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# Detection for Pulmonary Nodules using RGB Channel Superposition Method in Deep Learning Framework

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***Abstract*—The detection of pulmonary nodules is a very important research field in computer-aided diagnosis. In order to help doctors to identify pulmonary nodules more conveniently, especially for some small pulmonary nodules, a method based on RGB channel superposition to detect pulmonary nodules is proposed in this paper. We put the same ROI (region of interest) from three sequential lung CT slices into RGB channels to gain a pseudo-color image for deep learning. AlexNet and GoogLeNet is used as the deep learning network. We use 10000 patches of healthy tissues and 12000 patches of pulmonary nodules in LIDC-IDRI dataset for training and get a prediction model. The model is tested on 176 patients' CT images and gain the sensitive of 95.0% at 5.62 false positives per scan. The experimental results show that the proposed method can improve the detection rate of pulmonary nodules compared with some traditional feature extraction methods.**

## I. Introduction

A pulmonary nodule is a kind of granulomatous disease of unknown etiology affecting multiply systems and organs, which has attracted extensive attention in recent years as a possible sign of early lung cancer [1]. Lung cancer is one of the cancers with particularly high incidence and mortality rates in the world [2], [3], [4], [5], but most of lung cancer patients do not have obvious symptoms early on, so it is easy to ignore the disease and delay the optimal time for treatment. If a patient has lung cancer, early and prompt treatment can increase the survival chance, so the detection of pulmonary nodules is particularly important.

The traditional method of doing so is to use a lung CT scan to check whether patients have pulmonary nodules. Some examples of CT slices containing pulmonary nodules are shown in Fig.1, the white globular objects in the boxes are pulmonary nodules. It is apparent that large pulmonary nodules are markedly different from other healthy tissues while some other pulmonary nodules may be too small to be detected by unaided eyes easily. Usually, there are hundreds of CT slices for a patient, so it may cost a lot time and energy for doctors to recognize pulmonary nodules by looking at the lung CT slices.

Therefore, computer-aided diagnosis (CAD) becomes a helpful choice for doctors to save precious time by enhancing the process of diagnosis [6]. Traditional methods use feature extraction method to recognize pulmonary nodules. Gurcan et al. used feature extraction and linear discriminant analysis method to get the sensitivity of 84% with 5.48 false positive per slice [7]. In 2005, Zhang et al. combined feature extraction and discrete time cellular neural networks and get the sensitivity of 82.98% with 11.76 FP objects per case [8]. Since the lack of information on 2D CT slices, the previous and next slice are necessary to be considered in pulmonary nodules detection. Some 3D features are used in this field. In 2009, Ye et al. used 3D local geometry features to analyze the image and used SVM to reduce false positive. The result is sensitivity of 90.2% with 8.2 false positive per case [9]. Choi et al. used hierarchical 3D block classification to achieve the sensitivity of 95.28% with 2.27 FPs per case [10]. With the further study of feature extraction, the number of features are increasing. Ma et al. extracted 979 features of candidate nodules and used random forest as the classifier, reaching 88.9% sensitivity at 4 false positive objects per case [11].

Deep learning is one of the research fields in artificial intelligence, a very important branch of computer science. It is hailed as one of the most advanced technologies in this world, with the main research fields of artificial intelligence being machine perception, machine thinking, machine learning and machine behavior. In recent years deep learning has become a key research field of machine learning and new achievements based on deep learning have been made continuously. Deep learning constructs a network structure model containing multiple hidden layers to train large amounts of data. Some features can be extracted from the process of training, which can help in improving the accuracy of prediction or classification. The main difference between deep learning and shallow machine learning is that deep learning has more hidden layers. As a research hotspot, deep learning has been implemented into several aspects of our lives: Microsoft Research Institute, Baidu Institute of Deep Learning, Google and some other companies have combined deep learning with speech recognition and image recognition. Deep learning is also widely used in natural language processing [12], [13], [14].

Recent years, more and more artificial neural network and deep learning methods are used to pulmonary nodules detection. Setio et al. used multi-view convolutional networks to analyze nine different angles of candidates and get the

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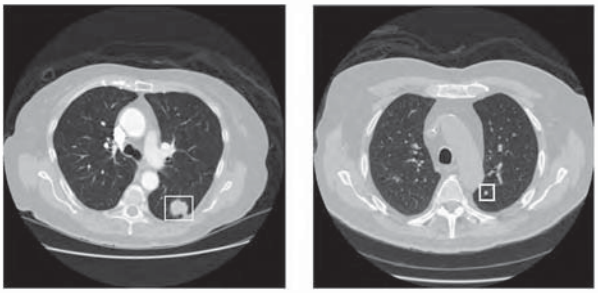
sensitivity of 87.9% with 4 FPs per case without extracting lung parenchyma [15] in 2016. Liu et al. used artificial neural network to analyze 3D features and achieve the result of 89.4% sensitivity with 2 FPs [16].

There are some pulmonary detection competitions in the past two years such as LUNA16(Lung Nodule Analysis 2016) and Kaggle Data Science Bowl. LUNA16 divides 888 patients' CT slices into ten subset and uses cross validation to evaluate the average sensitivity with 1/8, 1/4, 1/2, 1, 2, 4, 8 false positive. Kaggle Data Science Bowl computes a log loss to evaluate the results. The champion of Kaggel Data Science Bowl used the method of RPN(Region Proposal Network) to extract candidate nodules and used 3D convolutional neural network to analyze the most probably five candidates of each slice [17]. which reached the log loss of 0.39975.



(a) (b)

Fig. 1. Examples of CT slices containing pulmonary nodules

In this paper, a method to detect pulmonary nodules based on deep learning is proposed. A large amount of CT slice data is trained by deep learning and a model is created to recognize whether CT slices contain pulmonary nodules.

The contributions of this paper are as follows.

- We propose a method to superimpose three consecutive CT images' ROI into RGB channels to distinguish pulmonary nodules from healthy tissues.
- We train a large amount of data from LIDC-IDRI database with the method of deep learning and gain a prediction model to recognize whether a pulmonary nodule is presented on a ROI patch.
- We test the prediction model on 176 patients' images from LIDC-IDRI database and get the sensitive of 95.0 at 5.62 false positives per case.

The remainder of this paper is structured as follows. Section II introduces related work. In Section III, we propose a method to detect pulmonary nodules. Section IV shows the experiment results and Section V concludes the paper.

## II. Related Work

### A. Artificial Neural Network and Deep Learning

Deep learning originates from the study of artificial neural networks, a very important research field in artificial intelligence. An artificial neural network imitates the biological neural network in the human brain to deal with data. The neuron is the basic component and an artificial neural network is constructed by the connection of a huge number of neurons from different layers. The processing of data in each neuron is relatively simple and the learning of a network is shown in the strength of connection between its neurons.

The concept of deep learning was proposed by Hinton in Science in 2006 [18], and was distinguished from artificial neural networks. The structures of deep learning and artificial neural networks are similar, but the training methods are different. Traditional artificial neural networks use an iterative algorithm for training, while deep learning uses the method of initialization layer by layer which can effectively solve the problem of gradient diffusion in artificial neural networks.

### B. Convolutional Neural Network (CNN)

A convolutional neural network is a front feed neural network and is widely used in several important fields in image recognition and image processing such as face recognition [19], pedestrain detection and so on [20]. Convolutional neural networks have the characteristics of local perception and weight sharing. Local perception means that each layer's neurons are only connected to the neighbourhood neurons in the upper layer. Through the method of local perception, neurons can extract some primary visual features such as direction, segments, corners and so on. The characteristic of weight sharing can make it so the convolutional neural network has fewer parameters and needs less training data. Down sampling can reduce the scale of features and achieve the invariance to some change such as shifting and scaling.

The main components of convolutional neural networks are convolution layers, pooling layers and full connected layers. The convolution layer uses convolution kernels to perform convolution operations with image, to enhance the original signal's feature and reduce the noise in order to learn and recognize the image's features. The pooling layer is usually arranged after a convolution layer to extract and compress the main features. The main purpose of using a pooling layer is to cut down the computation load and the data dimension, in order to reduce the complexity of the algorithm. The full connected layer maps the features learned by the model to the sample space and output.

## III. Detection for Pulmonary Nodules

The research methodology of this paper is for the purpose of analyzing the preprocessed data sets via deep convolutional neural network. The first step of data processing is image segmentation to extract the lung parenchyma. Then the connected regions in the lung parenchyma are analyzed to obtain the centroid of pulmonary nodules candidates. According to the centroids' position, we can cut 64×64 patches from the raw CT slices, which are regions of interest (ROI). Finally, we cut other two 64×64 patches from the previous and next CT slices with the same center position and put the three patches into R, G, B (Red, Green, Blue) channels to superpose a pseudo-color image. By the method of superposing three continuous

patches, the trends of pulmonary nodules candidates can be shown in pseudo-color images, which can help us to distinguish the pulmonary nodules form vessels. The general steps of data training are shown in Fig.2.

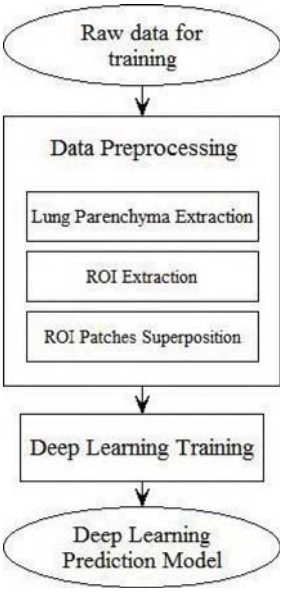



Fig. 2. The steps of data training

### A. Lung Parenchyma Extraction

The first step of data preprocessing is lung parenchyma extraction. We extract the lung parenchyma from the raw lung CT slices to reduce the effect of lung outline on the results since we only concern about part of the lung parenchyma. We erode the lung outline in the step of parenchyma extraction in order to separate some pulmonary nodules candidates which are adhered to the outline.

The detail steps of lung parenchyma extraction are: (1) transform the CT slice to binarized image by a fixed threshold, (2) extract the largest connected region from the binarized CT slice, which is considered as the preliminary lung outline, (3) fill the trachea and some holes in the outline, (4) erode the lung outline to separate some juxta-pleural pulmonary nodule candidates, (5) fill some small holes on the lung outline after eroded and then extract the largest connected region and dilate this region to obtain the real lung outline, (6) get the lung parenchyma mask according to the outline, (7) extract the lung parenchyma by the lung parenchyma mask and the raw CT slice. The steps of lung parenchyma extraction are shown in Fig.3.

### B. ROI Extraction

The second step of data preprocessing is ROI extraction. After extracting the lung parenchyma, the lung parenchyma images are analysed and the pulmonary nodules candidates are obtained, then we cut 64×64 patches from the lung parenchyma with the center of the pulmonary nodules candidates' centroid. These patches are regarded as the ROIs of this lung parenchyma.

The steps of ROI extraction are: (1) transform the lung parenchyma to binarized image by a threshold, (2) remove the interference regions with small areas, (3) remove the strip regions since pulmonary nodules are globose objects and the strip regions are vascular and other healthy tissues, (4) cut 64×64 patches from the lung parenchyma with the centroids of all connected regions in the image as centers and regard these patches as ROIs. The procedure of ROI extraction is shown in Fig.4.

### C. ROI Patches Superposition

The third step of data preprocessing is ROI patches superposition. After getting a ROI patch of a lung parenchyma, we find the previous and next CT slice from the CT slice sequence (sorted by z position) and the according lung parenchyma images. Then we cut 64×64 patches from these two lung parenchyma with the same center of the obtained ROI patch. Put the three patches into red, green and blue color channel to obtain a pseudo-color image. The superposed 64×64 pseudo-color images will be put into the training data set for deep learning training.

The operation of ROI patch superposition is used for enhancing the differences of the pulmonary nodules and other healthy tissues. Due to the globular feature of pulmonary nodules, the three ROI patches are almost overlapping, while the healthy tissues such as vessels are strip-like, so a gradient of red, green, blue can be found in pseudo-color image to show the trend of healthy tissues. Especially for some small pulmonary nodules which are difficult to recognize with the naked eye, the difference between pulmonary nodules and blood vessels can be significantly increased by the method of ROI patch superposition. Some typical samples of pseudo-color images of pulmonary nodules and healthy tissues are shown in Fig.5.

### D. Deep Learning Framework

In this paper, Convolutional Architecture for Fast Feature Embedding (Caffe) is used as the framework of deep learning. Caffe is developed by Berkeley Vision and Learning Center (BVLC) for convolutional neural networks [21]. Caffe has the characteristics of extensibility and fast speed. The server system is CentOS 7.3 with NVIDIA GeForce GTX 1080 GPU and CUDA 8.0 to speed up the calculation [22].

The data sets are trained and tested by AlexNet and GoogLeNet. AlexNet is a classic open source convolutional neural network and won the ImageNet Large Scale Visual Recognition Challenge (ILSVR) in 2012 [23]. AlexNet consists of five convolution layers, three pooling layers, three full connected layers and seven activation layers and has nearly sixty million free parameters. The structure of AlexNet is shown in Fig.6. The inputs of this network are 227×227 RGB images which are resized by the 64×64 pseudo-color patches.

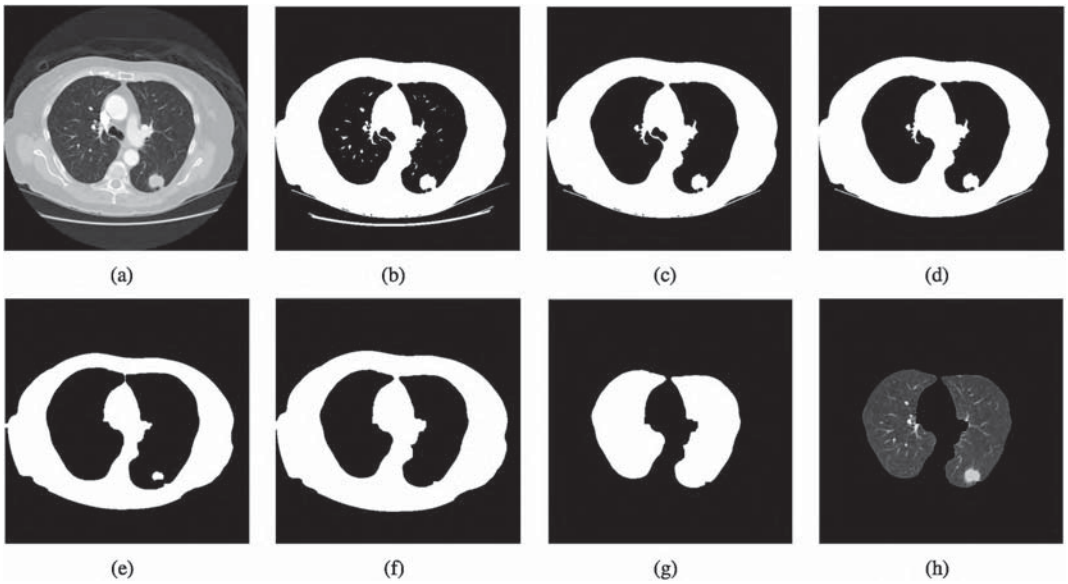



Fig. 3. Lung parenchyma extraction steps: (a) get a raw CT slice; (b) binarize the raw CT slice by a threshold to get a binary image; (c) extract the preliminary lung outline from the binary image; (d) fill the trachea; (e) erode the outline with an operator; (f) extract the outline and dilate it with the same operator to gain the final outline; (g) get the lung parenchyma mask; (h) get the lung parenchyma.

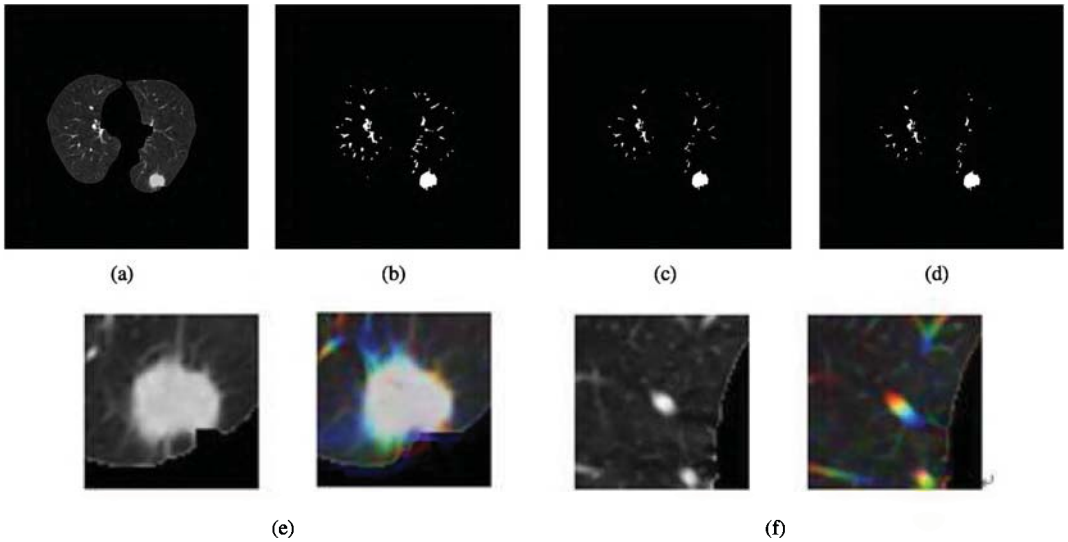
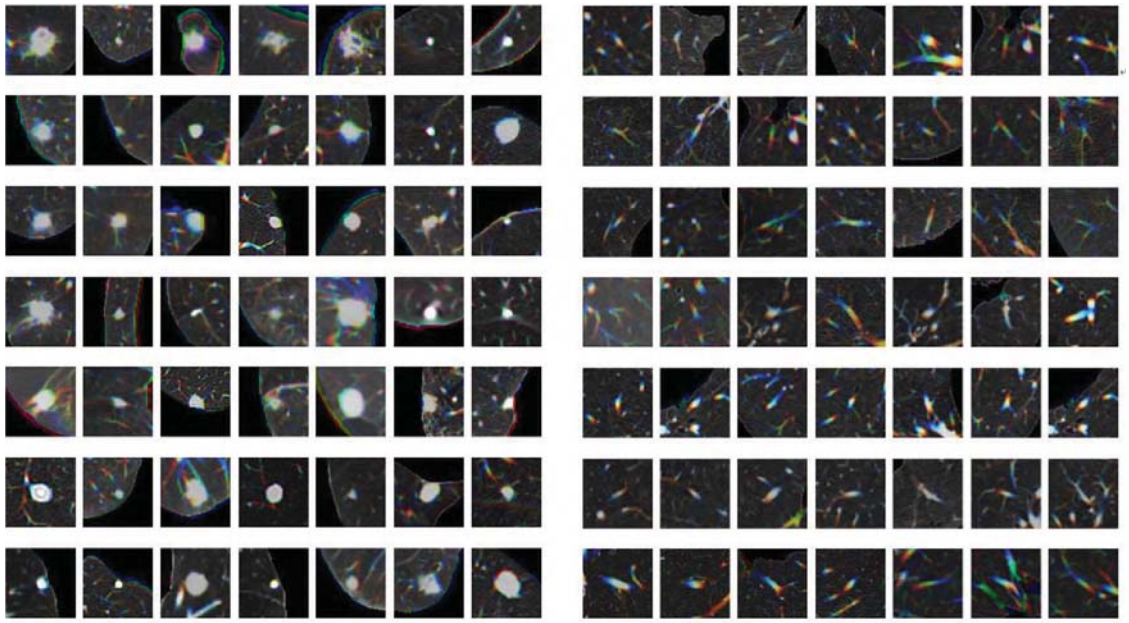



Fig. 4. ROI extraction steps: (a) lung parenchyma; (b) binarize the lung parenchyma with a threshold; (c) remove some too small regions in lung parenchyma; (d) remove some strip regions in lung parenchyma; (e) a pulmonary nodule in this lung parenchyma and the according pseudo-color patch; (f) a healthy tissue in this lung parenchyma and the according pseudo-color patch.

Convolution layers are the main layers to extract features from the images. There are ninety-six convolution kernels in the first convolution layer, two hundred and fifty-six convolution kernels in the second convolution layer, three hundred and eighty-four convolution kernels in the third and fourth convolution layers and two hundred and fifty-six convolution kernels in the last convolution layer. The convolution kernels' size are $11\times11$ in the first convolution layer, $5\times5$ in the second convolution layer and $3\times3$ in the last three convolution layers.

The common pooling methods are general pooling and overlapping pooling. General pooling includes mean pooling and max pooling. Mean pooling regards the mean value of a region as the value of this region while max pooling uses the max value. There is no overlap region between adjacent pooling windows in general pooling. Max pooling is used as the method of pooling layers in this model. The pooling kernels' size are $3\times3$.

The usual activation functions are Sigmoid function, tanh function, RELU function and so on. Sigmoid and tanh may have the problem of making the gradient disappear because of the saturation of function. RELU is the most usually used activation function since this problem can be avoid. In this



(a) pseudo-color images of pulmonary nodules (b) pseudo-color images of healthy tissues

Fig. 5. Typical samples of pseudo-color images

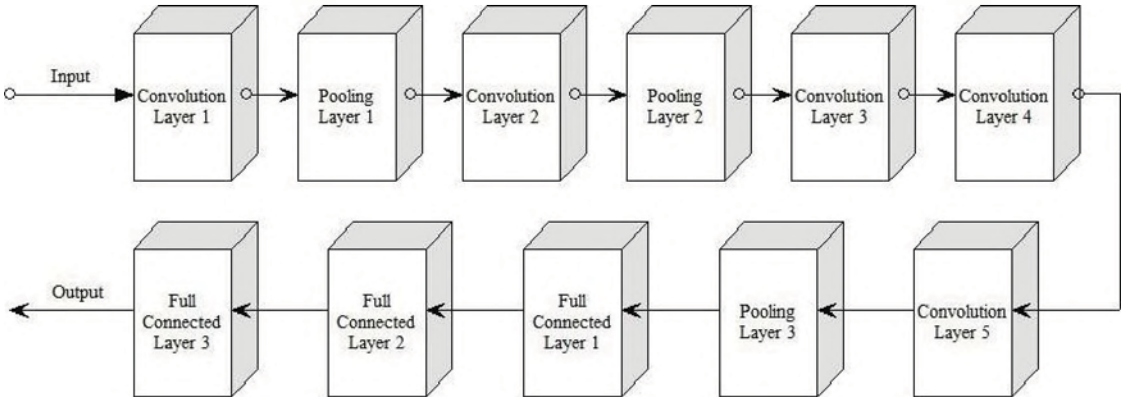



Fig. 6. The structure of AlexNet

model, RELU is used as the activation function in activation layers. The formula of RELU activation function is as follows:

$$f(x) = max(0, x) \tag{1}$$

The base learning rate is 0.01 and decreases by a factor of 10 every 10000 iterations. The max iteration times is 100000, the momentum is 0.9 and the weight decay is 0.0005. After training a large amount of images the max iteration times, a prediction model can be obtained to give the possibility of having a pulmonary nodules in a new patch.

GoogLeNet is the champion of ILSVRC 2014 [24] and has more layers than AlexNet. GoogLeNet has proposed an inception layer. Each inception layer contains six convolution layers and one pooling layer. The pooling layer uses max pooling method and the pooling kernels' size are 3×3. There are totally two convolution layers, two pooling layers and nine inception layers. The structure of GoogLeNet and its inception layer are shown in Fig.7 and Fig.8. GoogLeNet uses 1×1 convolution layer before 3×3 and 5×5 convolution layers in inception layer and uses average pooling layer to replace full-connected layers in order to reduce computing parameters.

## IV. Experimental Results

This paper uses Lung Image Database Consortium (Lung Image Database Consortium, LIDC-IDRI) for the extraction and analysis of pulmonary nodules. LIDC-IDRI database is

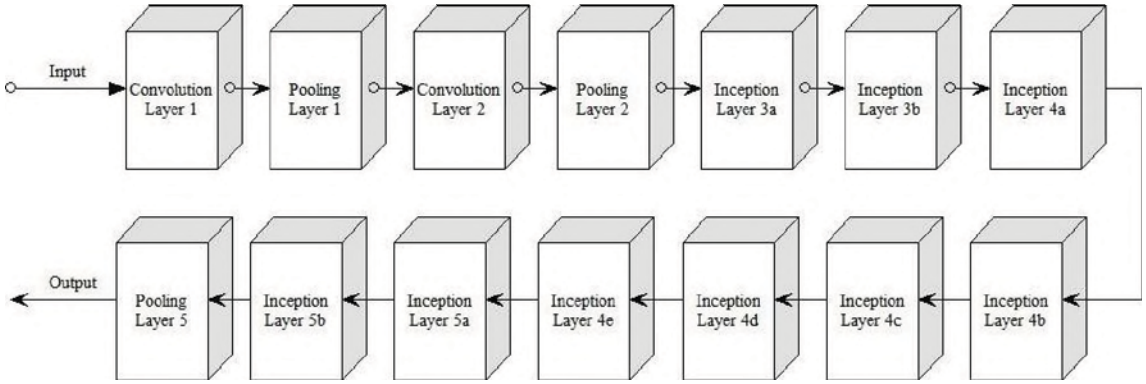



Fig. 7. The structure of GoogLeNet

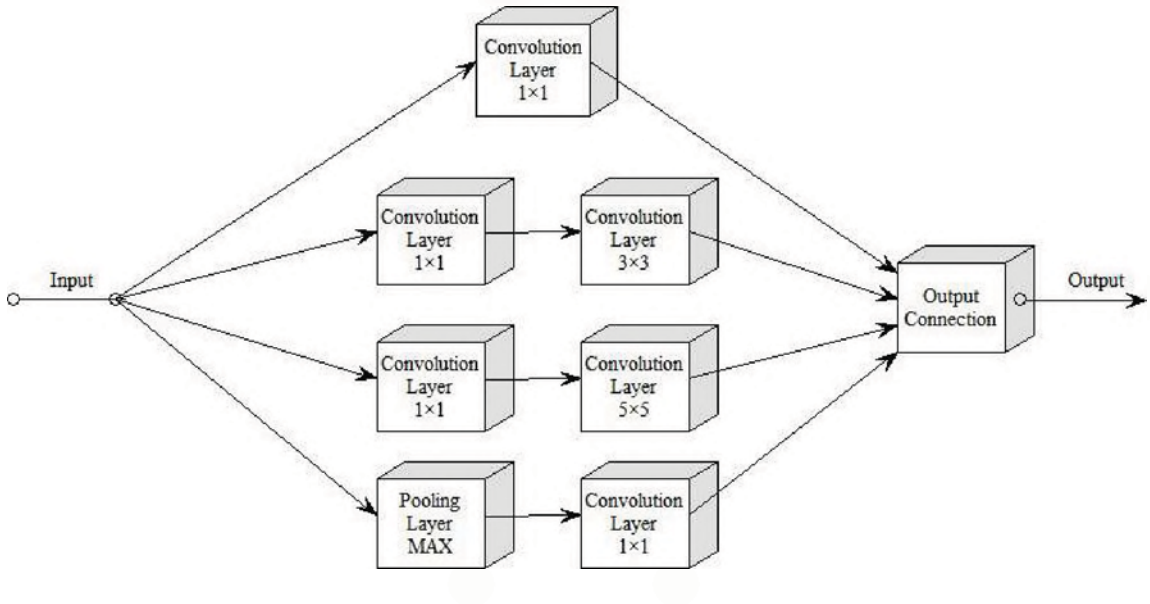



Fig. 8. The structure of inception layer in GoogLeNet

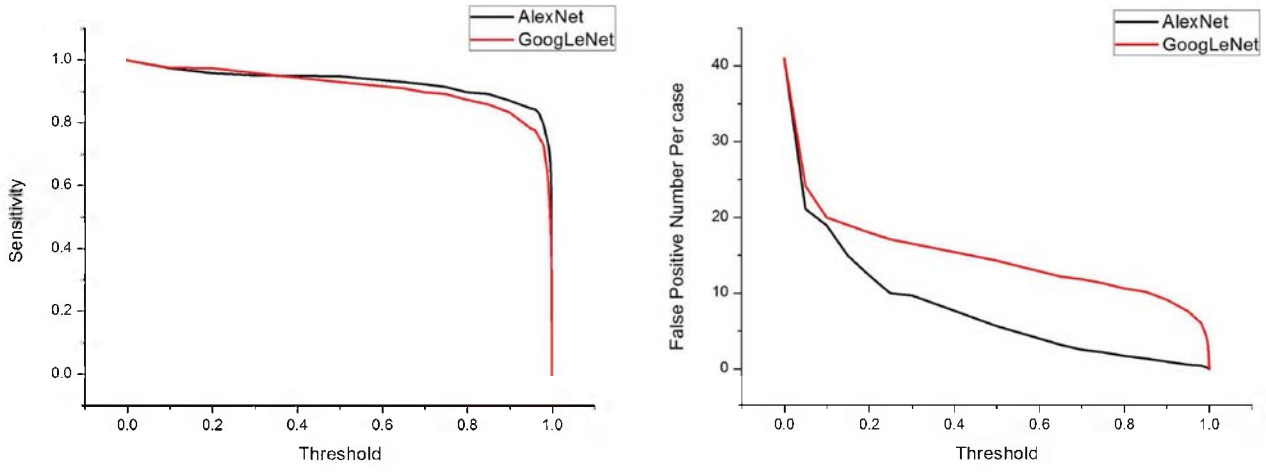
founded by a project funded by the National Cancer Institute (NCI) for the research of lung CT images and the development of computer-aided diagnosis [25]. It is one of the most widely used lung CT image databases. LIDC-IDRI database contains the complete lung CT slices and information of 1007 patients. Each patient has hundreds of CT slices. LIDC-IDRI database contains the pulmonary nodulesąf location, size and some other features as well.

We use the first 800 patients' CT slices to obtain 10000 pseudo-color images of pulmonary nodules and 12000 pseudo-color images of healthy tissues as the training data set. Then we use the deep learning method to analyze the training data set and get a prediction model. We use other 176 patients' CT images as the test data set which in total has 321 pulmonary nodules.

The description of some nouns are as follows:

- True Positive (TP): The number of pulmonary nodules which are detected.
- False Positive (FP): The number of healthy tissues patches which are predicted as pulmonary nodules.
- True Negative (TN): The number of healthy tissues patches which are predicted as healthy tissue.
- False Negative (FN): The number of pulmonary nodules which are predicted as healthy tissues.

After applied to a test image, the learned prediction model will provide a probability that it is a pulmonary nodule. The change of sensitivity and false positive number per case with different threshold of this probability is shown in Fig.9. The ROC curve of sensitivity and FPs/case is shown in Fig.10. It can be shown that AlexNet's performance is better than GoogLeNet, that may because overfitting occurred when using




(a) Sensitivity with different threshold

(b) FPs/case with different threshold

Fig. 9. Sensitivity and FPs/case with different threshold

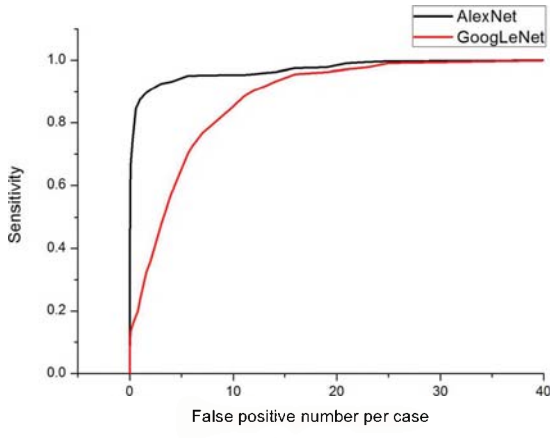



Fig. 10. ROC curve on 176 cases with different threshold

GoogLeNet.

According to the results using AlexNet on different nodules size, as shown in Table I, it can be seen that the size of undetected pulmonary nodules are all below 10mm. The detection results by nodule type is shown in Table II. The histograms of sensitivity of different pulmonary nodule sizes and different pulmonary nodule types are shown in Fig.11. It can be shown that the detection rate of isolated nodules is higher than that of juxta-pleural nodules.

TABLE I
DETECTION RESULTS BY NODULE SIZE

| Nodule size | True positive | False negative | Sensitivity |
|---|---|---|---|
| 3-5mm | 45 | 7 | 86.5% |
| 5-8mm | 55 | 8 | 87.3% |
| 8-10mm | 65 | 1 | 98.5% |
| 10-20mm | 77 | 0 | 100% |
| >20mm | 63 | 0 | 100% |
| Total | 305 | 16 | 95.0% |

TABLE II
DETECTION RESULTS BY NODULE TYPE

| Nodule type | True positive | False negative | Sensitivity |
|---|---|---|---|
| Isolated nodules | 213 | 7 | 96.8% |
| Juxta-pleural nodules | 93 | 9 | 91.2% |
| Total | 305 | 16 | 95.0% |

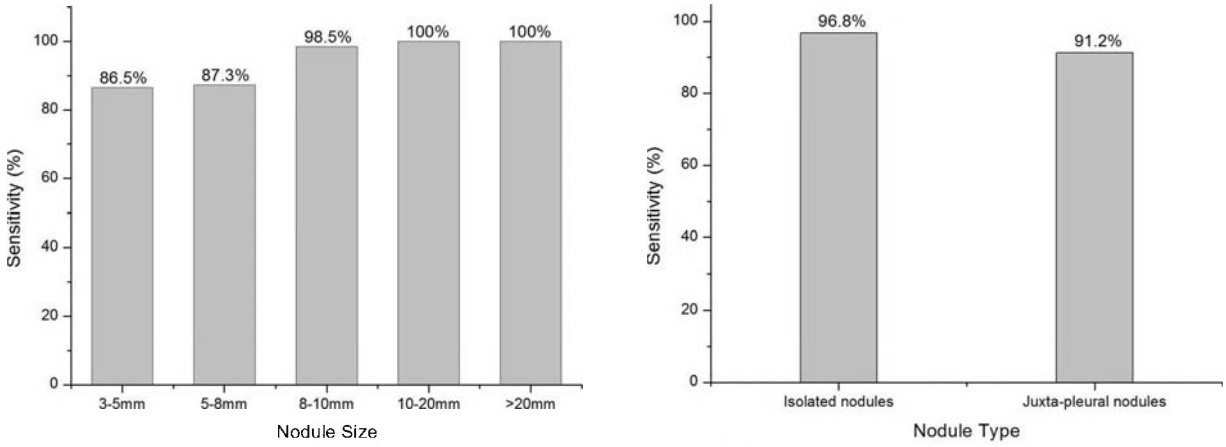
Table III shows the comparison of the experimental result with some other CAD systems. Most of these CAD systems used the LIDC-IDRI database. It can be shown that the sensitivity of proposed system is higher than most other CAD systems and the FPs/case is lower than that of some traditional methods.

TABLE III
PERFORMANCE COMPARISON OF PROPOSED METHOD WITH OTHER CAD SYSTEMS

| CAD systems | Sensitivity | FPs/case |
|---|---|---|
| Zhang et al. (2005) [8] | 82.98% | 11.76 |
| Ye et al. (2009) [9] | 90.2% | 8.2 |
| Choi et al. (2013) [10] | 95.28% | 2.27 |
| Setio et al. (2016) [15] | 90.1% | 4.0 |
| Ma et al. (2017) [11] | 88.9% | 4.0 |
| Liu et al. (2017) [16] | 89.4% | 2 |
| The proposed system | 95.0% | 5.62 |

## V. CONCLUSION

In order to help doctors identify pulmonary nodules more conveniently and quickly, this paper proposes a method to recognize pulmonary nodules based on deep learning. In this paper, a method of superimposing the ROI of three consecutive CT images into RGB channels to increase the difference of pulmonary nodules and healthy tissues is proposed. Deep learning is used as the main method to determine whether a patch contains a pulmonary nodule. We achieve a high sensitivity of 95.0% for all kinds of pulmonary nodules at the FPs/case rate of 5.62. The experiment results show that the




(a) Sensitivity of different pulmonary nodule sizes

(b) Sensitivity of different pulmonary nodule types

Fig. 11. The histograms of sensitivity

detection rate of pulmonary nodules by this method is higher than most other results which used a traditional method, such as feature extraction. This method is suitable for some juxta-pleural nodules and tiny pulmonary nodules, so it has a high universality. Further study will be conducted on the reduction of false positive and the classification of benign and malignant pulmonary nodules.

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