Weakly-Supervised and Unsupervised Liver Lesion Detection

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Liver lesions represent abnormal cellular growth occurring within otherwise healthy hepatic tissues. Traditional detection techniques typically employ supervised learning models trained on abnormal datasets (liver images with liver lesions) alongside pixel- or patch-level annotations. Nonetheless, these detailed annotation processes for training datasets are resource-intensive and time-consuming, requiring significant time investment from doctors for accurate labeling. In response to this challenge, recent trends in the field have gravitated toward unsupervised learning techniques, which necessitate only training on normal data (liver images without liver lesions). In the training phase, autoencoders learn the feature distribution of normal data. Subsequently, during the detection phase, abnormal test samples (images with liver lesions) will likely exhibit higher reconstruction errors than normal ones. However, these unsupervised learning methods generally need to improve their generalization ability. Specifically, autoencoders trained solely on normal data sometimes fail to accurately reconstruct unseen abnormal test samples or maintain the finer details of normal test samples, leading to similar reconstruction errors for both normal and abnormal samples, thus decreasing detection precision. We introduce a weakly-supervised learning framework for liver lesion detection to address these shortcomings. 'Weakly-supervised' in this context refers to using image-level annotation data for network training. Our method employs generative adversarial networks (GANs) to learn the feature distribution of both normal and abnormal data during training. Empirical results show that our method outperforms state-of-the-art unsupervised learning techniques regarding accuracy. Nevertheless, while our weakly-supervised approach necessitates training on actual abnormal data, the availability of such data is limited in real-world scenarios. To mitigate this constraint, we propose an unsupervised learning method that employs both normal and synthesized pseudo-anomaly data for training. Moreover, we introduce a discriminator network with a U-Net-like architecture that can extract local and global features, thereby providing the generator with more informative feedback. Further, we suggest a novel reconstruction-error scoring index based on the image gradient perception pyramid, which is superior to the existing mean squire error (MSE) for lesion detection. We conducted extensive experiments across different datasets for liver lesion detection, and our proposed method outperformed other state-of-the-art unsupervised anomaly detection methods, demonstrating its robustness and potential for clinical implementation.