Diagnosis of Pulmonary Nodules on CT Images Using YOLOv4

https://doi.org/10.3991/ijoe.v18i05.29529

Shital D. Bhatt[1(✉)], Himanshu B. Soni[1], Tanmay D. Pawar[2], Heena R. Kher[3]
[1] Gujarat Technological University, Ahmedabad, Gujarat, India
[2] Department of Electronics, Birla Vishvakarma Mahavidyalaya, V.V. Nagar, India
[3] Department of Electronics & Communication, A.D. Patel Institute of Technology, New V.V. Nagar, India
bhatt9182@gmail.com

Abstract—In this paper, the Scale-Invariant Feature Transform (SIFT) and Fast Library for Approximate Nearest Neighbors (FLANN) based algorithm is used to detect the abnormalities in the National Lung Screening Trial (NLST) CT scans as the exact clinical nodule locations are not provided in the dataset. These identified nodules on NLST CT Scans are then annotated using LabelImg tool. This process consumes time and so furthermore, the automatic nodule detection, You Only Look Once version 4 (YOLOv4) object detection model is implemented. The YOLOv4 object detection model is provided with total of 4187 labelled images in form of training (70%), validation (20%), and test (10%) datasets. Our YOLOv4 model achieves precision of 95%, sensitivity of 81% and mean Average Precision (mAP) of 89.1%.

Keywords—Fast Library for Approximate Nearest Neighbors (FLANN), Pulmonary nodules, Scale-Invariant Feature Transform (SIFT), You Only Look Once (YOLO)

1 Introduction

It has been demonstrated that low-dose computed tomography (LDCT) can detect smaller lung nodules [1]. The National Lung Screening Trial (NLST) done for heavy smokers showed a 20% decrease in lung cancer mortality [2, 3], but CT screening has been criticized because of its poor Positive Predictive Value (PPV) and high False-Positive Rates (FPR) [4].

Content Based Image Retrieval (CBIR) method can be used to retrieve the images from a large database that are identical to the image provided as a query [5]. The Scale-Invariant Feature Transform (SIFT) algorithm is used for the identification and extraction of features suggested by Lowe [6]. SIFT is popular for its ability to solve the problems of image rotation, affine transformations, intensity, and viewpoint change. Matching feature points is an important basis for image matching. Currently, Brute Force (BF) and Fast Library for Approximate Nearest Neighbors (FLANN) are the most common matching algorithms. FLANN is a series of algorithms optimized for quick, nearest

neighbor search in broad datasets with high dimensional features. It is applied for local feature matching to match the query image and reference image in data set [7].

During the last few years, object detection has become one of the important areas of computer vision, and many researchers are racing to get the best object detection model. The object detection method based on region proposal such as Region Based Convolutional Neural Networks (R-CNN) only focuses on the partial image information in the candidate frame during the detection process [8]. You only look once (YOLO) is one of the faster object detection algorithms which uses Darknet framework. Since YOLO convolves the entire image, it has a larger field of view when detecting the target [9]. Masni et al. [10] proposed simultaneous detection and classification of breast masses via a deep learning YOLO-based CAD system. This system identifies cases of difficult dense breast tissue using the masses located over the pectoral muscle. Sindhu et al. [11] suggested the DetectNet architecture based on YOLO, which makes use of a single convolutional network to find various bounding boxes and class probabilities for lung nodules. Since the output layer is a fully connected layer, when testing, it found difficulty in generalization of objects if the image is of other dimensions different from the trained image. The second version YOLOv2 [12] uses a custom deep architecture Darknet-19, an originally 19-layer network supplemented with 11 more layers for object detection. In YOLOv2, the fully connected layer has been removed and introduce anchor boxes to predict bounding boxes. One of the main issued that has to be addressed in the YOLO is that detection of smaller objects on the image. This has been resolved in the YOLOv2 by dividing the image into 13*13 grid cells which is smaller when compared to its previous version. The third version YOLOv3 [13] uses a hybrid approach between the network used in YOLOv2 (Darknet-19) and the residual network. It has 53 convolutional layers so it is called Darknet-53. Aly et al. [14] proposed YOLOv3 model along with the anchor boxes concept to correctly assigned and identify the breast masses. Xu et al. [15] proposed a new algorithm for detecting lung nodules based on YOLOv3. The model of YOLOv3 is much more complicated than the previous model, and the speed and accuracy can be weighed by changing the size of the model structure. The YOLOv4 object detection with the Cross Stage Partial (CSP) network retains maximum speed and accuracy. Network scaling approach used in YOLOv4 modifies the depth, width, resolution, and network structure. The architecture of YOLOv4 involves CSPDark used in backbone and CSPUp and CSPDown sampling in the neck blocks [16-17].

The main contributions of the proposed paper are described below.

In this paper, nodule locations of NLST CT scans have been detected using SIFT and FLANN algorithm. The abnormality in CT scan has been recognized by comparing the matched features obtained using FLANN with abnormality variables like slice number, location, margin and diameter. A bounding box is created for every image to cover the target nodule using LabelImg-a graphical annotation tool. After extracting and matching a set of robust features from input images, the TensorFlow object detection YOLOv4 model is used to detect nodules. Our approach achieves competitive precision, and is much faster during both training and inference.

2 Materials and methods

In this paper, the nodules extracted according to locations provided for CT scans of LIDC-IDRI dataset are used as templates for detecting and matching similar abnormalities on NLST CT scan dataset.

2.1 Dataset

LIDC-IDRI dataset has a total of 1,018 CT scans. All the image data are in DICOM format and standardized to size of 512x512. Every case of the LIDC-IDRI dataset consists of hundreds of images, and an XML file with the descriptions of the detected lung lesions. In order to extract the nodules and non-nodules, the CT scans were preprocessed and the candidates were extracted [18] which are used as templates for algorithm-1 as shown in Figure 1. The NLST is a randomized clinical trial to assess the decrease in the mortality in low-dose CT screening done on high-risk individuals. The exact clinical nodule locations are not given as annotation in NLST dataset. The work in this paper is accomplished on 622 CT scans among the provided 15000 CT scans. These CT scans belong to source group of screen-detected lung cancer.

2.2 Detection and description of the image

Detection and description of image features play a crucial role in the different applications. After extracting features and their descriptors from images, the matching of similar constructs between images is implemented.

Scale-Invariant Feature Transform (SIFT). The image feature extracted from the SIFT algorithm has a very high uniqueness, such that it can be used in a large database for accurate matching. The scale, rotation, illumination and viewpoint can be varied but still good results are achieved in SIFT algorithm. Constructing a scale space is the initial preparation which generates internal representations of the original image. The Laplacian of Gaussian (LoG) is great for finding key points in an image using a super-fast approximation. Maxima and minima are obtained by applying the Difference of Gaussian (DoG) on images. The edges and low contrast regions have been omitted in order to make the algorithm effective and robust.

Fast Library for Approximate Nearest Neighbours (FLANN). FLANN comprises of a wide array of algorithms designed for fast nearest neighbor search in large datasets having high dimensional features. Two dictionaries are required for FLANN based matcher. The first dictionary sets out the appropriate algorithm. The second dictionary defines the search criteria to be passed. This dictionary points out the number of times the trees in the index have to be recursively traversed. To minimize the number of false matches, the FLANN based matching is done by the distance ratio between the two nearest matches of the considered key point and is a successful match when this value is below the threshold. FLANN constructs an effective data structure that will be used to check for an approximate neighbor.

The algorithm shown in Figure 1 is used for detection and extraction of the abnormalities present in NLST dataset.

1. Find the key-points and descriptors on images and templates by applying SIFT algorithm.
2. Set FLANN parameters (index params, search params and matcher function).
3. Match query image and template image and store all the good matches as per Lowe's ratio test.
4. Get image and find the number of matches and check for major matches. Compute matches with distance less than 0.75.
5. Check if number of matches is greater than initialization and get template & query image key-points.
6. Obtain the coordinates of corner points of detected nodule on CT scan image.

Fig. 1. SIFT-FLANN based algorithm to detect and extract features of the abnormalities present in lung CT scans

The results of nodule features extracted and matched after applying algorithm 1 are shown in Figure 2. The left part of the figure shows the NLST lung CT scan image, with the nodule that we want to detect is marked by red circle. The right part shows the nodule templates of LIDC-IDRI dataset and NLST lung CT scans where the features detected are shown in red color and the matched features are shown by green line. In the figure the different types and sizes of nodules are detected.

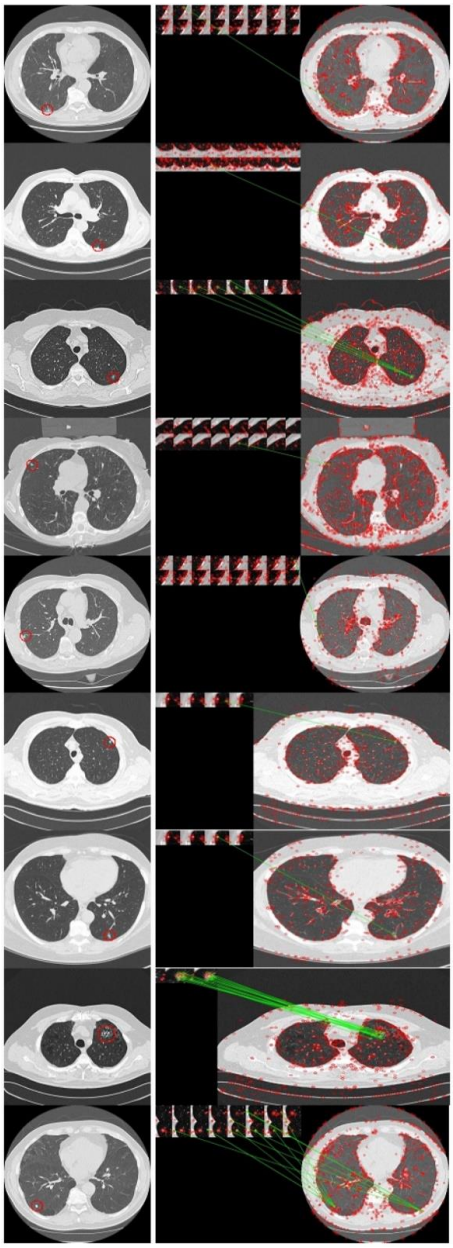


Fig. 2. The detected and matched nodule features obtained using SIFT-FLANN based algorithm

The algorithm shown in Figure 3 is applied to find the exact location of nodules on NLST CT scans by comparing the matched results obtained on CT scans using FLANN algorithm with the abnormality variables.

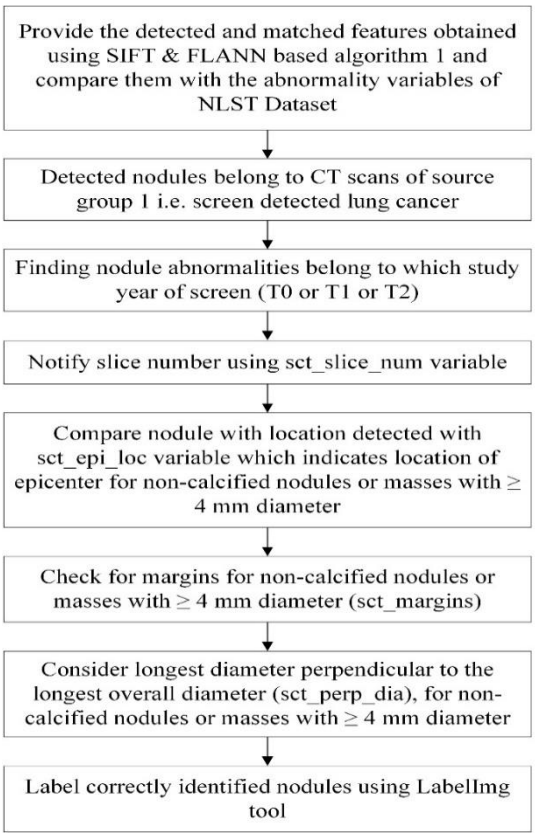


Fig. 3. Algorithm for identifying nodules on CT scan among NLST dataset by considering abnormality variables

2.3 You Only Look Once (YOLO)v4

Object detection is a core problem in computer vision. The object detection model is used to identify objects in the feature space. YOLO is a single convolutional network that simultaneously predicts multiple bounding boxes and class probabilities for those boxes.

Unlike sliding window and region proposal-based approaches, YOLO sees the complete image during training and test period such that it implicitly encodes qualitative information regarding classes as well as their appearances. YOLO is incredibly fast and doesn't require a complicated pipeline. The YOLO architecture allows end-to-end training while retaining high average accuracy.

In YOLOv4, the adjustment of the scaling factors is done in input, backbone, and neck regions. Through analysis of state-of-the-art object detectors, it's found that CSPDark, which is the backbone of YOLOv4, matches almost all optimal architecture features obtained by network architecture search technique. Figure 4 shows the architecture of YOLOv4 in which CSPDark is used in backbone and CSPUp and CSPDown

sampling is done in the neck blocks. Finally, the nodules are detected and probability of malignancy in the abnormality is predicted using the detector of the YOLO model.

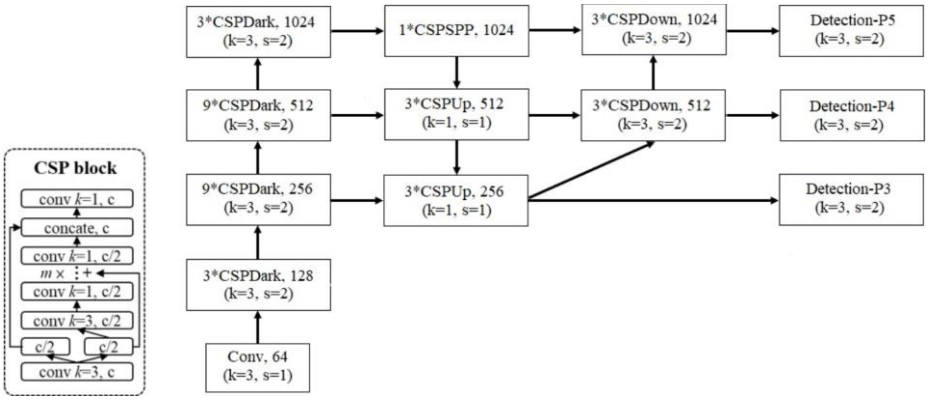


Fig. 4. YOLOv4 architecture

3 Implementation details and results

The complete algorithm applied for nodule detection in this paper is shown in Figure 5. As the nodule locations are not provided in NLST dataset so in order to find the similar feature in NLST CT slices, nodule templates are used. These nodule templates are extracted according to locations provided for CT scans of LIDC-IDRI dataset. As the feature extraction, matching and labelling requires time so the work is accomplished on only 622 CT scans belonging to source group category 1 which consists of Screen-Detected Lung Cancers.

In order to locate the nodules on NLST dataset, the features matched by FLANN are compared the annotations like abnormality slice number, margin, location and diameter. The nodules were then annotated as Cancer using the LabelImg tool. These labelled data were divided into train, validation and test sets which are then converted into pytorch record which are provided as input to the TensorFlow YOLOv4 model. The performance of our model was visualized on the Tensor board.

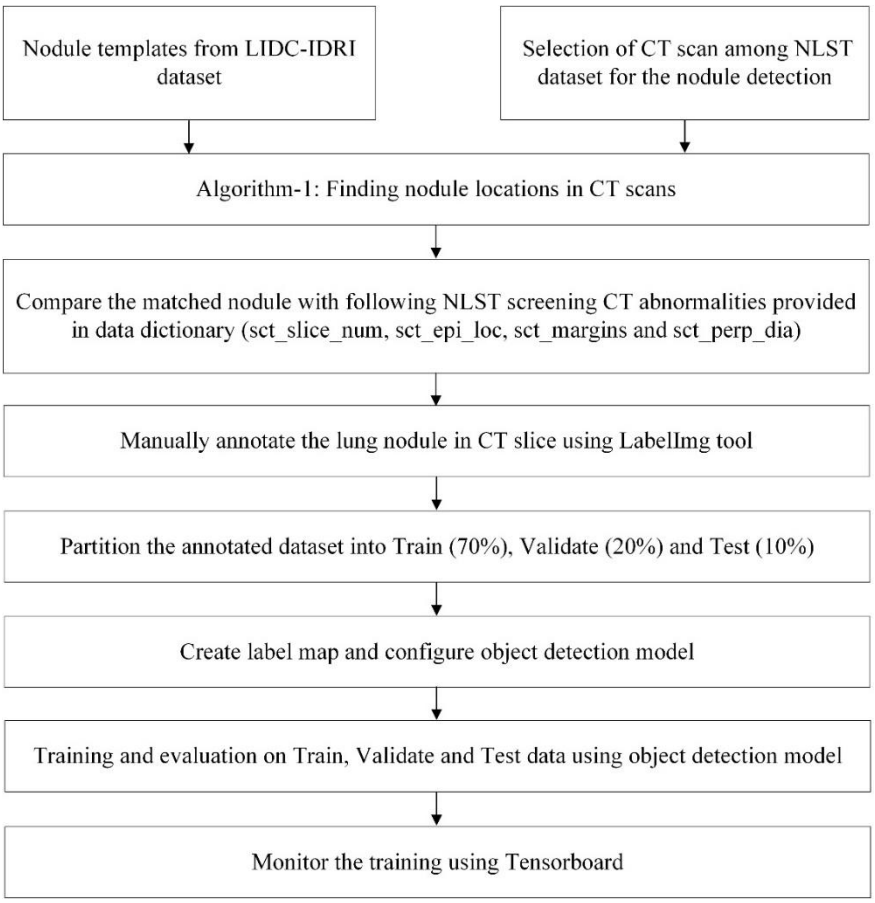


Fig. 5. Algorithm applied for nodule detection on TensorFlow object detection model

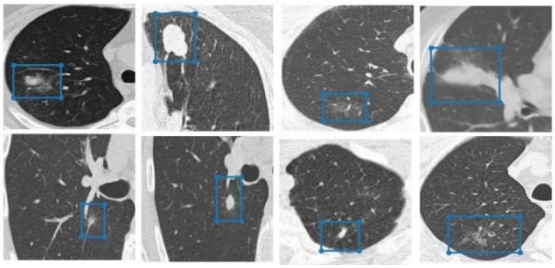
3.1 Details of implementation

To validate the proposed algorithm, labelled NLST dataset are divided into training (70%), validation (20%), and test (10%) sets i.e., 2984, 853 and 350 of training, validation and test images respectively. This model is provided with 416x416 size of input image having batch size of 16. The default IoU threshold is set to 0.5. In this study, only one clinical annotation per image is used to represent different types of nodules present in CT scans. The training time required for proposed single-class nodule detector is 12 hours on a NVIDIA GeForce RTX 2070 GPU for 1000 epochs.

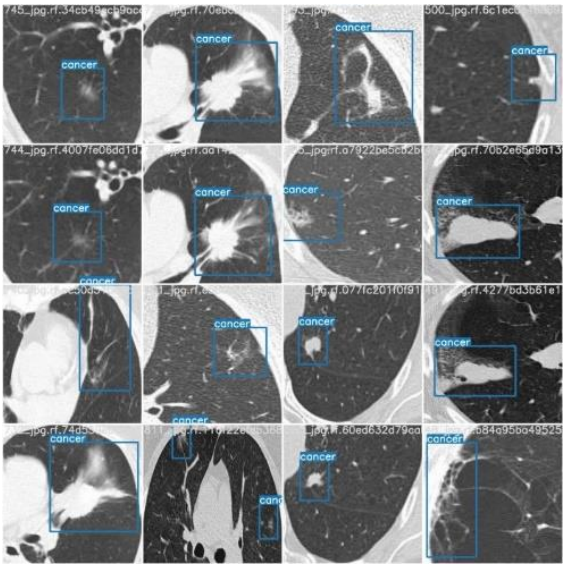
3.2 Results

The annotated training dataset applied to YOLOv4 model are shown in Figure 6 (a). Figure 6 (b) and Figure 6 (c) show the results on test dataset in form of annotated

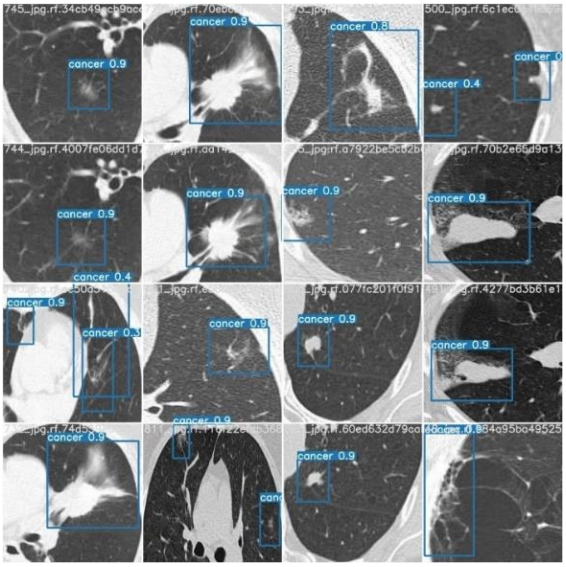
bounding box and confidence score respectively. The model first finds the location of nodule in terms of bounding box then based on the features the class name is mentioned and finally the ground truth and predicted object is used to calculate the confidence score.



(a)



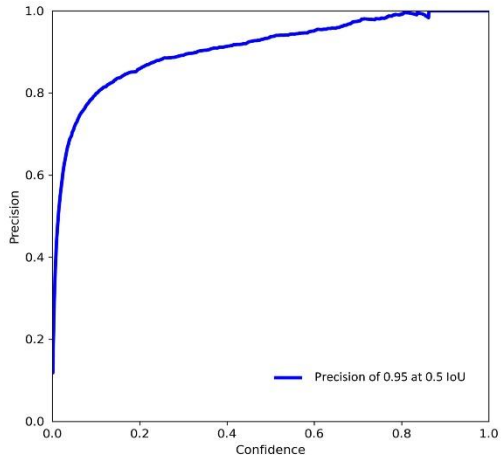
(b)



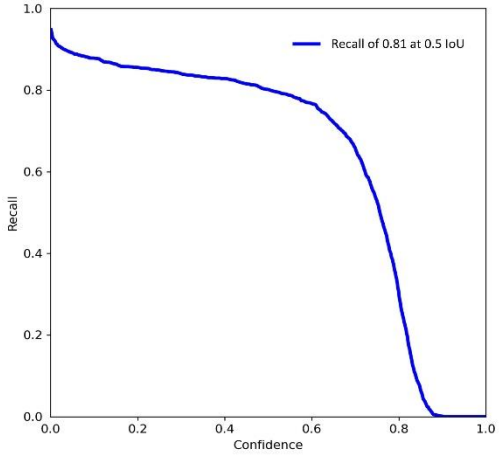
(c)

Fig. 6. (a) Annotated training dataset (b) Labelled test dataset and (c) Predicted confidence score on test dataset

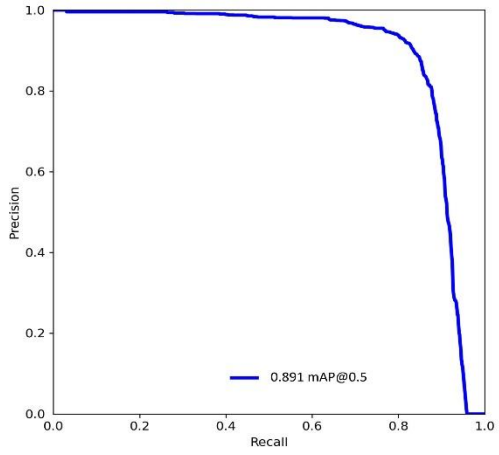
The precision and recall obtained using YOLOv4 model for 0.5 IoU threshold are shown in Figure 7.



(a)



(b)

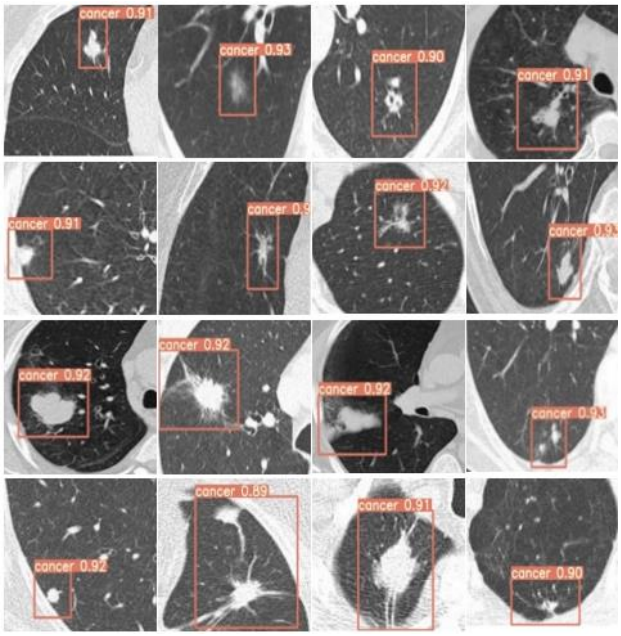


(c)

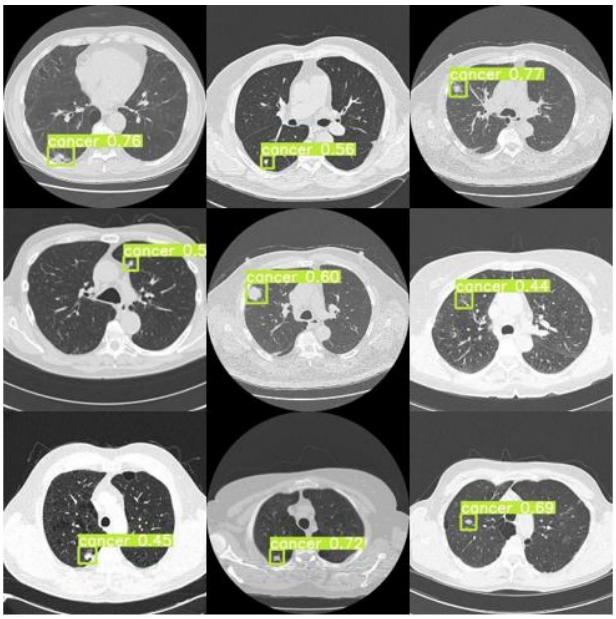
Fig. 7. (a) Precision curve (b) Recall curve and (c) Precision-Recall curve

Figure 7 (a) to Figure 7 (c) show the performance curves obtained depicting the precision and recall values. The results show the achieved precision of 95%, sensitivity of 81% and mean Average Precision (mAP) of 89.1%.

There are varying types and sizes of nodules considered for evaluation of model. The model first defined the box and then on basis of the features it calculates the objectness. Figure 8 (a) and Figure 8 (b) show the predicted results obtained on trained YOLOv4 model. The results show annotated bounding box and confidence score on cropped images and full CT scan images as shown in Figure 8 (a) and Figure 8 (b) respectively. The results of Figure 8 (b) show that the nodules are detected accurately though they are very difficult to be differentiated in presence of similar abnormalities.



(a)



(b)

Fig. 8. Annotated bounding box and confidence score on (a) cropped image and (b) full CT scan image

3.3 Comparative evaluation of the proposed method with the existing methods

The performance shown in Table 1 of past literature is applied on datasets having exact nodule locations. Conversely, in this paper, the nodule locations have been determined and then the bounding boxes are created.

Table 1. Comparison of results

Authors	Performance	Dataset	Numbers of CT scans
Dou et al. [19]	Sensitivity: 67.7%	LIDC-IDRI	888
Xie et al. [20]	Sensitivity: 74.4%	LUNA16	888
Shen et al. [21]	Sensitivity: 77%	LIDC-IDRI	1010
Ardila et al. [22]	Sensitivity: 81.5%	NLST	6716
Messay et al. [23]	Sensitivity: 82.66%	LIDC	84
Yan et al. [24]	Sensitivity: 81.1%, Precision: 80%	DeepLesion	32K
Dai et al. [25]	mAP: 83.6%	PASCAL VOC 2007	9963
Redmon et al. [9]	Precision: 59.2 mAP: 63.4	PASCAL VOC 2007	9963
Proposed method	Precision: 95%, Sensitivity: 81%, mAP: 89.1%	NLST	622

4 Conclusion and future work plan

Preliminary analysis done by SIFT and FLANN algorithms involves the feature detection and extraction methods to identify the location of nodules in lungs CT scans. The labelled data are then used as input for YOLOv4 object detection model, the result of which is found to be accurate in detecting and locating abnormalities on the test images. The YOLOv4 model generalizes well across all types of nodules, achieving precision of 95%, sensitivity of 81% and mAP of 89.1%. The findings indicate that an object detection model could aid radiologists in their practice as a decision support tool or as a second opinion, but this would involve more validation in a clinical environment.

The subjective nature of the nodule type classification could not be generalized in this work as different nodule types and sizes were not represented uniformly. As the NLST dataset does not include the nodule locations, we performed nodule detection as a reader study under artificial conditions that varied from those found in clinical practice. These shortcomings in our work are left as future work.

5 Acknowledgement

The authors thank the National Cancer Institute for access of NCI's data collected by National Lung Screening Trial (NLST).

6 References

[1] Lo, S.B., M.T. Freedman, L.B. Gillis, C.S. White and S.K. Mun. (2018). Computer-aided detection of lung nodules on CT with a computerized pulmonary vessel suppressed function. American Journal of Roentgenology, 210, 480-488. https://doi.org/10.2214/AJR.17.18718

[2] National Lung Screening Trial Research Team, D.R. Aberle, A.M. Adams, C.D. Berg, W.C. Black, J.D. Clapp, R.M. Fagerstrom, I.F. Gareen, C. Gatsonis, P.M. Marcus and J.D. Sicks. (2011). Reduced lung-cancer mortality with low-dose computed tomographic screening. New England Journal of Medicine, 365(5), 395–409. https://doi.org/10.1056/NEJMoa1102873

[3] Elnakib, A., Amer, H. M., & Abou-Chadi, F.E. (2020). Early Lung Cancer Detection using Deep Learning Optimization. International Journal of Online and Biomedical Engineering (iJOE), 16(06), pp. 82–94. https://doi.org/10.3991/ijoe.v16i06.13657

[4] Amer, H. M., Abou-Chadi, F. E., Kishk, S. S. and Obayya, M. I. (2019). A CAD System for the Early Detection of Lung Nodules Using Computed Tomography Scan Images. International Journal of Online and Biomedical Engineering (iJOE), 15(04), pp. 40–52. https://doi.org/10.3991/ijoe.v15i04.9837

[5] Bhatt, S. D. and Soni, H. B. (2021). Image Retrieval using Bag-of-Features for Lung Cancer Classification. 6th International Conference on Inventive Computation Technologies (ICICT), 531-536. https://doi.org/10.1109/ICICT50816.2021.9358499

[6] Songtao, Z., Li Chao and Li Liqing. (2017). An improved method for eliminating false matches. 2nd International Conference on Image, Vision and Computing, 133-137. https://doi.org/10.1109/ICIVC.2017.7984533

[7] Fu, C. and D. Cai. (2016). EFANNA: An extremely fast approximate nearest neighbor search algorithm based on KNN graph. Computer Vision and Pattern Recognition. arXiv:1609.07228.

[8] Su, Y., D. Li and X. Chen. (2020). Lung nodule detection based on faster R-CNN framework. Computer Methods and Programs in Biomedicine, 200, 105866. https://doi.org/10.1016/j.cmpb.2020.105866

[9] Redmon, J., S. Divvala, R. Girshick and A. Farhadi. (2016). You Only Look Once: Unified, Real-Time Object Detection. Computer Vision and Pattern Recognition, 779-788. arXiv:1506.02640. https://doi.org/10.1109/CVPR.2016.91

[10] Al-Masni, M.A., M.A. Al-antari, J-M Park, G. Gi, T-Y Kim, P. Rivera, E. Valarezo, M-T Choi, S-M Han and T-S Kim. (2018). Simultaneous detection and classification of breast masses in digital mammograms via a deep learning YOLO-based CAD system. Computer Methods and Programs in Biomedicine, 157, 85-94. https://doi.org/10.1016/j.cmpb.2018.01.017

[11] Sindhu, R.S., G. Jose, S. Shibon and V.V. Varun. (2018). Using YOLO based deep learning network for real time detection and localization of lung nodules from low dose CT scans. Medical Imaging: Computer-Aided Diagnosis. https://doi.org/10.1117/12.2293699

[12] Redmon, J. and A. Farhadi. (2017). YOLO9000: Better, Faster, Stronger. IEEE Conference on Computer Vision and Pattern Recognition, 7263-7271. https://doi.org/10.1109/CVPR.2017.690

[13] Redmon, J. and A. Farhadi. (2018). YOLOv3: An Incremental Improvement. Computer Vision and Pattern Recognition. arXiv:1804.02767.

[14] Aly, G.H. , M. Marey, S.A. EI-Sayed and M.F Tolba. (2021). YOLO based breast masses detection and classification in full-field digital mammograms. Computer Methods and Programs in Biomedicine, 200, 105823. https://doi.org/10.1016/j.cmpb.2020.105823

[15] Xu, K., H. Jiang and W. Tang. (2020). A New Object Detection Algorithm Based on YOLOv3 for Lung Nodules. Proceedings of the 6th International Conference on Computing and Artificial Intelligence, 233-239. https://doi.org/10.1145/3404555.3404609
[16] Wang, C-Y, A. Bochkovskiy and Liao H-Y Mark. (2020). YOLOv4: Optimal speed and accuracy of object detection. Computer Vision and Pattern Recognition. arXiv:2004.10934.
[17] Wang, C-Y, A. Bochkovskiy and Liao H-Y Mark. (2020). Scaled-YOLOv4: Scaling Cross Stage Partial Network. Computer Vision and Pattern Recognition. https://doi.org/10.1109/CVPR46437.2021.01283
[18] Bhatt, S.D. and Soni, H.B. (2021). Improving Classification Accuracy of Pulmonary Nodules using Simplified Deep Neural Network. The Open Biomedical Engineering, 15 (Suppl-2- M7), 180-189. https://doi.org/10.2174/1874120702115010180
[19] Dou Q., H. Chen, L. Yu, J. Qin and P.A. Heng. (2017). Multilevel contextual 3-D CNNs for false positive reduction in pulmonary nodule detection. IEEE Trans Biomed Eng., 64(7), 1558-1567. https://doi.org/10.1109/TBME.2016.2613502
[20] Xie, H., D. Yang, N. Sun, Z. Chen and Y. Zhang. (2019). Automated pulmonary nodule detection in CT images using deep convolutional neural networks. Pattern Recognition, 85, 109-119. https://doi.org/10.1016/j.patcog.2018.07.031
[21] Shen, W., Z. Mu, Y. Feng, Y. Dongdong, D. Di, Y. Caiyun, Z. Yali and T. Jie. (2016). Multi-crop convolutional neural networks for lung nodule malignancy suspiciousness classification. Pattern Recognition. https://doi.org/10.1016/j.patcog.2016.05.029
[22] Ardila, D., A.P. Kiraly, S. Bharadwaj, B. Choi, J.J. Reicher, L. Peng, D. Tse, M. Etemadi, W. Ye, G. Corrado, D.P. Naidich and S. Shetty. (2019). End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography. Nature Medicine, 25, 954–961. https://doi.org/10.1038/s41591-019-0447-x
[23] Messay, T., R.C. Hardie and S.K. Rogers. (2010). A new computationally efficient CAD system for pulmonary nodule detection in CT imagery. Med Image Anal., 14(3), 390-406. https://doi.org/10.1016/j.media.2010.02.004
[24] Yan, K., X. Wang, L. Lu and RM Summers. (2018). DeepLesion: automated mining of large-scale lesion annotations and universal lesion detection with deep learning. J Med Imaging, 5(3), 036501. https://doi.org/10.1117/1.JMI.5.3.036501
[25] Dai J., Y-L He and J. Sun. (2016). R-FCN: Object detection via region-based fully convolutional networks. Computer Vision and Pattern Recognition. arXiv:1605.06409.

7 Authors

Shital Bhatt received the B.E. degree in Electronics & Communication Engineering from Atmiya Institute of Technology, Saurashtra University, Gujarat, India in 2007, the M.E. degree in Communication Engineering from Chandubhai S. Patel Institute of Technology, Changa, Gujarat, India in 2010. She is currently working toward the Ph.D. degree at Gujarat Technological University, Gujarat, India. She is working as an Assistant Professor at Madhuben & Bhanubhai Patel Institute of Technology since 2010. She has published various papers in journals and conferences at international and national levels. Her area of interest includes Wireless Communication, Image Processing, Machine Learning and Deep Learning.

Himanshu Soni received the B.E. degree in Electronics & Communication Engineering from B.V.M. Engineering College, Sardar Patel University, Gujarat, India in

1997, the M.E. degree in Communication Engineering from Birla Institute of Technology and Science (BITS), Pilani, India in 2004. He obtained Ph. D from Indian Institute of Technology, Bombay, India in 2009. Currently he is working as a Professor in Electronics & Communication Department. and as a Principal of G H Patel college of Engineering & Technology, Gujarat, India. He has published more than 30 research papers in various international journals and conferences. He has been awarded Research Endowment Prize award: for his research paper published in EUSIPCO-Poland in year 2010 by Hari Ohm Ashram. He has attended various training programmes in area of communication engineering from India and abroad. His research interests include statistical signal processing, adaptive signal processing, wireless and mobile communication and UWB communication, 5G and IoT.

Tanmay Pawar received the B.E. degree Electronics & Communication Engineering from Dharmsinh Desai Institute of Technology, Gujarat, India in 1996. He obtained the M.Tech, and Ph.D. from Indian Institute of Technology, Bombay, India in 2002 and 2008, respectively. He is a Professor and Head of Electronics Engineering Department at Birla Vishvakarma Mahavidyalaya (BVM), Vallabh Vidyanagar, Gujarat, India. He is doing his research activities at BVM and the Gujarat Technological University (GTU), Gandhinagar, Gujarat, India. His research interests include Signal Processing, Image Processing and Biomedical Signal Processing with an emphasis on machine learning.

Heena Kher received the B.E. degree in Instrumentation and Control from Sarvajanik College of Engineering and Technology, Surat, Gujarat, India in 2001, M.E. in Microprocessors Systems and Applications from M. S. University, Baroda, Gujarat, India in 2006 and Ph.D. from Sardar Patel University, Vallabh Vidyanagar, Gujarat, India in 2014. She is working as an Assistant Professor in A. D. Patel Institute of Technology, New Vallabh Vidyanagar, Gujarat, India. She has 18 years of teaching experience. She has published around 30 research papers in journals and conferences at international and national levels. She is a reviewer of many reputed journals. Her areas of interest are Digital Image Processing, Machine Learning, Deep Learning, Biomedical Signal Processing, Data Analytics, Optimization Techniques.

Article submitted 2022-01-16. Resubmitted 2022-03-03. Final acceptance 2022-03-05. Final version published as submitted by the authors.