U-Net-Based Approaches for Effective Lung Segmentation in Medical Imaging

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Abstract

With the current advancements in technology, many assistive medical systems are increasingly involved in supporting healthcare professionals. The early diagnosis of diseases using artificial intelligence (AI) and related technologies has become a rapidly developing field of study. Covid-19 is typically identified using chest X-rays (CXR) and the interpretation of CXR images is subject to variability among radiologists, potentially leading to inconsistent diagnoses. Deep learning techniques have demonstrated the effective potential to achieve accuracy levels comparable to those of medical practitioners. This paper presents different U-Net based approaches for lung segmentation using CXR images. The results demonstrate that attention based UNet achieved highest accuracy and Dice Coefficient of 98.89% and 97.75% respectively. This paper underlines the ability of the attention-based U-Net model in improving the accuracy and robustness of the automated lung segmentation process to improve the results of Covid-19 diagnosis based on chest X-ray images.

Keywords: DL, COVID-19, UNet, Respiratory Diseases, Segmentation.

1. Introduction

Respiratory diseases including pneumonia, Tuberculosis, lung cancer, and other related ailments are some of the most prevalent and deadly diseases globally. These illnesses require timely and correct diagnosis in order to help manage and treat them appropriately [1]. Chest X-ray (CXR) imaging is amongst the most commonly used diagnostic modality for evaluation of lung pathology because of its advantages such as availability, rapidity and cost effectiveness. Nonetheless, interpretation of CXR images by radiologists may be labor-intensive and qualitative various especially when the CXR images are complicated or in areas with restriction in the number of radiology specialists. To overcome these challenges, unprecedented automated approaches for lung segmentation have become significant in the field of medical imaging. Lung segmentation aims at identifying lung contours within the acquired CXR images and is a crucial step for further processing of the images and identification of various lung diseases and their severity. Segmentation plays a critical role because subsequent diagnostic processes only concern the regions of interest, i.e. the lungs, significantly reducing the probability of obtaining erroneous results due to interference from surrounding tissues. Standard approaches of lung segmentation which are derived from traditional image processing methods, yield decent results; nonetheless, they may fail to account for variability in the size and shape of the lungs or constraints imposed by disease [2].

In the last decade, deep learning has emerged to be the center of medical image analysis as it introduced massive enhancements in algorithms that address image segmentation tasks [3]. Neural networks, especially convolutional neural networks (CNNs), and especially U-net based architectures, have shown great potential in segmenting specific anatomical parts in chest X-ray images, including the lungs. These networks use the hierarchical level information of deep learning to provide excellent segmentation even when encountering complicated samples. The present research study aims at investigating the advanced deep learning algorithms, more specifically, to study the U-Net algorithm and its improved models including ResNet-based and Attention-based U-Net for segmenting lungs from CXR images [4]. In this research, our goal is to determine which model yields better results than others regarding lung segmentation for a better diagnosis of lungs through the use of automatic diagnostic tools in real-life practice of radiology departments. Also, this study examines the possibility of using these models in early diagnosis of lung diseases with the aim of improving patients' wellbeing through appropriate treatment. In section 2, we describe the various studies related to the lung segmentation. Section 3 presents the materials and methods used in the study, followed by result and discussion discussed in section 4. Section 5 concludes the study and discusses the future work.

2. Related work

Lung segmentation is an important task, actively discussed among the researchers in the field of medical imaging, especially for the diagnostics of respiratory diseases such as Covid-19. There are quite many techniques that have been proposed over the years, form simple image processing approaches to complex deep learning methods. In the recent years, with the emergence of deep learning, especially CNN, a lot of fully automatic and more accurate lung segmentation methods proposed. The U-Net is fully convolutional network model with the ability to learn the spatial features and generate accurate segmentation maps even with limited training data. U-Net has thus become a reference for many variants and extensions, including multi-scale, multi-view, and attention-based architectures, all designed to enhance the level of segmentation detail and resilience. This section discusses the advancement made in the last three years in the lung segmentation and the significant role played by U-Net in enhancing the accuracy of the lung segmentation in medical imaging. Jain et al [5] employed a pre-trained ResNet101 which has an accuracy of 98.95%. However, an important drawback is that they have used a small dataset for their study, in turn, more focus should be given to the use of large datasets to study numerous variants. Further, the study conducted by Khan, et al. [6] used CoroNet and exception-based model and achieved a better accuracy, although, the dataset used by them was limited. Singh et al. [7] proposed an advanced depth wise convolution neural network for classifying X-ray images of the chest by applying the multi-resolution analysis. Apostol Poulos et al. [8] built upon the work using VGG19-mobile net and achieving an accuracy of 97.8% but have not compared them with the images they took before the outbreak of the coronavirus disease. Nasiri et al. [9] employed DNN, XGBoost, DenseNet169 to extract the image features. In two-class and multiple-class issues, they obtained average accuracy of approximately 98.24%. They achieve high performance, however, the data set they utilized in their experimentation was unbalanced. Dasare et al. [10] designed a computer-aided diagnostic model using deep learning that accepts a patient's chest radiology image and classifies it to be either non-pneumonia or pneumonia. To build and train the model, more than 5,000 X-ray images were employed. Narin et al. [11] used CXR images to classify COVID-19 patients and pneumonia patients using five pre-trained models: InceptionV3, ResNet152, ResNet101, ResNet50, Inception-ResNetV2, etc.

The prior work of lung segmentation has discussed the various deep learning methods frequently used for segmentation, and the generalized models like U-Net and its similar models preferred to treat medical images. Though, original U-Net models have been proved very effective in segmentation task, attention-based U-Net models have further enhanced the segmentation performance by providing attention on the relevant lung part. These developments demonstrate the constant progress in lung segmentation methods, thereby stressing how crucial accuracy is in computer-aided diagnoses. This work expands by comparing and analyzing various U-Net based techniques and intending to find the optimal model for accurate lung segmentation in chest X-ray images.

3. Materials and Methods

In this study, we have utilized 3616 images of Covid-19 along with their masks from the Covid-19 radiography database. In this work, we used several state-of-the-art deep learning networks for accurate lung segmentation from Chest X-ray (CXR) image. The primary model used was the U-net architecture as it has been found to be particularly useful in medical image segmentation because of the encoder-decoder nature of the architecture that allows the identification of fine details of a feature at different scales. To improve the performance of segmentation, we studied modifications of the U-Net architecture by using pre-trained deep convolutional models, such as ResNet and VGG. The ResNet-based U-Net has incorporated the idea of residual learning in ResNet model, which can make the model deeper while avoiding the problem of vanishing gradients and is effective in capturing more details in CXR images. Similarly, the Attention-based U-Net offers a strong base for feature extraction process while keeping the computational complexity at a reasonable level. Figure 1 describes the basic flow used in this study. In this work, we compared the standard U-Net with these modified architectures to determine the best model for segmenting lung regions in CXR images and examine the performance of each model in segmenting lung boundary across a variety of CXR images.

3.1 Attention U-Net

Attention U-Net is a more complex architecture of convolutional neural networks, in which attention mechanism is added in the standard U-Net. The model commences with an input layer that takes images of 128 x 128 pixels having a single channel (grey scale). It possesses a typical U-Net design in which each level of the network is a combination of two convolutional layers followed by ReLU nonlinearity and a max-pooling layer for reduction of the spatial dimensions. As for the convolutional filters at each level, it rises from 64 to 128, 256, 512, to 1024 in the bottleneck layer and its main function is to search for more and more detailed features of the input image. The up-sampling path of the U-Net where the spatial dimensions are reconstructed from feature codes. The attention blocks used in the architecture improve the feature maps by learning a form of attention weights that will enable the model to learn to give more attention to the most critical area in the image. In particular, the first attention blocks extract feature maps from the down sampling path and the second attention blocks extract feature maps from both, the down sampling and the up-sampling path and compute attention weights, to apply these weights as multiplicative factors on the feature maps obtained by the down sampling path.

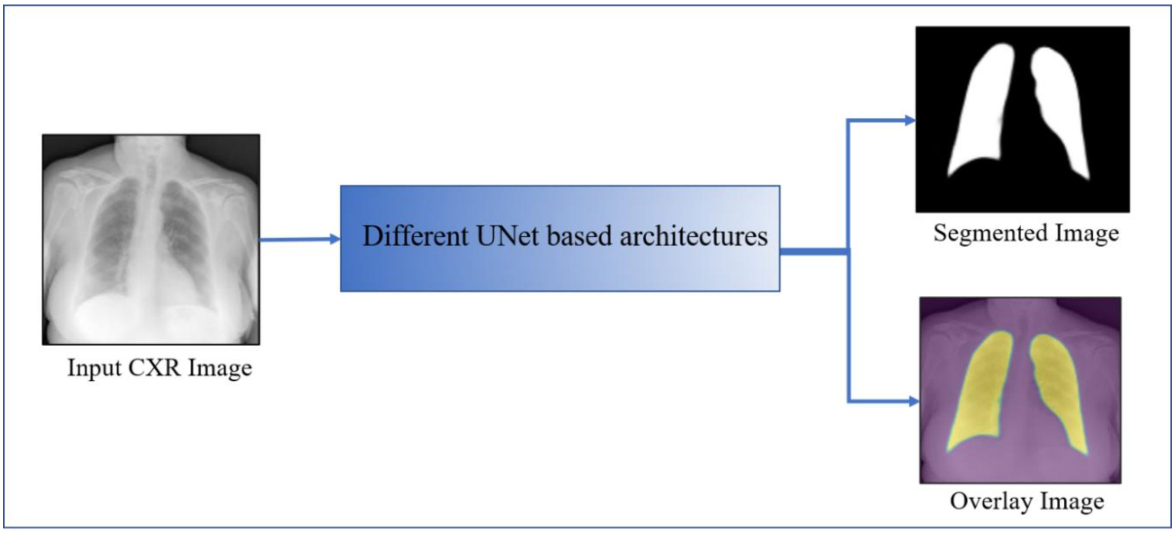


Fig. 1: Basic workflow used in the study.

This process helps in making sure that more important features are given more importance when the model is being up sampled. In every level of the up-sampling path, the model adds the feature maps which have been activated by attention to the feature maps that are up sampled. These two additional features of paying more attention to the area as well as up sampled feature allow the model to re-map the lung regions more accurately. The up-sampling layer starts reducing the number of filters in a similar manner with the down sampling layer until the final output layer of the model. The final layer is a convolutional layer with stride 1, gives the segmentation map or more specifically, a binary map of the lung part of the input image using Sigmoid non-linearity. It is compiled using the Adam optimizer and binary cross entropy loss, and its performance is measured in terms of accuracy.

3.2 U-Net model

The U-Net model for lung segmentation is a type of a convolutional neural network that is suitable to be used in image segmentation. It takes an input image of size 128×128 pixels with only one channel, usually it is a black and white image, and it passes the image through an Encoder-Decoder network. The encoder is made up of several convolutional layers that get more complex features of the input image as well as max pooling layers which in turn reduce the spatial dimensions. It begins with 64 filters and the number of filters is doubled at each level and it ends with the bottleneck layer with 1024 filters containing the most abstract features. The decoder is similar to the encoder but in the reversed order with the application of the up-sampling layers to progress the reconstruction of the feature maps. At each stage of up sampling, the feature maps from the corresponding encoder layer are concatenated with the up sampled features so that the model can combine them on higher and lower levels. This kind of skip connection is useful in maintaining actual local context which is very important when it comes to segmentation. The decoder successively removes the filters and the last layer presents a map of segmentation with only one channel where the probability of each pixel for belonging to the lung region is estimated using a sigmoid activation function. One important feature of this U-Net architecture is that it can employ global information as well as localize detailed features of an image.

3.3 ResNet-based U-Net model

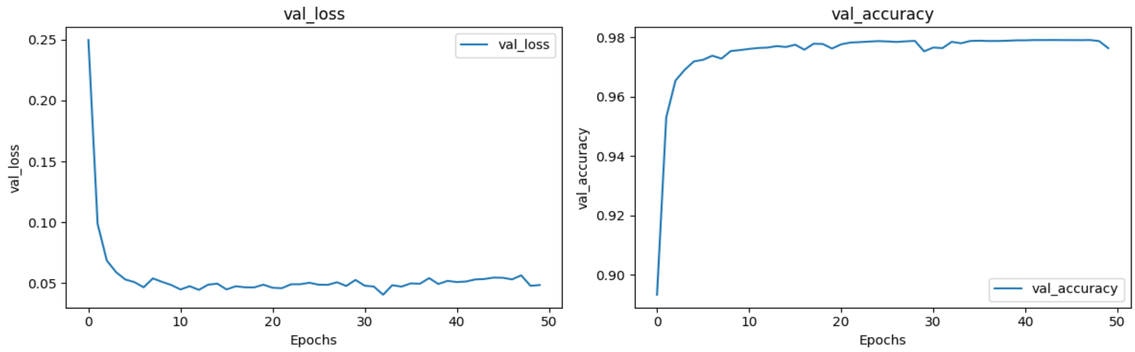
The proposed lung segmentation model, ResNet-based U-Net, utilizes the deep learning feature extracting capacity of ResNet50 and the U-Net architecture for image segmentation. The input to the model is an image of size 128x128 with three color planes (e. g. RGB). For the encoder, a pre-trained ResNet50 network is used without its last fully connected layers. These features are extracted from selected layers of ResNet, whereby each layer reflects a certain level of abstraction. The last layer of ResNet is named as encoder's output or the bridge where the information passes and goes to the decoder. The decoder deploys an up-sampling block to gradually up sample the features while integrating skip connections from the encoder that helps to preserve spatial information. Subsequently, following each up-sampling step, there is a convolutional layer to help sharpen the feature maps. At last, the segmentation mask with sigmoid non-linear transformation is created which yields the possibilities of existence of the lung at each pixel. This architecture effectively addresses the fine foreground and background separation that is ideal for medical image applications such as lung segmentation.

4. Results and Discussion

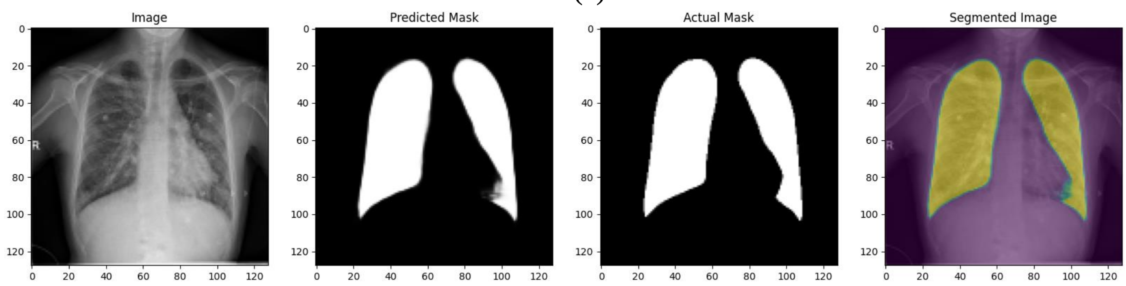
In this study, the UNet, ResNet-based UNet, and the Attention-based UNet achieved a moderate to high level of accuracy and provided rather dissimilar performances in the most crucial parameters for lung segmentation (as shown in Table 4). The experiment carried out on the UNet model shows high level of performance with an accuracy level of 97.15% suggesting that in classifying lung regions it performs very well. Figure 3 shows the results of UNet Architecture(a-b).

Table 4: Performance of different modes for COVID-19 lung segmentation

Models	Accuracy	Precision	Recall	F1-score	Jaccard Index	Dice Coefficient
UNet	97.15	95.06	93.50	94.27	89.16	94.27
ResNet based UNet	80.00	66.67	100.00	80.00	66.67	80.00
Attention based UNet	98.89	97.90	97.59	97.74	93.85	97.75



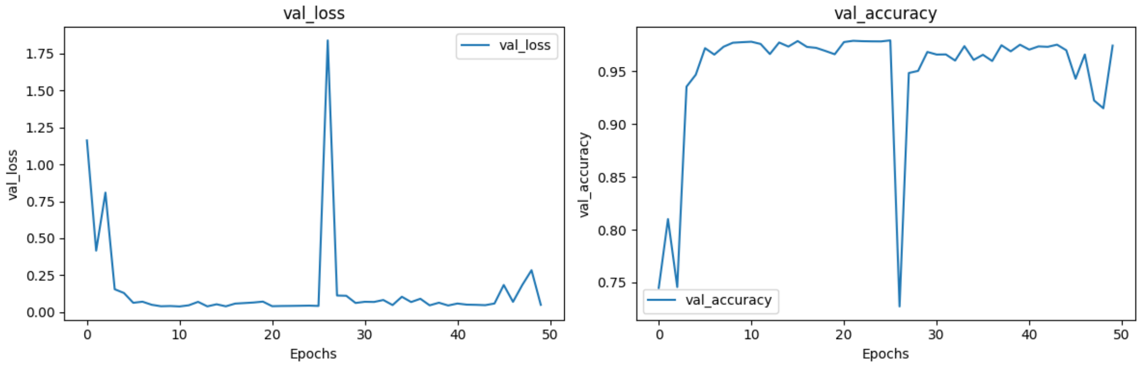
(a)



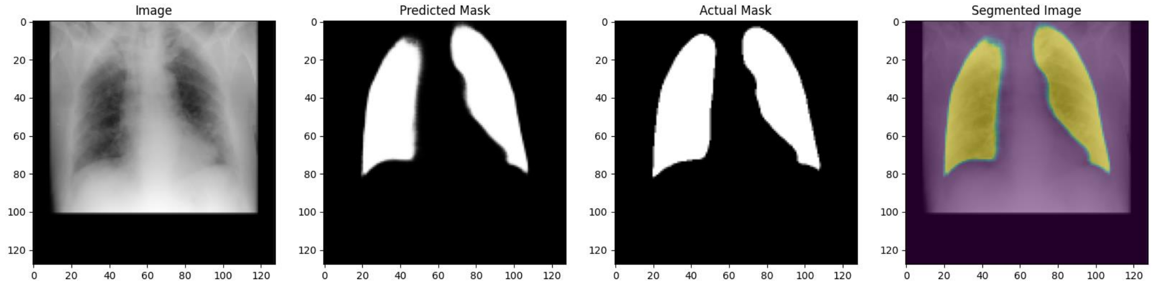
(b)

Fig. 3: Results Illustration of UNet Architecture(a-b)

Its precision of 95. 06%, and recall of 93.50% respectively prove that the method does well in detecting the lung areas and, at the same time, has a reasonable number of true positive values and low false positive values. The F1-score of 94. 27% also goes further to support this balance proving that the UNet model is accurate in its segmentation tasks. With a Jaccard Index of 89.16% and Dice Coefficient of 94. 27%, the model produces highly accurate and cohesive segmentations. The ResNet based UNet model performs comparatively well and has a mixed result. Figure 4 shows the results of ResNet based UNet Architecture(a-b). It achieves a perfect recall of 100%, which means that the potential lesion structures are captured without any of them being omitted, but at the cost of much lower precision of 66. 67%. This low precision means that the model is likely to give a high false positive that is, non-lung regions are classified as lung regions. Subsequently, the overall accuracy of the ResNet-based UNet has reduced to 80%, which is slightly lower suggesting the fact that the model is not as accurate as the UNet.



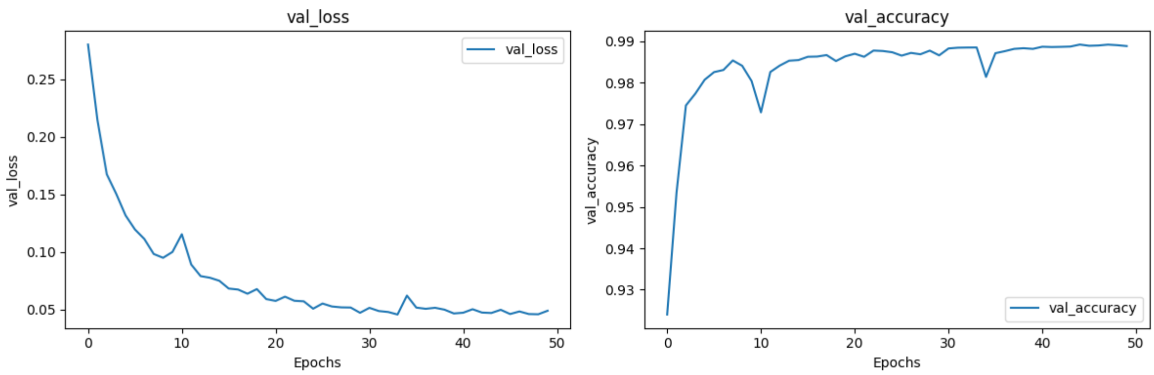
(a)



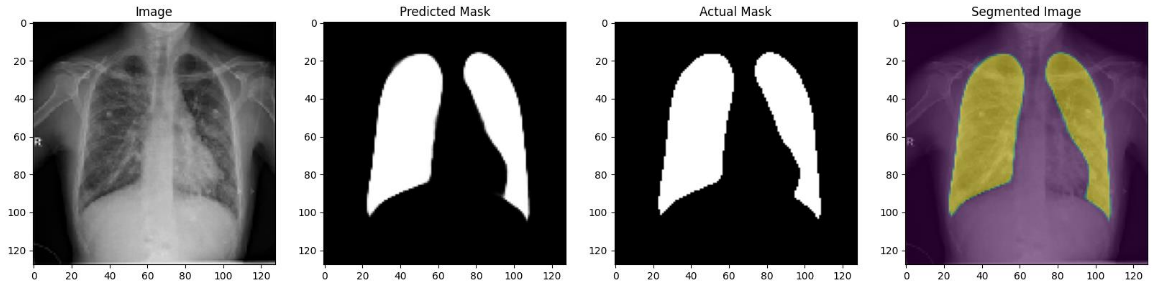
(b)

Fig. 4: Results Illustration of ResNet based UNet Architecture(a-b)

The F1-score of 80% demonstrates the increase in the gap between precision and recall showing that the performance of the model is dragged down by the inability of the model to correctly separate lung regions from non-lung regions. The Jaccard Index of 66.67% and Dice Coefficient of 80% shows moderate challenges between the identified predicted lung regions and the actual segments. On the other hand, the Attention-based UNet model yields a higher accuracy, a lower loss value and the highest F1 score. Figure 5 shows the results of Attention based UNet Architecture(a-b). For these particular demographics, the model has proven to be accurate about 98.89% and outperforms both the UNet and ResNet based UNet in terms of the accuracy of the results obtained for the lung regions. The results have demonstrated that precision of 97.90% and the recall of 97.59% is highly accurate in identifying the regions of the lungs while keeping the false negatives and false positives low. Hence, the Attention-based UNet achieves a highest of 93.85% Jaccard Index and the Dice Coefficient of 97.75%. This superior performance is because of the attention mechanism in the model. The Attention-based UNet performs best in comparison to the other two models as it achieves a lung segmentation model with superior accuracy, precision, and reliability.



(a)



(b)

Fig. 5: Results Illustration of Attention based UNet Architecture(a-b)

5. Conclusion and Future Work

This work demonstrates the importance of developing and utilizing more sophisticated deep learning architectures such as the attention-based U-Net for improving the performance and reliability of lung segmentation from the chest X-ray images. Comparing to prior studies, the attention-based suggested U-Net model outperforms the latter by reaching a higher level of accuracy as well as Dice Coefficient, which in turn decreases the level of variability, characteristic of manual analysis by radiologists. Based on the results of the research, this study strengthens the possibility of the use of AI-based approaches in assisting the healthcare professionals to identify Covid-19 at its early stage and thereby lead to more credible results among the patients. The use of AI in the evaluation and diagnosis of medical images contributes positively to healthcare delivery and as technologies advance, will result in even better diagnostic tools in the future.

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