

## A review of research and development of semi-supervised learning strategies for medical image processing

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### Abstract

Accurate and robust segmentation of organs or lesions from medical images plays a vital role in many clinical applications such as diagnosis and treatment planning. With the massive increase in labeled data, deep learning has achieved great success in image segmentation. However, for medical images, the acquisition of labeled data is usually expensive because generating accurate annotations requires expertise and time, especially in 3D images. To reduce the cost of labeling, many approaches have been proposed in recent years to develop a high-performance medical image segmentation model to reduce the labeling data. For example, combining user interaction with deep neural networks to interactively perform image segmentation can reduce the labeling effort. Self-supervised learning methods utilize unlabeled data to train the model in a supervised manner, learn the basics and then perform knowledge transfer. Semi-supervised learning frameworks learn directly from a limited amount of labeled data and a large amount of unlabeled data to get high quality segmentation results. Weakly supervised learning approaches learn image segmentation from borders, graffiti, or image-level labels instead of using pixel-level labeling, which reduces the burden of labeling. However, the performance of weakly supervised learning and self-supervised learning is still limited on medical image segmentation tasks, especially on 3D medical images. In addition to this, a small amount of labeled data and a large amount of unlabeled data are more in line with actual clinical scenarios. Therefore, semi-supervised learning strategies become very important in the field of medical image processing.

**Keywords:** Deep Learning; semi-supervised learning; Medical Image Processing; neural network

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### 1. Introduction

In recent years, various algorithms and methods of machine learning, especially deep learning, have been widely applied in various fields such as computer vision (including object detection, image classification, semantic segmentation, etc.), natural language processing (including text recognition, speech recognition, etc.). Deep learning methods have achieved many milestones in different fields, and these results have improved the state of the art in each field<sup>[1]</sup>. However, these milestones and technical improvements often require large amounts of

labeled data for training. Moreover, most of these methods require that the training data and the test data have the same distribution. In reality, in many application scenarios, large amounts of labeled data are not easily accessible, and it is very expensive and time-consuming to annotate different data for different tasks. This fatal drawback has become a bottleneck limiting the development of supervised learning methods, and makes many models have low generalization ability on different tasks.

Deep learning techniques and deep convolutional networks (CNNs) have been achieving great success for some time in computer-aided therapy including analysis of medical images, medical image segmentation,





















