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Title	医療画像分割の向上:モデルの精度、プライバシー、および効率に関する研究
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Abstract

Medical image segmentation plays a crucial role in quantifying diseases, assessing prognosis, and evaluating treatment results. However, manual segmentation is time-consuming, prone to interobserver variability, and limited by the availability of skilled experts. Despite advances in deep learning-based approaches for automatic segmentation, challenges such as precise boundary delineation, limited annotated data, and the trade-off between model complexity and performance persist. In addition, data privacy concerns hinder the sharing of medical images between institutions, preventing collaborative research and model development.

This dissertation focuses on improving medical image segmentation by addressing three key aspects: model accuracy, data privacy, and computational efficiency. This dissertation proposes novel deep learning architectures and techniques that leverage the power of attention mechanisms, transformer models, federated learning, and knowledge distillation to tackle these challenges.

Firstly, this dissertation introduce DA-TransUNet, a dual attention transformer U-Net architecture that integrates spatial and channel attention mechanisms with transformer models. DA-TransUNet effectively captures fine-grained details and long-range dependencies in medical images, leading to improved segmentation accuracy compared to state-of-the-art methods.

Secondly, this dissertation proposes MIPC-Net, a mutual inclusion mechanism for precise boundary segmentation. MIPC-Net uses complementary information from position and channel features to enhance the delineation of complex anatomical structures and small lesions, resulting in a more accurate boundary segmentation.

Thirdly, this thesis introduces FKD-Med, a framework for medical image segmentation that prioritizes privacy and optimizes communication. FKD-Med integrates federated learning and knowledge distillation techniques to enable collaborative model training between multiple institutions while preserving data privacy. It also improves model efficiency by distilling knowledge from complex models to lighter ones, reducing computational requirements without compromising segmentation performance.

Extensive experiments on multiple benchmark datasets demonstrate the superior performance of the proposed methods and frameworks in terms of segmentation accuracy, boundary precision, and computational efficiency. The contributions of this dissertation advance the field of medical image segmentation by proposing novel architectures, mechanisms, and frameworks that address key challenges related to model accuracy, data privacy, and computational efficiency.

Future research directions include exploring additional attention mechanisms and transformer variants, extending the proposed methods to 3D and volumetric segmentation tasks, integrating differential privacy techniques for enhanced data protection, developing advanced model compression and acceleration techniques, investigating the generalizability and transferability of the proposed approaches to different medical imaging modalities and anatomical regions, and improving the interpretability and explainability of the segmentation models.

By advancing the state-of-the-art in medical image segmentation, this dissertation contributes to the development of accurate, privacy-preserving, and efficient segmentation models that can be seamlessly integrated into clinical workflows, ultimately improving patient care through more precise diagnosis, treatment planning, and monitoring of various diseases and conditions.

Keywords: Medical Image Segmentation, Dual Attention, Mutual Inclusion, Federated Learning, Knowledge Distillation.