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Thesis Outline

Artificial intelligence (AI), particularly deep learning, requires vast amounts of data for effective model training. Recent studies suggest that multi-domain data pooled from various acquisition sites or centers can enhance model performance. However, due to strict data privacy regulations, sharing medical images across sites to build large datasets for model training is often not feasible. Federated learning (FL) offers a promising solution, enabling collaborative model training across healthcare institutions while preserving patient privacy and leveraging diverse datasets critical for robust AI in medical image analysis (MIA). Despite its potential, FL faces several practical challenges in MIA, notably label scarcity, data heterogeneity, and privacy leakage. This thesis addresses these challenges through a series of frameworks designed for the specific requirements of FL in healthcare. First, we investigate active learning (AL) and semi-supervised learning techniques to alleviate label scarcity, facilitating efficient model training under FL when only a small portion of each client's data is labeled. Second, we introduce FedLSM to tackle label set mismatch, a common scenario where each center's annotated data may cover different or even disjoint classes. FedLSM integrates adaptive training and aggregation strategies to effectively utilize unlabeled and partially labeled data, while mitigating errors from missing labels. Finally, we propose Federated Client Unlearning (FCU), a novel approach that ensures clients can remove their data contributions from trained FL models, addressing critical privacy concerns. We evaluate our frameworks on multiple real-world medical image datasets, demonstrating their ability to improve model performance, annotation efficiency, and privacy safeguards in federated healthcare applications.