COVID-19 Infection Segmentation from Chest X-ray Images using U-Net

***Abstract*—Chest X-ray imaging is a widely available and low-cost modality for assisting in the diagnosis of COVID-19. Beyond classification, segmenting infection regions provides valuable spatial information for clinical assessment. In this work, we address the task of COVID-19 infection segmentation from chest X-ray images using a classical U-Net architecture. Experiments are conducted on the COVID-QU-Ex dataset. Due to computational constraints, the model was trained for a limited number of epochs. Quantitative and qualitative results demonstrate the effectiveness of the proposed pipeline while highlighting its current limitations.**

I. Introduction

The COVID-19 pandemic has emphasized the need for fast and reliable diagnostic tools. Chest X-ray imaging has been extensively used as a complementary diagnostic technique due to its accessibility. While many studies focus on classification, segmentation of infected regions offers additional insights by localizing pathological areas.

Deep learning approaches, particularly convolutional neural networks, have become the standard for medical image segmentation. Among them, the U-Net architecture is widely adopted due to its simplicity and strong performance. This work investigates the use of a U-Net model for segmenting COVID-19 infection regions from chest X-ray images.

II. Dataset

Experiments were conducted using the COVID-QU-Ex dataset, which provides chest X-ray images and pixel-level annotations for multiple segmentation tasks.

In this study, only the *infection segmentation* subset was used. More specifically, we focused exclusively on COVID-19 samples, as infection masks are provided only for this class. The dataset is already split into training, validation, and test sets.

Table I summarizes the number of samples used in each split.

TABLE I
Dataset split for infection segmentation

Split	Number of samples
Training	1864
Validation	466
Test	583

III. Methodology

A. Preprocessing

All images were converted to grayscale and resized to a fixed resolution of 256×256 pixels. Infection masks were resized using nearest-neighbor interpolation and binarized. Simple data augmentation techniques, including horizontal and vertical flips, were applied during training.

B. Model Architecture

A standard U-Net architecture was employed. The network consists of an encoder-decoder structure with skip connections, enabling the combination of high-level semantic information and low-level spatial details. The model takes a single-channel X-ray image as input and outputs a binary infection mask. The total number of trainable parameters is approximately 7.76 million.

C. Loss Function and Metrics

To handle class imbalance, a combined loss function was used, consisting of Binary Cross-Entropy (BCE) loss and Dice loss. Model performance was evaluated using the Dice coefficient and Intersection over Union (IoU), which are standard metrics for segmentation tasks.

IV. Experimental Setup

The model was trained using the Adam optimizer with a learning rate of 10^{-3}. Due to hardware limitations, all experiments were conducted on CPU. The network was trained for three epochs, and the best model was selected based on validation Dice score.

V. Results

A. Training and Validation Performance

Table II reports the Dice and IoU scores obtained on the training and validation sets at the end of training.

TABLE II
Training and validation performance

Split	Dice	IoU
Training	0.636	0.504
Validation	0.479	0.343

The best validation Dice score achieved during training was 0.584.

B. Test Results

The final model was evaluated on the held-out test set. Table III summarizes the test performance.

TABLE III
TEST SET PERFORMANCE

Metric	Value
Loss	0.345
Dice coefficient	0.573
IoU score	0.440

C. Qualitative Analysis

Visual inspection of predicted masks shows that the model is able to localize infection regions reasonably well. However, the predicted boundaries remain coarse and sometimes incomplete. These limitations are mainly due to the restricted number of training epochs and the absence of GPU acceleration.

VI. Discussion

Despite its simplicity and limited training time, the proposed U-Net model demonstrates meaningful segmentation performance. The gap between training and validation results suggests mild overfitting, which could be mitigated with additional regularization and longer training.

More advanced architectures, such as Attention U-Net or U-Net++, as well as increased computational resources, could significantly improve performance.

VII. Conclusion

This work presented a complete deep learning pipeline for COVID-19 infection segmentation from chest X-ray images. Using a standard U-Net architecture and the COVID-QU-Ex dataset, we demonstrated the feasibility of infection region localization. Although trained for only a few epochs, the model achieved reasonable quantitative and qualitative results. This study provides a solid baseline and a clear foundation for future improvements.

References