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Deep Learning Based Nodule Detection from Pulmonary CT Images

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***Abstract*—In recent years, the morbidity and mortality of lung cancer are rising rapidly, and it has become one of the most malignant tumors with the highest morbidity and mortality. In the early stage of lung cancer, the pulmonary nodules are usually expressed in morphology. With the widespread use of CT technology, scanning can be used to detect malignant nodules in the lesion, which can greatly improve the survival rate of patients with lung cancer. However, the CT image is usually very high in dimensionality, which requires the doctor to spend a lot of time reading, and some tiny nodes are difficult to detect and easily lead to misdiagnosis. Computer aided detection technology can assist radiologists to diagnose, and effectively improve the efficiency and quality of diagnosis. Computer aided diagnosis of pulmonary nodules involves segmentation of lung parenchyma, suspected nodules extraction, and automatic recognition of pulmonary nodules. In this paper, segmentation of lung parenchyma and suspected nodules extraction are similar to traditional methods. The pulmonary parenchyma is extracted from original CT images by the maximum interclass variance method, and the connected regions are extracted in the lung parenchyma, which are the suspected nodules. Suspected nodules are classified by means of convolutional neural networks. Big data-driven artificial intelligence in the early diagnosis of lung cancer, not only can save the lives of countless patients, but also for the alleviation of medical resources and doctors and patients.**

Keywords-component; Pulmonary nodules; Image segmentation; Convolutional neural network; Feature extraction

I. INTRODUCTION

Lung cancer is the most common primary pulmonary cancer. For nearly half a century, the incidence and mortality of lung cancer have risen rapidly in countries around the world, especially in densely populated industrialized countries. With the development of industrialization, the incidence and mortality of lung cancer in China increased significantly. Lung cancer and other diseases, but also from the general to the special, from normal to malignant, from the molecular, cellular to systemic development process [1]. When the late diagnosis of lung cancer, patients generally lose the best treatment period, however after early diagnosis of lung cancer, the survival rate of patients will be greatly improved. So early diagnosis and treatment of lung cancer is of great significance in improving patient survival [2-4]. With the continuous development of medical imaging, various imaging tools, such as computer tomography, nuclear magnetic resonance, positron emission computed tomography, etc, play an important role for the early diagnosis of lung cancer [5,6].

Pulmonary nodules are round or oval, completely wrapped in the lung parenchyma, without lymph node disease, without atelectasis, hilar swelling and other pulmonary lesions. According to the size of nodules can be divided into small nodules (<1cm) and large nodules (1-3cm). CT is currently a good imaging method for detecting pulmonary nodules. CT images can often reach hundreds of layers. Numerous CT images and smaller nodules are prone to fatigue, thus lead to missed diagnosis [7]. In order to alleviate the burden of radiographers and the difficulty of correct diagnosis of radiologists due to fatigue, the computer-aided diagnosis system has a great advantage in solving the above problems, and more and more attention has been paid to the researchers. Computer-aided diagnosis is through the imaging, medical image processing technology and other possible physiological and biochemical means, combined with computer analysis and calculation, auxiliary detection of lesions, improve the accuracy of diagnosis [8]. So computer-assisted detection of pulmonary nodules will help doctors in the case of uncertainty and give a more fair third-party reference. Pulmonary CT images are shown in Figure 1.

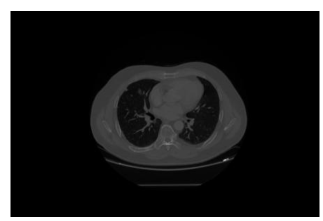


Figure 1. Pulmonary CT images of the patient

The traditional idea of identifying pulmonary nodules is the separation of pulmonary parenchyma, the extraction of suspected nodular regions and the automatic identification of pulmonary nodules. The method of segmentation of pulmonary parenchyma is based on the segmentation method based on threshold, region growth, one edge detection and some new theories of related disciplines such as genetic algorithm, simulated annealing algorithm, network methods and so on. The method of extracting nodular regions includes iterative method, clustering method, morphological method, method based shape and so on. The automated identification of pulmonary nodules includes feature extraction and classification testing. In the traditional automatic diagnosis of pulmonary nodules, the feature selection is extracted by hand, including the gray features, texture features and morphological features of CT images. The classification algorithm includes SVM (support vector machine), Bayesian classifier, linear discriminant classifier and so on. The recognition process includes feature extraction, classifier training and testing. Essentially deep learning is a characteristic learning method. The original data is transformed into a higher level, more abstract by some simple, non-linear model transformations, then the extracted features are trained and tested in the classifier. The advantage of deep learning is that it does not need to extract features as the traditional way, but rather learn from the data through a general learning process [9]. In the classification task, it strengthens the ability of distinguishing the input data in the high level and weakening the impact of irrelevant factors.

The rest of this paper is organized as follows. In section 2, a brief introduction to image segmentation and deep learning is presented. Experimental results and performance analysis are presented and discussed in section 3. Concluding remarks and future work are given in section 4.

II. Our Approach

A. Image Segmentation

Computer aided diagnosis of pulmonary nodules involves segmentation of lung parenchyma, suspected nodules extraction and automatic recognition of pulmonary nodules. The pulmonary parenchyma is extracted from original CT images by the maximum interclass variance method and the extracted image is opened and the regions of interest are extracted. Image segmentation process is shown in Figure 2.

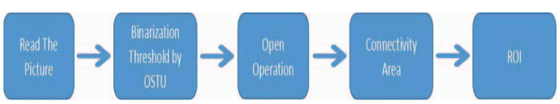


Figure 2. Lung parenchymal segmentation and extract ROI

Image thresholding segmentation is a traditional and most commonly used image segmentation method. It is the most basic and the most widely used segmentation technology because of its simple implementation, small amount of computation and stable performance. In many cases, it is a necessary image preprocessing process for image analysis, feature extraction and pattern recognition. The purpose of the image thresholding is to divide the set of pixels according to the gray scale and each subset is formed to have an area corresponding to the real scene. Each region has a consistent attribute. Such a division can be achieve- d by selecting one or more thresholds from the gray level.

Image segmentation includes region-based method, edge-based method and so on. Region-based method is still widely used in lung CT images and also has good performance. The common region-based methods include regional growth method, threshold method, clustering method and so on. Threshold met- hod mainly includes iterative threshold method, maximum interclass variance method and entropy method. The maximum interclass variance [10] method is an adaptive threshold method, which seeks the best threshold to make the target class and background class get the best separation, expressed by the variance of class.

The gray scale threshold k with the largest variance is the optimal segmentation threshold. The treatment of lung images includes lung parenchyma segmentation and nodules extraction. The images are processed by the Otsu method and eliminated noise by open operation. Finally the suspected nodes are extracted in the lung parenchyma. Several images in the process are listed in the Figure 3.

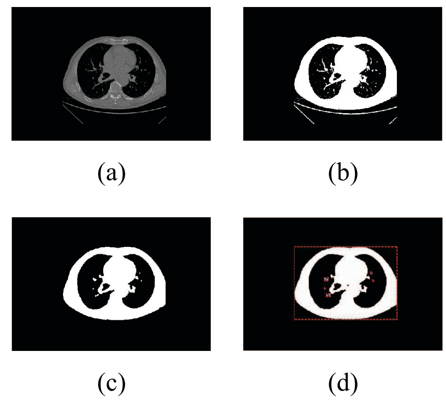


Figure 3. Image preprocessing results. (a) Original CT image. (b) Binary image after segmentation by Ostu. (c) Open arithmetic image. (d) Segmentation of suspected lung nodules.

B. Deep Learning Model

The feature vector is extracted by the convolution neural network and the feature of the high-level network is usually extracted. The feature acquired at this time is already a combination of abstract features. We need to train a neural network model for extracting eigenvectors. The neural network model is the core of the deep learning and the basis of the experiment. Different network models have different characteristics, we have chosen a different network to extract features. AlexNet network is shown in Figure 4 as an example.

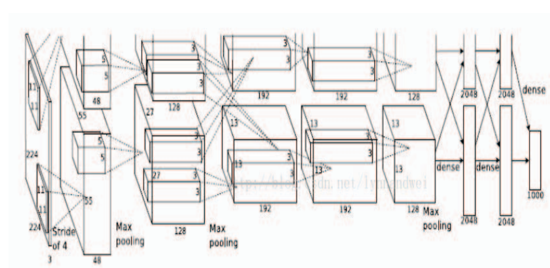


Figure 4. AlexNet network structure

There are eight layers in AlexNet, the first five layers are convolutional layers and the latter three layers are all connected layers. On the first layer, 11*11 convolution templates are used in the three channels, the convolution operation is carried out at intervals of four pixels on the sampling frequency. ReLU, Norm transformation and pooling are carried out after the basic convolution data are obtained. Then the output whose scale is 27*27*96 is transmitted to the next layer. The second layer is still a convolution layer and its processing process is similar to the first layer. The output of the first layer is used as input and the output size is 13*13*256 after convolution, ReLU, Norm and pooling. The processing process of the third and fourth convolution layers are basically the same. The process only includes convolution and ReLU, the output data sizes of the third and fourth layers are 13*13*384 and 13*13*324 respectively. The fifth layer is also a convolution layer which is different from one to four layers. On the basis of the third layer, the pooling operation is added and the output data size is changed to 6*6*256. After the five convolution processes, the sixth layer is the full connection layer and there are 4096 nodes after the full connection. The seventh layer process is similar to the sixth layer and the amount of this layer is 4096. The last lay- er, the full connection layer fc8, is the result by ReLU, dropout and full connection. The final output is entered into the softmax classifier [11,12].

The neural network is connected by multiple sensors, the whole network contains input layer, hidden layer and output layer [13,14]. In the multi-layer network structure model, the convolution neural network (CNN) is the first multi-layer network that can be successfully trained, and the number of parameters to be learned is reduced by convolution and pooling. Unlike deep confidence network (DBN), the convolution neural network belongs to the discriminant training algorithm [15-17].

In the CNN, each image block is input as a visual layer of a multilayer network. In the convolution layer through a group of filters and nonlinear layer transformation, local features of images are extracted. In order to reduce the number of weights needed to train, we introduce other optimization methods: weight sharing [18]. The feature vector obtained by the convolution layer is usually larger in dimension and redundant information is very easy to cause the calculation of the fitting. Thus, summarize the characteristics by down sampling operation at different locations in the layer, i.e., pooling. A significant feature of the observed samples for translation, scaling, and rotation can be obtained by the deep learning model formed by the combination of the multi-layer convolution layer and the pooling layer [19,20].

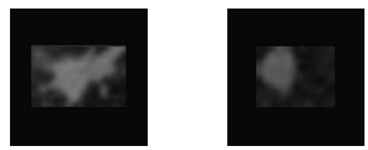
III. Experiment and Result Analysis

A. Data set

The data for this study were low-dose lung CT images (mhd format) of high-risk patients, each containing a series of axial sections of the thoracic cavity. The original image is a three-dimensional image, consisting of a different number of two-dimensional images. All data of CT images is in strict accordance with the international standards of medical information desensitization, desensitized by the hospital. Desensitized information includes hospitals' information, patients' information and labeling physicians' information, all data cannot be traced, so the security of data is guaranteed effectively.

We select multiple lung slices from different patients in the experiment, including as much as possible the level of lung information and hope that the data samples can have a better representation. First, all the lung slices in the experimental data were processed by the second chapter, the suspected lung nodes in the lung parenchyma of the CT image were extracted and the suspected nodes were labeled. The region of interest areas in different lung slices for CT images include the training set and the testing set. The radio of training set to testing set is 2 and we expand the region of interest from the pictures into the size of 227*227. Then it is convenient to make it suitable as input for the CNN nets. The input images are shown in Figure 5.

(a)



(b)

Figure 5. Input Image. (a) Non pulmonary nodule. (b) Pulmonary nodules.

B. Training network model and result comparison

The format of labeled pictures is transformed by Caffe and the data is trained and tested by convolutional neural network. AlexNet and ReNet are selected to train and test the data set in the experiment. According to the table can be seen the accuracy of the AlexNet model is relatively high in the experiment on the data set.

TABLE I. Training results of neural network

Network name	Training result
AlexNet	0.76
ResNet	0.58

IV. Summary and Prospect

This paper summarizes the processing methods of CT images, concepts of deep learning and the advantages of convolution neural network for image classification. According to the characteristics of CT images, we train different neural networks and compare the accuracy of different models. The automatic detection of pulmonary nodules in lung CT images is realized. Computer-aided diagnosis has always been a hot topic in the field of computer research. At present, deep learning is developing rapidly and has been widely used in many fields. It has a very broad space for computer-aided diagnosis. In this paper, an attempt was made on computer-aided diagnosis of pulmonary nodules in CT images based on deep learning. In the near future, the ability of machine learning will be further strengthened and auxiliary diagnostic ability will be greatly improved.

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