The Chinese University of Hong Kong
Department of Biomedical Engineering

Graduate Seminar – PhD Oral Defence

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Date	***:***	10 December 2025 (Wednesday)
Time	***:***	9:30 am
Venue	***:***	Room 1122, William M W Mong Engineering Building, CUHK

Title: Efficient Deep Learning for Medical Image Segmentation: Weak Supervision, Source-Free Domain Adaptation, and Hybrid CNN-Mamba Architectures

Advancing accurate medical image segmentation remains challenging due to two fundamental constraints: the scarcity of high-quality annotations and the presence of domain shifts across scanners, protocols, and clinical sites. Conventional fully supervised deep learning systems rely heavily on dense pixel-level labels, which are costly, time-consuming, and sometimes impractical in clinical workflows. Moreover, models trained on one dataset often degrade significantly when applied to another domain due to variations in contrast, noise, and anatomical appearance.

This thesis presents a unified and data-efficient learning framework that integrates weak supervision, semi-supervision, and source-free domain adaptation to reduce annotation burden while preserving accuracy and generalizability. The proposed methods address key bottlenecks such as local label noise, class confusion, low boundary fidelity, and cross-domain performance degradation, offering a scalable and clinically feasible solution for real-world medical imaging. To overcome domain dependence without requiring source data, the thesis introduces Superpixel-guided Class-level Denoised self-training (SCD), which refines pseudo-labels using superpixel-level structural priors and achieves robust cross-domain segmentation under the source-free setting. For sparsely labeled scenarios, SC-Net leverages superpixel-guided scribble propagation and class-wise contrastive regularization to improve segmentation accuracy using only minimal scribble annotations. Boundary accuracy under weak supervision is further enhanced through BD-Net, which integrates Boundary-Enhanced Modules and Density-Guided Contrastive Regularization to produce sharper and more reliable anatomical contours. Additionally, Visual Mamba-CNN combines CNNs with long-range dependency modeling to segment complex Photoacoustic Tomography images using synthetic data generated from MRI. For 3D Gross Tumor Volume segmentation in lung cancer, GM-Net employs a dual-encoder design to better capture tumor texture, boundaries, and spatial context. Collectively, these innovations form a comprehensive framework that significantly reduces annotation requirements, improves robustness across modalities, and delivers accurate, generalizable segmentation for cardiac MRI, CT, PAT, and lung cancer imaging.

***** ALL ARE WELCOME *****

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