SEGMENTATION OF BRAIN TUMOR FROM MRI IMAGES USING MACHINE LEARNING TECHNIQUES

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Abstract:
Detecting and classifying brain tumors is a critical and time-consuming task for medical professionals. To expedite this process and ensure accuracy, we explored the application of advanced technology, specifically deep learning models, for medical image segmentation. Our focus was on identifying a robust model for brain tumor segmentation using a public MRI imaging dataset consisting of 3064 TI-weighted images from 233 patients with meningioma, glioma, and pituitary tumors. In our study, we meticulously converted and pre-processed the dataset before delving into the methodology. We implemented and trained well-established image segmentation deep learning models, including U-Net, Attention U-Net with various backbones, Deep Residual U-Net, ResUnet++, and Recurrent Residual U-Net. We varied the parameters based on our comprehensive review of the literature on human brain tumor classification and segmentation. the applied approaches, the recurrent residual U-Net utilizing the Adam optimizer achieved a Mean Intersection Over Union of 0.8665. This model outperformed other state-of-the-art deep learning models in terms of accuracy. Visual findings showcased remarkable results in brain tumor segmentation from MRI scans, highlighting the algorithm's potential to automatically extract brain cancers and assist physicians in serving humanity more effectively. The efficiency of this approach offers promising implications for expediting diagnosis and treatment planning in the realm of neuro-oncology.

Keywords: Image Segmentation, Brain Tumor, MRI scans, Convolutional Neural Network, U-Net, Attention mechanism, Residual U-Net.

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1. Introduction

The abnormal growth of cells within the closed space of the human skull, which poses potential risks and complications, is referred to as a "brain tumor." Brain tumors are either benign or malignant. The malignant tumors initiate from cancer in different parts of the body and spread to the brain. Imaging tests, especially magnetic resonance imaging (MRI), assume a significant part in recognizing essential and optional growths. The capacity of MR imaging to produce accurate images through the utilization of magnetic fields makes it an ideal strategy for recognizing and diagnosing brain tumors also outperforming the accuracy of X-rays and CT scans. The study utilized a dataset consisting of TI-weighted MRI scans of patients who were afflicted with three kinds of brain tumors in order to address this diagnostic challenge, namely meningioma, glioma, and pituitary tumors. Utilizing the power of deep learning, a subset of AI, our methodology planned to process the vast information in MRI images for productive brain tumor recognition proof.

Deep learning methods, like Convolutional Neural Networks and U-Net, have essentially progressed clinical image segmentation, stressing the conservation and speculation of locations of Interest. The goal of our research is to use these methods to segment MRI images of the brain in order to locate and identify brain tumors more quickly and precisely.

The primary goals of our investigation are as per the following:

a) Execution of deep learning techniques for MRI image segmentation, improving prediction abilities.
b) Investigation and evaluation of cutting-edge deep learning segmentation techniques customized for brain tumors.

In the end, our research aims to make it easier for medical professionals to make quick and accurate decisions, allowing them to diagnose and locate brain tumors more quickly. The better accuracy obtained by these techniques can essentially influence patient results, particularly in complex situations where experienced clinical work force are expected to evaluate growth areas, contrast impacted tissues and adjoining areas, and convey definitive results.

2. Literature review

In recent investigations focused on the application of deep learning techniques for tumor detection in medical imaging, researchers have explored a variety of methodologies and models. Javaria Amin et al. conducted a comprehensive overview of current deep learning techniques employed in tumor detection, emphasizing the significance of choosing appropriate segmentation methods based on distinct imaging modalities such as MRIs, CT scans, and PET scans. This exploration led to the selection of MRI data for our research, with a preference for deep learning models like U-Net and its variants for optimal accuracy.

Getty N. et al. took a unique approach by reconstructing the network architecture, refining model parameters, and preprocessing MRI tumor images. While segmentation was deemed unnecessary for tumor type identification, the challenge of manually segmenting tumors for localization and description persisted. Meanwhile, BrainMRNet, developed by Toğaçar et al., introduced a deep learning model for mass detection in MRI scans, accompanied by a segmentation technique to identify specific brain lobes with concentrated tumor classes.

Gunasekara SR et al. proposed an end-to-end systematic method for MRI-based tumor segmentation and detection of meningiomas and gliomas. Their approach integrated a CNN algorithm for tumor classification, a Faster R-CNN network for localization, and the Chan-Vese algorithm for precise tumor segmentation, creating a cascade of algorithms. Suneetha and Rani presented an innovative method for early brain tumor detection involving pre-processing with the Optimized Kernel Probabilistic K-means method and image enhancement using an adaptive Double Window Modified Trimmed Mean Filter.

Kadkhodai et al. developed an image-enhancing model using 3D super voxels for segmentation, incorporating saliency detection-based features and edge-aware filtering techniques. Thaha et al. proposed the Enhanced Convolutional Neural Network (ECNN) with the BAT algorithm as the loss function, aiming for optimization-based segmentations through the use of small kernels and deep architectural design.

Ronneberger et al. introduced a symmetric architecture with contracting and expanding paths, winning the 2015 ISBI Cell Tracking Challenge in certain categories. Oktay et al. combined the attention gate model with the U-Net architecture, demonstrating improved efficiency and accuracy across diverse datasets. Zhang et al. recommended the use of ResUnet, a neural network for semantic segmentation blending residual learning with U-

Net, offering advantages in deep network training and information flow.

In addressing the challenge of distinguishing healthy cells from tumor boundaries in brain tumor diagnosis, Zeineldin et al. developed DeepSeg, an interactive decoupling framework utilizing a convolutional neural network for spatial information processing. Various CNN models, including DenseNet, NASNet, and ResNet, were explored in this study.

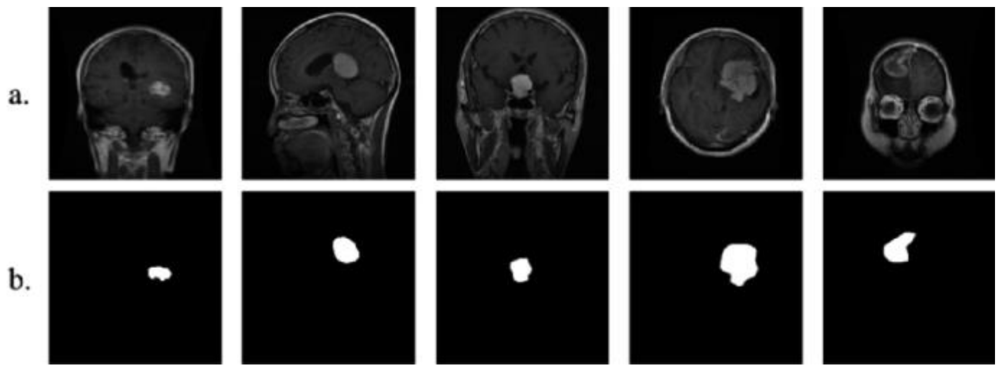
For colonoscopic image segmentation, Jha et al. introduced ResUNet++, an enhanced architecture incorporating residual blocks, attention mechanisms, Atrous Spatial Pyramidal Pooling, and squeeze and excitation blocks. Md Zahangir Alom et al. proposed models utilizing Residual and Recurrent Networks, and U-Net, emphasizing benefits such as enhanced feature representation, improved segmentation performance, and efficient training with the same network parameters in medical image segmentation tasks. These diverse approaches showcase the evolving landscape of deep learning applications in medical imaging for tumor detection and segmentation.

3. Methodology

The acquired images are divided into distinct datasets for training, validation, and testing purposes following the preprocessing phase. Using the allotted training and validation data, the model is trained once the appropriate hyperparameters have been found. Based on the validation dataset's inference results, the model's performance can be evaluated to determine which coefficients produce the best training results. After that, the model with these ideal coefficients is saved for later use. The saved model is then used to draw inferences from the testing dataset. To survey the viability of the model, a thorough examination between various strategies is embraced, using different measurements. This assessment gives experiences into the qualities and shortcomings of each methodology, working with a nuanced comprehension of their presentation with regards to the particular main job.

3.1 Image Dataset

This study's brain T1-weighted contrast-enhanced MRI dataset, which spans the years 2005 to 2010, was obtained from Tianjing Medical University and Nanfang Hospital in Guangzhou, China. The collection, which includes 3064 T1-weighted, contrast-enhanced images from 233 patients, includes 708 meningiomas, 1426 gliomas, and 930 pituitary tumors, as shown in Fig. 1. The dataset incorporates fundamental information fields, for example, cancer name, patient ID, picture information, as well as growth limit and cover information. A crucial preprocessing stage was carried out so that the data could be used effectively in a Python environment. This made sure that the analyses and model training that came after would be compatible with one another and work seamlessly together.



In the preprocessing stage, the underlying step included changing over the MATLAB-design records containing the brain T1-weighted contrast-enhanced MRI dataset. This change is planned to normalize the information as images, working with proficient use without the requirement for tedious stacking of each mat file and upgrading memory utilization. Utilizing the SciPy module, documents with the "mat" extension were imported as word references, uncovering fundamental information fields, for example, growth mark, patient ID, picture information addressed as grayscale values with three channels, cancer limit directions, and cancer veil information. The extracted mask and image data were then normalized between 0 and 1 and put into NumPy arrays. The OpenCV module was utilized to store the handled pictures in "png" design, accordingly ordering them into preparing (2485 cases), approval (274 occasions), and test (305 occurrences) sets.

The ensuing use of the U-Net engineering, initially intended for image segmentation, proved to be instrumental in biomedical image investigation where the objective stretches out past order to exact localization of the anomaly. The innovative feature of U-Net is its expanding path, in which feature maps are upsampled and concatenated with corresponding feature maps from the contracting path, allowing skip connections to direct the flow of high-resolution data to the decoder. This plan has exhibited better performance in correlation than prior procedures, offering straightforwardness and effectiveness in start to finish formulations.

Further improving U-Net, the attention component was consolidated in the Consideration U-Net. This system mirrors human mental cycles, permitting the model to focus on pertinent cases while overlooking immaterial basis data. By selectively focusing on relevant stimuli and suppressing responses in unrelated areas, the attention gate, which is incorporated into the skip connection within U-Net, enhances spatial information and ensures more accurate image classification.

The ResUnet model combined the advantages of deep residual learning with U-Net architecture to address issues with training very deep architectures. The incorporation of residual blocks worked with efficient training. By incorporating squeeze and excitation blocks, attention blocks, and Atrous Spatial Pyramidal Pooling, ResUnet++ extended this strategy to further enhance the model's capacity to identify crucial features and enhance segmentation accuracy.

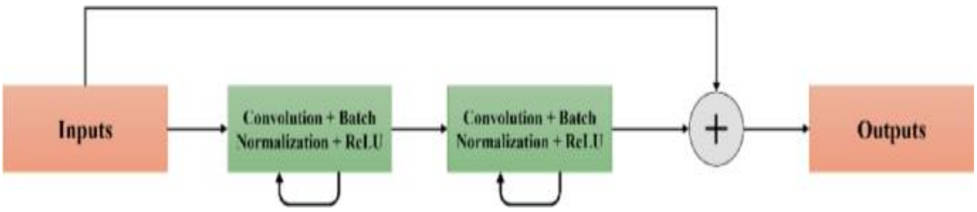


Fig -2

Over deep networks, the residual unit incorporates long/short skip connections to help prevent performance degradation, and the recurrent unit can withhold reasonable dependencies between pixel values by taking contextual data into account. In lieu of conventional forward convolutional layers, recurrent convolutional layers (RCLs) with residual units are utilized in the blocks of the encoder and decoder, assisting in the development of a deeper and more efficient model. This division approach shows the productivity of element collection from one piece of the organization to another and shows benefits for both preparation and testing stages

The Repetitive Remaining U-Net (R2Unet) acquainted repetitive convolutions with the U-Net design, consolidating leftover units and repetitive convolutional layers in both the encoder and decoder blocks. This reconciliation worked on the model's ability to incorporate setting data, improve include portrayal, and gather data successfully across the organization. The division approach exhibited the upsides of element amassing, showing benefits in both the preparation and testing stages.

4. Result

This study presents the foundation for segmenting and identifying tumors in medical images, particularly solid-structure tumors, such as those seen in MRI images. The grayscale image object recognition and segmentation framework are thought to be useful in a variety of medical situations. The essential test in conveying deep learning advances in medicine rotates around the size of the accessible dataset for preparing and approving convolutional neural networks (CNNs). The most recent version of the BraTS dataset, which includes 335 MRI images with annotations and includes MRI scans of brain tumors (BTs) from various institutions, is a useful resource for algorithm development and evaluation. This dataset has turned into a benchmark for making and surveying calculations intended for BT division and finding. The development and evaluation of BT segmentation and diagnosis algorithms frequently make use of the various modalities found in the BraTS dataset, such as FLAIR, T1-weighted, and T2-weighted images.

The execution of a deep convolutional neural network (DCNN) explicitly targets brain tumor segmentation. The Adam optimizer and a categorical cross-entropy loss function are used in the training process. The spatial dimensions of the feature maps are effectively reduced by concatenating feature maps from multiple convolutional layers and passing them through a series of Conv2D and MaxPooling2D layers. With a notable validation accuracy of 98%, the proposed model architecture demonstrates its ability to distinguish BTs within the BraTS dataset.

An ROC (Receiver Operating Characteristic) curve is used as a binary classifier to distinguish between tumors and non-tumors in the performance evaluation of the developed model. The True Positive Rate (TPR) and False Positive Rate (FPR) are compared using the ROC curve for various threshold values. The ROC curve provides insight into the classifier's ability to distinguish between patients with and without tumors in the context of BT segmentation. An ideal tumor classifier has a TPR between 1 and 0, and the curve closely follows the plot's top-left corner. The TPR is addressed on the y-pivot, while the FPR is addressed on the x-hub.

The CNN model achieved the highest accuracy, nearly 98%, when compared to the other two learning strategies. Performance differences between studies may be caused by factors like the size of the training dataset, the preprocessing methods used, and the specific implementation details of the models.

5. Conclusion

The possibility of computer-aided detection has come forth as a more accessible solution to the difficulties of detecting tumors through costly and specialized imaging procedures. The emphasis is on distinguishing a reasonable model for detecting tumors from MRI images, and the discoveries uncover that an encoder-decoder based Convolutional Neural Network (CNN) technique, improved with Recurrent and Residual units and prepared on a dataset of brain tumor MRI images utilizing the Adam enhancer, accomplishes remarkable results. Specifically, the proposed model outperforms other benchmarked models like U-Net, Attention U-Net, and various deep Residual U-Net variants with an F1 score of 0.8495 and an Intersection over Union (IoU) of 0.8665. The qualitative results show that these algorithms can ease the burden on healthcare professionals, make MRI scans more accessible, and cut costs by performing consistently across a variety of representations. Prominently, the study features the meaning of residual blocks in relieving the vanishing gradient issue, and the attention mechanism's part in zeroing in on significant elements for division. The study suggests that experimenting with various preprocessing techniques and incorporating larger and more diverse datasets can further enhance accuracy. Progressing endeavors likewise include investigating elective designs to connect the semantic gap among encoder and decoder feature maps, integrating dense skip connections with improved gradient flow. Through these combined undertakings, the point is to foster a deeply precise model for tumor segmentation, in this manner propelling the viability and openness of medical services provisions.

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