The Early Diagnosis of Lung Cancer Based on Soft Parameter Sharing of Transfer Learning

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Abstract

The medical image diagnosis of lung nodules is an important indicator of early lung cancer. Through the artificial intelligence, computer aided diagnosis method is useful for the medical image clinical diagnosis, improve diagnosis efficiency and accuracy. The pathological diagnosis of lung cancer is costly and harmful to patients. Simultaneously, image diagnosis is easier with reading CT images, and more data can be obtained. It is an idea to transfer pathological diagnosis knowledge to image diagnosis to help improve the accuracy of image diagnosis. The paper proposes a more efficient U-Net structure to extract features of lung nodules, and a partially soft parameter sharing method to transfer learn between image diagnosis and pathological diagnosis. The achievements of paper develops a computer-aided the early diagnosis classifier of lung cancer. In the NLST datasets, the result of experiment shows that the method of paper is more accurate than others.

Keywords

Early Lung Cancer; NLST; Lung image; Transfer Learning; Multi-tasking learning; Soft Parameter Sharing.

1. Introduction

The image diagnosis of lung nodules is an important indicator of early lung cancer^[1]. Radiologists use lung images to judge whether the patient has early lung cancer. But this diagnosis is not accurate. Through the artificial intelligence, computer aided diagnosis method is useful for the medical image clinical diagnosis, improve diagnosis efficiency and accuracy^[2]. The pathological diagnosis of lung cancer requires surgery such as thoracotomy or puncture. Therefore, the pathological diagnosis of lung cancer is costly and harmful to patients. Simultaneously, image diagnosis is easier with reading CT images, and more data can be obtained^[3].

Transfer learning, which transfers the knowledge from the source domain as a priori information to other tasks, is an effective solution to the learning difficulties of small data sets^[4]. An iterative competitive fine-tuning method was proposed by combining deep learning and migration learning, results were achieved in multi-task image classification tasks by exploring the feasible fine-tuning depth of the network^[5]. A deep sparse discriminative transfer model was used to achieve good classification performance in cross-domain image classification^[6]. A method uses pre-train CNN as the feature extractor, fixes the network convolution layer parameters, inputs the chest X-ray image into the pre-train model and fine tunes the full connected classification layer^[7].

The paper proposes a more efficient U-Net structure to extract features of lung nodules, and a partially soft parameter sharing method to transfer learn between image diagnosis and pathological diagnosis.

2. Datasets and Preprocession

The datasets are the National Lung Screening Trial (NLST) datasets, which was a randomized controlled trial conducted by the Lung Screening Study group and the American College of Radiology Imaging Network. The screening for lung cancer with low-dose helical computed tomography (CT) are helpful for the early diagnosis of lung cancer in high-risk individuals. The data include over 1,200 CT lung images form over 75,000 CT screening exams. The label datasets include participant characteristics, exam results, diagnostic procedures, and mortality. The data are comprised of adenocarcinoma, squamous cell carcinoma, bronchio-alveolar carcinoma, large cell, small cell, carcinoid tumor, pleomorphic sarcomatoid and unclassified carcinoma slide images.

The pathological features of lung images are lung nodules in the lung parenchyma. The images of lung parenchyma should be segmented form the original images. The lung parenchyma images are characterized by grayscale binary images. The OTSU method be used to convert original images to binary images. The image is divided into foreground and background (binary images), and the image background be removed.

The erosion operations were used to remove a radius of 2 pixels from the lung nodules. The closure operations were used to attach a radius of 5 pixels to let the nodules to the lung wall. The filling operations were used to overlay small holes in the lung mask. The lung parenchyma segmentation is shown in Fig. 1

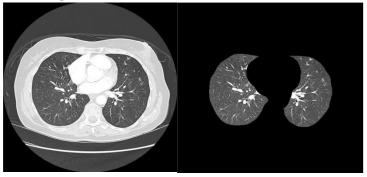


Fig. 1 Lung parenchyma

3. Segmentation of Lung Nodules Based on The Improved U-Net

Net is a variant of Fully Convolutional Networks (FCN), which divided into three parts: feature extraction, copy and corp, up-conv. Feature extraction part is a shrinking network, which reduces the size of the image through four downsamplings. In the process of downsampling, the feature is extracted from shallow information. The purpose of copy and corp is to fuse feature information to connect deep and shallow information. It is not only the image size should be consistent, but also the feature channels should be the same.Up-conv is an expansion network, is used to extract deep information with four upsamplings. During the upsampling process, the image size becomes larger, the number of channels in the image is halved. The process of upsampling combines the shallow information. The structure of U-Net, see Fig. 2.

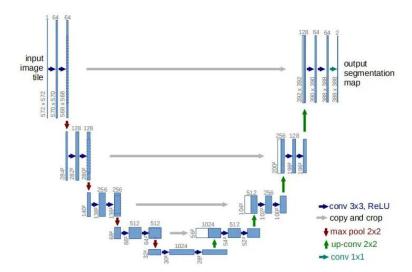


Fig. 2 The structure of U-Net

The paper proposes to add denseNet block to the network decoder to enhance the feature reuse. The Batch Normalization module is added to the network encoder to prevent over-fitting. The structure of improved U-Net, see Fig. 3

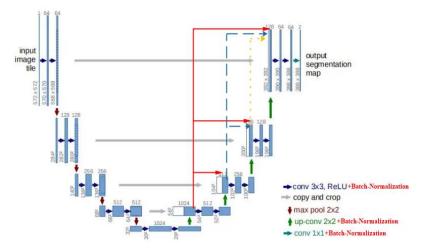


Fig. 3 The structure of improved U-Net

The lung nodule sections, see Fig. 4.

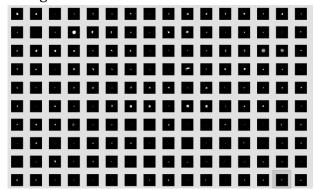


Fig. 4 Lung Nodules

4. The Early Diagnosis of Lung Cancer based on Transfer Learning

Pathological results are difficult to obtain, which requires invasive intervention. The patient needs to endure painful operation. But pathological result is more accurate for the early diagnosis of lung cancers. The accuracy of medical image diagnosis is not high, but the cost is

low. The paper propose a improved transfer learning method to improve the accuracy of medical image diagnosis.

The multi-task learning is an important branch of transfer learning. It puts multiple related tasks together to learn. These tasks all use the same network structure. Image diagnosis and pathology diagnosis learn in same deep network, and share their parameters. It can improve the accuracy of image diagnosis.

Soft parameter sharing method of multi-tasks learning reduces the over-fitting and improves the accuracy. The paper propose to reduce sharing more, share only in the pooling layer and the fully connected layer. But the method cannot be degenerated into single task learning. It is a partial soft parameter sharing method. The comparison of network structure, see Fig. 5 and Fig. 6

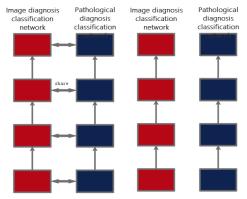


Fig. 5 The structure of Soft Parameter Sharing and Single Task Learning

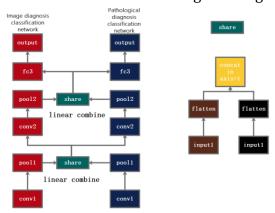


Fig. 6 The Structure of partial soft parameter sharing method

The improved soft parameter sharing method improves the accuracy of image diagnosis. The method removes the parameter sharing of conv1 and conv2. The parameters of two tasks are linear combined in pool layers and the full connection layers. The pathological diagnosis classifier parameters are helpful for improving the accuracy of image diagnosis classifier.

5. Experimental Testing

According to the pathological diagnosis in NLST datasets, images were divided into 9 categories, including 0-normal, 1-adenocarcinoma, 2-squamous cell carcinoma, 3-bronchio-alveolar carcinoma, 4-large cell, 5-small cell, 6-carcinoid tumor, 7-pleomorphic sarcomatoid and 8-unclassified carcinoma. The experimental environment is shown in the Table 1.

Table 1: The experiment environment

Name	Value
RAM	16GB
GPU	Tesla v100

VRAM	8GB		
CUDA	11.0		
Python	python3.7		
Framework	PaddlePaddle 1.8.0 (TensorFlow)		
Calculation package	Paddorch (pytorch)		

The experimental result is shown in the Table 2and Fig. 7.

Table 2: The experimental result

global_step_value	epoch	loss_total_value	accuracy_train_value	accuracy_test_value		
100	2	3.6882436	0.6289062	0.5558441		
200	4	3.3388233	0.5585937	0.5571428		
300	6	3.2287679	0.1328124	0.0967532		
400	8	3.0206234	0.1328124	0.1146103		
500	10	2.6285636	0.1640621	0.1009740		
600	12	2.3938682	0.1367187	0.1149350		
700	14	2.2445056	0.1406253	0.1262898		
800	16	1.7637627	0.1328122	0.1311688		
900	18	1.7248832	0.3554687	0.3162337		
1000	20	1.5626466	0.4101562	0.3532467		
1100	22	1.2806146	0.6445312	0.5318182		
1200	24	1.7929072	0.7070312	0.5883117		
1300	26	1.0552963	0.7773437	0.6321428		
1400	28	0.9944974	0.8320312	0.6314935		

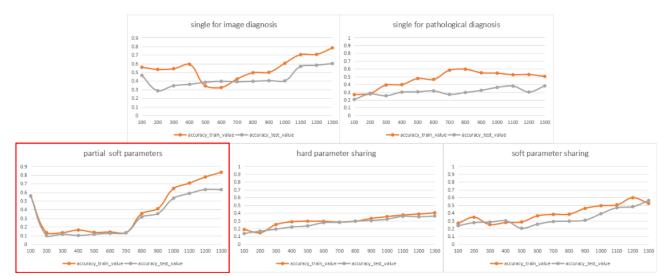


Fig. 7 The comparison of algorithm accuracy

The result of experiment shows that the partially soft parameters is more accurate than other methods.

6. Conclusion

The paper proposes a more efficient U-Net structure to extract features of lung nodules. And the paper proposes that a partially soft parameter sharing method uses cheap and many image diagnosis to transfer learn to expensive and few pathological diagnosis. The achievements of

paper develops a computer-aided the early diagnosis classifier of lung cancer. In the NLST datasets, the result of experiment shows that the method of paper is more accurate than others.

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