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Deep Residual U-Net Based Lung Image Segmentation for Lung Disease Detection

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Abstract. The World Health Organization (WHO) estimated that by the year 2030, lung disorders such as Chronic Obstructive Pulmonary Disease (COPD) would be one of the leading cause of death all over the world. Consequently, accurate and timely detection of lung diseases may prevent further death. It is therefore vital that the early detection may lead to treatment and prevention of mortality among patients. However, there are only a minimum number of experts or well-trained radiologists reading Chest X-Ray (CXR) that delays the timely diagnosis of lung diseases. In order to aid the radiologist in reading CXR images, a computer-aided tool is proposed. Before the processing of images, it needs to be segmented to make it easier for the machine to understand. This study is focused on developing a model that will segment the lung from CXR images. Using Residual U-Net (ResUnet) architecture based semantic segmentation, the researchers were able to develop and train a model using a set of 562 CXR images and lung mask images, 70% of the images were used as training data and 30% as test data. The model was trained with 40 epochs and a batch size of 16. Dice coefficient was used to assess the similarity of the segmented result and the ground truth mask. The developed model has achieved a Dice coefficient of 0.9860. The developed model can then be used in classifying lung diseases by focusing on the segmented image rather than focusing on the entire CXR image.

1. Introduction

Lung diseases are disorders affecting the lungs which include asthma, chronic obstructive pulmonary disease (COPD), tuberculosis, influenza, lung cancer, pneumonia and other breathing problems. Worldwide population are affected by huge number of related lung diseases[1] and respiratory tract infections are the top cause of death and disability[2]. World health organization (WHO) estimates that by 2030, lung diseases such as COPD will be one of the top causes of mortality. To prevent further death, accurate and timely diagnosis of pulmonary disease is needed [1]. Hence, to treat the disease, it is essential that at its early stage the disease is detected[3]. Often, chest X-Ray is the first procedure patients undergo if doctors suspect lung disease. This is due to the fact that it is economical, an effective diagnostic tool and because of its noninvasive characteristics in showing pathological modifications. Chest X-Ray(CXR) gives an overall orientation as an underlying symptomatic examination and is particularly valuable in the conclusion of pneumonia, malignant growth and COPD [4]. By analyzing CXR image, radiologists can diagnose many lung related diseases[5]. Skilled

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radiologists use CXR to recognize diseases, for example tuberculosis, pneumonia, interstitial lung malady, and cancer [6].

Classifying CXR irregularities is considered as a dreary task for radiologists[5]. Many studies have been conducted in the domain of Artificial Intelligence to aid radiologists in reading CXR Images. In the study conducted by Ramalho et. al, a new approach was proposed for classification of lung illnesses. CXR images were segmented using Adaptive Crisp Active Contours Models(ACACM) and a novel method for lung illness identification using feature extraction for segmented lung structure[1]. In the study of Abiyev and Ma'aitah, they demonstrated that classifying chest pathologies in CXR utilizing conventional and deep learning strategy is viable. The researchers presented Convolutional neural networks (CNN) in diagnosing chest illnesses[5]. Another study conducted by Kumar et. al, focuses on finding nodules, early symptoms of cancer diseases, appearing in patient's lungs. The researchers utilized an altered watershed segmentation strategy to segregate the lung in an x-ray image[7].

For better classification of lung diseases, CXR images must be first segmented. The area of interest must be first separated from the entire image. Through segmentation, it aims to divide the image in a series of region based on the characteristics of the image that are almost constant in each of the region[8]. Lung segmentation is an important step in developing a Computer-aided Diagnosis (CAD) system for the diagnosis of lung illnesses in radiographs[9]. The purpose of image segmentation is to extract the area or region of interest (ROI) in an image may it be automated or semi-automated procedure. Its goal in medical field is to extricate quantitative facts like morphometric data with regard to an organ of interest. There are two related tasks to be considered in segmentation problem, one is object recognition and the second is delineation. In the first task, the location of the object on the image is determined. The object's composition is drawn in the object delineation task[10].

Many research works have been undertaken on the use of image segmentation especially in the medical field. Norouzi et al. made a comparison of the different algorithm used in medical image segmentation. In their study, they categorized image segmentation into four: clustering method, region-based method, classifier method, and hybrid method. The pros and cons of each method were discussed. Each algorithm of the four methods was discussed for the examination of grey-level images. It was further stressed that image segmentation procedures can be chosen based on different parameters[11]. In the study of Christ et. al., cascading fully convolutional neural networks (CFCNs) and dense 3D conditional random fields (CRFs) were used in automatically segmenting liver in CT images. In their study, a 2-fold cross-validation on 3DIRCAD was used in training CFCN models. Based on their findings, CFCN-based semantic liver segmentation attained a dice score of more than 94% for liver with calculation under 100 s per volume[12].

Deep learning is also gaining popularity in image segmentation. It has been the primary option for images segmentation, medical image segmentation in particular. Deep learning-based image segmentation has been set up as a vigorous instrument in image segmentation and has been generally used to isolate homogeneous areas as the first and basic part of diagnosis and treatment pipeline[13]. Alom et. al. proposed models for medical image segmentation: A Recurrent Convolutional Neural Network (RCNN) and Recurrent Residual Convolutional Neural Network (RRCNN), both are based on U-Net architecture. The proposed models were tried on three different standard datasets. Compared to other models, the outcomes show predominant performance on segmentation tasks [14]. In the study of Vesal, Ravikumar and Maier, they proposed a deep learning framework to segment organs-at-risk (OAR) in thoracic CT images, explicitly for the trachea, heart, aorta and esophagus. They employed in the bottleneck of U-net network an expanded convolutions and collected residual connections. The model attained a final Dice score of 91.57% on 20 not yet seen samples[15]. Numerous researches have also been conducted in segmenting the lungs from CXR images like the study conducted by Kalinovsky and Kovalev, which presented the result of the first exploratory stage of research and development on segmentation of lungs in X-rays using deep learning methods and encoder-decoder convolutional neural network(EDCNN). The result obtained in this study concludes that EDCNN networks may be considered as an encouraging tool for lung segmentation in large-scale projects[16].

IOP Conf. Series: Materials Science and Engineering **803** (2020) 012004 doi:10.1088/1757-899X/803/1/012004

In the study of Heo et. al, U-Net was utilized to segment the lung from CXR. The segmented images were then used for the detection of tuberculosis. In training the U-Net, the researchers used 140 images with lung mask. The trained U-Net attained a mean Dice Coefficient of .9621 for 60 validation sets[17]. Considering the very small number of images in training the U-Net model, it was able to achieve high result. If the number of images can still be increased, the accuracy may still be improved.

This prompted the researchers to conduct a study that will create a model for lung segmentation based on Deep Residual U-net architecture to be used for lung disease detection. Specifically, the study aims to:

a. identify CXR images and its equivalent lung mask to be used in training the model.

b. Develop a model based on Deep Residual U-Net Architecture to segment the lungs from CXR image for lung disease detection.

2. Methodology

2.1. Data Collection

The dataset used in training the model was downloaded from the National Institute of Health(NIH) particularly Shenzhen hospital X-ray set. The dataset was collected by Shenzhen hospital in Shenzhen, Guangdong province, China. It contains a mixture of normal and abnormal x-rays. Another dataset was obtained from Kaggle, a manually segmented lung masks dataset for Shenzhen X-ray set which were manually created by teachers and students of Computer Engineering Department of National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute".

2.2. Deep Residual U-Net Architecture

In developing the model for lung image segmentation, the researcher utilized a deep learning technique U-Net with residual connections. U-Net Architecture was created for Bio-Medical Image Segmentation by Olaf Ronneberger et. al.[18]. U-Net can still be enhanced through residual unit instead of plain unit. Through residual connection, it will maximize the performance and the capability of the network to learn. Figure 1 shows the structure of the deep residual U-net (ResUnet) Architecture. ResUnet combines both the strength of U-Net and residual neural network. The residual

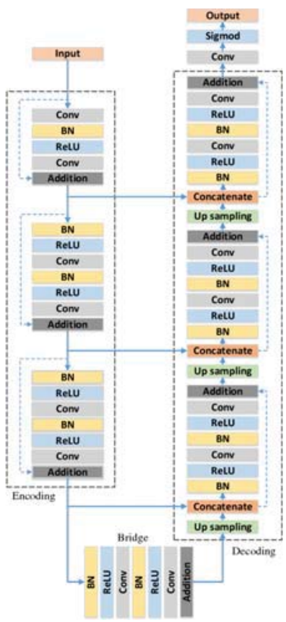

Figure 1. Deep Residual U-Net Architecture

will allow easier network training and the skip connection in the residual unit will make the propagation of information easier without degradation. ResUnet is comprised of 3 main parts, the encoding, bridge and decoding. In the encoding part, the image which serves as an input is encoded into a denser representation. The decoding part on the other hand, recovers the depictions to a pixel-wise categorization. The bridge joins the encoding and decoding paths. These parts are created with residual units consisting of two convolution blocks with a size of 3 x 3 and an identity mapping which joins the input and the output of the unit. The convolution block has a branch normalization layer (BN) and it also contains both a Rectified linear unit activation (ReLu) and a convolutional layer. The size of the feature map is reduced by half using a stride of 2 in the convolution block instead of utilizing pooling operation in each of the residual unit in the encoding part to downsample the feature map size. Prior to the residual unit in the decoding part, there is an up-sampling of maps from lower part and joining of maps from the related encoding part. A sigmod activation layer and a convolution layer with a size of 1 x 1 is utilized to project the multi-channel maps in the target segmentation next to the final part of decoding path[19].

U-Net based with residual unit semantic segmentation was preferred by the researchers because it works with very few training samples and provides better performance for segmentation tasks [11]. Moreover, U-Net was basically created for biomedical image segmentation which is suited for this study.

2.3. Training the Model

The model in segmenting lung from CXR image was developed and trained using Python, Tensorflow, and Keras. Keras is a high-level neural network API which can run on top of Tensorflow. The use of Keras allows the researchers to do fast experiments without writing large number of codes.

The training dataset consists of the original CXR images and manually segmented mask images. The dataset consists of 562 sets of mask and unmask CXR images which were divided into training and validation data. 70% of the images were used for training and 30% were used for validation. The images were resized and were trained in batches to facilitate faster training without the need for additional computing resources.

2.4. Dice Coefficient

To assess the similarity of the manually mask CXR images and the result, dice coefficient was used. Dice coefficient is a measure of intersection between objects. The measure ranges from 0 to 1 where a dice coefficient of 1 means perfect and complete overlap[20]. It can be calculated using the formula:

$$\mathrm{DC} = \frac{2TP}{2TP + FP + FN} = \frac{2|X \cap Y|}{|X| + |Y|}$$

where TP are the true positives,
FP are false positives, and
FN as false negatives

The number of true positives are the numbers that the model finds or correctly identify while false positives are the negative that the model classify as positive.

3. Results and Discussions

The developed model, which was based on U-Net architecture were trained using 562 sets of CXR images and manually mask images from Shenzhen No. 3 hospital. The images were resized and trained with a batch size of 16 at 40 epochs or the times the whole dataset is passed through the neural network both forward and backward path.

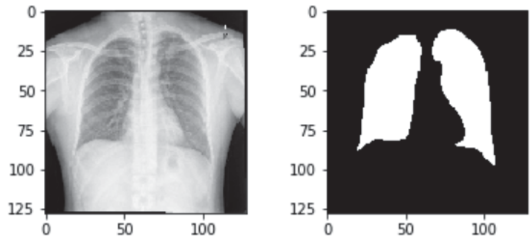

Figure 2. CXR Image Sample

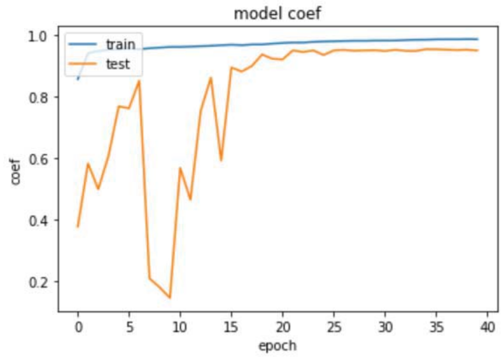

Figure 3. Training and Validation Dice Coefficent

Figure 2 shows a sample dataset image. The image on the left is a sample CXR image from Shenzhen Hospital and the image on the right is the manually mask CXR image prepared by teachers and students of National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute". Figure 3 shows the dice similarity coefficient graph of the model. The blue line indicates training dice

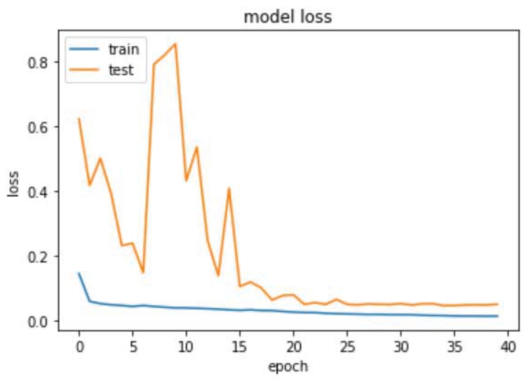

Figure 4. Training and Validation Loss Graph

coefficient graph while the orange line indicates the validation dice coefficient graph. The trained model was able to achieve a training dice coefficient of 0.9860 and validation dice coefficient of

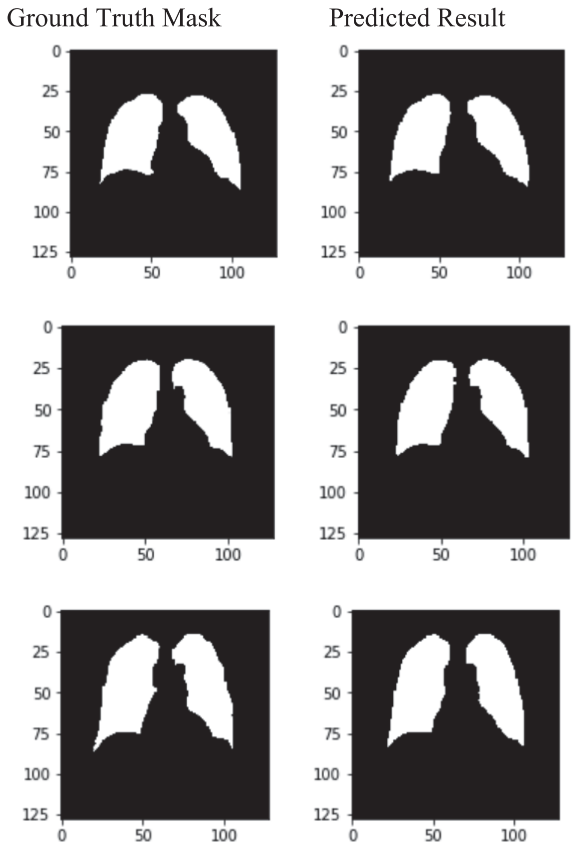

Figure 5. Sample Prediction Results

0.9496. The result shows that the comparison between the ground truth mask and segmented result are almost identical. Moreover, the validation and accuracy loss are very low as seen in Figure 4. At around 30 epochs, validation and training loss stabilized which indicates that trained model is neither overfit nor underfit. A model is said to be overfit when the train set's performance continuously improves while the validation set's performance improves at a certain point and then begins to go down. Underfit model on the other hand, is when the training dataset performs well while validation dataset performs poorly. A good fit is when both training and validation dataset perform well and it stabilized at some point[21]. Based on the graph as seen in figure 3, the model exhibited a good fit model. This indicates further that the model could predict unseen CXR images with high prediction accuracy and with very little margin of error.

Figure 5 shows sample prediction results of the developed model. The images on the left are the ground truth mask CXR images while the images on the right are the predicted lung mask of the CXR images. The ground truth and the predicted lung mask are almost identical which shows that the prediction accuracy of the model is very high.

4. Conclusion

In this paper, the researchers were able to create a model that can segment the lungs from CXR images based on Deep Residual U-Net architecture. 562 CXR images with manually mask lungs were used in training the model. 70% of the model were used as train data and the remaining 30% was used as testing data. The trained model was able to achieve a validation dice coefficient of 0.9496 and a loss of 0.0504. Therefore, the trained model can segment the lungs from CXR images with high accuracy.

The model can be used in segmenting the lungs from CXR image before predicting lung diseases as CXR includes structures other than the lungs, such as the heart and spine. These structures are not important or might hinder in detecting lung diseases[8]. Through the developed model, the classification and detection of lung diseases can be much faster as it only focuses on the lung structure rather than the entire CXR image. The findings in the study will also be useful for future researchers who will be conducting studies in the field of biomedical imaging.

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