentation pipeline involves data preprocessing, data augmentation, model training, and validation of segmentation result [23]. This study aims to contribute to the progress of this field by providing a comprehensive overview of the pipeline and utilizing state-of-the-art deep learning methods. The stages in postoperative brain MRI segmentation typically include the following: data pre-processing: pre-process the MRI images by normalizing the intensity levels, cropping, and resizing to a standard size. According to researchers [24], [25]: to increase the diversity of the training data, perform data augmentation techniques such as random rotation, flipping, zooming, and elastic deformation. Network architecture: choose an appropriate deep learning architecture, such as U-Net, V-Net, or 3D-CNN, depending on the task and available data. Training: train the network on the pre-processed and augmented data using a loss function, such as dice or cross-entropy loss, and an optimizer, such as Adam or SGD [26]–[28]. Validation: validate the trained model on a separate dataset to evaluate its performance and optimize the hyperparameters if necessary.

Post-processing: apply post-processing techniques such as morphological operations, connected component analysis, and region growing to refine the segmentation and remove false positives. Evaluation: evaluate the performance of the segmentation model using quantitative metrics such as dice score, sensitivity, and specificity. Figure 1 illustrates a general pipeline for postoperative brain MRI segmentation utilizing deep learning methods.

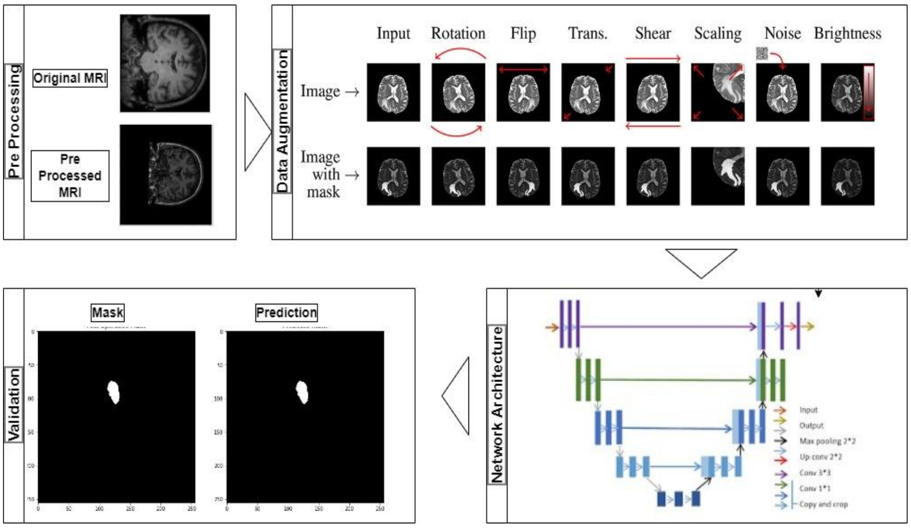

Figure 1. A general pipeline for postoperative brain MRI segmentation using deep learning methods

4.1. Data pre-processing

Data preprocessing is essential in analyzing post-operative brain MRI datasets, encompassing techniques like brain extraction, resampling, and image enhancement. Ghaffari *et al.* [8] converted digital imaging and communications in medicine (DICOM) to NIfTI, generating segmentation masks and aligning images with the brain tumor image segmentation benchmark (BraTS) dataset. Lotan *et al*. [26] used co-registration, skull-stripping, and intensity normalization. Arnold *et al*. [23] manually segmented resection sites, normalized 3D images, and saved 2D slices for training. Billardello *et al*. [27] co-registered images, converted postoperative data, and applied free surfer for brain mask extraction. Research gaps persist, notably in the need for robust, automated skull-stripping methods, particularly when tumors are close to the skull. Additionally, optimizing segmentation pipelines remains an area for exploration. These improvements would enhance efficiency, automation, and analysis, providing a better understanding of surgical interventions and improving patient care.

4.2. Data augmentation

Post-operative brain MRI segmentation benefits from essential data augmentation techniques [28], [29], including rotations, translations, scaling, flipping, and intensity variations. Advanced methods like elastic deformations, non-linear transformations, and generative models further enhance segmentation accuracy. Ghaffari *et al.* [8] employed random rotation, scaling, mirroring, and registration-based augmentation using healthy subjects. Gazit *et al.* [30] applied intensity normalization, random shifting, scaling, and flipping. Lotan *et al.* [26] used flipping and random volume shifting and scaling. These techniques diversify the training dataset, improving model performance and generalization. Pérez-García *et al.* [22] utilized TorchIO transforms, enhancing robustness through random sampling, flipping, and cropping.

4.3. Postoperative cavity segmentation: state-of-the-art techniques

In the field of postoperative brain MRI segmentation, only limited works contributed to advancements in the field. Table 1 shows the major contributions to the field of postoperative brain MRI segmentation. It is important to acknowledge the efforts made by researchers in pushing the boundaries of postoperative brain MRI segmentation. In 2016, Zeng *et al.* [31] proposed a semiautomatic method called GLISTRboost, which utilized a hybrid generative-discriminative model. This work served as an early milestone in postoperative brain MRI segmentation. In 2018, Jungo *et al.* [32] introduced the fully convolutional DenseNet, a deep learning model specifically designed for segmentation tasks. This model utilized dense connections and convolutional layers to achieve accurate segmentation results.

Table 1. Contributions to the field of postoperative brain MRI segmentation

Authors	Method/model	Dice score
Zeng *et al*. [31]	Semi-automatic hybrid generative-discriminative model	0.82
Jungo *et al*. [32]	Fully convolutional DenseNet	0.81
Chang *et al*. [33]	3D Unet	0.82
Pérez-García *et al*. [22]	Self-supervised 3D CNN	0.79
Lotan *et al*. [26]	Autoencoder regularization–cascaded anisotropic CNN model	0.81
Gazit *et al*. [30]	Neural network Unet (NNUnet)	0.80
Arnold *et al*. [23]	Modified U-Net model	0.84
Ghaffari *et al*. [8]	Transfer learning method	0.83
Helland *et al*. [34]	3D Unet	0.81

The current state-of-the-art segmentation techniques for postoperative MRI can be broadly classified into two categories: manual segmentation and automated segmentation. Manual segmentation involves the manual delineation of the tumor and cavity regions on the MRI images by a radiologist or a neurosurgeon. Although manual segmentation is considered the gold standard, it is time-consuming and subject to inter- and intra-observer variability. Automated segmentation techniques have been developed to overcome the limitations of manual segmentation. Table 2 shows U-Net architectures utilized in post-operative brain MRI segmentation. Each architecture has its own advantages and the selection of a model is based on the specific requirements of the segmentation task and available computational resources.

Table 2. Variants of U-Net models and their hyperparameters in recent research studies

Model	Batch size	Kernel size	Residual blocks	Attention blocks	Dense blocks	Convolutional layers	Drop out rate	Activation function	Optimizer
U-Net [35]–[37]	4	3×3	-	-	-	4	0.2	ReLU	Adam
V-Net [38]	1	3×3×3	-	-	-	5	0.3	LeakyReLU	RMSprop
ResU-Net [39]	4	3×3	6	-	-	4	0.25	ReLU	SGD
Attention U-Net [40]	2	3×3	-	2	-	4	0.1	ReLU	Adam
Dense U-Net [41]	4	3×3	-	-	3	4	0.4	Swish	Adadelta
Dilated U-Net [42], [43]	4	3×3	4	2	3	8	0.3	ReLU	Adam

5. EXPERIMENTAL SETUP AND RESULTS

We evaluated different U-Net models (U-Net, V-Net, ResU-Net, attention U-Net, dense U-Net, and dilated U-Net) [44] on the EPISURG dataset, with 240 samples for training and 20 for testing. Using TensorFlow in the colab pro environment, the training dice scores were: U-Net 0.8150, attention U-Net 0.8534, V-Net 0.7602, ResU-Net 0.7945, dense U-Net 0.83, and dilated U-Net 0.80. To address performance issues, we fine-tuned the best-performing attention U-Net by introducing dilated convolutions and residual connections in the encoder, improving the dice coefficient to 0.87. This highlights the importance of further research in selecting efficient models, retraining layers with extensive image data, and fine-tuning parameters for enhanced feature extraction. Table 3 and Figure 2 present architectural details and training dice scores for various models and the fine-tuned attention U-Net.

Table 3. Training dice score of various U-Net models in post operative cavity segmentation context

Model	Dice score
U-Net	0.81
Attention U-Net	0.85
V-Net	0.76
ResU-Net	0.79
Dense U-Net	0.83
Dilated U-Net	0.80
Fine-tuned attention U-Net	0.87

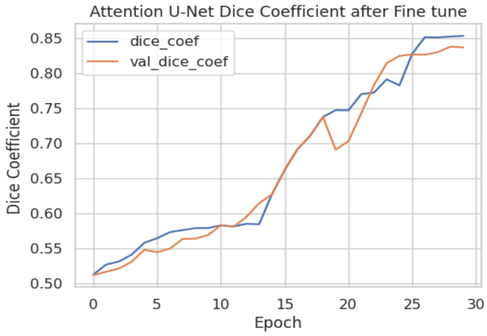

Figure 2. Training and validation dice scores of fine-tuned attention U-Net model

In summary, this study emphasizes key findings: larger datasets enhance model robustness and generalizability, ensuring consistent performance across various scenarios. Fine-tuning, as demonstrated by Pérez-García *et al.* [22] is a valuable strategy for tailoring segmentation models to specific nuances, optimizing their performance for targeted applications. While the insights from discussed studies are invaluable, it's essential to acknowledge limitations, including dataset-specific biases, the need for standardized evaluation metrics, and challenges with model interpretability. The study underscores the transformative impact of deep learning on RC segmentation in postoperative brain MRI scans.

6. CONCLUSION

In conclusion, this study underscores the significance of postoperative brain MRI in assessing tumor resection and monitoring surgical outcomes. The challenges in segmenting surgical cavities, attributed to artifacts and tissue reorganization, are addressed through an exploration of advancements in postoperative brain MRI segmentation. The analysis focuses on various U-Net models, including U-Net, V-Net, ResU-Net, attention U-Net, dense U-Net, and dilated U-Net, utilizing the EPISURG dataset. Training dice scores reveal the performance of each model, with attention U-Net emerging as the best-performing model with a score of 0.8534. The study proposes a fine-tuning approach for further enhancement, incorporating dilated convolutions and residual connections into the attention U-Net model. This refinement yields a dice coefficient of 0.87, emphasizing the potential for improvement through architectural modifications. The study addresses challenges related to limited annotated training data, recommending the use of data augmentation techniques to overcome scarcity. Future research directions should prioritize the utilization of pre-trained encoders and transfer learning techniques to further improve post-operative segmentation accuracy and, consequently, advance the field of neurosurgery for the benefit of patient outcomes.

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