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# Implementing UNet++ Segmentation Model for Respiratory Disease Detection


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# Abstract

In this study, we use UNet++, a new architecture created for segmenting medical images, for the segmentation of Lung Images with the purpose of detecting various respiratory problems. There are existing researches based on the U-Net architecture, which has already shown to outperform previous methods on challenges for segmentation of neuronal structures and cell tracking. But with an average Intersection over Union (IoU) gain of 3.9 and 3.4 points, respectively, trials on a variety of medical picture segmentation tasks show that UNet++ with deep supervision outperforms U-Net and wide U-Net designs in terms of IoU scores [1]. The original U-Net architecture has been extended into UNet++ in order to fix several issues and improve its performance in a variety of tasks. UNet++ minimizes the semantic gap between encoder and decoder networks using stacked, dense skip routes. Our study demonstrates a model built using the mentioned architecture, for the sole purpose of segmenting lung images. This model has been able to achieve a relatively high score considering the limitations of the dataset.

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# Chapter 1

# Introduction

## 1.1 Motivation

Medical image segmentation is crucial to the precise and prompt identification of many disorders in contemporary healthcare. Because it has the potential to improve patient outcomes and treatment options, the early diagnosis of respiratory disorders using lung imaging has unique value in this context. With respiratory diseases ranking among the leading causes of mortality worldwide, timely and accurate diagnosis becomes paramount for effective intervention and management [2].

In this context, the UNet++ architecture stands out as a noteworthy development that merits consideration in this setting. The original U-Net model has previously proven itself useful in jobs requiring the segmentation of medical images. UNet++ is an advanced iteration of U-Net, bringing significant advantages that enhance its potential for this task. UNet++ maintains the flexibility and simplicity of the original U-Net architecture, making it easy to implement and adapt for various segmentation tasks. Researchers and practitioners can still use the same basic building blocks and concepts from U-Net while reaping the benefits of the hierarchical design of UNet++. In a study focused on lung nodule segmentation, UNet++ outperformed several contemporary models, displaying superior boundary preservation and segmentation accuracy [3].

In recent years, there have been progressive research works on Lung Image Segmentation using U-Net. Those works focused on detecting different respiratory diseases including tuberculosis, pneumonia, lung cancer etc. But there are no existing works on lung image segmentation for detecting tuberculosis or lung cancer specifically. In order to fill the void in this sector, we aimed to study comprehensively on the existing works and models which are based on U-Net architecture. We wish to implement UNet++ on a popular U-Net model used for lung image segmentation for detecting respiratory diseases and test it thoroughly.

The importance of examining UNet++'s application in the field of lung image segmentation is underscored by its potential to improve accuracy and empirical proof of higher performance.

## 1.2 Objective

The primary objective of this study is to implement a UNet++ architecture on the foundation of a U-Net architecture as they are highly compatible with each other. Also, we aim to use the same basic building blocks and concepts from U-Net, in order to maintain the simplicity and adaptability of the model, while enjoying the benefits of the hierarchical design from UNet++. We conducted the study to evaluate the performance of UNet++ in accurately segmenting lung images, aiming to achieve higher precision and recall rates compared to traditional methods. We also want to investigate the practical viability of UNet++ in real-world clinical scenarios, gauging its potential to assist medical professionals in early disease detection.

Besides achieving these goals, we further hope to conduct research in this field to contribute to the advancement of medical image analysis, offering a robust solution for enhanced respiratory disease diagnosis and treatment planning.

# Chapter 2

# Related Works

A crucial part of any lung disease diagnosis is lung image segmentation. The UNet++ architecture expands on the original U-Net model's base to overcome some of its shortcomings. UNet++ adds a hierarchical framework that improves context integration and feature extraction, making it ideal for complex lung structures. This innovation has shown promise in various medical imaging applications.

The research conducted by Li et al. [4] emphasized the importance of contextual information in lung image segmentation. U-Net is a network and training strategy that has already shown to outperform previous methods on challenges for segmentation of neuronal structures and cell tracking. It is also fast, with segmentation of a 512x512 image taking less than a second on a GPU [5].

Another paper introduces a network called Attention U-Net, which automatically learns to focus on target structures in medical images eliminating the need for explicit external localization modules and improves prediction performance while maintaining computational efficiency [6].

Existing U-Net type networks have limitations such as fixed receptive field size, lack of theoretical underpinning, and sensitivity to noise [7]. Researchers needed to mitigate these problems, while also addressing the need for more accurate segmentation in medical images. A study conducted in 2018 [1] introduced UNet++ by proposing a segmentation architecture based on nested and dense skip connections, which would yield significant performance gains over U-Net and wide U-Net. It aims to reduce the semantic gap between the feature maps of the encoder and decoder sub-networks.

# Chapter 3

# Methodology

Our goal is to accurately segment and mask the lung images gathered from a Lung Mask Image Dataset [8] from Kaggle which included ChestXRay images containing test, train and validation data. A UNet++ architecture was designed for this purpose. A U-Net model was configured to the state where UNet++ would be able to perform seamlessly in order to generate mask image from the input images. Here, we first built our convolutional UNet++ model with multiple epochs for better training and completed the preprocessing of the dataset. Then, we implemented a U-Net model and configured it so that it would match the dataset format for the segmentation of lung images. As the main convolutional architecture, we replaced U-Net with UNet++. We further processed and modified our model so that it would meet the basic requirements of the UNet++ architecture.

Our model consists of several convolutional layers, having max-pool layers in-between two convolutional layers along with dropout and concatenate methods. Throughout the process we used a dropout of 0.5. We prepared our training dataset with 3500 random images and validation dataset with 1500 random images from a total of 16932 images in the dataset. We also converted the images from gray-scale to RGB as it was required by UNet++. After generating all the proper training and testing datasets, we compiled our model using Adam optimizer and Binary Crossentropy as the loss function. We selected 20 epochs for training, with 50 steps per epoch, and 10 more epochs for validation.

# Chapter 4

# Results

Accuracy and Loss value is the metric we used for the evaluation of our model. The accuracy was 71.4% until the 17th epoch. After which, it started rapidly increasing. It leaped up to 83.5% as we finished the 20th epoch of our model (figure 4.1). We assume that further training would certainly help increase this accuracy more.

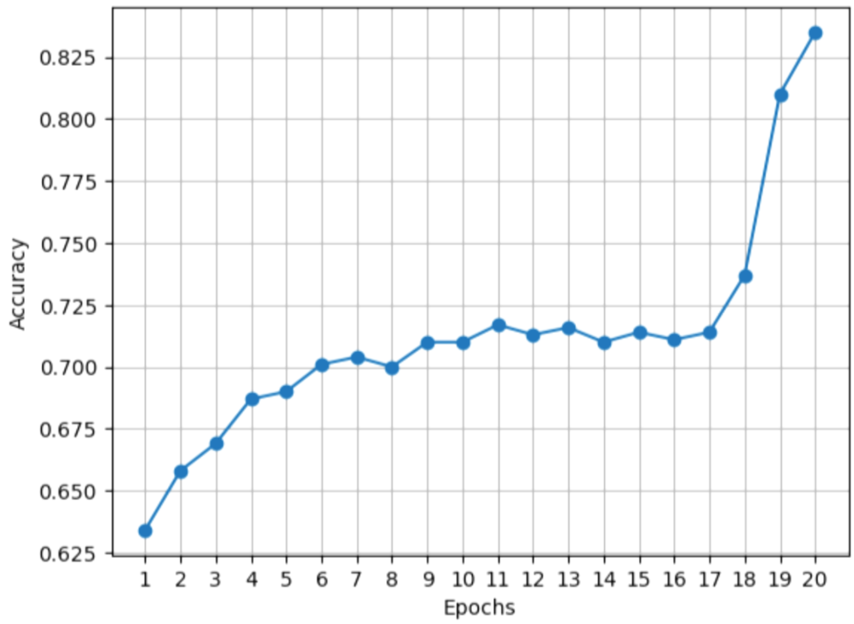


Figure 4.1: Accuracy over epochs

When it comes to loss value, it showed a continuous decrease the further we trained the model. Up until epoch 17, the loss value was around 50%. But after 20 epochs, we saw this value decrease to about 29.3% (figure 4.2).

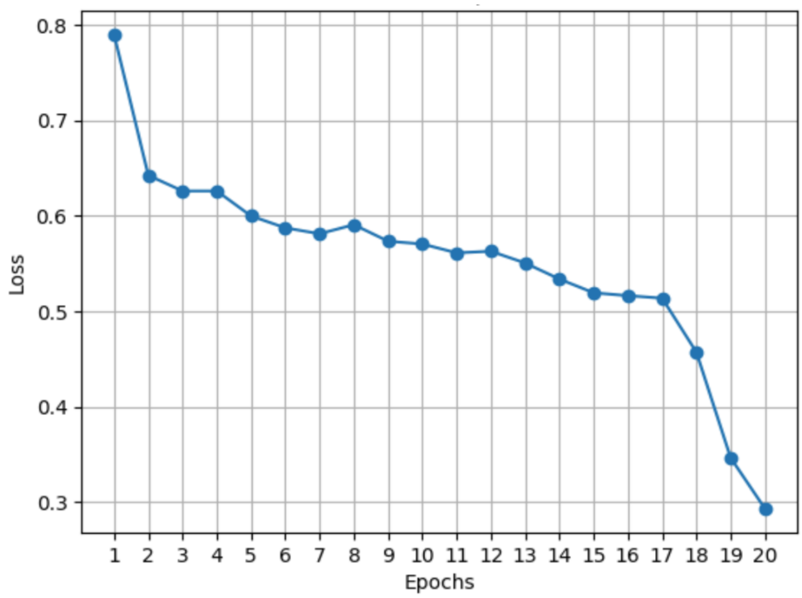


Figure 4.2: Loss over epochs

We also calculated the validation loss as well as the validation accuracy. The validation loss showed a central tendency around the 50%-55% mark (figure 4.3) and the validation accuracy was near the 72% mark across the whole training process (figure 4.4)

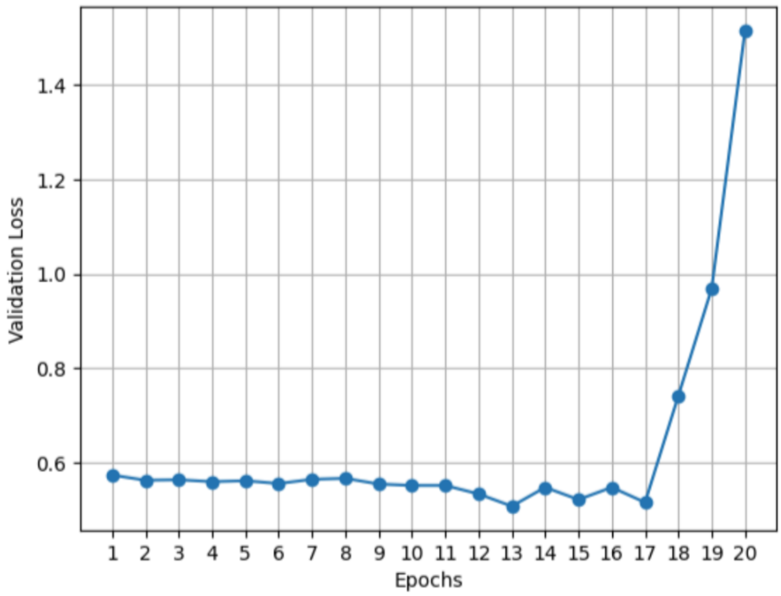


Figure 4.3: Validation loss over epochs

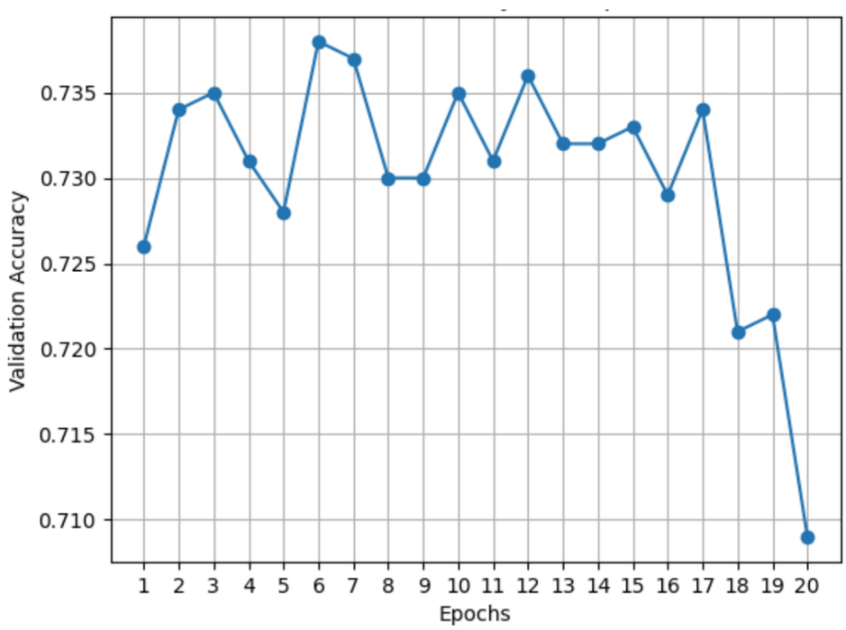


Figure 4.4: Validation accuracy over epochs

## 4.1 Discussion

Our model that uses the UNet++ architecture shows high adaptability to a U-Net centered model, further proving its flexibility. Though the accuracy of our model is high enough, considering the amount of data we used to train and test our model with, it can be better if we increase the amount of training and testing data. Moreover, increasing the number of epochs and steps per epoch should also greatly increase its accuracy to predict and generate masked, segmented image of lungs. Exploring the fine-tuning of hyperparameters and architecture modifications could potentially further improve UNet++'s performance. Additionally, investigating the transferability of the model across different populations and disease types would enhance its generalizability.

We can also see the loss value getting decreased as we increased the number of epochs. So we can say that this model has high possibility of accurately segmenting lung images given appropriate and relevant datasets.

# Chapter 5

# Conclusion

In the pursuit of accurate and timely diagnosis of respiratory diseases, the application of advanced computational techniques has become pivotal. This work delved into the realm of lung image segmentation using the UNet++ architecture, aiming to enhance disease detection.

This study demonstrated that UNet++, with its hierarchical design and multi-scale skip connections, holds immense potential for accurately segmenting lung images to detect respiratory diseases. It also showed the superiority of UNet++ in terms of both accuracy and boundary preservation. The architecture's versatility and adaptability bode well for real-world scenarios, where precise and efficient diagnosis is of utmost importance.

As the medical field continues to embrace technological advancements, the findings of this study can contribute to a growing body of knowledge that has the potential to shape the future of medical imaging and healthcare practices.

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