Lung Pattern Classification Via DCNN

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Abstract—Interstitial lung disease (ILD) causes pulmonary fibrosis. The correct classification of ILD plays a crucial role in the diagnosis and treatment process. In this research work, we propose a lung nodules recognition method based on a deep convolutional neural network (DCNN) and global features, which can be used for computer-aided diagnosis (CAD) of global features of lung nodules. Firstly, a DCNN is constructed based on the characteristics and complexity of lung computerized tomography (CT) images. Then we discussed the effects of different iterations on the recognition results and influence of different model structures on the global features of lung nodules. We also incorporated the improvement of convolution kernel size, feature dimension, and network depth. Thirdly, the effects of different pooling methods, activation functions and training algorithms we proposed has been analyzed to demonstrate the advantages of the new strategy. Finally, the experimental results verify the feasibility of the proposed DCNN for CAD of global features of lung nodules, and the evaluation shown that our proposed method could achieve an outstanding results compare to state-of-arts.

Index Terms—Interstitial lung disease (ILD), Lung nodules classification, deep convolutional neural network (DCNN)

I. Introduction

Deep learning approaches have been broadly used for health diagnosis applications. Interstitial Lung Disease (ILD) is a group disease characterized by diffuse alveolitis and alveolar structural disorders that ultimately lead to pulmonary fibrosis. In clinical work, due to its etiology and the pathogenesis is unclear, causing difficulties in diagnosis and treatment. In the diagnosis and treatment process, imaging diagnosis plays a crucial role, especially in the ILD classification, which requires multidisciplinary to participate in the discussion. Accurate ILD classification knowledge and imaging diagnostic features will help to to serve the clinic and patients better [1].

Most ILD patients have flu-like symptoms at the onset of the disease, presumably related to viral infections. Generally, it is a subacute onset, with mild symptoms, and occasionally manifests as acute respiratory distress syndrome or respiratory failure. As illustrated in Figure 1, imaging lesions are diverse, including Emphysema, ground glass, fibrosis, micronodules [2]. The most common are fibrosis, followed by ground glass, often mixed in a variety of performances.

Different types of ILD have some characteristics on the High-resolution computed tomography (HRCT) scan [1], but there are overlaps and similar signs between them. Therefore, it is difficult to rely on artificial images for differential diagnosis. Sometimes it is even impossible. Lung tissue shows a similar appearance among different tissue types, but there are also significant differences between various subjects of the same tissue type (e.g., emphysema). This can be reflected not only in the sense of image gray value but also in the geometric structure of the tissue. Therefore, for image classification of ILD, rapid, accurate and robust feature learning techniques are the keys to correct diagnosis. As one of the most malignant tumors with the highest morbidity and mortality in the world, lung cancer seriously threatens people's health and life. Because lung cancer patients have no obvious symptoms or imaging abnormalities in the early stage, it is difficult to find and diagnose, which leads to the middle and late stage of diagnosis and misses the best time for treatment. Therefore, early diagnosis and early diagnosis are very important for patients with lung cancer. In the early diagnosis of lung cancer, multi-slice spiral CT can clearly show the characteristics of cross-sectional, sagittal and coronal lesions through reconstruction technique. In the mid-term diagnosis, spiral CT diagnosis combined with surface masking and multiplanar reconstruction can clearly show the tumor site and internal structure, edge characteristics, blood supply, invasion of surrounding tissue and changes in surrounding tissues, with high diagnostic accuracy [3], therefore, CT images provide an important reference for the diagnosis and identification of lung cancer, for massive medical image data, doctors with CAD, the workload can be reduced, the diagnosis rate can be improved, and the rate of misdiagnosis and missed diagnosis can be reduced.

The purpose of this paper is to overcome the shortcomings in the prior art and to provide a lung nodules recognition method based on deep CNN and global features [4]. This paper constructs DCNN for the identification of CT global feature images of lung nodules. Based on the constructed DCNN, the effects of different model parameters, model structure and optimization algorithms on recognition performance are discussed. The feasibility of deep CNN for the diagnosis of global features of lung nodules is verified. The influence of different influencing factors on network recognition results is also discussed. To the extent, it provides the optimal DCNN for lung nodules recognition and provides a reference for CAD of lung nodules.

This research work verified the feasibility of deep CNN for the diagnosis of global features of lung nodules. The influence of different influencing factors on network recognition results is also discussed. To the extent, it provides the optimal DCNN for lung nodules recognition, and provides a reference for

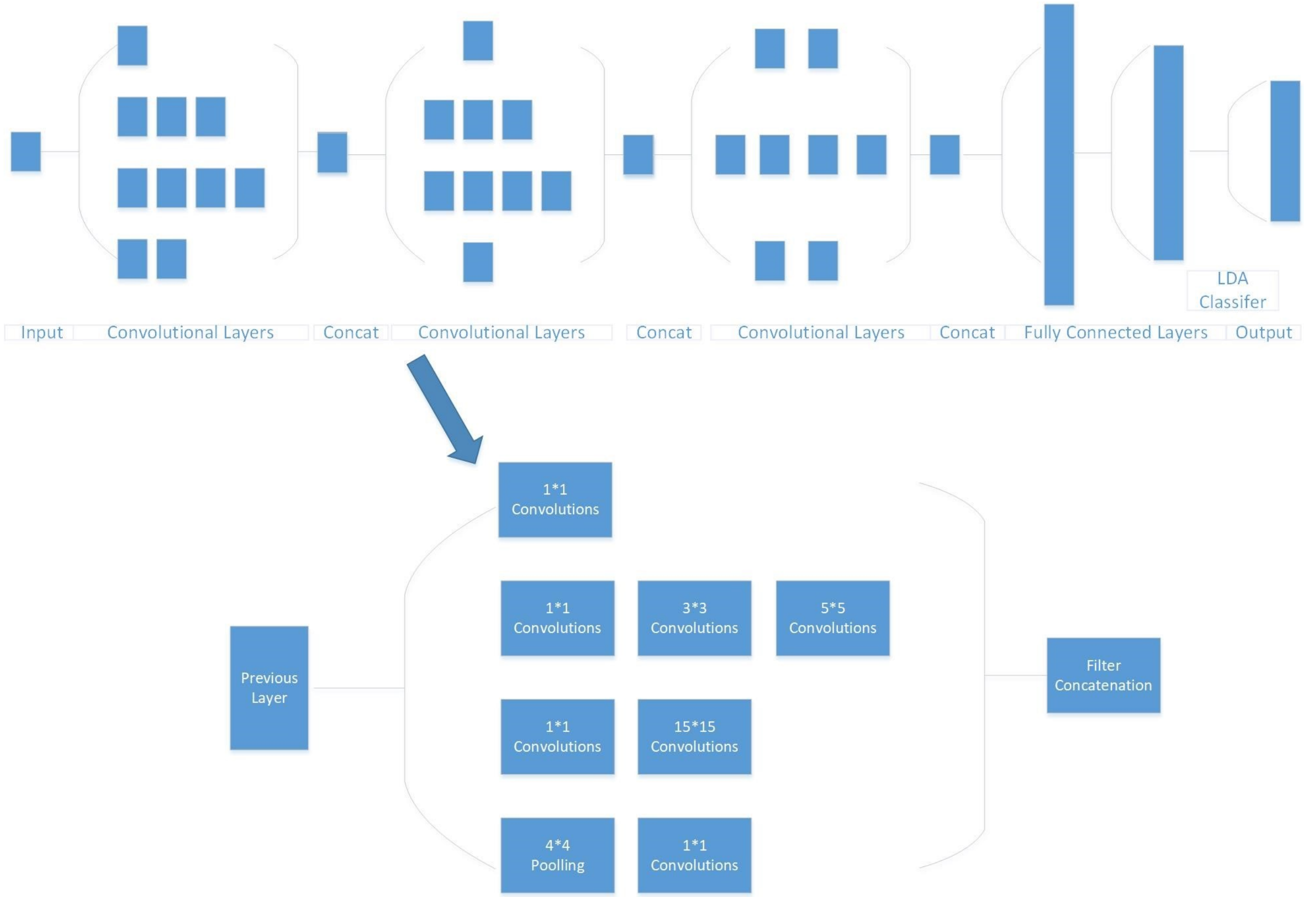

Fig. 1. Proposed DCNN Architecture.

CAD of lung nodules.

II. RELATED WORK

Deep learning, as a field of machine learning research, can effectively obtain the complex mapping between input and output by establishing and simulating human brain analysis and interpretation data, especially the unique deep structure of CNN, with good feature learning and Generalization [5]. At present, the design of DCNN models mainly focuses on model parameters, activation functions, receptive field sizes, and pooling layer operations. Based on the structure of the classic model LeNet-5, T. Xiao et al. [6] constructed a few different convolutional neural networks for optical digital identification by adjusting the number of parameters of the layers of the network model and the connection methods between the layers. C. Zhang et al. [7] removed the LeNet-5-layer 3 convolutional layer and replaced the Softmax classifier in the final output layer with the SVM classifier for the identification of street view house number, which improved the classification efficiency of the simplified network structure [8]. In 2012, Hinton et al. deepened the network layer and used five layers CNNs to achieve good results on the ImageNet dataset [3]. X. Zhang et al. [9] performed whitening preprocessing on pictures based on traditional CNN and used Stochasticpooling method at the sub-sampling layer to improve the generalization ability of the network for image classification. S. Branson et al. [10] constructed a 7-layer DCNN for the recognition of 5 types of vehicles and compared the main parameters with a recognition rate of 96:8%. The DCNN designed by T. Rumbell et al. [11] is used for handwritten character recognition. The experimental results show that the size of the receptive field significantly affects the number of model parameters and has little effect on the recognition rate. Receptive field size provides theoretical and practical reference. K. Simonyan et al. [12] explored how to balance the number of layers, the number of feature maps, and the size of the convolution kernel in a convolutional neural network in terms of limited training time and computational complexity, indicating that it has a smaller convolution kernel and a deeper depth The CNN structure is easier to get good recognition results than a CNN with a large convolution kernel and a shallow depth. In short, the manual setting method is often used to construct the model structure and determine the model parameters for different research problems, and then the recognition performance of the training model is obtained according to the experimental observation [13]. Finally, the most suitable parameters and model structure are determined according to the training time and the recognition result. DCNN [14] can automatically extract the high-level features of the image and effectively express the image. By multi-layer linear or nonlinear transformation of the input data, the data is mapped into a new space to express the image stably and efficiently. Essential characteristics, but corresponding optimization and improvement are needed for specific research objects and application areas.

III. PROBLEM STATEMENT

Different types of ILD have certain features in high-resolution CT scans, but there are overlapping and similar signs between them. Therefore, it is difficult to perform differential diagnosis on the image. Given 18793 Images, we'd like to classify them into five categories ((a) Healthy (b) Emphysema (c) Ground glass (d) Fibrosis (e) Micronodules).

During CT scan, slight postural changes may result in rotational bias of lung CT images and breathing has a great influence on lung volume. Lung tissue patterns can be better represented by multi-scale rotation invariant features rather than gray-scale images. First, local binary pattern (LBP) features can describe the spatial structure of local lung image texture. Secondly, the multi-scale Gabor filter decomposes the gray image into several sub-images to preserve valuable information at different scales. Thirdly, in order to reduce the rotation change, the rotation invariant Gabor filter and LBP are used to characterize the lung tissue pattern.

Although multiscale rotation-invariant convolutional neural network (MRCNN) [15], uses Gabor filter and LBP to make some changes to the input image in advance, and by increasing and decreasing the overlap size to improving the accuracy of CNNs identification, the results obtained are not very satisfactory. Because CNN is susceptible to rotation changes, which may reduce its predictive ability. The result shows that the classification accuracy is 79%, which is equivalent to other feature learning methods. However, it is worse than hand-crafted features [16].

(1) Lung tissue images are decomposed into rotationally invariant Gabor filtering images with different scales. (2) Rotation invariant LBP is used to further characterize Gabor filtered images. (3) Connect all Gabor LBP images together as multiple channels of CNN to learn advanced features.

The brains can easily identify the same object, but CNN does not have this ability. It can only achieve similar capabilities by expanding the amount of data trained. In the image classification, once the convolution kernel detects features such as health, emphysema, fibrosis, ground glass and micronodules, from the data point of view, the convolution kernel is convolved to a large value. Then the image will be classified into the categories. However, during a CT scan, changes in the patient's posture and the effect of breathing on the size of the lung volume may result in a rotational bias of the lung image, since there is no dominant direction.

Compared with the prior art, the beneficial effects brought by the technical solutions of our method are as follows: 1. Using the feature representation ability of deep CNN, the depth convolution can be directly performed without image processing and feature extraction. The proposed DCNN is used for CT global feature classification and recognition of lung nodules. The model parameters, network structure and training algorithm are compared and analyzed. The results verify the feasibility of the DCNN for CT global features of lung nodules. In combination with the resolution of the input image, it is necessary to select the appropriate convolution kernel size, the number of feature maps and the number of network layers to ensure good recognition performance, and the good feature learning ability and good generalization ability and robustness of the deep CNN are verified. 2. In the deep CNN model structure, the deeper the number of layers and the larger the number of feature maps, the larger the feature space that the network can represent, and the stronger the network learning ability, but the computational complexity is also larger and easier. But it causes overfitting. Therefore, the network depth, the number of feature maps, the size of the convolution kernel and other parameters should be appropriately selected in the actual application process for a specific field. The optimal network deep CNN is obtained by the proposed method to train a better model while ensuring relatively little training time.

Since the CNN can directly input the original image and has obvious advantages for the recognition of complex images, CT is widely used in the diagnosis of lung nodules recognition. However, because the lesion area in the CT image occupies a small area of the whole image, the feature is not obvious. It is difficult to distinguish, so the deep CNN constructed in the embodiment extracts the deep features of lung nodules for CAD.

A. Data Sets

The data comes from the openly available database of ILD CT scans from the University Hospital of Geneva, which contains HRCT images with a slice thickness of 1mm. It consists of 109 HRCT scans of different ILD cases with 32 32 pixels per slice. We also focus on the classification of five lung tissue patterns-healthy (H), emphysema (E), ground glass (G), fibrosis (F) and micronodules (M). The details are summarized in Table I.

TABLE I
FIVE TYPES OF LUNG TISSUE PATTERNS AND NUMBER OF PATCHES

Tissue Category	Patients	Patches
Healthy(H)	14	5530
Emphysema(E)	9	1177
GroundGlass(G)	31	2226
Fibrosis(F)	31	3039
Micronodules(M)	15	6821

We use 5 folds for all samples were randomly assigned to 5 equal sized groups at the patch level. In the 5 groups, a single group is used as the test data, and the remaining 4 groups are used as training data. The process is repeated 5 times so that each group can be used only once as the test data. The five results are averaged to produce the results.

IV. SOLUTION

In this section, we first introduce CNN and the proposed DCNN in details, then the proposed DCNN as the solution of ILD classification.

A. The proposed DCNN

The format of the 18793 CT images is TIFF format, wherein the number of CT images having lung nodules and the number of normal CT images each account for 80% of the total number of CT images of the lungs.

Research on different model parameters based on the same model structure. Output depth CNN of intermediate feature map for image recognition, it is based on the recognition of hidden layer abstract features. The characteristics of hidden layer are similar to global features. After convolution operation, the image size is reduced, and the CNN is the recognition of the image itself, not the extracted features. After inputting the whole CT image of the lung, the three-layer convolution layer and the three-layer sampling layer respectively extract and output the features of the original image at different angles, and randomly select the intermediate feature map output results of the two images. The first two layers extract the edge information and contour information of the input image, that is, the underlying convolution layer extracts low-level features such as edges, lines, angles, etc. of the image, and the number of layers after are higher semantic for the image. The abstraction of information and essential information is basically invisible to the naked eye. This is also the embodiment of the superior learning ability of deep learning. In short, the underlying layer of the proposed DCNN can learn physical features such as edges and shapes and can learn as the number of hidden layers in the network increases. To more complex, abstract visual features.

As the number of iterations increases, the recognition rate increases first and then decreases, while the training time increases with the number of iterations. The main reason for the increase and decreases of the recognition rate is that when the number of iterations is lower than the normal number, the learning of the CNN is insufficient, and the trained model cannot obtain accurate expected classification results. As the number of iterations increases, the network's sufficient recognition rate is obtained during the sufficient training and learning process, but when the number of iterations continues to increase, the recognition accuracy of the network model decreases as the number of iterations increases, indicating that the number of iterations is appropriate. The trained network model, each parameter has been optimized to the optimal state, and the network also enters the convergence phase. Currently, the network model performs best. The increase in the number of network iterations will affect the change of training time, and this change presents a positive correlation, and the change of test time is not directly related to the change of the number of iterations.

In general, the deep network structure can promote the reuse of features and obtain more abstract features in high-level expressions. Therefore, as the number of network layers increases, the recognition rate also increases, but the number of network layers is too large, requiring convolution and the sampling operation increases and the network parameters increase, which makes the training time increase rapidly. In short, an appropriate increase in the number of network layers will ensure that the recognition rate is improved under the condition that the running time is basically unchanged, but too many layers will lead to excessive parameters and over-fitting. The occurrence of this will reduce the recognition rate. When the number of hidden layers was 5 layers, the indicators had the highest value, indicating that the recognition efficiency and fitting effect of the network structure were the best.

Classification and Recognition Based on Different Optimization Methods In this example, by studying the DCNN model structure and model parameters, the optimal DCNN model structure is selected to explore different optimization methods. The effects of optimization methods based on batch gradient descent method and elastic momentum based gradient descent method on the DCNN recognition results are compared by optimizing the training method. 1. Maximum pooling and average pooling Depth Convolution The neural network model is mainly composed of two special hidden layers, convolutional layer and downsampling, while the downsampling layer can greatly reduce the feature dimension and reduce the amount of network computation. Prevent overfitting from occurring and provide some degree of translational and rotational invariance. At present, the commonly used down-sampling methods include average-Pooling and Max-Pooling, which average the feature points in the neighborhood, and the maximum pooling takes the maximum value of the feature points in the neighborhood.

V. EXPERIMENT RESULT

In summary, the proposed DCNN is superior in the identification of CT global features of lung nodules. According to the pattern recognition theory, the error of feature extraction mainly comes from two aspects. The first is the variance of the estimated value caused by the limited size of the neighborhood, and the second is the offset of the estimated mean value caused by the error of the convolutional layer. Average pooling can reduce the first type of error, more retaining the background information of the image, while the maximum sampling can reduce the second error and retain more texture information. In the average sense, it is similar to the average pooling, and in the local sense, it obeys the criterion of maximum pooling. Therefore, for the recognition of lung CT images, it should be concerned with the lesion area, that is, more textures that retain the local region of interest (ROI) area information.

The gradient descent method with elastic momentum is higher than the batch gradient descent method, and the recognition rate is 66:8%, indicating the gradient drop based on elastic momentum. The proposed DCNN is better for lung CT recognition. The momentum gradient method is used to train the network, which reduces the oscillation trend of the neural network learning process, so that the network can reach convergence quickly, and the momentum method can reduce the sensitivity of the network to the local details of the error surface. Effectively suppress the network into a local minimum.

Different convolution kernel sizes. With the structure of the deep convolutional neural network fixed, use a network of different convolution kernels to train CT images of the lungs, and explore the impact of different convolution kernel sizes on the DCNN recognition results. Based on the initial use of a convolution kernel [17] of 5 3 2 and a recognition rate of 49:8%, first reduce the convolution kernel (1) size to 1 3 2 and the recognition rate. Reduce it to 44:6%, then increase the size of the convolution kernel (2) to 5 3 1, the recognition rate will rise to 48:2%, and then continue to increase the size of the convolution kernel (3) to 6, the recognition rate will continue to increase to 51:2%. When the convolution kernel (4) increases to 11 3 4, the recognition rate starts to decrease.

In short, the CNN network is not sensitive to the convolution kernel. As the convolution kernel increases, the running time also increases. The smaller the convolution kernel, the more training time. The training parameters of a small convolution kernel have less space complexity and time complexity, but when the convolution kernel is too large or too small, the recognition rate will decrease, because the size of the convolution kernel determines a neuron receptive field When the convolution kernel is too small, effective local features cannot be extracted, and when the convolution kernel is too large, the complexity of the extracted features may far exceed the representation ability of the convolution kernel. Generally, small convolution kernels able to process images finely, but need to increase the number of layers to achieve a good abstraction effect, large image ha better abstract effect, but will need more training parameters. The proposed DCNN uses p3 3 3 and LDA classifiers, which effectively improves accuracy without using large convolution kernels.

LDA focuses on maximizing the separability among known categories. It tries to Maximum separation between means of projected classes, and minimum variance within each projected class.

$$S = \frac{\sigma^2_{between}}{\sigma^2_{within}} = \frac{(\vec{w}\cdot\vec{\mu}_1 - \vec{w}\cdot\vec{\mu}_0)^2}{\vec{w}^T\Sigma_1\vec{w} + \vec{w}^T\Sigma_0\vec{w}} = \frac{(\vec{w}\cdot(\vec{\mu}_1 - \vec{\mu}_0))^2}{\vec{w}^T(\Sigma_0 + \Sigma_1)\vec{w}} \quad (1)$$

As showing in Formula (1), when two classes of LDA observations have means and covariances. Then the linear combination of features will have means and variances for $i = 0; 1$.

LDA maximize the distance between means and minimize the variation (which LDA calls "scatter") S2 within each category. If more than two classes, LDA is an ideal linear classification method. when find the point that is central to all the data, it maximizes the distance between each category and the central point while minimizing the scatter for each category. With three points, we can draw two lines to optimize separation. Likewise, if the data set is not separate linearly, LDA will attempt to establish the data set in another way to maximize separability.

Regardless of what learned features are used, it is crucial and challenging to choose an appropriate classifier that can optimally handle the properties of the created feature space. Many different approaches can be found. Fig. 2 is showing the experimental results of comparing different classifiers. Under the condition of ensuring the structure of the DCNN model, the recognition rate of LDA classifier is 66:8%, which is the highest both in F-score and accuracy.

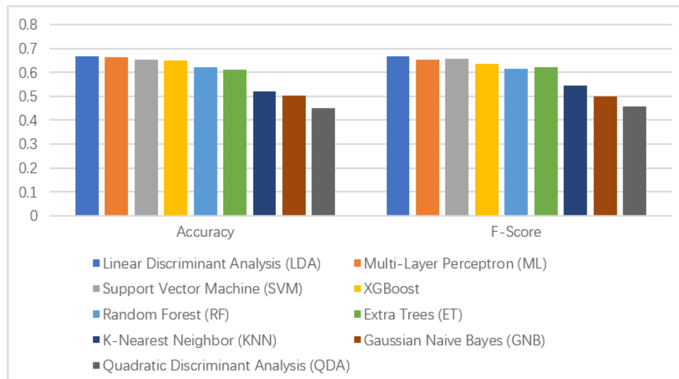

Fig. 2. Experiment of implementing different Classifiers

And the recognition rate of Support Vector Machine (SVM) classifier is 65:3%. Use XGBoost classifier to achieve 64:9% recognition rate. Compared with other classifiers, LDA has faster convergence speed and can get lower training errors. Moreover, its training time is significantly reduced, so LDA classifier can be used to speed up the convergence speed, reduce training time, and improve recognition performance.

Also, In Fig. 3, we can clearly understand that if the same color points are mostly clustered together there is a high chance that we could use the features to train a classifier with high accuracy.

Compared with M. Anthimopoulos et al. [17], this study uses a multi-view 2D CNN method and Q. Wang et al. [15] used a shallow CNN to improve the results obtained in the step of screening false positive nodules (Both were performed using the same data set as the present invention). Obviously, the method of this research work can obtain a more accurate detection effect. We use the LDA classifier to classify five lung tissues and compare the classification performance between different balanced data in Fig. 4. LDA can perform classification tasks as a classifier and a dimensionality reduction algorithm. The main principle of LDA is to transfers the classes linearly to a different feature space, so if the data set is separate linearly and only uses LDA classifier, good outcomes will be obtained. However, if the data set is not separate linearly, LDA will attempt to form your data set in another way to get maximized separability [28].

As shown in Fig. 4., the accuracy obtained by our method using LDA is obviously better than the other two methods. It can be seen from the results that the SoftMax classifier used

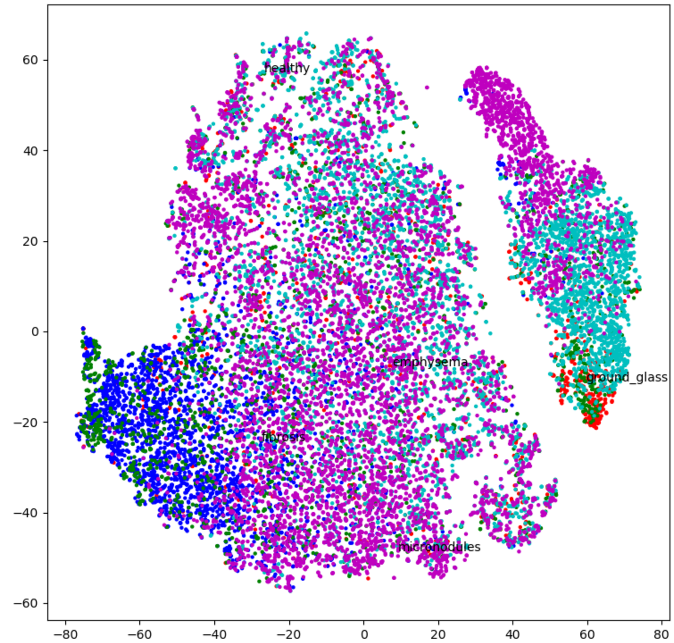

Fig. 3. t-Distributed Stochastic Neighbor Embedding (t-SNE) showing 5 clustered types of ILD. (Purple) Healthy, (Cyan-blue) Emphysema, (Green) Ground glass, (Blue) Fibrosis, (Red) Micronodulessis (LDA)

Fig. 4. The classification of accuracy, comparing our model with LPCNN [17] and MRCNN [15] in 5 categories. (H) Healthy (E) Emphysema (G) Ground glass (F) Fibrosis (M) Micronodules

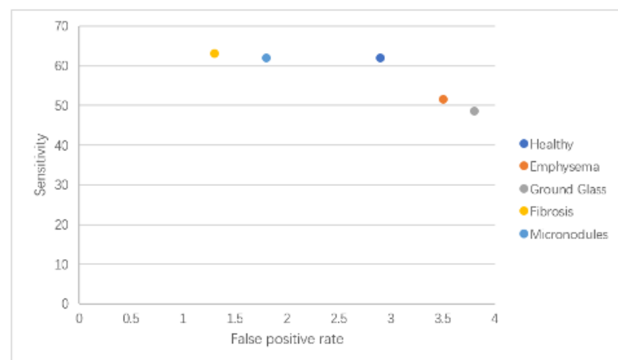

Fig. 5. Sensitivity vs false positive rate at confidence threshold 0.5

by the other two methods is a single-layer classifier network, which does not sufficiently extract the feature information of the image. Our method mainly maps high-dimensional data to low-dimensional space through the method of data dimensionality reduction. Here, we retain most of the feature information as the classification basis, so the highest Health and Emphysema recognition accuracy rates are 74:6% and 68:4%, respectively. Using the method in MRCNN, the classification accuracy of image data after feature extraction has been improved over the algorithm in LPCNN, which is mainly due to the increase in the number of network layers for network feature extraction. However, the classification accuracy and the time of feature extraction are not as good as our method. It can be seen that when classifying multiple images, using our classification method to extract high-level features of the image can achieve better classification results. Models based on deep learning can achieve non-missing detection of malignant pulmonary nodules, have higher nodule detection sensitivity than physicians, and reduce false positive rates after excluding minor nodules. As showing in Fig. 5, the sensitivity indicates the number of recognitions of normal images in the lungs compared to the recognition ratio of all images, and the false positive rate indicates the case where the lung nodule images are predicted to be normal images.

The overall false positive rate of nodule detection of the proposed DCNN is at an acceptable level. The major misdiagnosis reasons are mainly due to emphysema and ground glass have very similar patterns. For the other three categories: healthy, fibrosis and micronodules, the classification false-positive rates are lower. In addition, the cause of false positives may be related to the threshold value of the detected nodule size. Our deep learning model has fast computation speed. With the continuous accumulation of experience and continuous iteration of the model, its diagnostic sensitivity and accuracy will continue to rise, and the false positive rate will be controlled.

TABLE II
COMPARISON OF THE PROPOSED METHOD WITH OTHER CNNS

Methods	F-avg	Accuracy
ProposedDCNN	0.667	0.668
LPCNN	0.487	0.498
MRCNN	0.539	0.544

Table II provides the comparison of average F-score and Accuracy with other CNNs. The LP CNN network obtained rather low results on our dataset, it may be due to the following reason: from the analysis of experimental results, the number of feature maps in the first layer is small, and the number of feature maps in the back layer increases by a factor of two, achieving the highest recognition rate. However, due to the small number of feature maps, the feature description is insufficient, and overfitting may occur. Therefore, when selecting the number of intermediate feature maps, that is, the number of convolution kernels, the size of the data image used should be referred to, and the feature dimensions should be adjusted according to the features and complexity of the actual samples. Generally, more convolution kernels will be used to obtain better results. Performance, appropriately increasing the number of feature maps will help the overall algorithm to achieve the desired classification effect. As of MRCNN, the batch size is closely related to the recognition result. The smaller the batch, the longer the running time, but the recognition rate will increase continuously, but when the batch is too small, the recognition rate will be basically maintained at a certain level, because the batch is too small, training Not enough, the adjustment of the parameters is not enough, so the recognition rate is reduced. Therefore, it is necessary to combine the size of the training set and select the appropriate batch size to ensure that each parameter adjustment is based on enough training and backpropagation.

VI. CONCLUSION

In summary, using the feature representation ability of deep CNN, DCNN can be directly used for CT global feature classification and recognition of lung nodules without image processing and feature extraction, from model parameters, network structure, and training algorithm. Comparing and analyzing the results, the results verify the feasibility of the proposed DCNN for CT global features of lung nodules. Experiments show that in combination with the resolution of the input image, it is necessary to select the appropriate convolution kernel size, the number of feature maps, and the network layer to ensure proper. The recognition performance is too large or too small to make the feature learning insufficient or the parameter over-fitting. For the lung nodules image recognition, the maximum pooling result is better than the average pooling. The selection of the ReLU activation function can speed up the convergence and reduce the running time. The gradient method based on elastic momentum not only improves the recognition rate but also makes the proposed DCNN recognition rate of CT global features of lung nodules reach 66:8%, which verifies the good feature learning ability and good generalization ability of DCNN. In short, in the deep CNN model structure, the deeper the number of layers and the larger the number of feature maps, the larger the feature space that the network can represent, and the stronger the network learning ability, but the computational complexity is also larger and easier. Therefore, the network depth, feature map, convolution kernel size and other parameters should be appropriately selected in the actual application process for a specific field to train a better model while ensuring relatively less training time.

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