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Automatic Image Segmentation for Lung using Deep Learning and Convolutional Neural Network

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***Abstract*— With advance in technology, rapidly growing medical treatment and healthcare which can cure or pre-detect the diagnosis. Lung segmentation (LS) is prerequisite step for lung image analysis to provide accurate lung image. Doctors usually detect diagnosis by checking X-ray which is very time consuming and tedious. Here, we demonstrate LS in using CXR images and evaluate which contents of the image influenced the most. Semantic segmentation (SS) was performed using a U-Net CNN architecture, and the classification using three CNN architectures. Segmentation with deep learning (DL) is having very similar accuracy as detecting diagnosis by doctors. Here, we demonstrate LS by using chest X-ray and segmentation was performed using U-net architecture. In this project we have connected this model which can easily separating Lung. The paper is detailed analysis and discussion of U-Net results and implementation of U-Net in LS using X-ray.**

***Keywords*—Lung Segmentation, Semantic Segmentation (SS); U-net; CNN Architectures; Deep Learning (DL); API; Android Application**

I. Introduction

Medical Image Segmentation is known to beone of complicated problems in image processing and image analysis field [1]. Incorrect detection of objects' borders affects all the subsequent steps severely, so segmentation of target image objects comes before other image analysis stages. This paper deals with chest X-ray images which are training datasets for model.

Chest X-rays produce images of your heart, lungs, blood vessels, airways and the bones of your chest and spine. Chest X-rays can also reveal fluid in or around your lungs or air surrounding a lung.The image helps your doctor determine whether you have heart problems, a collapsed lung, pneumonia, broken ribs, emphysema, cancer or any of several other conditions. In this case of lung segmentation, the results of fully automatic extraction of lung region remains unsatisfactory in many cases. The problem of an automatic and accurate segmentation worsened even further in the scenario of massive screening of population [2] where it moves into the Big Data domain [3].

A. Background

Lower-middle and low-income countries face a scarcity of trained radiologists, especially in the country's rural areas. In these types of outlooks, large-scale screening of analyzing CXR images can be done using a computer-aided diagnosis (CAD) system. Recent advancements in GPUs and computer vision and the availability of large-currently being utilized to detect sickness early on. In [4], designing a lung carcinoma screening tool based on DL structures was carried out to reduce the false-positive rate in low-dose CT scan lung carcinoma screening.

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Moreover, in [5], existing deep neural network frameworks were compared for breast cancer image segmentation, and a new framework was also introduced. The liver, brain, kidneys, bones, tissues, and other biological parts were subjected to picture segmentation algorithms. In [6], researchers implemented a so-called fully connected convolutional layer, and in [7], they extended the architecture of FCCNs to the next level. Solutions based on ML and DL have been suggested for many medical applications, especially in diagnosing a brain tumor, lung nodules, pneumonia, breast cancer, etc. DL encourages image classification and segmentation results, hence widely adopted by the research community. The concept of using DL and ML to evaluate lung segmentation in identifying pneumonia caused by different microorganisms using CXR images obtained from various sources.

B. Our works

We put forward concept of CNN for lung segmentation from chest X-ray pictures in this research study. UNet is the architecture that we presented. We inspected these designs and attempted to uncover the best solutions for chest X-ray image segmentation using GPU training. This proposed Unet model takes advantage of the INPUT given is always greater than OUTPUT generated because no padding was present in every convolution layer.
The rest of the paper is organized as follows: Literature review,Methodology, Results, Discussion, Conclusion, References.

II. LITERATURE REVIEW

The automatic Lung Segmentation is difficult because of the lung size and area. In additionally, lung's X-ray has soft tissues and bones which also affect the segmentation and this is a major issue in lung segmentation. Many researchers have presented a variety of methods for lung parenchyma segmentation [8].k
Rehman et al. [11] generated lung segments from X-ray images using U-Net with mean_iou of 92.82 and they performed classification using pre-trained models like ResNet, Vgg-16, and Vgg-19 on segmented images with a test accuracy of 98.14%. Shaoyong Guo et al. The threshold iteration method is preferred for lung parenchyma segmentation to avoid problems due to juxtapleural nodules (Xiao 2018) [9]. Amanda and Widita compared three threshold-based methods of lung segmentation using InsightToolkit-4.7.0 (ITK) in which connected threshold method outperformed compared to the neighborhood connected and level set method (Amanda and Widita, 2016) [10]. Chen Zhou et al. [12] developed an automatic segmentation model by integrating (3D) V-Net and spatial transform network (STN) to segment pulmonary parenchyma in CT images and analyze texture and features from the segmented pulmonary parenchyma regions to assist the radiologist in COVID-19 diagnosis. Four different CNN models (Vgg-
16, Vgg-19, ResNet-50, and GoogLeNet) were explored, and the results generated by these models were analyzed (Yaakob et al. [13]).
Based on the above literature review, it is found that plenty of architecture used ML and traditional DL architecture to detect lungs diseases and achieved accuracy up to 90% and more. In medical applications, robust and flexible algorithms or methods can increase the accuracy of the CAD system to diagnose TB from chest X-ray images and make the system reliable [14].

III. METHODOLOGY

This section contains comprehensive information about the dataset, preprocessing techniques, algorithm and U-net segmentation models. In this research paper, we explored u-net model in segmentation field of limited lung CXR images of medical field. The attention net has an additional mechanism that adds more parameters to the model, resulting in increased training time [14]. This model requires powerful Graphical Processing Units (GPUs) to train. These are some facts for using a U-net models.

A. Datasets Description

Datasets consists of collected from publicly available chest X-Ray (CXR) images. The datasets consisted of 800 X-ray chest images meanwhile only 704 images are labeled. Whole dataset was randomly divided into train (0.8 of total) validation (0.1 splited from train) and test parts. Our main task is to implement pixel wise segmentation on this particular data to detect lung area [19].

B. Preprocessing Techniques

All the images in the dataset are in different shapes, so it will throw an error while passing the images through the CNN architecture. We made all the photos into (256 and 256) forms to solve this problem. Because all these photographs were in RGB format, we converted them into gray scale to save time. It implies that the we modified the shape of the photographs from (256 × 256 × 3) to (256 × 256 × 1).

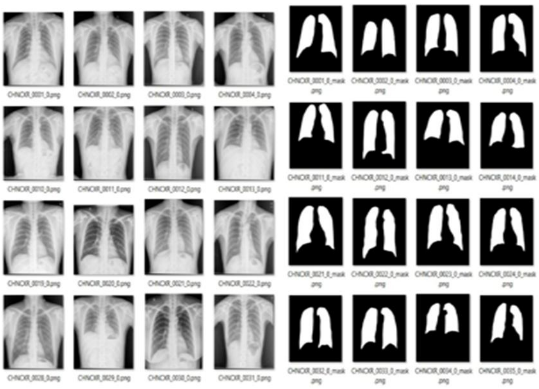


Figure 1. Chest X-ray (CXR) & their labeled images[19]

C. Unet

There are various segmentation models available for medical image processing such as DeepLab v1, ResUNet, UNet, UNet++, V-Net, SegNet, etc. In this research paper, we chose Unet algorithm, which show highly accurate result in a wide area of biomedical images.

The UNet architecture is based on the fully convolutional network and aims to improve medical imaging segmentation outcomes. It is in the shape of a U. There are two pathways in the UNet: one for encoding and one for decoding [15], both of which are remarkably similar. They obtain the same shape in the UNet as the output that we entered as the input. There are three indispensable structures in UNet: (1) scale down, (2) bottleneck, and (3) scale up. In auto encoders, the neural network's encoder squeezes the input into a latent space representation, and the decoder derives the output from the squeezed or encoded representation. However, unlike traditional encoder–decoder arrangements, the two portions are not dissociated in this case. Skip connections are accustomed to moving fine-grained data from low-level analysis paths to a synthesis path's high-level layers. This information is needed to create correct fine-grained reconstructions.

Figure 2 shows the architecture of UNet. In this architecture, we have implemented two convolutional layers of kernel_size = (3 × 3) followed by a MaxPool layer of size (2 × 2) for the contraction until they obtain the image's form (32 × 32). After that, they started up sampling the image to transpose the layer and concatenate the transpose layer and the corresponding feature map. In addition, for the output, we used (1 × 1) as the kernel_size of the convolutional layer. Because the activation function of the final network layer is sigmoid, the network training procedure employs the cross-entropy cost function [16].

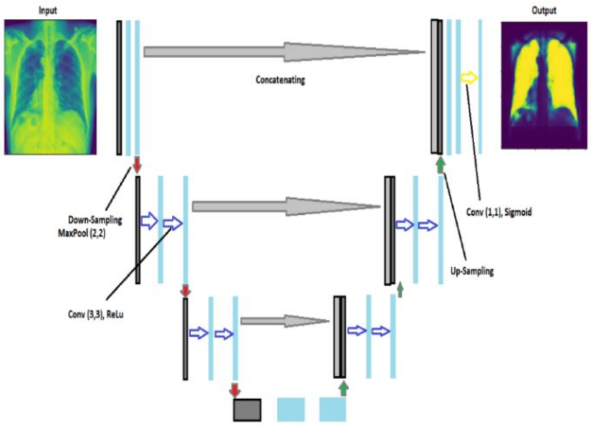


Figure 2. Unet Model Architecture[21]

IV. Results And Analysis

In this research paper, we chose Unet algorithm. We have tried different sets of hyper parameters (i.e., learning rate, number of epochs, optimizer, batch size) to optimize Unet architectures. Our experiment was based on pytorch which is written in python and runs seamlessly on CPU and GP0U. Thus, our network was trained on a google colab GPU. Hence, we run our code on a GPU in order to greatly accelerate the execution. The network parameters were set to:

- Batch size: 04
- Number of epochs: 100

In order to evaluate the performance of our network, we use the dice coefficient index as a similarity metrics considering that it is currently the most popular similarity measurement which is calculated with this formula:

```
def dice(y_true, y_pred):
    """ Dice a.k.a f1 score for batch of images
    """
    num = y_true.size(0)
    eps = 1e-7

    y_true_flat = y_true.view(num, -1)
    y_pred_flat = y_pred.view(num, -1)
    intersection = (y_true_flat * y_pred_flat).sum(1)

    score =  (2 * intersection) / (y_true_flat.sum(1) + y_pred_flat.sum(1) + eps)
    score = score.sum() / num
    return score
```

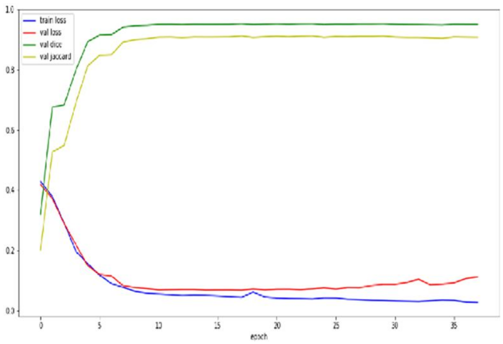
Figure 3. Dice Formula[20]

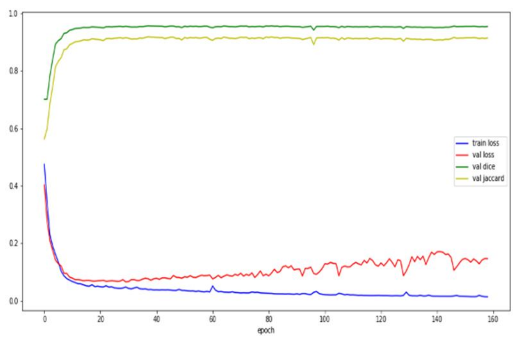
We use Jaccard which also known as the **Jaccard similarity coefficient**, is a statistic used forgauging the similarity and diversity of sample sets. And this is calculated with this formula:

```
def jaccard(y_true, y_pred):
    """ Jaccard a.k.a IoU score for batch of images
    """
    num = y_true.size(0)
    eps = 1e-7

    y_true_flat = y_true.view(num, -1)
    y_pred_flat = y_pred.view(num, -1)
    intersection = (y_true_flat * y_pred_flat).sum(1)
    union = ((y_true_flat + y_pred_flat) > 0.0).float().sum(1)

    score = (intersection) / (union + eps)
    score = score.sum() / num
    return score
```

Figure 4. Jaccard Formula[20]

Now in our trained model, we measured loss for training and validation. Loss adequately predicts how well the model performs and forecasts the model error. In below image shows difference of training and validation losses at different epochs.





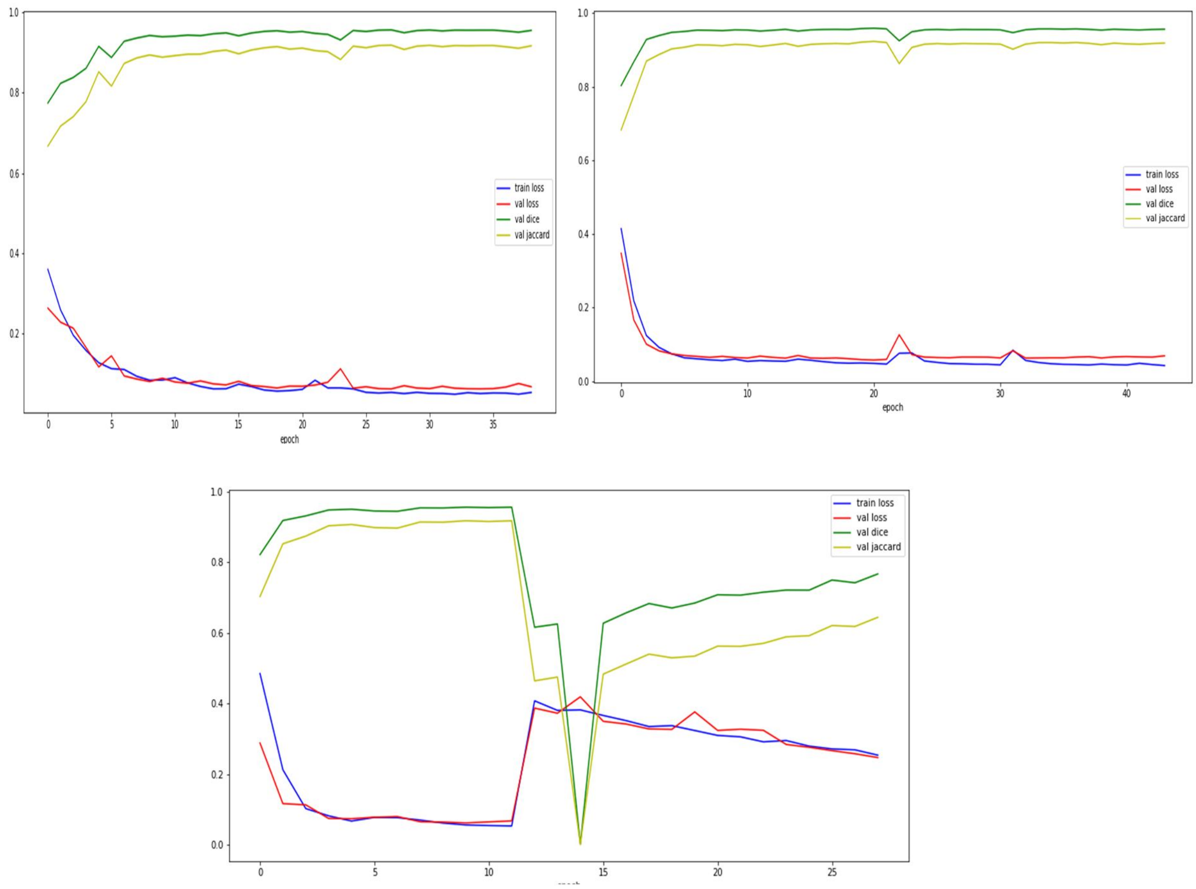


Figure 5.Graphical comparison of training and validation [20]

V. DISCUSSION

In this study, we present a new method for rapid and automated lung segmentation from mouse CT scans, based on a U-Net CNN. On two test datasets, the model achieved high precision. These results indicate that the CNN segmentations and reference lung masks were almost perfectly overlapping, and that there were no substantial shape mismatches. The trained CNN enabled fully automatic and accurate segmentation in lung images. The Sørensen-Dice similarity coefficient, the Hausdorff distance as well as the strong correlation between manually and automatically derived lung volumes suggest an overall very good performance of the new approach with no significant drawbacks with respect to the cumbersome manual processing applied so far [17].

We summarized the previous studies of scholars and found that their work needs to be supplemented by later scholars. Most scholars are used datasets, which do not contain lung segmentation in complex cases (severe pneumonia, foreign body shielding, lung deformation, etc.) Of course, some scholars try to label the NIH Chest X-ray dataset for lung segmentation22. But they do not verify the segmentation performance of the model on the benchmark dataset and do not summarize the segmentation scores of different CXR images. Our work complements these defects. In this study, we evaluated the efficacy of our model for lung segmentation on the complex datasets. Five segmentation performance indexes: Accuracy, Sensitivity, Specificity, Dice coefficient, and Jaccard index, are used to evaluate the model. We achieved excellent lung segmentation results. The segmentation score shows the reliability of our segmentation model. It is found that the transparency of the lung region, whether there is occlusion, and the shape of the lung will affect the results of lung segmentation to varying degrees.

In addition, the automatic lung segmentation model is poor in dealing with severe lung deformation caused by congenital or acquired factors. Singh et al.[18] recently published their lung segmentation study. Their scores far exceed those of previous scholars. But their data is absurd. Generally speaking, the Jaccard index is smaller than the Dice coefficient. But their result is just the opposite, which is very suspicious. So, we didn't compare their experimental data.

VI. CONCLUSION

In conclusion, we evaluated an automatically lung segmentation using U-net model. In general, Lung segmentation is one of the major pre-processing techniques in the lung cancer or lung nodule detection methodology. The accuracy of the lung disease detection also depends upon the faithful segmentation of lung. Segmentation divides the image into multiple sets of pixels and focuses on the essential features of images. It helps doctors to concentrate on the infected region of the body part. Using the segmentation algorithm in the image segmentation will increase the accuracy of the model, and it will try to focus on the specific region.

According to a comprehensive assessment utilizing various datasets, the Unet architectures in delivering semantically correct predictions. The proposed method for accomplishing the generalizability aim architecture might serve as a good starting point for additional research. Toward developing a therapeutically effective technique, our model might benefit from post processing approaches to improve segmentation results even further.

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