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Hybrid Deep Learning based Lung Disease Detection and Classification

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Abstract
Early precise detection of lung nodule is overwhelming of time and susceptible to error factor of the radiologist analysis work. Recent lung nodule detection are based on CNN and Faster RCNN results good accuracy and superior performance in classification. However, this is an object detection algorithm means find where the objects are present. Apart from object detection Mask RCNN is an extension of faster RCNN implementing segmentation on image means separating the pixels that belongs to particular object .Image segmentation work with the help of Mask RCNN, We can perform object detection and also specifically locate the position of cancer tumor in lung. We proposed a 3D Mask RCNN for Simultaneous detection and Segmentation of lung nodule probing more number of training and testing data to reduce the false positive reduction and achieve higher accuracy and sensitivity. For further advancing the performance of our work we investigated more than 2000 ground truth nodules from publically available LIDC/IDRI dataset advantageous to boost our Mask RCNN detection. Experiment results shows that the proposed network succeeds accuracy of 96.8%., sensitivity of 94.8% and specificity of 97.2%. After evaluation and investigation the results of segmentation our proposed method outperformed compared to other literature.

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I. Introduction

The second utmost common and primary cause of death for both men and woman is Lung cancer .In this year 2021 totally 131880 peoples (62470 women and 69410 men) are estimated that died because of Lung cancer. Around 25% of cancer death will occur due to lung cancer among all types of cancer. Since 2002 death rate dropped by 30% in women and 54% in men. Each year from 2014 to 2018 people with lung cancer the death rate was reduced by 5% in men and 4% in women [1]. Most of the Research shows that these regressions are mainly due to development in medical diagnosis using different CAD system using 2D and 3D data analysis with advanced AI system. Survival rates of lung cancer depends on many factors like the stage and subtype. Five year Survival rate of lung cancer for women is 24% and for men is 17%.

There are two types of Lung cancer named small and non-small cell lung cancer, among this 84% of the lung cancer are non-small cell lung cancer resulted in medical diagnosis. Based on statistics indicate that 235,760 peoples including 116,660 women and 119,100 men are diagnosed

with lung cancer and the rate will be declined by 2% per year since mid-2000. Non-small cell lung cancer is easily estimated by different techniques. If it is not detected at early stage it can spread somewhere in the body through a process. Knownas metastasis and also affect lymph nodes.
Professionals in medical field use TNM classification system for cancer diagnosis to characterize earlier stage to advanced stage of cancer of malignant tumors. It is very difficult to perform biopsy if earliest stage of lung cancer was detected accidentally and prognosis finally for better to survive. Instead it is very easy to diagnosis advanced stage with biopsy even if the diagnosis is worse.

Majority group of people who got earliest stage of lung cancer are detected while diagnosis for some other lung disease during CT scanning. The foremost challenge in medical image analysis is that IA classification because of small tumor size approximately less than 3mm and it's also very difficult to detectby using CT scan and need advanced algorithm to detect correctly.

Researchers developed more Computer aided detection systems and computer aided diagnosis system to detect benign and malignant tumor in lung. In recent years deep learning plays a vital role to assist radiologist to analysis and handle the issues in IA classification and help in increase survival rate of the patients and also reduce the death rate by reasonable percentage.

The main goal of this research work is to increase the survival rate of people by improving the advanced diagnosis system to detect small nodule size by developing effective novel deep learning algorithm. Deep Learning perform well against very hard and small lung nodules.

CNN plays an important role in progress of image classification and recognizing the nodule detection. Now a days artificial intelligence detection methods like RCNN, Fast RCNN and Faster RCNN shows moreaccurate result and high speed detection.

II. Existing System

Sarkar et al [1] achieved higher accuracy by lung nodule instance segmentation and multiple classification from CT scanned images used K means clustering algorithm. But the proposed algorithm failed to detect nodules size less than 7mm. Zhang et al [2] used Mask RCNN with Feature pyramid Network resulted good accuracy on small nodules compared to larger one. Lin et al. proposed mono stage object detection perform well in speed compared to faster RCNN.

Li et al [3] estimated modification of different faster RCNN on 3D MRI scanned images of private dataset. The proposed architecture succeed 85.2% of sensitivity at 3.47 FP per image. Wang et al [4] implemented faster RCNN for nodule detection by nodule size adaptive model to estimate nodule size from 3mm to 70mm and clustering methods also used to detect 3D nodule candidate from 2D anchor boxes. Finally V4 networks was used for classification phase to reduce false positive reduction. In this paper publically available LUNA 16 dataset was analyzed and achieved the accuracy of 90% with CPM score 90.3%.

Fan et al [5] proposed a method of self-configuring bounding boxes by Self organizing data analysis algorithm and achieved the 93.6% of sensitivity for 0.15 FP per scanned image. This paper also used clustering method to produce Faster RCNN which was hardly fit for nodules with different shape and size in images. In our work novel Mask RCNN was proposed to improve the architecture of Mask RCNN to learn the size of bounding boxes by the ground truth size of nodule in training dataset. Paul et al [7] implemented a 2D and 3D networks to improve the detection rate of objects with combined segmentation. In the year of 2017 G. Gkioxari [16] proposed Mask RCNN with optimal solutions for detecting small objects but fail in detecting larger objects.

In 2018 Zhang [17] shown improved accuracy by implementing RCNN with features pyramid Networks. Q. Song [18] classify the cancer in to three classes and each architectures are evaluated on same dataset basis. A. M. Suzan et al. [19] proposed SIFT to extract the features and feature bags are specified by this features and then it was classified by KNN classifier and evaluate AUC as a performance metric for comparison.

Gupta et al.[20] investigated 1390 nodules size greater than 3mm with three radiologists across whole LIDC dataset and shown the improved sensitivity and False Positive per scan. Girshick et al.[21] used selective search methods to find existence of the object and bounding box extraction. Feature map of each bounding box classified by SVM classifier and the final outputs are adjusted using non maximum suppression.

III. Proposed System

We proposed novel deep learning architecture to detect lung nodules using mask RCNN. This architecture divided into two stages RPN followed by RCNN and Mask. Main aim of this research work is to detect the small size nodule by modifying 2D architecture of mask RCNN [8] suitable to handle 3D images. 3D implementation of Mask RCNN is faster when training both RPN with backbone together. The detection rate is improved simultaneous training of both instance segmentation and detection by reducing IOU and focal loss [9]. Over fitting issues in this model is avoided by dropout and augmentation techniques. Non mask suppression filter intersecting bounding boxes by scan the image with overlying sliding windows. False positive rate was reduced by keeping the boxes with segmentation mask volume greater than zero.

a. Preprocessing Lung CT Image

In order to remove the annoying noise and reduce memory consumption upper and lower bound set as 3000 and 1000HU for bone and air and then convert 16bit into 8bit data intensity values of CT volumes in the range of 0-255. After apply diffusion filtering to retain the boundary data than isotropic diffusion filter was used to smoothing the edges.

b. Nodule detection model

With the help of Feature pyramid Network performance of Mask RNN has been improved and well perform on small nodule detection. Based on different task it need many hyper parameters for optimization. Mask RCNN has two branch called classification and regression. We used RESNET 101 architecture for feature extraction and RPN is used to produce ROI. First the feature maps are extracted from the image by using ConvNet and then it passed s an input to RPN results bounding boxes. After by applying ROI pooling layer on this generated bounding boxes to get same scale and size. Because the result of RPN is in different scale and dimension. So the ROI pooling layer bring all in to same size. Finally the output of ROI pooling layer connected to FCN for classification and result the bounding boxes.

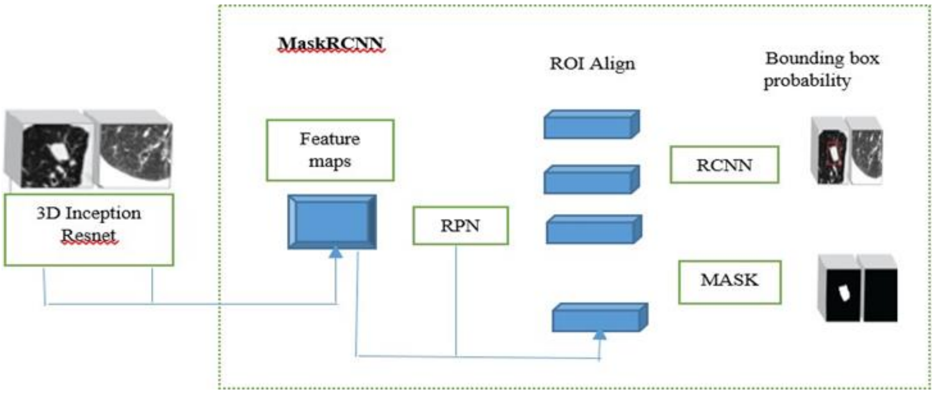

Figure.1 Mask-RCNN model

c. *Region proposal network (RPN) model*

RPN receives the extracted features to identify the location of lung nodules by producing a set of ROI. Each and every pixels in the extracted feature map was scanned with two anchors of size 16 and size 64 with ratio of one. It uses the window size 3x3 and pass via the convolutional layer. Region proposals are generated at each location by using sliding window. For each proposal it extract vector length of 512 and fed into FCN named binary classification and regression or prediction layer. The binary classification is used to detect the region with candidate object or background and regression layer identify the coordinates of anchor box of the nodules. RPN with scores > 0.1 are given as an input to ROI align layer. If no anchor are found highest scores of 10 anchors are passed to ROI Align layer. To reduce the FN the threshold value was chosen very low value and their IOU and ground box is 0.5(0.1), the anchors are positive (negative).

IV. Experimental Results

a. *Database*

We used publically available dataset from the database LIDC/IDRI to experiment our model. We considered 1088 CT scans with nodule size greater than 3mm. The dataset contains 1018 patients information collected from imaging companies and academic centers. This dataset contains the information about lesion area via two process analyzed by radiologists. In the first stage identify the type of nodule and in the second stage unknown marks are analyzed by radiologist individually. To improve the accuracy of the proposed model radiologist tried to find as more non nodules as much as possible.

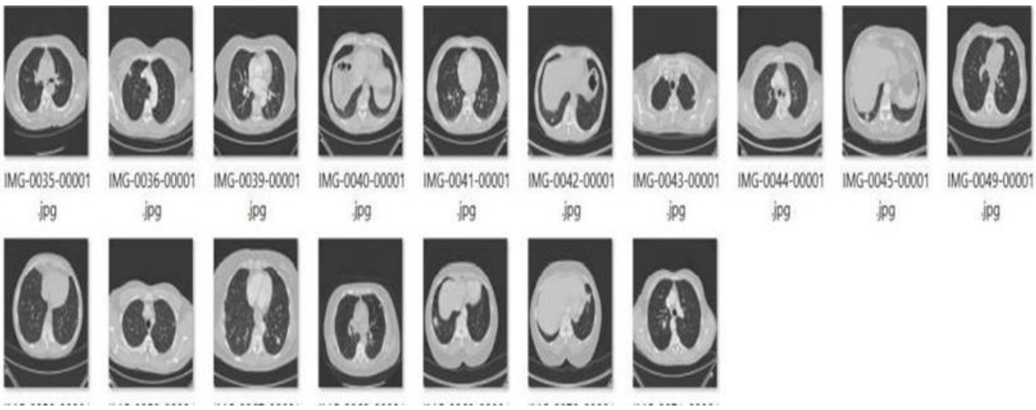

Figure.2 Sample Benign images

b. Data Enhancement

Over fitting problems will straightforwardly affect the accuracy of detecting nodules in lung if the deep network not trained with sufficient data. So it is very important to enhance the data when using deep neural network. Data was enhanced by adding noise, image size changing, tilting the image, apply transformation on the images. In our proposed method along with this data augmentation larger, medium and smaller nodules marked by the radiologist also added to dataset. Data enhanced to 8000 slices from 3024 nodules as a whole dataset used in our work.

c. Data Annotation

After data enhancement data annotation was performed. To label the image VGG annotator tool was used by selecting region shape and attributes and create the JSON file format. The generated file contain all information related to the image like pixel size and rectangular box position which is used to detect the nodule in lung image.

Evaluation process consider the performance in the following cases. First case consider the nodules greater than 3mm and second one including all size nodules. Our proposed model achieved the Competition Performance Metric of 0.892 with a one inference phase. The result is improved with the score of 0.82 when the second phase false positive reduction. Our experiment result shows that Mask RCNN succeeds the high sensitivity 9-10 false positives per image with true positive less than two per image.

Compared with previous published literature our proposed SDS method showed enhanced detection and segmentation sensitivity one FP per scan with the benefit of data annotation. Our proposed methodology perform well multitask operation including detection, segmentation and classification and proved the improved sensitivity.

V. Simulation Output

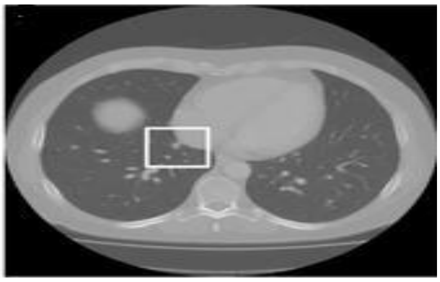

Figure 3. Input Nodule image

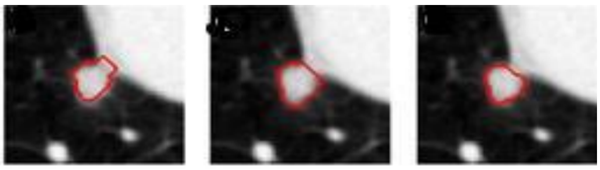

Figure 4. Segmentation Result and ground truth

Table 1: Comparison of Detection

Model	*Sensitivity*	*False Positives per image*	*CPM*
MaskRCNN	0.922	7	0.812
2DRCNN +#DCNN[10]	0.946	<15	0.891
ZNET[11]	NA	NA	0.811
Gupta [20]	0.856	0.835	NA

To validate the result of segmentation for two sets of data measured with the help of Dice similarity coefficient. It is hard to compare our result with other papers because most of the previous works are deal with predefined Region of interest whereas our experimental results are based on 3D images. One more important note that test set [12] handled only 113 lung nodules whereas we used 1088 nodules.

Table 1: Comparison of various Segmentation Result

Model	*DSC*
MaskRCNN	70±10
2DRCNN +#DCNN[10]	79±19
PN-SAMP-S1[13]	74±3.57

For reliable measurement of size our evaluation results shows that strong correlation between ground truth and segmentation volume are indeed. Most of the existing segmentation methods does not directly involved in Hausdorff Distance reduction. Our proposed method achieved accuracy of boundaries considered with HD is 2.32mm±2.02mm.But for small nodule segmentation this methods are not suitable.

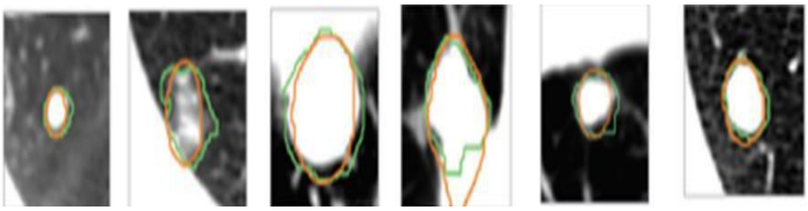

Figure 5. Segmentation result and ground truth

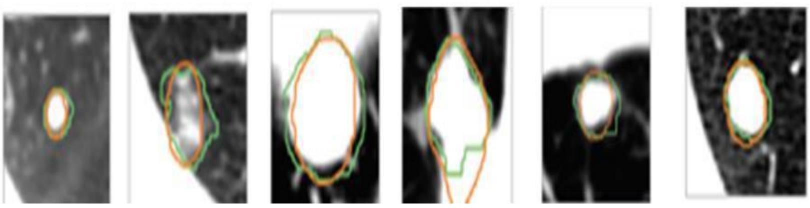

Figure 6. True Positives

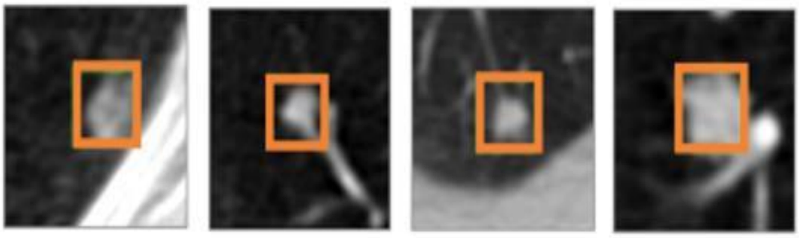

Figure 7. False Positives

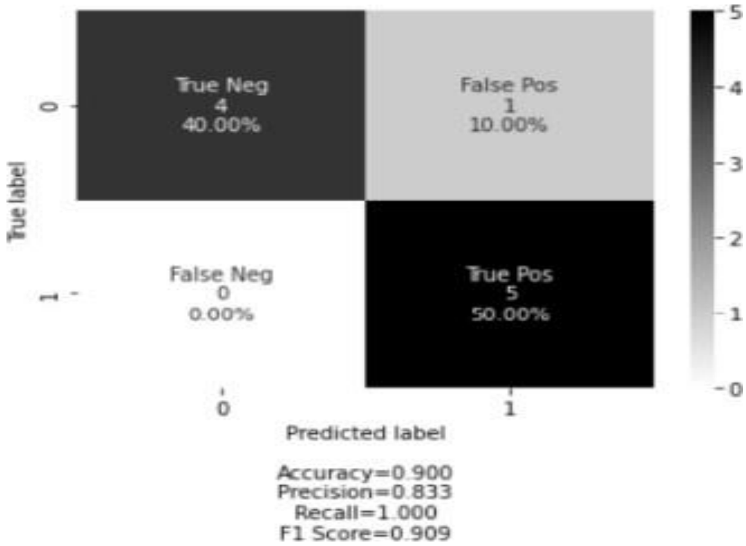

Figure 8. Final Improved model Accuracy

VI. CONCLUSION

Deep learning plays an important role in classification of images in the field of medical imaging. Most of the studies shows CNN significantly improved the classification accuracy in medical image data pool competition. In our research work deep learning structural design based on MASK-RCNN successfully classified benign and malignant nodules with improved accuracy and sensitivity. Our proposed model succeed in both detection and segmentation methods. In most of the research work deep learning is the use of debt in order to improve the accuracy and great influence on small pulmonary nodule detection in lung. Numerous work combine both detection and classification and the outcomes shows the proof. This work uses the same dataset to perform the experiment and analyzes the detection and segmentation accuracy. Experimental results shows that the improved Mask RCNN algorithm superior than faster RCNN in terms of accuracy with the improved accuracy rate exceeded 25%.

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