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（博士課程）
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論 文 要 旨

THESIS SUMMARY

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要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

Artificial intelligence (AI), particularly deep learning, has revolutionized numerous fields, including healthcare. The remarkable performance of deep learning models across various tasks largely depends on the availability of large-scale labeled datasets. However, in the healthcare domain, such datasets are often challenging to obtain due to stringent privacy regulations and concerns. To address this issue and leverage data from multiple centers, federated learning (FL) has emerged as a promising solution. FL is a distributed machine learning approach that allows multiple institutions to collaboratively train a global model while ensuring that their data remains securely on-site.

Overall, this thesis makes significant contributions both technically and clinically by addressing critical gaps in federated learning (FL) for medical image analysis. Technically, we developed novel frameworks to tackle key challenges in FL, including annotation efficiency, domain shift, label set mismatch, and privacy preservation. These frameworks integrate active learning, semi-supervised learning, domain generalization, and unlearning techniques to enhance the robustness, efficiency, and security of FL in medical applications. Clinically, our work focuses on practical issues such as reducing the workload of annotation, ensuring model generalization across diverse healthcare settings, and safeguarding patient privacy, thus facilitating the adoption of FL in real-world medical imaging scenarios. Importantly, we highlighted and addressed problems in medical imaging often overlooked by previous studies, such as the impact of label scarcity, non-IID data distributions, and privacy concerns in decentralized settings.

In Chapter 2, we introduced Federated Active Learning (FedAL), a novel FL framework that integrates active learning strategies to optimize annotation efficiency. By utilizing ensemble entropy-based sampling, this approach achieves state-of-the-art performance with up to 50% fewer labeled samples compared to full-data training, all while maintaining patient privacy.

In Chapter 3, we proposed Domain-Generalized Federated Semi-Supervised Learning (FedSemiDG) to address the domain shift problem. This framework combines semisupervised learning with domain generalization techniques, leveraging perturbation-invariant alignment and dual-teacher adaptive pseudo-label refinement to enhance model robustness across unseen domains.

In Chapter 4, we tackled the challenge of label set mismatch with Federated Learning for Label Set Mismatch (FedLSM). This framework employs adaptive aggregation and local training strategies to utilize labeled and unlabeled data effectively, mitigating errors caused by missing labels.

In Chapter 5, we focused on ensuring data privacy through Federated Client Unlearning (FCU). By introducing mechanisms for secure data removal from the global model, including model-contrastive unlearning and frequency-guided memory preservation, this framework enhances compliance with privacy regulations while maintaining model integrity.

These contributions have been extensively validated on diverse real-world medical image datasets, demonstrating their efficacy in improving model performance, enhancing annotation efficiency, and safeguarding patient privacy. This work advances the application of FL in medical imaging, offering solutions to practical challenges encountered in privacy-sensitive healthcare environments.

While the proposed frameworks have shown significant promise, there are several directions for future exploration:

· Advanced Sampling Strategies: Future research could focus on developing adaptive sampling methods to better represent underrepresented classes or rare medical conditions, particularly in long-tailed datasets.

· Robustness to Noisy Data: Addressing noisy labels and data inconsistencies in federated settings remains a critical challenge. Integrating noise-robust learning techniques could further enhance model performance and reliability.

· Expansion to Diverse Modalities: Extending the frameworks to other imaging modalities, such as PET, ultrasound, or multi-modal data, will broaden their applicability to various clinical tasks, including 3D segmentation and multi-organ analysis.

· Strengthening Privacy Mechanisms: Incorporating advanced cryptographic techniques, such as homomorphic encryption or secure multi-party computation, could further reinforce privacy guarantees in FL systems.

Real-world Deployment: Collaborating with healthcare institutions to deploy these frameworks in real-world federated environments is essential. This would enable the assessment of scalability, usability, and adaptability under practical constraints.

· Personalized Federated Learning: Developing personalized FL methods that balance global knowledge with client-specific adaptation could improve local performance while preserving privacy.

· Integration with Clinical Workflows: Enhancing the integration of FL frameworks with existing clinical workflows could facilitate seamless adoption, ensuring that these solutions meet the needs of healthcare professionals effectively.

By addressing these directions, future research can further refine and expand the capabilities of FL in medical imaging, bridging the gap between theoretical advancements and practical implementation in healthcare settings.