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Lung Nodule Diagnosis using Feature Fusion & YOLOv8

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ABSTRACT-

This paper discuss unique strategies used in identifying lung nodule and mark that nodule in the CT pictures. Although identity of nodule have many challenges because the algorithms did now not offers the appropriate consequences. Day by day, numerous methods are observed to become aware of lung nodule. In this paper we discuss and compare strategies of classification thru tables.

Keywords: Lung nodule, identification, CT images.

I. Introduction

In the sector of healthcare & clinical imaging, the early detection and exact evaluation of pulmonary abnormalities, which includes lung nodules, play a pivotal feature in enhancing affected person effects. Lung nodules are small, rounded or odd growths inside the lungs that can be indicative of diverse conditions, such as benign and malignant tumours. The functionality to right away discover and decide those nodules is crucial for well timed clinical intervention and improved analysis.

Over the years, the healthcare employer has witnessed huge enhancements in pc-aided diagnosis (CAD) systems, with a specific attention on deep analyzing and synthetic intelligence. In this context, the combination of current-day strategies, inclusive of Feature Fusion and YOLOv8 (You Only Look Once version 8), has emerged as a approach for enhancing the accuracy and performance of lung nodule analysis.

This survey ambitions to provide an in-depth exploration of the modern kingdom of studies and realistic programs inside the realm of lung nodule prognosis the usage of Feature Fusion and YOLOv8. We will delve into the key thoughts and methodologies, highlighting the advantages, traumatic situations, and capability future instructions on this subject. Through a complete evaluation of current literature and relevant studies, we aim to shed light on the contributions of Feature Fusion and YOLOv8 in advancing the diagnosis of lung nodules, therefore improving the remarkable of healthcare services and affected person care.

The following sections will tough on the fundamentals of lung nodule diagnosis, the principles of Feature Fusion and YOLOv8, and the innovative strategies in which these strategies had been leveraged to revolutionize the procedure of nodule detection and characterization. Furthermore, we will communicate the realistic implications and traumatic conditions related to this period, and finish with a glimpse into the thrilling opportunities for the destiny of lung nodule analysis.

II. Literature Review

Presented a system the uses YOLOv7 and YOLOv8 deep learning techniques, achieves better results in object detection for images. [1]YOLOv8 processed image file at 1.3ms/frame, with high precision and recall, making it a robust solution for complex scenarios.

This study addresses the challenge of timely detection with help of deep learning and the V-Net architecture. The aim is to accurately differentiate between malignant and benign nodules, especially in the early stages, using the LUNA-16 dataset.[2]

Proposed a Deep Transfer Learning with semi supervised framework for diagnosing benign and malignant nodules. They used transfer learning to differentiate nodules. [3] This framework shows promise as an effective tool for lung nodules in clinical practice.

The system detects and classifies lung nodules as benign or malignant. This study proposes a multi-level feature fusion algorithm to enhance classification accuracy.[4] By fusing context features at different levels and conducting classification at multiple levels, the method achieves reliable results through voting. Experiments on the LUNA16 dataset demonstrate its effectiveness in lung nodule classification.

Presented system YOLO-lung, a practical pulmonary nodule detection system prioritizing both effectiveness and efficiency in hospital applications. [5]By integrating techniques like depth wise convolution and focal loss, the model enhances accuracy, achieving 90.5% precision and 25 FPS on the LIDC-IDRI dataset. Outperforming existing methods, YOLO-lung stands as a valuable reference for practical pulmonary nodule detection model development.

Presented a system in which various computer-aided diagnosis approaches were reviewed to help radiologists in detecting & classifying lung nodules from CT images. [6] The discussed both handcrafted and learned methods, highlighting their potential to aid in nodule detection and classification, providing a comprehensive analysis of these approaches.

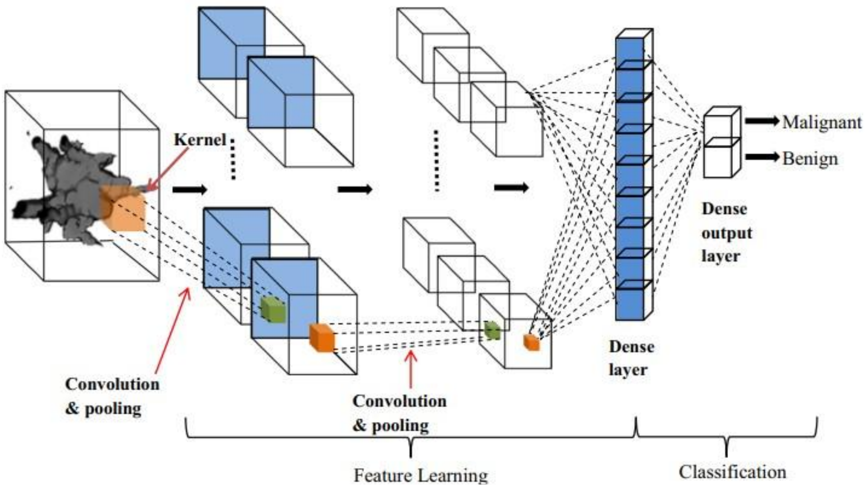

Fig. 5: 3D CNN Architecture ([6] Thakur SK et al., 2020)

Introduced a SSAC model for classifying benign and malignant nodules. Traditional Deep CNN often face a shortage of labelled data. [7] Additionally, MK-SSAC utilizes three SSACs to characterize nodules in terms of appearance, shape, and texture across nine views.

Presented is a lung nodule detection system for chest X-rays, crucial in diagnosing lung cancer. To address false positives, a cascade method using CNN is proposed. [8] The approach involves transfer learning for pinpointing nodules and targeted training of a non-nodule filter, effectively reducing false positives in experiments on a dataset of 2954 Chest X-rays and the JSRT dataset.

Proposed system which uses A fusion model called 3D Convolutional ConvNet is recommended for detecting nodules in CT scans.[9] Two 3D ConvNet models are trained, one on the LUNA dataset and another on augmented data to learn nodule features, and the other on original data. Both models are combined to minimize the risks of overfitting.

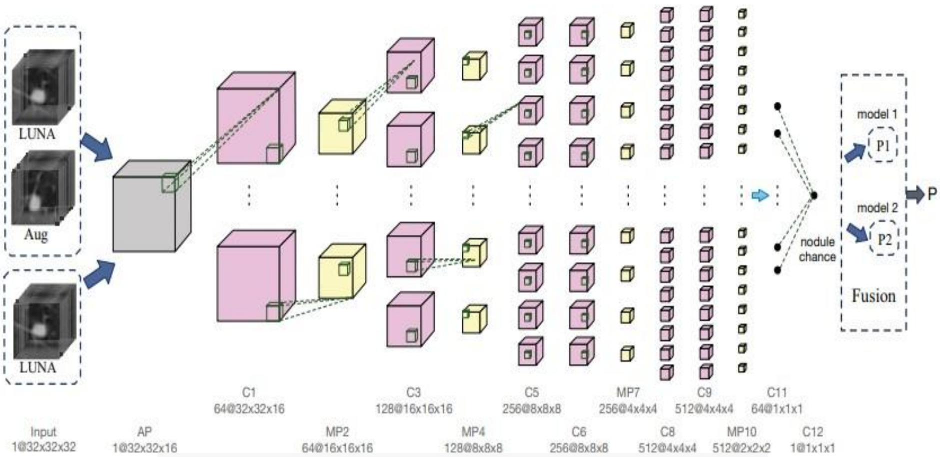

Fig. 6: Architecture of proposed model ([9] Guitao Cao et al., 2018)

This system proposes a lung nodule detection and segmentation approach utilizing a fully convolutional network (FCN), the level set method, and image processing techniques. It involves lung segmentation using FCN, nodule detection within the lung area, and subsequent segmentation using the level set and threshold methods.[10] Experimental results indicate a 100% detection accuracy and a 0.9 dice overlap index for segmentation, making it a valuable reference for clinical diagnosis in lung cancer.

A classification scheme for diagnosing malignant and benign nodules on CT scans is proposed. [11] The scheme involves nodule segmentation based on inputs, extraction of image features (Gray, shape, and texture), and classification using an improved Random Forest (RF) algorithm.

Proposed a CAD system for classify the CT images with unmarked nodules from the Kaggle Data Science Bowl 2017 dataset.[12] The approach involved thresholding for segmentation, followed by the use of a modified U-Net which is trained on LUNA16 data for nodule candidate detection. Subsequently, parts with potential nodules were fed into a GoogleNet based 3D CNN & vanilla 3D CNN for lung cancer classification.

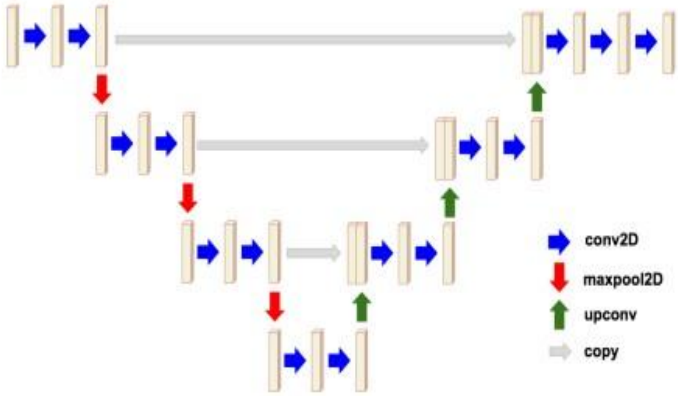

Fig. 7: Proposed Modified U-Net architecture ([12] A. Chon et al., 2017)

Presented is YOLO, a novel object detection approach framing the task as a regression problem for bounding boxes and class probabilities. The unified architecture achieves real-time processing, with the base YOLO model at 45 frames per second and the Fast YOLO version at an impressive 155 frames per second, doubling the map of other real-time detectors.[13] While YOLO may have more localization errors, it demonstrates lower false positives on background and excels in generalizing representations across domains compared to state-of-the-art detection systems like DPM and R-CNN.

Presented is a lung cancer detection system leveraging computer tomography scans and image processing.[14] The proposed algorithm utilizes mathematical morphological operations for lung region segmentation and extracts Haralick features. Artificial neural networks are then employed for the classification of cancer, aiming for early detection to improve prognosis and reduce mortality rates.

Presented approach for detecting and classification of nodules in Computed Tomography images. Lung segmentation is then performed using thresholding and for vascular tree segmentation Hessian method is used.[15] Multiple segmentation techniques are applied to extract precise nodule features, facilitating subsequent classification. Various classifiers and their combinations are employed to classify malignant and benign nodules, resulting in a promising 98% classification accuracy.

Presented a CAD system aimed at the early detection of lung cancer.[16] The method follows several key steps, including image enhancement, region of interest cropping, morphological operations for blood vessel suppression and nodule enhancement, nodule identification, feature extraction, and classification using neural networks. Notably, it achieved an impressive overall accuracy of 92.2% in detecting lung nodules.

Introduced an automated system for lymph node (LN) detection in CT scans, addressing the challenges of low contrast, varying sizes, poses, shapes, and sparse distribution of LNs. [17] The system then utilized a 2.5D technique to decompose 3D VOIs into multiple random 2D orthogonal views. These views were used for training Deep CNN classifier.

System aims to enhance the accuracy of the system. Linear-filtering is used for noise removing & pre-processing steps, for image segmentation. Fuzzy inference system is used for classifying nodules. [18]

System aims to get efficient results using the number of segmentation and enhancement methods. Images are then compared by Gabor filter; they used fast Fourier transform techniques.[19] For segmenting images Thresholding & Watershed were used.

This system introduces ANODE09, a database comprising 55 thoracic computed tomography scans. It also presents a web based framework for evaluating nodule detection algorithms objectively.[20] Results highlight significant performance variations among the algorithms and demonstrate that combining their outputs leads to substantial performance enhancements, emphasizing the need for benchmarking and collaboration in pulmonary nodule detection research.

III. DATASET

In this section, we provide a concise overview of the patient dataset utilized for training in our study. The proposed investigation involved the utilization of 1440 CT images encompassing both male and female subjects. The training dataset was meticulously curated from The Iraq-Oncology Teaching Hospital/National Centre for Cancer Diseases (IQ-OTH/NCCD). Additionally, the images utilized for testing purposes were sourced from Latur Super speciality Hospital Private Limited.

IV. METHODOLOGY

Fig. 2 presents a comprehensive overview of the suggested system. The system, in brief, uses three main modules—the classification module, fusion module and the detection module—on lung CT images that are taken input. Pre-processing is applied on input images and then further passed to first module which consist of two deep learning models i.e., ResNet50 and VGG16 for better feature extraction. Second Module comprises of concatenating the features extraction from both the deep learning modules. In third module the nodule is detected with the help of YOLOV8 model which creates highlighting border for the existing nodule. The steps of the proposed system are explained in the sections that follow.

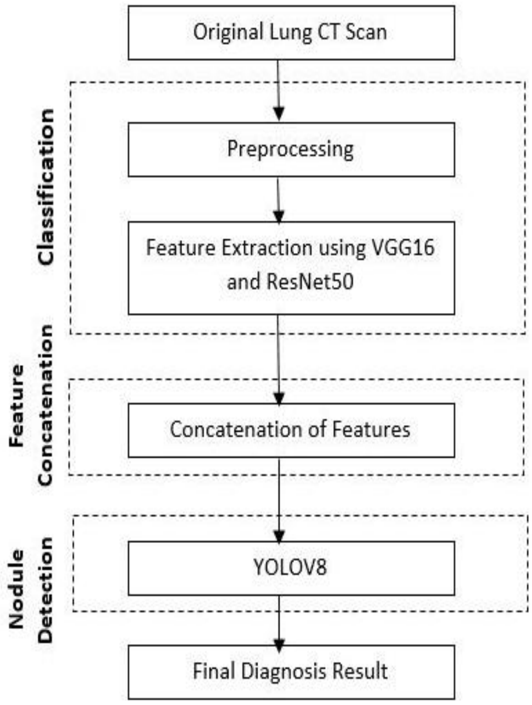

Fig. 2: Flow of Proposed system

Classification Module

Classification Module in this module consists of 2 steps

Pre-processing

Image preprocessing is a technique that improves key features seen in CT images while removing major noise and distortion in image. Applying transformations such as rotation, scaling, translation, flipping, contrast correction, elastic deformation, noise addition, cropping, and padding is known as augmentation preprocessing for lung CT scans. Lung orientations can be modified by rotation, size and position can be changed by scaling and translation, perspectives can be obtained by flipping, and illumination variations can be simulated by adjusting contrast. Elastic deformations simulate anatomical differences, whereas noise addition helps handle noisy data. Padding and cropping highlight crucial areas. When these methods are used with ImageDataGenerator transformations, the model's performance and resilience for lung nodule analysis are improved.

Feature Extraction

Important visual features from lung CT scan pictures are extracted using convolutional neural network (CNN) models which are already pre-trained through the utilization of VGG16 and ResNet50 feature extraction techniques. Deep learning architectures like VGG16 and ResNet50 can identify complex patterns and structures in photos since they have been trained on big datasets such as ImageNet. Models which are pretrained like these are effective feature extractors in the context of lung nodule classification. We may use these models' learned representations to extract useful information from input lung CT images by loading them and then removing the top layers. Subsequent layers (like dense layers) utilize the extracted features, which represent the main attributes of the lung nodules, as input for classification. Our model's effectiveness and efficacy in correctly recognizing and categorizing lung nodules as benign or malignant based on their extracted features is improved by this transfer learning strategy, which enables us to take advantage of the rich visual representations learned by VGG16 and ResNet50.

Concatenation Module

This is uses convolutional neural network (CNN) models which are pretrained, those are VGG16 and ResNet50, in particular and transfer learning to classify lung nodules. Since these models were initially trained on massive picture datasets like ImageNet, transfer learning enables us to apply the learnt characteristics to a new job. Prior to obtaining the output tensors, input images must first be passed through the pre-trained models to load them. The extracted features from the input photos are represented by these output tensors. Concatenating the retrieved features from both models along a designated axis results in a single feature representation. The final classifier for differentiating between lung nodule classifications is a new Keras model, which receives this concatenated feature representation as input and then a dense layer is used to store the end result of the classification which uses softmax activation function.

By calculating the exponents for every output and normalizing every value by the sum of those exponents to ensure that the total output vector adds up to one, the SoftMax function converts logits values into probabilities. The softmax function guarantees that the results of our probability values added together will always equal one.

$$S(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^{n} \exp(y_j)}$$

An uploaded lung CT picture is pre-processed which then runs it to provide predictions. The resultant output shows the image together with the predicted class and related probability. With the help of their acquired representations, pre-trained CNN models can be used in medical image analysis in a quick and effective manner, improving the accuracy of tasks including the categorization of lung nodules.

Nodule Detection -YOLOV8

A cutting-edge deep learning model called YOLOv8 is intended for computer vision applications that require real-time object recognition. YOLOv8 has completely changed the object detection sector by enabling precise and effective detection of objects in real-time settings with its sophisticated architecture and state-of-the-art algorithms. You can use pre-trained models with YOLOv8 that have already been trained on a large dataset like COCO (Common Objects in Context). These models are appropriate for a variety of object identification applications since they can recognize and categorize a large variety of things.

In this study we have used this model for the detection of the Lung Nodules by highlighting the nodule area with a border which can precisely help to detect the location of the nodule and diagnose it. And the end output is the classification of the input image along with its detection.

V. SYSTEM PERFROMANCE MESUREMENT

Up to 1000 CT scans of men and women, gathered from the IQ-OTHNCCD lung cancer dataset, were used in this investigation. The suggested method classifies possible objects in each image as either non-nodule or nodule. There are three classes in the acquired dataset: normal, benign, and malignant instances. The effectiveness of the classification models that are often and extensively utilized in automated medical diagnosis can be evaluated using a variety of indicators. True positive (TP), true negative (TN), false positive (FP), and false negative (FN) are these measurements. The number of accurate forecasts that result in a positive instance is known as TP. The number of forecasts when the instance is negative is denoted by FN. FP stands for false positives in a certain number of inaccurate predictions. The number of forecasts where an instance is negative is called TN. We could compute the following metrics to assess the system's performance based on these metrics.

1) **Accuracy** (Acc) is the proportion of accurately recognized examples to all test examples as:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

2) **Sensitivity** (Sn) measures proportion of positives correctly identified by the classifier. Numerically, sensitivity is the number of true positives divided by sum of true positives and false negatives, i.e.

$$Acc = \frac{TP}{TP + FN}$$

3) **Specificity** (Sp) measures the proportion of negatives correctly identified by the classifier. Numerically, specificity is the number of true negatives divided by the sum of true negatives and false positives, i.e.

$$Acc = \frac{TN}{TN + FP}$$

4) **G-mean** is a combination of sensitivity and specificity. A high G_{mean} value indicates good sensitivity and specificity values.

$$Gmean = \sqrt{Sn \times Sp}$$

5) **Precision** (Prc) the metric indicates the number of predicted nodes that are actually cancer related.

$$Prc = \frac{TP}{TP + FP}$$

6) **F-measure** is a combination of precision and sensitivity. A high F-measure value indicates a high value for both accuracy and sensitivity.

$$F - measure = \frac{2 \times Sn \times Prc}{Sn + Prc}$$

Table. System Performance Measurements

Proposed method	System Performance Measurements			
	Acc	Re	Pre	F-measure
ResNet50	80.12	81.12	80.13	80.10
VGG16	96	96.08	96.08	96.08
Concatenated model	98.08	94.32	98.10	96.63

VI. CONCLUSION

To measure effectivity of proposed system for diagnosis of lung nodules, operations are performed on IQ-OTH/NCCD database mentioned above. In first phase Classification, firstly preprocessing of image is done, by methods like flipping, zoom-in, zoom-out, cropping. Then, specific features (rounded, circular shapes) of object were fed to classification phase. For feature extraction VGG16 & ResNet50 pretrained models are used. Then in second phase Concatenation is done the output feature vector of both models are concatenated and fused output is returned. The SoftMax function converts logits values into probabilities. The softmax function guarantees that the results of our probability values added together will always equal one. Last phase which is Nodule Detection by using pretrained model YOLOv8, which is used for the detection of the Lung Nodules by highlighting the nodule area with a border which can precisely help to detect the location of the nodule and diagnose it. And the end output is the classification of the input image along with its detection.

REFERENCES :

1. P. Das, A. Chakraborty, R. Sankar, O. K. Singh, H. Ray and A. Ghosh, "Deep Learning-Based Object Detection Algorithms on Image and Video," 2023 3rd International Conference on Intelligent Technologies (CONIT), Hubli, India, 2023, pp. 1-6

2. G. Bhatia, S. Nanda, S. Udupa, M. Ayyappan and R. Kadakoti, "Detection of Lung Carcinoma using Volumetric Convolution (V-Net)," 2022 3rd International Conference for Emerging Technology (INCET), Belgaum, India, 2022, pp. 1-4

3. F. Shi et al., "Semi-Supervised Deep Transfer Learning for Benign-Malignant Diagnosis of Pulmonary Nodules in Chest CT Images," in IEEE Transactions on Medical Imaging, vol. 41, no. 4, pp. 771-781, April 2022

4. C. Liu, B. Wang and M. Zhu, "Benign and malignant classification of pulmonary nodules based on multi-level feature fusion," 2021 International Conference on Intelligent Computing, Automation and Systems (ICICAS), Chongqing, China, 2021, pp. 75-79

5. S. Mei, H. Jiang and L. Ma, "YOLO-lung: A Practical Detector Based on Imporved YOLOv4 for Pulmonary Nodule Detection," 2021 14th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Shanghai, China, 2021, pp. 1-6, doi: 10.1109/CISP-BMEI53629.2021.9624373.

6. Thakur SK, Singh DP, Choudhary J. Lung cancer identification: a review on detection and classification. Cancer Metastasis Rev. 2020 Sep;39(3):989-998.

7. Y. Xie, J. Zhang, and Y. Xia, “Semi-supervised adversarial model for benign–malignant lung nodule classification on chest CT,” Med. Image Anal., vol. 57, pp. 237–248, Oct. 2019.

8. C. Liu, B. Wang, Q. Jiao and M. Zhu, "Reducing False Positives for Lung Nodule Detection in Chest X-rays using Cascading CNN," 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA), Xi'an, China, 2019, pp. 1204-1207, doi: 10.1109/ICIEA.2019.8833699.

9. G. Cao, T. Huang, K. Hou, W. Cao, P. Liu and J. Zhang, "3D Convolutional Neural Networks Fusion Model for Lung Nodule Detection on Clinical CT Scans," 2018 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Madrid, Spain, 2018, pp. 973-978

10. Y. Chunran, W. Yuanvuan and G. Yi, "Automatic Detection and Segmentation of Lung Nodule on CT Images," 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Beijing, China, 2018, pp. 1-6

11. H. Hu and S. Nie, "Classification of malignant-benign pulmonary nodules in lung CT images using an improved random forest " 2017 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD), Guilin, China, 2017, pp. 2285-2290

12. Chon, N. Balachandar, and P. Lu, “Deep convolutional neural networks for lung cancer detection,” 2017.

13. J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 779-788, doi: 10.

14. M. Vas and A. Dessai, "Lung cancer detection system using lung CT image processing," 2017 International Conference on Computing, Communication, Control and Automation (ICCUBEA), Pune, India, 2017, pp. 1-5

15. O. Elsayed, K. Mahar, M. Kholief and H. A. Khater, "Automatic detection of the pulmonary nodules from CT images," 2015 SAI Intelligent Systems Conference (IntelliSys), London, UK, 2015, pp. 742-746

16. Lakshmi Narayanan A and Jeeva J.B, "A Computer Aided Diagnosis for detection and classification of lung nodules," 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO), Coimbatore, India, 2015

17. H. Roth et al., “A new 2.5d representation for lymph node detection using random sets of deep convolutional neural network observations,” Medical Image Computing and Computer-Assisted Intervention MICCAI 2014, pp. 520–527, 2014

18. Chaudhary, A., & Singh, S. S. (2012, September). Lung cancer detection on CT images by using image processing. In Computing Sciences (ICCS), 2012 International Conference on (pp. 142-146). IEEE

19. B. van Ginneken et al., “Comparing and combining algorithms for computer-aided detection of pulmonary nodules in computed tomography scans: The anode09 study,” Med. Image Anal., vol. 14, pp. 707–722, 2010

20. Hashemi, A., Pilevar, A. H., & Rafeh, R. (2013). Mass Detection in Lung CT Images Using Region Growing Segmentation and Decision Making Based on Fuzzy Inference System and Artificial Neural Network. International Journal of Image, Graphics and Signal Processing(IJIGSP), 5(6), 16.