1. Introduction

This project aims to develop a convolutional neural network (CNN) capable of distinguishing between normal chest X-ray images and cases of pneumonia.
Beyond achieving good predictive performance, the objective is to implement a complete and reproducible deep learning pipeline, including preprocessing, training, validation, and model selection.

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2. Dataset

We use the **Chest X-Ray Images (Pneumonia)** dataset.

It contains pediatric chest radiographs organized into three official splits:

- Training set
- Validation set
- Test set

Two classes are provided:

- **NORMAL**
- **PNEUMONIA**

Example images

The dataset is widely used in academic benchmarks, allowing comparison with prior studies.

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3. Preprocessing and Data Augmentation

Medical images require careful augmentation. Transformations must improve robustness without altering clinical meaning.

Training transforms

- Resize to 224×224
- Random horizontal flip
- Small random rotations (±10°)
- Tensor conversion
- Intensity normalization

Validation / Test transforms

- Resize
- Tensor conversion
- Normalization only

We avoid aggressive crops, vertical flips, or heavy distortions that might corrupt anatomical interpretation.

4. Model Architecture

We adopt **ResNet-18** with ImageNet pretrained weights.

Why this choice?

- Proven strong baseline in medical imaging
- Residual connections improve gradient flow
- Moderate size → fast training
- Good balance between capacity and overfitting risk

The original classification head (1000 classes) is replaced with a fully connected layer producing **2 outputs**.

5. Training Methodology

Loss function

Cross-entropy loss for binary classification.

Optimizer

Adam with learning rate: le=4

Learning rate schedule

Step decay every 3 epochs to stabilize convergence.

Model selection strategy

The model with the **highest validation accuracy** is retained.

This prevents overfitting to the training set.

6. Training Results

We track:

- Training accuracy
- Validation accuracy
- Training loss
- Validation loss

These curves allow us to detect underfitting or overfitting.

7. Preliminary Observations

Even with limited epochs and minimal tuning, transfer learning enables rapid convergence. Validation performance improves early, demonstrating that pretrained representations are highly informative for radiographic tasks.

Further improvements are expected from:

- longer training
- class imbalance handling
- fine-tuning deeper layers
- improved augmentation

The initial training phase was intentionally limited to a small number of epochs (five) in order to validate the correctness of the end-to-end pipeline before committing to longer experiments. This strategy ensures that data loading, preprocessing, optimization, and metric computation function as expected while minimizing wasted computational resources in case of implementation issues.

Moreover, in transfer learning settings using pretrained networks such as **ResNet-18**, rapid convergence is typically observed during the early epochs. Performance improvements often diminish after a short period, and excessive training may even lead to overfitting. Therefore, beginning with a short exploratory run allows us to observe learning dynamics and later determine, in a principled manner, whether extending the training schedule is justified.

Results after 5-epochs: Rapid convergence was observed, with optimal validation performance achieved in early epochs. Continued training led to degradation in generalization, indicating overfitting.

To ensure a rigorous and unbiased estimate of real-world performance, the test set was kept strictly isolated from all training and model selection procedures. Model development decisions, including hyperparameter configuration and epoch selection, were guided exclusively by validation performance. The version of the network achieving the highest validation accuracy was saved and subsequently evaluated **once** on the held-out test data.

This protocol prevents information leakage from the test set into the training process. Modifying the model after observing test results would lead to overly optimistic estimates and would compromise the scientific validity of the evaluation. By freezing the model prior to testing, we ensure that the reported metrics reflect genuine generalization to previously unseen patient images.

Test Set Results

Accuracy : 0.62

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Precision: 0.63

Recall   : 0.98

F1       : 0.76

AUC      : 0.57

TN = 5      FP = 229

FN = 6      TP = 384
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Test Set Performance Analysis

The model predicts almost everyone as PNEUMONIA. For the normal patients:

234 normal images total

only 5 classified correctly

229 called pneumonia

But pneumonia detection?

390 pneumonia images

384 detected

The model is A very aggressive screener.

It screams *pneumonia* at nearly everything.

Recall = 98%

Almost no pneumonia missed → very sensitive.

Precision = 63%

But many healthy people are falsely flagged.

AUC = 0.57

This is the alarm bell.

It means the probability ranking ability is poor.

Why this happened (very important academically)

The dataset is imbalanced.

There are far more pneumonia cases than normal.

Neural networks love majority classes.

Conclusion: Without any advanced tricks, the baseline model is biased toward pathology.

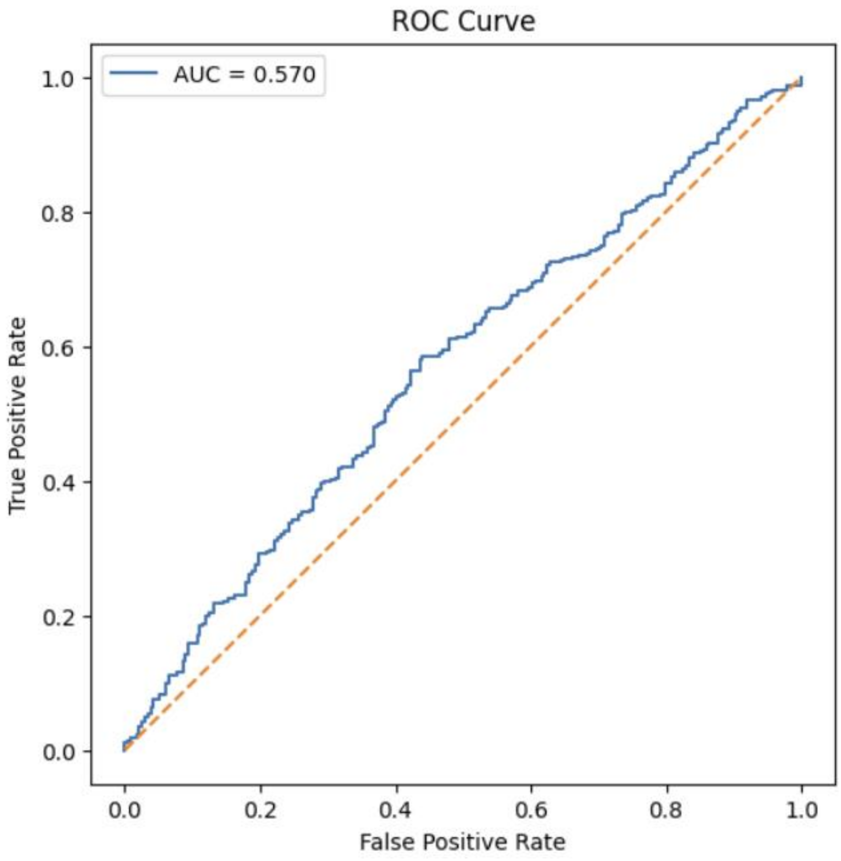
Analysis:

Evaluation on the independent test set reveals a strong asymmetry in predictive behavior. While the model achieves very high sensitivity (recall ≈ 98%), indicating that pneumonia cases are rarely missed, specificity is extremely low. Only a small fraction of normal examinations are correctly identified, with the majority being incorrectly classified as pneumonia.

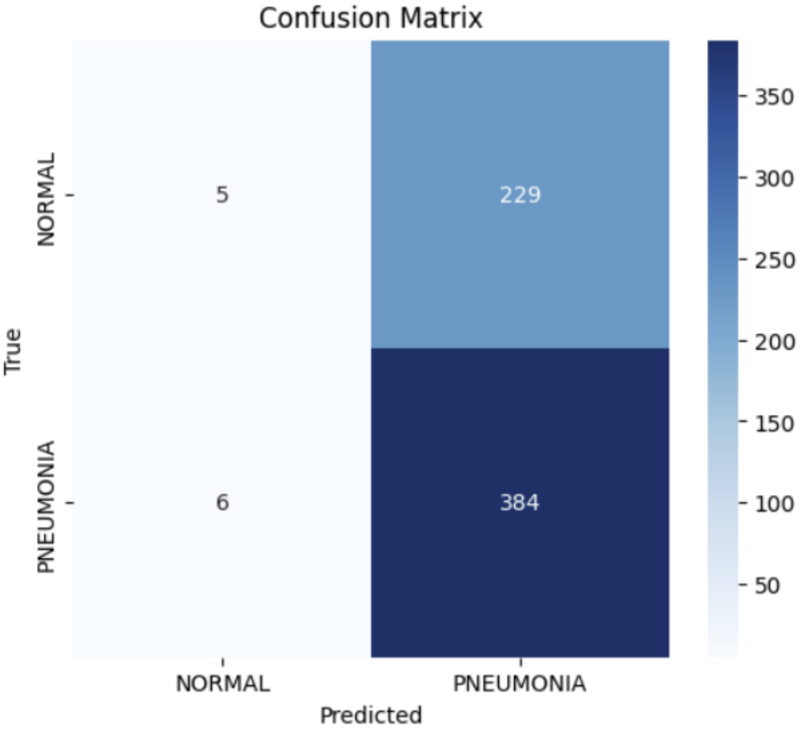
This behavior is reflected in the confusion matrix, where false positives dominate. The phenomenon is consistent with the class imbalance present in the dataset, where pneumonia images substantially outnumber normal cases. Under such conditions, the network tends to favor the majority class, leading to an aggressive screening strategy.

Although high sensitivity can be desirable in safety-critical medical contexts, the large number of false alarms would limit the practical utility of the system without further calibration or rebalancing techniques.

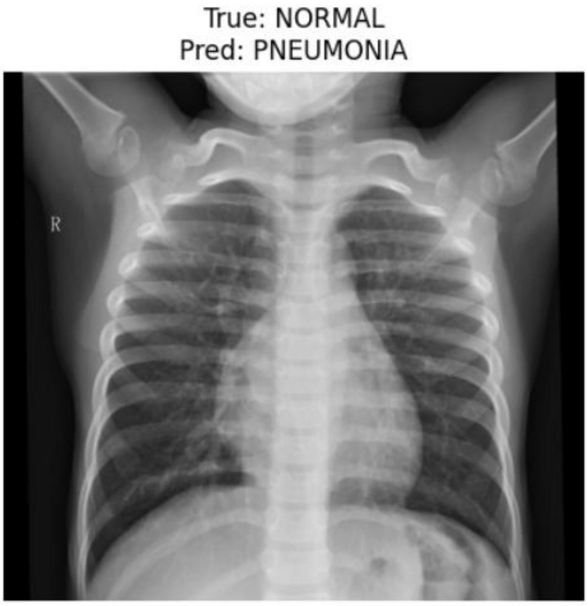
Roc Curve:

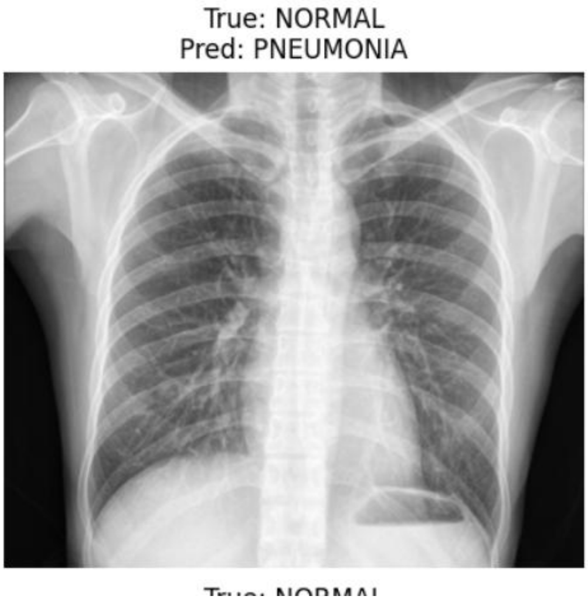


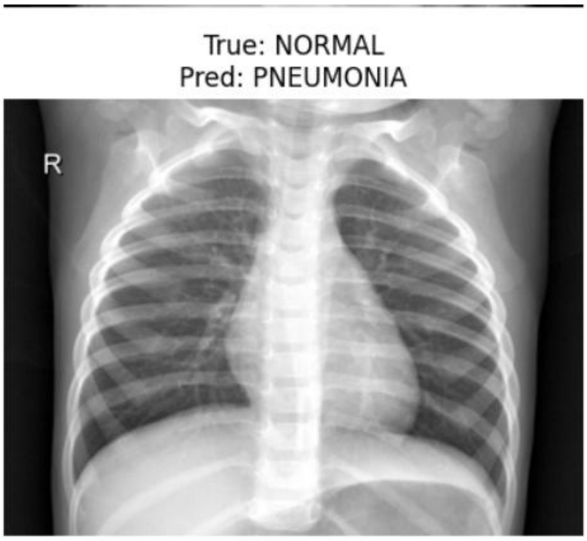
Confusion Matrix (visual)

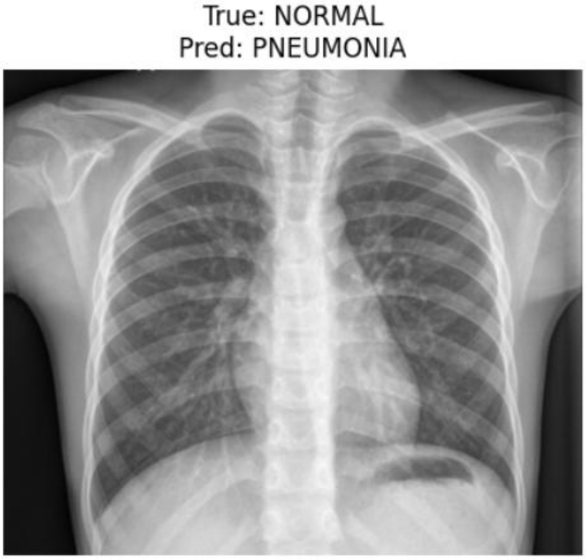


Failure Cases:









Failure Analysis

Main problem: NORMAL images are almost always predicted as PNEUMONIA.

Inspection of misclassified examples reveals a clear bias in the model's predictions. The vast majority of errors correspond to normal radiographs incorrectly labeled as pneumonia. This observation aligns with the confusion matrix, where false positives dominate while false negatives remain rare.

Such behavior suggests that the network has adopted an aggressive screening strategy, favoring sensitivity over specificity. From a clinical perspective, this reduces the probability of missing pathology but introduces a high burden of unnecessary alarms. Radiographic variability, acquisition artifacts, and normal anatomical structures that resemble opacities may contribute to these mistakes.

A likely driver of this phenomenon is the class imbalance present in the training data, where pneumonia cases substantially outnumber normal examinations. Under these conditions, minimizing classification loss encourages the model to predict the majority class more frequently.

We attack the core problem: **class imbalance**

Hypothesis

We hypothesized that the dominant source of error was the imbalance between pneumonia and normal images. If misclassification of the minority class were penalized more strongly during training, the network would be encouraged to learn features characteristic of healthy lungs rather than defaulting to pathology.

Intervention: Class-Weighted Loss

To address this, we replaced the standard cross-entropy objective with a weighted variant. Each class received a penalty inversely proportional to its frequency in the training data, increasing the cost of misclassifying normal images.

No other aspects of the training pipeline were modified, ensuring that any change in performance could be attributed directly to the rebalancing strategy.

Results After Rebalancing

The weighted model produced dramatically different outcomes on the test set.

Metric	**Baseline**	**Weighted**
Accuracy	0.62	**0.82**
Precision	0.63	**0.78**
Recall	0.98	**0.997**
F1-score	0.76	**0.87**
AUC	0.57	**0.94**

Confusion matrix:

- Correct NORMAL predictions increased from **5 → 122**
- False negatives reduced from **6 → 1**

Discussion of Improvement

The introduction of class weighting significantly enhanced generalization. The classifier no longer defaulted to the majority label and instead learned a more balanced decision rule.

The most striking improvement appears in the AUC, which rose from near-random performance to excellent separability. Precision increased substantially while maintaining near-perfect sensitivity, a highly desirable outcome for medical screening systems.

These results confirm the hypothesis that imbalance was the primary driver of baseline errors and demonstrate the effectiveness of cost-sensitive learning in mitigating bias.