Research on the Automatic Detection Method of Pulmonary Nodules Based on Deep Learning

Jingwen Yu, Dongbi Zhu* and Xinyi Xiao

College of Engineering, Yanbian University, Jilin, China

*Corresponding author

Abstract. Lung cancer has become the highest incidence and mortality of malignant tumors in China and even the world. It is truly the “first killer of cancer”. Pulmonary nodules are the early manifestation of lung cancer. Early detection, early treatment and early diagnosis of pulmonary nodules can greatly reduce the mortality of lung cancer. Due to their different sizes and complex structures, it is difficult for doctors to recognize the specific characteristics of pulmonary nodules. In order to help doctors detect and analyse pulmonary nodules faster and more accurately, based on deep learning, this paper proposed a new method to detect pulmonary nodules by cascades of improved VGG network model and improved Resnet network model. The improved network was evaluated on the LIDC-IDRI database, and the experimental results demonstrate the effectiveness and robustness of the model, which can help doctors accurately and effectively detect pulmonary nodules.

1. Introduction

According to the World Health Organization survey, about 1.2 million people are diagnosed with lung cancer every year around the world, and 400 thousand people are newly diagnosed with lung cancer every year in China. In both developed and developing countries, the incidence of lung cancer is on the rise, and the first death rate is lung cancer[1]. Although lung cancer has a very high mortality rate, early lung cancer is small in size, no metastasis and diffusion, and the survival rate of radical resection can reach 60-90%. Therefore, "early detection, early diagnosis and early treatment" can greatly improve the survival rate of lung cancer patients and reduce the mortality of lung cancer.

At this stage, the main methods of pulmonary nodule detection are high-resolution CT, CT, MRI, X-ray and other techniques. Among them, lung high-resolution CT is a very effective technique for detecting pulmonary nodules[2]. Doctors need to visually observe hundreds of CT slices of the lung to find out whether each CT image contains pulmonary nodules. It is easy to misdiagnose or miss the diagnosis of pulmonary nodules due to subjective factors and reading fatigue. Deep learning method successfully surpasses the limitations brought by traditional learning methods. Even without manual design and extraction functions, it can extract important characteristics of disease judgment from data set. Therefore, the automatic detection of pulmonary nodules has become the focus of clinical diagnosis research. So it is necessary to propose a computer-aided diagnosis method based on convolutional neural network to help doctors improve the detection efficiency of pulmonary nodules[3]. Therefore, after studying a large amount of data, this paper proposes a more in-depth and complex convolutional neural network model through improvement. This model is mainly to improve VGGNet and RESNet models and cascade them to detect pulmonary nodules. The improved model can prevent model over fitting and improve network performance. In section 2, this paper introduces the achievements of domestic and foreign researchers in the detection of pulmonary nodules. In section 3,
it introduces a new method based on deep learning to detect pulmonary nodules. In section 4, it introduces the experimental results and analysis, In section 5, it introduces the conclusion.

2. Related Works
For the past few years, with the continuous innovation of computer technology, the application of artificial intelligence technology has penetrated into our daily life. It is an important part of medical field to use artificial intelligence medical imaging technology to diagnose pulmonary nodules.

On the one hand, some scholars at home and abroad use traditional methods to detect pulmonary nodules. Firmino M et.al[4] use watershed and histogram techniques, and support vector machine algorithm to train 420 lung cancer patients to detect pulmonary nodules. The accuracy rate is 94.3%. Gao T et.al[5] calculated the adaptive template and the three-dimensional normalized cross-correlation coefficient by using the similarity principle. When the threshold value is higher than the set threshold value, the marked target area is the pulmonary nodule. Lin D T et.al[6] have known that the pixel values of pulmonary nodules and blood vessels are high and round like through prior knowledge, and through the analysis of image histogram, find out the pixel values with high gray level as the candidate points of suspected nodules. However, these methods have their inherent shortcomings. Traditional SVM algorithms assume that all features have the same effect on target classification, so most of the above algorithms are suitable for small-scale data sets, not for large-scale data sets such as hospitals. Moreover, the accuracy of the algorithms can only be determined by uniform comparison. In addition, these algorithms are based on artificial feature extraction method, Which one needs a lot of time and energy to do. With the development of medical image big data trend, the traditional machine learning algorithm does not show enough excellent performance to solve the big data problem.

On the other hand, deep neural network is used to detect pulmonary nodules. Gruetzemacher.et.al[7] used convolutional neural network to distinguish the benign and malignant of solid pulmonary nodules. Finally, through the network structure of 10 layers of hidden layer, the pulmonary nodules were detected with an accuracy of 82.10%, but the generalization ability of the network was not strong. Shelia Ramaswamy.et.al[8] used the existing CNN model Alex net and Google net to identify 15562 lung CT images, with an accuracy of 89.6%. Liu J.[9] uses CNN to identify the benign and malignant attributes of pulmonary nodules, and takes the residual network as the backbone network. When the confidence threshold is 0.58, the accuracy rate is 90.8%. Wang.et.al[10] proposes a multi view convolutional neural network (mv-cnn), which integrates three branches of the convolutional neural network using the full connection layer, and can effectively detect a variety of pulmonary nodules. These methods have the common characteristics of high sensitivity, low specificity, low recognition rate and large research space.

3. Materials and Methods
3.1. Data Collection
This data set is from LIDC-IDRI open source data set, which is composed of chest medical image file and corresponding diagnosis result pathological annotation. A total of 1012 research cases are included in the data set. For the images in each case, four experienced chest radiologists performed two-stage diagnostic tagging. In the first stage, each physician independently diagnosed and marked the patient's location. In the second stage, each physician independently reviewed the other three physicians' marks and gave their final diagnosis results. Such two-stage annotation can annotate all results as completely as possible. The annotation content mainly includes nodal coordinates and other information. Each patient's CT image data is composed of several 512 * 512 size slices.

3.2. Data Preprocessing
Most of the doctors' diagnoses are based on lung X-ray results, however, this low radiation image is difficult to determine with the naked eye. Therefore, in order to improve the accuracy of pulmonary nodules detection, we need to preprocess the image data set to improve the image quality, as well as data enhancement and pulmonary parenchyma segmentation.
3.2.1. Pulmonary parenchyma segmentation. In order to reduce the detection area, save the calculation time and improve the detection accuracy, the correct segmentation of lung parenchyma is particularly important in the computer-aided diagnosis of lung diseases. Lung parenchyma segmentation can remove peripheral useless data, and only retain the lung parenchyma needed for training.

The first step to segment the lung parenchyma is histogram equalization. Histogram equalization is to flatten the gray histogram of an image so that the distribution probability of each gray value in the transformed image is the same. Histogram equalization can increase the image contrast before further processing. The transformation function in histogram equalization is the cumulative distribution function of the pixel value in the image. After the processing of histogram equalization is completed, we can find in the following figure that the image contrast after equalization is enhanced, and the details of the gray area of the original image become clearer.

Figure 1. Histogram equalization.

After histogram equalization processing, the gray value of each tissue will have a certain gap, which will interfere with the segmentation of lung parenchyma area, so it is necessary to binarize the image. For the binary image, lung parenchyma is filled, lung parenchyma and background are separated, and lung parenchyma image is obtained. Region growing method is used to effectively separate left and right lung adhesions, and the largest connected area is extracted, then hole filling and mask subtraction are performed. After removing the connected area less than 1000, the lung parenchyma segmentation image can be obtained by multiplying the original image with mask. The specific process is shown in Figure 2. All the lung CT images needed in the experiment can be well segmented, and the segmentation results can be used in subsequent experiments.

Figure 2. Pulmonary parenchyma flow chart.

3.2.2. Dataset enhancements. Since we use data sets manually labeled by doctors as training samples, such data sets are limited. The low detection rate caused by the phenomenon of overfitting is easy to occur. This requires a large number of amplified datasets. The solution is to use affine transformation and random transformation to enhance the lung CT image data set.

1) the affine transformation is used to enhance the dataset, mainly for horizontal and vertical mirror operations.
2) the lung nodule image is randomly cropped to obtain more data sets. According to the different proportion of positive and negative samples, the number of random cropped is also different.
3.3. Method
Deep learning is a multi-level network structure, which can combine the underlying features to form more abstract attribute categories or high-level representations of features, so as to discover the distributed feature representations of data. Taking images as input, convolutional neural network can effectively learn corresponding features from a large number of samples, avoiding complex feature extraction.

3.3.1. Convolutional neural network model. Convolutional neural networks are very similar to normal neural networks in that they are composed of neurons with learnable weights and bias constants. Convolutional neural networks can extract more abstract features from images, and the whole process requires only a small amount of human involvement. Convolutional neural network is usually composed of input layer, convolutional layer, activation layer, pooling layer, full connection layer and final output layer.

![Figure 3. Convolution neural network model diagram.](image)

3.3.2. Improved convolution neural network model. In this paper, the improved VGG network model is used to detect pulmonary nodules, which can be referred to as candidate nodule detection model. Then we use the improved RESNET model to carry out false-positive inhibition, which is called false-positive inhibition model for short. The candidate nodule detection model and the false-positive inhibition model can be cascaded to detect the pulmonary nodule finally.

Candidate nodules detection model of network structure is mainly composed of convolution layer, active layer, the largest of pooling and full connection layer, the network is improved by VGGNet model, as the longitudinal deepening network, the network has two parts, the first part of VGG - 1, by a convolution of module and a maximum pooling layer, the second part of VGG - 2, network contains three convolution module and the two biggest pooling layer, the last layer using softmax and cross entropy function. The convolution module of each part of the network has two convolutional layers, and the size of the convolution kernel in the convolutional layer is 3*3. The activation function USES the Relu function.

The network structure of the false-positive suppression model is improved by the ResNet model, where the network connects five residuals after one convolutional layer, and the last residuals are followed by the batch-normalization layer, the relu layer, and the maximum pooling layer, the activation function USES the relu function, and the last layer uses softmax.

The reason why RESNET model is adopted is that with the increase of network depth, there will be a degradation problem, that is, when the network becomes deeper and deeper, the accuracy of training will tend to be gentle. In order to solve this problem, we introduce residual block. The difference between the residual network and the ordinary network is the introduction of jump connection, which can make the information of the previous residual block flow into the next one unimpeded, improve the information flow, and also avoid the problem of disappearance gradient and degradation caused by the over depth of the network.
Figure 4. Residual block in residual network.

The network structure diagram of this paper is shown in the following figure:

Figure 5. Network structure flow chart.

4. Analysis of Experimental Results

Based on LIDC-IDRI open source lung database, the CT images of 1000 patients were preprocessed and data enhanced. About 10000 lung nodule images and 20000 health images were extracted as training data samples. The data were studied and analyzed by the model of deep learning, and finally a prediction model was obtained. The sensitivity (SEN), specificity (SPEC) and accuracy (ACC) were used to evaluate the performance of the model, and the good robustness of the model was verified. In the experiment, the CT images of some patients who are not in the training set are used as the test set to test the model. The experimental results show that the accuracy of training set is 96.8%, the accuracy of test set is 90.9%, and the network is effective. Figure 6 is an example of detection of pulmonary nodules. As can be seen in Figure 6, pulmonary nodules are well detected.

Figure 6. Original and detection of pulmonary nodules.

The experimental results of this algorithm are compared with those of other CAD systems as shown in Table 1. The experimental results show that the detection rate of this method is higher than other CAD methods.

Table 1. Comparison of the detection rate of pulmonary nodules between this method and other methods.

| CAD system                | Experimental method                  | Detection rate |
|---------------------------|--------------------------------------|----------------|
| Ross Gruetzemacher et.al  | Convolutional neural network          | 82.1%          |
| Shelia Ramaswamy et.al    | AlexNet,GoogleNet                   | 89.6%          |
| Algorithm in this paper   | Improved convolutional neural network | 90.9%          |
5. Conclusion
Task for medical images, this paper puts forward a kind of new convolution neural network model to detect lung nodules, namely with the improved VGGNet and ResNet network model of the cascade, using random cutting and affine transformation for data amplification, in the process of model training, use Adam methods of optimization, and regularization and dropout, accuracy of training set is 96.8%, the accuracy in test set was 90.9%, to verify the effectiveness of the network. The test results show that the improved network model is better than other network models in performance, so it can be detected more accurately. This method not only improves the detection accuracy of pulmonary nodules, but also makes the diagnosis of pulmonary nodules more objective and accurate, which has important scientific significance and clinical application value.

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