Computer aided detection system for early cancerous pulmonary nodules by optimizing deep learning features

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Computer aided detection system for early cancerous pulmonary nodules by optimizing deep learning features

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ABSTRACT

In this paper, a deep learning technique for the early detection of pulmonary nodules from low dose CT (LDCT) images is proposed. The proposed technique is composed from four stages. Firstly, a preprocessing stage is applied to enhance image contrast of low dose images. Secondly, a transfer learning is utilized to extract deep learning features that describe the LDCT images. Thirdly, a genetic algorithm is learned on the extracted deep learning features using a training subset of the data to optimize the feature-set and select the most relevant features for cancerous nodules detection. Finally, a classification step of the selected features is performed using supported vector machines (SVM) to detect cancerous pulmonary nodules. Preliminary results on a number of 320 LDCT images acquired from 50 different subjects from the International Early Lung Cancer Action Project, I-ELCAP, online public lung image database has achieved a detection accuracy of 92.5%, sensitivity of 90%, and specificity of 95% Comparison results has shown the outstanding results of the proposed method. These preliminary results confirm the promising of our proposed method.

CCS Concepts

• **Applied computing→Computer-aided design**

Keywords

Lung Cancer; Nodules; Detection; LDCT; Deep Learning; Transfer Learning; Image Processing; Support Vector Machine

1. INTRODUCTION

According to the world health organization (WHO), cancer is the second leading cause of death, with an estimate of 9.6 million deaths, around the world, in 2018.Among all different types of cancer, lung cancer has the highest rate of cancer incidence and mortality rates. In 2018, WHO reported an estimate of 209 million lung cancer cases worldwide, accounting for around 1.76 million deaths. Clinical reports indicate that early detection of lung cancer will increase the survival rate. Therefore, early detection of lung nodules has been investigated extensively by many medical corporations as well as research groups around the world.

Computed tomography (CT) is the medical modality of choice to detect and follow up the lung nodules [1]. However, CT images suffer from extensive ionized X-ray radiation that is not recommended by radiologists to be acquired repeatedly for the same patient. Low-dose CT (LDCT) has been recommended by physicians to reduce the dose levels with the hope to offer early nodule detection [1]. This paper analyze LDCT chest data for the purpose of early detection of lung nodules, where data is acquired from the International Early Lung Cancer Action Project, I-ELCAP [2].

The goal of early lung nodule detection systems is to assist the radiologists to detect lung nodules automatically. These systems, called Computer Aided Detection (CADe) systems, have a general framework of five steps: acquiring the CT images, pre-processing, lung segmentation, nodule detection, and false positive reduction[3, 4].The design of such a system is challenging because the introduction of low dose images reduces the image contrast. In addition, targeting low size nodules for the aim of early detection make this process very difficult.

CADe systems can be categorized into two groups: classical systems[5-7] and deep-learnable systems [8-10]. Classical CADe systems usually start by extracting lung regions from CT images then uses intensity, texture, and shape features extracted from the extracted lung regions to detect the nodules. For example, Li et al. [5] used a thresholding method to exact lung regions from images, then a supported vector machine (SVM) classier is trained on a number of extracted features from lung regions, including the contrast, correlation, energy, homogeneity, and gray Level co-occurrence matrix (GLCM) in order to detect lung nodules. Rattan et al. [6] segmented lung regions, then features are extracted and an artificial neural network ensemble is used for lung cancer detection. Amer et al. [7] extracted the lung regions using bi-level thresholding technique followed by a number of morphological operation. Then they used a genetic algorithm to make a fusion between ~~a~~ several types of features: statistical features, histogram-based features, and the texture based on wavelet coefficients to detect lung nodules from LDCT images.

On the other side deep-learnable CADe systems has been recently invoked to solve the challenge of cancerous lung nodules detection[8-10].Deep learning techniques and convolutional neural networks (CNN) in particular, are the most popular approaches for medical image analysis as well as

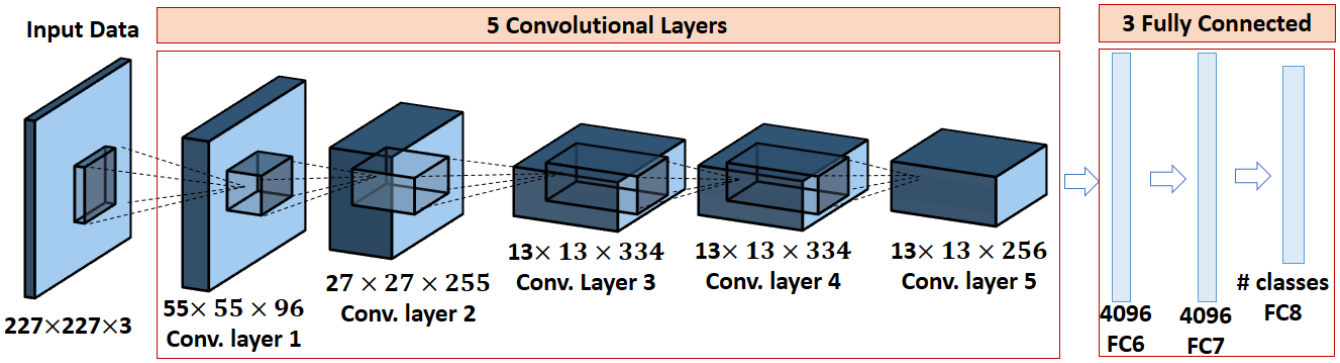

Figure 1. AlexNet architecture developed by Alex Krizhevsky [11], composed of 5 convolutional layers and 3 fully connected layers

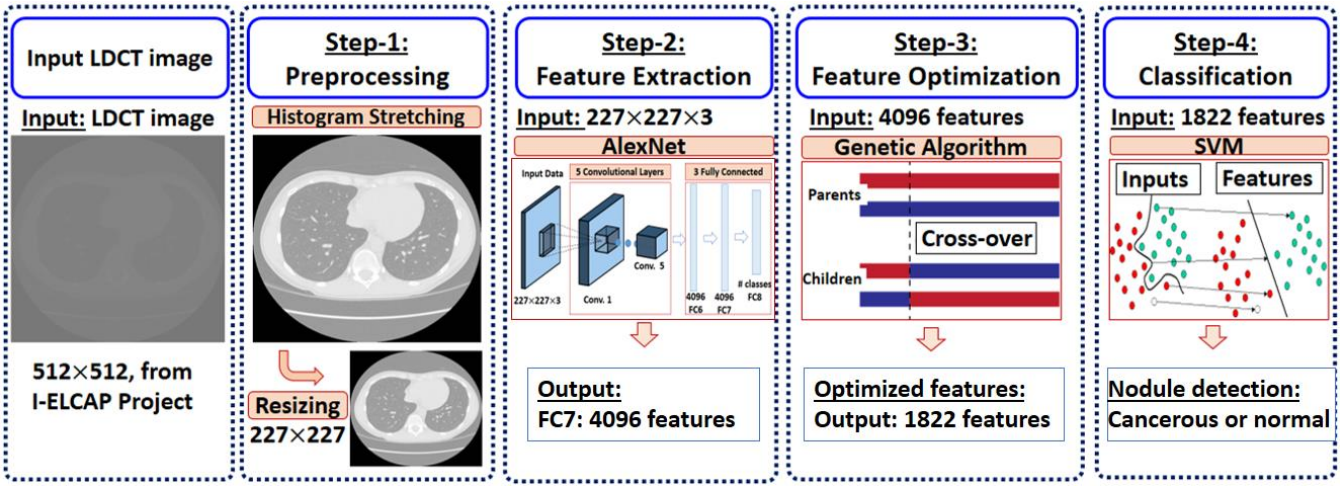

Figure 2. Proposed computer aided detection (CAD)system for early cancerous pulmonary nodules

computer vision applications. The basic idea behind deep learning techniques is to efficiently extract data features that describe the current problem through many layers-networks. These networks transform input data (e.g. medical images) to outputs (e.g. detection or diagnosis) by encoding their low-level and high-level features throughout their layers. As reported in [11], CNNs are the most successful deep-learning medical image analyzer. They are based on a small extent of convolutional filtering layers to encode the images into corresponding higher level features. Many researchers have adopted deep learning CADe systems to detect lung nodules [8-10]. For example, Duo et al. [8] used 3-D CNN networks to reduce false positives in lung nodule detection achieving remarkable improvement. Jin et al. [9] used segmented lung volumes as input samples to train a 3D CNN architecture, consisting of 11 layers, in order to extract features for detecting cancerous nodules. Their method has achieved 87.5% prediction accuracy. Shen et al. [10] built a CNN architecture using a multi-crop pooling of convolutional features to detect and extract lung nodules. They have achieved a classification accuracy of 87.14% over a sample test database composed of 275 nodules. These results highlight the promise of using deep-learning architectures to extract compact and efficient features that describe the problem of early cancerous nodule detection.

In this paper, we used the CNN architectures to extract deep learned features for the problem of lung nodule detection. The proposed framework uses AlexNet architecture developed by Alex Krizhevsky [12] (Figure. 1). AlexNet used a very large database to extract general compact features that have shown a success to be applicable for different problems. Our proposed framework automatically optimize the extracted set of features using genetic algorithm (GA) to select the most relevant features that describe the cancerous nodule detection. The proposed framework used an SVM classifier to detect the cancerous lung nodules. The results, comparing to those reported in the literature, confirm the promise of our proposed method.

The rest of this paper is organized as following. Section 2 illustrates the details of the proposed framework. Section 3 presents our results as well as their comparison to competitive techniques. Finally, section 4summarizes conclusion.

2. METHOS

The proposed framework, shown in Figure 2,is composed of four main steps. First, the input LDCT image is preprocessed to enhance its image contrast and resize it to the standard input size of the AlexNet. In the second step, a transfer learning using AlexNet is utilized to extract the LDCT image features. In the third step, a genetic algorithm is implemented to optimize the extracted features and select, using a subset of training data, the most relevant features for lung tumor detection. Finally, an SVM classifier is used to detect the cancerous lung nodules. A detailed description of the proposed framework is given in the following subsections.

2.1 Database Description

The proposed framework is tested using the Early Lung Cancer Action Project (ELCAP) database [2], an online database

available publically. Forty low dose CT (LDCT) scans containing 320 regions of interest (ROI) are selected for testing our framework. The original images are available in format of Digital Images and Communication in Medicine (DICOM). The image resolution is $0.76 \times 0.76 \times 1.25$ mm. Early nodule detection is considered in this work, with pulmonary nodules varying from 3 mm to 30 mm. A typical example of the LDCT image is shown in Figure.3 (as the input image).

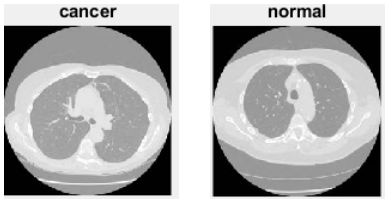

Figure 3. Typical normal and cancerous LDCT image

2.2 Preprocessing of LDCT Images

LDCT images are preprocessed in two stages. First, the contrast is enhanced using histogram stretching [13]. Then, the stretched image is resized to the standard size of the input of AlexNet (227×227× 3). The details of the preprocessing step is shown in Figure. 2.

2.3 Deep-learning Feature Extraction

For the purpose of feature extraction, the proposed framework uses transfer learning of the well-known CNN architecture, namely AlexNet [12] to extract compact and high-level features to represent the LDCT images. As shown in Figure 1, AlexNet is a deep CNN architecture composed of eight layers, five of them are convolutional and the last three layers are fully-connected. In our framework, we adopted a deep transfer learning scheme that used the vector of activities of the fully connected layer of FC7 layer in AlexNet to represent the feature descriptor of the LDCT images.

2.4 Deep-learning Feature Optimization

Since the feature descriptor extracted using transfer learning is generic, in this step, we attempt to optimize the feature set descriptor in order to select the most relevant features for early lung nodule detection. The genetic algorithm first initiate a random population with binary gene representation, where each bit in the gene is either logic one or logic zero. Each gene size is determined as the length of the feature set to be optimized, i.e., 4096 features of the AlexNet FC7 output activations. Logic one indicates that this feature is selected, whereas logic zero indicates that this feature is not relevant. The genetic algorithm runs through a number of iterations on a subset of training images, in order to select the most relevant features related to LDCT lung tumor detection. The iteration optimizes a cost function that represents the detection accuracy on the training database. The output of the genetic algorithm is the selected optimized feature descriptors(reduced in size) that achieve that maximum detection accuracy on the training database. The flowchart of the proposed genetic algorithm is shown in Figure. 4.

2.5 Classification

In this step, an SVM is used to classify the LDCT images based on the selected features. The size of this selected feature descriptor is determined from the genetic algorithm. The test database (new subset of the data that are not included in training the genetic algorithm) is used to test the accuracy of the SVM to detect the cancerous lung nodules using the standard performance evaluation metrics for lung nodule detection.

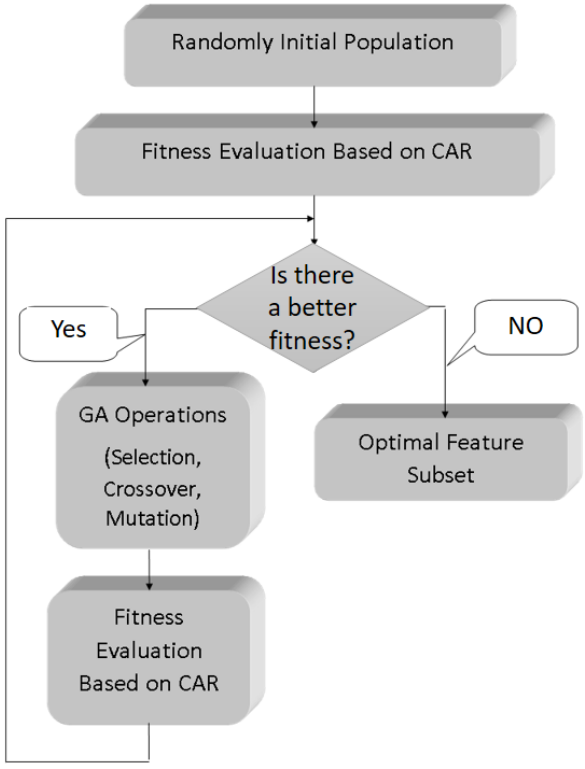

Figure 4. Proposed genetic algorithm for optimal feature selection

2.6 Performance Evaluation

We have evaluated our framework using well-known metrics, namely, classification accuracy rate (CAR), the sensitivity (S) and the specificity (SP). The sensitivity (S), specificity (Sp), and classification accuracy rate (CAR) are defined as [14]:

$$S = \frac{TP}{TP+FN} \times 100\% \quad (1)$$

$$SP = \frac{TN}{TN+FP} \times 100\% \quad (2)$$

$$CAR = \frac{TP+TN}{TP+TN+FN+FP} \times 100\% \quad (3)$$

where TP is the true positive, $TN$is the true negative, $FN$is the false negative, and FP is the false positive.

3. RESULTS AND DISCUSSION

Data has been divided into two groups: a training and testing ~~sets~~. The training set consists of 75% of the whole data, i.e., 240 of randomly selected images out of the total 320 images. The test set consists of 25% of the data, i.e., 80 randomly selected images out of 320 total images. Each group (the train and the test) is composed of the same number of normally-classified-images and cancerous-classified-images in order to avoid any bias in the classifier decisions.

3.1 Visual Results

In order to test the accuracy of our proposed framework, visual results of correctly classified LDCT images from different subjects and different cross-sections of test dataset is shown in Figure. 5.

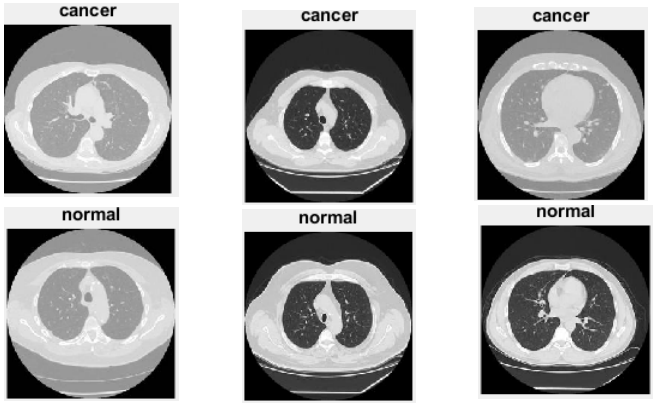

Figure 5. Example of correctly classified LDCT images of different subjects at different cross sections using our proposed framework. First row shows correctly classified cancerous images (TP), and second row shows correctly classified normal images (TN)

3.2 Quantitative results

In order to determine the accuracy of the proposed system several quantitative results has been evaluated based on three standard metrics, sensitivity (S), specificity (Sp), and classification accuracy rate (CAD). To investigate the strength of using AlexNet to extract efficient descriptor of LDCT images, we calculate the three performance metrics for using AlexNet features directly (all FC7 features) to learn the classification stage. For classification, we tested two types of classifier, a K-nearest neighbor classifier (KNN) with K=2 and a supported vector machine classifier. As shown in Table. 1, both classifiers achieve a high CAD rates with more than 80% corrected labels. However, using SVM as expected, achieved a better accuracy that reaches 88%. This is due to the sophisticated nature of the classifier that leads to improved accuracy. Therefore, for the proposed framework, we adopted using the SVM classifier.

Table 1. Results of proposed framework for early nodule detection

Frameworks	S	Sp	CAD
All AlexNet FC7 features + KNN	85%	97.5%	81.25%
All AlexNet FC7 features + SVM	75%	97.5%	88.75%
Proposed optimized AlexNet features + SVM	90%	95%	92.5%

To investigate the effect of the integration of the genetic algorithm to the proposed framework, we compare between using the whole 4096 FC7 features and using the optimal feature set resulted from our proposed genetic algorithm optimization, a set of 1822 relevant features. As shown in Table. 1, all the three performance metrics show significant improvement. In additional to the performance improvements, the genetic algorithm optimization was able to reduce the number of features from 4096 to 1822 relevant features, accounting for around 44% of the total features.This improves the speed of the SVM classifier and release the burden of using too much irrelevant features.These results highlight the privilege of our optimization step and the whole proposed framework.

3.3 Discussion

To investigate the improvement of the results, one should look at the misclassified images. Examples of misclassified LDCT images of different subjects at different cross sections using our proposed framework is shown in Figure 6. As shown in the top row of the figure, the vascular network of the normal lung images looks close to nodules shape, however that the image in normal. Bottom row shows the cancerous nodules, indicated by the blue circles that are not detected. These nodules were still on its initial appearing among the CT slices, so they are challenging to be picked. In the future, we will investigate including more relevant features to capture these cases.

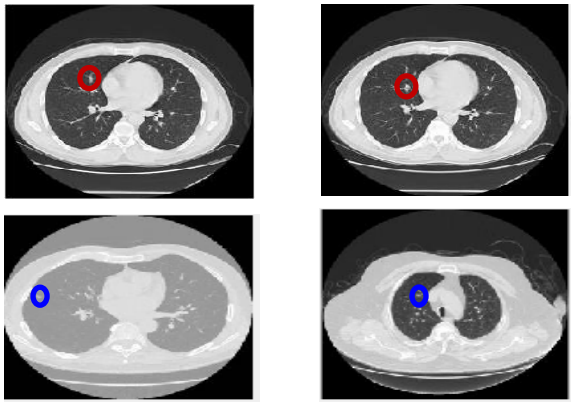

Figure 6. Example of misclassified LDCT images of different subjects at different cross sections using our proposed framework. First row shows misclassified normal images (FN), and second row shows misclassified cancer images (FP), blue circles point to the cancerous nodules

4. CONCLUSION

This paper presents a framework for early lung nodule detection using the International Early Lung Cancer Action Project, I-ELCAP, online public lung image database. The key success of our framework is the optimization of the generic transfer learned features of the well-known AlexNet [12] convolutional neural network. The optimization is done via a genetic algorithm to select the most relevant features for the early detection of lung cancer nodules. Experimental preliminary results on 320 images from I-ELCAP database show the promise of our framework. In the future, we will investigate testing our framework on larger databases in order to test its robustness.

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