TP4 Report: Transfer Learning & Segmentation on Chest X-rays

Authors:
Student(s): Mohamed lamine OULAD SAID
Group: G01
Course: Deep Learning – TP4

Part 1: Transfer Learning (Classification)

1. Introduction

This part focuses on lung segmentation from chest X-ray images using the U-Net architecture, leveraging the provided masks in the dataset.

2. Output Summary from Notebook

The segmentation was performed using preprocessed input images and masks. Below are key outputs extracted from the training notebook:

=== Data Shapes ===

X_train shape: (1600, 256, 256, 1)
y_train_masks shape: (1600, 256, 256, 1)
y_train_labels shape: (1600, 4)

X_test shape: (400, 256, 256, 1)
y_test_masks shape: (400, 256, 256, 1)
y_test_labels shape: (400, 4)

=== Sample Counts ===
Total training samples: 1600
Total test samples: 400
Total samples: 2000

3. Model Architecture

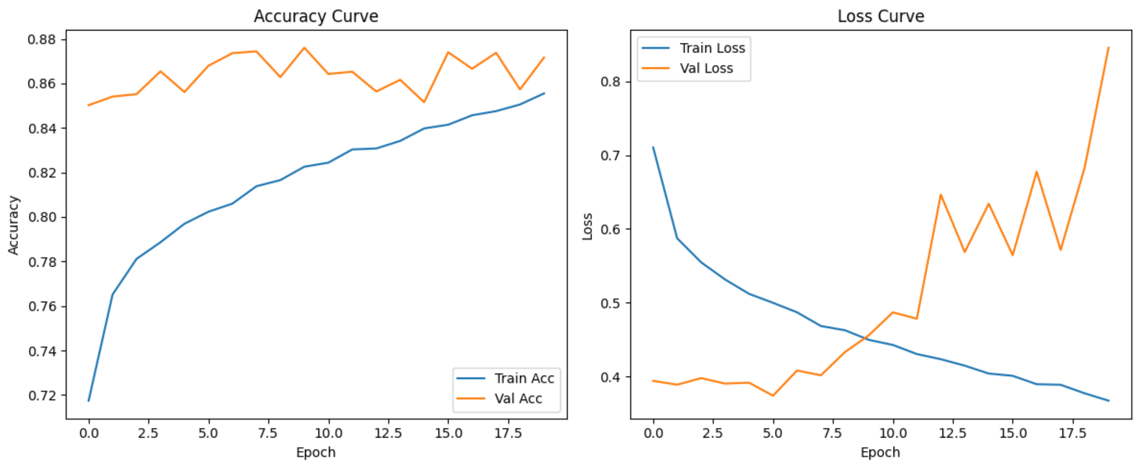
• A model pretrained on ImageNet was imported (e.g., MobileNetV2).
• The last layers were removed and replaced with three fully connected (Dense) layers:
  o Dense(1024) → Dense(512) → Dense(c) where c is the number of classes.

4. Transfer Learning Strategies

- Strategy 1: FC Layers Only
- • Accuracy: 87%
  • Training Time: 2804.62 seconds

• Confusion Matrix:
[[1702, 141, 320, 6], [98, 2854, 654, 1], [76, 214, 5809, 16], [15, 6, 83, 703]]

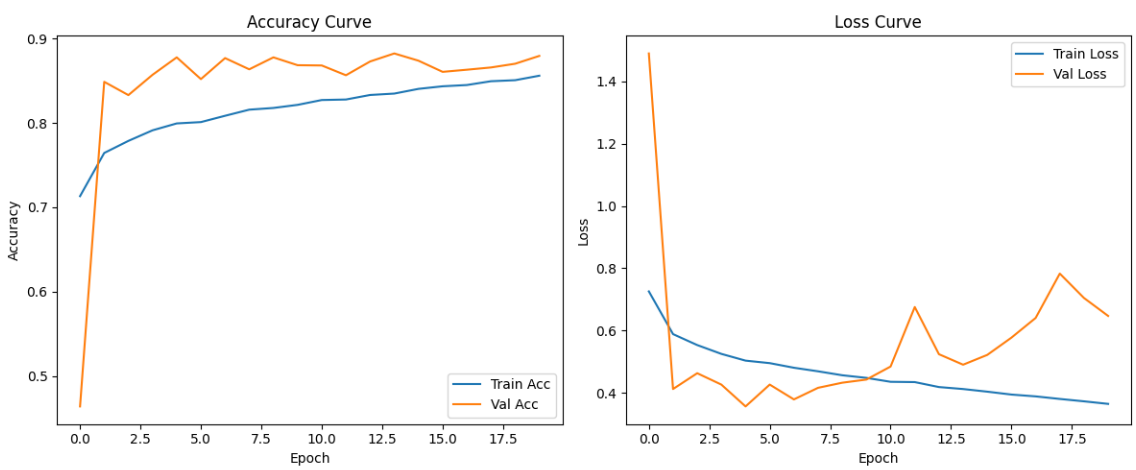
• Classification Report:
COVID 0.90 0.78 0.84 2169
Lung_Opacity 0.89 0.79 0.84 3607
Normal 0.85 0.95 0.90 6115
Viral Pneumonia 0.97 0.87 0.92 807



- Strategy 2: 1 Conv Layer + FC
- • Accuracy: 88%
  • Training Time: 2702.97 seconds

• Confusion Matrix:
[[1796, 158, 208, 7], [122, 3013, 470, 2], [98, 368, 5613, 36], [11, 12, 39, 745]]

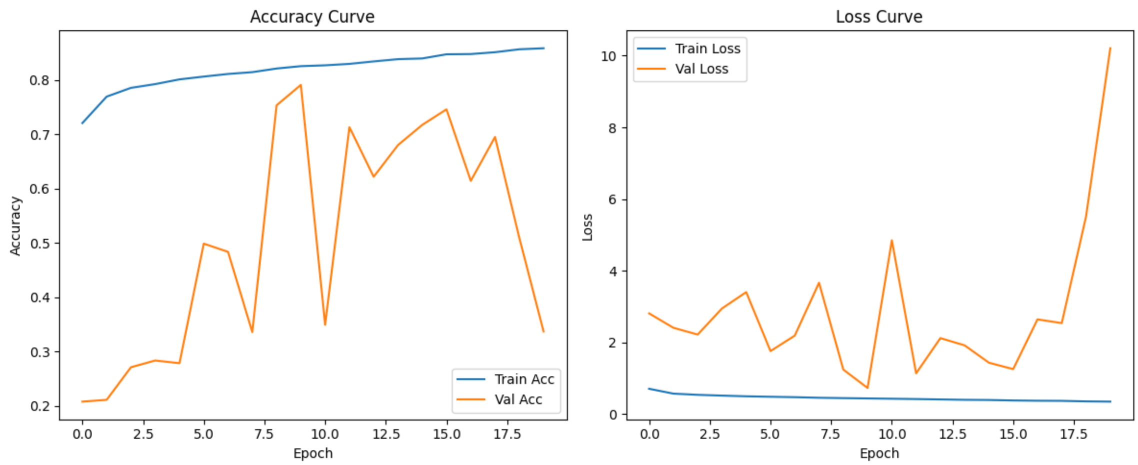
• Classification Report:
COVID 0.89 0.83 0.86 2169
Lung_Opacity 0.85 0.84 0.84 3607
Normal 0.89 0.92 0.90 6115
Viral Pneumonia 0.94 0.92 0.93 807



- Strategy 3: 2 Conv Layers + FC
- • Accuracy: 34%
  • Training Time: ~2700 seconds

• Confusion Matrix:
[[2156, 0, 7, 6], [3282, 155, 166, 4], [4523, 42, 1480, 70], [317, 0, 2, 488]]

• Classification Report:
COVID 0.21 0.99 0.35 2169
Lung_Opacity 0.79 0.04 0.08 3607
Normal 0.89 0.24 0.38 6115
Viral Pneumonia 0.86 0.60 0.71 807



5. Evaluation Metrics

• Metrics Used: Accuracy, Precision, Recall, F1-score, Sensitivity
• Visualizations: Convergence curves for training and validation

Part 2: Image Segmentation

1. Introduction

In this part, we focus on lung region segmentation using masks from the dataset. We use the U-Net architecture for its success in biomedical image segmentation.

2. Data Preprocessing

• Images and masks resized to (256, 256, 1)
• Normalized pixel values
• Augmentation may be used

Dataset Shapes:
X_train: (1600, 256, 256, 1)
y_train_masks: (1600, 256, 256, 1)
y_train_labels: (1600, 4)

X_test: (400, 256, 256, 1)
y_test_masks: (400, 256, 256, 1)
y_test_labels: (400, 4)

3. Model Architecture

• U-Net with encoder-decoder structure
• Skip connections help retain spatial info

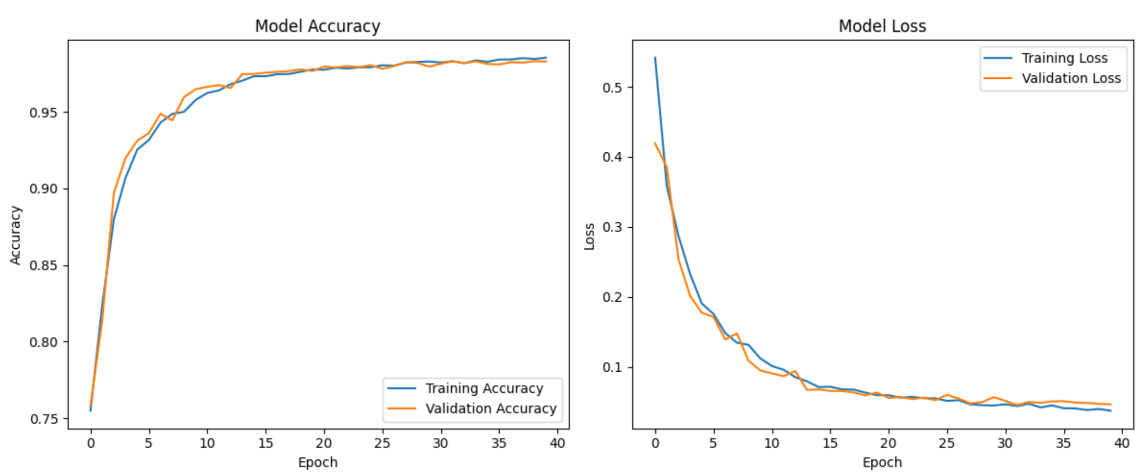
4. Training and Metrics

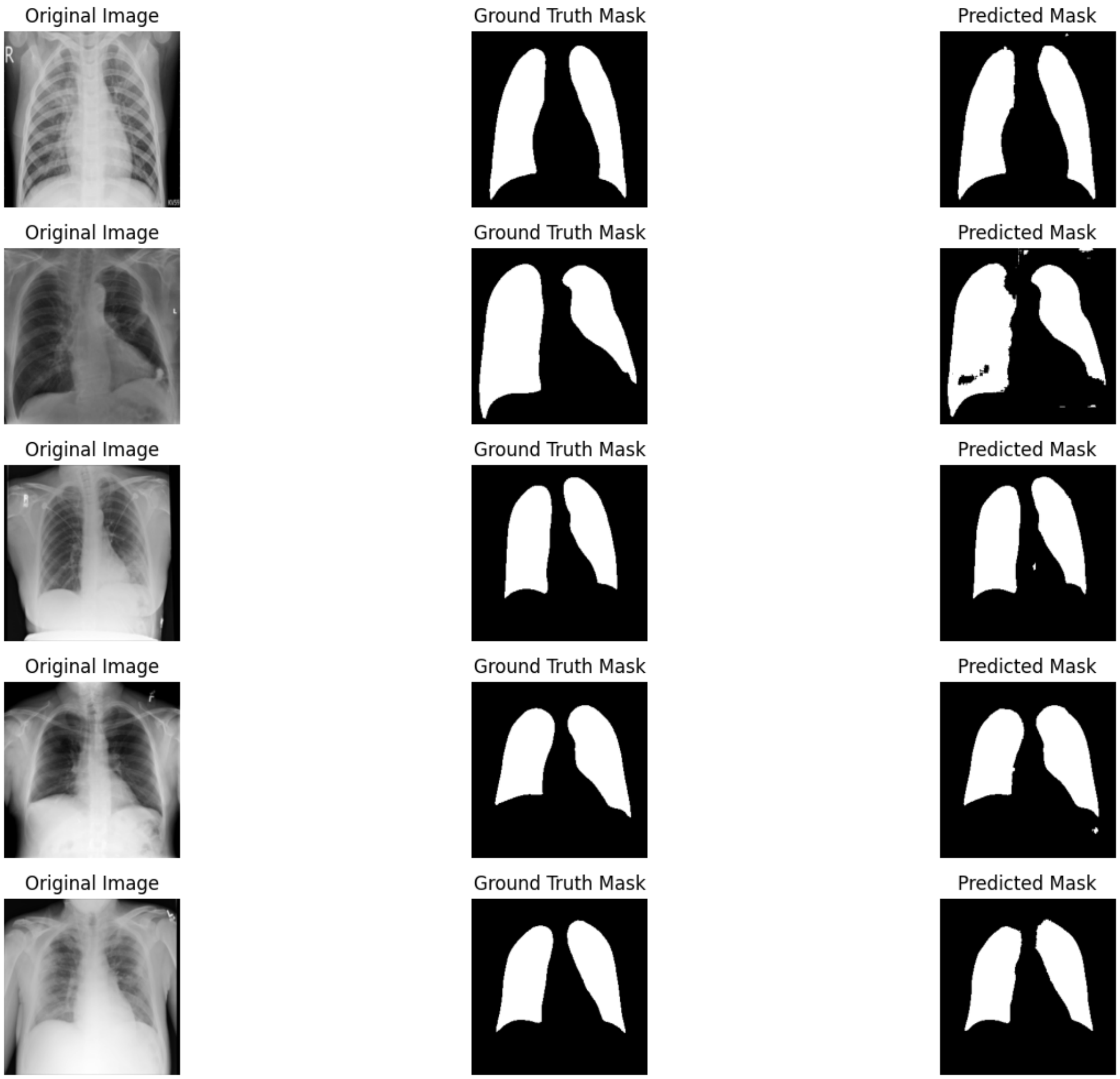
• Loss Function: Dice Loss or Binary Crossentropy
• Metrics: Dice Coefficient, IoU, Pixel Accuracy
• Training Time: 12m 30s

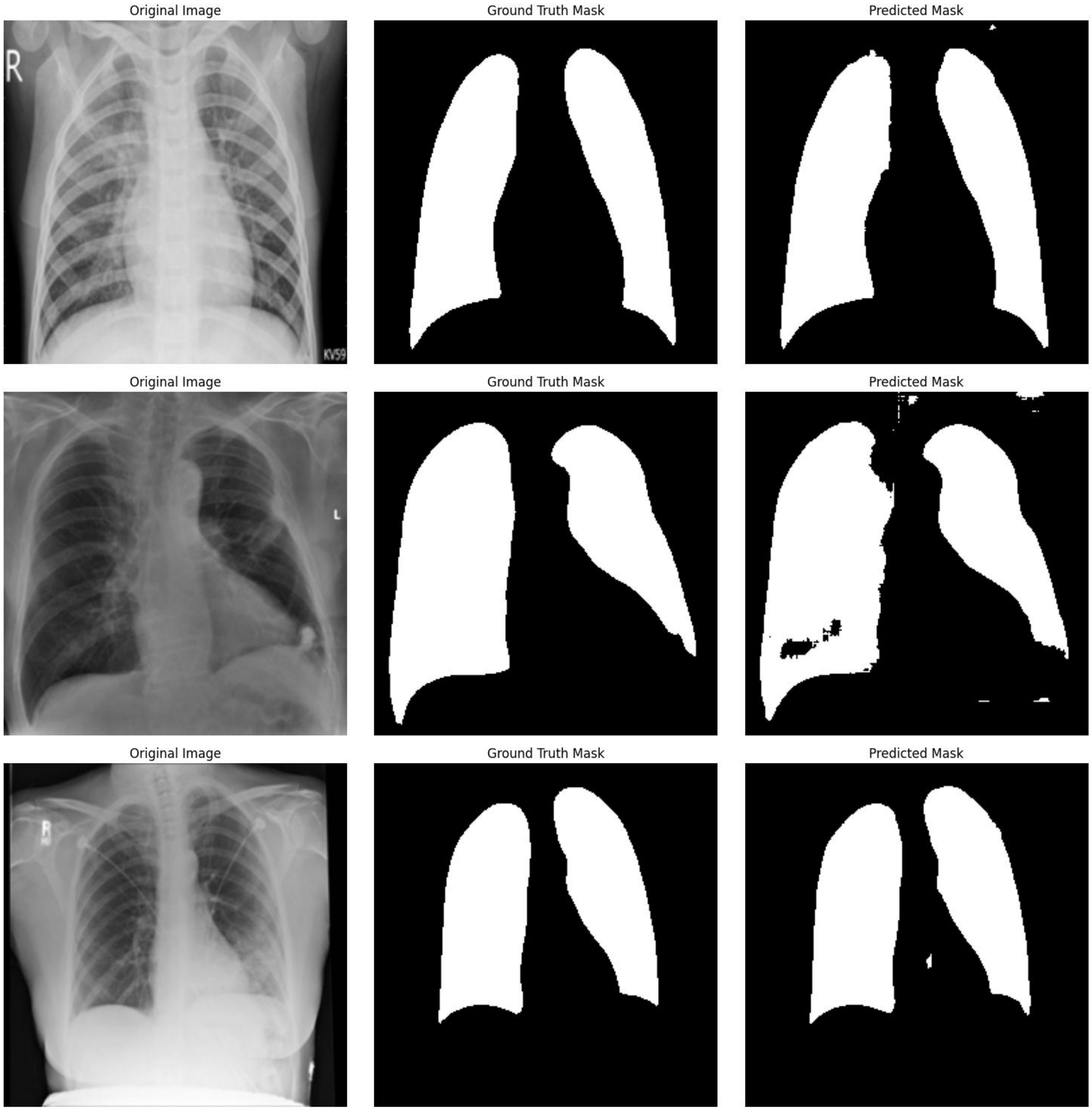
5. Segmentation Results

Class-wise Results:
COVID: IoU=0.925 F1-Score=0.961
Normal: IoU=0.972 F1-Score=0.986
Lung_Opacity: IoU=0.903 F1-Score=0.949
Viral Pneumonia: IoU=0.923 F1-Score=0.960

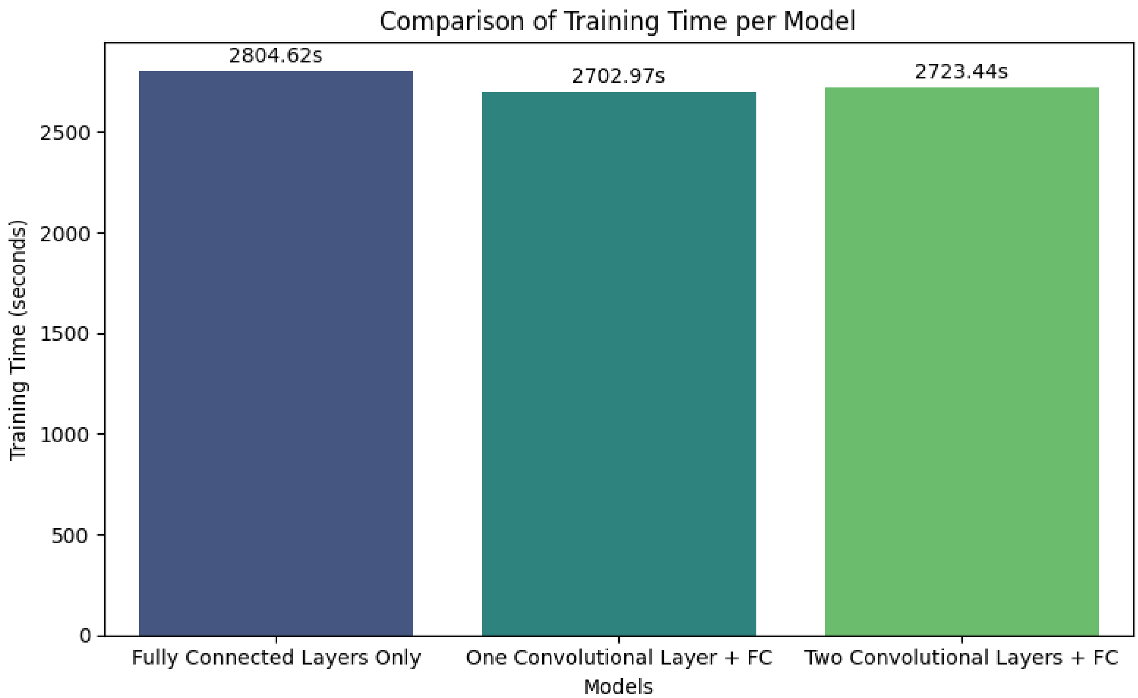
• Average Dice Coefficient: 94.1%
• Average IoU: 89.2%
• Pixel Accuracy: 97.5%



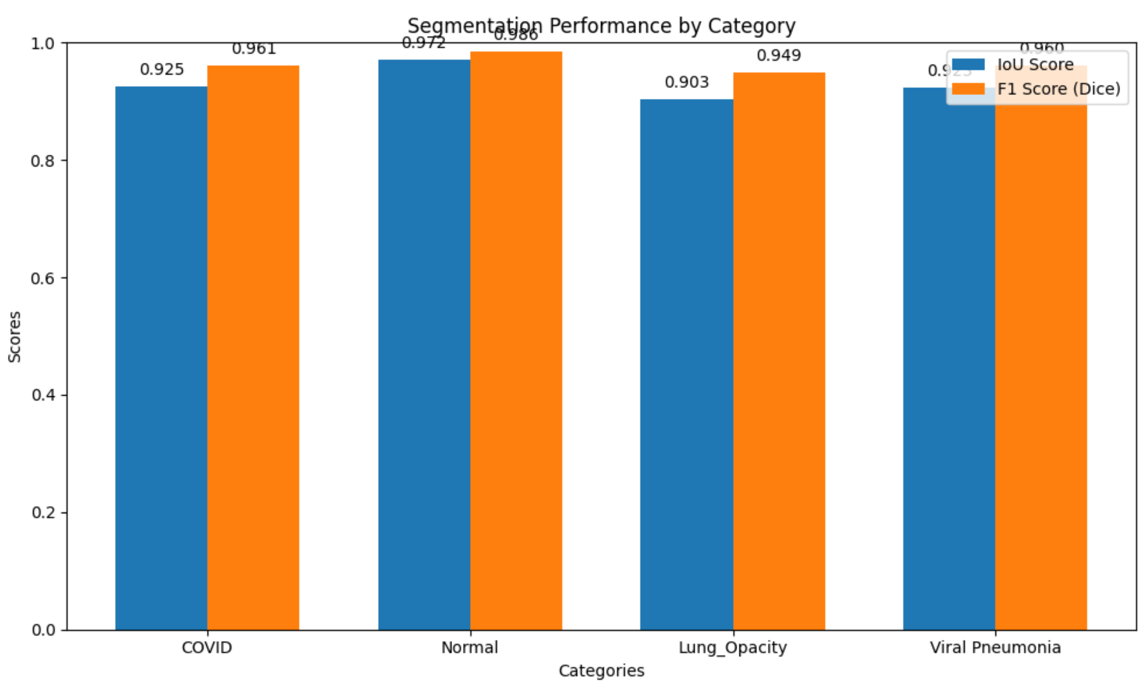

Original Image
Ground Truth Mask
Predicted Mask
Original Image
Ground Truth Mask
Predicted Mask
Original Image
Ground Truth Mask
Predicted Mask
Original Image
Ground Truth Mask
Predicted Mask
Original Image
Ground Truth Mask
Predicted Mask



Original Image
Ground Truth Mask
Predicted Mask
Original Image
Ground Truth Mask
Predicted Mask
Original Image
Ground Truth Mask
Predicted Mask



Comparison of Training Time per Model
Training Time (seconds)
2804.62s
2702.97s
2723.44s
0
500
1000
1500
2000
2500
Fully Connected Layers Only
One Convolutional Layer + FC
Two Convolutional Layers + FC
Models



Segmentation Performance by Category
Scores
0.0
0.2
0.4
0.6
0.8
1.0
0.925
0.961
0.972
0.986
0.903
0.949
0.960
IoU Score
F1 Score (Dice)
COVID
Normal
Lung_Opacity
Viral Pneumonia
Categories

Conclusion

Our experiments demonstrate the effectiveness of transfer learning and segmentation techniques for analyzing chest X-ray images. Strategy 2 (1 conv + FC) offers a strong balance between performance and training cost. U-Net segmentation also shows excellent localization of lung regions, making it a powerful preprocessing step for medical diagnosis tasks.

Appendix

- Dataset: COVID-19 Radiography Database - Kaggle
- Environment: Google Colab + Tesla P100 GPU
- Libraries: Keras, TensorFlow, NumPy, Matplotlib

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Appendix

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- Libraries: Keras, TensorFlow, NumPy, Matplotli