RESEARCH PAPER

Application of Medical Image Detection Technology Based on Deep Learning in Pneumoconiosis Diagnosis

Shengguang Peng[1,2†]

[1]School of Engineering and Management, Pingxiang University, Pingxiang 337055, Jiangxi, China

[2]School of Information and Control Engineering, China University of Mining and Technology, Xuzhou 221000, Jiangsu, China

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ABSTRACT

Pneumoconiosis is a disease characterized by pulmonary tissue deposition caused by dust exposure in the workplace. In China, due to the large number and wide distribution of pneumoconiosis patients, there is a high demand for the case data of lung biopsy during the diagnosis of pneumoconiosis. This text studied the application of medical image detection technology in pneumoconiosis diagnosis based on deep learning (DL). A medical image detection and convolution neural network (CNN) based on DL was analyzed, and the application of DL medical image technology in pneumoconiosis diagnosis was researched. The experimental results in this paper showed that in the last round of testing, the accuracy of ResNet model including deconvolution structure reached 95.2%. The area under curve (AUC) value of the working characteristics of the subject is 0.987. The sensitivity was 99.66%, and the specificity was 88.61%. The non staging diagnosis of pneumoconiosis improved the diagnostic sensitivity while ensuring high specificity. At the same time, Delong test method was used to conduct AUC analysis on the three models, and the results showed that model C was more effective than model A and model B. There is no significant difference between model A and model B, and there is no significant difference in diagnostic efficiency. In a word, the diagnosis of the model has high sensitivity and low probability of missed diagnosis, which can greatly reduce the working pressure of diagnostic doctors and effectively improve the efficiency of diagnosis.

† Corresponding author: Shengguang Peng (Email: LB20060019@cumt.edu.cn; ORCID:).

1. INTRODUCTION

According to the statistics on the number of disabled and dead people worldwide released by the World Health Organization, 580000 people died of pneumoconiosis in 2017. Computer technology has made certain achievements in the medical field and promoted the progress of new technologies and new ideas in this field. However, in China, due to historical reasons, the diagnosis results of pneumoconiosis vary greatly in different regions. The reason for this problem is that grass root hospitals are not equipped with enough high-quality and authoritative medical imaging diagnostic equipment, which is easy to be misdiagnosed. Based on this, improving the diagnostic efficiency of clinical pneumoconiosis has become one of the urgent problems to be solved. Deep learning technology is an artificial intelligence method, which extracts the optimal weight model from the deep neural network and applies it to the deep learning system to achieve the learning goal with high accuracy. Therefore, this paper would design and study the problem of medical image big data analysis based on DL network based on DL model, and study its application and development in pneumoconiosis diagnosis. Medical image processing technology based on DL usually takes image extraction and feature extraction as the ultimate goal in traditional computer simulation methods, and further improving diagnostic efficiency based on DL training model has become a hot spot in the current medical field. This paper studied the application of medical image detection technology in pneumoconiosis diagnosis based on deep learning, hoping to make some contributions to pneumoconiosis.

According to the existing research progress, different researchers have also conducted corresponding cooperative research in the diagnosis of pneumoconiosis. Qi Xian-Mei reviewed the epidemiology, protective procedures, diagnosis and treatment of pneumoconiosis, and reviewed recent research and prospects [1]. Zhang Yuan aimed to explore a multi-scale feature mapping technology to help grading and auxiliary diagnosis of pneumoconiosis [2]. Yang Fan aimed to establish a computer aided diagnostic system for human and pneumoconiosis by combining X-ray and DL [3]. Zhang Liuzhuo planned to develop an artificial intelligence based imaging diagnostic model to assist imaging physicians in screening and grading pneumoconiosis [4]. However, these scholars lack some technical demonstration on the diagnosis of pneumoconiosis. It found that DL can play a better role in the diagnosis of pneumoconiosis. In this regard, it consulted the relevant literature on in-depth learning.

Some scholars have also done some research in depth learning: Wang Xiaohua aimed to evaluate the application value of DL technology in the diagnosis of pneumoconiosis, and compared it with certified radiologists [5]. Sun Wenjian proposed a complete in-depth learning paradigm for pneumoconiosis staging, including segmentation procedure and staging procedure [6]. Dong Hantian aimed to establish a successful DL mode by using data enhancement technology to explore the clinical uniqueness of chest X-ray imaging features of coal miners' pneumoconiosis [7]. However, these scholars did not study the application of medical image detection technology in the diagnosis of pneumoconiosis based on DL, but unilaterally discussed its significance.

In order to solve the problem of great demand for lung biopsy case data in the diagnosis of pneumoconiosis, this paper proposes a convolution neural network algorithm based on deep learning. Through the analysis of the imaging characteristics of the lung, a medical image detection method based on deep learning is constructed, and the application of medical image detection technology in the diagnosis of pneumoconiosis is simulated., According to the experimental results, the medical image detection model based on depth learning has high sensitivity, that is, the probability of missed diagnosis is very small, which can greatly reduce the workload of clinicians. The innovation of this paper is that this paper proposes a neural network model based on deep learning, and applies it to the diagnosis of pneumoconiosis, which can reduce the detection time and misdiagnosis rate, and improve the survival rate of pneumoconiosis patients.

2. APPLICATION OF MEDICAL IMAGE DETECTION TECHNOLOGY IN PNEUMOCONIOSIS DIAGNOSIS

2.1 Imaging Characteristics of Lung

The clinical manifestations of pneumoconiosis mainly include early symptoms and severe symptoms [8–9]. The main symptoms in the early stage were cough, expectoration, chest pain and dyspnea, which were close to the pulmonary function after activity or rest. As the disease progresses, the main symptoms may be chest tightness, expectoration, shortness of breath, and dyspnea. As shown in Figure 1, it is pneumoconiosis. Pulmonary insufficiency can also be manifested as dyspnea, shortness of breath, dyspnea, etc. When death or quality of life declines due to long-term respiratory failure, pneumoconiosis patients may have symptoms such as chest tightness and asthma, or metabolic diseases such as anorexia, fatigue, emaciation, menstrual disorders, and complications such as palpitation and chest pain [10–11]. In the early stage, the patient's symptoms were mild, and the lung X-ray examination often showed atypical pulmonary nodules, which confirmed the disease. There may be respiratory failure and organ failure in different degrees in the middle and late stages. If late treatment is not timely, it would cause complications such as brain edema and pulmonary embolism.

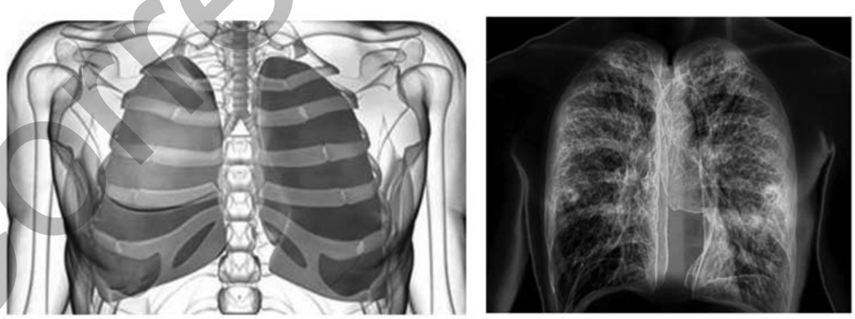

Figure 1. Pneumoconiosis.

Lung biopsy is one of the main methods to detect lung tissue and lung function, which can accurately evaluate and quantify clinical symptoms and imaging features. Although lung biopsy has a high accuracy in diagnosing early pneumoconiosis, due to the particularity of the lung structure and its vulnerability to noise interference, its accuracy in diagnosing dust exposure history or dust exposure history is still insufficient, especially in some patients with early pneumoconiosis [12–13]. The biggest disadvantage of lung biopsy is that it has no specificity for local lesions. Therefore, for some patients with obvious lung lesions but no specific manifestations, further imaging examination can be considered to make a clear diagnosis. In order to reduce the economic losses caused by misdiagnosis and missed diagnosis in the diagnosis of pneumoconiosis and the burden of hospitalization expenses of patients, some scholars have proposed to add a small amount of grayscale in the electronic computer tomography in recent years, which reflects the structure and function of patients' lung tissues through grayscale values [14–15]. However, because the gray area itself has no specificity, it is often impossible to identify the factors such as the pneumonia tissue composition and bronchial structure of patients with different types of pneumoconiosis [16–17]. In addition, in the application of computer tomography for pneumoconiosis diagnosis, attention should be paid to minimizing the damage to the lung caused by image blurring and reducing the therapeutic effect.

2.2 Medical Image Detection Based on DL

In the traditional medical image classification system, due to the limitations of different image features and different medical image quality, traditional medical image classification methods usually use traditional random feature filtering methods, random feature fusion methods and random feature learning methods to classify medical images. However, due to the large number of nonlinear factors in traditional network design, it is difficult to adapt to the feature differences of different medical images, so many medical images with important application value can not be used well after accurate classification.

2.3 CNN Based on DL

Because a large number of concepts such as convolutional neural networks and decision trees are used in the DL model, these convolutional neural networks classify and predict image data by continuously using the neural networks trained by the convolutional neural networks. By continuously correcting, correcting and improving the training data, the deep learning software can finally achieve an ideal effect. However, compared with the traditional machine learning model, the DL model has certain advantages in the automatic diagnosis of pneumoconiosis. First of all, the technology does not require long-term hospitalization for pneumoconiosis patients, reducing the cost of treatment. Secondly, this technology can quickly reflect the diagnosis results, making the diagnosis process easier and faster. Furthermore, the DL model has great advantages in the auxiliary diagnosis of pneumoconiosis. This technology can be used to mine and analyze the chest image data of pneumoconiosis patients, so as to find features such as pulmonary fibrosis, decreased pulmonary activity of pneumoconiosis patients, and crescent shaped areas of pneumoconiosis patients' pulmonary lesions [18]. Figure 2 shows the application of DL technology in pneumoconiosis.

CNN is the most widely used network in the world. Modern CNN has three basic structures: convolution layer, pooling layer and full connection layer.

(1) Convolution layer: the convolution layer can be used to study the input characteristics of the model and perform different convolution kernel operations. Specifically, different convolution cores are used to

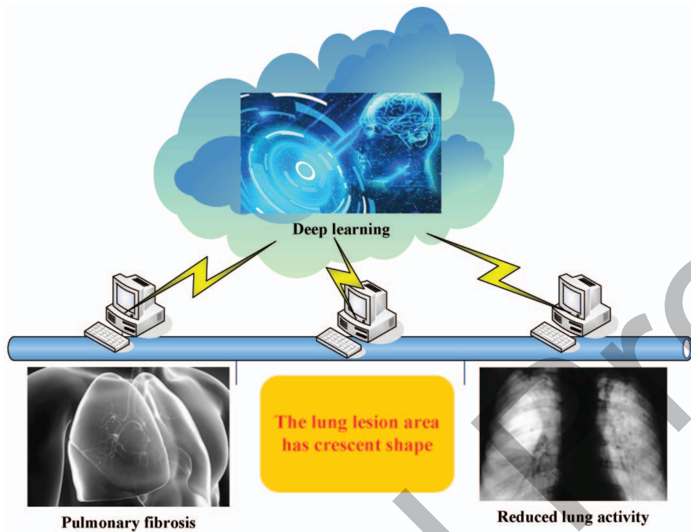

Figure 2. Application of DL technology in pneumoconiosis.

make the weight of each convolution core change with the change of the input matrix. In the process of motion, the corresponding weight matrix of each convolution core is also different, and the results of its input matrix are also different. The formula for convolution calculation is shown in the following formula.

$$s_{o,k} = g\left(\sum_{z=0}^{Z}\sum_{m=0}^{M} e_{z,m}c_{o+z,k+m} + e_n\right) \quad (1)$$

$c_{o,k}$ represents the element of row o and column k in the image matrix, and $e_{z,m}$ represents the weight of row z and column m in the convolution kernel. e_n represents the offset term of the convolution kernel, and $s_{o,k}$ represents the elements in row o and column k of the feature graph extracted by the convolution operation. $g(\cdot)$ is used to represent the activation function, and the activation function strengthens the nonlinear change, so that the network can handle the nonlinear separable problem well, and has good expressiveness. Because different networks have different tasks, there are many types of activation functions, the most common of which are Sigmaid function and Relu function.

(2) Pooling layer: main function is to reduce the dimension of the output vector of the convolution layer, reduce the model parameters, and to some extent avoid over fitting, thus enhancing the generalization performance of the model. In the process of image processing, it usually appears behind the convolution layer. The combination of convolution layer and pooling layer can make the extracted features more abstract and semantic richer.

(3) Full connection layer: in the convolutional neural network, "classifier" is generally used to map the learning characteristics of the original convolution layer and pooling layer to the sample mark space. In CNN, in order to give the weight of the previously extracted features, the late level full connection layer is generally used.

At the beginning of CNN training, the weight of convolution kernel is random, and it cannot extract some special characteristics from the image. In the case of forward propagation, the early output value cannot explain anything, so it cannot be classified reasonably. In order to evaluate the prediction effect scientifically, it is necessary to establish a loss function to determine the deviation between the prediction result and the actual label. If there is a small deviation between the prediction results and the real data, the model has a higher prediction accuracy. Backpropagation is a new fully connected network. Its core is to define the error function, determine the partial derivative of each output variable by calculating its partial derivative, and then use the chain rule to obtain its weight matrix and the gradient of the offset vector, and update the parameters with the optimal method. The back propagation of convolutional neural network is more complex, because both convolutional layer and pooling layer contain convolutional layer.

For a deep CNN, l_{qw} represents the elements in row q and column w of the convolution kernel weight matrix, n^a represents the offset vector of layer a, and the activation function is $u = g(\cdot)$ network's loss function is $A(\cdot)$. In the case of forward propagation, the convolution mapping realized by the convolution layer of layer a is:

$$c_{ok}^{a} = g\left(x_{ok}^{a}\right) = g\left(\sum_{q=1}^{l}\sum_{w=1}^{l} c_{(o+q-1,k+w-1)}^{(a-1)} \times l_{qw}^{a} + n^{a}\right) \tag{2}$$

Based on the chain law, solve the partial derivative function of the loss function to the convolution kernel weight of layer a:

$$\frac{\partial A}{\partial l_{qw}^{(a)}} = \sum_{o}\sum_{k}\left(\frac{\delta A}{\delta c_{ok}}\frac{\delta c_{ok}}{\delta l_{qw}^{(a)}}\right) = \sum_{o}\sum_{k}\left(\frac{\delta A}{\delta c_{ok}}\frac{\delta c_{ok}}{\delta x_{ok}^{(a)}}\frac{\delta x_{ok}^{(a)}}{\delta l_{qw}^{(a)}}\right) \tag{3}$$

The partial derivative function of the offset term is:

$$\frac{\partial A}{\partial n^{(a)}} = \sum_{o}\sum_{k}\left(\frac{\delta A}{\delta c_{ok}^{(a)}}\frac{\delta c_{ok}^{(a)}}{\delta n^{(a)}}\right) = \sum_{o}\sum_{k}\left(\frac{\delta A}{\delta c_{ok}^{(a)}}\frac{\delta c_{ok}^{(a)}}{\delta x_{ok}^{(a)}}\frac{\delta x_{ok}^{(a)}}{\delta n^{(a)}}\right) \tag{4}$$

The error items are defined as:

$$\delta_{ok}^{(a)} = \frac{\delta A}{\delta x_{ok}^{(a)}} = \frac{\delta A}{\delta c_{ok}^{(a)}}\frac{\delta c_{ok}^{(a)}}{\delta x_{ok}^{(a)}} \tag{5}$$

The convolution operation is to multiply and add the elements at the corresponding positions in the two matrices. However, if people want to carry out backpropagation, they need to rotate the convolution kernel 180 degrees clockwise to find the error. Therefore, the recursive formula of the error term is as follows:

$$\delta^{(a-1)} = \delta^{(a)} * rot180(L) \odot \frac{\delta c_{ok}^{(a)}}{\delta x_{ok}^{(a)}} \tag{6}$$

By calculating the error term, the weight and bias term of the convolution kernel can be modified. The working principle of convolutional neural network is basically to train each training image for a period of time in a learning cycle, and then conduct the optimal output to make the network achieve the corresponding effect.

The convolution neural network model and deep reinforcement learning algorithm are used to extract the features of pneumoconiosis data, and the parameters obtained through training are classified and recognized, and then the early diagnosis model of pneumoconiosis is established. Convolution neural network is a new type of deep neural network. The CNN obtained through a large number of training can well extract the deep features of image information. The size and number of output layers of CNN can be determined by network parameters by using different number of convolution kernels for training. The deep reinforcement learning algorithm uses its powerful strategy reasoning ability to learn new strategies and model parameters, so the deep reinforcement learning algorithm has a very good effect for data classification prediction. In the early diagnosis of pneumoconiosis, random forest algorithm is widely used in related fields because of its strong generalization ability and good stability. This paper constructs a deep reinforcement learning network for pneumoconiosis diagnosis model.

3. ANALYSIS OF EXPERIMENTAL RESULTS OF THE APPLICATION OF MEDICAL IMAGE TECHNOLOGY OF DL IN THE DIAGNOSIS OF PNEUMOCONIOSIS

3.1 Experimental Environment Setting

In this paper, image - based DL technology is used to diagnose pneumoconiosis. There are many kinds of current DL network model architectures, and typical network model architectures include convolutional neural networks such as ResNet, DenseNet, Inception, etc. ResNet has a simpler structure and good portability. Many network models are based on ResNet. In this paper, three models ResNet-50 (A), ResNeXt-50 (B) and ResNet (C) with deconvolution structure are used to diagnose pneumoconiosis. In the training process, the size of each chest image would change with the change of the training model, and the size of its input would also be different.

In order to solve this problem, re sampling was conducted during the training. Resampling can be divided into random oversampling, random undersampling, mixed sampling and manual mixed sampling. On this basis, random oversampling can effectively improve the classification effect. Therefore, it adopted the random sampling method to randomly duplicate a small number of positive groups, so as to achieve the same chest radiograph training rate of positive and negative groups, and improve the model performance.

The statistical model can be used for diagnosis, and the accuracy, sensitivity, specificity, positive likelihood ratio (+LR), negative likelihood ratio (- LR), F1 value (as a measure of the accuracy of the binary classification model, it can be regarded as the harmonic average of the model sensitivity and prediction results) and other indicators can be calculated to evaluate the diagnostic effect of the model. According to the results, the ROC curve of the subjects was drawn, and AUC could be calculated. Different modes of AUC were compared through DeLong of MedCalc 19.7.2 software. Except for the comparison between ROC curve and AUC, other data are expressed in SPSS25.0 and percentage. Hypothesis test is bidirectional, $P<0.05$ is significant difference.

3.2 Comparison of Three Models in the First Round

In the research of DL technology, convolutional neural network technology has the following advantages: it can use traditional learning methods to extract features from a large number of data for recognition and classification. This method can not only effectively reduce the time cost and space cost, but also improve the recognition accuracy of artificial intelligence. In the first model test, 8361 chest X-ray films were collected. The three different models are labeled with test sets, and the diagnostic efficiency of the three modes is given, as shown in Figure 3. Figure 3 (a) shows F1 value, accuracy, sensitivity and specificity; Figure 3 (b) shows the Yoden index,+LR, - LR, AUC.

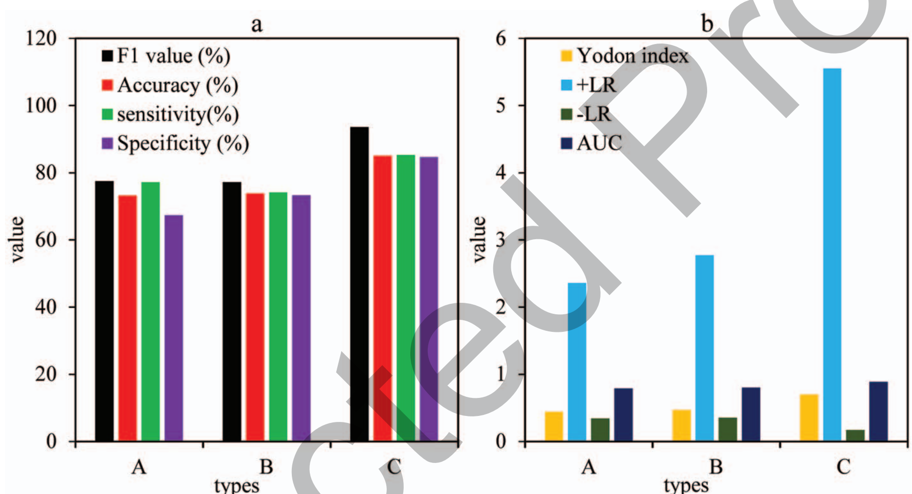

Figure 3. Comparison of diagnostic efficacy of three models of pneumoconiosis in the first round.

In model A, when the Yodon index is 0.44, the diagnostic accuracy is 73.2%, and the sensitivity is 77.18%. The specificity was 67.33%, F1 value was 77.44%, AUC value was 0.788.

In model B, when the Yodon index is 0.47, the diagnostic accuracy is 73.8% and the sensitivity is 74.16%. The specificity was 73.27%, F1 value was 77.14%, AUC value was 0.8.

In the C model, when the Yodon index is 0.7, the diagnostic accuracy is 85% and the sensitivity is 85.23%. The specificity was 84.65%, F1 value was 93.51%, AUC value was 0.887.

In the three modes, the Delong test method was used to conduct AUC analysis for the three modes. The results are shown in Table 1: The diagnostic efficiency of mode C is better than that of modes A and B. A. There is no significant difference in mode B, and the diagnostic efficiency is the same. The ROC curve comparison of the three models is shown in Figure 4.

Table 1. The first round of AUC clinical study on three pneumoconiosis models.

Model	C~B	C~A	B~A
AUC difference	0.087	0.099	0.012
standard deviation	0.025	0.023	0.028
Z value	3.61	4.11	0.43
P value	P<0.001	P<0.001	P=0.649

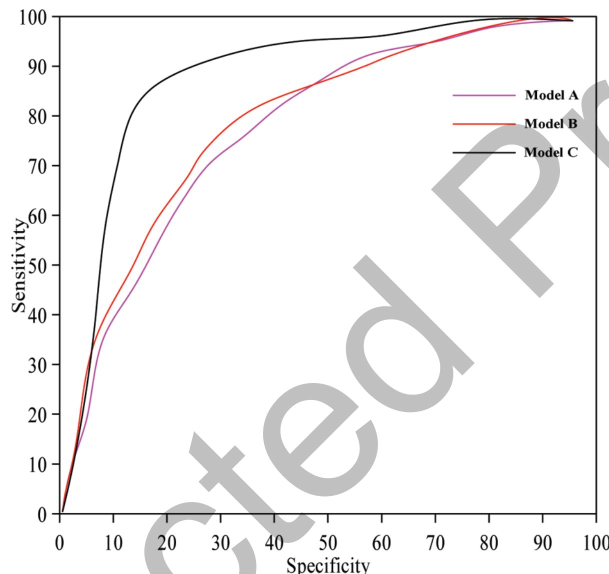

Figure 4. ROC analysis and comparison of three models of the first round pneumoconiosis.

3.3 Comparison of Three Models in the Second Round

In the second round of model test, 14339 chest X-ray films were collected. The diagnostic efficiency of the three models in the test set is shown in Figure 5. Figure 5 (a) shows F1 value, accuracy, sensitivity and specificity; Figure 5 (b) shows the Yoden index,+LR, - LR, AUC.

In model A, the Yodon index is 0.62, the diagnostic accuracy is 80.4%, the sensitivity is 86.91%, the specificity is 75.25%, the positive likelihood ratio is 3.51, the F1 value is 84.78%, the negative likelihood ratio is 0.17, and the AUC value is 0.857.

In model B, the Yodon index is 0.65, the diagnostic accuracy is 83.4%, the sensitivity is 87.25%, and the specificity is 77.23%. The positive likelihood ratio was 3.83, and the F1 value was 86.23%. The negative likelihood ratio was 0.17, and the AUC value was 0.868.

In model C, the Yodon index was 0.84, the diagnostic accuracy was 92.6%, and the sensitivity was 94.3%. The specificity was 90.1%, and the positive likelihood ratio was 9.52. F1 value was 93.82%, negative likelihood ratio was 0.06, AUC value was 0.948.

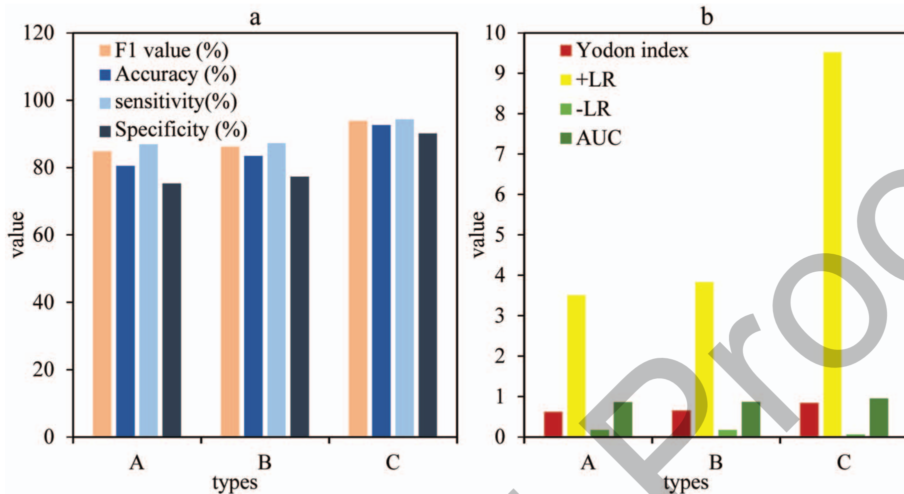

Figure 5. Comparison of diagnostic efficacy of three models of pneumoconiosis in the second round.

AUC analysis of three models was conducted by Delong test method, and the results are shown in Table 2. The diagnostic efficiency of model C is better than that of model A and model B. No significant difference is found between model A and model B, and the diagnostic efficiency is basically the same. The comparison of ROC curves of the three models is shown in Figure 6.

Table 2. Clinical analysis of three pneumoconiosis models in the second round of AUC.

Model	C~B	C~A	B~A
AUC difference	0.08	0.091	0.011
standard deviation	0.018	0.022	0.023
Z value	4.09	4.15	0.41
P value	P<0.001	P<0.001	P=0.647

3.4 Comparison of Three Models in the Third Round

In the third round of model test, 24887 chest X-ray films were collected. The diagnostic efficiency of the three models in the test set is shown in Figure 7. Figure 7 (a) shows F1 value, accuracy, sensitivity and specificity; Figure 7 (b) shows the Yoden index,+LR, - LR, AUC.

In model A, the Yodon index was 0.67, the diagnostic accuracy was 84%, and the sensitivity was 85.91%. The specificity was 81.19%, F1 value was 86.48%, and positive likelihood ratio was 4.57. The negative likelihood ratio was 0.17, and the AUC value was 0.912.

In model B, the Yodon index was 0.72, the diagnostic accuracy was 87%, and the sensitivity was 89.93%. The specificity was 82.67%, the F1 value was 89.18%, and the positive likelihood ratio was 5.19. Negative likelihood ratio 0.12, AUC value 0.911.

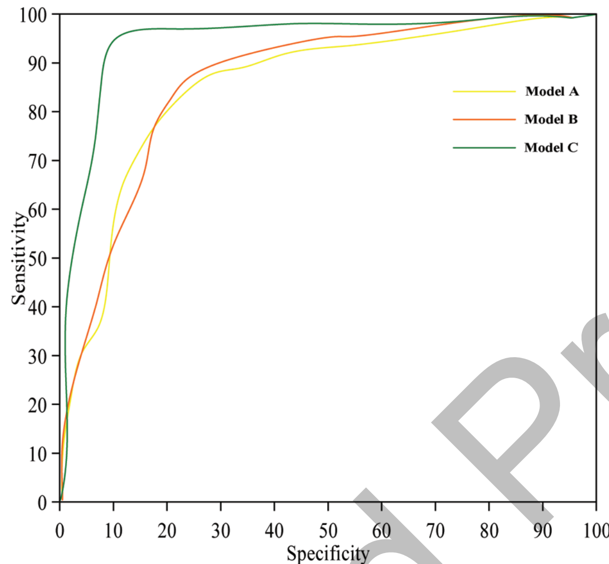

Figure 6. ROC analysis and comparison of three models of the second round pneumoconiosis.

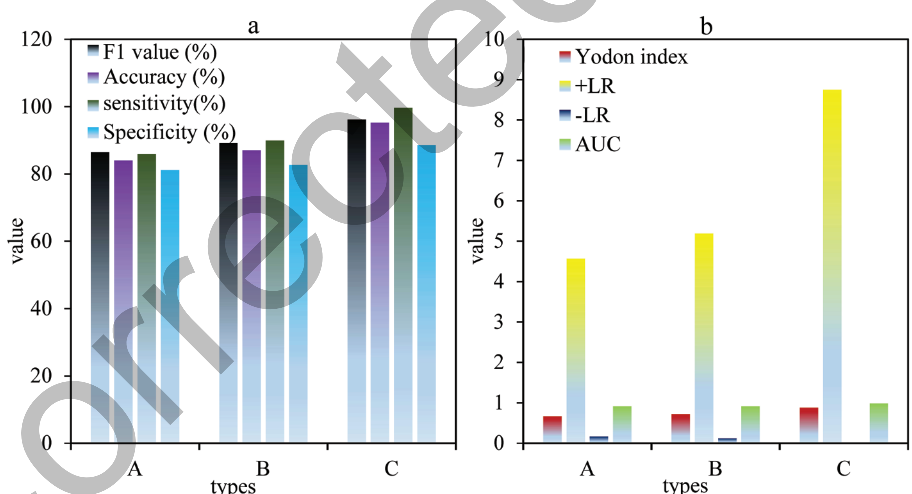

Figure 7. Comparison of diagnostic efficacy of three models of pneumoconiosis in the third round.

In model C, the Yodon index was 0.88, the diagnostic accuracy was 95.2%, and the sensitivity was 99.66%. The specificity was 88.61%, the F1 value was 96.11%, and the positive likelihood ratio was 8.75. The negative likelihood ratio was 0.01, and the AUC value was 0.987.

The Delong test method was used to conduct AUC analysis for the three models. The results are shown in Table 3. The diagnostic efficiency of model C is better than that of model A and model B, and there is no significant difference in the diagnostic efficiency between model A and model B, and the diagnostic efficiency of both models is basically the same. The ROC curves of the three models are compared as shown in Figure 8. Convolutional neural network as a neural network learning method can effectively reduce the accuracy and training time in pneumoconiosis diagnosis, and improve the efficiency of pneumoconiosis diagnosis.

Table 3. Comparative study on the diagnosis of pneumoconiosis in three different models by the third round of AUC.

Model	C~B	C~A	B~A
AUC difference	0.076	0.075	0.001
standard deviation	0.015	0.011	0.020
Z value	5.19	6.41	0.05
P value	P<0.001	P<0.001	P=0.971

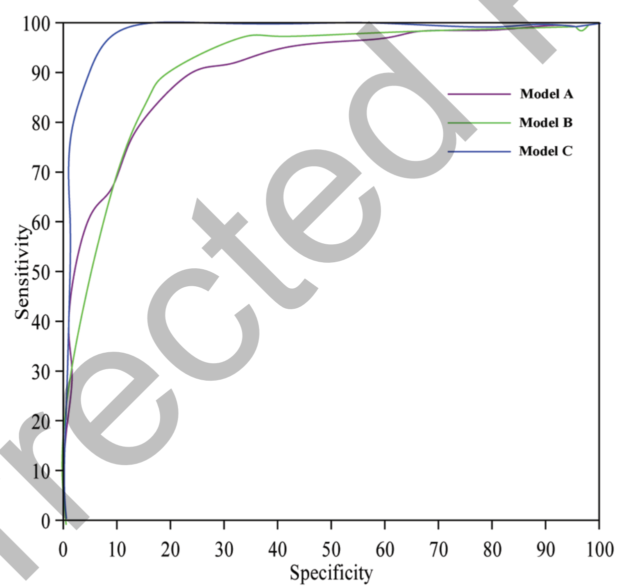

Figure 8. ROC analysis and comparison of three models of the third round pneumoconiosis.

Through comparative analysis of the three models, it is found that with the gradual increase of data, the diagnostic efficiency of the model is also getting higher and higher, and the difference between the AUC of the two models is significant. This is consistent with the characteristics of DL. When the data capacity increases, the diagnostic efficiency would be effectively improved. ResNet model including deconvolution structure is a current computer aided diagnosis method. Doctors diagnose patients according to the judgment of medical imaging. Because of the high sensitivity of the model, the probability of misdiagnosis can be reduced, which greatly reduces the work pressure of diagnostic personnel and improves the work efficiency of diagnosis. Deep reinforcement learning is a typical machine learning algorithm. It can use massive data or a large number of training sets to learn potential patterns and parameters in different tasks and apply them to different tasks. The new pneumoconiosis detection model established in this paper has a higher accuracy than the traditional classification method.

In this paper, the DL neural network is used to study the diagnosis of pneumoconiosis. It is found that the algorithm in view of convolutional neural network has the characteristics of high accuracy, fast speed, easy learning and simple operation. By applying the DL neural network to the diagnosis of pneumoconiosis, the detection time and misdiagnosis rate can be reduced, and the survival rate of pneumoconiosis patients can be improved. This paper mainly studies the diagnosis of pneumoconiosis by combining convolutional neural network technology with lung imaging information, laying a foundation for further improving the diagnostic accuracy of pneumoconiosis. The research results show that the longer the detection time is, the stronger the learning ability of neural network is, and it is obviously helpful for disease diagnosis. It can enhance the diagnostic efficiency of pneumoconiosis and effectively avoid misdiagnosis in a way.

4. CONCLUSIONS

In order to meet the goal of pneumoconiosis prevention proposed by the World Health Organization, from prevention to treatment, people must strengthen the prevention and treatment of pneumoconiosis. Different from other diseases, pneumoconiosis patients do not need to be treated, but at present, many hospitals can provide a variety of treatment methods, such as active treatment measures for pneumoconiosis patients. Therefore, this problem must be further solved. The image classification technology represented by CNN in this paper has shown good results in diagnosing pneumoconiosis, and DL has made outstanding achievements in its application. DL network has strong learning ability and computing power, and can solve practical problems well, reduce training costs, speed up system output, and adapt to practical application scenarios. By introducing different neural networks and DL algorithms, the ability of DL network to recognize dust is improved. In addition, parameters such as tumors in different parts, different tissue morphology and components can also be obtained through model learning. Therefore, a variety of medical detection methods can be applied to the field of pneumoconiosis in practical problems. However, due to the limitations of time and technology, the problems encountered in the study of pneumoconiosis were not described in detail in this paper, which would be further discussed in the future.

REFERENCES

[1] Qi Xian-Mei, Ya Luo, Mei-Yue Song, Ying Liu, Ting Shu, Ying Liu, et al. “Pneumoconiosis: current status and future prospects.” Chinese Medical Journal 134.08 (2021): 898–907.

[2] Zhang Yuan. “Computer-aided diagnosis for pneumoconiosis staging based on multi-scale feature mapping.” International Journal of Computational Intelligence Systems 14.1 (2021): 1–11.

[3] Yang Fan, Zhi-Ri Tang, Jing Chen, Min Tang, Shengchun Wang, Wanyin Qi, et al. “Pneumoconiosis computer aided diagnosis system based on X-rays and DL.” BMC Medical Imaging 21.1 (2021): 1–7.

[4] Zhang Liuzhuo, Ruichen Rong, Qiwei Li, Donghan M. Yang, Bo Yao, Danni Luo, et al. “A DL-based model for screening and staging pneumoconiosis.” Scientific reports 11.1 (2021): 1–7.

[5] Wang Xiaohua, Juezhao Yu, Qiao Zhu, Shuqiang Li, Zanmei Zhao, Bohan Yang, et al. "Potential of DL in assessing pneumoconiosis depicted on digital chest radiography." Occupational and Environmental Medicine 77.9 (2020): 597–602.

[6] Sun Wenjian, Dongsheng Wu, Yang Luo, Lu Liu, Hongjing Zhang, Shuang Wu, et al. "A Fully Deep Learning Paradigm for Pneumoconiosis Staging on Chest Radiographs." IEEE Journal of Biomedical and Health Informatics 26.10 (2022): 5154–5164.

[7] Dong Hantian, Biaokai Zhu, Xinri Zhang, Xiaomei Kong. "Use data augmentation for a DL classification model with chest X-ray clinical imaging featuring coal workers' pneumoconiosis." BMC pulmonary medicine 22.1 (2022): 1-14.

[8] Kovaleva A.S., N. S. Serova, and I. V. Bukhtiyarov. "COMPUTED TOMOGRAPHY IN THE DIAGNOSIS AND DIFFERENTIAL DIAGNOSIS OF PNEUMOCONIOSIS." Diagnostic radiology and radiotherapy 11.3 (2020): 38–43.

[9] Zhao Jun-Qin, Jian-Guo Li, and Chun-Xiang Zhao. "Prevalence of pneumoconiosis among young adults aged 24-44 years in a heavily industrialized province of China." journal of Occupational Health 61.1 (2019): 73–81.

[10] Hu Wei-Syun, and Cheng-Li Lin. "Risk of atrial fibrillation in patients with pneumoconiosis: A nationwide study in Taiwan." Clinical Cardiology 43.1 (2020): 66–70.

[11] Huang Ruixue, Ting Yu, Ying Li, Jianan Hu. "Upregulated has-miR-4516 as a potential biomarker for early diagnosis of dust-induced pulmonary fibrosis in patients with pneumoconiosis." Toxicology research 7.3 (2018): 415–422.

[12] Jp Naw Awn, Momo Imanaka, and Narufumi Suganuma. "Japanese workplace health management in pneumoconiosis prevention." journal of Occupational Health 59.2 (2017): 91–103.

[13] Zheng Ran, Lanlan Zhang, and Hai Jin. "Pneumoconiosis identification in chest X-ray films with CNN-based transfer learning." CCF Transactions on High Performance Computing 3.2 (2021): 186–200.

[14] Okumura Eiichiro, Ikuo Kawashita, and Takayuki Ishida. "Computerized classification of pneumoconiosis on digital chest radiography artificial neural network with three stages." Journal of digital imaging 30.4 (2017): 413–426.

[15] Wang Xiaohua, Juezhao Yu, Qiao Zhu, Shuqiang Li, Zanmei Zhao, Bohan Yang, et al. "Potential of DL in assessing pneumoconiosis depicted on digital chest radiography." Occupational and Environmental Medicine 77.9 (2020): 597–602.

[16] Masanori Akira. "Imaging diagnosis of classical and new pneumoconiosis: predominant reticular HRCT pattern." Insights into Imaging 12.1 (2021): 1–9.

[17] Fan Li, Zelin Wang, and Jianguang Zhou. "LDADN: a local discriminant auxiliary disentangled network for key-region-guided chest X-ray image synthesis augmented in pneumoconiosis detection." Biomedical Optics Express 13.8 (2022): 4353–4369.

[18] Blackley David J., Cara N. Halldin, and A. Scott Laney. "Continued increase in lung transplantation for coal workers' pneumoconiosis in the United States." American journal of industrial medicine 61.7 (2018): 621–624.

AUTHOR BIOGRAPHY

Shengguang Peng was born in Xingning, Guangdong, China. In 2004, he graduated from Jiangxi Normal University with a master's degree. Currently, I am studying for a doctor's degree in the School of Information and Control Engineering, China University of Mining and Technology. My research direction is intelligent medical treatment and applied mathematics.

E-mail: LB20060019@cumt.edu.cn