Detection and Classification of Pulmonary Nodules

1st Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

2nd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

3rd Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

4th Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

5th Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

6th Given Name Surname
dept. name of organization (of Aff.)
name of organization (of Aff.)
City, Country
email address or ORCID

***Abstract*—Pulmonary nodule detection and classification represent two of the most common tasks in the computer aided analysis of chest CT images. Methods have been proposed for each task with deep learning based methods heavily favored recently. However training deep learning models to solve each task separately may be sub-optimal - resource intensive and without the benefit of feature sharing.**

***Index Terms*—pulmonary nodule detection and classification , deep convolutional neural network**

I. Introduction

Pulmonary nodules are defined as focal, quasi-circular, dense or asfirm lung shadows with imaging findings of diameter $\leq$ 3 cm. [1] CT is the most important means for diagnosis, follow-up and efficacy evaluation of pulmonary nodules, but there is radiation during scanning, which has certain effects on human body.In general, low-dose CT can be used, at one-fifth or less of the conventional dose, with minimal impact on the human body.The normal population is recommended to have a yearly scan. Thin-section CT, enhanced CT, MAGNETIC resonance imaging, positron emission computed tomography (PET) and other imaging examinations can be used to analyze the properties of pulmonary nodules from the aspects of morphology and metabolic function, which is of great reference value for the diagnosis of pulmonary nodules.But it's not a diagnosis.Therefore, from the perspective of diagnosis, clinical diagnosis can be made by analyzing the cell or tissue samples obtained from pulmonary nodules through bronchoscopy, percutaneous puncture, surgical methods, etc.

II. Literature Review

III. Model

A. Preprocess the Data

The data of LUNA16 came from a larger data set, LIDC-IDRI, which had a total of 1018 CT scans, or 1018 cases. Each CT image had a label file in XML format. The data of this data set came from seven different academic institutions, which used different scanners and related parameters. In LIDC - IDRI data set, there are three areas will be marked, nodules $>$ 3 mm in diameter, diameter $<$ 3 mm nodules and the nodules (but lung distortion area), return to LUNA16, in 888 CT, a total of 36378 nodes were marked (LIDC - IDRI annotation), in LUNA16, only diameter $>$ 3 mm nodules as sample, diameter $<$ 3 mm nodules and the nodules are not included. To train the data, the first step is to genrate the mask of pulmonary nodules. The annotations.csv annoatates the coordinates of X, Y, Z as well as the diameter of pulmonary nodules, with these data, the cube area is generated, and finally the Mask image file is output. The second step is image denoising. We set the window width and window level (-1000,600) to remove the noise in the CT image, such as bone highlights, metal lines of the CT bed, etc., and normalize the image to (0,1). The third step is to crop the picture to the same size. The CT image with a layer thickness greater than 1mm and the corresponding Mask image were sampled with interpolation (linear interpolation method was used for CT image and nearest-neighbor interpolation method for Mask image), and the layer thickness after interpolation sampling was 1mm. The size of Patch area (96,96,16) in CT image and Mask image was taken according to a certain step length, and the valid Patch Mask image and corresponding Pactch image were judged and retained. The final step is to prepare benign and malignant pulmonary nodules classification data.Coordinates are read from the candidates.csv file, and images of the size of (48,48,48) are taken as candidate pulmonary nodules images centering on this coordinate, and the images are divided into two categories according to the label value (0 or 1). After doing these steps, we have data that we can train with. And we found that There were 1,351 pulmonary nodules and 549,714 non-pulmonary nodules.There's a huge difference between positive and negative samples.Therefore, we performed data enhancement processing on the data, and randomly sampled 20% of the data from 549714 non-pulmonary nodules images, which were enlarged by 40 times (rotation, translation, inversion, etc.) for 1,351 pulmonary nodules images. A total of 601 of the 888 cases had pulmonary nodules in the CT data, and a total of 16,475 patches were taken out from the 601 cases.We

chose 80 percent of the data for training and 20 percent testing.

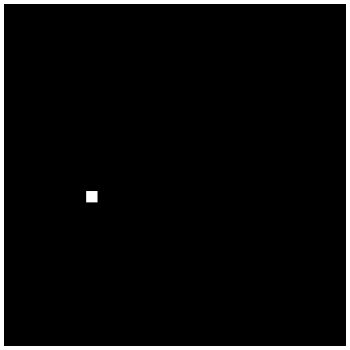

Fig. 1: Accorind to cadidattes.csv, we generate the mask pulmonary nodule

B. Nodule Detection

We use 3DVNet network model to achieve detection. could be seen in 2. And to illustrate, the following poi should be noted:

- The Conv layer connecting the output layer adopts convolution kernel of 1x1x1 size, while the remaini Conv layer adopts the convolution kernel of 3x3x3 si
- 3dMaxPooling layer is adopted in the pooling layer.
- The Upsample layer is implemented by the deconvoluti layer.
- Concate layer splices the results of Conv layer a Upsample layer in the decoding network.

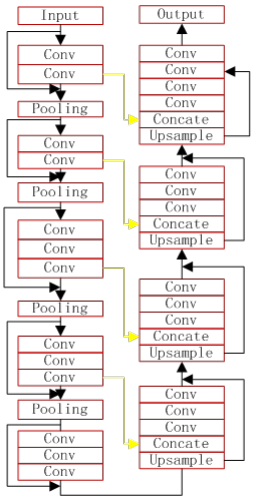

Fig. 2: Network structure of 3dVNet

What's more, The residual connection is also used to prevent the gradient disappearing during the training. Our parameter is set as learning rate is 0.001, Batchsize is 6, and epoches is 10. And the loss function is as followed:

$$\text{dice} = \frac{2^* \text{abs}\,(A^* B)}{A^2 + B^2} \tag{1}$$

The result could be seen in 3

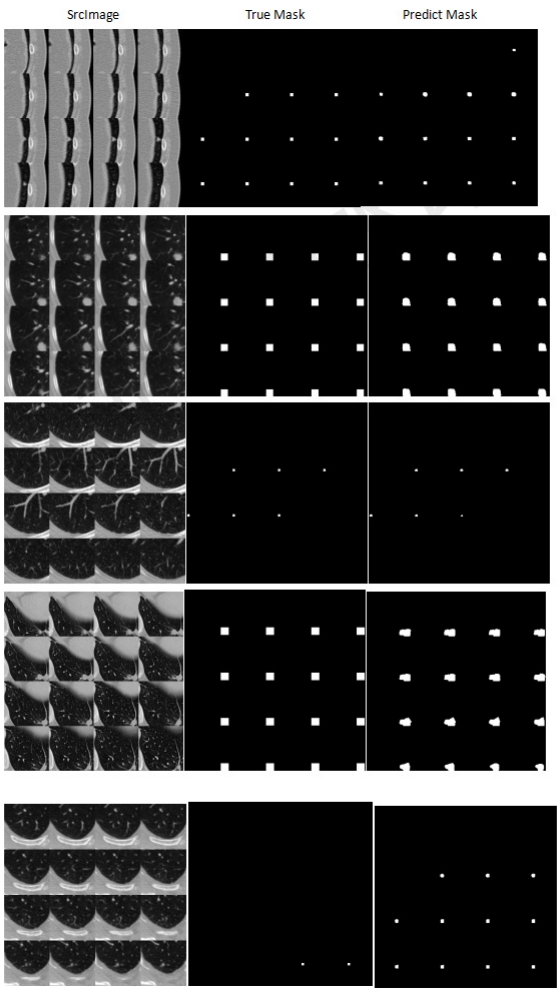

Fig. 3: Our result of detection on the test data. The original image is predicted and compared with the gold standard image.The original image is shown on the left, the gold standard image is shown in the middle, and the predicted image is shown on the right.

C. Nodule Classify

Classification network is a mature network, and there are many network models with good performance.We use an improved version of THE VGG network to achieve benign and malignant classification. The structure could be seen in4.And to illustrate, the following points should be noted:

- All Conv layers adopt 3x3x3 convolution kernel.
- 3dMaxPooling layer is adopted in the pooling layer.
- The FC layer is the full connection layer. The first FC USES Relu activation function, while the second FC USES Softmax activation function.

The residual connection is also used to prevent the gradient disappearing during the training. Our parameter is set as learning rate is 0.001, Batchsize is 32, and epoches is 5. And

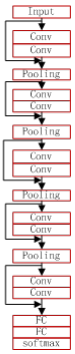

Fig. 4: The structre of ResVGGNet

we adopt cross entropy function as loss function.

$$\text{loss} = -\sum_{i=1}^{n} y_i^* \log\left(y_{i\_}\right) \tag{2}$$

IV. Results

The result of detection could be seen in 3 and 5. And the accuracy could reach to 62% and it is still going up. Due to the time limited, we cannot train it completely.

The result of classification could be seen in 6. By analyzing

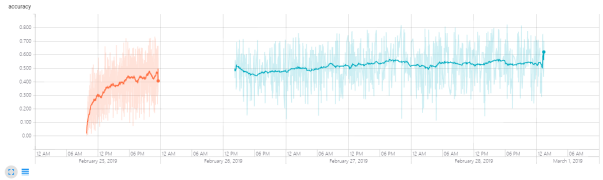

Fig. 5: The result of detection.The red line is the first training, and the blue line is the result of the first training

the confounding matrix, the overall accuracy rate of the classifier is 98.73% , the false positive rate is 1.718% and the omission rate is 0.394%.

真实 \ 预测	0	1
0	19513	341
1	40	10106

Fig. 6: The result of detection.The red line is the first training, and the blue line is the result of the first training

V. Future Studies

Due to the time and device limited, we only use one model to achieve the detection and classification of pulmonary nodules. With the research of convolutional networks, more models are put award. And in the future we will use these models to improve accuracy of classification and detection.

Acknowledgment

Thanks very much for my group members in this internship. I would also like to express my gratitude for Dr Teoh Teik Toe for his discussion of topic selection and guidance on some issues in the early stage of my project. I also have a new dream school, and I hope I can meet the graduate student in NTU again.

References

[1] 王静, “肺结节,我们该如何对待,” 家庭健康：医学科普, vol. 000, no. 3, p. 20, 2019.