COMP 448/548 – MEDICAL IMAGE ANALYSIS

SURVEY

BRAIN TUMOR SEGMENTATION

Brain tumor segmentation is a crucial task in medical imaging. In this task, the main goal is to accurately identify tumor tissue within MRI brain scans. This process is vital for diagnosing brain tumors, planning treatments, and monitoring their progression over time. The challenge lies in analyzing high-resolution MRI images to distinguish tumor-like areas from normal brain tissue. This step often requires classifying each small part of the image. Because brain tumors can vary widely in appearance and may look different across patients or even in different scans of the same patient, and this situation makes the task very complex. Effective segmentation not only aids in precisely picturing tumor boundaries for surgical and rehabilitative planning, but also ensures that treatments are specially targeted and appropriate, addressing the specific needs of each patient.

As mentioned above, brain tumors represent a significant medical challenge due to their varied morphology and complex treatment requirements. Traditional diagnostic methods often fall short in offering the precision necessary for optimal treatment planning. The advancement in deep learning methods has brought significant improvements in the detection and definition of brain tumors.

Group 1: Convolutional Neural Network (CNN) Architectures

A Deep Learning Approach for Brain Tumor Classification and Segmentation using a Multiscale CNN [5] implements a multiscale CNN architecture. This setup is designed to handle the segmentation and classification of brain tumors by processing MRI images at various scales with kernel sizes of 11x11, 7x7, and 3x3, classifying each pixel using a sliding window size of 65x65. This method ensures that the model attentively captures features from very fine to coarse resolutions. The direct integration of multiscale processing allows the model to effectively manage the diversity in tumor appearances and sizes. This approach makes it highly effective for both classifying and segmenting tumors based on their unique characteristics. Capturing multiscale features also makes possible the simultaneous implementation of multi-tasks, such as classification and segmentation. Unlike this paper, the second and third papers implement a single pathway with fixed-size kernels.

An Improved Framework for Brain Tumor Analysis Using MRI Based On YOLOv2 and CNN [6] combines the detection capabilities of YOLOv2 with the detailed segmentation and classification abilities of CNNs. The method implemented in this paper relies on the robust detection capabilities of YOLOv2 to handle various tumor sizes quickly localizing the regions of interest across the entire image. The regions of interest are then processed by the CNN architecture for a detailed analysis of the localized regions. This approach prioritizes speed and localization accuracy.

DeepSeg: Deep Neural Network framework [2] implements a U-Net architecture powered by various advanced CNN models like VGGNet, ResNet, DenseNet, Xception, and MobileNet. The goal in this approach is to exploit the architectural strengths of these models to boost the feature extraction phase of the segmentation process. While it benefits from the multiscale capabilities of U-Net and the depth of feature extraction from integrating various models, it does have the dedicated multi-pathway implementation for processing the data. Although this paper also focuses on multi-scale feature extraction, it achieves this by integrating various CNN models instead of implementing different scales of kernel sizes like the first paper.

Group 2: Integration of Advanced Methodologies

The second group includes studies that implement advanced methodologies such as attention mechanisms and multi-task learning frameworks to fulfill the segmentation process.

Compared to the papers in Group 1, this paper has a different approach in terms of capturing feature information from the data. Instead of using various kernel size or different combinations of CNN models, **Brain Tumor Segmentation Based on Deep Learning [2]** focuses on enhancing segmentation accuracy by implementing an attention mechanism. The main contribution in this paper is the use of attention mechanism to selectively concentrate on significant areas of multi-model MRI images, such as different types of brain scans like T1, T2, FLAIR, etc. This method improves the model's ability to realize difficult-to-perceive differences and similarities across various modalities. The attention mechanism makes it possible for the network to dynamically focus on the most relevant features of the input data.

One-pass Multi-task Networks [8] implements a multi-task learning model that combines cross-task guided attention mechanism. This is achieved through simplifying the process by handling multiple segmentation tasks within a single pass through the network. The contribution in this paper is the use of guided attention to enhance the performance across these tasks by defining inter-task relationships. This approach not only improves efficiency but also enhances accuracy by ensuring that the learning process is mutually beneficial across different but related segmentation tasks. This cross-task guided attention mechanism helps the network adjust its focus based on its relevance across multi-tasks.

Group 3: Autoencoder Based Architecture

3D MRI Brain Tumor Segmentation [7] implements an encoder-decoder architecture adapted from traditional autoencoders to segment tumors from 3D MRI scans. The model uses a CNN architecture with an asymmetrically designed encoder and decoder. The encoder is more complex than the decoder, so it can extract more complex features from the MRI images before down-sampling them to a lower-dimensional space for segmentation. The encoder part of the architecture implements ResNet block with group normalization and ReLu activation. The decoder part of the architecture mirrors the encoder in structure but mainly focuses on progressively upsizing the feature maps back to the original size using bilinear up-sampling and 1x1x1 convolutions. Due to the small size of the training dataset, the approach in this study adds a variational auto-encoder branch to reconstruct the input image itself. This helps to regularize the shared encoder and impose additional constraints on its layers. It ensures that the model learns robust features.

Group 4: Machine Learning Based Models

Brain Tumor Segmentation Using Machine Learning Classifier [1] implements a combination of image processing techniques, such as contrast enhancement, double thresholding, morphological operations) to preprocess the images before segmentation. This contrasts with the other papers mentioned above which use more direct or partially preprocessing methods tied into their deep learning architectures. In this study, feature extraction is performed using the Gray-Level Co-occurrence Matrix. This is a statistical method of examining texture that takes the spatial relationship of pixel into account. Considering the deep learning-based models, this method differs from the deep learning approaches that automatically learn features from raw data. In the segmentation part, this paper implements a triple technique combining K-means clustering, K-Nearest Neighbors, and Fuzzy C-means clustering for segmentation. The use of traditional clustering and segmentation methods mainly focuses on interpretability and simplicity in model design.

Brain Tumor Segmentation using Community Detection Algorithm [4] implements a method related to graph theory.

The segmentation process is approached by first converting the image into a graph of super-pixels. Super-pixels are essentially clusters of pixels that naturally share similar color, intensity, or texture information. This method significantly reduces the dimensionality and computational load. In this way, super-pixels serve as a more manageable, summarized representation of the original data. Community detection algorithms are mainly used in social networks. This algorithm's goal is to find clusters of nodes that are more densely connected internally. For an image segmentation task, this situation means identifying groups of super-pixels that together infer a distinct region of the image, such as a tumor.

Conclusion:

While the segmentation techniques across the eight studies above may show similarities, each paper distinctly diverges in its approach to feature extraction. The six papers focusing on deep learning implement CNNs to automatically gather feature maps from raw MRI data. These papers incorporate innovations like multi-scale processing to capture feature maps at various resolutions and auto-encoders to improve model generalization. Conversely, the two papers focusing on machine learning methods approach feature extraction traditionally. One of these papers implements community detection algorithm to group super-pixels based on their structural similarities. The other one implements classical clustering algorithms combining K-means clustering, K-Nearest Neighbors, and Fuzzy C-means clustering to features obtained from image processing.

References

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