Squeeze-and-Excitation Convolutional Neural Network for Classification of Malignant and Benign Lung Nodules

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***Abstract*—Lung cancer is the world's highest morbidity and mortality cancer, which seriously threatens the life and health of the public. Early detection and diagnosis of lung nodules is an important prerequisite for lung cancer prevention and diagnosis. This paper designs a new structure which is a Squeeze-and-Excitation Convolutional Neural Network. Experimental results show that SE-CNN can recognize the benign and malignant lung nodules. SE-CNN is more effective than CNN for classification of benign and malignant lung nodules.**

***Index Terms*—squeeze-and-excitation convolutional network, classify, lung nodules, the LIDC-IDRI database**

I. Introduction

According to the "Global Cancer Statistics 2018" report, lung cancer is the world's highest morbidity and mortality cancer, which seriously threatens the life and health of the public [1]. Early detection of lung cancer can improve survival [2]. Lung nodules are an early manifestation of lung cancer. Early detection and diagnosis of lung nodules are an important prerequisite for lung cancer prevention and diagnosis. Computer-Aided Diagnosis (CAD) of lung cancer based on computed tomography mainly includes two aspects: One is to detect lung nodules automatically by computer. And the other is to diagnose benign or malignant of a lung nodule [3]. This article focuses on the automatic diagnosis of benign or malignant a lung nodule.

At present, the diagnosis of lung cancer mainly depends on the naked eyes of experienced doctors. As Computer Tomography technology matures, one CT volume datum can be generated only in seconds. To find lung nodules accurately, one person should have several CT volume with different parameters. One CT volume datum includes 40 to 60 images. This is a big burden for doctors. Moreover, only CT images are not enough to determine the benignancy or malignancy of a lung nodule finally. It needs some other information such as pathological images. This paper only focuses on CT images. Some methods of image processing, pattern recognition and computer vision tried to determine the benignancy or malignancy of a lung nodule. However, some features of benign and malignant lung nodules need be extracted. It is not an easy task to find these features [4], [5]. Convolutional Neural Networks (CNN) [6], [7] can not only extract features of benign and malignant lung nodules automatically, but also classify the benign or malignancy of a lung nodule. Some papers [8], [9] had proposed convolutional neural network based methods for classification of benign or malignant of a lung nodule. However, the proposed CNN methods have low accuracies, because they cannot extract some "good" features of benignancy and malignancy of a lung nodule.

The paper designs a new structure with CNN which is called a Squeeze and Excitation Convolutional Neural Network (SE-CNN). The proposal can not only find some "good" features of benign and malignant lung nodules, but also can improve recognition rate on the benign and malignant lung nodules. The highest recognition rate on the benign and malignant lung nodules is 0.852 to the LIDC-IDRI [10]. SE-CNN was applied with the data from Tianjin Chest Hospital. Experimental results show that SE-CNN can recognize the benign and malignant lung nodules. SE-CNN is more effective than CNN for classification of benign and malignant lung nodules.

The following shows the structure of this paper. Section II introduces the background on Convolutional Neural Networks and Squeeze-and-Excitation block. Section III proposes the proposal of this paper which is a Squeeze-and-Excitation Convolutional Neural Network (SE-CNN). Section IV introduces some experiments to explain SE-CNN can classify the benign and malignant lung nodules effectively. Section V draws some conclusions and gives future works.

II. Background

A. Convolutional Neural Network

Convolutional neural network is a multilayer supervised learning. The basic structure of CNN includes convolutional layer, pooling layer, fully connected layer and output layer. The convolutional layer (Conv.) is to extract features from input data. The pooling layer is to select features and filter some information. Fully

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Connected (FC) layer is to non-linearly combine the extracted features. The output layer is to output the classification results. CNN uses the gradient descent method to minimize the loss function by adjusting the weight parameters in the network layer by layer. The classification of input images can be obtained by the adjusted weights in CNN.

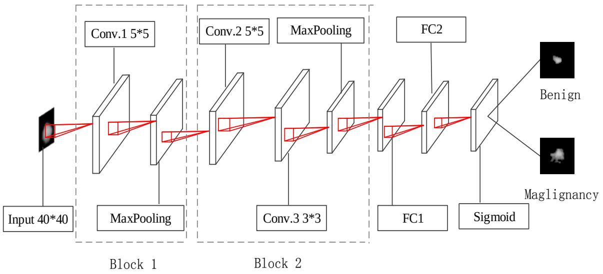


Figure 1. CNN for classification of benign or malignant lung nodules.

Fig. 1 is an example on how to classify the benign and malignant lung nodules. There are 2 blocks to extract features of an input image. Every block includes Convolutional layers and pooling layers. The first block is to extract low features such as edges and lines. The second block is to extract complex features from the first block. The two fully connected layers are to enlarge differences between the benign and malignant lung nodules based on features. The benign and malignant lung nodules can be recognized by using sigmoid function.

B. Squeeze-and-Excitation Block (SE Block)

SE block [11] can automatically enhance the importance of features and suppress unimportant features by adjusting the weights. Fig. 2 shows the structure of SE block. There are three operations for recalibrating the previously obtained features.

Squeeze operation ① is to extract U features from H×W×C. H×W represents the size of a pitch. C represents the number of channels. The number of channels on input should be the same as the number of channels on output during squeeze operation ①.

Excitation operation ② is to generate some weights on channels. The weights can represent the correlation among feature channels.

Scale operation ③ is to resize channels with weights of ② and U features. Thus, the same size of U features can be obtained as the input of SE block. This is a process on recalibration of U features.

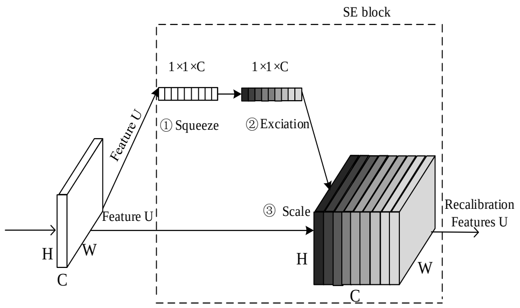


Figure 2. SE block.

III. Squeeze-and-Excitation Convolutional Neural Network

CNN cannot extract some appreciate features to classify the benign and malignant lung nodules, even if it can classify some input images. SE (Squeeze-and-Excitation Networks) can extract some features which can help doctors to classify the benign and malignant lung nodules, but it cannot extract some features from some input images. Thus, the paper designs a new structure named with a Squeeze-and-Excitation CNN combining CNN and SE. The proposal can not only extract some features from some input images, but also can select "good" features to help doctors classify the benign and malignant lung nodules.

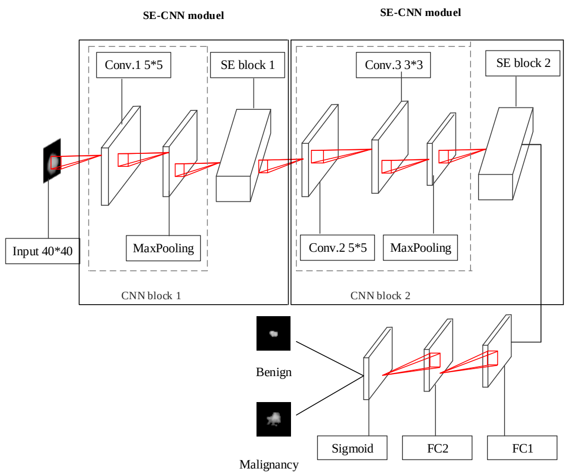


Figure 3. SE-CNN.

TABLE I. The Parameters of SE-CNN

Layers	Type	Input	Kernel	Output
CNN block 1	Conv. 1	40×40×1	5×5	40×40×32
	MaxPooling	40×40×32	2×2	20×20×32
SE block1	Re-calibration	20×20×32		20×20×32
CNN block 2	Conv.2	20×20×32	5×5	20×20×64
	Conv.3	20×20×64	3×3	20×20×64
	MaxPooling	20×20×64	2×2	10×10×64
SE block2	Re-calibration	10×10×64		10×10×64
FC	FC1	10×10×64	10×10	512×1
	FC2	512×1	1×1	2×1
Output	Sigmoid	2×1		Benignancy/malignancy

SE-CNN showed at Fig. 3 includes three plain convolutional layers, two max pooling layers, two SE blocks, and two fully connected layers. Convolution layers are to extract the features of lung nodules. Two SE blocks are to find the correlation among features so that "good" features can be obtained. The two fully connected layers compute the differences between the benign and malignant lung nodules by adjusting some parameters. Some parameters are showed at Table I based on Fig. 3.

Fig. 4 shows the structure of SE-CNN. SE-CNN includes CNN and SE. CNN is to extract some features from input images. SE is to select good features from the complete set of features. U features can be obtained from CNN. Rearranging U features and their channels is done by using global pooling as Squeeze operation. The weights are computed by using two fully connected layers to find the correlations among features. In order to reduce some parameters, the number of dimension is reduced with 1/r. In this paper, r is set as 8. Sigmoid function is to normalize all features from 0 to 1. Scale operation is to recalibrate U features with their corresponding weights. The extracted features can represent the lung nodules very well by using the SE-CNN module.

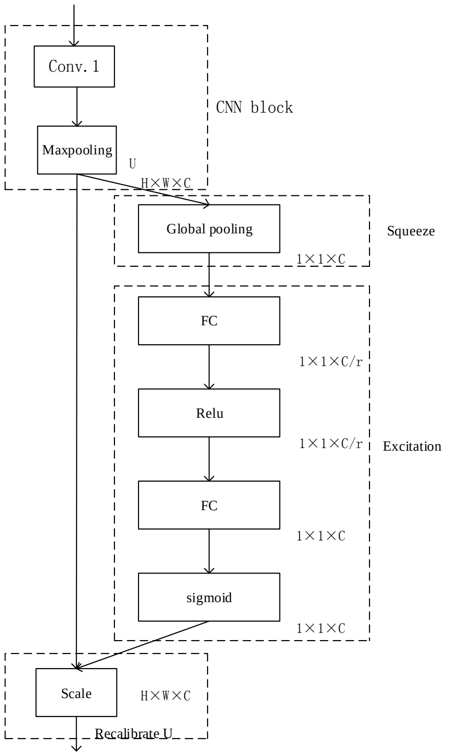


Figure 4. The SE-CNN module.

IV. Experiment

SE-CNN can classify the benign and malignant lung nodules very well, because it can extract some good features, which can represent the benign and malignant nodules. Two databases are used for discussion of SE-CNN effectively. One is the LUNA16 open database [12] and the other is from Tianjin Chest hospital. The institutional review board of Tianjin chest hospital, China approved this study and informed consent was obtained from each patient.

A. Preparation of Input Data

In order to apply CNN effectively some preprocessing of the input data is need, the same goes for SE-CNN. Moreover, there are only near 1000 data for CNN and SE-CNN. The results of these methods maybe are inaccurate since there is not enough data. Thus, data augmentation was used to counter this problem.

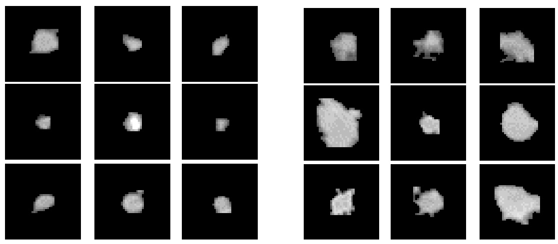
1) Segmentation of lung nodule from CT images

Input data from LUNA database [12] and Tianjin chest hospital can be obtained with the following steps. The size of input data is set at 40×40, because the size of lung nodules are from 3mm to 40mm. The number of lung nodules is 998 (448 are malignant; 550 are benign). Input data can be obtained by following three steps.

Step 1: Lung mask slices are obtained from CT volume data by using morphological image processing. And then the lung slices are obtained based on the original CT volume data.

Step 2: The Region of Interest (ROI) mask of one slice is obtained by binarization and removal of small regions. At last, the ROI of one slice is obtained based on lung slices.

Step 3: Input data can be obtained according to the center coordinates and diameter of lung nodules on each slice. The resulting benign and malignant nodules are shown in Fig. 5.

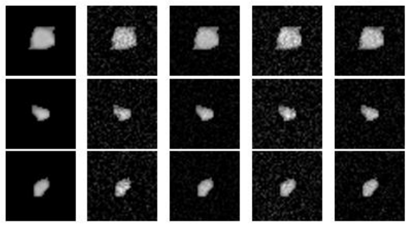


Benign nodules Malignant nodules

Figure 5. Input data.

2) Incrementing number of data based on the original data

This paper provided two methods to augment the number of data in order to from good training models for SE-CNN and CNN. One was to add Gaussian noise with different variances and the other was rotation with different angles. Gaussian noise with a mean value of 0 and variances of 0.01, 0.02, 0.002, and 0.005 were used. Rotation angles are set to with 45 degrees, 90 degrees, 135 degrees, and 180 degrees. The images are shown in Fig. 6 and Fig. 7 respectively.



a b c d e

Figure 6. Original images vs. images with Gaussion noises (a. Original image, b, c, d and e represent mean 0 and variance 0.01, 0.02, 0.002, and 0.005 respectively).

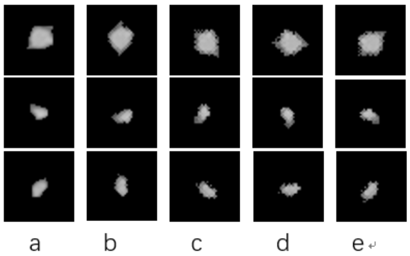


Figure 7. Original images and images with rotations (a. Original image, b, c, d and e represent images rotated by 45 degrees, 90 degrees, 135 degrees, and 180 degrees respectively).

B. Experimental Results with SE-CNN and CNN

There are 4 databases to verify the proposal can classify the benign and malignant lung nodules very well. The 4 databases are the original database from LUNA [12] which is showed as D1, the Gaussian noise database which is added to the original database showed as D2, the rotation database which is added to the original database showed as D3 and the mixed database which is to the original databased showed as D4. Here, the mixed database includes the Gaussian noise and the rotation transformation. To every database, there are training set, validation set and test set which are summarized in Table II.

TABLE II. 4 DATABASES

databases	D1	D2	D3	D4
Training set	699	3495	3495	3495
Validation set	102	510	510	510
Test set	197	985	985	985
Total	998	4990	4990	4990

SE-CNN and CNN have the same parameters as showed below. Learning rate: 0.0001; Dropout: 0.2; Batch size: 32; Epoch: 30; Loss function: Adam. Table III~VI are the results and Fig. 8~Fig. 11 are the ROC from test set on the 4 databases. x-axis represents false positive rate of the ROC, and y-axis represents true positive rate of ROC. The formulas are for *Accuracy*, *Sensitivity*, *Specificity*, *Precision*, *FPR*, and *TPR* are shown in (1), (2), (3), (4), (5), (6), where *TP*, *FP*, *TN*, and *FN* indicate true positive, false positive, true negative, and false negative respectively.

$$Accuracy = (TP + TN)/(TP + FP + FN + TN) \quad (1)$$

$$Sensitivity = TP/(TP + FN) \quad (2)$$

$$Specificity = TN/(TN + FP) \quad (3)$$

$$Precision = TP/(TP + FP) \quad (4)$$

$$FPR = FP/(FP + TN) \quad (5)$$

$$TPR = TP/(TP + FN) \quad (6)$$

The results of SE-CNN are better than CNN from Table III~VI on accuracy, sensitivity, specificity, precision except sensitivity of D1 database, specificity and precision of D4. The ROCs of SE-CNN contain the ROCs of CNN. Thus, SE-CNN is more effective than CNN.

There are 4 training models on SE-CNN and 4 training models on CNN from 4 databases. The training models are inputted from the 10 data from Tianjin Chest hospital. The results are showed at Table VII. The results of the data from Tianjin chest hospital showed that SE-CNN is better than CNN. B is benignancy and M is malignancy of a lung nodule.

TABLE III. D1 DATABASE

	Accuracy	Sensitivity	Specificity	Precision
CNN	0.807	0.926	0.650	0.770
SE-CNN	0.812	0.917	0.682	0.781

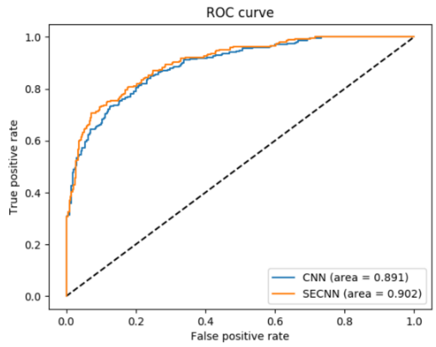


Figure 8. The ROC curve of D1 database.

TABLE IV. D2 DATABASE

	Accuracy	Sensitivity	Specificity	Precision
CNN	0.817	0.853	0.773	0.823
SE-CNN	0.837	0.890	0.773	0.829

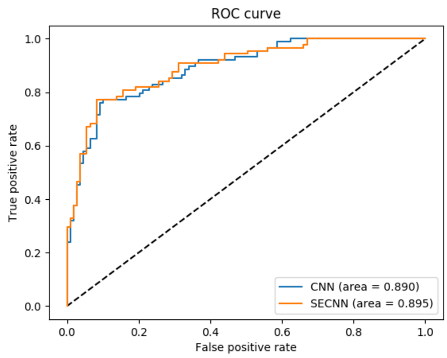


Figure 9. The ROC curve of D2 database.

TABLE V. D3 DATABASE

	Accuracy	Sensitivity	Specificity	Precision
CNN	0.842	0.872	0.807	0.848
SE-CNN	0.852	0.881	0.818	0.857

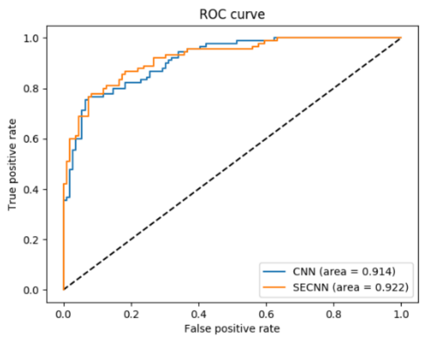


Figure 10. The ROC curve of D3 database.

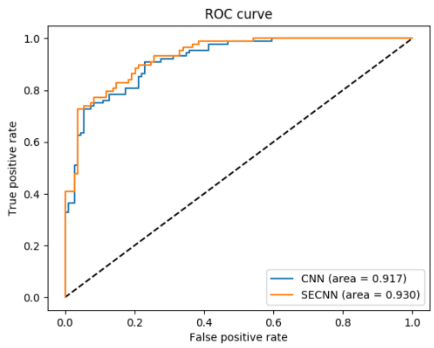


Figure 11. The ROC curve of D4 database.

TABLE VI. D4 DATABASE

	Accuracy	Sensitivity	Specificity	Precision
CNN	0.827	0.862	0.784	0.832
SE-CNN	0.843	0.917	0.750	0.820

TABLE VII. DATABASE FROM TIANJIN CHEST HOSPITAL

Case	Ground truth	D1		D2		D3		D4	
		CNN	SE-CNN	CNN	SE-CNN	CNN	SE-CNN	CNN	SE-CNN
1	B	M	B	M	B	M	B	M	B
2	B	B	B	B	B	B	B	B	B
3	B	B	B	M	B	B	B	B	B
4	M	B	M	M	M	M	M	B	M
5	M	M	M	M	M	M	M	M	M
6	M	M	B	M	B	M	B	M	B
7	B	B	B	B	B	M	M	B	B
8	M	M	M	M	M	M	M	M	M
9	M	M	M	M	M	M	M	M	M
10	M	M	M	M	M	M	M	M	M

V. CONCLUSION

This paper proposes a new network structure named SE-CNN. The proposal not only extract "good" features on the benign or malignancy of a lung nodule, but also suppress the features which are not useful to determine the benign or malignancy of a lung nodule. Moreover, experimental results show SE-CNN to be more effective than CNN. However, the best performance of SE-CNN is only 85%. This is not a high accuracy. In future work, a new learning model should be proposed to extract the good features which are representative of benign and malignant lung nodules aiming for a higher accuracy.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ying Chen, Weiwei Du, Xiaojie Duan, Yanhe Ma and Hong Zhang conduct the research. Ying Chen did the experiments and wrote the paper. Weiwei Du analyzed the data and also wrote the paper. Xiaojie Duan gave his advice. Yanhe Ma and Hong Zhang provided the lung nodule data of Tianjin Chest Hospital. All authors had approved the final version.

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