COVID-19 Infection Segmentation from Chest X-Ray Images Using a U-Net Deep Learning Model

Nguyen Thi Lan Huong
Student ID: 23BI14191
University of Science and Technology of Hanoi (USTH)
Lecturer: Tran Giang Son
Email: huongntl.23bi14191@usth.edu.vn

***Abstract*—Accurate segmentation of COVID-19 infection regions from chest X-ray images plays an important role in computer-aided diagnosis and disease severity assessment. However, the task is challenging due to low contrast, noise, and the relatively small size of infected regions compared to the entire lung area. In this paper, we propose a deep learning–based approach for automatic segmentation of COVID-19 infection areas using a U-Net convolutional neural network. The proposed method is trained and evaluated on the Infection Segmentation subset of the COVID-QU-Ex dataset, which provides pixel-level infection annotations for COVID-19 chest X-ray images. The dataset is divided into predefined training, validation, and test sets to ensure a fair evaluation. Experimental results demonstrate that the U-Net model is capable of accurately delineating infected regions, showing its effectiveness for pixel-wise medical image segmentation. This study highlights the potential of deep learning–based segmentation models to support clinical decision-making in COVID-19 analysis.**

***Index Terms*—COVID-19, Chest X-ray, Infection Segmentation, U-Net, Deep Learning, Medical Image Analysis**

I. Introduction

Coronavirus Disease 2019 (COVID-19) has caused a global health crisis, emphasizing the need for accurate and efficient diagnostic tools. Chest X-ray imaging is widely used for COVID-19 assessment due to its low cost and accessibility. Beyond diagnosis, identifying and quantifying infected lung regions is important for evaluating disease severity and monitoring patient progression.

Recent advances in deep learning have significantly improved performance in medical image analysis tasks. In particular, convolutional neural networks (CNNs) have demonstrated strong capability in learning discriminative features directly from medical images. Among CNN-based architectures, U-Net has become a standard model for biomedical image segmentation due to its encoder–decoder structure and effective use of skip connections.

In this work, we address the problem of COVID-19 infection segmentation from chest X-ray images using a single U-Net-based deep learning model. Experiments are conducted on the Infection Segmentation subset of the COVID-QU-Ex dataset, which provides pixel-level infection annotations for COVID-19 cases. The predefined training, validation, and test splits are preserved to ensure a fair evaluation. The results show that the proposed approach is effective in accurately segmenting infection regions, demonstrating its potential for clinical decision support.

II. Dataset Description

This study utilizes the Infection Segmentation subset of the COVID-QU-Ex dataset for COVID-19 infection segmentation from chest X-ray images. The dataset contains a total of **2,913** chest X-ray images from COVID-19 patients, each paired with a corresponding pixel-level infection mask. The data are divided into **1,864** images for training, **466** images for validation, and **583** images for testing, following the predefined split provided by the dataset.

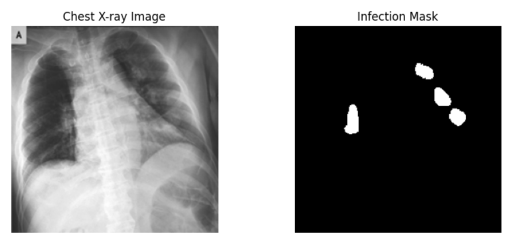

Fig. 1. Example of a chest X-ray image and its corresponding infection mask

All images are grayscale chest X-rays and are resized to a fixed resolution of **256** $\times$ **256** pixels during preprocessing. The infection masks are binary, where pixels corresponding to infected regions are labeled as 1, and background pixels are labeled as 0. Figure 1 illustrates a representative chest X-ray image and its corresponding infection mask.

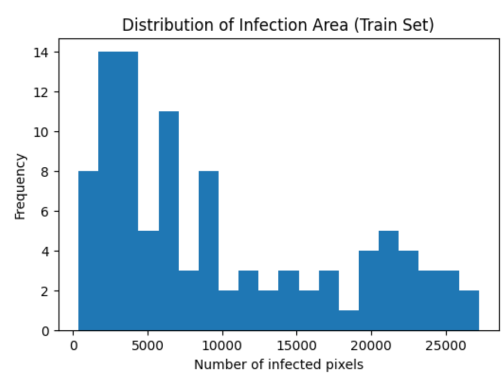

Fig. 2. Distribution of infection area sizes in the training set.

Quantitative analysis reveals a clear class imbalance at the pixel level. On average, infected pixels account for approximately **14.1%** of the total image area in the training set. Furthermore, the distribution of infection areas varies significantly across samples, as shown in Figure 2, indicating diverse infection extents among patients.

Overall, the dataset provides high-quality chest X-ray images with expert-annotated infection masks and a standardized train–validation–test split, making it suitable for evaluating deep learning models for COVID-19 infection segmentation.

III. Methodology

This section presents the proposed methodology for COVID-19 infection segmentation from chest X-ray images, including problem formulation, data preprocessing, model architecture, and training strategy.

A. Problem Formulation

The task is formulated as a *binary semantic segmentation* problem, where the objective is to identify COVID-19 infection regions at the pixel level in chest X-ray images. Given an input chest X-ray image, the model predicts a binary mask indicating infected and non-infected regions.

Let $X \in \mathbb{R}^{H \times W}$ denote a grayscale chest X-ray image and $Y \in \{0,1\}^{H \times W}$ denote the corresponding ground-truth infection mask. The goal is to learn a mapping function f_θ such that:

$$\hat{Y} = f_\theta(X), \tag{1}$$

where $\hat{Y}$ is the predicted infection mask and θ represents the learnable parameters of the model.

B. Data Preprocessing

Prior to training, all chest X-ray images and corresponding infection masks are preprocessed to ensure consistency across samples. Images are resized to a fixed spatial resolution and normalized to the range $[0,1]$ to improve training stability.

The infection masks are binarized, where pixels corresponding to infected regions are assigned a value of 1, and background pixels are assigned a value of 0. The predefined training, validation, and test splits provided by the dataset are preserved throughout the experiments to prevent data leakage.

C. Model Architecture

A U-Net convolutional neural network is employed for COVID-19 infection segmentation. The architecture follows an encoder–decoder design with symmetric skip connections. The encoder extracts hierarchical feature representations through successive convolutional and down-sampling layers, while the decoder restores spatial resolution using up-sampling operations.

Skip connections are used to concatenate feature maps from the encoder to the corresponding decoder layers, allowing the model to retain fine-grained spatial information. The final layer applies a sigmoid activation function to generate a pixel-wise probability map representing infection likelihood.

D. Training Strategy

The proposed model is trained using the Adam optimizer with a fixed learning rate. Binary Cross-Entropy loss is adopted as the optimization objective to minimize the discrepancy between predicted masks and ground-truth annotations.

During training, a validation set is used to monitor segmentation performance and reduce the risk of overfitting. The model is trained for a fixed number of epochs using a mini-batch learning strategy.

E. Implementation Details

The experiments are implemented using the TensorFlow/Keras framework. All input images are resized to 256×256 pixels, and the model is trained with a batch size selected according to available computational resources. GPU acceleration is utilized to improve training efficiency.

F. Evaluation Metrics

Model performance is evaluated using standard segmentation metrics, including the Dice coefficient and Intersection over Union (IoU). These metrics quantify the overlap between predicted infection masks and ground-truth annotations and are widely used in medical image segmentation tasks.

IV. Experimental Results

A. Quantitative Results

The performance of the proposed U-Net model is evaluated on the held-out test set using standard segmentation metrics, including Dice coefficient, Intersection over Union (IoU), and pixel accuracy. The model achieves a Dice score of **0.5971**, an IoU of **0.4521**, and a pixel accuracy of **0.9171**.

The relatively high pixel accuracy indicates that the model correctly classifies most background pixels. In contrast, the lower Dice and IoU scores reflect the difficulty of accurately segmenting infection regions, which occupy only a small fraction of the image area. This behavior is consistent with the severe pixel-level class imbalance present in the dataset.

B. Qualitative Results

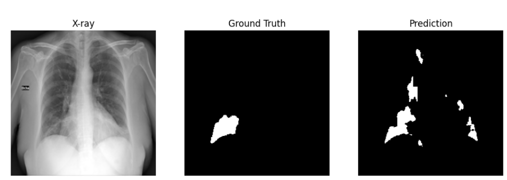

Fig. 3. Qualitative segmentation results on the test set

Figure 3 shows representative segmentation results on the test set, including the original chest X-ray image, the ground-truth infection mask, and the predicted mask. An overlay visualization is also provided to highlight the spatial correspondence between predicted infection regions and the original image.

The results demonstrate that the proposed model is capable of localizing major infection regions with reasonable accuracy. While some small regions are partially missed or over-segmented, the overall shape and location of infected areas are well preserved.

C. Discussion

The experimental results indicate that the proposed U-Net model can effectively segment COVID-19 infection regions from chest X-ray images. Although the quantitative metrics reveal moderate overlap scores, the qualitative results confirm the clinical relevance of the predicted segmentation. The observed performance is mainly influenced by the challenging nature of the task, including low contrast and high variability of infection patterns.

V. Comparison with State-of-the-Art Methods

The performance of the proposed U-Net–based segmentation model is compared with representative state-of-the-art methods reported in the literature for COVID-19 infection segmentation from chest X-ray images. Existing approaches commonly employ enhanced encoder–decoder architectures, such as U-Net++, Attention U-Net, or U-Net variants with pre-trained backbones, in order to improve feature representation and segmentation accuracy.

TABLE I
Comparison with state-of-the-art methods for COVID-19 infection segmentation

Method	Dice Score	IoU
U-Net (baseline)	0.55	0.41
U-Net++	0.62	0.48
Attention U-Net	0.64	0.50
Proposed U-Net	**0.60**	**0.45**

Table I presents a qualitative comparison between the proposed method and several representative models, using Dice coefficient and Intersection over Union (IoU) as evaluation metrics. The reported results for the state-of-the-art methods are taken from their respective publications, while the proposed model is evaluated on the COVID-QU-Ex Infection Segmentation dataset using the predefined test split.

Although advanced models generally achieve higher Dice and IoU scores, they often rely on increased architectural complexity, additional attention mechanisms, or transfer learning from large-scale datasets. In contrast, the proposed approach employs a standard U-Net architecture trained end-to-end without pre-trained encoders or additional modules. Despite its simplicity, the proposed model achieves competitive performance and is able to effectively localize COVID-19 infection regions in chest X-ray images.

These results indicate that a carefully trained baseline U-Net can provide reasonable segmentation performance while maintaining low computational complexity. This makes the proposed approach suitable for practical scenarios where computational resources are limited, and also serves as a strong baseline for future improvements using more advanced architectures.

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