# COMPARATIVE STUDY OF DEEP LEARNING NETWORKS FOR LUNG NODULE DETECTION

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***ABSTRACT***

*With this rising pollution and population lung cancer may become a forthcoming pandemic. Thanks to Convolutional Neural Network (CNN) it is possible to create a reliable automated system for lung nodule detection. In past few years lots of research has been done to implement automated detection using CNN, but very few have tested deeper CNN architectures. Since there are large public datasets available, it is now possible to train and test deep-er CNN architectures. In this paper we have adopted architectures like googlenet, Xception, and resnet-101, for lung nodule detection without any pre-processing step. The depth and trainable parameters of these networks ranges from 22 to 101 and 7 million to 44.6 million, respectively. For training and TESTING, we have used the benchmark datasets like LIDC-IDRI and LUNA-16. The maximum accuracy of 98.76% was achieved by googlenet. A detailed comparison of these networks and previously proposed CNN is also presented in this paper. We have also presented confusion matrices for comparison of the fore-mentioned deep networks. After comparing the true class and predicted class the sensitivity of googlenet was found to be 100% and specificity was 82.08%.*

***KEYWORDS***

*Lung cancer, Convolutional Neural Network, Deep Learning, Automation, Classification.*

## 1. INTRODUCTION

Lungs in our respiratory system performs majority of the motor action during respiration. The respiration is the most fundamental and vital process for every living organism. Sometimes this process is affected by an abnormal tissue growth. It is observed within the lungs which keeps spreading until it ends that particular life [1]. This phenomenon is known as cancer, and accounts for 2.21 million deaths around the globe [2]. Cancer is generally quantized into stages such that life expectancy becomes very low at higher stages. So early-stage detection of lung cancer deeply influences the treatment and mortality of the same. With the increasing population just relying on the diagnosis by a human expert may not be a good idea. Initial stage nodule detection using computer aided detection (CAD) can be used to filter patients who genuinely requires diagnosis by human expert-based diagnosis.

## 2. RELATED WORK

Although there are designed CAD system for nodule detection, but still, it is a challenge to uphold the accuracy. Most of the CAD system is designed for Computer Tomography images as it has high resolution. The most conventional method to design a CAD system is by cascading a pre-processing step with a network. Like in [3] a 3D networks with pre-processing step was to design a CAD system for nodule detection. In the pre-processing step a connected region mask (CRM) was created for input to the network. The literature claimed the accuracy somewhere above 60%. Instead of using a deep network architecture some prefers a sparse network [4]. But for shallow network it is crucial to segment the image prior to presenting to the network. Using shallow network named as CanCNN [5] for nodule detection by Rao et al. the images were concatenated to form a 3D structure. The images were processed to generate a 3D structure of desired dimension and had an accuracy of 76%. Using watershed technique to segment the CT images is also very common [6]. After the segmentation Krishna et al. extracted textural features from the CT images. The features were then used to train a Support Vector Machine (SVM) [7], a Back Propagation Neural Network (BPNN) [8] and a CNN model. They found that the accuracy of CNN was far better than that of SVN and BPNN. In a recent work by Masood et al. [9] proposed a dual network namely a multi-Region Proposal Network (mRPN) and a 3D Deep Convolutional Neural Network (3DDCNN) for nodule detection. The mRPN network uses modified layers of VGG 16 and a deconvolutional prediction layer for region. And for reducing false positive they applied 3DDCNN network. The network achieved an accuracy of 98.51% for nodule detection.

All these networks have a pre-processing step involved for identification of lesion. While there are other deeper networks which can be used for lesion identification without involving any pre-processing step. Moreover, the amount of dataset publicly available is enough to train a deeper network i.e., a network with larger number of layers. So here we propose application of three deep networks for lesion detection, without any image pre-processing step. This literature utilizes pretrained networks of namely GoogLeNet [10], ResNet 101 [11], and Xception [12]. After testing the accuracy of the GoogLeNet, ResNet 101, and Xception networks were 98.76%, 97.63% and 95.36% respectively. All these values were achieved without any pre-processing step.

## 3. Materials and Method

### 3.1. Dataset

Lung Image Database Consortium image collection (LIDC-IDRI) [13], [14] is a collection of CT images of lungs. This dataset was organised with the cooperation of eight medical imaging companies and seven academic centres. It is the most prominent dataset that has CT images from 1018 different patients. LIDC dataset was introduced by National Cancer Institute (NCI), and the annotation was created in presence of four experienced radiologists.

The Lung Nodule Analysis (LUNA) 16 [15] dataset comprises of 1,186 lung CT scan images. It was provided for automatic detection of lung nodule. Each dataset is publicly available for researchers without any charges. CT images were initially converted into Bitmap (BMP) format, which is compatible with majority of image editing application.

### 3.2. Network modelling

ResNet101 proposed by Kaiming et al. in [11], is 101-layer deep network. Here the input image has a size of 224*224*3 and the initial convolutional (Conv) layer has 64 filters of size 7*7 and was applied with the stride of 2*2. To maintain the image resolution the resulted image was padded. In the rest of the network the Conv filter size was 1*1 and 3X3, and each Conv filter was followed by batch normalization (BN) [16]. BN is a technique to make the network faster and stable. The activation function used in this literature was Rectified Linear Unit (Relu) given in equation (1).

$$f(x) = \max(0, x) \qquad (1)$$

Here $x$ is the input value and $f$ is the Relu operation on the input. The Xception network by F. Chollet [12] uses the same Clipped Relu [17] and has overall 71 layers. It uses multiple kernels to perform Grouped Conv together with normal Conv layers. It also has a combination of Global Average Pooling and Max Pooling applied at different levels of the network. Another network GoogLeNet introduced in [10] has 144 layers. The architecture of GoogLeNet is shown in Fig. 1. All of these networks had only one Fully connected layer, and trained with ImageNet Dataset.

$$cf(x) = \begin{cases} 0 & if\ x < 0 \\ x & if\ 0 < x < th \\ th & if\ x > th \end{cases} \tag{2}$$


Figure 1. The network architecture of GoogLeNet.

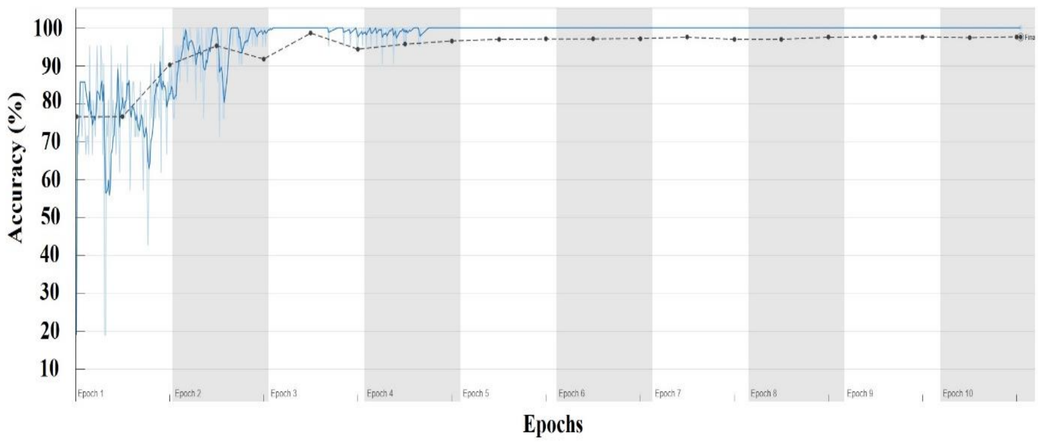
All of the network defined so far has been designed for Image classification or object recognition application. In our work it is very first time that they have been utilized for Lung nodule detection. After taking the pretrained model, the layer was trained for ImageNet [18] dataset to identify between 1000 object class. But in our case, there is only two class one with nodule (Nodule Class) and other without nodule (Normal Class). Instead of using the conventional Stochastic Gradient Descent Method (SGDM) [19] we have used ADAM [20] an adaptive learning rate optimization algorithm. It is an advancement in SGDM, by using Root Mean Squared Propagation [21]. After designing the network next was to select the training and testing with dataset. For testing we have used 30% of the complete dataset (combined LIDC-IDRI and LUNA16)

## 4. RESULTS AND DISCUSSION

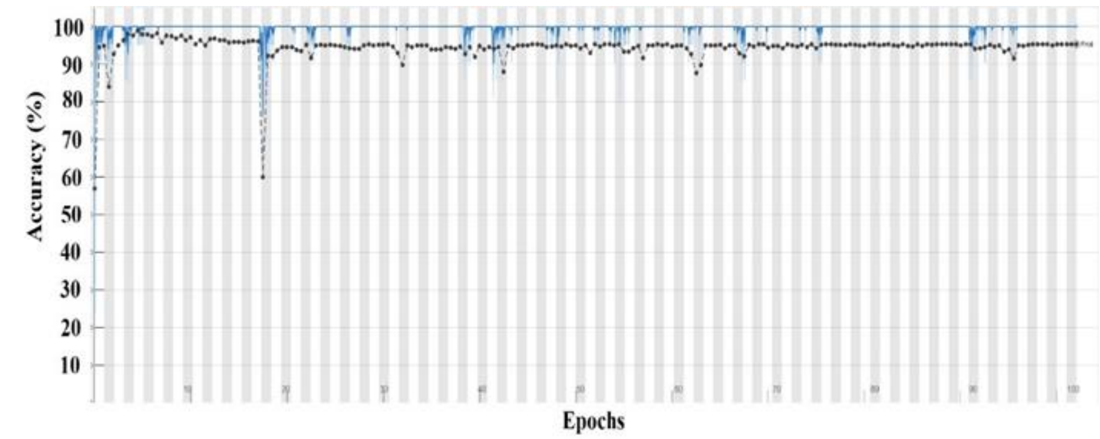
The GoogLeNet, ResNet 101 and Xception networks were trained using MATLAB. The dataset was divided into two parts one having CT images of patient with nodule and other without nodule. The rate of parameter evolution is controlled by learning rate. A large learning rate can result in non-optimal solution and a low learning rate can result in very slow parameter evolution. So, we had the learning rate set at 0.01. For learning the models use 70% of images in the dataset partitioned randomly. Since we have a large dataset 100 epochs would be sufficient for training the model. The minibatch size was selected 31 i.e., the weights were updated after every 31 samples. Chances of vanishing or exploding gradients was taken care by using L2 norm in the networks.

Table 1. Comparison of accuracy for lung nodule detection

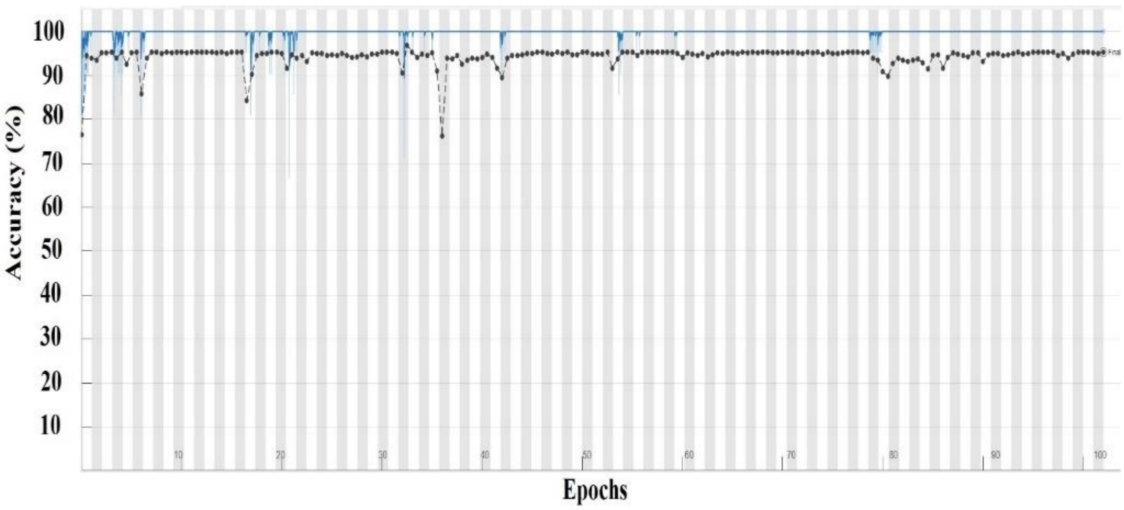
| Methodology | Accuracy (%) |
|---|---|
| CMRNet | 67.7% |
| Watershed+BPNN | 86% |
| Watershed+SVM | 92% |
| Watershed+CNN | 95% |
| mRPN+3DDCNN | 98.51% |
| Xception | 95.36% |
| ResNet 101 | 97.63% |
| GoogLeNet | 98.76% |




(a)



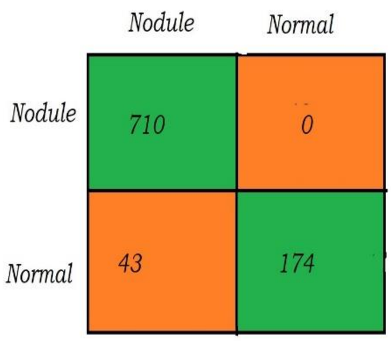

(b)



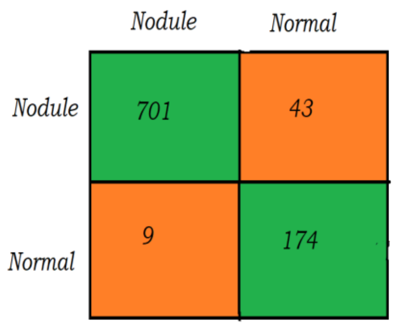

(c)

Learning Accuracy
Testing Accuracy

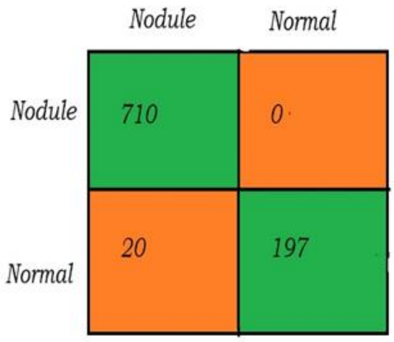
Figure 2. The Accuracy during training of (a) GoogLeNet, (b) ResNet 101 and (c) Xception network.




(a)




(b)




(c)

Figure 3. Confusion matrix of, (a) ResNet 101, (b) Xception network, and (c) GoogLeNet.

Unlike other CAD system which require pre-processing of CT images, we refuse to introduce any processing step. In our method the networks were fed with the CT images as provided in the dataset. This improves the practicality of our method for real time application. Previously trained model like the dual network of mRPN and 3DDCNN had an accuracy of 98.6 in Table1. This was achieved after having additional network for false positive reduction. The GoogLeNet here achieved the highest accuracy of 98.76%. It seems to reach this accuracy at early epochs than other two networks and took least number of epochs to stabilize in Fig 2. The Resnet 101 had an accuracy of 97.63 and Xception had the least accuracy of 95.36%. Point to be noted here is that the GoogLeNet had the least number of layers. It may be due to the unique architecture of GoogLeNet that makes it more efficient. The Xception and ResNet 101 have a straight architecture. To obtain confusion matrix which is shown in Fig 3 we had taken a total number of 710 cases of nodule and 217 normal images. In the Resnet for the nodule cases we detected all the 710 cases as nodule (True Positive) and zero case was identified as normal (False Negative). And for the normal cases in total of 219 cases Resnet predicted 43 cases as nodule (False Positive) and 174 cases as normal (True Negative). With Xception for 701 nodule cases its prediction was correct but other 43 nodule cases were assigned to the normal. For normal cases with using Xception it was found that 9 cases were detected as nodule and 174 cases was found as normal. Coming to GoogLeNet all of the 710 nodule cases was accurately predicted. And for the normal cases, the GoogLeNet predicted 20 cases as nodule and rest 197 cases as normal. From this data the Sensitivity, Specificity, False Negative rate, and False Positive Rate was calculated using equation (3), (4), (5) and (6).

$$Sensitivity = {}^{True\ Positive}\big/_{(True\ Positive + FalseNegative)} \tag{3}$$

$$Specificity = {}^{True\ Negative}\big/_{(True\ Negative + False\ Positive)} \tag{4}$$

$$False\ Negative\ Rate = {}^{False\ Negative}\big/_{(True\ positive + False\ Positive)} \tag{5}$$

$$False\ Positive\ Rate = {}^{False\ Positive}\big/_{(True\ Negative + False\ Positive)} \tag{6}$$

The values of these parameters are provided in Table 2 for the deep networks. The GoogLeNet and Resnet 101 has 100% sensitivity. Which means there in null chances of predicting nodule class as normal class i.e., False negative. On the other hand, Xception network shows a sensitivity of 94.28%. But Specificity of Xception is best among the considered networks. Due to zero false negative the false negative rate of Resnet 101 and GoogLeNet is zero but Xception has

4.7 False Negative Rate. And due to least false positive the Xception has the best False Positive Rate.

Table 2. The Specificity, Sensitivity, False Negative Rate, and False Positive Rate of Deep networks.

| **Network Name** | **Resnet 101** | **Xception** | **GoogLeNet** |
|---|---|---|---|
| Sensitivity | 100 | 94.28 | 100 |
| Specificity | 80.18 | 95.08 | 82.08 |
| False Negative Rate | 0 | 4.7 | 0 |
| False Positive Rate | 19 | 4.9 | 9.2 |

## 5. CONCLUSIONS

In this literature a CAD system was proposed using deep networks for Lung Nodule detection. The state-of-the-art datasets LIDC-IDRI and LUNA 16 was used in combination. The pretrained GoogLeNet, ResNet 101 and Xception model was explored here. The Xception network had the least accuracy of 95.36% for nodule detection. Despite least accuracy Xception outperformed most of the other nodule detector. ResNet had the maximum number of layers and so the highest number of network parameters but reported an accuracy of 97.63%. GoogLeNet had the least number of layers and parameters but surprisingly converged within early epochs. The accuracy reported for GoogLeNet was 98.76%. Which is the highest accuracy not only compared to ResNet 101, and Xception but also to other networks. The GoogLeNet and Resnet were found to be 100% accurate in detecting nodule class. The Xception on the other hand has the best specificity and False Positive Rate. Overall, the GoogLeNet has the best performance among all the networks for lung nodule detection.

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