Collaborative Augmentation and Disentanglement Learning for Semi-Supervised Domain Generalization in Medical Image Segmentation

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ABSTRACT

The rapid growth of medical imaging technologies has significantly enhanced disease diagnosis and treatment planning. However, medical image segmentation models often suffer from performance degradation when deployed across unseen domains due to variations in imaging devices, acquisition protocols, and patient demographics. To address this challenge, the proposed framework titled **"**Collaborative Learning of Augmentation and Disentanglement for Semi-Supervised Domain Generalized Medical Image Segmentation" introduces a unified learning paradigm that integrates collaborative augmentation learning, feature disentanglement, and semi-supervised domain generalization into a single robust architecture. The proposed system aims to improve segmentation accuracy and generalization capability across multiple unseen domains while utilizing limited labeled data. The model leverages a disentangled representation learning strategy that separates domain-invariant content features from domain-specific style features. A shared encoder extracts deep feature representations, which are decomposed into content and style components. The content features are optimized to remain invariant across domains using adversarial domain learning, while style features capture domain-specific variations such as contrast, noise patterns, and imaging artifacts. This separation enables the segmentation network to focus on anatomically relevant structures independent of domain-specific distortions. To further enhance robustness, a collaborative augmentation policy network is integrated into the framework. Instead of relying on manually designed augmentations, the augmentation module learns optimal transformation strengths (e.g., brightness, contrast, blur, noise) in a differentiable manner. This adaptive augmentation strategy works collaboratively with the segmentation network to simulate domain shifts during training, thereby improving the model's ability to generalize to unseen data distributions. Additionally, the framework incorporates semi-supervised learning mechanisms to reduce dependency on large annotated datasets, which are costly and time-consuming to obtain in medical contexts. A combination of supervised segmentation loss, consistency regularization, and pseudo-labeling is employed. The consistency constraint enforces prediction stability across augmented views of unlabeled images, while high-confidence pseudo-labels guide the network in leveraging additional unlabeled samples effectively.Experimental validation using synthetic multi-domain medical imaging data demonstrates that the proposed approach achieves improved Dice similarity and Intersection-over-Union (IoU) scores compared to conventional fully supervised and single-domain training strategies. The integration of augmentation learning, disentangled representation, and domain adversarial training provides enhanced robustness, reduced overfitting, and improved cross-domain adaptability.