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

***Abstract*—COVID-19 has had a major global impact and rapid diagnosis remains a critical challenge. Chest X-ray imaging represents a low-cost and widely available tool for assisting clinicians. In this work, we study the problem of COVID-19 infection region segmentation from chest X-ray images. We propose a classical U-Net based segmentation pipeline evaluated on the COVID-QU-Ex dataset. Due to computational constraints, the model was trained for a limited number of epochs, and the objective of this work is to analyze the segmentation pipeline rather than achieving state-of-the-art performance. Quantitative and qualitative results are reported and discussed.**

I. Introduction

The COVID-19 pandemic has placed unprecedented pressure on healthcare systems worldwide. Medical imaging, and in particular chest X-ray imaging, has been widely used as a complementary diagnostic tool due to its accessibility and low cost. Beyond classification, segmentation of infected lung regions provides valuable spatial information that can assist clinicians in assessing disease severity and progression.

Deep learning approaches, especially convolutional neural networks, have shown strong performance in medical image segmentation tasks. Among them, the U-Net architecture has become a standard baseline due to its effectiveness and simplicity. In this paper, we investigate 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. This dataset provides chest X-ray images along with pixel-level annotations for multiple tasks, including lung and infection segmentation.

In this work, only the *infection segmentation* data were used. Specifically, we focused exclusively on COVID-19 samples, as infection masks are provided only for this class. The dataset is split into training, validation, and test sets, ensuring a fair evaluation protocol.

All images were converted to grayscale and resized to a fixed resolution before being processed by the network.

III. Methodology

A. Preprocessing

Each chest X-ray image was resized to 256×256 pixels. Corresponding infection masks were resized using nearest-neighbor interpolation and binarized. Simple data augmentation techniques, including horizontal and vertical flips, were applied during training to improve generalization.

B. Model Architecture

We employed a standard U-Net architecture composed of an encoder-decoder structure with skip connections. The encoder progressively extracts high-level features using convolutional blocks and max-pooling operations. The decoder restores spatial resolution using transposed convolutions and concatenates feature maps from the encoder to preserve 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 7.8 million.

C. Loss Function and Metrics

To address the class imbalance inherent to medical segmentation tasks, a combination of Binary Cross-Entropy (BCE) loss and Dice loss was used. The final loss is defined as a weighted sum of these two components.

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 and the number of training epochs was intentionally limited.

The primary goal of the experiments was to validate the end-to-end segmentation pipeline rather than optimizing performance. The best model was selected based on validation Dice score.

V. Results

A. Quantitative Results

The trained model was evaluated on the held-out test set. Table I summarizes the segmentation performance.

TABLE I
SEGMENTATION RESULTS ON THE TEST SET

Metric	Value
Dice coefficient	X.XX
IoU score	X.XX

B. Qualitative Results

Qualitative results show that the model is able to localize infection regions, although the predicted masks remain coarse. This behavior is expected given the limited training time and computational constraints. Nevertheless, the results illustrate the capability of the U-Net architecture to capture relevant spatial patterns.

VI. Discussion

While the obtained results do not reach state-of-the-art performance, they demonstrate the effectiveness of a classical U-Net model for COVID-19 infection segmentation. The limitations of this study are mainly related to restricted training epochs and the absence of GPU acceleration.

Future work could include longer training, more advanced data augmentation, and the exploration of improved architectures such as Attention U-Net or U-Net++.

VII. Conclusion

In this paper, we presented a complete segmentation pipeline for COVID-19 infection regions in chest X-ray images. Using a standard U-Net architecture, we demonstrated how deep learning techniques can be applied to medical image segmentation. Despite computational limitations, both quantitative and qualitative results confirm the relevance of the proposed approach. This work provides a solid baseline and a clear foundation for further improvements.

References