Lung Nodule Detection Based on 3D Convolutional Neural Networks

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Abstract—With the increasing number of lung cancer patients, the CAD system is playing an increasingly important rule in the field of automatic identification for medical images. Since the 3D characteristics of low-dose CT images make the 3D convolution more suitable than 2D convolution, in this paper ,we propose a method to detect lung nodule of lung CT images using 3D convolutional neural networks. Combined with the traditional morphological preprocessing methods, 3D convolutional neural networks are applied to lung CT images. The experimental accuracy indicates that this method is suitable for the problem of lung nodule detection and has great room to improve. The experimental results also demonstrate that the application of deep learning in the medical field will bring great progress for medical development.

Keywords—3D convolutional network, CT lung image, nodule detection, deep learning

I. Introduction

The latest data in 2017 shows that more and more Chinese are diagnosed with lung cancer. As shown in National Cancer Center data, there are 1.2 million people diagnosed with cancer and 7700 people died of cancer on average in 2015. And it is estimated that 1.8 million lung cancer cases were diagnosed each year globally. The number of lung cancer deaths among women surpasses those from breast cancer [1]. Since Computed Tomography (CT) is an important means of lung cancer detection, and in view of the complexity of the pulmonary nodule, the large number of CT images scanned by the lungs, especially the high-resolution scanned images makes the number of images of a patient is more than 300 slices, and some of the lesion features are not obvious, which leads to the heavy work for doctors. Therefore, artificial intelligence used in the nodule detection of lung CT images is really necessary.

In recent years, the image processing techniques are used widely in medical areas for improving earlier detection, in which the factor of time is very important to discover the disease in the patients, especially in various cancer tumors, such as the lung cancer and breast cancer. This system generally first segments the area of interest (lung) and then analyzes the separately obtained area for nodule detection in order to diagnosis the disease [12].

The geometric characteristics of pulmonary nodule can be seen as the spherical shape. In terms of gray-scale distribution, it has a Gaussian distribution. Whereas, because of the imaging environment and other lung tissue interference, the naked eye may be difficult to separated pulmonary nodule from other organization, which is particularly difficult to extract vascular adhesions pulmonary nodule. The study of pulmonary nodule detection algorithm has always been a difficult and hot spot in the field of computer-aided diagnosis of medical images. And the traditional machine learning algorithms are applied to most of the abnormal detection of lungs. The traditional methods are strongly depended on the segmentation and preprocessing of CT images. The final prediction and classification results strongly depend on the segmentation results.

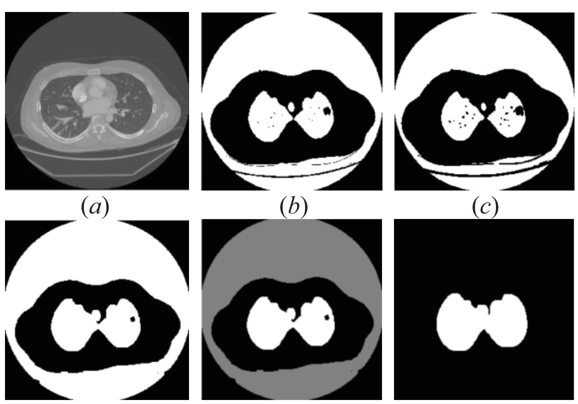
Many methods have been proposed over the last decades, such as morphological method of segmenting the pulmonary nodule [2]. As corrosion and expansion parameters are not easy to control, resulting in under-segmentation or over-segmentation, nodule edge burr may also be eliminated. 2-dimensional images are processed with the threshold segmentation, modeling, nodule segmentation, and so on [3]. However, as the model is less targeted, the effect of pulmonary nodule segmentation of vascular adhesions is poor. When using the gradient direction to determine the difference between blood vessels and nodule, nodule can be extracted with EM and Means-Shift method [3]. It is not suitable for vascular adhesion when its area greater than nodular. The dimensional reconstruction of 2-dimensional sequence image can reduce the nodular space characteristics but requires high-definition images [4]. Five phases involved in the proposed CAD system are extraction of lung region from chest computer tomography images, segmentation of lung region, feature extraction from the segmented region, formation of diagnosis rules form the extracted features and classification of occurrence and non occurrence of cancer in lungs [9]. A novel template-matching technique based on a genetic algorithm (GA) template matching (GATM) for detecting nodule existing within the lung area. The GA method was used to determine the target position in the observed image efficiently and select an adequate template image from several reference patterns for quick template matching [10]. Even though plenty of methods were proposed, it also has difficulties in image segmentation when using traditional methods. Deep learning has great advantages on big data processing, and it provides a rich set of modeling languages. The language systems can express the data relationship and structure inherently, and it can use raw data directly, learning features layer by layer automatically. The whole process optimizes an objective function directly.

Recently, convolutional neural networks (CNNs) leveraging the learned high-level features have revolutionized natural image processing [7]. Among these CNN architectures, 2D CNNs does not take the relationship between adjacent consecutive frames in 3 dimensional space into account. Therefore, in this paper, we will use 3D convolutional neural networks to the automatic detection of pulmonary nodule. Due to the characteristic of the "black box" of CNNs, it can learn features that the traditional machine learning methods cannot learn, thus bring better detection result.

II. PROPOSED METHODS

A. Image segmentation

First, the image is transfered from grayscale to RGB. Then a series of operations such as threshold segmentation, corrosion, expansion are performed. Finally, the connected area is used to obtain the mask of the CT image.



(*a*) (*b*) (*c*)

(*d*) (*e*) (*f*)

Fig 1. (*a*) original image (*b*) threshold segmentation result (*c*) the eroded image (*d*) the dilated image (*e*) marked the connected area (*f*) ROI area

B. 3D CNN Architecture

Based on the 3D convolution described above, the corresponding CNN architecture can be designed. The 3D-CNN is built upon 3D convolutional autoencoder [8]. The 3D CNN architecture for lung anomaly detection at CT images is shown in Fig 2.

As shown in Fig. 2, we consider 20 slices with size of 50 × 50 as input to the 3D CNN model. Firstly, a set of hardwired kernels are used to generate multiple channels from the input slice, which obtain 1×20 feature maps in the second layer. Secondly, 3D convolution with the kernel size of 3×3×3 is applied on each channel. In order to increase the number of feature maps, two different convolutions is applied at each location, resulting in two sets of feature maps in the C2 layer.

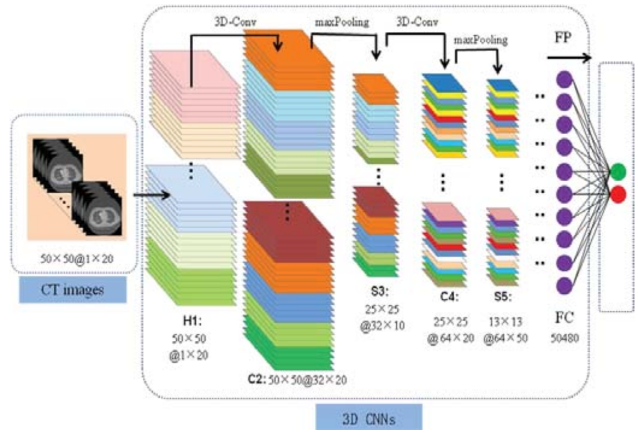


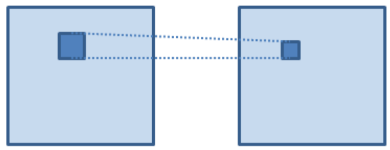
Fig 2. 3D CNN architecture for lung anomaly detection based on CT images.

Each group consists of 32×20 feature maps. Thirdly, 3d max-pooling layer with the kernel size of 2 × 2 × 2 applied on each of the feature maps in the C2 layer, which leads to the same number of feature maps of C2. The size of each slice is 25×25. Fourthly, 3D convolution with the kernel size of 3×3×3 is applied on S3, which can obtain 64×10 feature maps with the size of 25×25. Fifthly, 3d max-pooling layer with the kernel size of 2×2×2 applied on each feature maps in the C4 layer. We can obtain the same number of feature maps with C4 layer with the size of 13×13. Finally, the fully connected layer change the size of 13×13×5×64 which is equal to 54080 in 1024. And a dropout layer with the rate of 0.8 is used after reshape the shape of S5 in 28×28.Among the 3D-CNN structure, we add a ReLU activation function at each inner layer.

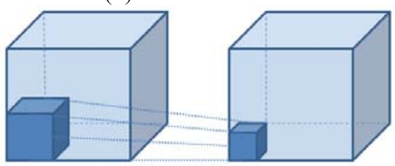
After the neural network training is completed, it is finalized by a fully-connected layer and a *softmax* layer with learning rate of 0.001.

C. 3D Convolution and Pooling

In 2D CNNs, convolutions are applied on the 2D feature maps to compute features from the spatial dimensions [5]. 3D convolution is a cube by stacking multiple successive frames, the 3D convolution kernel is used in the cube. In this structure, each feature map in the convolution layer is connected to a number of adjacent consecutive frames in the upper layer. Lung CT image is the body of the lung arranged into a number of cubes according to a certain thickness level, which means the basic unit is voxel. When the convolution of the network used in the identification of CT image, in order to capture multiple consecutive frames, we propose a 3D convolution in the CNN convolution stage to compute the 3D space features.
The 3D kernel is convoluted with a cube formed by superimposing a plurality of adjacent frames. This structure allows the feature map in the convolution layer to be connected to multiple successive frames.



(*a*) 2D convolution



(*b*) 3D convolution

Fig 3. Comparison of (a) 2D convolution and (b) 3D convolution.

Studies show that 3D ConvNet is well-suited for spatiotemporal feature learning. Compared to 2D ConvNet, 3D ConvNet has the ability to model temporal information better owing to 3D convolution and 3D pooling operations. In 3D ConvNets, convolution and pooling operations are performed spatio-temporally while 2D ConvNets are only in spatial [6].

III. EXPERIMENTS

We have obtained CT scans of about 1500 patients. Then we build another file that contains the labels of this data. Finally, the 3D convolutional neural networks is used to lung cancer recognition on this dataset.

A. CT Lung Image Data Set

1) Computer Tomography image

Computer tomography (CT) use x-ray to the human body with a certain level of scanning. The reconstructed image is obtained after processing by computer. CT images are really anatomical layers, the images are white on the skeleton, and the liver of the brain is black. According to the differences of the density among the tissues, it is shown in different degrees of gray.

The lung CT images have low noise when compared to scan images and MRI images. Thus, we can take the CT images for detecting the lungs. The main advantage of the computer tomography image are better clarity, low noise and distortion. The mean and Variance can be easily calculated. The calculated value is very closer to the original value [12].

2) Digital Imaging and Communications in Medicine

Digital Imaging and Communications in Medicine(DICOM), an international standard for medical imaging and communication. It is a medical document that stored in DICOM standard format with a suffix of '.dcm'. It is usually composed of DICOM files and an image data set.

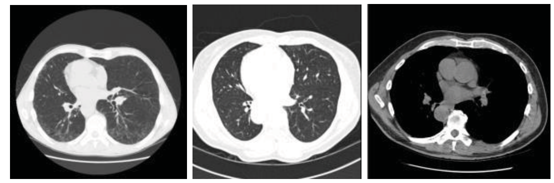


Fig 4. Lung CT images

We have obtained a dataset of CT scans about 1500 patients. Then we have another file that contains the labels for the data. Fig 4 shows some of the lung CT images among our dataset.

B. Lung CT Image Preprocessing Step

1) Handing data: At this point, we have obtained the list of patients by their Ids. And their associated labels is stored in a dataframe. Now, we begin to iterate through the patients and gather their respective data.

2) Processing and viewing our data

a) Resizing the images from 512×512 to 150×150 which is shown in Fig 5.

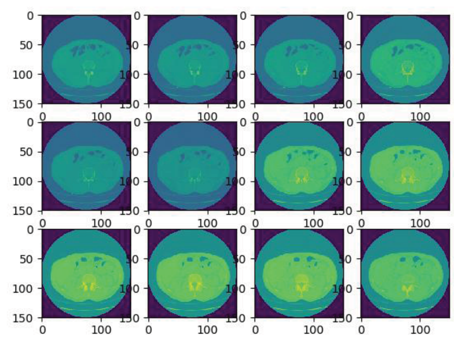


Fig 5. Result image

b) In the dataset, the number of slices contained in patients' CT images is not uniform. We unified the number of slices into 20. The gray scale colormap shown in Fig 6 indicate that some scans are just darker than others overall.

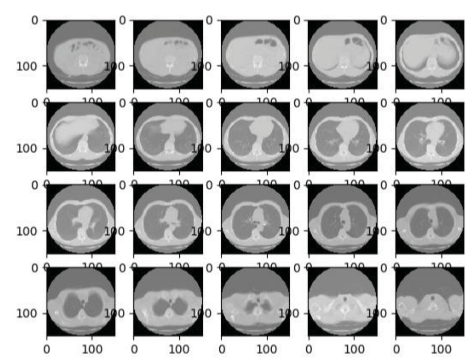


Fig 6. Gray scale image

c) Preprocessing all of the data into one file which makes the training likely be faster

3) 3D convolutional neural network

We define the weights and biases of the convolutional neural network. The weight of conv1 is 3×3×3 patches, the input size of 1, the output size of 32. The weight of conv2 is of size 3×3×3 with the input size of 32 and the output size of 64. The size of fully-connected layer is 1024. The biases of conv1 is 32, which corresponding to 32 feature maps. And the biases of conv2 is 64, the biases of fully-connected layer is 1024, the classes of output layer is 2. Then the formula of fitting, activate function, and dropout are defined with 80%. Finally, the results are given.

C. Result

TABLE I. RESULT I

Pulmonary Nodule Detection based on Feature Extraction and SVM Classification				
Sample number	***kernel function parameter***	***penalty factor***	***Total sample***	***Accuracy***
1	0.2	1000	20	65%

TABLE II. RESULT II

Lung CT Image Nodule Recognition
Accuracy
67.7%

As for the identification of pulmonary nodule, the feature extraction combined with LS-SVM has been applied to it, the results is shown in Table I. And the result of our experient is shown in Table II. After 10 epoches, the accuracy rate can reach above 60%.

By analyzing the results, we can conclude that SVM has lower classification accuracy than 3D convolutional neural networks in the same number of samples. With the increasing number of samples, its training speed and performance are worse than 3D convolutional neural networks. And 3D convolutional neural networks used in CT pulmonary nodule detection is only in the initial stage, which has greater room to improve.

IV. Conclusion

Since deep learning applied to medical images is still at embryonic stage, 3D convolutional neural networks has some achievements in the detection of lung CT abnormalities as shown in this paper. The results show that the 3D convolutional neural networks are effective in the detection of lung cancer. And the reason why the result is not really ideal greatly is that the database is not large enough, the image preprocessing is not very suitable for the networks. Later, we will make some improvement in these part.

Acknowledgements

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