Practical Work 3 - COVID-19 Infection Segmentation from Chest X-ray Images

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I. Introduction

COVID-19 infection segmentation from chest X-ray images is a critical task in medical imaging for diagnosis and treatment planning. Accurate identification of infection regions helps clinicians assess disease severity and monitor progression.

In this paper, I implement a cascade segmentation approach using deep learning. The pipeline consists of two stages: (1) lung segmentation to localize the region of interest, and (2) infection segmentation constrained by the lung mask. This approach leverages prior knowledge that infection regions must lie within lung boundaries.

II. Dataset Overview

The COVID-QU-Ex dataset contains chest X-ray images with corresponding lung and infection masks:

- **Lung Segmentation Data:** Images with lung masks for three classes (COVID-19, Non-COVID, Normal)
- **Infection Segmentation Data:** Images with infection masks for the same classes
- **Train/Val/Test split:** Approximately 70/15/15 distribution
- **Total samples:** 33,920 chest X-ray images

The dataset structure allows for a two-stage cascade approach where lung masks guide infection segmentation.

III. Methodology: Cascade Segmentation

A. Architecture: U-Net with EfficientNet-B3

I use U-Net architecture with EfficientNet-B3 encoder pretrained on ImageNet. EfficientNet-B3 extracts features from images, and U-Net decoder reconstructs segmentation masks. Pretrained weights help the model learn faster.

B. Stage 1: Lung Segmentation

The first stage segments the entire lung region to establish a coarse localization:

Input: 3-channel RGB images (grayscale X-rays converted to RGB for pretrained encoder)

Output: Binary lung mask

Training configuration:

- Image size: 448×448
- Batch size: 32
- Epochs: 15 (with early stopping patience=5)
- Learning rate: 1e-4
- Weight decay: 1e-4
- Loss: DiceBCELoss (0.7×Dice + 0.3×BCE)

Lung segmentation is relatively easy due to high contrast between lung and background, achieving Val Dice of 0.97 within 5-7 epochs.

C. Stage 2: Infection Segmentation

The second stage segments infection regions using a 4-channel input that includes the lung mask:

Input: 4-channel (RGB + lung mask from Stage 1)

Output: Binary infection mask constrained by lung boundaries

Training configuration:

- Image size: 448×448
- Batch size: 32
- Encoder: EfficientNet-B0 (4M params)
- Learning rate: 1e-4
- Weight decay: 1e-3
- Dropout: 0.3
- Gradient clipping: 1.0
- Loss: CombinedLoss (0.5×Dice + 0.3×BCE + 0.2×Focal)
- Epochs: 50 (early stopped at 27, patience=12)

D. Data Augmentation

Training augmentations include:

- Horizontal flip (p=0.5)
- Shift-scale-rotate (±10%, ±15°)
- Random brightness/contrast (±20%)
- Gaussian noise
- ImageNet normalization

Validation uses only resize and normalization.

E. Loss Function and Metrics

I use **DiceBCELoss** which combines two objectives:

- Dice Loss: measures overlap between prediction and ground truth
- BCE Loss: pixel-wise binary cross-entropy
- Combined: 0.7×Dice + 0.3×BCE

Evaluation metrics:

- **Dice Coefficient:** overlap ratio (0-1, higher is better)
- **IoU Score:** intersection over union (similar to Dice)

IV. Results

A. Stage 1: Lung Segmentation Performance

Table I shows the lung segmentation results.

Lung segmentation achieves excellent performance with Val Dice of 0.97, indicating near-perfect localization of lung regions. The model converged within 6 epochs due to the simplicity of the task.

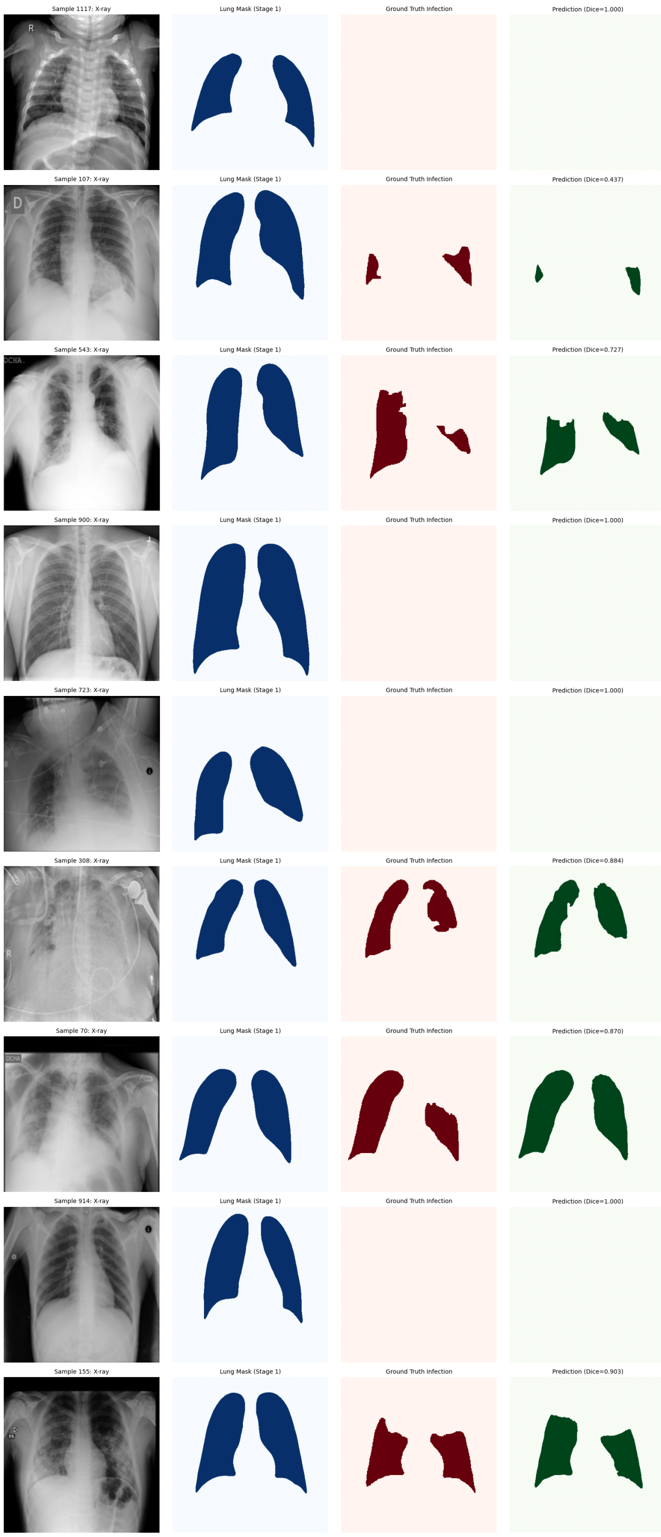

Fig. 1: Sample test predictions showing cascade segmentation results. Columns from left to right: original X-ray, lung mask from Stage 1, ground truth infection mask, and predicted infection mask. The model achieves Dice scores above 0.85 across different severity levels.

TABLE I: Stage 1: Lung Segmentation Results

Metric	**Train**	**Val**
Dice Coefficient	0.9732	0.9774
IoU Score	0.9478	0.9561
Loss	0.0329	0.0274

B. *Stage 2: Infection Segmentation Performance*

Table II shows the infection segmentation results using the improved model (EfficientNet-B0 encoder with enhanced regularization).

TABLE II: Stage 2: Infection Segmentation Results (Improved Model)

Metric	**Train**	**Val**	**Test**
Dice Coefficient	0.7157	0.8912	0.8854
IoU Score	-	-	0.7896
Loss	0.1351	0.3106	0.3082
Epochs Trained	27 (early stopped)		

V. Conclusion

This cascade segmentation pipeline achieves high accuracy for COVID-19 infection detection from chest X-rays. Stage 1 lung segmentation provides robust localization (Val Dice 0.9774), while Stage 2 achieves Test Dice of 0.8854 for infection segmentation.

Future improvements could include:

- Multi-task learning to jointly optimize both stages
- Attention mechanisms to focus on infection-prone regions
- Ensemble methods combining multiple encoder architectures