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Lung Nodule Classification Algorithm Based on Fusion Features

Shengyu Lu+

Software School, Xiamen University, Xiamen City, Fujian, China, 361005

Abstract. Lung nodules are the lesion areas of lung, and malignant lung nodules may led to lung cancer. Nowadays, computer-aided diagnosis based on CT images are important for lung cancer. However, the existing methods of feature extraction of CT image did not perform effect. This paper proposes the DSS algorithm for lung nodules classification based on fusion features. The DSS adopts the local-global model to extract the depth features of images, and jointly uses the shape descriptors based on medical knowledge. Besides, it combines the fusion features into the Support Vector Machine (SVM) for lung nodule classification. This paper has evaluated the DSS algorithm on LIDC-IDRI data set and the method performs effect for lung nodules classification.

Keywords: Lung nodule; CT image; DSS; fusion features; SVM;

1. Introduction

Lung cancer is also known as primary bronchial pulmonary carci-noma [1]. It is a malignant tumor that mainly occurs in bronchial epithelial cells (BEC) and a few occurs in the alveolar tissue. It is a primary malignant tumor of the lung with the high frequency. The clinical manifestations of lung cancer are complicated and diversified[2]. The symptoms and signs of lung cancer depends on the location of the tumor, the type of pathology, the degree of metastasis complications, patient response or tolerance. The main manifestations of lung cancer includes cough, blood or hemoptysis in the sputum, tightness of breath, chest pain and other symptoms. As the disease worsens, there will be lymph node, kidney and digestive tract metastasis, and clinical manifestations caused by metastasis. Lung cancer is one of the most serious malignant tumor with the fastest growth in the morbidity and mortality and has a large threat to people's health and life[3]. In the past 50 years, many countries have reported a significant increase in the morbidity and mortality of lung cancer.

Solitary pulmonary nodule (SPN) refers to single, clear boundary, opaque images with a diameter less than 30 mm surrounded by lung tissue. SPN divided into two categories: benign lesions and malignant lesions[4]. Benign lung nodule mainly includes tuberculosis, granuloma, etc., malignant lung nodule is usually the early form of lung cancer[3]. Therefore, it can effectively detect lung cancer in early stage by judging the benign or malignant properties of lung nodules. Patients can receive treatment in time and improve the survival rate of lung cancer. At present, the clinical detection of lung cancer combined with CT images mainly depends on doctors' visual detect frame-by-frame. However, due to the knowledge, experience and subjective deviation of doctors, diagnostic errors may happen. The computer-aided pulmonary nodule diagnosis system will provide an advice for doctors, which can reduce the workload of doctors and improve diagnosis accuracy[5].

Now the most important screening technique of lung cancer is computed tomography (CT)[5]. It uses only 1/6 of the radiation for CT examination, but can detect lung nodules with a diameter of nearly 2 mm. The sensitivity of CT is 10 times than X-ray. The technology is relatively inexpensive and suitable for lung cancer detection in early stage in the public. Through the clinical studies of more than 100,000 people, the

+ Corresponding author. Tel.: 18059204016.
E-mail address: lu.s.y@foxmail.com.

use of CT screening for lung cancer can reduce the mortality rate of patients by 20%. It confirmed the importance of CT in lung cancer screening, and provided an important basis for clinical application[2]. Although the research on computer-aided pulmonary nodule diagnosis system based on CT detection images has attracted people's attention, there are gaps in clinical application. The main problems are as follows[6]: (1) due to the nature of lung nodules, it is difficult to accurately detect and segment lesions from CT images; (2) different types of lung nodules have some similar expression types. How to distinguish lung nodules accurately is difficult; the available data of lung nodules for research are limited and distributed unbalanced[7]. Therefore, traditional medical image analysis methods cannot implement satisfactory results.

For the CT images, this paper proposes the DSS algorithm for lung nodules classification [8], which uses the deep convolutional network to extract the depth feature representation. The method implements the classification of images to determine whether malignant lesions have occurred. In addition, it considers the shape descriptors of CT images because the shape descriptors are essential for lung cancer diagnosis. The figure1 is the framework of DSS algorithm. The DSS combines the depth and shape features into the classification of lung nodules [9]. Experiment result reflects that DSS algorithm can improve the accuracy of the diagnosis. The DSS algorithm has these contributions:

(1) The method proposes the local-global model to extract the depth features of lung nodule regions[9]. Both of the global region and local region have effect for the diagnosis. How, the existing deep neural network used the convolution operation to extract the features of CT images, which only consider the local region information and neglect the global region. Therefore, it combines the normal resolution and low resolution in deep convolution neural network to obtain the global-local depth features.

(2) It jointly uses the fusion features combining the shape descriptors and depth features for the diagnosis of CT images. According to the medical knowledge, some shape descriptors are typical symptoms of lung cancer such as depression and cavity of lung nodules. Therefore, the addition of shape descriptors can improve the effect of diagnosis

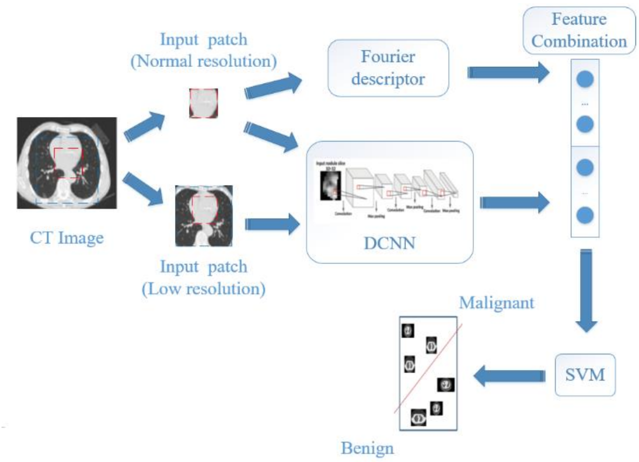

Fig. 1: The framework of DSS algorithm.

2. Background and Related Work

In recent years, deep learning has developed rapidly and achieved significant results in many fields, such as image recognition[10], machine translation[11], and information recommendation[12]. However, applying deep learning technology to the CT image for lung nodule detection[13], three problems need to solved. (1) the quality of CT image is relatively poor, and it has some difficulty to process CT image data; (2) There are fewer CT images, so it needs to have the ability to process small sample data; (3) As the number of samples increases, deep learning technology requires structural evolution capabilities to process the differences of various samples. Deep learning has applied in the some fields of medical image analysis and computer-aided diagnosis[14].

The Google team published a paper in the Journal of the American Medical Association (JAMA), which proposed a deep learning algorithm that can explain signs of diabetic retinopathy in retinal photographs, which can help diagnose more patients.

The Stanford team proposed a deep learning method for diagnosing skin cancer. In the meantime, deep learning technology has made some progress in the detection and diagnosis of lung nodules[15].

Teramoto et al. extracted the features of lung regions and candidate nodule regions. They used the convolutional neural network to extract the lesion information from CT images and PET images, and finally classified by SVM[16].

Shen et al. proposed a multi-pruning convolution network, which does not require image segmentation and manual feature extraction to implement diagnosing for malignant pulmonary nodules.

3. Method

The DSS algorithm extracts the fusion features from CT images and takes them into SVM for lung nodules classification. In this section, it will introduce the feature extraction from global-local model, shape descriptors and SVM in detail.

3.1. Global-local model

Global-local model consists of two modules based on VGG network. It proposes the global-local model to extract the depth features of CT image[17]. Comprised with single deep convolutional neural network, It combines the global and local features. Different regions have different weights for the effect of classification. Therefore, it sets two parameters α and β to assign different weight for global region and local region. Figure2 descripts the architecture of Global-local model.

$$\mathrm{H} = \alpha H^{global} + \beta H^{local} \tag{1}$$

Here, α and β are learned parameter between 0 and 1 in the global-local model. H^{global} and H^{local} respectively represent the feature map which are outputted in the VGG network. H is the combination features consist two processes of low resolution and normal resolution.

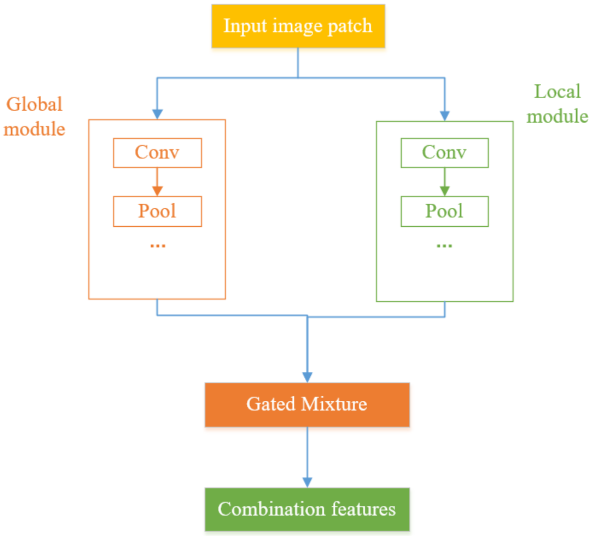

Fig. 2: The architecture of Global-local model

It selects 8000 image patches randomly from the dataset, and resizes them into the dimension of 32*32. It applies these image patches to train the deep convolutional neural network of VGG. As seen in figure3, VGG network consists of 16 convolutions layers, 16 max-pooling layers[18]. The VGG-16 network model is a deep CNN model consisting of 16 convolution layers connected with ReLU excitation layer and max pooling layer. The ReLu() is a Nonlinear transformation to improve the nonlinear expression of the model. The pooling layer uses a 3×3 filter to reduce the parameters of the network and increase the fitting ability of the model. The receptive field of VGG-16 is 32×32, which has a great performance effect, and the model structure is simple and convenient to modify.

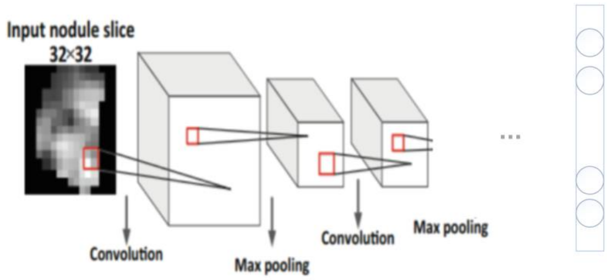

Fig. 3: The structure of VGG network

3.2. Shape descriptor extraction

The DSS algorithm considers the effect of shape features for the lung nodules classification and uses the Fourier algorithm to extract the shape descriptors of CT images [19]. The figure4 is the flow chart of Fourier algorithm. Fourier has a great effect in shape analysis of images. The Fourier descriptor treats the shape of an object as a closed boundary curve. This boundary curve can be treated as the cyclic moving of the point P(l) in the cycle of the boundary curve. The change of point P coordinates are periodic and represent them by Fourier descriptors. The Fourier coefficient is a series of data related to the boundary curve.

It lets the point set (x_s, y_s) represent the boundary curve of the object. N is the number of pixels in boundary curve. The Curvature function K(s) defines as following:

$$\mathrm{K(s)} = \frac{d\theta(s)}{ds} \tag{2}$$

$$\theta(\mathrm{s}) = \arctan(\frac{y_z'}{x_z'}) \tag{3}$$

$$y_z' = \frac{dy_z}{ds} \tag{4}$$

$$x_z' = \frac{dx_z}{ds} \tag{5}$$

where, $\theta(\mathrm{s})$ is the tangential angle on the boundary curve of the current point s.

It lets R(s) represent the distance between the boundary point and the centroid (x_c, y_c) of the object. R(s) defines as:

$$\mathrm{R(s)} = \sqrt{(x_z - x_c)^2 + (y_z - y_c)^2} \tag{6}$$

Then make a Fourier transformation:

$$\mathrm{Z(s)} = (x_z - x_c) + j(y_z - y_c) \tag{7}$$

After that, each point will regard as a complex coefficient and the set of coefficients are relevant to the mapping of the shape of the object in the frequency domain. These coefficients can divide into high frequency components and low frequency components. The high frequency components represent some details of the shape, and the low frequency components describe the macroscopic properties of the shape.

Due to the symmetry of the Fourier, the curvature function only needs to consider the positive coordinate axis. The equations of all Fourier shape descriptors based on the curvature function shown as following:

$$f_k = [|F_1|, ||F_2|, ||F_3|, , , , ||F_{M/2}|]$$

f_i represents the ith parameter in Fourier transform. Likely, the shape descriptors of the centroid function as:

$$f_R = [|\frac{F_1}{F_0}|, ||\frac{F_2}{F_0}|, ||\frac{F_3}{F_0}|, , , , ||\frac{F_{M/2}}{F_0}|]$$

The shape descriptors of Fourier as following:

$$f_Z = [|\frac{F_{-(\frac{M}{2}-1)_1}}{F_1}|, \dots, ||\frac{F_1}{F_1}|, ||\frac{F_2}{F_1}|, , , ||\frac{F_{M/2}}{F_1}|]$$

It obtains f_Z as the shape features of images and combine them with depth features to generate fusion futures [20].

3.3. Classification

The DSS algorithm inputs the fusion features into SVM for classification. SVM is a type of machine learning method, which is widely used to solve the problem of classification [14]. SVM method can transform the problem of nonlinear separable problem into a linear problem with some kernel functions by finding the hyperplane that can maximize the margin between data.

The SVM method performs effect in solving the problem of classification. The key idea is to find an optimized hyperplane to separate the positive and negative samples. Which is similar to the classification of begin and malignant nodules. The optimization of hyperplane implements by this function:

$$\min \varphi(W) = \frac{1}{2}||w||^2 + \mathrm{C}\sum_{i=1}^{N} \rho_i$$

where, W is the weight vector, which is determined by train samples. C is the regular parameter that can balance the model complexity and empirical risk. Besides, ρ_i is positive parameter which represent the distance between the optimal hyperplane and misclassified sample.

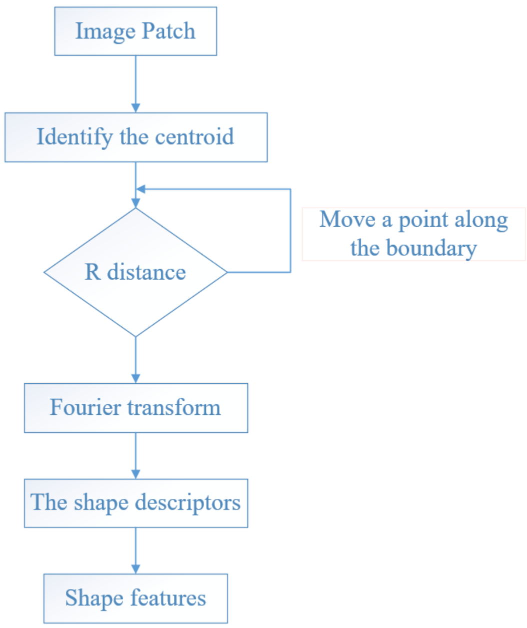

Fig. 4: The flow chart of Fourier algorithm

4. Experiment

4.1. Data set

The experiment uses the data set from Lung Image Database Consortium image collection (LIDC-IDRI) database and evaluates the effects of our algorithm. The database includes diagnostic and CT images of lung cancer with marked-up lesions. The data set is comprised of 862 images of lung nodules. There are 586 benign nodules and 278 malignant nodules. The lung nodules in experimental dataset are as figure5. The begin nodules are in the first row and malignant nodules in the second row.

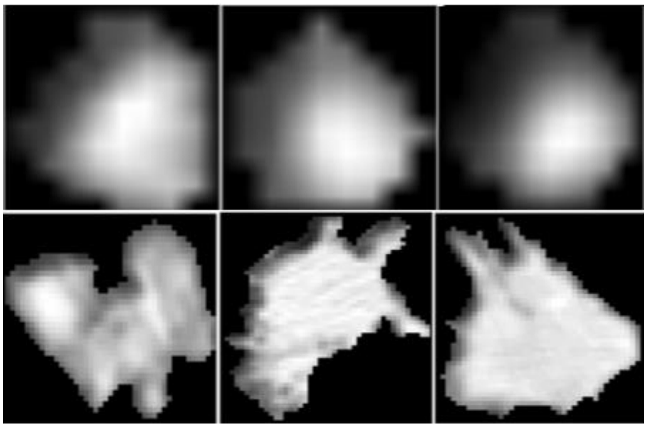

Fig. 5: The lung nodules in data set

4.2. Evaluation metrics

It lets the accuracy and specificity as the evaluation metrics. They represent the rate of correct cases and true negative case respectively. They defines as:

$$\text{accuracy} = \frac{A + D}{N}$$

$$\text{specificity} = \frac{D}{B + D}$$

where, N is the total number of patients. A,B,,D represents the number of patients sick and positive, not sick and positive, not sick and negative respectively.

4.3. Baseline methods:

It used these four methods as baseline methods:

SVM: SVM finds optimal hyperplane to separate two categories. It minimize the empirical error and maximize the geometric edge regions [14].

Bayesian: Bayesian assumes the probability distribution of categories, and computes the joint probability distribution of features to classify [21].

BP neural network: BP neural network is a multi-layer feed-forward network that train the model according to the error inverse propagation. [22].

DNN: DNN is the deep neural network using convolution operation to extract features of images [12].

4.4. Experimental result and analysis

Table1 shows the classification accuracy and specificity of the DSS algorithm with fusion features. The algorithm performs better than without global-local model or Fourier. This confirmed that combining depth features and the shape features benefited for classification and improved the accuracy and specificity.

Table 1: Experimental results of different combination

Method	Accuracy	Specificity
DCNN	81.52%	90.82%
Local-Global model	84.22%	93.64%
DSS	86.54%	95.19%

It compared the DSS with other baseline methods. From figure6 and figure7, it can be seem that the DSS can perform better than other baseline methods in terms of accuracy and specificity. In addition, it can find that the results of accuracy of all methods are not too high. It related to the unbalanced distribution of data set. In the future, it will use some strategies for the unbalanced distribution of data set.

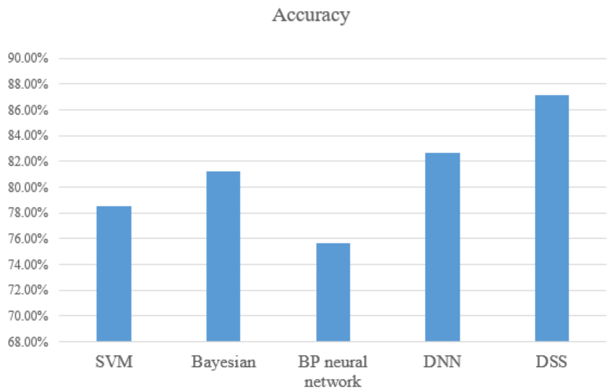

Fig. 6: The experimental results of accuracy

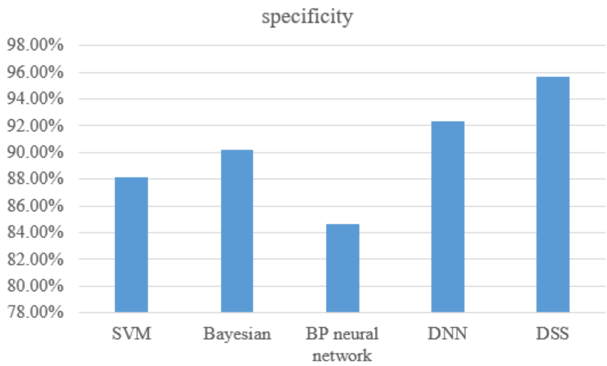

Fig. 7: The experimental results of specificity

5. Conclusion

This paper proposes the DSS algorithm for lung nodule classification. The method improves the deep neural network and uses the global-local model to extract depth features from CT images. Moreover, it considers the shape information of CT images and adopts the Fourier algorithm to extract the shape features. It inputs the fusion features combing the depth features with shape features into SVM for classification. Experimental results reflect that the DSS algorithm can implement great performance effects. It has a significance for the diagnosis of lung nodules. In future work, it will consider solving the problem of unbalanced distribution in lung nodule data set.

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