Topic: Effective Disjoint Representational Learning: A Systematic Investigation of Multi-Decoder Networks and Parameter Sharing Strategies for Anatomical Segmentation

Accurate segmentation of anatomical structures during laparoscopic surgery is vital for computer-assisted interventions and surgical navigation. However, challenges persist in segmenting smaller structures due to their size and visual indistinctiveness. Despite advancements in deep learning-based medical image segmentation, as demonstrated by [1], [2], achieving real-time performance without sacrificing segmentation accuracy remains an open problem. Furthermore, [3] highlights the potential of transferring learning from binary to multi-class segmentation, but this approach requires further exploration to enhance its utility. The Dresden Surgical Abdominal Dataset (DSAD) [4], offering comprehensive annotations for eleven anatomical structures, provides a robust platform to investigate these challenges. Existing methods often treat multi-organ segmentation as a monolithic task, potentially overlooking organ-specific features that could improve accuracy.

This thesis seeks to explore architectural strategies for multi-organ segmentation in laparoscopic surgery. Specifically, it aims to:

1. Investigate the impact of parameter-sharing strategies in multi-decoder networks.
2. Develop attention mechanisms tailored to enhance segmentation accuracy, particularly for smaller anatomical structures.
3. Design computationally efficient architectures capable of real-time performance.

To address these objectives, the thesis will involve:

1. **Literature Review:** Analyze existing deep learning approaches in medical image segmentation, focusing on parameter-sharing strategies and attention mechanisms.
2. **Baseline Development:** Implement and evaluate baseline architectures such as DeepLab, Seg-Former, U-Nets as well as attention-enhanced variants.
3. **Dataset Preparation:** Prepare and preprocess the DSAD dataset, including data augmentation pipelines and standardized evaluation protocols.
4. **Architecture Design:** Develop and test novel parameter-sharing strategies in multi-decoder networks.
5. **Training Frameworks:** Build training frameworks incorporating specialized loss functions and optimization strategies for various architectural variants.
6. **Evaluation:** Quantitatively evaluate models using standard metrics like DICE and IoU while analyzing computational efficiency and runtime performance.
7. **Documentation and Thesis Writing**

This research will yield a comprehensive evaluation of multi-decoder architectures and parameter-sharing strategies for surgical organ segmentation. Key outcomes include:

1. Development of novel architectural designs that balance segmentation accuracy and computational efficiency.
2. Insights into the role of attention mechanisms in improving segmentation performance, especially for smaller structures.
3. A foundational framework that can be extended for real-time segmentation in surgical settings.

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