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Lung Cancer Detection Considering Convolutional Autoencoder Neural Network

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Abstract: Recently, smog has reappeared, which is seriously affecting people's lives and endangering people's health. Under the influence of air pollution such as smog and PM2.5, the number of lung cancer patients in various countries and even the world has shown a significant upward trend. This paper aims to investigate lung cancer detection considering convolutional autoencoder neural networks. After studying the research status at home and abroad, this paper further discusses the existing problems and problems. For big data CT images, an automatic diagnosis model of benign lung nodules based on the established automatic neural network. Variants are saved as examples. Using samples to train a nonlinear network model to achieve objective diagnosis of benign and malignant pulmonary nodules. This method can improve the classification accuracy and classification speed of pulmonary nodules on the basis of avoiding complex algorithms such as feature extraction. By building a neural network model, this work reduces the complexity of the algorithm, improves the overall detection rate of pulmonary nodules, and reduces the false-positive rate and missed-diagnosis rate during testing and verification of large data samples. This provides doctors with an accurate, efficient and convenient way of diagnosis and has a positive effect on the early diagnosis and treatment of lung cancer.

1. Introduction

When diagnosing lung cancer, doctors combine what they have learned with daily reading experience, and use CT images to analyze and diagnose pulmonary nodules, in which experience plays an important role. Statistics from a research group in Boston show that 60.5% of doctors miss the diagnosis, and the misdiagnosis rate is around 10% [1-2].

In the research of lung cancer detection considering convolutional self-encoding neural network, many scholars have studied it and achieved good results. For example, Suresh S combines 2D and 3D thin-layer imaging features to detect and classify lesions, which can reduce the misdiagnosis rate [3]. Based on the research results of domestic and foreign experts' computer-aided research programs, Hatuwal BK believes that it is possible to use low-dose CT thin-slice imaging for computer-aided early diagnosis of lung cancer [4].

This paper builds, tests, and tests a robust network model. In this work, the cognitive model is derived from the convolution of various neural network parameters. Model understanding was validated, analyzed, and evaluated by the Pulmonary Nodule Classification Evaluation Index. We first combined neural network and principal component analysis (PCA) to extract lung nodule features. After statistical analysis, collect samples to train and test the relevant network, collect the middle and end parts of the network, and obtain the end parts by reducing the size of PCA and fusion. Through classical methods such as SVM, the obtained features are compared with other methods to analyze the logic, reliability and accuracy of the experiments.

2. Research on Lung Cancer Detection Considering Convolutional Autoencoder Neural Network

2.1. Forward Propagation

Assuming that there is a fixed sample set containing m samples $\{(x^{(1)},y^{(1)}),K,(x^{(m)},y^{(m)})\}$, the entire network model has n 1 layer, where the first layer represents the input layer, and the n 1 layer represents the output layer [5-6].

Definition:

F (g): activation function;

$a_1^{(1)}$ The activation value of the ith neuron in the first layer, when l=1, $a_1^{(1)}=x_i$;

The input weighted sum of the ith node in layer 1;

$W^{(1)},b^1$: weights and biases of the lth layer ;

Then, the forward propagation of the entire neural network can be defined concisely in the following form:

$$z^{(l+1)}=W^{(1)}a^{(1)}+b^{(1)} \tag{1}$$

$$a^{(l+1)}=f\left(z^{(l+1)}\right) \tag{2}$$

2.2. Autoencoders

The autoencoder expects the y-code to be a categorical representation that captures the first element of the variable in the data. This is also similar to the forecasting method of PCA, which captures the main drivers of changes in the data. This difference between autoencoders and PCA is especially important when planning to combine multiple encoders (and their corresponding decoders) to create an autoencoder [7-8] .

Since we can think of the y-intercept as a lossy variable for the x-input, it is not the sum of all the x-inputs. The optimization function will give y-encoding good compression for training samples, and other inputs guarantee good compression, but that doesn't mean good compression for any input. The automatic calculation method can be summarized as follows: the manual transformer can produce test samples with the same distribution as the training samples with low reproducibility error, but high reproducibility error for random samples drawn from input points.

The idea of the autoencoder training algorithm: for each input x of the autoencoder, carry out forward propagation to calculate the activation value of the hidden layer, then obtain the output in the output layer $\hat{x}$, calculate $\hat{x}$ the deviation relative to x, and backpropagate the error , and update the weights [9-10] .

2.3. Neuron Modeling

The structure of a neural network is determined by the way neuron units and neurons are interconnected. Each neuron is simulating a biological neuron, each unit has multiple inputs x1,i=1,2,...,n and a unique y corresponding to the output after the activation function, corresponding to each input There is a weight, as shown in Figure 1 [11-12].

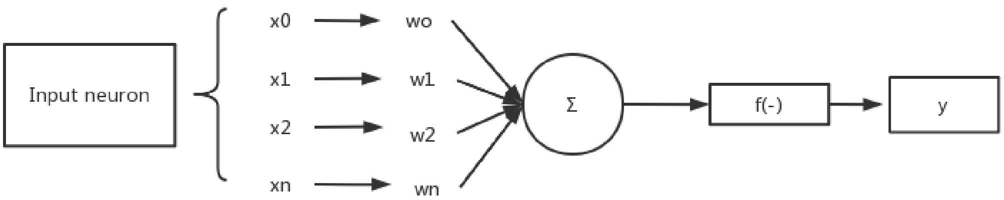

Figure 1. Neuronal model

A classic convolutional network for digit recognition is LeNet-5, which achieves good detection results on the Mnist sample set of the handwritten digits database. The network consists of 5 layers, an input layer, an intermediate layer and an output layer. The intermediate layer includes a convolution layer and a downsampling layer, and each layer contains trainable parameters. The size of the convolution kernel is 5×5 [13-14].

The image size of the detection sample set is 64×64. After convolution and downsampling, the hidden layer features will be obtained. The feature dimension is not proportional to the features it describes. The increase of the dimension may lead to the increase of the classification time and the invalid dimension reduced accuracy due to interference [15-16].

3. Research Design Experiment for Lung Cancer Detection Considering Convolutional Autoencoder Neural Network

3.1. Dataset Generation

After preprocessing the data, a 64x64 patch is used as the input image of the convolutional self-generated neural network. Using a small image can reduce the number of parameters. At the same time, because the nodules account for a small proportion of the entire image, use the complete image. The learned features of the images are difficult to express the nodules.

The neural network model in this paper uses two datasets:

D1: Unsupervised training uses an unlabeled sample set with a total of 50,000 64×64 images. These small image patches are randomly selected from segmented lung parenchyma. When performing unsupervised training, a training sample set and a testing sample set for unsupervised training will be obtained in a ratio of 4:1. The test set is used to select the best optimization parameters and perform performance evaluation.

D2: Classified and labeled sample set, including 5500 64×64 images, of which 2669 contain nodule images and 2831 have no nodules. The samples in the dataset come from the intersection of the labeled data of two professional radiologists. Taking the lung nodule area marked by the doctor as the center, a 64×64 image is extracted, and its label is set to 1, indicating that there is a lung in the image nodules. Images without lung nodules were randomly selected from unlabeled regions in the lung parenchyma region, and their label was 0. The sample set of D2 is divided into training sample set and test sample set using uniform distribution, so the training set includes 4465 64x64 images, and the test set contains 1035 64x64 images [17-18] .

3.2. Experimental Design

This paper first studies the training time and algorithm accuracy based on the size of the convolution kernel in the auto-encoding neural network, and selects three convolution kernels of different sizes for experiments comparison of recognition accuracy.

4. Experimental Analysis of Lung Cancer Detection Considering Convolutional Autoencoder Neural Network

4.1. Convolution Kernel

Experiments by deep learning show that the size of the convolution kernel determines the number of FeCNN layers. The number of layers directly affects the fit of FeCNN to the data. The number of layers is large and the network structure is complex, which leads to the long training time of FeCNN; the number of layers is small and the training time is short, which may lead to low accuracy. The convolution kernel is discussed in this paper, and the results are shown in Table 1.

Table 1. Table of convolution kernel size experimental results

	Training time	Accuracy rate
9×9	5854	4.65%
13×13	5789	96.47%
17×17	3285	97.12%

As can be seen from Figure 2, since the size of the sample is 64×64, the traditional 5×5 convolution kernel is too small, and the convolution kernel is too small, the effective information of the feature cannot be extracted, and the network cannot be classified. Therefore, the appropriate choice of convolution kernel size is related to the performance of the entire network. After many experiments, it is found that when the size of the convolution kernel is 17 × 17, the FeCNN training time is also shorter while ensuring high accuracy and the FeCNN is the most stable.

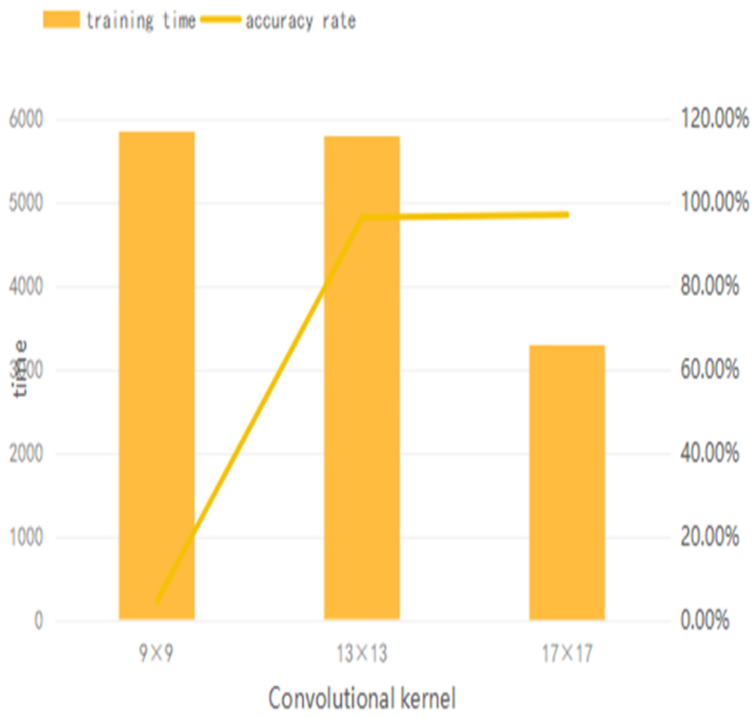

Figure 2. Effect of the size of the convolution kernel on the training time and accuracy

4.2. Comparison of Accuracy Rates of Different Classification Models

This paper classified the various characteristics of lung cancer detection, and analyzed the accuracy of different lung cancer detection. The specific experimental data are shown in Table 2.

Table 2. Classification accuracy of the different classification models

	Morphological features	Textural features	Spicule sign	Fusion feature vectors
SVM	79.67	84.25	82.74	93.18
BP neural network	86.13	87.92	91.23	95.19
CNN	90.23	93.12	92.23	97.33

As can be seen from Figure 3 , Features are not only the premise of classification, but also the guarantee of accuracy, and effective features can greatly shorten the training time of the classification model and reduce the time complexity.The classification accuracy and speed of this algorithm are better than other algorithms.

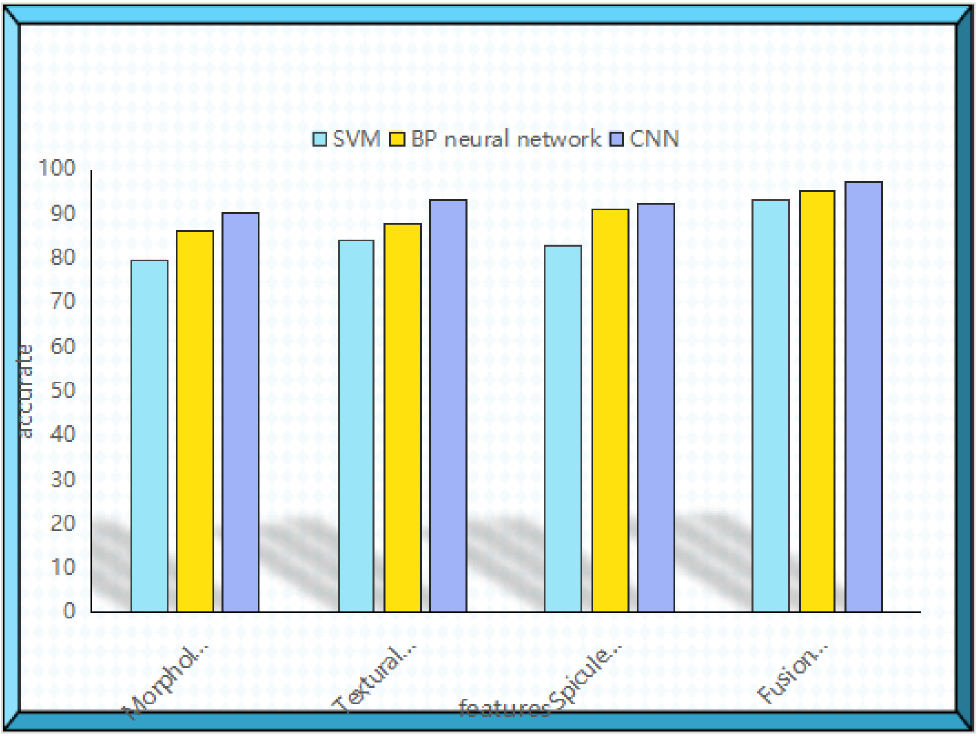

Figure 3. Accuracy comparison of different classification models for different features

5. Conclusion

In this paper, CT is mostly used in the early detection of lung cancer to detect whether there are pulmonary nodules in the lungs. Early detection of pulmonary nodules can significantly control the incidence and mortality of lung cancer and improve the cure rate. This paper extensively investigates and analyzes the current pulmonary nodules. Section examines the current state of research and theoretical knowledge. Considering the most commonly used CT thoracic examination technology in chest radiography, this paper proposes a convolutional autoencoder neural network to address factors such as difficulty in obtaining labeled lung CT images, complex and time-consuming manual feature design. The innovation of this paper is: combining rich unlabeled lung CT data for unsupervised feature learning, and using limited labeled lung CT data for supervised fine-tuning to improve the performance of detecting lung nodules from CT images . The main research work is as follows: (1) In view of the current situation that labeled lung CT images are difficult to obtain, and unlabeled lung CT images are rich in data, unsupervised feature learning using unlabeled data is proposed. The unsupervised learning used in this paper no longer uses traditional autoencoders for learning, but uses convolutional operation-based autoencoders (referred to as convolutional autoencoders in this paper) for lung image data. Convolutional autoencoders The controller will fully learn the lung CT image features to obtain the initial values of the parameters of the convolution operation. (2) Use a small amount of labeled data for supervised fine-tuning. Given the limited labeled lung CT image data, the initial values of the convolution kernels and biases of the neural network used for fine-tuning are no longer initialized randomly, but are obtained using unsupervised pre-training. Finally, in order to verify the performance of the neural network model structure proposed in this paper, this paper proposes three comparison algorithms: autoencoder, convolutional neural network, and multi-cropped convolutional neural network. It can be seen from the comparative experiments that the convolutional auto-encoding neural network not only has better performance than the other three algorithms on the whole, but also in the case of less labeled lung CT image data, the convolutional auto-encoding neural network has better performance than the other three algorithms. The network shows better performance.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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