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Ultrasound Image Segmentation of Uterine Adenomyoma Based on Deeplab

Shijie Xing[1], Qiaodan Zhang[2], Mingying Zhang[1], Mei Li[1, *]

[1]School of Information Engineering, China University of Geosciences (Beijing), Beijing, China
[2]Beijing Kwai Technology Co., Ltd, Beijing, China

Abstract

Uterine adenomyoma is a common disease in women. Its symptoms and pain have seriously troubled the physical and mental health of contemporary women. Because of the advantages of no damage to the body and low cost, so ultrasound is usually used to obtain the medical image of adenomyoma in medicine. Uterine adenomyoma is different from human epidermal diseases. The boundary of the image obtained by ultrasound is not clear and the interference is large. Moreover, due to the influence of noise and artifact of ultrasound image, image segmentation is difficult, and the clinical diagnosis results are lack of reliability. In order to solve the above problems, this paper preprocesses the obtained ultrasound images, then constructs the ultrasound image data set, sets the network parameters, inputs the ultrasound images into the deeplab model network for training, and finally optimizes the edge details of the lesions through the hole convolution algorithm and the full connection conditional random field, and uses the average intersection ratio and pixel accuracy as the evaluation criteria for semantic segmentation. In order to ensure the accuracy of the test data and the superiority of the algorithm. And constantly optimize the network training to achieve the fine segmentation of the lesion area. The accuracy and feasibility of the model in medical image segmentation are demonstrated by experiments, which fills the blank of deep learning in this application field.

Keywords

Adenomyoma, Ultrasound Image, Deeplab Model, Hole Convolution Algorithm, Deep Learning

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1. Introduction

1.1. Research Background

Adenomyoma is a benign disease with Endometrium Glands and interstitial tissue that has growth function invading the uterine myometrium and accompanied by compensatory hypertrophy and hyperplasia of the surrounding muscle cells[1-2]. The disease is mostly found in middle-aged women, and its incidence rate has increased year by year. In the initial stage of disease screening, doctors will first use medical imaging examination. Ultrasound imaging is one of the most commonly used cross-sectional diagnostic imaging methods in medical practice, and also the most important auxiliary way in gynecological disease diagnosis. The advantages and disadvantages of ultrasound imaging are very clear, because of its low price, no radiation, simple operation, real-time image acquisition and other advantages, it is often used as the first imaging choice for many diseases diagnosis. However, there are some problems such as unclear edge information, serious noise interference, artifact and so on, which have higher requirements for doctors' clinical experience and discrimination ability. In recent years, in the field of machine learning blowout development research, the research of cross application with various disciplines has also attracted the attention of researchers. Therefore, this paper focuses on the application of image segmentation method based on deeplab model to medical ultrasound images.

1.2. Research Status

In recent years, segmentation model based on deep learning

* Corresponding author
E-mail address: maggieli@cugb.edu.cn (Mei Li)

has been widely used in medical image processing. The so-called segmentation in medical field is to divide the similar regions into two or more regions according to the image features and texture information. In general, it is involved in the fields of fetal, brain, large blood vessel, tumor, liver and so on. And cancer tumor (such as breast cancer, liver cancer) and other lesions of tissue recognition, segmentation. There are various types of medical images in clinical application, which are suitable for screening and diagnosis of different diseases, including MRI It is widely used in nuclear magnetic resonance, X-ray imaging, X-ray imaging and X-ray imaging. However, in the field of deep learning segmentation, most of the segmentation objects are high-definition and well-defined CT and MRI images. For ultrasound images with serious noise interference, few people study them. Therefore, there are still many problems to be solved in the study of ultrasound images.

Medical ultrasound image research is widely used in clinical practice, but the ultrasonic image analysis technology is far behind other methods. The reason is related to its own image characteristics. At present, more and more industries and fields need to use artificial intelligence model algorithm to solve practical problems. Machine learning (especially deep learning) is a promising method to improve medical image analysis, disease classification and computer-aided diagnosis. However, in the existing field of image processing, the research and application of medical ultrasound image is relatively less, and there are still many problems and difficulties in this field, which are worthy of being solved and discussed. [3-4]

Carneiro, g et al [5] Proposed a semi supervised learning model to segment the left ventricle in order to solve the problem of inaccurate training of small amount of data. Looney P et al [6] First tried to use the improved CNN model, deepmec model, to complete automatic segmentation of 3D ultrasound images of placenta in the second trimester of pregnancy. Zhang y et al [7] Proposed a coarse to fine stacked cfs-fcn network, through 80 training set images for model training, completed the task of segmenting ultrasound images of lymph nodes. Milletari et al [8] Completed the segmentation method of automatic localization based on CNN by Hough voting on the region of interest, and completed the segmentation of 26 regions of cranial MRI image.

In general, the application of machine learning in ultrasound images is still in its infancy, and the above-mentioned papers use databases of dozens or hundreds of images. Only a few papers use databases with large amount of data, because most ultrasound images are collected from a single device type and a single site, and there is no publicly accessible challenge database based on medical ultrasound images, such as Imagenet. These external conditions greatly limit the generality of these models and methods, and it is difficult to standardize the evaluation effect. At present, there are several challenges in applying deep learning method to ultrasound images: (1) Obtaining consistent annotation data is a difficult problem, because there are subjective differences between different doctors. In order to reduce the uncertainty, it is necessary to build a larger database, but there is no large open ultrasound image data set. (2) The noise interference of ultrasonic image brings resistance to the recognition of deep learning, which will greatly affect the training effect. (3) At present, most of the deep learning research on ultrasound image is focused on disease classification and detection, but the focus segmentation and edge detection are not mature, so it is urgent to further explore. It can be seen that the focus segmentation of ultrasound images is still in its infancy at home and abroad. It is urgent for researchers to develop innovative ideas and knowledge reserves to study advanced machine learning, especially deep learning segmentation network, to fill the gap in the field of ultrasound image lesion segmentation, which is also the key to build a complete medical computer-aided diagnosis technology in the future.

2. Model Architecture Description

2.1. Hole Convolution

Hole convolution introduces the concept of "dilation rate" into the traditional convolution layer, which defines the distance between pixels in convolution kernel. In this way, the receptive field of the network is changed by inserting 0 between the weight parameters of convolution kernel while ignoring some pixels. The principle is shown in Figure 1.

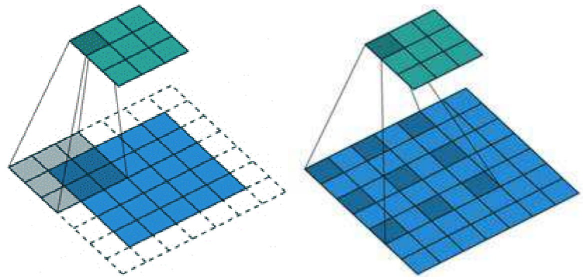

Figure 1. Schematic diagram of standard convolution and hole convolution.

(a) The standard convolution with the convolution kernel of 3x3
(b) the hole convolution of the convolution kernel 3x3 (the expansion rate is 2)

The three images in Figure 2 show the size of receptive field with expansion rate of 1, 2 and 4. Figure 2 (a) corresponds to normal convolution, and the receptive field size is 3x3. (b) The graph corresponds to the receptive field with expansion rate = 2, and the convolution kernel is still 3X3, but the receptive field size is 7x7. (c) The graph shows the operation with expansion rate = 4, reaching the receptive field of 15x15. It can be seen that even without pooling, the range of receptive field can be enlarged, so that the model can retain more information during segmentation.

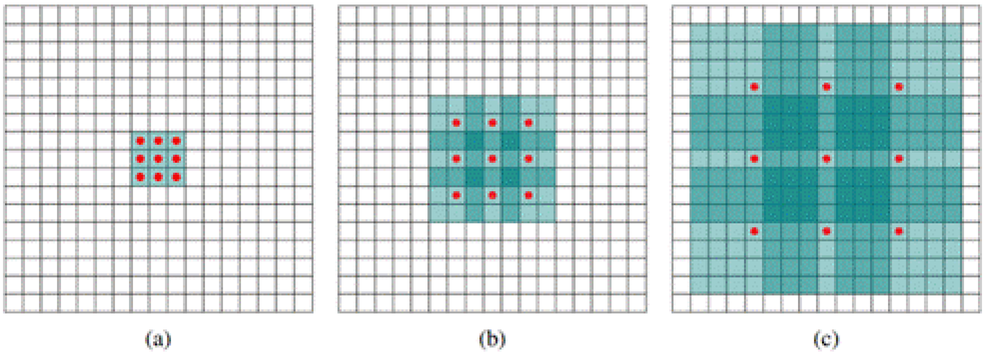

Figure 2. Schematic diagram of receptive field with different expansion rates.

2.2. Fully Connected Random Fields

There is an unavoidable drawback in deep convolution network, that is, the deeper the network model is, the better the classification effect is. However, with the increase of the number of layers, the larger the receptive field will lead to smoother results, the more fuzzy the position information, and unable to describe the boundary details of objects. However, CRF can avoid the coupling of pixels with similar edge features in the image, consider the global information of the image, refine the edge details of the image, and the coupling effect of CRF with the deep convolution network is better.

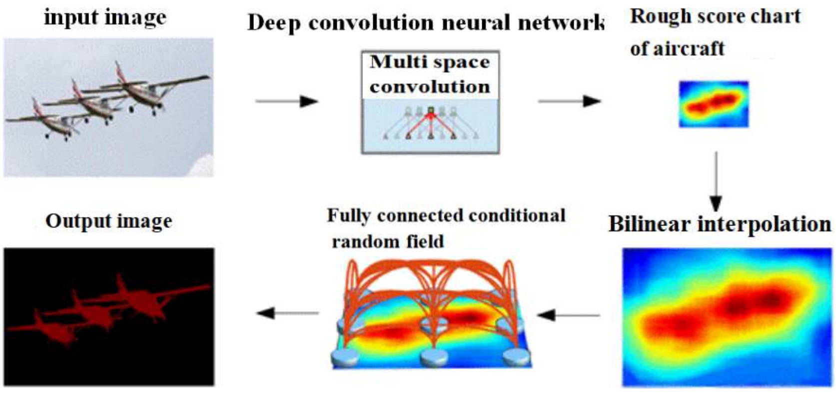

Figure 3. High level schematic diagram of deeplab model.

Figure 3 is a high-level schematic diagram of the deep lab model. Firstly, the input image is processed by porous convolution, which can effectively prevent oversampling, get rough score map, obtain semantic features, and then use bilinear interpolation method to restore the original size [9]. Finally, CRF is used to optimize the details of the image again to capture more edge information. In the actual model training, the model also has the advantages of high efficiency and fast speed.

In fact, the deeplab model is an improved VGG-16 network. After replacing the full connection layer and the last two pooling layers, the hole convolution method is used to expand the receptive field and reduce the stride length. The first fully connected convolution layer in VGG is replaced by two smaller convolution layers, which can expand the receptive field and save the computational cost. Finally, the last layer of the model is replaced by classifiers, and the number of classifiers is equal to the final target region when the dataset is labeled. Then the loss function is set and the stochastic gradient descent function is used to optimize each layer.

2.3. Ultrasound Image Segmentation of Uterine Adenomyoma Based on Deeplab Model

2.3.1. Environment Configuration

This model training is developed by tensorflow under Windows operating system, and a single GPU training network is used. The specific hardware configuration and software environment of the experiment are shown in table 1.

Table 1. Experimental software and hardware configuration.

CPU	AMD Ryazen 7 1800X
GPU	NVIDIA GeForce GTX 1060
Memory	16G
Deep learning framework	TensorFlow 1.12.0
Development interface	Python 3.6
operating system	Windows 10 professional

The quality of network training is closely related to the parameter setting, so reasonable parameter adjustment is an important link. The experimental setting parameters in this chapter are shown in table 2.

Table 2. Network parameter setting of deeplab.

Batch size	4
Batch quantity (Global_step)	36675
Maximum number of iterations (epoch)	50
Weight attenuation	0.0005
Learning rate	0.00025

2.3.2. Model Evaluation Index

Generally speaking, the standard measure of evaluating semantic segmentation is mean intersection ratio (Miou). The accuracy is represented by the ratio of intersection and union of two numerical sets. In segmentation, these two sets are true values and predicted values. The ratio of the two can be expressed as the true ratio of the sum of true, false negative and false positive. Then, IOU is calculated in each category to calculate the mean value. The specific calculation formula is formula (1)

$$\mathrm{MIoU} = \frac{1}{k+1}\sum_{i=0}^{k}\frac{p_{ii}}{\sum_{i=0}^{k} p_{ij} + \sum_{j=0}^{k} p_{ij} - p_{ii}} \tag{1}$$

The calculation process of a class of IOU is as follows: for example, when I = 1, it means that the number of pixels originally belonging to category 1 and predicted to be class 1 is true; that is, the number of pixels that originally belong to category 1 but are predicted to be of other classes; that is, the number of pixels that belong to other categories but are predicted as class 1 is calculated twice at the denominator, so one must be subtracted.

In addition to Miou, pixel accuracy (PA) is also an evaluation method, which means the proportion of the number of pixels with correct category in the total number of pixels.

In the experiment, PA and Miou were used to evaluate the segmentation accuracy of uterine adenomyoma image, and the actual effect of the image set was observed to comprehensively compare the effect of the model.

3. Data Set Generation and Preprocessing

3.1. Data Set Construction

In order to complete the training and testing of the model and accurately evaluate the segmentation effect, it is necessary to use as many high-quality data sets as possible. However, there is no public database about adenomyosis in the field of medical image segmentation. Few people have studied the focus segmentation of adenomyosis at home and abroad. Therefore, the ultrasound image data set of uterine adenomyoma used in this paper is from 211 patients with adenomyoma who were treated in the gynecological minimally invasive center of Beijing obstetrics and gynecology hospital from 2014 to 2019. Each case has 5-10 ultrasound images, and each ultrasound image contains two ultrasound images of the lesion, transverse and longitudinal, as shown in Figure 4. The images were collected from different patients by gynecologists and obstetricians who had many years of experience in ultrasound diagnosis and clinical treatment of adenomyosis, and had been diagnosed by gold standard in medical field, so the data set was true and reliable. We selected the patients who had been confirmed and had participated in the ablation operation, and found the corresponding lesions before and after the operation, and collated and matched the transverse and longitudinal ultrasound images, which laid the foundation for the follow-up evaluation work.

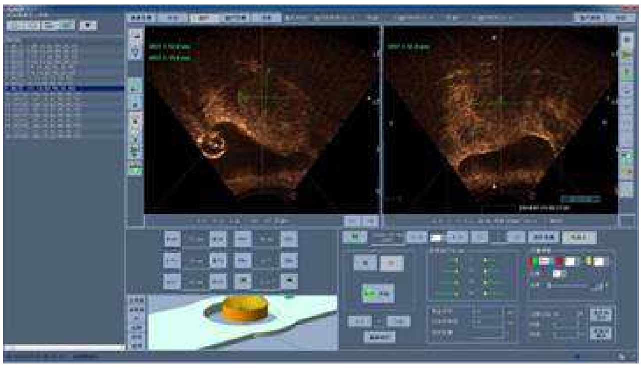

Figure 4. Ultrasound image acquisition of uterine adenomyoma.

The images were selected from 211 patients with adenomyoma treated by high intensity focused ultrasound (HIFU). The images were complete in cross section and longitudinal section, complete in preoperative and postoperative images, and clear and suitable for labeling. Finally, 1589 images were selected to form the data set.

Next, the image is preprocessed to remove the equipment information in the image, desensitize the patient information, and automatically locate the region of interest in the ultrasound image by writing a series of programs to intercept the imaging area of the lesion. In order to facilitate the calculation of tumor volume, it is necessary to number each patient's data in batch naming of images, distinguish the transverse and longitudinal sections of tumors and distinguish the preoperative and postoperative images. These differences are only reflected in the naming, and will not be differentiated in the training of the model. On the one hand, it can avoid the interference of useless information on the model training, on the other hand, it is convenient for subsequent review of segmentation results. At the same time, the patient number is also a desensitization operation to protect the privacy of patients. The processed image is shown in Figure 5

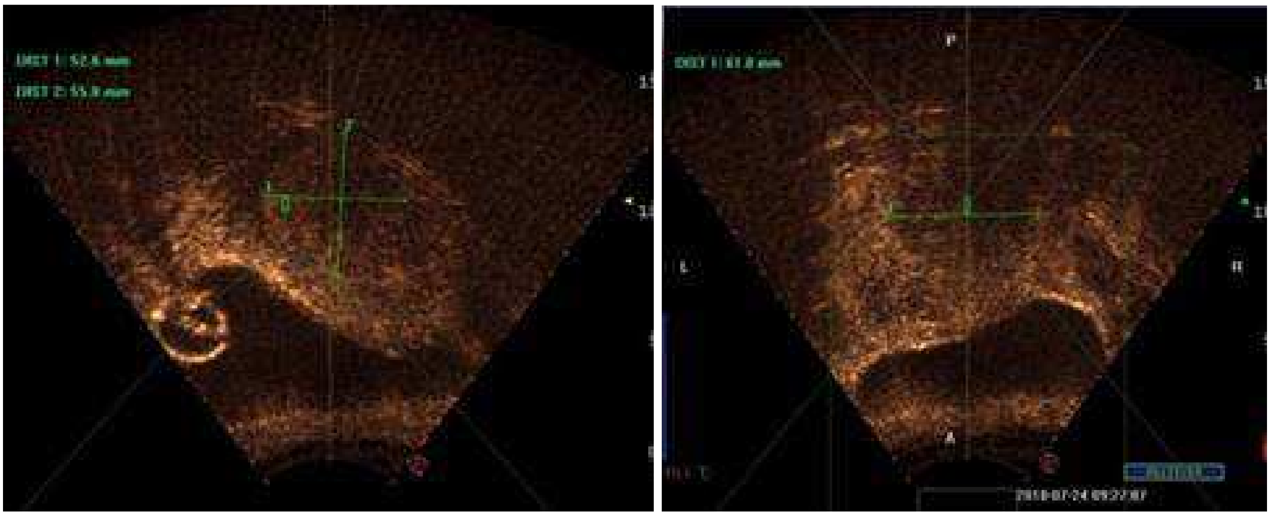

Figure 5. Imaging area of the lesion (cross section on the left and longitudinal view on the right).

According to the structure of uterus and abdominal cavity, the doctor can judge the area and shape of the lesion by echo and mass gray change of the image. The labeling work is completed by deep learning the labeling tool labelme. The labeling area must completely surround the outer edge of the myoma and fit the outer contour as much as possible to ensure the accuracy of the myoma area. The labeling is shown in Figure 6. After saving, the generated JSON file is converted into label image. Finally, the binary image is generated by Python script. The background pixel is 0 and the label area is 1.

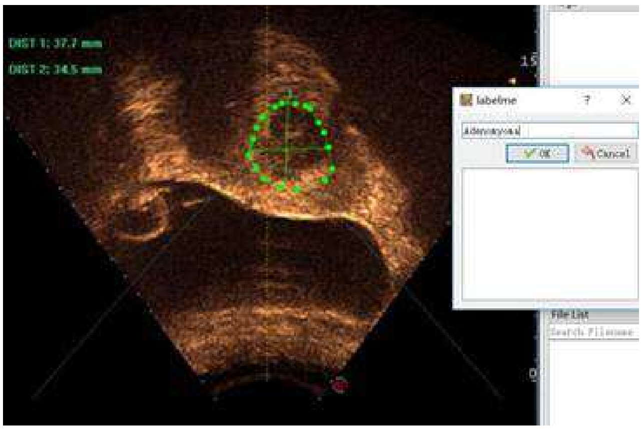

Figure 6. Image annotation of dataset.

In order to prevent the effect of the test set affected by the strong correlation between the preoperative and postoperative images of the same patient, the training set was divided by the patient as the unit, each patient corresponding to 4 pictures (preoperative transverse section, preoperative longitudinal section, postoperative transverse section, postoperative longitudinal section), a total of 170 groups of patients, and the remaining ultrasound images of uterine adenomyoma that could not be grouped were included in the training set. In order to ensure the accuracy and accuracy of the model network, 1 / 4 of the number of patients was randomly selected as the test set.

3.2. Experimental Results and Model Evaluation

After preprocessing the data of the image training set of uterine adenomyoma, it is input into the deeplab network for training, and then the test set is input into the network to get the segmentation results. The segmentation marked data is used as the "gold standard" to evaluate the quality of the model, and the algorithm is evaluated. The actual flow chart is shown in Figure 7.

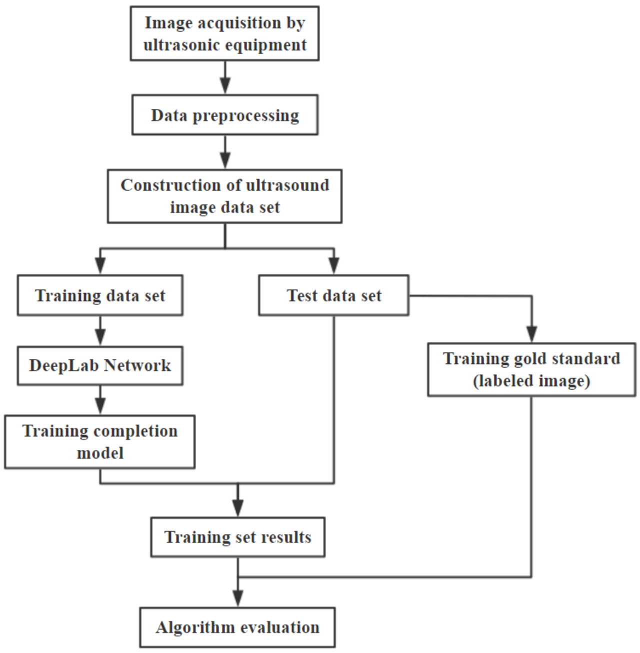

Figure 7. Flow chart of uterine adenomyoma

The effect of using deeplab network to output the actual test set is shown in Figure 8.

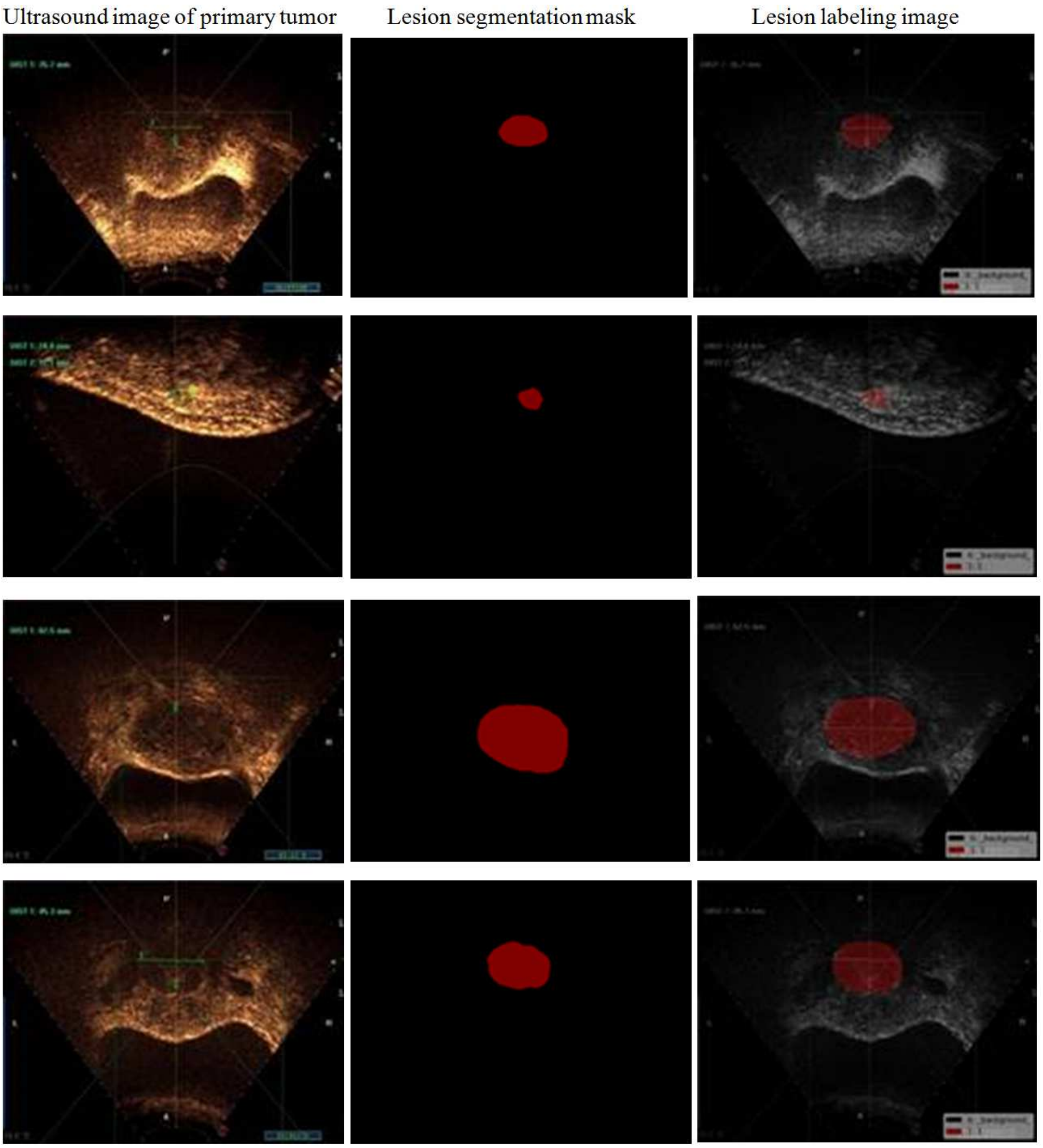

Figure 8. Comparison of output results of deeplab test set.

It can be seen from the annotation image in Figure 8 that the tumor pixel is set as "1" and the background image is set as "0" in the experiment. Because the number of tumor pixels will be much larger than the proportion of background pixels, and the data between classes are balanced, the final segmentation accuracy rate of tumor like pixels is 0.7277, and the overall pixel accuracy of the image reaches 0.9893. It can be seen that the use of deep lab semantic segmentation network for uterine adenomyoma ultrasound image segmentation is of practical significance. Although the data set samples are relatively small, it achieves good training results with relatively small data sets.

4. Conclusion

The deeplab segmentation network proposed in this paper realizes the automatic segmentation of ultrasound images of uterine adenomyoma, and improves the efficiency of initial diagnosis and treatment. According to the characteristics of the data and the actual needs of diagnosis and treatment, the data image is preprocessed to form a data set for segmentation of uterine adenomyoma. The experimental results show that the deeplab network has a great advantage in segmentation. With the advantages of low cost, high precision and high boundary fineness, the model is more suitable for the ultrasound image segmentation of uterine adenomyoma, with an average intersection ratio of 84.76%, which can achieve a more accurate segmentation effect. The experimental results show that the algorithm proposed in this paper is suitable for the clinical auxiliary diagnosis system of uterine adenomyoma, and has certain value in clinical application. It is helpful for doctors not limited by clinical experience, but also can quickly identify the lesion area. However, there are still some limitations in the research and processing of image boundary in this paper, which needs further improvement and perfection.

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