A Study of Infection Segmentation in X-ray images of COVID 19 patients

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1 Introduction

For the study, I built an U-Net model which is combined with Residual Block in the encoder part to generate the segmentation masks of the infected areas in X-ray images of COVID 19 patients. This model was trained with 2 different loss functions: binary cross-entropy (BCE) and a combination of BCE and Intersection over Union (BCE + IoU).

2 Data Analysis

The dataset used in this study is the COVID-QU-Ex Dataset. It contains 2913 X-ray images of COVID 19 patients. For data preprocessing, I resized all the images to 256x256 pixels in 1 channel and normalized them to the range [0, 1].

3 Model

Instead of ultilizing the original U-Net model like in the previous study, I added Residual Block to the encoder part of the U-Net model, which is expected to improve the ability of extracting features more effectively.

3.1 U-Net Architecture with Residual Block

This U-Net model is a convolutional neural network for fast and precise segmentation of images. The architecture contains two paths: the contraction path (encoder) and the symmetric expanding path (decoder). At the encoder part, the Residual Block is adapted in the down-sampling path in order to mitigate the vanishing gradient problem, whereas the decoder part is the same as the original model.

3.2 Loss Functions

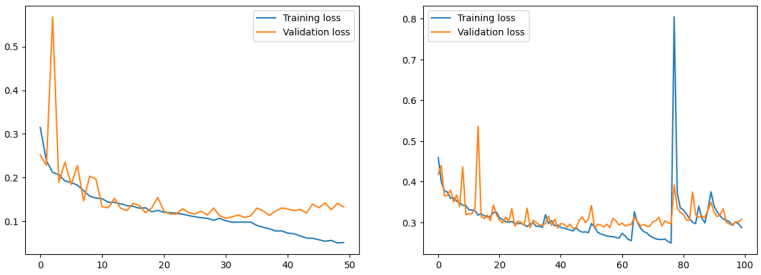
I used 2 loss functions to train the U-Net model: binary cross-entropy (BCE) and a combination of BCE and Intersection over Union (BCE + IoU). For the combined loss function, I weighted the BCE and IoU loss with a hyperparameter α. The following equation shows the combined loss function:

$$BCE\_IoU = \alpha * BCE + (1 - \alpha) * IoU \tag{1}$$

4 Results

4.1 For detecting the infected segmentation masks

Observing the loss values of the U-Net model training in 100 epochs with different loss functions, the model with only BCE loss seems to fit the X-ray dataset better than using combined model with BCE and IoU loss. The results demonsrated that the combination loss function were not suitable for this task.



(a) BCE loss (b) BCE + IoU loss

Table 1: Loss values of the U-Net model with Residual Block by different loss functions

Loss function	MAE	IoU
BCE	16.321	0.138
BCE + IoU	102168.546	0.138

Table 2: MAE and IoU values of the model with different loss functions on the test dataset

Besides the evalution metrics, I also visualized the Infected Segmentation of the 181st, 182nd and 184th images of the test dataset inferenced by the U-Net model with different loss functions. The results are shown in the figures 1 to 3.

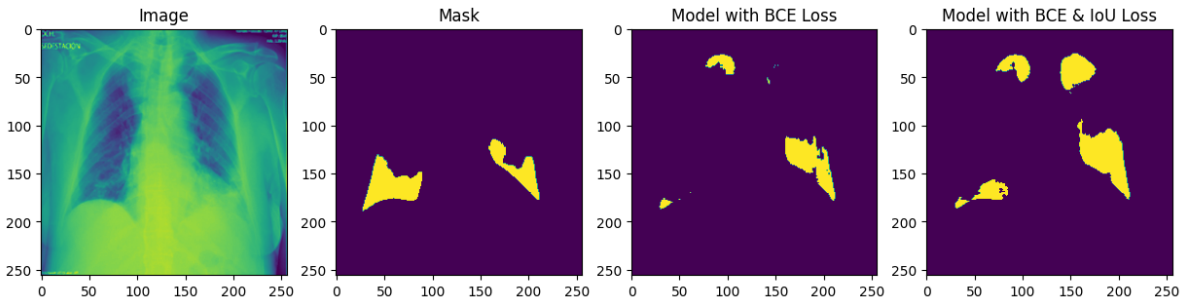


Figure 1: Infected Segmentation 181st image of the U-Net model with different loss functions

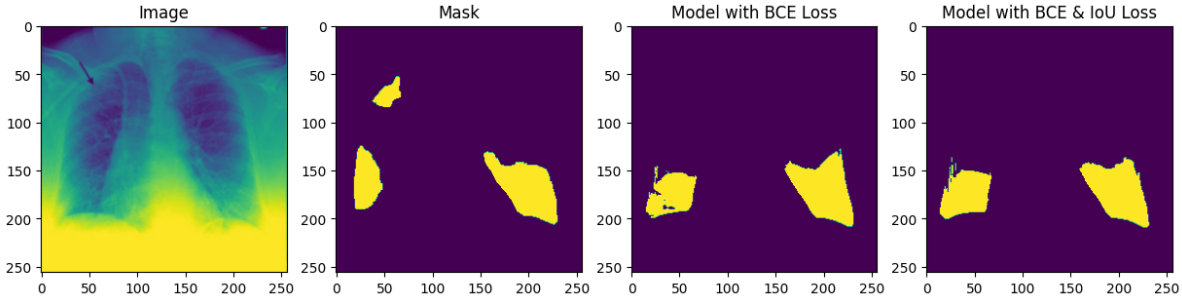


Figure 2: Infected Segmentation 182nd image of the U-Net model with different loss functions

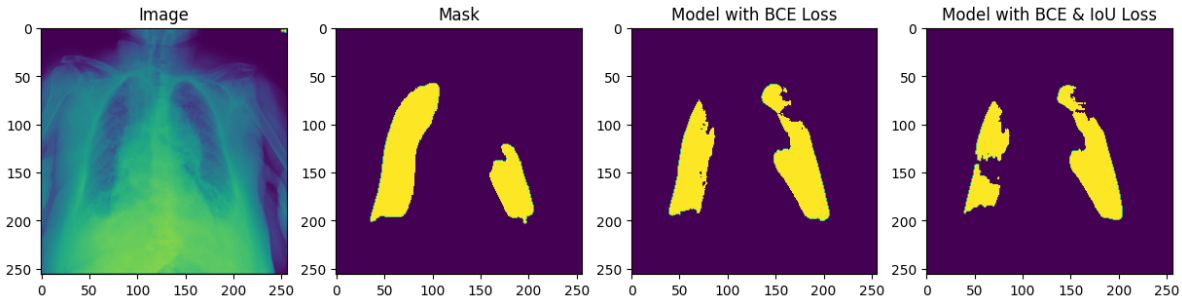


Figure 3: Infected Segmentation 184th image of the U-Net model with different loss functions