Diagnosis of Pulmonary Nodules using Multi-Size Multi-Branch 3D-CNN Architecture

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Abstract:

Early prediction of lung cancer is very crucial now-a-days. 3D-CNN are widely used to extract dominant features from the given medical images. So, in this paper we designed a novel 3D-CNN architecture based on the size of the pulmonary nodule. In this architecture three branches S, M, and L are divided considering the diameter of the nodule as 9 mm, 15 mm, and above. All the features obtained from the three branches are concatenated to get the result. The designed model is validated with the publicly available LUNA-16 database is used. The model gives promising results with 92.6% CPM values.

Keywords: Lung Cancer, Computer-aided diagnosis (CAD) technology, Computed Tomography (CT), Lung Nodule Detection, Deep Learning.

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1. Introduction

There are various deadly dangerous diseases known to human existence, where some are uncurable. Lung cancer, among them, accounts for the majority of cancer-related deaths worldwide. [1]. Lung cancer starts when the cells begin to grow uncontrollably and form a tumor. This lung cancer is identified mostly at stage III or IV. Early-stage lung cancer is not having any symptoms which result in the highest death rates. The early diagnosis of lung cancer will reduce the death rate which will be possible by identifying the small nodules.

The lung cancer is detected by the CT scans. For the early detection of lung cancer, there is difficult to examine all the nodules from many CT images and also in the decision-making process. Imaging diagnosis helps to improve the sensitivity of nodule detection. Low Dose Computed Tomography (LDCT) is used for initial screening. The computer-assisted detection tool is developed for effective image reading and to know the malignancy of the small nodules [2,3]. This automated lung nodule detection would reduce the burden on radiologists and also helpful for increasing the true positive rates.

2. Related Work

Hongyang Jiang et.al [4] applied frangi filter to the lung images of group I to eliminate the tiny noises. The proposed images are grouped as group II. In comparing groups, I and II the unsuspicious images in group I are deleted and Suspicious group II images are given to CNN as input to improve the sensitivity of nodule detection. Haichao et al [5] designed a multi-branch network in 3D CNN by integrating the three different networks by using ensemble learning to reduce the false-positive reduction and differentiate between true nodule and false nodule.

Ranveer Joyseeree et.al [6] detect the several classes of the healthy and diseased lung tissue by the fusion of Riesz and deep learning features. The Interstitial lung disease (ILD) dataset is used. The texture signatures from the Riesz representation are generated for the ILD dataset. The features from the deep CNN by the inception v3 architecture are done for the same ILD dataset. The fusion of Riesz and deep CNN features are combined in a joint softmax model for the classification. Haichao Cao et al [7] implemented a two-stage CNN that involves improved U Net architecture based on Res Dense structure for rough detection of nodes and a sampling strategy is designed for the nodule. In the second stage, in 3D CNN ensemble learning architecture dual pooling layer is replaced with the max-pooling layer for initial lung nodule detection rate and to eliminate false positives.

Amrit Sreekumar et al [8] to detect the malignant lung nodule and predict the malignant score, a preprocessing mask is used to extract the lung region from CT. By using a 3D CNN model based on C3D architecture the features are extracted. Vinisha Vimal Kumar Skula et al [9] proved the deep learning method followed by convolutional neural network feature extraction is more effectively done by the Squeeze Net than the other networks. Weihua Liu et al [10] implemented a deep multi-task learning approach that involves the integration of lung parenchyma segmentation and nodule detection to improve the performance of lung nodule detection. Yu Gu, [11] et al summarize all existing CAD approaches for lung nodule detection and clearly showed that deep learning methods are showing effective results for lung nodule detection at the initial stage.

3. Methods

The designed 3D-CNN architecture is explained in this section. Sections 3.1 gives the frame work of the proposed method, section 3.2 gives selection of multi-branches for the architecture, and section 3.3 gives training and implementation details.

3.1 Structure of Multi-Scale CNN

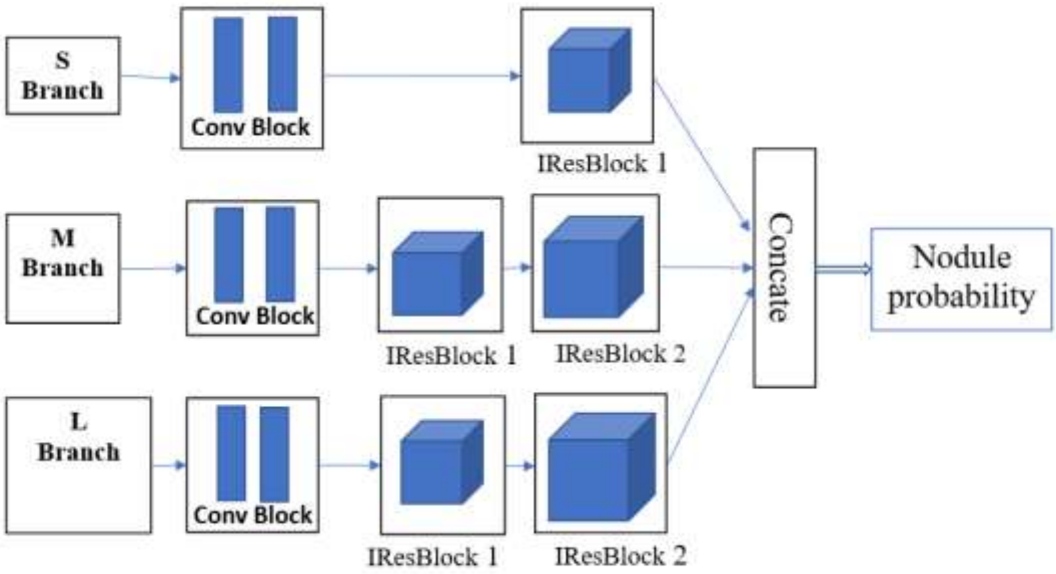

Figure 1: Proposed 3D multi-branch Inception ResNet (3DMB-IResNet)

Our proposed 3D CNN consists of the inception Resnet model. To the IResNet, we extract features from the three different scales of 3D data from a given candidate nodule. On analysing the result from the three branches by concatenating, the malignant or benign nodules are detected.

3.1.1 3D Multi Branch Inception Resnet

The designed 3D-CNN Multi-Branch architecture is as shown in figure 1. It consists of three branches: Branch-S (small), Branch-M (medium), and Branch-L(large). The Branch-S consists of fifteen convolution layers followed by single Inception- ResNet (IRes) block. The Branch-M consists of twenty-eight convolution layers followed by two stacked Inception- ResNet (IRes) blocks such as IRes Block1 and IRes Block2. Branch-L and Branch-M are identical but differs in feature maps. The internal architecture of each Inception-ResNet (IRes) block is as shown in figure 2. All the features obtained from the three branches are concatenated to get nodule probability.

3.2 Multi Scale Architecture

In the traditional architectures ignoring the size of the nodule, networks are designed which gives false positives in nodule detection. To overcome this problem a multi branch 3D CNN architecture is designed in this paper. The selection of nodule size affects classification performance. If the nodule size is small, then the network is not getting sufficient information for training. If the nodule size is too large then the redundant data is added along with noise which affects the performance of the network. To overcome this challenge, a multi-branch network with multi-scale input is designed.

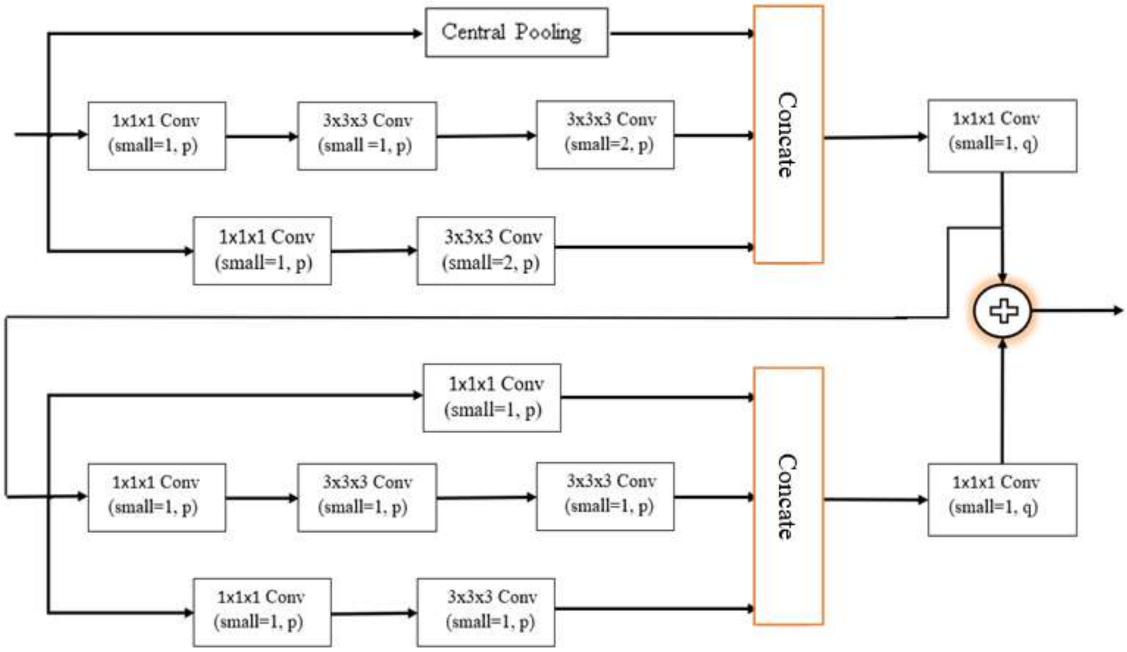

Figure 2: Diagram of the 3D Inception ResNet block

Figure 3 gives size variation curve for the nodules available in LUNA16 database. This is available in the database separately in an excel file. We choose different input sizes on observation of several nodules with diameters, the peak nodule with a diameter of 9. So, the first input size is 18x18x18 for small nodules which contain sufficient information. Secondly, for the nodule diameter of less than 15, the input size is 30x30x30 for the medium size nodules which contain rich information. At last, the input size of 40x40x40 for large nodules will also add some noise but is better handled for large nodules.

3.3 Training

The proposed model is trained by minimising Adam Optimizer loss function. The hyperparameters used for training are set as momentum 0.9, batch size as 64, epochs as 500 and Xavier weights as bias. The model is implemented on a personal PC with intel i7 processor with NVIDIA Cuda GPU, MATLAB 2020b software.

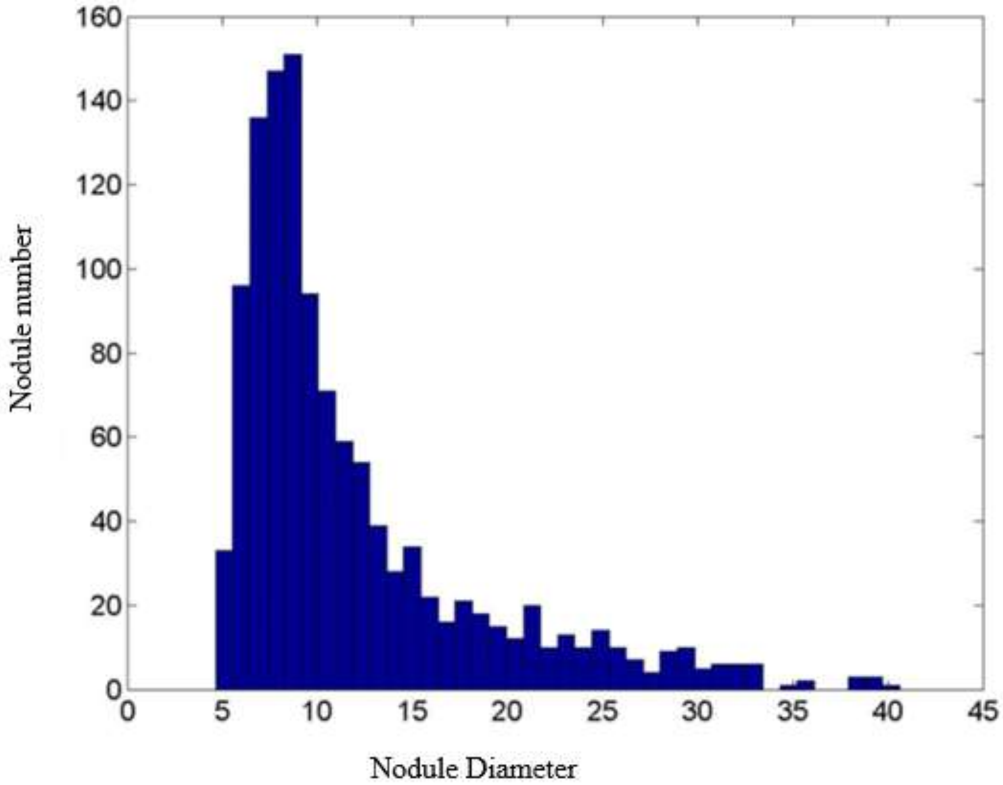

Figure 3. Size distribution of lung nodule from LIDC-IDRI Dataset

4. Materials and Performance Metrics

To develop the nodule detection by the deep learning methods for automated detection of nodules from CT images, the LIDC-IDRI dataset [3] is used. The LIDC (Lung Imaging Database Consortium) is a public dataset. It consists of 1018 CT scan Images of the 1010 patients. The nodules in the dataset are annotated by four radiologists. The nodules in the dataset are examined independently by the radiologists. The nodules in the LIDC dataset are in the DICOM format. The annotation of the nodules by the radiologists is recorded in XML files. From the annotations of the radiologists of nodules in the dataset, the nodules are classified into three different categories as nodules >= 3mm diameter, <3mm diameter, and non-nodules >=3mm diameter. According to the above classification there are 1186 lung nodules. The LUNA 16 challenge which is the subset of LIDC-IDRI scans of thickness greater than 2-5mm contains 888 CT scans.

To validate the performance of the designed architecture, the FROC curves are used. In this, the characteristics of the designed model is compared with the exiting methods in graphical format. The competition performance metrics (CPM) is another metric for the performance detection of the proposed method.

$$CPM = \frac{1}{N} \sum_{i=\{0.125,0.25,0.5,1,2,4,8\}} Recall_{fpr=i} \quad ..(1)$$

Where the N=7, ‘‘*fpr*’’ stands for average number of false positives/ scan.

5. Results and Discussions

The proposed 3D-CNN architecture is evaluated on the publicly available LIDC-IDRI dataset. The model shows better performance giving 92.6% CPM value on a 8- cross fold validation. The FROC curve is as shown in figure 4. To validate the performance of the designed architecture, we analyzed the performance of the other three networks (i.e., 3D Vggnet, 3DResnet, 3D Dense Net). The sensitivities of these networks are not good in terms of false-positive reduction rate / scan.

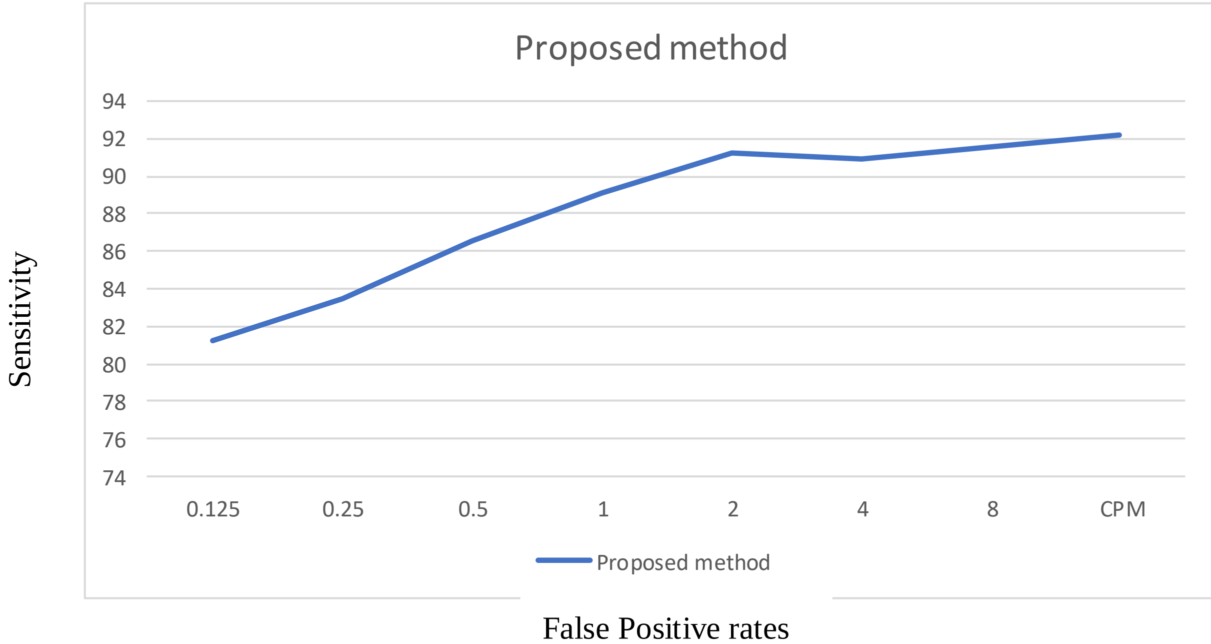

Figure 4: FROC of Proposed method

But the Inception Resnet achieved the sensitivities above 90% which results in the CPM value of 92.2 which indicates that the multi-scale 3D-CNN architecture can extract the different features from the LDCT scan images. The FROC curves drawn for the network architectures are shown in the figure 5. These analysis results that the greater sensitivities are achieved by the Inception Resnet architecture.

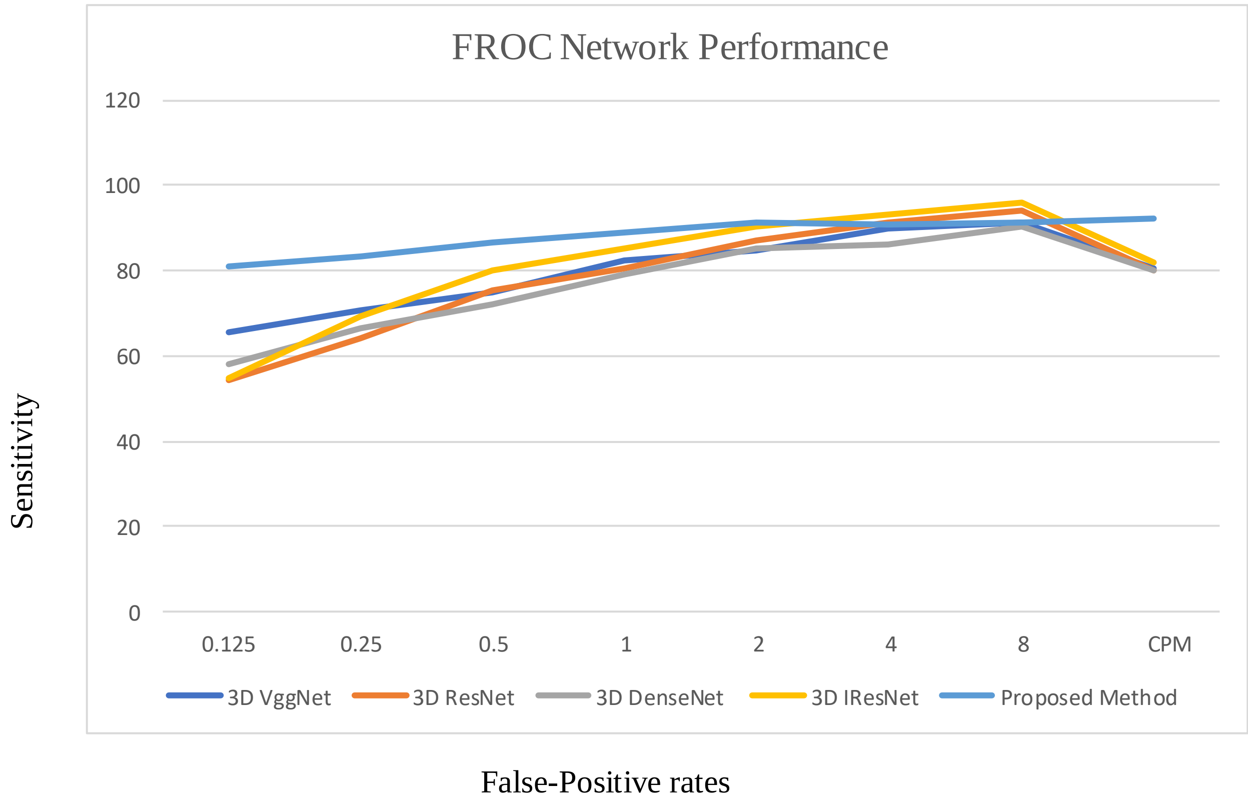

Figure 5: Comparisons of different networks (FROC)

5.1 Comparison with other Techniques

To test the efficacy of the proposed method table1 shows the comparison of other false positive reduction methods. The sensitivities and CPM of the final score are in percentage. The experimental results proposed by Lee et al [12] extracts only basic features of the nodule and the got CPM value as 54.8 which is not efficient. Roth et al [13] network considered different spatial angles, Dobrenkii et al [14] implemented a false positive reduction method based on 3D CNN and acquired better results that utilize maximum spatial information. Gong et al [16] used a 3D tensor filtering approach and local image features on the two datasets LUNA16 and ANODE09 by 8-fold cross-validation, achieving the sensitivity of 79.3 at 4 false positive detections for scans.

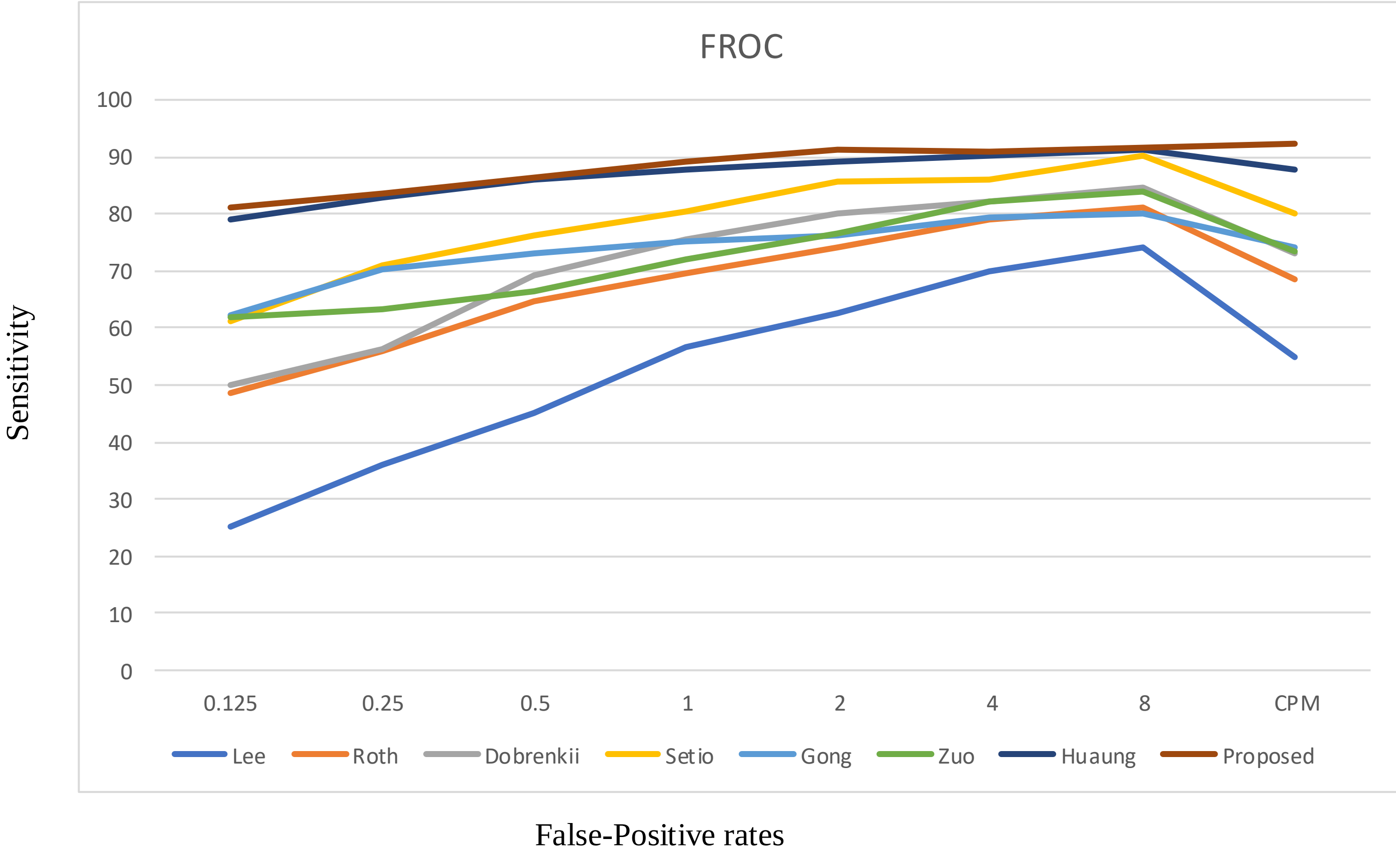

Figure 6: Comparisons of different techniques (FROC)

Table 1. Comparison with recent works

Technique	**0.125**	**0.25**	**0.5**	**1**	**2**	**4**	**8**	**CPM**
Lee [12]	25.1	35.9	45.1	56.6	62.7	69.8	74.2	54.8
Roth [13]	48.7	55.8	64.6	69.5	74.2	79.1	81.1	68.4
Dobrenkii[14]	50.1	56.2	69.3	75.4	80.1	82.1	84.6	72.9
Setio [15]	61.1	71.1	76.3	80.4	85.7	86.1	90.1	80.1
Gong [16]	62.3	70.2	72.9	75.2	76.1	79.3	80	74.2
Zuo [17]	61.9	63.2	66.4	72	76.4	82.3	84	73.4
Huang [18]	79.1	82.7	85.9	87.8	89	90.1	91.4	87.6
Proposed	81.2	83.5	86.5	89.1	91.2	90.9	91.5	92.2

Zuo et al [17] implemented a 3D convolutional neural network to analyze a large number of candidates nodules for classification which is trained from a multi-resolution 2D convolution network by LUNA16 dataset and obtained CPM scores in false reduction with sensitivities of 61.9 and 64 at 0.125 and 0.25. Huang et al [18] trained amalgamated CNN by LUNA16 dataset. The sensitivity of a CNN reached 81.7% and 85.1% for false positives per scan respectively.

6. Conclusion

In this paper a multi-scale multi branch 3D-CNN is designed for the false positive reduction of the lung nodules. The challenges in identifying the true nodules can be overcome by using the proposed model. The inputs are divided into three different scales with three different branches and final probability is obtained by fusion the output of the three branches. This type of multi scale division of the input reduces the redundancy in nodule information and also collects rich contextual information from the input sample. To evaluate the proposed model LIDC-IDRI dataset is used. The proposed model gives a Competition Performance Metric (CPM) of 92.6% (95% CI: 88.7%-98.6%) for validation on 89 CT scans from the LIDC-IDRI dataset. In future, we will extend to more datasets.

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