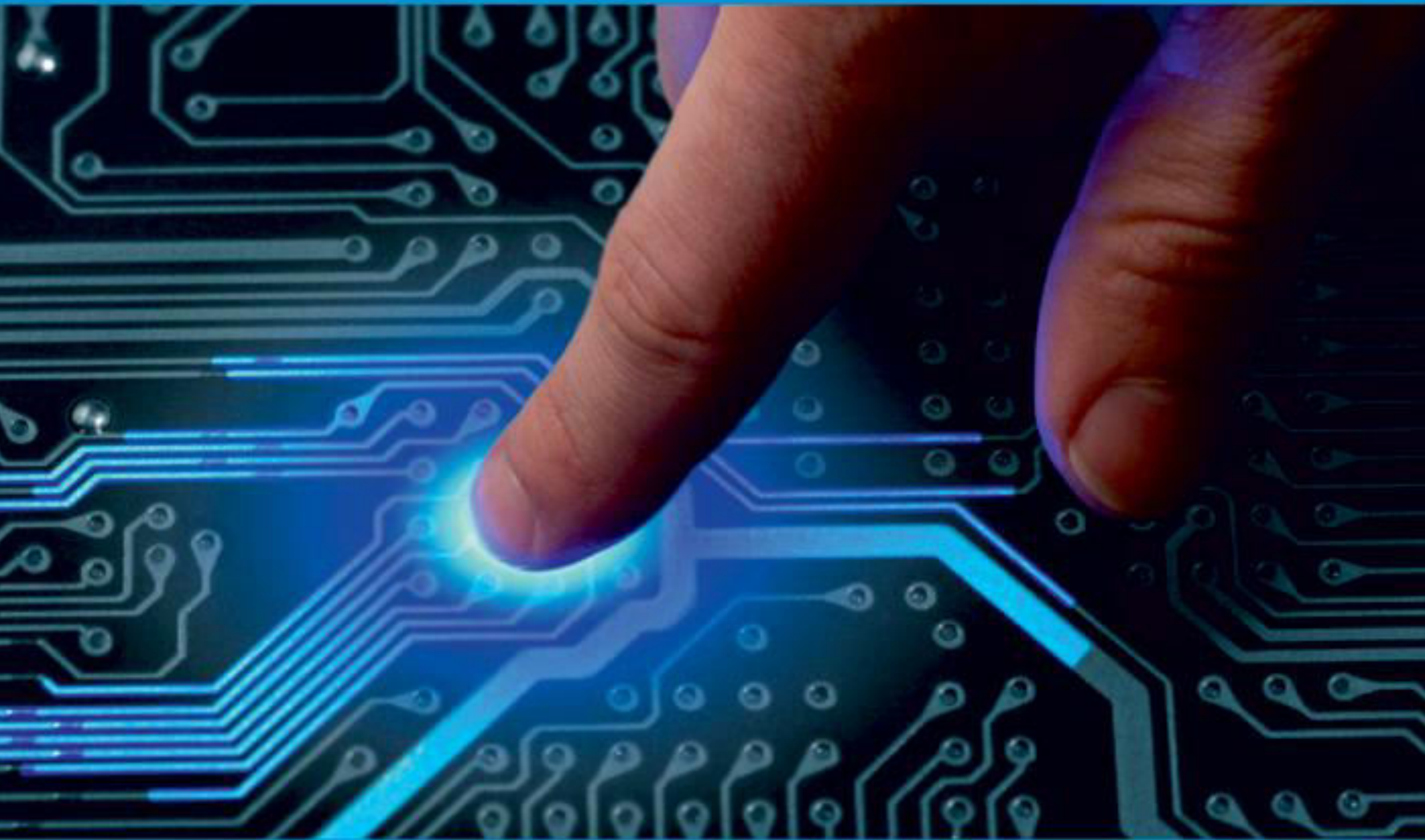
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 5, May 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005283 |

Lung Portion Segmentation on HRCT Images Using Deep Learning

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ABSTARCT: Lung Cancer is the most perilous cancer. Early detection of the disease can improve survival rate. Automation of detection of lung nodules aid radiologists in quickly and accurately diagnosing the disease. Lung segmentation is the process of segregating lungs region from other tissues in the CT image. Methods we used deep learning model U-Net, already used in many biomedical image segmentation tasks, our small image dataset is composed of 42 studies of patients with lung diseases, of which only 32 were used for the training phase. We compared the performance of the two models in terms of the similarity of their segmentation outcome with the gold standard and in terms of their resources' requirements. In this study U-Net ConvNet has been implemented on lungs dataset to perform lungs segmentation. The lungs dataset consists of 267 CT images of lungs and their corresponding segmentation maps. The accuracy and loss achieved is 0.9678 and 0.0871 respectively. Conclusions We demonstrated that deep learning models can be efficiently applied to Rapi Deep Learning segment and quantify the parenchyma of patients with pulmonary fibrosis, without any radiologist supervision. An architecture called U-Net convolutional network has been proposed and implemented exclusively for the segmentation of biomedical images.

KEYWORDS: Deep Learning; lung segmentation; high resolution computed tomography; radiomics; U-Net;

I. INTRODUCTION

Early detection of lung cancer increases the survival rate, but is like searching for needle in the haystack. Computed Tomography (CT) is an important diagnostic modality to detect lung nodules. There are 1.8 million new lung cancer cases diagnosed annually and 1.6 million deaths worldwide. The automation of detection and diagnosis of lung nodules benefits both the radiologists and patients. Accurate detection of lung nodule at an early stage leads to proper treatment and saves patients life. Acquiring lung images, processing them and interpreting them clinically are crucial to achieving global reductions in lung- related deaths.

A naive lung segmentation algorithm was applied to 60 scans, 17% of nodules were not detected as a consequence of improper lung segmentation, only 5% of nodules were not detected, due complexity in lung region and the existence of the arteries, veins, bronchi and bronchioles Deep Learning methods are more efficient than classical statistical approaches in unravelling enormous amounts of data. A Deep Learning-based workflow is defined by the following

i. The training/testing data set (in our case biomedical images, e.g., HRCT).
ii. The outcome variable (in our case, image masks defining the segmentation output).
iii. Training and testing algorithm.
iv. A performance evaluator algorithm.

II. RELATED WORK

Automatic lung segmentation is a challenging task due to inhomogeneity of lungs region. Rigorous amount of research has been carried out and is still pursued with different techniques. Several algorithms have been proposed that address the problem of accurately extracting lung region from the CT im- ages. Conventional methods mostly rely on the intensity values of different regions on the CT image. The notion of having same intensity values for similar regions has yielded a popular method for segmentation called thresholding. The field of biomedical image analysis is constrained by the lack of huge annotated samples. To overcome this problem authors in [12] have proposed U-Net, a special kind of

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convolutional network designed for biomedical image analysis. Primarily U-Net employs data augmentation technique to increase the size of the data. The developed U-Net ConvNet consists of 23 convolutional layers. Segmentation of neuronal structures on electron microscopic recordings and cell segmentation tasks in light microscopic images were performed. The U-Net won segmentation challenge in inter- national symposium in biomedical imaging 2015.

III. U-NET CONVOLUTIONAL NETWORK

A.U-NET ARCHITECTURE:

U-Net ConvNet architecture consists of ConvNet layers arranged in a top-down and bottom-up manner forming a u-shaped network. Hence this type of ConvNet with two paths from upwards to downwards followed by downwards to up- wards is called a U-Net ConvNet. The top-down path is called contracting path and bottom-up path is called expansive path. Contraction is used to capture the context of the image and expansion is used to efficiently localize the region of interest. The contracting path is composed of 3 blocks, each block con- sists of two convolutional layers. The expansive path is composed of 3 blocks. Two blocks contain convolutional layer, concatenation layer and up sampling layer each. The last block contains three convolutional layers, concatenation, up sampling layers followed by two convolutional layers, a dropout layer and an output layer.

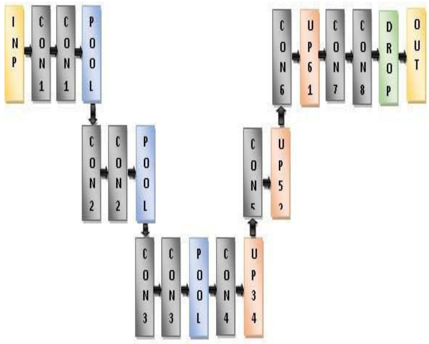

Fig. 1: U-Net ConvNet for Lung Segmentation.

Its purpose is to perform concatenation of corresponding layers in contracting and. expansive paths. Expansive path is useful to identify, localize and segment the object of interest. Figure 1 presents the U-Net ConvNet architecture developed in this work.

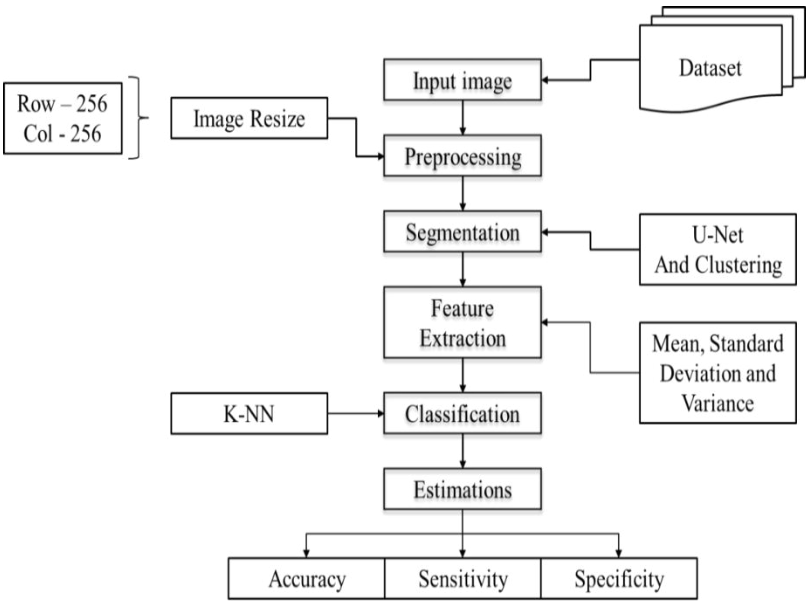

Fig 2: Flow chart of U-net Architecture-based segmentation.

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B. MODULES:

- Input Image
- Preprocessing
- Segmentation
- Feature Extraction
- Classification

Input Image: An image is a rectangular array of values (pixels). Each pixel represents the measurement of some property of a scene measured over a finite area. The values are normally represented by an eight-bit integer, giving a range of 256 levels of brightness. Read an image into the workspace, using the "imread" command.

Pre-Processing: Image Resize. In computer graphics and digital imaging, image scaling refers to the resizing of a digital image. In the case of decreasing the pixel number (scaling down) this usually results in a visible quality loss.

Future Extraction: A pattern consists of multiple instances of a feature. Select a pattern type and define dimensions, placement points, or a fill area and shape to place the pattern members.
The result of the operation is a feature pattern.

C. U-NET CONFIGURATION:

Totally there are 11 convolutional(conv) layers. The first layer is the input layer. Image size in input layer is 32x32. Con1 layer takes 8 filters of size 3x3. Image dimension remains the same. con1 is joined with another con1. con layers are followed by relu in the entire network. Next is pool1 of size 2x2. Pool1 reduces the image size to 16x16. con2 uses 16 filters. Pool2 makes the image 8x8. con3 has 32 filters and pool3 change the size to 4x4. Until pool3 it was contracting path. From con4 expansive path begins. con4 has 32 filters of size 1x1 and is concatenated with con3. Up sampling up1 follows concat yielding increased image size of 8x8. Con5 takes 32 filters concatenated with con2. Up2 modifies the size to 16x16. Con6 has 32 filters concatenated with con1. Up3 increases the size to 32x32. Con7 has 16 and con8 takes 64 filters. Filter size is 2x2 in con5, con6 and con7. Con8 filter size is 1x1. Dropout occurs after con8. Output layer has one filter of size 1x1 and operate on image size of 32x32.

D. ALGORITHM:

Lung Segmentation algorithm developed in the present work accepts 267 Images of lung CT scan and their corresponding masks. The dimension of each image is 128x128. The images are of gray scale resolution. The output is the segmented lung region image. The process begins by loading the dataset into memory followed by rescaling each image size to 32x32 dimensions. The image rescaling is necessary to allow faster processing of images. Normalization of images follows rescaling operation. Then the dataset is split into training and test set in the percentage of 70% and 30%. Training samples are augmented using rotation operation. Each training sample is augmented with 8 different rotated versions.

Algorithm 1 Algorithm for Lung Segmentation.

Input: LungCT Scans, Lung Masks
Output: Segmented Lung Fields
1: INITIALIZATION:
Learning rate=0.8 Dropout=0.5 Optimizer=Adam Loss=Crossentropy Epochs=10
Steps per epoch=200
2: Rescale and Normalize input images
3: Define input, convolutional, pool layers
4: Specify upsampling and concatenation layers
5: Create and Compile the model
6: Train the model

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7: Evaluate and visualize the training results
8: Test the model and visualize the results

The U-Net ConvNet is created from different blocks of layers in contracting and expanding path. Initially input layer is defined with the augmented dataset. Subsequently the convolutional, non-linearity and down sampling layers are defined. Each operation on convolution is to apply the filter on the image followed by non-linearity and then max-pooling that reduces the size of the image. Next the concatenation of corresponding layers in contracting and expanding paths is performed followed by up sampling operation which results in increasing the image size. The output layer generates the image with segmented lung region.

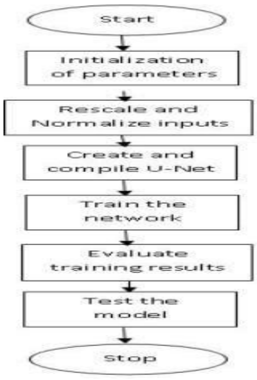


Fig. 3: Flowchart depicting the process of lung segmentation.

E. DATA TRAINING:

In typical machine learning and Deep Learning approaches, the dataset is divided into three parts, namely training/validation/testing sets. The testing set is also called the hold-out set, which is set aside during the training process and is only used for reporting final results.

The available data are divided into k-folds. One of the folds is then treated as the validation set and the remaining folds combined into the training set. This process is repeated several times using each fold as the validation set and other remaining sets as the training set.

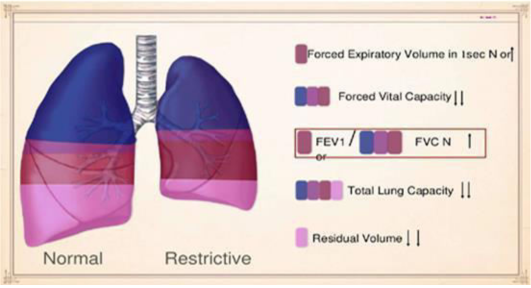
We trained 5 models by combining 4 of the 5 folds into a training set and keeping the remaining fold of 6 or 8 patients as a validation fold. Since all considered network models are 2D models, we extracted individual slices from each study in the training fold and used these individual slices as input to our models.

Data augmentation is a common strategy used to train neural network models, which helps to reduce overfitting, especially in case of limited training data. In total, we used 6 different types of data augmentation techniques. During the training process, we allowed each network to train for a maximum of 100 epochs.

F. DATA ANALYSIS:

To assess the performance of automatic segmentation, for each clinical case, we computed a set of performance indicators routinely used in literature for shape comparison, Sensitivity, positive predictive value (PPV), dice similarity coefficient (DSC), volume overlap error (VOE), volumetric difference (VD), and average symmetric surface distance (ASSD) were calculated as mean, standard variation (std), and confidence interval (CI). Analysis of variance (ANOVA) on the DSC was used to assess statistical differences among network.

IV. LUNG DISEASES



1. *Fig 4: Restrictive lung disease*

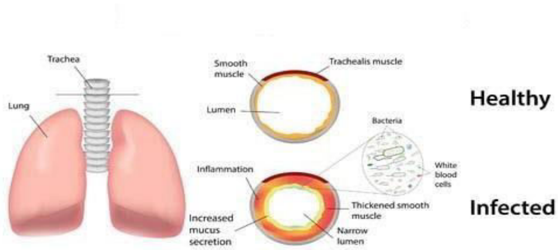


Fig 5: Respiratory tract infections

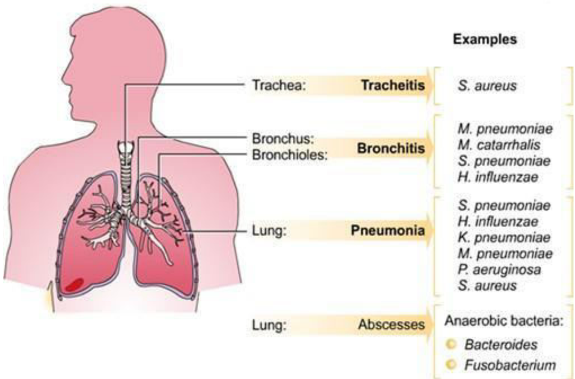


Fig 6: Lower Respiratory tract Infection

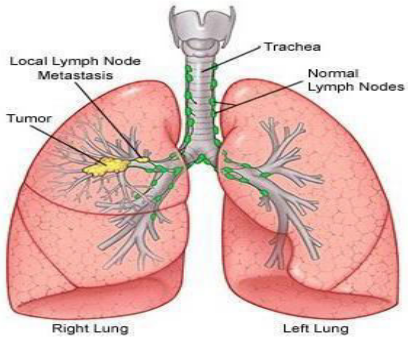


Fig 7: Tumour in lungs

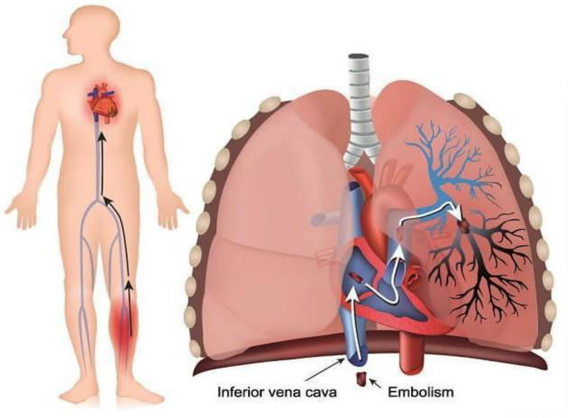


Fig 8: Pulmonary vascular disease

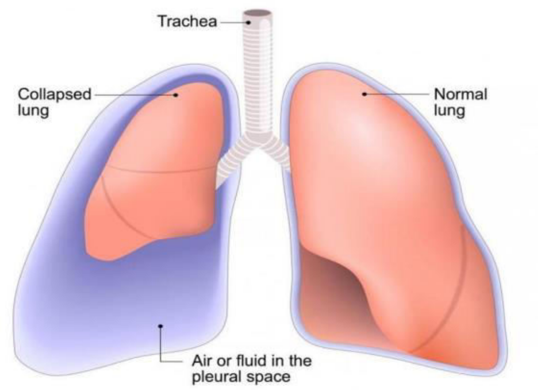


Fig 9: Pleural cavity disease

V. RESULTS

We applied Deep Learning methods to obtain the contour of the parenchyma region. Examples of obtained lung segmentations are shown in Figure. Additionally, 3D reconstructions of lungs produced using our in-house processing tool developed in MATLAB® R2016a (The MathWorks, Natick, MA, USA) are shown in Figure.

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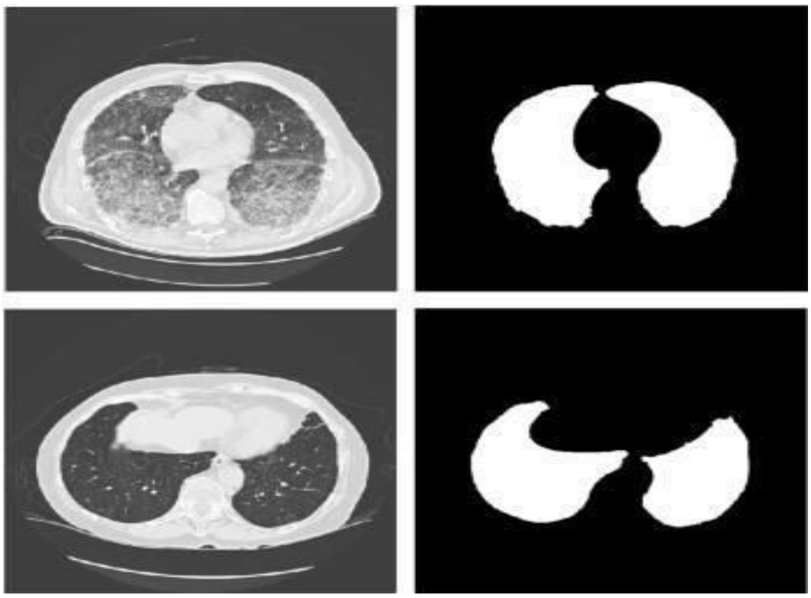

Fig 10: The Lung region segmentation using U-Net.

Performance results for the testing dataset (10 patient studies) obtained as the average of the results computed from U-Net and using the region growing algorithm.

10 Testing Dataset (10's Patient Studies)						
	U-Net			Region-Growing		
Parameter	**Mean**	$\pm std$	$\pm CI(95\%)$	**Mean**	$\pm std$	$\pm CI(95\%)$
Sensitivity	96.45%	4.24%	2.66%	97.48%	11.15%	2.37%
Accuracy	98.42%	1.86%	1.16%	85.91%	8.32%	2.23%
Specificity	96.34%	3.30%	2.14%	88.15%	11.53%	2.57%
Precision	97.73%	4.42%	2.78%	87.85%	14.40%	3.34%
DSC	95.72%	2.33%	1.97%	89.43%	12.34%	3.52%

VI. CONCLUSION

This research is focused on creating a system that can help radiologists to extract the parenchyma from HRCT images of patients with lung diseases, we demonstrated the feasibility and efficacy of two different DL approaches using

i. The Tversky loss function into the training process,
ii. A suitable data augmentation technique,
iii. The k-fold strategy.

Both Deep Learning models highlighted good segmentation accuracy with a DSC of about 96%, with differences related to the training time and data requirements; U-Net, which has been. Furthermore, we are interested in experimenting by applying several domain and application specific pre-processing and post-processing schemes to our model.

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