Medical Image Segmentation with Graph Reasoning

Di Zhao, Yi Tang, Dmitry Pertsau, Dziana Kupryianava and Alevtina Gourinovitch

Belarusian State University of Informatics and Radioelectronics, Minsk, Belarus,
3189124246@qq.com

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This paper introduces a novel Synergistic Edge-Guided Graph Reasoning Network (SEGRNet) designed to address the limitations of traditional Convolutional Neural Networks (CNNs) in medical image segmentation, particularly in capturing global information and modeling complex topological relationships. Existing CNN-based methods, such as U-Net and its variants, suffer from limited receptive fields, hindering their ability to capture comprehensive global context, especially in structurally complex biological tissues. To overcome these challenges, SEGRNet incorporates Graph Convolutional Networks (GCNs) to leverage the feature extraction strengths of CNNs with GCNs' capability to model graph structures. Specifically, SEGRNet utilizes Res2Net50 as the backbone and integrates an edge-guided module and a region-guided module to process low-level edge features and high-level semantic features.

The core of the SEGRNet architecture is its Synergistic Edge-Guided Graph Reasoning (SEGR) module, which enhances the model's ability to perform cohesive and adaptive reasoning across edge and region features. This is achieved through a three-step graph reasoning process: projection, interaction, and reverse projection, allowing the model to capture both local and global dependencies, significantly improving segmentation accuracy.

Experiments were conducted on the Low-Grade Glioma (LGG) dataset, sourced from the National Cancer Institute's Cancer Imaging Archive. The results demonstrate that SEGRNet consistently outperforms state-of-the-art methods across multiple evaluation metrics. Specifically, SEGRNet achieves a mean Dice coefficient (mDice) of 0.849, mean Intersection over Union (mIoU) of 0.760, S-Measure of 0.904, F-Measure of 0.856, and E-Measure of 0.962. These results surpass competing models such as ResUnet++ and PraNet, with significant improvements in mIoU, which is essential for evaluating the overlap between predicted and ground truth segmentations. Future work will focus on optimizing the model's computational efficiency and expanding its applicability to other datasets to further enhance its generalization and robustness.

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