Deep Learning Based Lung Nodules Detection from Computer Tomography Images

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Abstract. Lung cancer is among the dominant cause of deaths due to cancer. Lung cancer survival largely depends on the stage at which it is diagnosed with early stage diagnosis significantly improves the survival rate of patients. Radiologist diagnoses the Computerized Tomography images by detecting lung nodules from the images. Detection of initial stage lung cancer is very challenging as the sizes of lung nodules are very small and are difficult to locate. Many computer aided detection systems to detect lung nodules were proposed to assist radiologist. Recently, Deep learning neural network has found its way into lung nodule detection system after the success it has exhibited in computer vision tasks. In this paper, we propose a novel deep convolutional neural network based system for lung nodule detection and localization. Our objective is to provide radiologist with a tool to correctly diagnosis Computer Tomography (CT) scans of patients. The system developed was able to detect and localize with the sensitivity of 92.9%. LIDC-IDRI world largest publicly available database for computer tomography scans of human lungs was used for this research.

Keywords: Convolutional neural network · Lung nodules · Deep learning · Computer tomography · Nodule detection

1 Introduction

As per Lancet reinforced Report and World Health Organization's (WHO), there were around 18.1 million cancer cases registered in 2018 worldwide [1]. The report also estimates that the cancer will be cause of 9.7 million deaths in the world in this year. Breast and lung cancers top the list with each being culprit in 12.3% of the total number of new cases registered in 2018 worldwide. Among them, Lung cancer leads the list of mortalities with anticipated to claim one in each five deaths because of cancers. Radiologists detects lung nodules from computer tomography scan of human lungs. The work load of radiologist is rising as the lung cancer has become one of the leading cancers in the world. Computer aided detection (CAD) systems that detect nodules automatically are intended to assists radiologists and reduces their workload [2]. A CAD system for lung nodule detection typically consists of three stages [3], lung CT scan pre-processing, detection of nodule candidate's and reduction of false positives. The first part focuses

on separating lung lobes from all other body parts. The second part aims for detection of nodule candidates from the segmented scans and the third part focuses on reduction of the number of false positives from the second stage.

The contribution of this paper is to detect nodule candidates. Our main objective is to apply 2D convolutional based deep learning neural network for detection of nodules. The proposed CAD system should be able to detect nodules which are even less than 3 mm in diameter for detection of early stage lung cancer from a 2D lung CT scan of 512×512 pixels. A sample of a lung nodule on a 2D CT scan slice is shown in Fig. 1. The proposed CAD system will comprise of two stages ie., CT scan preprocessing and lung nodule detection. Our aim is to achieve high accuracy and sensitivity with just two stages.
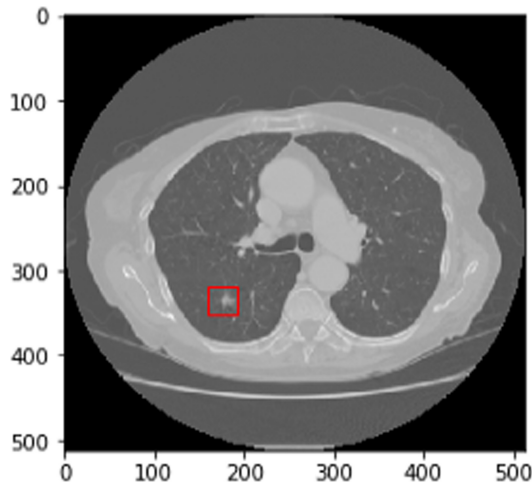

Fig. 1. Slice of pulmonary CT scan with lung nodule indicated by red box (Color figure online)

2   Background

To localize a nodule on a slice means to locate specific position of probable nodules in the lungs. A position is a group of (x, y) coordinate points on a 2D plane of a scan wherein the nodules lies. The proposed system aims is to locate these positions. The success of AlexNet [4], the deep convolutional neural networks (CNN) developed by Alex Krizhevsky in the image classification challenge laid a pathway to solve different image classification and object detection problems. This motivated researchers to apply CNNs to various tasks of computer vision. Deep learning algorithms are these CNNs with large number of layers and are usually referred as deep convolutional neural networks DCNNs. DCNNs also found their way into the medical applications and many CAD systems were developed using DCNNs for classification and detection in medical images over the years. One of these application were DCNNs had promising performance was the detection of lung nodules. In [5] a 2D CNN was implemented which had nodule

detection accuracy of 60.2% with 2.1 average false positives per scan. A 3D CNN was implemented in [6] and was able to achieve sensitivity of 80% with false positives of 22.4 per scan. A multi-level 2D MU-Net was developed in [7] which was able to detect lung nodules with sensitivity of 94.4% with average of 215 candidates per scans. In [8], a vanilla 3D CNN was used which was named as DeepMed had a sensitivity of 93.9% for detection of lung nodules with false positives of 4 per scans. A 3D CNN with multi-scale prediction strategy was developed in [9] which was able to detect nodules with sensitivity of 93.4% and 4 false positive per scans.

3   Chest CT Scan Dataset

LIDC-IDRI public archive [13] was used for patient lung CT scan for the experimentation. 8 medical imaging companies and seven academic centers collaborated together to create this public archive. It is a collection of thoracic CT scans of 1018 cases for lung cancer screening and diagnostics. The archive is also linked with marked-up annotated lesions in a XML files. The annotation of the CT scans was done in two phases, i.e., blind phase and open diagnosis phase by four experienced radiologists. The CT scan consists of axial slice of around 100 to 400 images for each patient. Each slice contains scan of 512×512 pixels. All the scans are available in Digital Imaging and Communications in Medicine (DICOM) format.

4   Method

The first stage of the proposed system is to preprocess the CT scan slices to segment lung from other parts of body such as human tissues, organs, bones etc. The segmentation is followed by the splitting of image into 32×32 pixels windows from 512×512 pixels slice giving a total of 256 windows. This windows are utilized to generate heatmaps from the annotation given in XML files to create labels. Figure 2(a) shows a slice of CT scan and the label generated for the slice from XML annotated file is shown in Fig. 2(b). Our initial approach was to generate heatmap of probable lung nodules directly from the input preprocessed slices by applying it to a 2D DCNN, but result were very poor. To overcome this we converted 32×32 pixels windows ($16 \times 16 = 256$ of them) into categorical labels consisting of 256 categories corresponding to 1 for each window. Then we trained the proposed 2D CNN architecture to find the probability of whether a window has nodule or not.

4.1   Preprocessing and Segmentation

The CT scans pixels values are given in Hounsfield Unit (HU) [15–17, 19]. The HU is the measurement of radio density of different objects under the scan. The first step was to transform the voxels values outside the bore of the CT scan into 0. Then a morphological operation based segmentation technique is carried out to segment lung from other parts such as outside air, bones, tissues and body parts that would make the data noisy. The segmentation was done by extracting two largest regions by area from
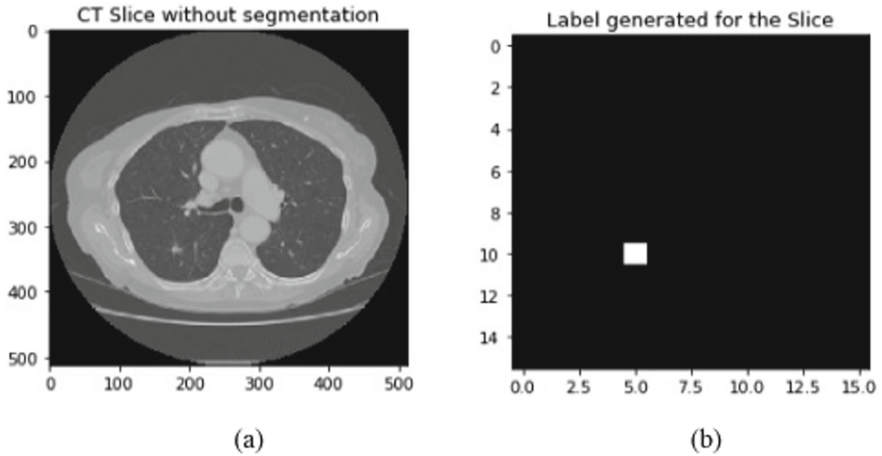
Fig. 2. Example of CT scan slice (a) CT scan slice. (b) Label generated from the XML annotation file.

the image. To these two regions we applied erosion operation and to include nodules attached with the walls of lungs we applied dilation operation to it. Next closing and filling operation was applied to generate mask. Finally the mask was superimposed on the slice to generate lung segmented slice. The original 2D scan slice is shown in Fig. 3(a) and the preprocessed slice is shown in Fig. 3(b).
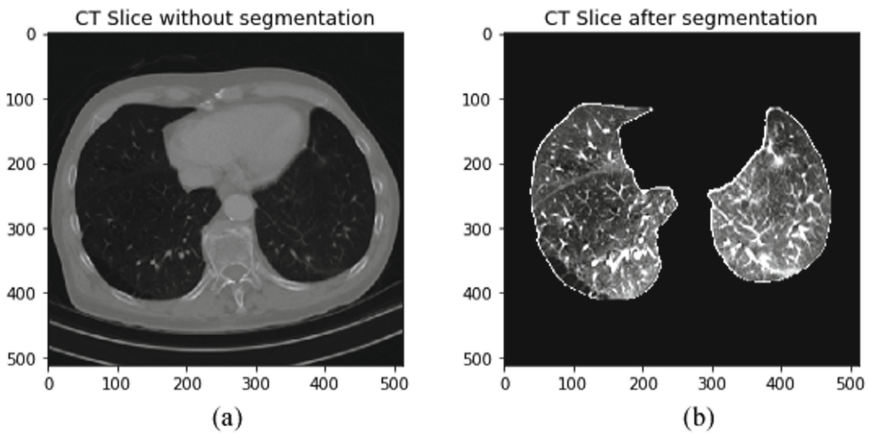

Fig. 3. Example of preprocessing (a) Original slice of CT scan (b) Slice after preprocessing.

4.2   Nodule Detection

The crucial step in any CAD system is candidate detection. The nodule candidate detection method should be able to detect large number of nodule candidate detection with

high sensitivity. We propose a novel 2D Deep Convolutional Neural Network (DCNN) architecture for nodule candidates detection from CT scans. Our initial approach was to generate heatmaps of 16×16 (each pixel for subimage of 32×32 mask), but the results were poor. We then decided to flatten the 16×16 giving us 256 categories where the category is 1 if the nodule candidate is present in that mask and all others 0. The proposed DCNN initiates with an input layer of size 512×512. It consists of 13 convolution layer with 8, 16, 32, 64, 128 and 256 batches. The convolution was performed by small kernel of 3×3 and activated by Rectified linear units (ReLU). It consists of 5 Max-pooling layer with kernel of size 2×2 and a fully connected layer which was activated by softmax activation function to giving final output of 256 categories. This DCNN architecture is shown in Fig. 4 and there details are given in Table 1.
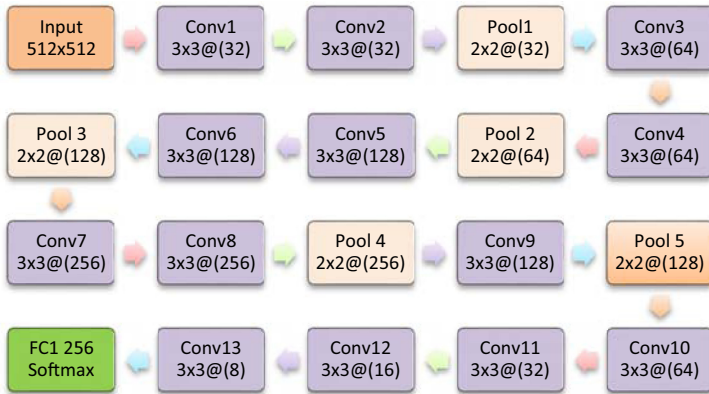

Fig. 4. Deep convolution neural network.

Table 1. Details of deep convolution neural network

Layers	Params	Activation	Output
Input	0		$512 \times 512 \times 1$
Conv1	320	ReLu	$512 \times 512 \times 32$
Conv2	9248	Relu	$512 \times 512 \times 32$
Pool1	0		$256 \times 256 \times 32$
Conv3	18496	Relu	$256 \times 256 \times 64$
Conv4	36928	Relu	$256 \times 256 \times 64$

(*continued*)

Table 1. (*continued*)

Layers	Params	Activation	Output
Pool1	0		$128 \times 128 \times 64$
Conv5	73856	ReLu	$128 \times 128 \times 128$
Conv6	147584	Relu	$128 \times 128 \times 128$
Pool2	0		$64 \times 64 \times 128$
Conv7	295168	ReLu	$64 \times 64 \times 256$
Conv8	590080	Relu	$64 \times 64 \times 256$
Pool3	0		$32 \times 32 \times 256$
Conv9	295040	ReLu	$32 \times 32 \times 128$
Pool4	0		$16 \times 16 \times 128$
Conv10	73792	ReLu	$32 \times 32 \times 64$
Conv11	18464	ReLu	$32 \times 32 \times 32$
Conv12	4624	ReLu	$32 \times 32 \times 16$
Conv13	1160	ReLu	$32 \times 32 \times 8$
Flatten	0		2048
Dense	524544	Softmax	256

5   Experimental Results

LIDC-IDRI was used to evaluate the performance of the proposed CAD system. We have chosen slices with nodule candidates only for the experimentation and ignored all slices without nodule candidates. These slices are divided into batch of 80% dataset for training process and 20% dataset for testing. The 80% dataset for training processes if further divided into 70% dataset for training and 30% dataset for validation. The result of top 5 predictions on some samples is shown in Fig. 5. Figure 6 shows the graph of the sensitivity of proposed CAD system against candidates per scan. From the figure it can be noted that the sensitivity of the system becomes almost constant after 5 candidates per scan. Table 2 compares the results of the proposed CAD system with other CAD system illustrated in [18]. The proposed CAD system was able to achieve the sensitivity of 92.9% with only 5 false positives per scan on testing dataset. With simple 20 layer Deep Learning architecture and by converting the problem to categorical classification problem, we were able to produce comparable results without false positive reduction stage.
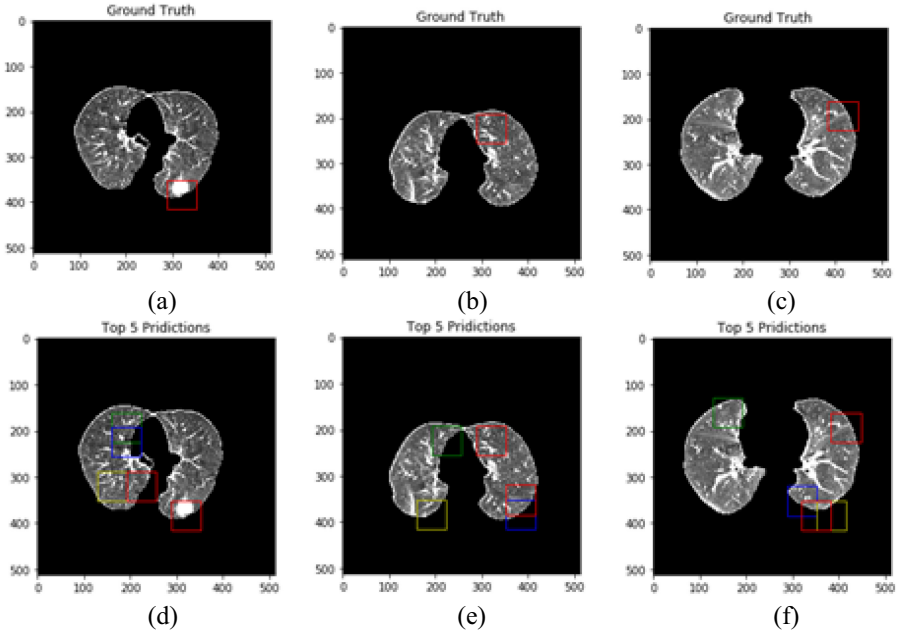
Fig. 5. Experimental result of three CT scans slices. (a) Ground truth of slice 1. (b) Ground truth of slice 2. (c) Ground truth of slice 3. (d) Top 5 predictions slice 1. (e) Top 5 predictions slice 2. (f) Top 5 predictions slice 3.
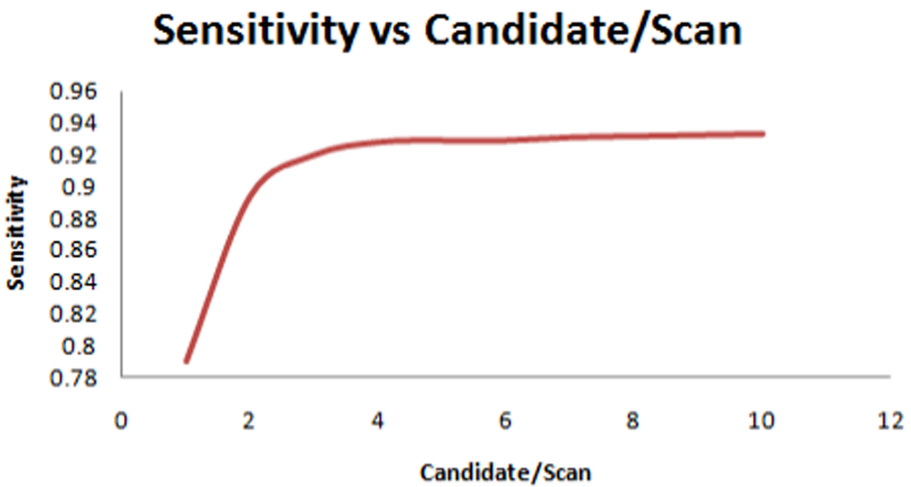

Fig. 6. Sensitivity of the proposed CAD system vs number of candidates per scans.

Table 2. Comparison of DCNN based CAD systems for detection of lung nodules.

System	Sensitivity	Candidates/Scan
ISI-CAD	0.857	335.8
Subsolid CAD	0.369	290.7
Large CAD	0.317	47.5
M5L	0.769	22.3
ETRO-CAD	0.930	333.0
Baseline-CAD (4 anchors)	0.895	25.8
R-CNN	0.946	15.0
Proposed CAD	0.929	5.0

6 Conclusion and Future Scope

In this study, a novel 2D deep convolution neural network for the detection of pulmonary nodule candidate is proposed. The experimentation results carried out on LIDC-IDRI indicates that the proposed CAD system produces comparable result even without implementation of false positive reduction. We will try to implement other deep learning architecture like U-Net, R-CNN to improve the sensitivity of proposed system without effecting false positives in future. We will also try to implement false positive reduction stage to achieve same sensitivity with less number of false positives per scans.

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