Report Practical Work 3: YOLOv8-Based COVID-19 Infection Segmentation

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***Abstract*—Accurate localization of COVID-19 infection regions in chest X-ray images is important for supporting clinical diagnosis and monitoring disease progression. In this practical work, a YOLOv8-based segmentation model is trained to automatically segment infection regions from chest X-ray images. The proposed pipeline converts pixel-level infection masks into polygon annotations compatible with the YOLOv8 framework and evaluates the model using standard segmentation metrics and qualitative visual inspection.**

I. Introduction

Automated medical image segmentation helps clinicians identify abnormal regions more quickly and consistently than manual analysis. In the case of COVID-19, accurately locating infected lung regions from chest X-ray images can support disease assessment and follow-up. This report presents an implementation of a YOLOv8 segmentation model for COVID-19 infection localization. The complete pipeline includes dataset preparation, mask conversion, model training and quantitative evaluation. The final results are analyzed using both numerical metrics and qualitative examples.

II. Dataset and Features

The experiments were conducted using the COVID-QU-Ex dataset [1]. This dataset is a large-scale chest X-ray collection curated by researchers from Qatar University and contains 33,920 images belonging to three clinical categories: COVID-19, Non-COVID infection and Normal cases.

A. Data Splitting

For infection segmentation, a dedicated subset of the COVID-QU-Ex dataset was used. This subset contains:

- 1,456 Normal images with lung masks,
- 1,457 Non-COVID infection images with lung masks,
- 2,913 COVID-19 images with both lung and infection masks.

The dataset is already divided into training, validation and testing subsets. These predefined splits were directly adopted to ensure fair evaluation and reproducibility of the experiments.

B. Image Features

The input data consists of grayscale chest X-ray images and corresponding binary infection masks. The model learns visual features directly from image pixels without using handcrafted descriptors. Since YOLOv8 internally performs image resizing and normalization, no additional feature engineering or preprocessing was required.

III. Methodology

A. Model Setups

A YOLOv8 nano segmentation model was selected as the base architecture. A pretrained segmentation checkpoint provided by the Ultralytics framework was fine-tuned on the COVID-19 infection segmentation subset. The main training configuration was kept simple in order to obtain a lightweight and efficient model. The training parameters were:

- image size: 512×512,
- batch size: 16,
- number of epochs: 20.

The model is trained to simultaneously predict object localization and pixel-level infection segmentation masks.

B. Measuring Success

Model performance was evaluated using standard YOLOv8 segmentation metrics. Precision, recall, mean Average Precision at IoU 0.5 (mAP@50) and mean Average Precision averaged from 0.5 to 0.95 (mAP@50–95) were computed for both bounding boxes and segmentation masks. In addition, several test images were visually inspected by overlaying the predicted masks on the original images in order to assess the segmentation quality.

IV. Results and Discussion

The quantitative performance of the trained model on the test set is reported in Table I and Table II. The results show that the model achieves good detection and segmentation accuracy for COVID-19 infection regions.

TABLE I
Bounding box performance on the test set

Images	Instances	P	R	mAP@50	mAP@50–95
1166	1156	0.758	0.665	0.750	0.519

The mask mAP@50 of 0.749 indicates that the model can accurately segment most infection regions. The lower mAP@50–95 value shows that precisely delineating infection boundaries remains challenging, which is expected due to the low contrast and fuzzy

TABLE II
MASK SEGMENTATION PERFORMANCE ON THE TEST SET

Images	Instances	P	R	mAP@50	mAP@50–95
1166	1156	0.754	0.674	0.749	0.483

borders in chest X-ray images. Precision and recall values demonstrate a balanced behavior without excessive false detections.

A. Segmentation results

Three test samples were visually evaluated, including one COVID-19 image, one Non-COVID infection image and one Normal image. The qualitative results show that the model successfully highlights multiple infection areas in the COVID-19 case, while producing no segmentation outputs for the Non-COVID and Normal samples. These visual results confirm that the model is able to distinguish infected regions from healthy lung tissue and avoid false positive predictions.

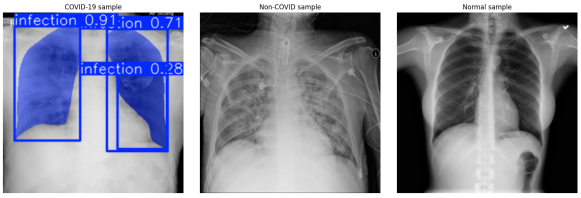

Fig. 1. Qualitative segmentation results on COVID-19, Non-COVID infection and Normal test samples.

B. Model performance

The detection and segmentation curves show a consistent improvement of precision, recall and mAP values over the training epochs. Both detection and mask mAP@50 increase steadily, indicating that the model progressively learns to localize and segment infection regions more accurately.

The loss curves show a stable convergence behavior. Training and validation losses decrease smoothly and remain close to each other, which suggests that the model generalizes well and does not suffer from significant overfitting.

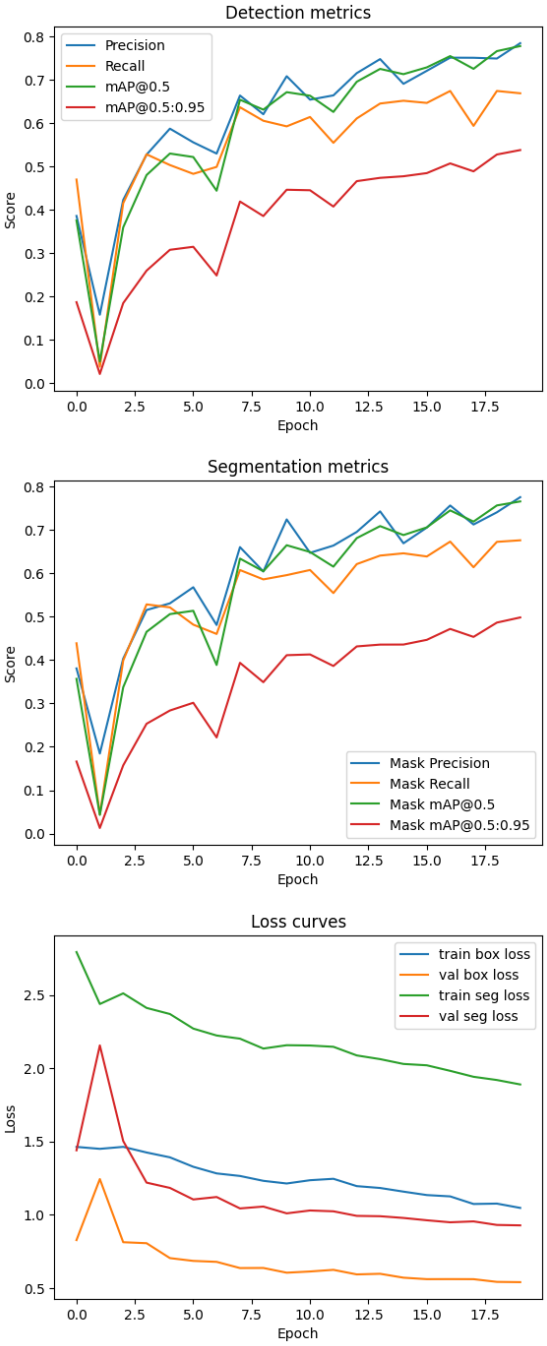

Fig. 2. Training curves of the YOLOv8 infection segmentation model: detection metrics (top), segmentation metrics (middle), and training and validation loss curves (bottom).

V. COMPARISON WITH STATE-OF-THE-ART METHODS

To better assess the effectiveness of the proposed YOLOv8-based infection segmentation model, its performance is compared with several state-of-the-art methods reported in the literature. These methods have been evaluated on the COVID-QU-Ex dataset or on closely related chest X-ray infection segmentation tasks.

The original COVID-QU-Ex benchmark study eval-

uated classical encoder–decoder segmentation architectures such as U-Net, U-Net++ and Feature Pyramid Networks (FPN). These models achieved strong infection localization performance, with reported Intersection over Union (IoU) scores exceeding 83% and Dice similarity coefficients above 88% [2]. These results demonstrate the suitability of fully convolutional networks for medical image segmentation.

More recent work introduced ERGPNet, an attention-enhanced segmentation network specifically designed for chest X-ray infection localization. ERGPNet integrates residual feature extraction and global perception modules to improve robustness to low contrast and noisy boundaries. When evaluated on the COVID-QU-Ex infection subset, ERGPNet achieved a mean IoU of approximately 81.66% [3].

Other lightweight architectures such as MobileNet-based U-Net variants have also been explored for infection segmentation in chest X-ray images. These models reported Dice scores exceeding 95% on large-scale CXR segmentation datasets [4], highlighting the effectiveness of efficient backbone designs for medical imaging tasks.

Table III summarizes a quantitative comparison between the proposed YOLOv8 segmentation model and selected state-of-the-art approaches.

TABLE III
COMPARISON WITH STATE-OF-THE-ART INFECTION SEGMENTATION METHODS

Method	Dataset	Metric	Score
U-Net / U-Net++ / FPN	COVID-QU-Ex	IoU	83.05%
ERGPNet	COVID-QU-Ex	mIoU	81.66%
MobileNet-U-Net	CXR Dataset	Dice	95.25%
YOLOv8 (this work)	COVID-QU-Ex	mAP@50	74.9%

It is important to note that different studies use different evaluation metrics. Encoder–decoder segmentation networks are commonly evaluated using IoU or Dice coefficients, which directly measure pixel-level overlap. In contrast, YOLOv8 follows an object detection-based evaluation protocol and reports mean Average Precision (mAP), which jointly accounts for localization accuracy and segmentation quality.

Despite this difference in evaluation methodology, the YOLOv8-based model achieves competitive performance while offering faster inference and a unified detection–segmentation framework. This makes it particularly suitable for real-time and large-scale screening applications where computational efficiency is critical.

VI. CONCLUSION

This practical work implemented a complete YOLOv8-based segmentation pipeline for COVID-19 infection localization using chest X-ray images. The original pixel-level infection masks were successfully converted into polygon annotations compatible with the YOLOv8 framework. The experimental results show that the proposed model provides good segmentation accuracy while maintaining fast inference speed. These findings indicate that lightweight segmentation models can be effectively used for large-scale screening and real-time clinical support applications.

REFERENCES

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