CAP 5516 Programming Assignment #1

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Course: CAP 5516 - Medical Image Computing
Semester: Spring 2026
Due Date: March 1, 2026, 11:59 PM EST **Code Repository:** Assignment1-CAP5516

1. Experimental Setup

1.1 Dataset Description

Dataset: Chest X-Ray Images (Pneumonia)
Source: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia

- Total images: 5,863 JPEG images
- Classes: `NORMAL`, `PNEUMONIA`
- Patient population: pediatric chest X-rays
- Provided split: `train`, `val`, `test`

1.2 Hardware and Software

- GPU: `NVIDIA RTX A5000`
- Framework: `PyTorch`
- Logging: `TensorBoard`
- Environment details: `Python 3.10 / CUDA 12.1 / PyTorch 2.4.1`

1.3 Model

- Backbone: `ResNet-18`
- Output classes: `2`

2. Experiment 1 : 30 epoch setup

2.1 Implementation Details

Hyperparameter	Task 1.1 Scratch	Task 1.2 Fine-tune
Epochs	30	30
Batch size	64	64
Base learning rate	1e-3	1e-3

We use a CosineAnnealingLR throughout the training. All validations and checkpoint saves were made every 5 epochs. The checkpoint with best validation accuracy and the last checkpoint are saved.

2.2 Training and Validation Loss Curves

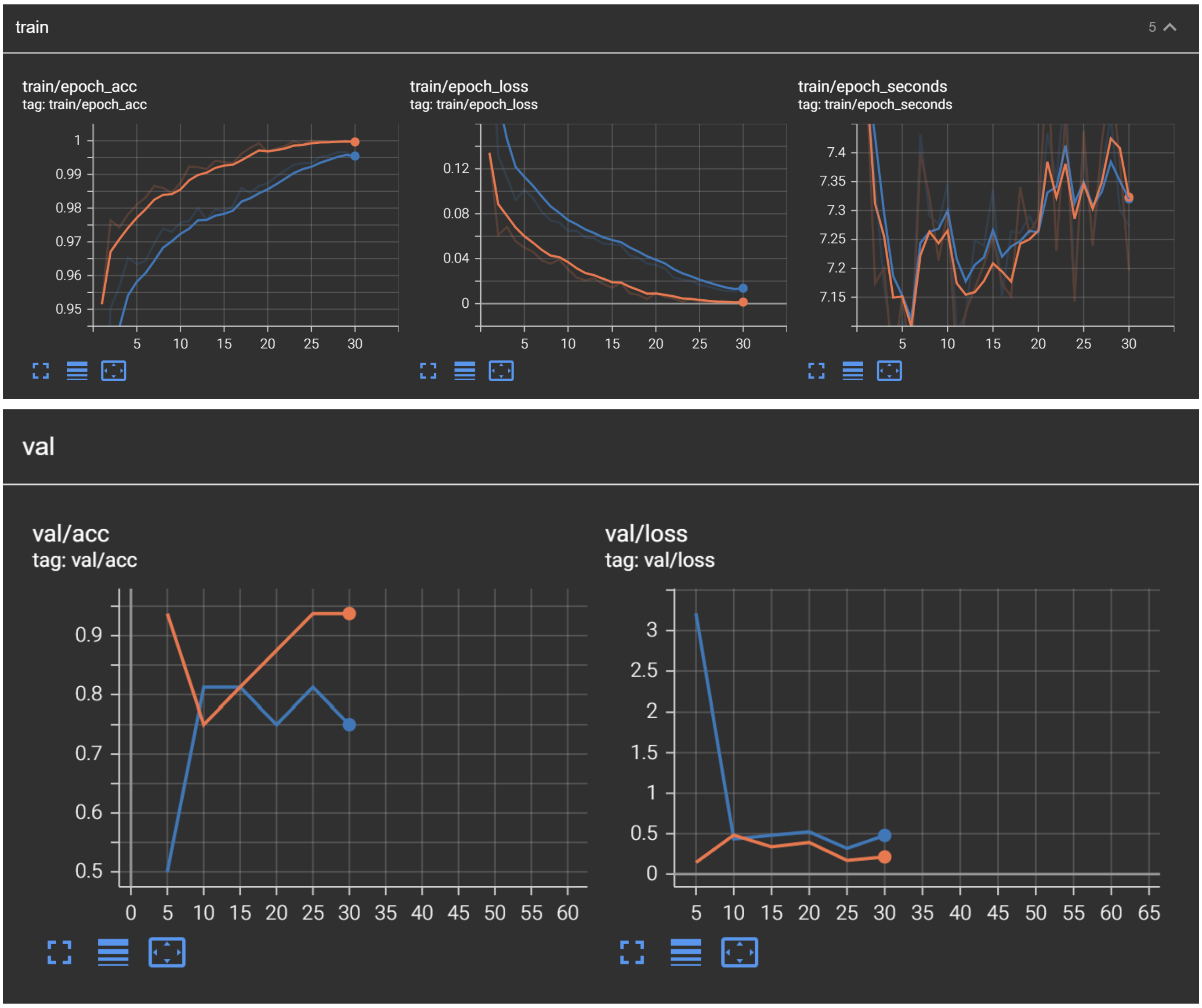


Figure 1. Training and validation loss curves for ResNet-18 trained from scratch. Blue = Scratch, Orange = Finetuned. It can be observed that the finetuned version performs better than scratch, for both accuracy and loss.

2.3 Testing Performance

Metric	Task 1.1 Scratch (best)	Task 1.1 Scratch (last)	Task 1.2 Fine-tune (best)	Task 1.2 Fine-tune (last)
Test loss	0.6561	1.3939	0.3324	1.2600
Test accuracy	0.8365	0.7692	0.9199	0.8317
NORMAL accuracy	0.5940	0.3889	0.8248	0.5556
PNEUMONIA accuracy	0.9821	0.9974	0.9769	0.9974

2.4 Example ailure Cases

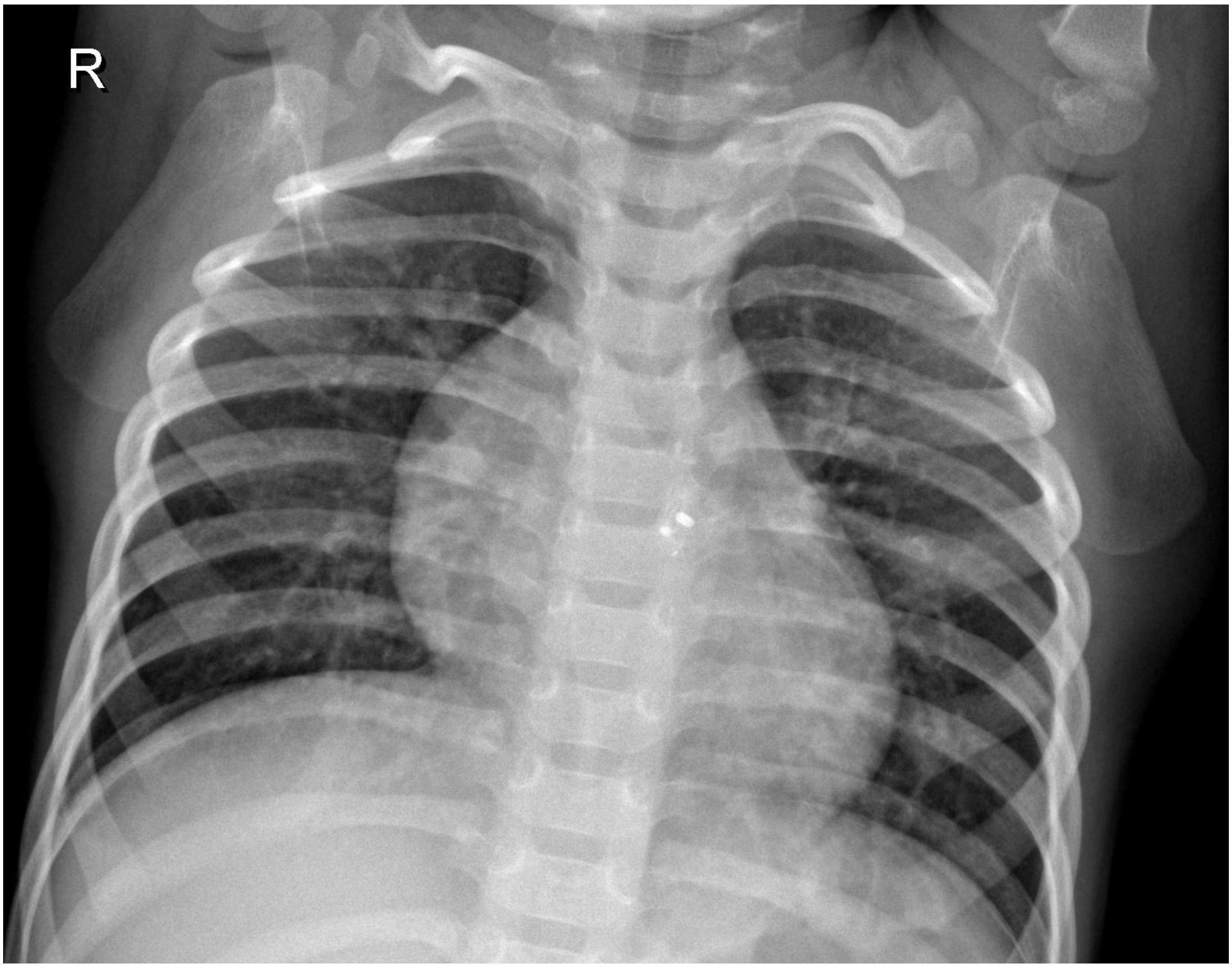


Figure 2. Example failure case : test/PNEUMONIA/person154_bacteria_728.jpeg. Predicted as NORMAL despite being PNEUMONIA.

3. Experiment 2 : 500 epoch setup

3.1 Implementation Details

Hyperparameter	Task 1.1 Scratch	Task 1.2 Fine-tune
Epochs	500	500
Batch size	64	64
Base learning rate	1e-3	1e-3

We use a CosineAnnealingLR throughout the training. All validations and checkpoint saves were made every 5 epochs. The checkpoint with best validation accuracy and the last checkpoint are saved.

3.2 Training and Validation Loss Curves

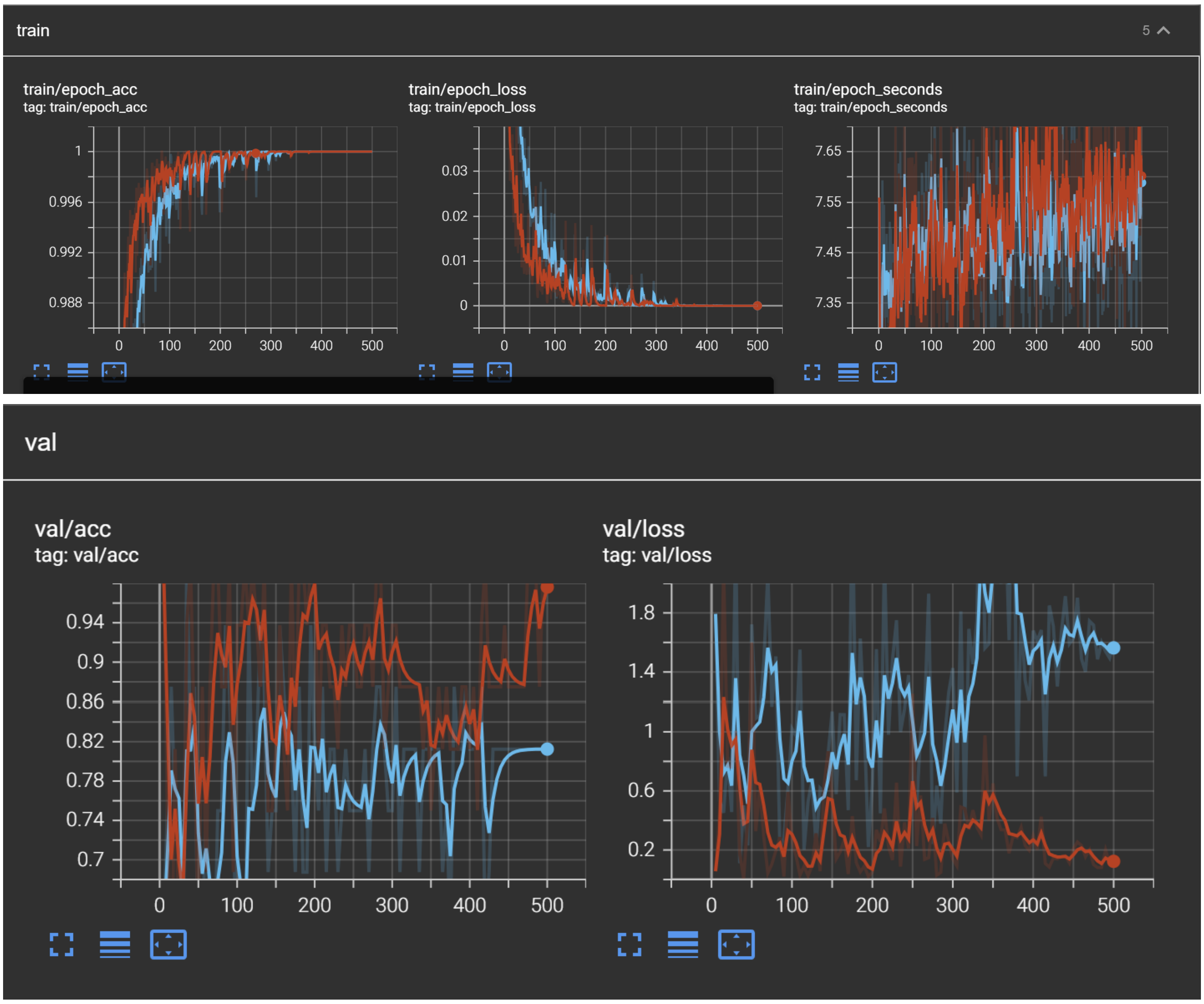
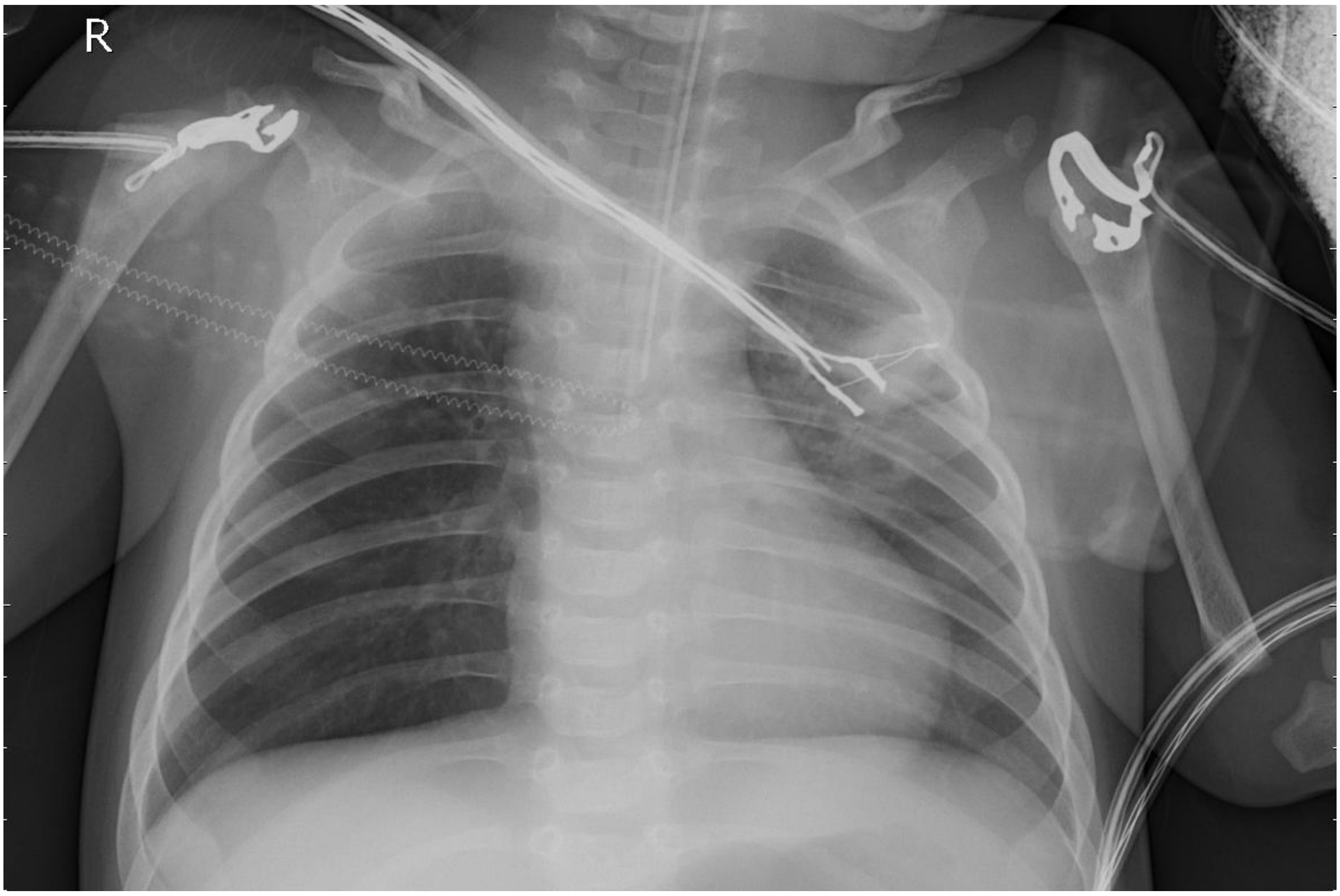


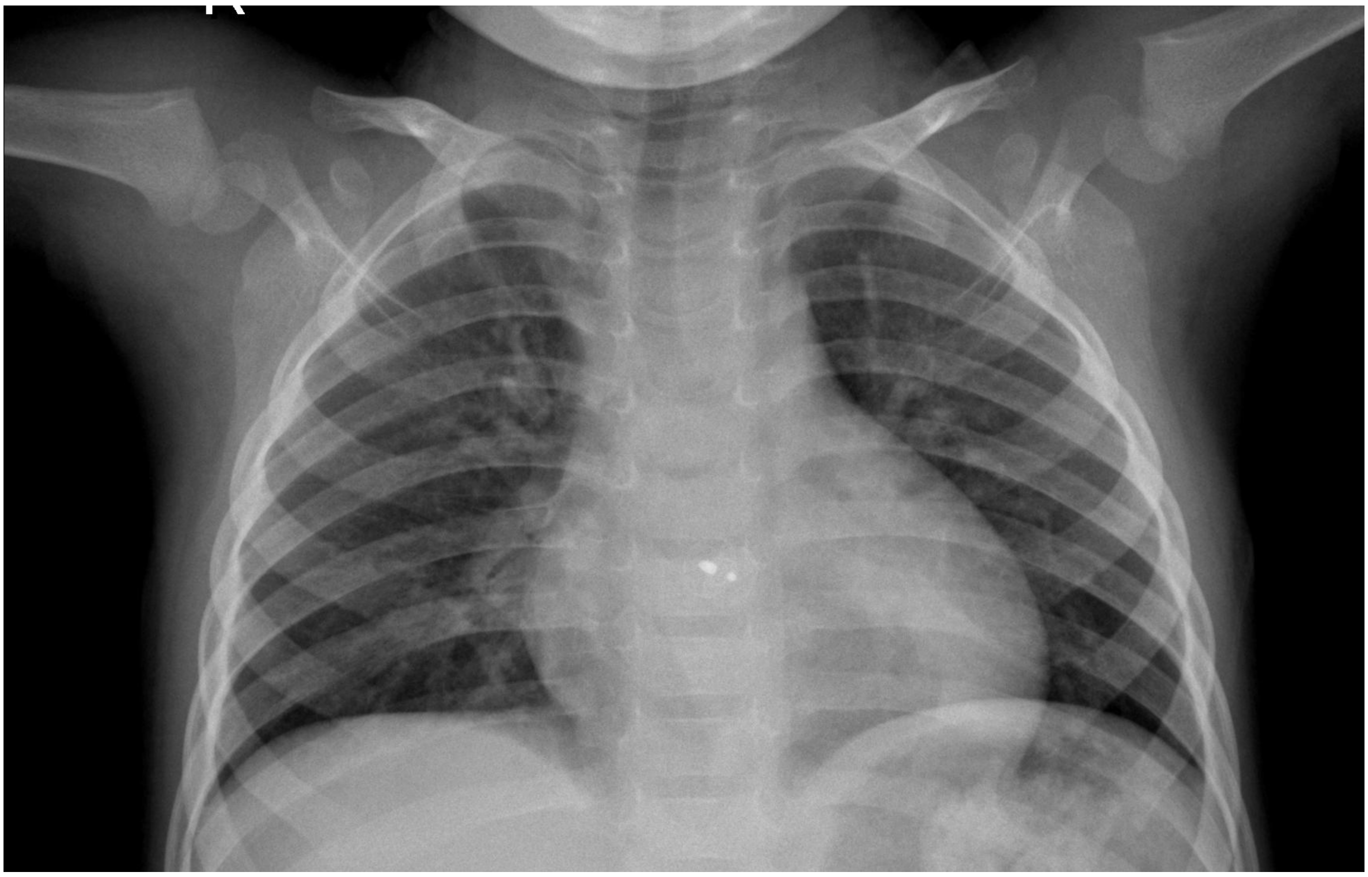
Figure 3. Training and validation loss curves for ResNet-18 trained from scratch. Sky Blue = Scratch, Red = Finetuned. It can be observed that the finetuned version performs better than scratch, for both accuracy and loss.

3.3 Testing Performance

Metric	Task 1.1 Scratch (best)	Task 1.1 Scratch (last)	Task 1.2 Fine-tune (best)	Task 1.2 Fine-tune (last)
Test loss	0.9944	3.1254	0.3920	3.7072
Test accuracy	0.7869	0.8285	0.9087	0.8333
NORMAL accuracy	0.4487	0.5513	0.7650	0.5641
PNEUMONIA accuracy	0.9897	0.9949	0.9949	0.9649

3.4 Example Failure Cases


R



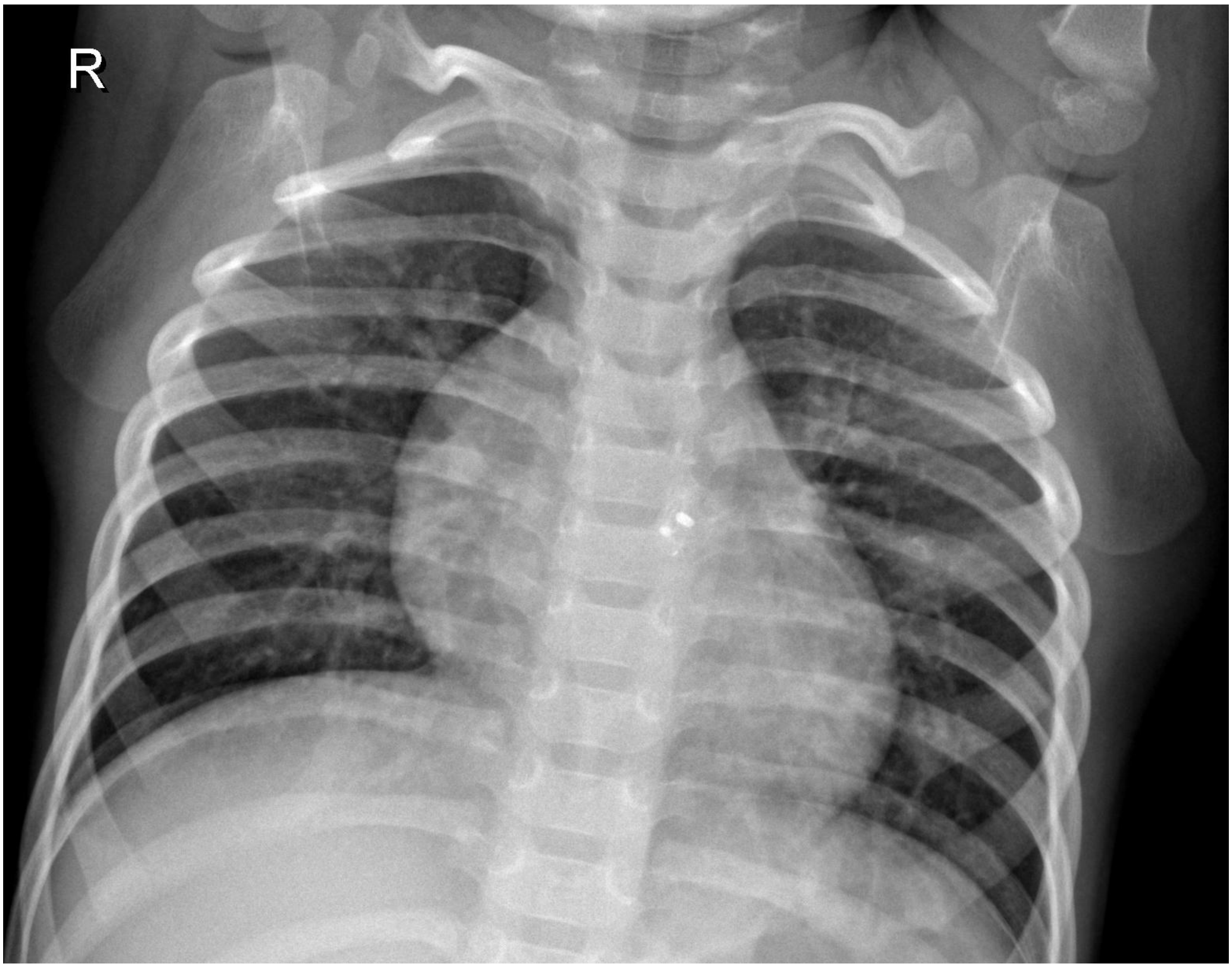


Figure 4. Example failure cases : Predicted as NORMAL despite being PNEUMONIA.

4. Experiment 3 : 500 epoch setup, with more training strategies (All Finetunbe)

4.1 Implementation Details

We add additional techniques such as warmup epochs, label smoothing, and data augmentation. We compare between the session without data augmentation (Option 1) and with data augmentation (Option 2).

Hyperparameter	Vanilla Finetune	Option 1	Option 2
Epochs	500	500	500
Batch size	64	64	64
Base learning rate	1e-3	1e-3	1e-3
Weight decay	1e-4	1e-4	1e-4
Warmup epochs	0	5	5
Label smoothing	0	0.1	0.1

Hyperparameter	Vanilla Finetune	Option 1	Option 2
Xavier init	False	True	True
Random erasing prob	0.0	0.0	0.25
Cutout prob	0.0	0.0	0.5

We use a CosineAnnealingLR throughout the training, except for cases with Warmup epochs, which we use a LinearLR for the warmup epochs. All validations and checkpoint saves were made every 5 epochs. The checkpoint with best validation accuracy and the last checkpoint are saved.

4.2 Training and Validation Loss Curves

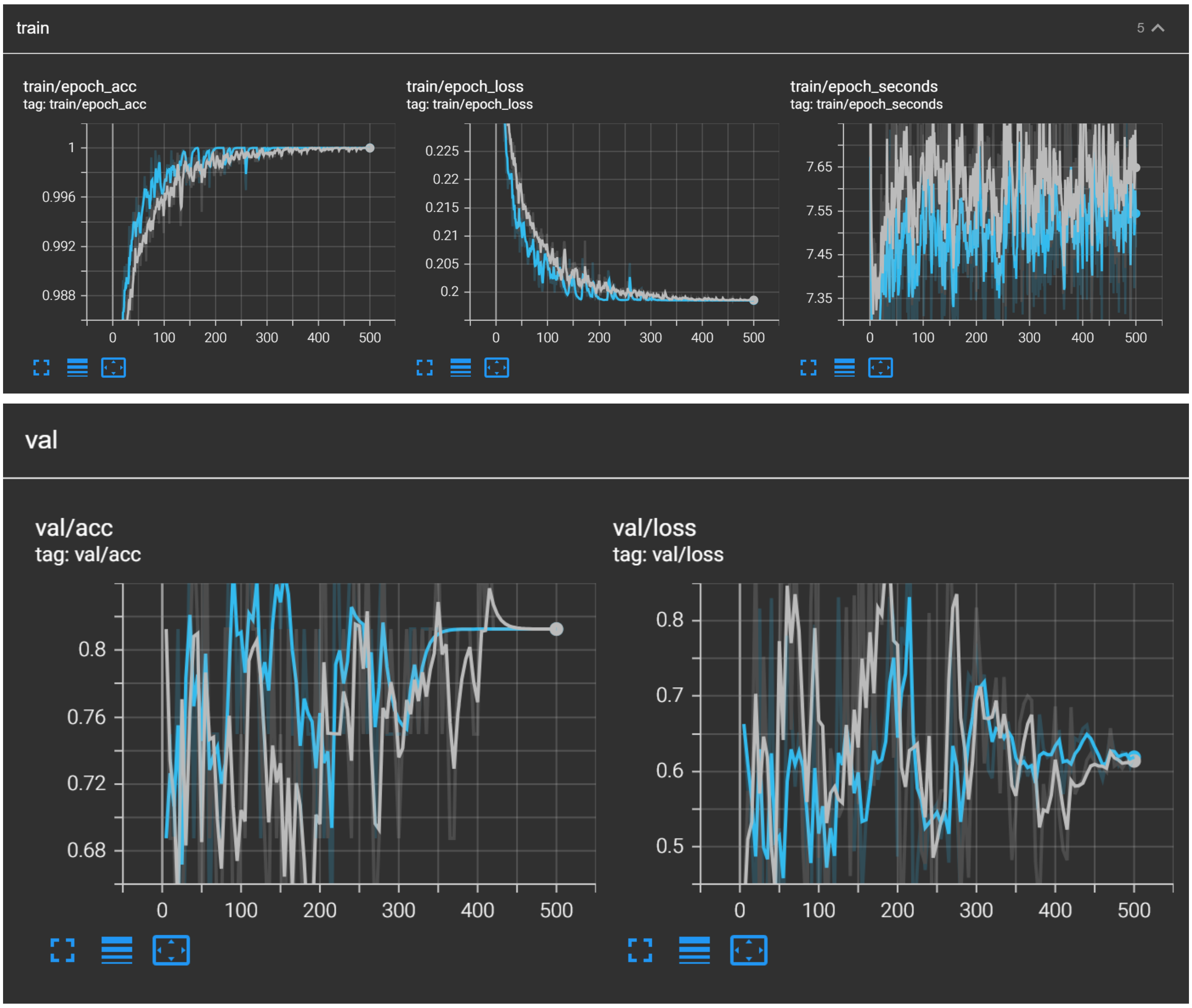


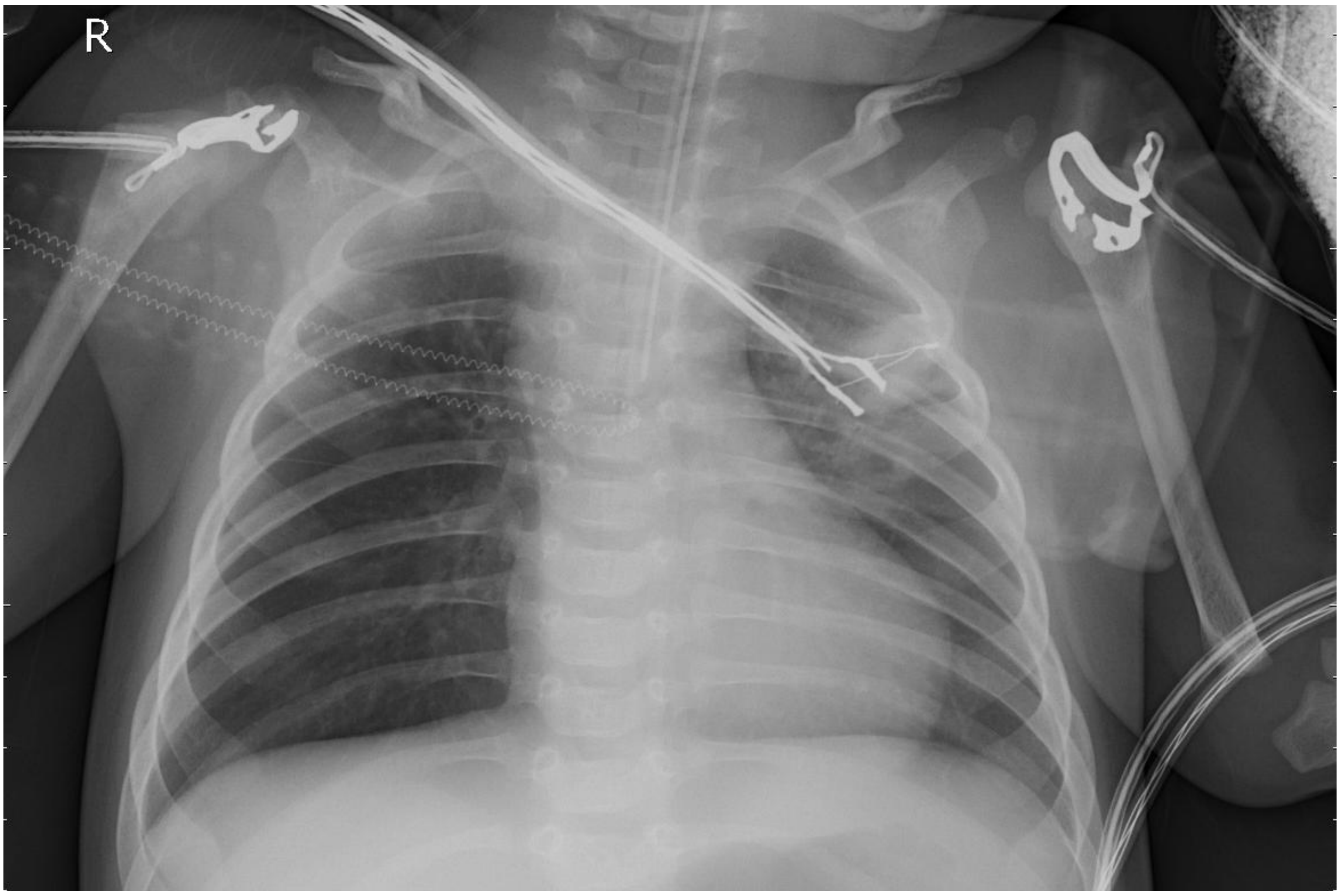
Figure 3. Training and validation loss curves. Silver = Option 1. Sky Blue = Option 2.

4.3 Testing Performance

Metric	Vanilla Fine-tune (best)	Vanilla Fine-tune (last)	Option 1 (best)	Option 1 (last)	Option 2 (best)	Option 2(last)
Test loss	0.3920	3.7072	0.5844	0.5467	0.7567	0.5413

Metric	**Vanilla Fine-tune (best)**	**Vanilla Fine-tune (last)**	**Option 1 (best)**	**Option 1 (last)**	**Option 2 (best)**	**Option 2(last)**
Test accuracy	0.9087	0.8333	0.8013	0.8189	0.7099	0.8157
NORMAL accuracy	0.7650	0.5641	0.4786	0.5256	0.2308	0.5214
PNEUMONIA accuracy	0.9949	0.9649	0.9949	0.9949	0.9974	0.9923

4.4 Example Failure Cases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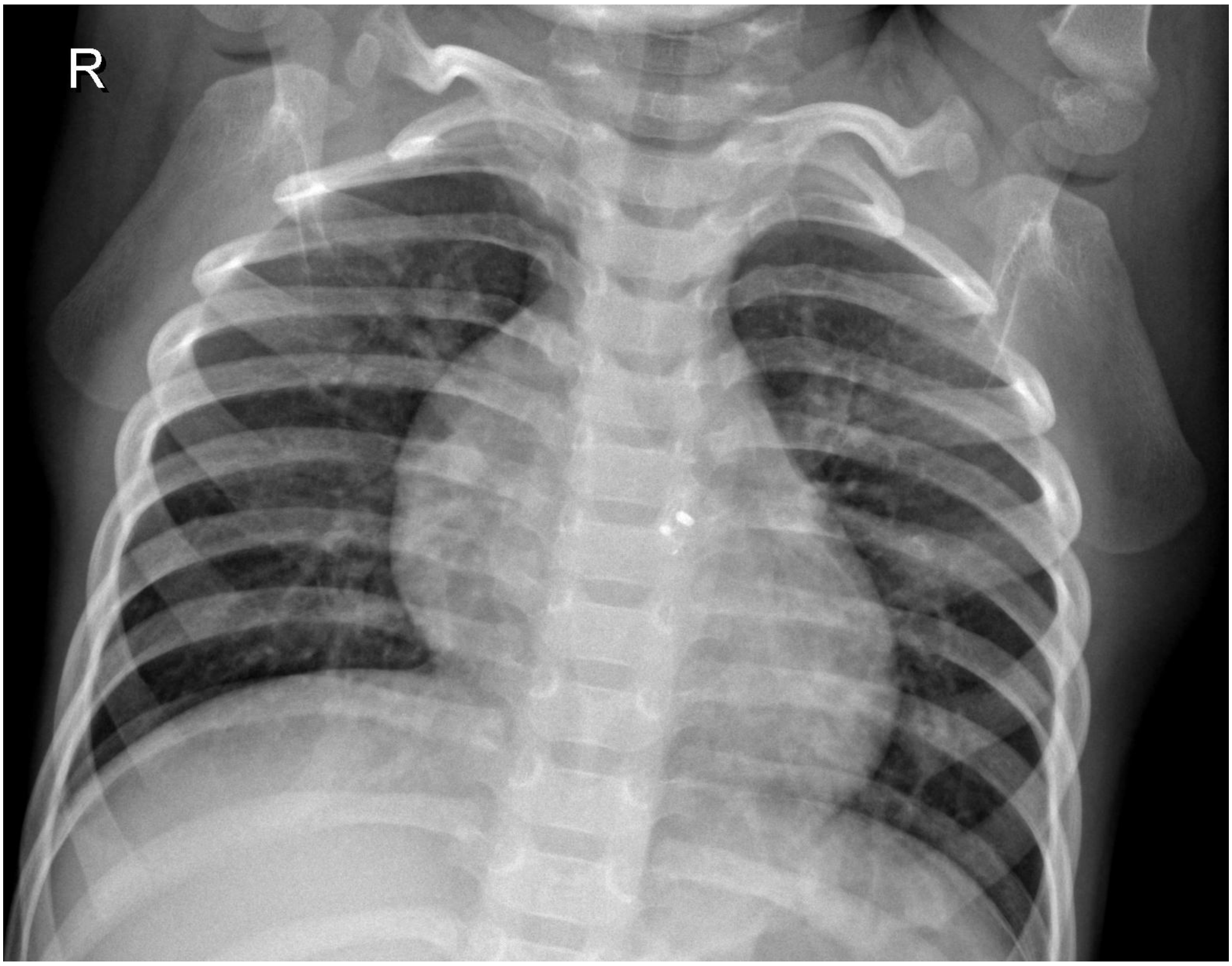
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Figure 4. Example failure cases : Predicted as NORMAL despite being PNEUMONIA.

6. Conclusion and Discussion

The fine-tuned ResNet-18 consistently performed better than the scratch model. In the 30-epoch setup, fine-tuning improved test accuracy from `0.8365` to `0.9199`, and in the 500-epoch setup from `0.7869` to `0.9087`. The curves also show faster convergence with pretraining.

The 500-epoch runs suggest overfitting, since the last checkpoints were often worse than the best checkpoints, especially in test loss. Another clear pattern is that `NORMAL` was harder than `PNEUMONIA`, with pneumonia accuracy staying very high across almost all experiments.

The main failure cases were pneumonia images predicted as normal. The extra Bag-of-Tricks settings in experiment 3 did not improve results over the vanilla fine-tuned baseline, so pretraining was the most useful factor in this project.

Main takeaway: `ImageNet pretraining was more beneficial than training from scratch or adding extra tricks, and best-checkpoint selection was critical to avoid overfitting.`

7. Reproducibility

7.1 Code

- Training script: train_resnet18.py
- Testing script: test_resnet18.py
- Dataset download script: download_kaggle_dataset.py
- Github Repository: Assignment1-CAP5516

7.2 Run Commands

```
# Train from scratch
python3 train_resnet18.py --mode scratch

# Fine-tune from ImageNet pretrained weights
python3 train_resnet18.py --mode finetune

# Test a saved checkpoint
python3 test_resnet18.py --checkpoint
outputs/<run_name>/checkpoints/best.pt

# Launch TensorBoard
tensorboard --logdir outputs
```

- Once the download_kaggle_dataset.py is executed, the folder should look like the following:

```
datasets/chest-xray-pneumonia/chest_xray
├── test
```

```
├────── NORMAL
├────── PNEUMONIA
├── train
├────── NORMAL
├────── PNEUMONIA
├── val
├────── NORMAL
├────── PNEUMONIA
```

- All training logs will be stored on `outputs/`
- All test results will be stored on `test_results/`