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A CAD System for Pulmonary Nodule Prediction Based on Deep Convolutional Neural Networks

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***Abstract*—Computer-aided diagnosis (CAD) systems, have the ability to detect pulmonary nodules, that plays an important role in the diagnosis and early treatment of lung cancer. A method for detecting pulmonary nodules based on an improved neural network is presented here. The prediction of malignancy of the nodules that have the capability to analyze the shape and size of a nodule using Deep Learning is implemented here. An improved convolutional neural network (CNN) framework to detect nodules is designed. There were a total of 551065 annotations taken from the LIDC-IDRI dataset. The proposed CNN model is trained using the LUNA16 datasets from the LIDC-IDRI and its performances are evaluated.**

Keywords—Computer Aided Diagnosis; Deep Learning; Convolutional Neural Netwok; Lung Image Database Consortium

I. INTRODUCTION

Lung cancer causes more deaths worldwide than any other type of cancer [1]. People with early stage lung cancer do not present any clinical symptoms. Hence, early detection is decisive for lung cancer survivability. In lung CT, automatic detection of pulmonary nodules plays an important role in a computer-aided diagnosis (CAD) system [2] that determines the predictive value of a CT scan for malignant nodules. A CAD system for detecting pulmonary nodules usually involves four stages: lung segmentation, nodule detection, feature analysis, and false positive elimination [3]. Current clinical methods acquire thousands of images per patient, and it would be very difficult for a physician to accurately analyze all the photos in detail. Computers can apply a given procedure frequently in a short time and with high precision. In addition, the knowledge of many experts can be implemented computationally; thus computers are often trained in a specific field by a team of several human experts. In this regard, the movement in medicine toward CAD systems, which is due to a quantitative analysis of CT lung images, can improve CT image analysis (which may contain pulmonary nodules), diagnosis of the disease, detection of smallest cancerous nodules (which with much difficulty can be detected by a physician) and reduce diagnostic time [4]. A computer aided diagnosis systems, which use an automated image classification technique, can be used to help radiologists in terms of both their accuracy and speed [5]. Deep learning is a fast and evolving field that has a lot of significance on CAD systems [6]. CNN is one of the most popular deep learning methods for recognition of early lung cancers. [7]. CNNs have much fewer connections and parameters and so they are easier to train with adequate amount of data [8]. An important feature of CAD is its ability to calculate size, volume, and density of nodules in one click, which is extremely important in screening lung cancer and also in assessing prognosis and response to therapy in metastatic workup cases that saves time of the radiologists [9]. Here, a neural network model is proposed to detect pulmonary nodules that can optimize some of the parameters required to detect pulmonary nodules and improve the sensitivity of the detection steps involved in pulmonary nodule detection in a CAD system.

CAD System using CNN for detection of Pulmonary Nodules

A. CNN flowchart for detection of nodules

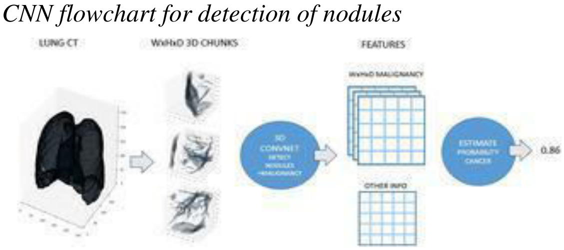

Fig1. CNN detection of pulmonary nodules.
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CNNs are one of the most popular deep learning methods. Here an advanced neural network model is proposed to detect pulmonary nodules that can optimize some parameters of the pulmonary nodules and improve the sensitivity of detection in a CAD system. Fig 1 shows a basic CNN flowchart for

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detecting pulmonary nodules. Convolutional neural networks (CNN) a sub category of neural network that have characteristics of neural network, as a fast, ascendable, and end-to-end learning framework, dreadfully advanced the landscape of computer vision, such as in image classification, object detection, semantic segmentation, and action recognition tasks, etc. As a traditional neural network uses the fully-connected layer as the final classification layer, some details and spatial features of the image will be lost when the final feature is displayed. Therefore, the outline of the nodule cannot be judged based on this approach—true nodules are highly similar to FP nodules (as shown in Fig 2).

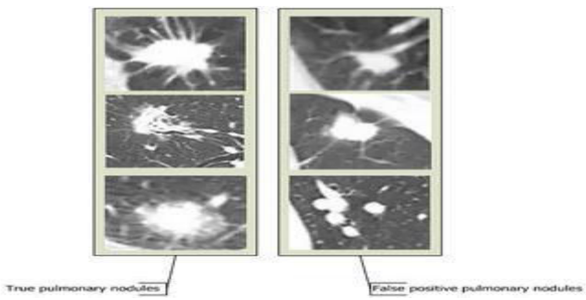

Fig 2. Comparison of true pulmonary nodules and false positive pulmonary nodules.

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But in some details, there are many differences between positive pulmonary nodules and false positive pulmonary nodules. For example, the margin of positive pulmonary nodules is coronal radiation, with needle-like protuberances on the margin, non-smooth margins, and transparent areas in the interior and ground glass elements; while the margin of false positive nodules is smooth, without ground glass elements. Therefore, it is difficult to identify FP pulmonary nodules using a traditional CNN, and traditional CNNs achieve low accuracy scores for malignant pulmonary nodule discovery. For this reason, a new network framework is proposed, to improve the sensitivity of lung nodule detection. With the recent advances in deep neural networks, especially in image analysis, CAD systems are consistently outperforming expert radiologists in both nodule detection and localization tasks. However, results from various researchers show a wide range of detection from 38–100%, with a FP rate from 1–8.2 per scan by the CAD systems [7].

B. Classification of nodules

The classification between benign and malignant nodules is a challenging problem due to very close resemblance at early stages. Benign and malignant nodules have considerable feature overlaps, but still are differentiated on the basis of morphology and location at early stages.

The three different categories (benign, primary malignant, and metastatic malignant) of lung nodules are shown in Fig 3

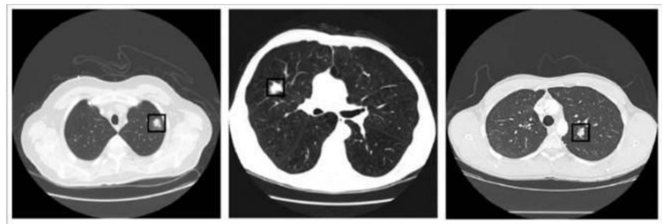

Fig3. Categories of lung nodules in a CT Scan (benign, primary malignant, metastatic malignant), (left to right), Source: https://www.ncbi.nlm.nih.gov

II. Convolutional neural network

CNN are important classes of feed-forward neural networks producing multilevel learnable representations. Deep CNNs, in particular, are composed of several different kinds of layers, such as convolutional layers, nonlinear layers, and pooling layers. They are learned jointly, in an end-to-end manner, to solve a particular task. In a CNN, a convolutional neural network perform the role of feature extractor, however they are not hand designed.

a) Convolutional Layers

The heart of the Convolutional network that does most of the computational heavy lifting is the convolutional layer. In this layer most user specified parameters are present inside network. Highly important parameters are the kernels and the kernel size. This layers parameters consists of a set of learnable filters. Each one filter is limited dimensionally (along height and width), but spreads through the full depth of input volume.

b) Pooling

The pooling layer is another important operator in a CNN. It is commonly placed between two successive convolutional layers in ConvNet architecture. A pooling operator runs on individual feature channels, coalescing nearby feature values into one by the application of a suitable operator. Common choices include max-pooling or average-pooling.

c) Activation Function

The activation function, which is applied to each component of a feature map, introduces nonlinearity in CNN. Here the Rectified Linear Unit (ReLU) is used as the activation function in this article.

d) Softmax Classifier

A softmax classifier can be used for multiple category classification, which is equivalent to a logistic classifier when only two categories are involved. In effect, the last layer of the neural network is a softmax classifier and it uses the cross-entropy cost function.

e) Block Diagram

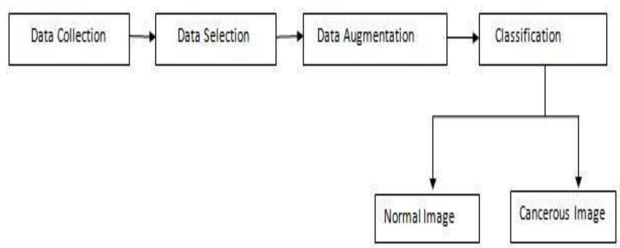

Fig4. Block Diagram of CNN Architecture

Here we briefly discuss about lungs cancer detection based on chest CT images using CNN. In the first stage, lung regions are extracted from CT image and in that region each slices are augmented to get tumors. The augmented tumor regions are used to train CNN architecture. Then, CNN is used to test the patient images. The main objective of this study is to detect whether the tumor present in a patient's lung is malignant or benign. Fig4 shows the block diagram of the proposed system. As from the fig above, the trained system will able to detect the cancerous presence in lung CT image.

III.Training and Simulation

a) Dataset Preparation:

The data taken here is from the Lung Image Database Consortium and Image Database Resource Initiative [(LIDC/IDRI) database]. But due to its huge (124 GB) size the reformatted data is used which is available at LUNA16 . This dataset is mainly designed for the global analysis of "Lung Cancer Detection" problem, which was initially released for the contest LUNA16 in the year 2016. The images were formatted as .mhd and .raw files. Each CT scan has dimensions of $512\ 512\ n$, where n is the number of axial scans. There are about 200 images in each CT scan. There were a total of 551065 annotations. Of all the annotations provided, 1351 were labeled as nodules, rest were labeled negative. So there is a big class imbalance. The easy way to deal with it is to under sample the majority class and augment the minority class through rotating images.

b) Data Augmentation

Deep learning frameworks usually have built-in data augmentation utilities, but those are inefficient or lacking some required functionality. For which the following augmentation techniques are applied to generate more lung nodules for training the model:

(i) Rotating from −25° to 25° with a 5° step

(ii) Flipping horizontally

(iii) Flipping vertically

(iv) Flipping both horizontally and vertically

A large number of positive samples and negative samples are needed to satisfy the neural network training. Here, the image processing operation of translation, rotation, and flip is obtained before the image was input into the neural network, which increased the sample data of the input image. Large number of sample data can effectively improve the neural network training and testing accuracy, reduce the loss function, and ultimately improve the robustness of neural networks. After augmentation, we have 1351 positive patches (those that are too close to the slice's edges are discarded).

Generating patches

A script (using python) generates 50 x 50 grayscale images for training, testing and validating a CNN. While another script under-samples the negative class such that every 1 in 6 images had a nodule. The data set is still vastly imbalanced for training. So, to augment the training set is performed by rotating the images. Total 9796 images are collected out of which 1351 are malignant and 8445 are benign which are divided into training and testing as per the below table.

Table 1: Classification of nodules in Training and Testing

	Total	**Training**	**Testing**
malignant	**1351**	**845**	**506**
benign	**8445**	**6756**	**1689**

Training:

The CNN system that is proposed to implement is designed keeping the previous cnn architectures in mind. The proposed automated lung nodule detection and classification system works on deep learning to decrease FP results and increase sensitivity. Deep learning-based CT scan analysis techniques outperform radiologists in the detection of lung nodules, especially of nodule sizes of <6 mm in diameter, but classification between benign and malignant nodules is a significant and challenging task due to considerable overlap of features. Fig 5 shows the proposed CNN model for the lung nodules detection.

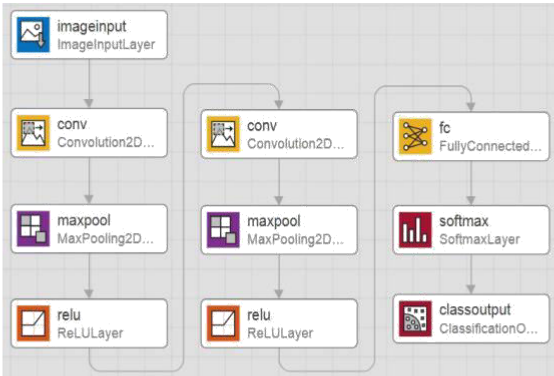

Fig 5 : Proposed CNN architecture

Table 2 breifly describes about the layers that has been used in the proposed CNN model.

Layer	Name	Type	Description
1	Image input	Image Input	50x50x1 images with 'zerocenter' normalization
2	conv_1	Convolution	20 9x9x1 convolutions with stride [1 1] and padding [0 0 0 0]
3	maxpool_1	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
4	relu_1	ReLU	ReLU
5	conv_2	Convolution	10 5x5x20 convolutions with stride [1 1] and padding [0 0 0 0]
6	maxpool_2	Max Pooling	2x2 max pooling with stride [2 2] and padding [0 0 0 0]
7	relu_2	ReLU	ReLU
8	fc	Fully Connected	2 fully connected layer
9	softmax	Softmax	Classifier
10	classoutput	Classification Output	crossentropyex with classes '0' and '1'

Table2: The CNN Layers Description

IV Results

A total of 9796 images of lung nodules are used. Among them, 1351 cases are malignant pulmonary nodules, rest are labelled negative. The nodule detection model is trained through the LUNA16 dataset which contains 9496 images, divided into training and testing datasets with augmented data. The nodule classification model is trained on LIDC-IDRI that contains 1018 CT scans in which four radiologists identified 1351 nodules/lesions. To address the issues of class imbalance among the FP candidates and true nodules, different augmentation techniques such as translation, rotation, flipping, and cropping are applied to increase the training data and reduce class imbalance. These datasets contain well-labeled data, which is necessary for the training of the new models. The data is separated for training, validation, and testing purposes to train the model efficiently. The weights are learned with CNN. The purpose of training is to minimize the difference between the network's output and ground truth data. There are two main reasons to stop the training process. Firstly, the network has reached its smallest error rate, and secondly, the loss function on validation data does not change anymore. Fig 6 below represents the training progress that has been conducted for the nodule detection.

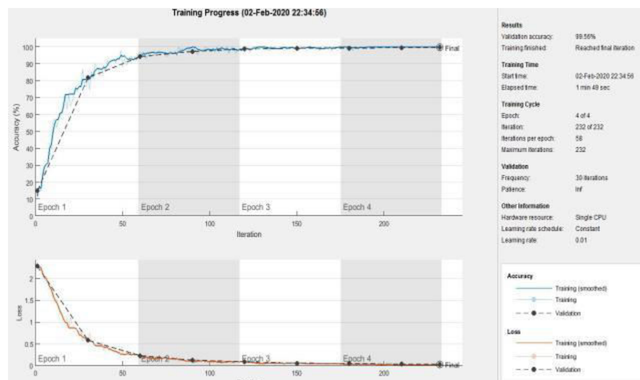

Fig 6: Training Progress

PERFORMANCE METRICS

Accuracy (ability to differentiate the nodule and non-nodule cases correctly), sensitivity (ability to determine the nodule cases correctly), and specificity (ability to determine the non nodule cases correctly) are used to measure the correctness of the classification. These metrics are widely used in binary classification problems and are defined as follows:

$$accuracy \quad \frac{TP \quad TN}{TP \quad TN \quad FP \quad FN}$$

$$sensitivity \quad \frac{TP}{TP \quad FN}$$

$$specificity \quad \frac{TN}{TN \quad FP}$$

where TP (true positive) represents the number of cases correctly identified as nodules; FP (false positive) represents the number of cases incorrectly identified as nodules; TN (true negative) represents the number of cases correctly identified as non nodules; and FN (false negative) represents the number of cases incorrectly identified as non nodules. Fig 7 below represents the accuracy graph of the training progress whereas Fig 8 represents the loss rate or the error.

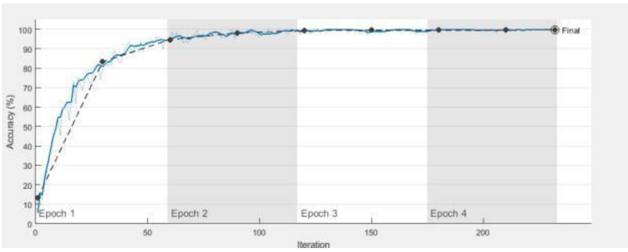

Fig 7: Validation accuracy during training and cross entropy loss vs. focal length

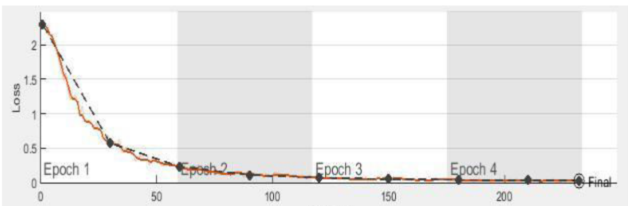

Fig 8: Loss (error rate) occurred during training

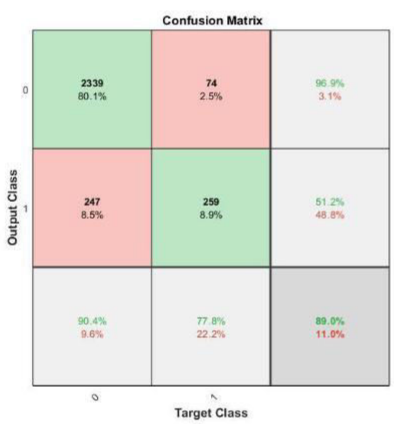

Fig 9: Confusion Matrix

Fig 9 above is a confusion matrix formed by training the system. The matrix is a table that is used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It is a table with 4 different combinations of predicted and actual values.

V Conclusion

Here, deep neural networks are exploited and extensively evaluated. The prediction in the classification of benign and malignant pulmonary nodules is compared in LIDC-IDRI. A lot of experiments are performed on the publically available LUNA16 and LIDC-IDRI datasets. Results show the superiority of the proposed system with lesser computational cost with an accuracy of 89%, sensitivity of 90% and specificity of 77.7%. The experimental results suggest that the CNN model achieved a good performance .At present the trained CNN architecture resulted more than 90% of results, still the result can be improvised with the incorporation of other feature extractors. As this may increase the feature volume, so feature reduction also can be carried out. The proposed method can be expected to improve accuracy of the other database. The method can be generalized to the design of high-performance CAD systems for other medical imaging tasks in the future.

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