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ORIGINAL ARTICLE

Role of Segmentation in Lung Nodules CT Scan Images for High Performance: Case of Recent Findings

MADHURA J[1], S. RAVIRAJA[2], RAMESH BABU D R[3]
[1]*Research Scholar, Department of Computer Science and Engineering, DSCE, India*
[2]*Professor & Dean, Faculty of Computer Studies, University of Garden City, Khartoum, Sudan. Founder Chair & Principal Investigator, Royal Research Foundation, India*
[3]*Professor & Head, Department of Computer Science and Engineering, DSCE, India*
Correspondence to: Madhura J, Email: madhu-ise@dayanandasagar.edu

ABSTRACT
Early stage of lung cancer detection is being very vital in today's scenario. Several promising technological diagnostic automated tools developed and are used to predict the patient's survival using intelligent lung nodules analysis in Computed Tomography (CT) images. Recently, the advancement of human health diagnostic technologies, Computer-Aided Detection Systems (CADe) are developed diurnal rhythms to provide higher accuracy and better performance rate. In this research work, we focuses on a documenting the automatic segmentation of lung cancer nodules by various methods developed in recent years of the timeline with respect to the realization. The proposed work is criterion based objectives to establish the performance measures and to propose new solution for Lung nodules segmentation and detection on CT Scanned digital images, which is the fundamental and epochal measure to attain the high level of performance. In analyzing each of these technical execution on detection on lung nodule, and experimented to 4 different kinds of lung nodules CT scanned digital images. The phenomenon show segmentation methods involving convolution neural networks were better when compared to other existing methods. U-Net method gave improved accuracy. Dice score 0.981±0.009 and sensitivity 0.994±0.002 are maximum by using the method Dense R2UNet. F1-score 97% is best achieved by Cascade Convolutional Network. Recall rate is achieved to the maximum 99.1% through Improved 3D-UNet Neural Network. Precision 0.982±0.009 and accuracy 0.988±0.018 are best attained by Dense R2UNet. In the case, semi-transparent nodules segmentation, Watershed method found to be highly appropriate select. Watershed arse nodules segment correspond well to vessels and semi-transparent nodules, and exhibit low sensitivity in solitary or lone nodules. The higher rate of efficient segmentation is directly proportional to higher rate of performance.
Keywords: CNN, Lung Cancer, CT Image Segmentation, Watershed, R2Unet.

INTRODUCTION
The advancement in medical digital image processing has considerably changed the health-care systems, significantly in the diagnosing of medical digital images and in quick recognition of varieties of human diseases. Lung cancer is the major cause for high rate of mortality with highest mortality rates world-wide. In 2020 [38], according to the statistics from GLOBOCAN and reported approximated around 19.3 and 10.0 million new cases and cancer deaths occurred respectively. The second major contributor (11.4%) for death rate is lung cancer. Lung malignant neoplastic disease remained the foremost cause of high rate of cancer mortality, recorded around 1.8 million deaths (18%) and with a less than 20% of 5-year survival rate. The incidence and mortality rates are drawn in Tab 1 and Fig. 1. Research on lung malignancy is very essential for critical diagnosis, treatment and increasing survival rate and quality of life of patients. Lung cancer testing aids in saving lives. CT is one such potential screening test. Image denoising is required for enhancing the quality of medical images and also in preserving the edges. Precise lung nodule segmentation from CT images serves a vital role for radiologists in pulmonary nodule analysis [1].

Table 1: Globocan 2020 – Asia Statistics

Lung Cancer	No. of estimated new cases		No. of estimated new deaths	
	Incidence	%	Mortality	%
Males	10.1 million	49.9	5.5 million	60.6
Females	9.2 million	48.6	4.4 million	55.5
Both Sexes	19.3 million	49.3	9.9 million	58.3

In medical imaging, process of segmentation is very crucial as the region of interest is extracted either by an automatic or semi-automatic process. Image is alienated into many areas based on specific features for segmentation of tumor or detection. The pulmonary nodules accurate quantification is substantial aid in the fundamental detection of lung cancer, increasing the chances of a patient's survival [2]. The pixels with similar labels should be having similar visual feature characteristics. In medical imaging, segmentation is a significant process. It can disclose very important information masked in the images. Classification of image regions into descriptive regions or pathological regions such as cancer plays a vital role in many medical applications. Identification of redundant pixels is one of the most important task in segmentation. The broad performance of computerized lung cancer detection is very much dependant on the quality of the best segmentation process. Out of many research outcome it is clear that medical image segmentation is always a biogenic component of any such vision based disease detection systems. However, the simulation of an algorithms that specifically attempt to segment having higher accuracy prove to perform finest advisable for any such automated diagnostic model.

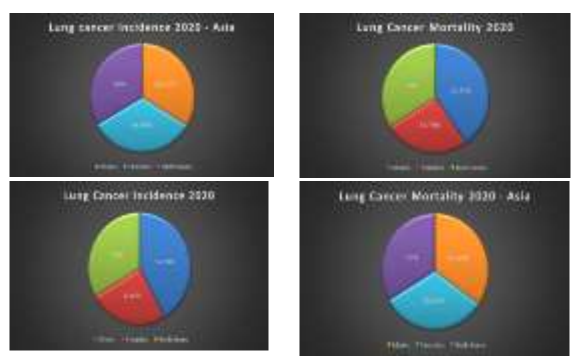

Fig 1: Lung cancer -Incidence and Mortality rate

Considering the importance of the role of Segmentation in Lung Nodules Computed Tomography Scan Images for High Performance, we consider the following aims and objectives and to achieve the terminal contributions of the manuscript as below:

- Recent developments in lung disease detection - in last 3 years
- Focus on analyzing segmentation of Lung diseased CT images
- Evaluation of accuracy, performance and efficiency

RELATED REVIEW ON EXISTING METHODS

In the process of detection and segmentation of lung cancers, Jue Jiang et al. presented network model that aggregate data across various images resolutions and feature levels using residual connections. The method used and the details about metric and datasets are provided in table 2. Authors used different datasets and different methods for CT lung images, however the results vary with respect to various datasets. Hence the method is considered to be nearly efficient [5].

Table 2: Method: Incremental-MRRN approach

Datasets	Metric: DSC	NSCLC
TCIA	0.740.13	377
MSKCC	0.750.12	304
LIDC	0.680.23	523

Kaushik Dutta presented a Dense Recurrent Residual CNN for image segmentation. Lung Nodule Analysis dataset is used. In order to conducting the training and testing authors were considered 80% and 20 % for training and testing. Performance metrics such as Dice Similarity Coefficient(DSC), Jaccard Score(JS), Precision, Recall, Sensitivity, Specificity, Accuracy and Area Under the Curve are considered. Dense R2UNet method achieved the following results 0.981 ± 0.009(DSC), 0.961 ± 0.016(JS), 0.982 ± 0.009(Precision), 0.988 ± 0.018(Recall), 0.994 ± 0.002(Sensitivity), 0.988 ± 0.018(Specificity), 0.988 ± 0.018(Accuraccy) and 0.989 ± 0.008(AUC). When matched to standard UNet and Residual UNet, the presented Dense R2UNet-model performs improved during both the training and validation phases [38].

Segmentation Block diagram: Process of segmentation of CT image is supported on image processing scheme as shown in Fig 1. A Pre-processing is performed on the input CT scanned digital image. Noise removal process is carried out. Denoised image is then used for nodule detection. Region of interest is located and features are extracted. It is then forwarded for testing. Finally segmentation is carried out for the nodules.

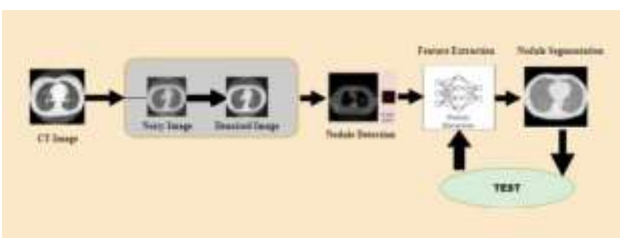

Fig 2: Segmentation Process

The critical objective study of the related works stated in this research article and authors conducted several vital experimentation out of the literature. Experimental finding suggests that the below mentioned methods perform better and yields better results in terms of higher performance.

An Algorithm: An machine-driven algorithm to recognize and segment the lung in a CT scanned 3D-Pulmonary X-ray images.
The following major processing steps were incorporated in this method: To begin, the lession of the lung was separated from the encompassing area using the best thresholding- technique. Later a 3D Mask was created. Further, in direction to locate nodules adhering to the wall of the lung, every mask slice was compared to the preceding slice. To repair the mask picture in the existence of juxta-pleural nodules, a reconstruction approach based on various morphological processes was used. The advantage of this thresholding approach is its speed; for example, lung segmentation takes less than 10 seconds for 300 photos [38].

Level-setting approach based on labeling and clustering: The Connected-Component-Labeling (CCL) algorithm assigns a transient label, evaluate the comparable categories and swaps each transient label with a tiny label of the related class. The K-means method separates the labeled data onto clusters, with members of the identical clusters being comparable to one another but not to members of the other clusters. [22].
Clustering of Fuzzy-C-Means: The morphological reconstruction method is used to optimize the data distribution in this procedure. The histogram of the morphologically reconstructed image is subjected to the FCM clustering algorithm. Finally, a median filter is used to modify the membership partition. The tumour regions are segmented from a series of CT imaging slices, which leads to 3D reconstruction and tumour volume estimation [39].

RESULTS & DISCUSSION

The study analysis and criterion based relative experimentation certainly reassert the significance of segmentation. Criterion based analysis is made on datasets used for evaluation.

Luna 16: The **LUNA16** dataset is consider in the segmentation process of lung. Dataset comprises of 1,186 number of lung nodules annotated in 888 CT scans. Segmentation methods such as Convolution neural network trained with simple diameter information, Improved 3-DUNet neural network, U-Net fused with dilated convolution, Modified U-Net deep neural network grounded on reduction of kernels number in each layer and dense recurrent residual CNN methods have very prominently used LUNA 16 dataset. Convolution neural network based methods majorly use this dataset for evaluation purpose and have achieved performance improvement with greater accuracy.

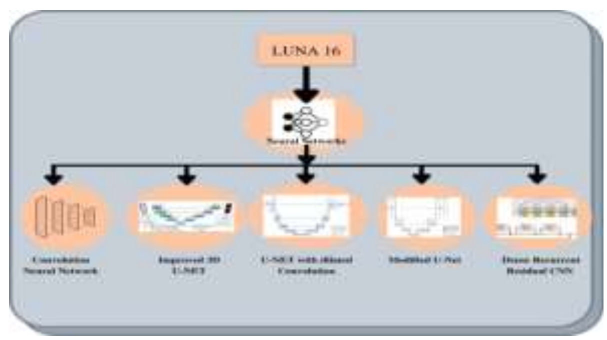

Fig 3: LUNA 16 database

Collection of LIDC: The Dataset includes thoracic CT digital scan images with asterisked annotated lesions for diagnostic for screening purposes. Adaptive Region of Interest (AROI) with multi-view residual learning, for example, was employed in the segmentation process, Collaborative deep learning, Active contour techniques, labeling and clustering based methods use LIDC-IDRI datasets for evaluation.

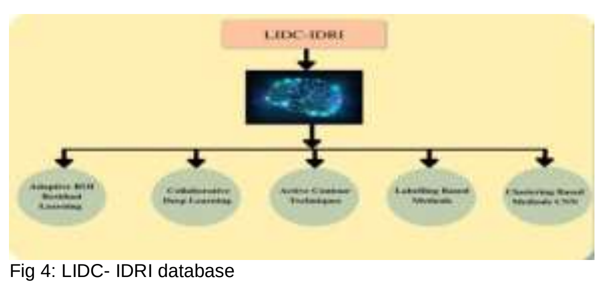

Fig 4: LIDC- IDRI database

Decathlon lung dataset and NSCLC: A collection of medical picture segmentation datasets makes up the Medical Segmentation Decathlon. It contains a total of 2,633 threedimensional photos gathered from various anatomies of interest, modalities, and sources. Images (422) of Non-Small-Cell-Lung-Cancer (NSCLC) patients are included in the NSCLC collection. Methods such as Transfer learning and combined networks make use of this dataset.

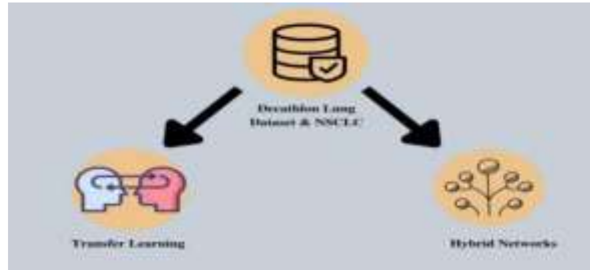

Fig 5: Decathlon and NSCLC database

Table 3: Database Details

Sl	Database Name	Author name	Link	Training Set	Validation Set	Testing set
1	LUNA16 dataset	Chang-Mo Nam et al. [1], Zhitao Xiao et al.[6], Kuan-bing Chen et al.[16], Dathar Abas Hasan et al.[25], Kaushik Dutta et al.[37]	https://doi.org/10.5281/zenodo.2595812 https://doi.org/10.5281/zenodo.2596478	70% for training [25] 7500 datasets[16] 80% for training and validation[37]	10% [25]	20% [25] 5000 [16] 20% [37]
2	LIDC-IDRI Dataset	Muhammad Usman et al.[4], Xianling Dong et al. [5], Spoorthi Rakesh, Shanthi Mahesh et al.[19], K. Yamuna Devi and · M. Sasikala et al.[22], Gopi Kasinathan et al.[30]	https://wiki.cancerimagingarchive.net/display/Public/LIDC-IDRI	600 lung nodules for training[5]	-	274 lung nodules[5]
3		Qingji Tian et al.[9]	https://doi.org/10.7910/DVN/6ACUZJ	Lung CT-Diagnosis database	-	-
4	200 lymph node samples from Tri-Service General Hospital, Taiwan.	Chung-Feng Jeffrey Kuo et al.[10]	-	-		-
5	Altered phantom dataset	Marko Savic et al.[12]	https://wiki.cancerimagingarchive.net/display/Public/Collections	-	-	-
6	Decathlon lung dataset. and NSCLC	Mizuho Nishio et al.[13], Jue Jiang et al.[28]	http://medicaldecathlon.com/	-	-	-
7	UCSD-AI4H/COVID-C.	Ramin Ranjbarzadeh et al.[14]	https://github.com/UCSD-AI4H/COVID-CT	70% for training	10%	20%
8	QIN	Jiaxing Tan et al.[15]	https://wiki.cancerimagingarchive.net/display/Public/QIN+LUNG+CT	70% for training	10%	20%
9	TCIA	Jinzhu Yang et al.[17]	https://www.cancerimagingarchive.net/access-data/	-	-	-
10	3Dircadb	Devidas T. Kushnure and Sanjay N. Talbar [18]	https://www.ircad.fr/research/3dircadb/	-	-	-
1. 1	CT dataset	Amirhossein Aghamohammadi et al. [21]	https://www.kaggle.com/kmader/siim-medical-images	-	-	-
2. 2	SPIE- AAPM	M. S. Kavitha et al. [24]	https://wiki.cancerimagingarchive.net/display/Public/SPIE-AAPM+Lung+CT+Challenge	-	-	-
3. 3	RIDER from the American cancer image library	He-xuan Hu at al.[32]	https://wiki.cancerimagingarchive.net/display/Public/Collections	-	-	-

Imitative datasets or publicly available datasets and real datasets are considered for the analysis purpose. As per literature review of various segmentation methods and the respective datasets used by these methods it is found out that real datasets are used very minimal. Further experiments should be performed on real datasets to see the performance variation. Considering the literature review, here we attempt to evaluate the existing findings.

Table 4: Segmentation methods and results

Segmentation Methods	Dice score	Sensitivity	F1 score	Recall rate	Precision	Accuracy
Segmentation with convolutional neural network[1]	78.18%	91.70%	-	-	-	-
Improved 3D-UNet Neural Network[6]	95.30%	-	-	99.1%	-	96.97%
U-Net network fused with dilated convolution[16]	0.9743	-	-	0.9699	0.9731	97%
Densely Connected Recurrent Residual (Dense R2UNet) CNN[37]	0.981±0.009	0.994±0.002		0.988±0.018	0.982±0.009	0.988±0.018
Labeling and clustering-based level set method[22]	-	91.67%	-	-	98.79%	97.5%
ACM and CNN classifier[31]	-	91.67%	-	-	98.79%	97.5%

DL and converged search and rescue algorithm[9]	-	-	96.41%	96.07%	96.35%	96.65%
Cascade Convolutional Network[14]	-	-	97%	97%	96%	-
MSDS-UNet[17]	0.675	0.731	0.682	-	-	-
Recurrent feature fusion learning[20]	67.75±23.41	73.18±25.58	-	-	71.64±27.28	99.15±0.76

It is very evident from Table 4 that, segmentation methods involving convolution neural networks were better when compared to other existing methods. U-Net method gave improved accuracy.

This research article demonstrates the extensive study of CADe and CADx of Lung nodule on CT scan images. The referred recent research articles since 3 years are mainly deepened from reputed journals and conferences. In recent experimentation, segmentation is supplemented to solve or meliorate a higher rate of performance. However, various multi-tasks methods are combined in decease detection and classification. This research article work cater an exhaustive assessment of contemporary lung segmentation formulation on images of CT that manoeuvre clinicians while selecting instruments to segment the lung region and the respective applications. Basic lung nodules segmentation methods are reviewed critically in this paper. This objective criterion based experimentation demonstrated a comprehensive overview of segmentation strategies thru CNN and associated methods with UNets applied to LUNA 16 datasets and achieved performance improvement with greater accuracy. Recurrent fusion network used FD dataset and gave highest accuracy of segmentation when compared to other existing methods. The performance of ACM is average. In terms of lone nodules, networks that hybridise features across the aggregate resolution of the image and feature levels have a high False-Negative rate. Collaborative deep learning with labeling and clustering based methods gave higher precision value and enhanced performance. Sensitivity was increased in methods based on convolution neural networks and deep neural network models. Furthermore, a hybridizing compatible methods are foreseen to have a improved performance. In order to get a higher accuracy of segmentation level on various nodule CT images in the future, it will be necessary to use ML.

CONCLUSION

The experimental outcome proves that the segmentation methods involving CNN were better when compared to other existing methods. U-Net method gave improved accuracy. Dice score 0.981±0.009 and sensitivity 0.994±0.002 are maximum by using the method Dense R2UNet. F1-score 97% is best achieved by Cascade Convolutional Network. Recall rate is achieved to the maximum 99.1% through Improved 3D-UNet Neural Network. Precision 0.982±0.009 and accuracy 0.988±0.018 are best attained by Dense R2UNet. Furthermore, to perform the semi-transparent nodules segmentation, we propose Watershed is highly desirable selection. Watershed method proven to be very efficient, cohere well to vessels and semi-transparent nodules, and exhibit to have low sensitivity in lone nodules. Through the study we strongly emphasizes that the role of segmentation in Lung Nodules CT Scan Images is highly significant in achieving the higher rate of performance.

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