Medical Image Segmentation Research Status and Development Trends

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Abstract. As one of the important steps in medical image processing, medical image segmentation plays a pivotal role in clinical surgery and is widely used in application scenarios such as preoperative diagnosis, intraoperative navigation, and postoperative evaluation. In this paper, medical image segmentation technology is studied, and a variety of medical image segmentation methods are categorized and compared in an attempt to explore the development law of medical image segmentation technology. Firstly, the medical image segmentation technology is classified and studied according to its different methods, and this paper mainly researches and organizes the deep learning method for medical image segmentation; secondly, the principle, advantages and disadvantages, and applicable scenarios of each model are analyzed; and lastly, the latest progress of the medical image segmentation technology is objectively described. inherent deficiencies and solutions of the existing techniques, and provides a direction for continued improvement in the future. As one of the important steps in medical image processing, medical image segmentation plays a pivotal role in clinical surgery and is widely used in application scenarios such as preoperative diagnosis, intraoperative navigation, and postoperative evaluation. In this paper, we explore the critical role of medical image segmentation in medical image processing, particularly in clinical surgery and its various applications such as preoperative diagnosis, intraoperative navigation, and postoperative evaluation. Our study focuses on categorizing and comparing different medical image segmentation methods, with a special emphasis on deep learning techniques. We delve into the principles, advantages, disadvantages, and suitable scenarios for each model. Additionally, we objectively present the latest progress in medical image segmentation technology, addressing existing deficiencies and proposing potential solutions. This research provides valuable insights to foster continuous advancements in the field.

Keywords: medical image segmentation; deep learning.

1. Introduction

Image segmentation techniques are usually used to determine the boundary range of objects in an image for the purpose of simplifying or changing the expression of image information to make the image easier to understand and analyze. Medical image segmentation is a major application in this field and has a key role in medical diagnosis. Medical image segmentation is to process and analyze certain feature information in an image, which plays an important application in preoperative diagnosis, intraoperative navigation, and postoperative evaluation. Medical image segmentation technology has been developing rapidly in the last 20 years, and it can provide effective and clear insight into the diseased parts of the human body, thus helping clinicians to make diagnosis.

Image segmentation techniques are commonly employed to identify object boundaries within an image, with the aim of simplifying or altering image information expression, thereby enhancing image comprehension and analysis. Among the various applications of image segmentation, medical image segmentation holds a prominent position, playing a critical role in medical diagnosis. This technique involves processing and analyzing specific features within medical images, proving valuable in preoperative diagnosis, intraoperative navigation, and postoperative evaluation. Over the past two decades, medical image segmentation technology has experienced rapid development, enabling clinicians to effectively and clearly discern diseased areas within the human body, thereby facilitating accurate diagnosis.

In the development process of medical image segmentation, numerous segmentation algorithms have been generated, such as: threshold-based segmentation algorithm and region growth-based segmentation algorithm and other traditional. Meanwhile, with the rapid development of computer vision field, deep learning-based segmentation algorithms have been widely studied. Deep learning-based segmentation method is to train a multilayer perceptron to get a linear objective function, and then use the decision function to classify the pixel points. Due to the powerful computational ability of deep learning [1][2]in image processing tasks, applying it to the medical field not only improves the accuracy of image segmentation, but also provides a solid foundation for position detection, segmentation extraction, and 3D reconstruction and display. In the field of medical images, there are numerous methods for image segmentation, such as convolutional neural network (CNN), fully convolutional network (FCN), etc. Due to the ultra-high performance of deep learning, segmentation methods based on deep learning provide a lot of convenience for tasks such as medical image classification, detection, etc., and at the same time, it can easily cope with a variety of medical images in medical image segmentation algorithms.

This study consists of two main parts: Methods and Summary. The methods section describes the main, popular segmentation models used for medical images, along with their advantages and disadvantages. The summary section compares the current medical image segmentation techniques in various application scenarios, outlines the challenges faced by each current method, and also provides an outlook on the field of medical image segmentation.

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2. Medical image modalities

Common medical images include: ultrasound, X-rays, computed tomography, MRI images, and positron emission tomography.

Ultrasound imaging [3][4][5]technology applies high-frequency sound waves (ultrasound) to scan human organs and tissues, so as to obtain information on the internal structure of the human body image, which is widely used in a wide range of medical images of the kidneys, breasts, cardiology, thyroid, liver, blood vessels, musculoskeletal, obstetrics and gynecology, prostate and other medical images It is a very important medical imaging technique. In the meantime, with computer science and technology, 3D ultrasound imaging techniques [6]are gradually coming into the limelight and overcoming the numerous drawbacks of 2D ultrasound imaging.

X-ray imaging utilizes the physical and chemical properties of X-rays, such as penetration and light sensitivity, to examine the internal organs of the human body, and X-ray diagnostic technology is the world's earliest non-invasive internal organ examination technology. Since the density and thickness of human tissues vary, the number of X-rays absorbed by individual tissues that pass through the body may also vary. Therefore, the difference in light intensity can be used to reflect the imaging information of the tissues. Literature [7]X-rays in their largest application: medical diagnostic imaging and image-guided therapy.

The principle of computed tomography imaging is to use X-rays to scan the human body, the detector receives X-rays through the human body and converts them into visible light, which is converted into electrical signals, and then converted into digital signals by analog-to-digital converters and input into the computer for processing. According to different shades of gray reflecting the degree of absorption of X-rays by human organs and tissues, thus displaying the images of human organs and tissues. In order to improve the quality of CT images, the literature [8]has reviewed the reconstruction of CT images, noise in CT images, and CT denoising techniques. CT imaging systems are widely used, especially in the diagnosis of lung diseases [9][10].

MRI images are a powerful non-invasive medical imaging diagnostic technique [11], which visualizes the body's tissues and organs based on the difference in the rate of decay of the released energy in different structures, which is detected by magnetic resonance instrumentation for precise localization and differentiation. The resolution is excellent for soft tissues such as the brain [12]bladder, uterus, and muscles.

Positron emission tomography integrates PET and CT, providing more accurate diagnostic information than PET or CT alone, and is an important imaging tool in oncology [13].The literature [14]provides important methods as well as examples of PET-CT techniques for lung detection.

3. 2D medical image segmentation technology

Convolutional Neural Network (CNN)

A CNN is a very important network structure for deep learning, consisting of various layers in which each neuron in a layer responds to only one region of the previous layer. The sequence of successive convolutional, activation and pooling layers is called a hidden convolutional unit (Fig. 1). The convolutional layer presents the result of convolving a certain number of filters with the input data and acts as a feature extractor. The size of the filter layers is arbitrary and can be personnel defined depending on the size of the kernel. Each neuron responds only to a specific region of the previous layer, which is called the "receptive field". The output of each convolutional layer is considered an activation map, which highlights the effect of applying a specific filter on the input. The pooling layer reduces the size of the input and guarantees shift invariance for feature detection. [1][15].

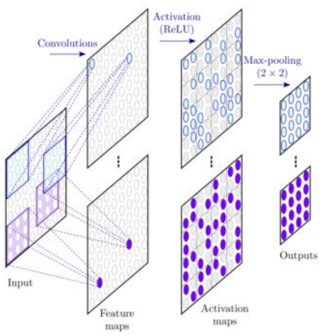

Fig. 1 CNN structure diagram[15]

Yang[16]et al. proposed a joint CNN-Swin Transformer model and applied it to segmentation of breast lesions in ultrasound images. The visualization of the segmentation results on the dataset shown in Fig. 2 is compared. Transformer-based methods outperform traditional CNN methods. He [17]et al. proposed a hybrid CNN-Transformer network for breast ultrasound image segmentation. The encoder of this network combines the inductive bias of CNN for spatial association modeling and the power of Transformer for remote dependency modeling, which makes up for the lack of CNN in obtaining global context information and the lack of Transformer in developing local details. In the decoder part, the method utilizes the SCA module to fuse the feature mappings in the encoder and decoder sub-networks, thus solving the problem of inconsistent semantic information. Che [18]et al. proposed a new deep learning model that utilizes a multi-feature-guided multi-scale residual Convolutional Neural Network (CNN) architecture to capture the features of different receptive fields. Images are combined with corresponding local phase filtered images and radial symmetry transformed images as multi-feature inputs to the network.

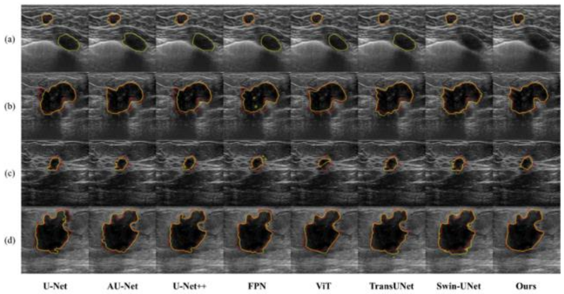

Fig. 2 Visual comparison of segmentation results of different segmentation methods on the dataset (a) - (d) represent four different breast ultrasound images[16]

Fully Convolutional Network (FCN)

FCN was first proposed by Long [19]et al. who combined layers of the feature hierarchy and improved the spatial accuracy of the output (see Figure 3). This significant improvement allows the network to have dense pixel-by-pixel predictions. For better localization performance, high-resolution activation maps are combined with the up sampled output and passed to the convolutional layers to assemble a more accurate output. This improvement allows the FCN to make pixel-by-pixel predictions from full-size images instead of patch-by-patch predictions, and also performs predictions on the entire image in a single forward pass.

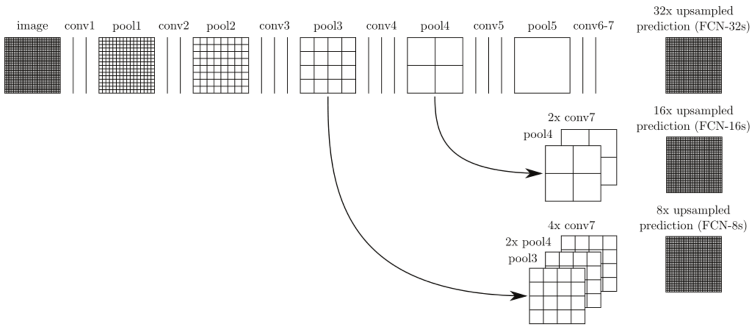

Fig. 3 FCN network structure [19]

Bi[20]et al. proposed a dual-path adversarial learning (DAL)-based method for FCN medical image segmentation. DAL learns ROI features with different levels of difficulty, which improves the diversity of features in the training data. Hemalatha [21]et al. proposed a new Fractal CovNet architecture to segment chest CT scan images using fractal blocks and U-Net to localize lesion regions. Qian [22]et al. proposed a new method for ultrasound image segmentation based on improved multi-scale unfolded convolutional FCN. The method improves the full convolutional neural network by constructing four expansion convolutions with different expansion rates to capture the multi-scale contextual feature information.

U-Net

The UNet network was originally proposed by Ronneberger [23]and others for cell segmentation tasks. This symmetric model structure transforms an image from a high to a low dimension, downscaling a constant-size image so that its size matches the corresponding display region. The network architecture is shown in Fig. 4, which includes a contraction path (left side) and an expansion path (right side). In the contraction path, the model acquires the image as input and applies multiple 3x3 convolution, maximum pooling, and ReLU activation functions to double and expand the number of channels in the contraction path to obtain the feature map, aiming to extract more detailed image features. In the expansion path, the network uses transposed convolution operations to decode feature information from the image and produce a segmentation mask of the image, and the rest of the operations are similar to those in the contraction path. The difference with the normal network model with contraction and expansion paths is that the U-Net network uses jump connections, a set of jump connections between symmetric paths allowing for precise localization in the output image. The low-resolution layers in the contraction path are fused with the high-resolution layers obtained in the expansion path through cropping and copying operations, allowing rich contextual information to be propagated into the higher-resolution layers, which helps the network to capture sharper image details and obtain a more accurate output image. In addition, the U-Net network allows segmentation of images of arbitrary size, which is suitable for a variety of biomedical image segmentation tasks[24].

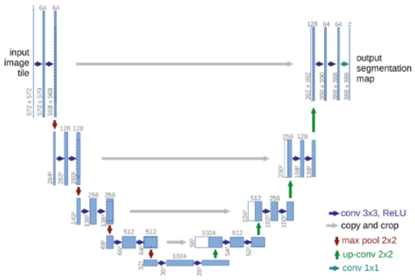

Fig. 4 U-Net network structure model[23]

Amiri[25]et al. propose a two-stage ultrasound image segmentation method based on U-Net and test time enhancement. The method demonstrates the impact of the detection phase added to the segmentation workflow by comparing the results of this two-stage strategy with the results of the one-stage strategy. A schematic of these two approaches is shown in Fig. 5. Gaál [26]et al. propose a new deep learning method for lung segmentation that uses state-of-the-art fully convolutional neural networks combined with an adversarial critic model. It generalized well to CXR images with unseen datasets with different patient profiles. Maayan [27]et al. improved chest film anatomical structure segmentation using U-Net and ImageNet pre-trainer encoders. One of the best performing architectures by Maayan's team was an improved U-Net that benefited from pre-trained encoder weights. Ahmed [28]et al. propose a two-dimensional network consisting of two CNN models called CU-Net. The approach is a dual segmentation model, where the first U-Net model segments the liver and passes this data to the second model, and then the second model detects the tumors on the liver.

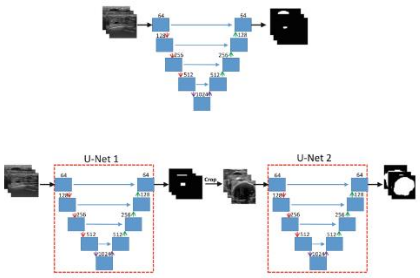

Fig. 5 Schematic diagram of the Amiri method [25]

4. 3D medical image segmentation technology

This has been exacerbated by the rapid development of convolutional neural network (CNN)-based architectures, which have been adopted by the medical imaging community to assist clinicians in disease diagnosis [29].

Convolutional Neural Network (CNN)

Fausto[30]et al. proposed a new method for segmentation that utilizes the abstraction capabilities of convolutional neural networks. The method is based on Hough voting for fully automated localization and segmentation of anatomical structures of interest, not only using CNN classification results, but also by exploiting features generated in the deepest part of the network. The method is modality independent, scalable to multiple regions, and leverages the impressive classification capabilities of CNN and deep learning for applications in clinical settings. Farnaz[31]et al. proposed an Adapt Ahead optimization algorithm for deep CNN learning for MRI segmentation. The algorithm features deep and hierarchical extraction during model training. Fu[32]et al. proposed a convolutional neural network (CNN) deep learning (DL) model for accurate segmentation of liver, kidney, stomach, intestine and duodenum in 3D MR images. The model contains a voxel label prediction CNN and a correction network consisting of two sub-networks. The parameters of each subnetwork are trained independently using a segmented training method. Jose [33]et al. proposed a new method based on a deep CNN ensemble for segmenting isointense infant brains in multimodal MRI images. The method utilizes a semi-dense architecture in which the features of each convolutional layer are aggregated as inputs to the first fully connected layer.

Fully Convolutional Network (FCN)

Sun[34]et al. proposed a new model based on a 3D fully convolutional network. The method applies multipath architecture to feature extraction, and uses 3D dilated convolution to extract different feature acceptance fields on each path, thus effectively extracting features from multimodal MRI images. Meanwhile, the method extracts features from the input data stream over multipath convolutional layers and then fuses these multipath feature maps into transposed convolutional layers. Zeng[35]et al. proposed a multistream 3D FCN multimodal equal-intensity infant brain Mr image segmentation method based on multiscale depth supervision, which can directly map the whole volume data to its volume label after training. Meanwhile the method is designed with multi-scale depth supervision so as to alleviate the problem of potential gradient vanishing during the training process. Zhou [36]et al. propose a deep learning anatomical structure segmentation method based on the FCN voting method for 3D CT image sections. The method is analogous to a fully convolutional network consisting of "convolutional" and "anti-convolutional" layers in 2D semantic image segmentation, and extends the core structure to adapt to 3D CT image segmentation by 3D-2D-3D transformation. The intermediate results of chest CT images delivered by the trained network are shown in Fig. 6. Li [37]et al. proposed a deep learning based variational segmentation method for automatic fusion of multimodal information in PET/CT images. The method proposes a fuzzy variational model to combine the probability map with PET intensity images for accurate multimodal tumor segmentation using the probability map as an affiliation prior.

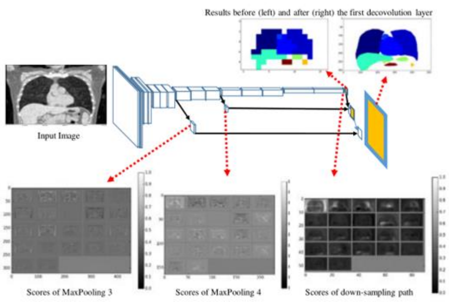

Fig. 6 Effectiveness of FCN network[36]

U-Net

Ibtehaz[38]and others studied the classical U-Net architecture and confirmed that it lacks in some aspects and proposed some modifications to improve the U-Net model, on five different datasets, each with its own unique challenges, and relative performance improvements of 10.15%, 5.07%, 2.63%, 1.41%, and 0.62% were obtained, respectively. Literature[39]proposes non-local U-Nets which are equipped with flexible global aggregation blocks for biomedical image segmentation. These blocks can be inserted into the U-Net as size-maintaining processes, as well as downsampling and upsampling layers. SONG [40]et al. proposed a network architecture n-fold based on Un-Net.In the Un-Net model, the convolutional units are connected to the output features as jump connections. Thus, the Un-Net network utilizes the output features of the convolutional units in the nodes. Meanwhile, the team investigated U2-Net and U3-Net for segmentation of liver and liver tumors, will the network nodes also use the extended convolution (DC) and dense structure. Seo [41]et al. proposed a deep learning segmentation network with more robustness, for both liver region or tumor region, for effective segmentation. The network is designed by including residual paths and object-related up-sampling, the network avoids duplication of low-resolution information, estimates higher-level feature mappings that are more representative of the high-resolution edge information of large object inputs, and learns to extract higher-level global features of small object inputs. The method does not require any preprocessing and can therefore be generalized to other organs or other images with poor contrast, as well as extended to other medical images such as MRI, PET, or ultrasound. Rehman[42]et al. proposed a BU-Net based method for region segmentation and classification of brain tumors with modifications to the encoder structure, which resulted in explicit segmentation of brain tumors. The method introduces two new blocks, Residual Extended Skip (RES) and Wide Context (WC), to the existing U-Net architecture. The increase in the effective acceptance field is realized using the RES block, improving the overall performance. BU-Net shows a good improvement over other existing efficient segmentation models such as the baseline U-Net architecture (shown in Fig. 7).

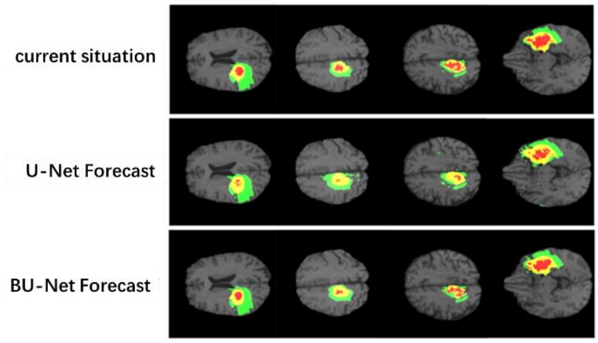

Fig. 7 Cutting Comparison of Segmented Irregular Image[42]

Fully automated segmentation methods have become an important direction in the field of medical image segmentation due to the expensive, tedious and error-prone steps of manual segmentation during segmentation. Chen[43]et al. proposed a novel separable 3D U-Net architecture S3D-UNet using separable 3D convolutions. The architecture divides each 3D convolution in a parallel manner into three branches, each with a different orthogonal views, i.e., axial, sagittal, and coronal. Lee[44]et al. proposed a patch-based U-net architecture for automatic segmentation of brain structures in structural MRI. The method uses a patch-based U-net without overlap, which preserves more localized information. For slices from MRI scans are segmented into non-overlapping patches that will be fed into the U-net model along with the corresponding ground truth patches to train the network. Fabian[45]et al. propose a robust adaptive framework, U-Net, based on 2D and 3D vanilla U-Nets. The framework puts the focus on performance and generalization with leaky ReLU (negative) replacement of the ReLU activation function and using instance normalization instead of batch normalization. Feng[46]et al. proposed a cascaded U-Net-based method for automated segmentation of CT livers and tumors. The first U-Net of the method is used to segment the liver, and the liver is the input to the second U-Net. The experimental results show that as shown in Fig. 8 the accuracy of this method is 91.3% and 89.8% for liver segmentation and 82.4% and 86.6% for tumor segmentation, respectively.

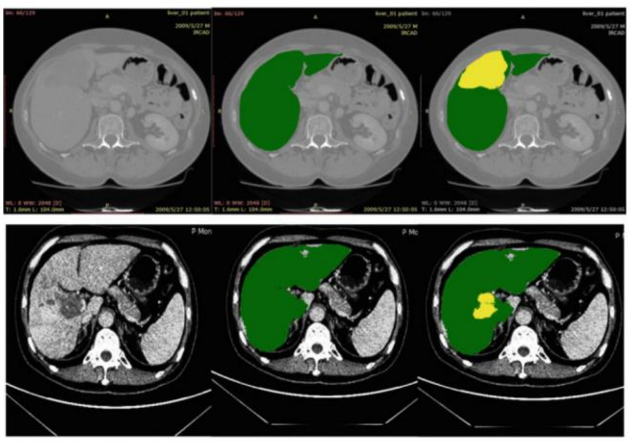

Fig. 8 Experimental effect diagram of Feng's method[46]

Higher accuracy is often required in the field of medical image segmentation, where errors in edge segmentation may cause poor results in clinical procedures and may lead to significant bias in subsequent computerized diagnosis. Therefore, there is a need to design more effective image segmentation architectures to efficiently recover the fine details of target objects in medical images. To meet the need for more accurate segmentation of medical images, Zhou et al. proposed a new segmentation architecture, U-Net++, based on nesting and dense jump connections [47]. After that, many others applied and improved on the basis of U-Net++.Wu [48]et al. found that as the depth of the network increases, especially for U-Net++ which has a complex structure and many parameters, the extra computation time and memory consumption may be immeasurable and unaffordable. So they use extended conclusions to replace the traditional convolution without increasing its depth. The results show that better multi-organ segmentation performance can be obtained by applying extended convolution in U-net ++. NEIL [49]et al. proposed a variant of the U-Net++ model and evaluated its brain tumor segmentation capability. The method differs from the standard U-Net++ model in a number of ways, including the loss function, the number of convolutional blocks, and the use of deep supervision, while data augmentation and post-processing techniques were also implemented and observed to significantly improve model predictions. Li [50]et al. proposed a nested attention-aware segmentation network UNet++. The method features a deeply supervised encoder-decoder architecture and a redesigned dense skip connection, while introducing an attention mechanism between nested convolutional blocks that allows features extracted at different levels to be merged with task-relevant choices. In addition, due to the introduction of deep supervision, which speeds up the prediction of the pruned network at the cost of a moderate performance degradation, the learning results are shown in Fig. 9 ((a1) and (a2) are CT images, which are real in LiTS. (b1) ~ (f1) are the attention coefficients of the first layer of attention gates for different training periods. (b2) ~ (f2) are the attentional coefficients of the second layer of attentional gates for different training epochs).

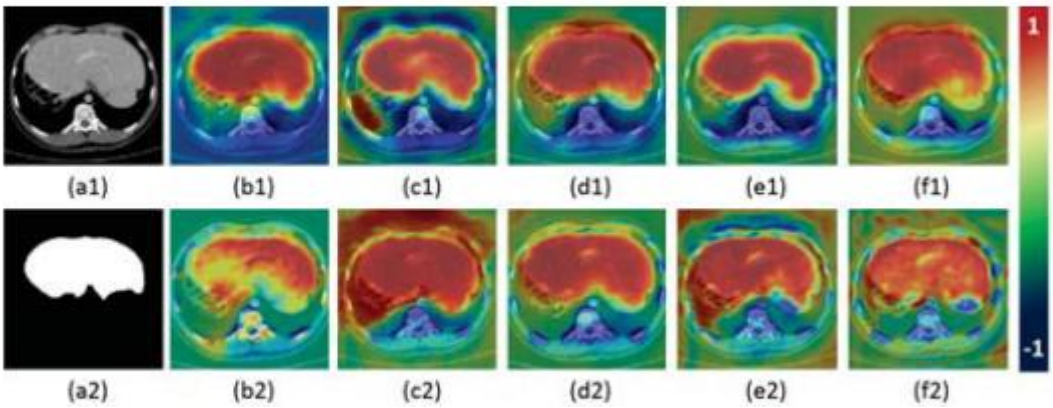

Fig. 9 Learning results of Li method[50]

5. Summary and trends

Medical image segmentation methods hold immense research significance and social value, as they effectively segment lesions to aid doctors in making accurate diagnoses. This paper provides a detailed description of various segmentation methods for medical images in both 2D and 3D, all based on deep learning techniques. The methods are comprehensively summarized, enabling a swift and thorough grasp of the advancements and current state of medical image segmentation. Our findings demonstrate that when dealing with extensive data, employing deep learning methods not only enhances segmentation accuracy but also mitigates issues like excessive memory consumption and computational complexity. Moreover, these methods have paved the way for quantitative analysis and 3D visualization research. However, it is essential to acknowledge that deep learning-based segmentation may still encounter imperfections due to noise and artifacts, necessitating further investigation in future studies. Additionally, most deep learning approaches are focused on specific medical images, warranting research and promotion of these methods across various image types. Simultaneously, the deep learning model itself has inherent drawbacks that call for improvements and refinements in network structure design, 3D data segmentation model design, and loss function design. Addressing these aspects will contribute to the ongoing enhancement of medical image segmentation methodologies.

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