Automatic Lung Segmentation on Thoracic CT Scans using U-Net Convolutional Network

Humera Shaziya, K. Shyamala and Raniah Zaheer

***Abstract*—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. Developing computer aided diagnosis (CADx) systems for lung cancer is a challenging task. Several components make up CADx and one of the most significant components is lung segmentation. Segmentation of lungs is an essential prerequisite to efficiently detect and classify lung nodules. Lung segmentation is the process of segregating lungs region from other tissues in the CT image. Conventional methods for lung segmentation either do not accurately segments normal and abnormal lungs or rely heavily on user generated features for the lungs. Deep learning has outperformed other methods in image processing and computer vision tasks. An architecture called U-Net convolutional network has been proposed and implemented exclusively for the segmentation of biomedical images. 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. Hence U-Net ConvNet can be used for the segmentation of lungs in CT scans.**

***Index Terms*—U-Net Convolutional Networks (ConvNet), Deep Learning, Lung Cancer, Automatic Lung Segmentation.**

I. INTRODUCTION

Globally, lung cancer is the leading cause of cancer mortalities. There were 1.69 million deaths in 2015 due to lung cancer [1]. Early detection of lung cancer increases the survival rate, but is like searching for needle in the haystack. Abnormal small, round or oval shaped growth in the lung called lung nodules may be the first sign of lung cancer and detection of those is very exhaustive given the complex structure of lungs. Computed Tomography (CT) is an important diagnostic modality to detect lung nodules. 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. There are several computer aided diagnosis (CAD) systems developed over the years to assist in the diagnosis of lung cancer. CAD system components include lung segmentation, nodule detection and segmentation, false nodule reduction, nodule classification. Each component is complicated in its own way. The significance of segmentation of the lungs from chest CT scans has been elaborated in [2]. Lung segmentation is a prerequisite for the subsequent automated analysis of lung nodules since it allows for the estimation of lung volumes and detection and quantification of abnormalities within the lungs. In case of erroneous lung segmentation, findings might be missed or findings outside the lungs might be included in the analysis. The importance of accurate lung segmentation for the automated detection of nodules is illustrated in [3]. Their experiments have showed that accuracy of nodule detection has increased when lung segmentation has been applied. A naive lung segmentation algorithm was applied to 60 scan, 17% of nodules were not detected as a consequence of improper lung segmentation. Another lung segmentation algorithm improved the results and only 5% of nodules were not detected. The task of lung segmentation is challenging because of the complexity in the lung region and the existence of similar density structures, such as arteries, veins, bronchi and bronchioles, and the use of different scanning devices with different scanning protocols [4]. In general, the existing techniques for lung segmentation can be classified into different categories based on threshold [5], region [6], boundary [7], shape [8], edge [9], and machine learning techniques [10].

Convolutional Neural Networks (CNNs) or ConvNets have showed remarkable results in image recognition and classification tasks. The performance of ConvNets largely depends on the size of the dataset. ConvNets results are more accurate when it is trained with huge data. Biomedical data does not exist in enormous quantity, it is limited. A relatively new architecture of ConvNet called U-Net convolutional network is designed exclusively for biomedical image analysis. The objective of this work is to apply U-Net to extract lung fields from the CT scans.Essentially U-Net is a kind of ConvNet combined with data augmentation techniques to increase the amount of medical data.

The paper is organized as follows: Section II presents related work on lung segmentation. Section III elaborates the methodology of the present work with the details of model architecture, model configuration and proposed algorithm. Section IV discusses environment, data, augmentation methods and the results. Section V concludes the paper and provides future directions.

II. RELATED WORK

Automatic lung segmentation is a challenging task due to inhomogeneity of lungs region. Rigorous amount of research

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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 images. 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. Enormous number of research papers have developed thresholding methods with many variations. A paper [11] has developed thresholding based lung segmentation algorithm, which consists of three steps. First step is to extract the lung region using gray-level thresholding. Next is to separate the lung lobes using dynamic programming. The last step is to perform post-processing by applying morphological operations to smooth the irregular boundaries. Next are the group of algorithms based on region methods. Region growing, region splitting and merging are the examples of region based segmentation. The authors in paper [6] implement region growing that begins with a position in the image known as seed point which is provided by the user. The method progresses developing distinct regions that satisfy the condition of seed point. The process then followed by the connected component analysis.

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 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. The data augmentation techniques employed are shift and rotation. 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 international 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 upwards 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 consists of two convolutional layers, followed by relu activation function then max pooling with a size of 2x2. The contracting path is identical to typical ConvNet. The expansive path is composed of 3 blocks. Two blocks contain convolutional layer, concatenation layer and upsampling layer each. The last block contains three convolutional layers, concatenation, upsampling layers followed by two convolutional layers, a dropout layer and an output layer. The expansive path is unique to U-Net ConvNet. Its purpose is to perform concatenation of corresponding layers in contracting and expansive paths. To increase the image size using upsampling operation. 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.

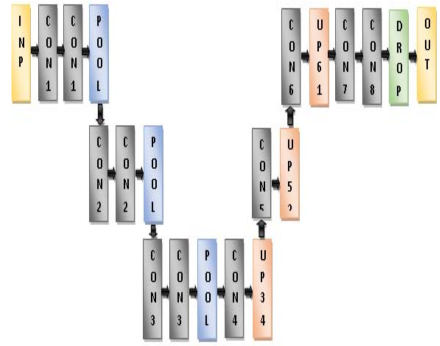


Fig. 1: U-Net ConvNet for Lung Segmentation.

B. U-Net Configuration

Table 1 presents the configuration of the U-Net ConvNet. There are five columns in the table. First column is the name of the layer, second gives the number of filters, third denotes the filter/pool size, next indicate the dimension and the last shows the layers that are concatenated together. 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. Upsampling 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.

C. 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

TABLE I: U-Net ConvNet Configuration

Layer	Fil	F/P size	Dim	Concat
Input	-	-	32x32	-
Con1	8	3x3	32x32	Input
Con1	8	3x3	32x32	Con1
Pool1	-	2x2	16x16	Con1
Con2	16	3x3	16x16	Pool1
Con2	16	3x3	16x16	Con2
Pool2	-	2x2	8x8	Con2
Con3	32	3x3	8x8	Pool2
Con3	32	3x3	8x8	Con3
Pool3	-	2x2	4x4	Con3
Con4	32	1x1	4x4	Pool3
Up1	-	2x2	8x8	Con4 n Con3
Con5	32	2x2	8x8	Up1
Up2	-	2x2	16x16	Con5 n Con2
Con6	32	2x2	16x16	Up2
Up3	-	2x2	32x32	Con6 n Con1
Con7	16	2x2	32x32	Up3
Con8	64	1x1	32x32	Con7
Drop	-	0.5	-	Con8
Out	1	1x1	32x32	Drop

of itself. 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 downsampling 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 upsampling operation which results in increasing the image size. The output layer generates the image with segmented lung region. The U-Net ConvNet is created with the all the layers defined and finally trained. Numerous parameters of the model are specified such as dropout as 0.5, learning rate as 0.8, optimizer as adam, loss function as crossentropy, evaluation metrics as accuracy, epochs as 10, number of steps per epoch as 200. Filters are used in varying number in each layer described in detail in the model architecture section. The trained U-Net ConvNet is tested with the test data and the result is visualized. Algorithm 1 lists out the steps performed to segment the lung region in CT image. Figure 2 is the flowchart showing the process of lung segmentation.

IV. RESULTS

A. Environment

The model has been developed on windows 10 using python 3.6, keras 2.0, tensorflow-GPU 1.2, anaconda 3-4. CUDA 8.0 and cuDNN 6.0 are also installed for tensorflow-GPU

Dataset includes 267 lung images and their corresponding masks [13]. It has been divided up into training and testing set of 70% and 30%. The images are of gray scale. The size of each image is 128x128. The preprocessing reduces the dimensions of the images to 32x32. 128x128 dimensions has been resized to 32x32 to ease the training on low-compute devices. Each image is normalized. Figure 3 shows one CT sample image on the left side and its corresponding segmentation map with the ground truth on the right side.

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

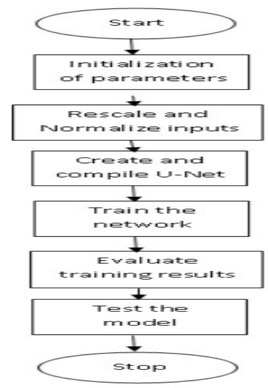


Fig. 2: Flowchart depicting the process of lung segmentation.

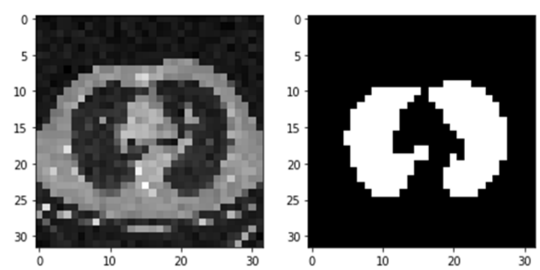


Fig. 3: Left: CT image of lung. Right: CT image Mask.

B. Data Augmentation

Various methods of data augmentation are: rotation, shift, flipping, zoom, cropping. In this paper rotation operation is applied to the CT image to augment the number of CT images. Figure 4 shows eight different versions of a lung CT image obtained using rotation operation.

Figure 5(a) shows the training accuracy and validation accuracy. X-axis denote the no of epochs and y-axis specify the accuracy achieved for the epoch number. The accuracy obtained for the training set is 0.9678 and the validation

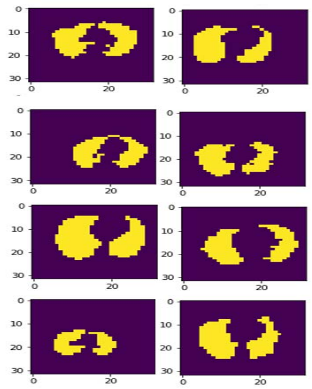
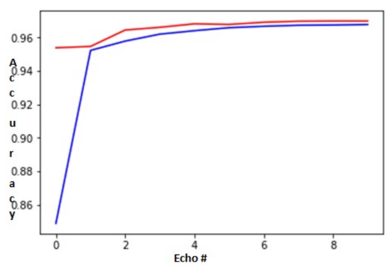
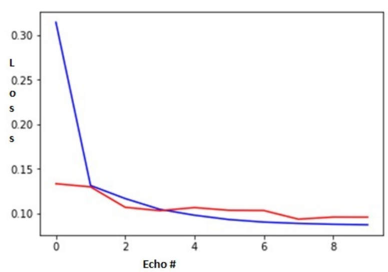


Fig. 4: Data Augmentation using Rotation Method.



(a) Plot for training accuracy



(b) Plot for training loss

Fig. 5: Training Accuracy and loss.

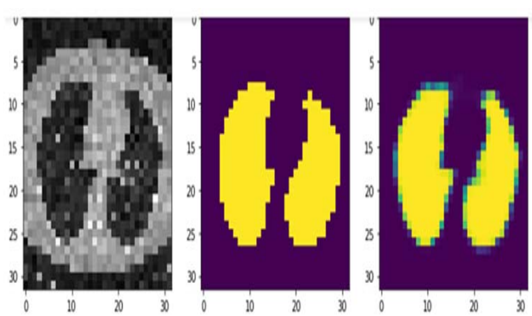


Fig. 6: Left: CT image Middle: Ground Truth Right: Segmented lung.

accuracy is 0.9698. figure 5(b) presents the training and validation loss. X-axis indicate the no of epochs and y-axis denote the crossentropy loss for different epochs. The training loss is 0.0871 and the loss of validation is 0.0959. Figure 6 contains three images. Left image is the CT image that includes lungs and others adjacent objects. Middle one is the segmentation map of the ground truth of the CT image. Right side is the output of the U-Net ConvNet that yields the segmented lung region from the CT image. It is observed that the model's result is close to the ground truth with an accuracy of 96.78%.

V. Conclusion and Future Work

The lung segmentation step is a prerequisite for any automated analysis of lung CT image to detect and diagnose lung disease. Several papers on lung segmentation have been published with a focus on improving the accuracy of the segmenting task. Basic methods such as thresholding and the more advanced deep learning methods have been applied for lung segmentation task. U-Net ConvNet has performed exceptionally good on the segmentation of cell and neurons in electron microscopic images. In the present study, U-Net ConvNet is developed to be used to segment lung regions. The accuracy obtained for lung segmentation using U-Net is 0.9678. U-Net originally developed for segmenting microscopic images have been successfully applied to lung segmentation on CT images. The work has performed rescaling of images to reduce dimensions of images from 128x128 to 32x32. The network consists of total 11 convolutional layers. Further the accuracy can be increased by training the U-Net using the original image dimensions of 128x128. The number of convolutional layers and the size of filter can also be increased to improve accuracy.

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