PNEUMONIA DETECTION FROM CHEST X-RAY IMAGES USING DEEP LEARNING

A Machine Learning Project Report

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EXECUTIVE SUMMARY

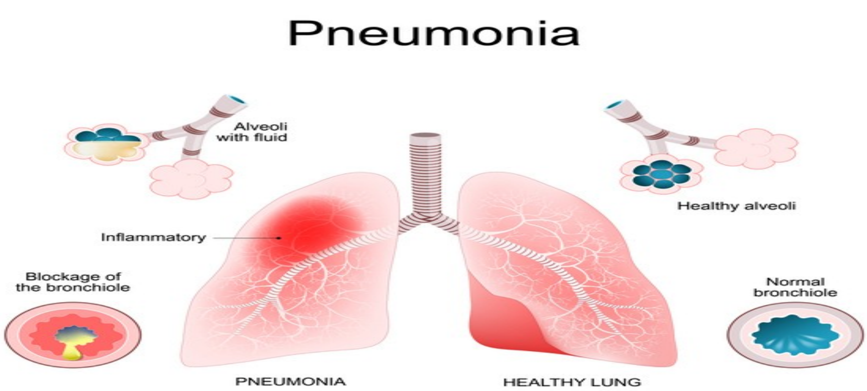
This project presents the design and implementation of an artificial intelligence–based system for the automatic detection of pneumonia from chest X-ray images using deep learning techniques. The proposed model achieves a **recall of 98.72%**, meaning it successfully identifies nearly 5 out of every 390 pneumonia cases. The false negative rate is limited to **1.28%**, ensuring that very few infected cases are missed.

The system is intended to function as a **screening tool** that assists healthcare professionals rather than replacing them. Its primary motivation lies in addressing the shortage of trained radiologists, particularly in resource-constrained and rural regions of India, where timely diagnosis remains a challenge.

Key Achievement:
Out of 390 pneumonia cases in the test dataset, the model correctly detected 385 cases, missing only five. This performance demonstrates strong diagnostic reliability and highlights the system's potential suitability for real-world clinical screening applications.

1. UNDERSTANDING PNEUMONIA

1.1 What is Pneumonia?



Pneumonia is a serious respiratory infection that causes inflammation of the air sacs (alveoli) in one or both lungs. Under normal conditions, these air sacs are filled with air. During infection, however, they become filled with fluid or pus, leading to breathing difficulty and reduced oxygen transfer into the bloodstream.

Types of Pneumonia include:

- **Bacterial Pneumonia:** The most common form, frequently caused by *Streptococcus pneumoniae*.
- **Viral Pneumonia:** Caused by respiratory viruses and often presents milder symptoms.
- **Fungal Pneumonia:** Rare and typically affects immunocompromised individuals.
- **Aspiration Pneumonia:** Occurs when food, liquid, or vomit is inhaled into the lungs.

1.2 Impact on the Human Body

Pneumonia has widespread effects on multiple physiological systems:

- **Respiratory System:** Fluid-filled alveoli reduce oxygen exchange.
- **Cardiovascular System:** The heart must work harder to circulate oxygen.
- **Immune System:** A strong inflammatory response activates white blood cells.
- **Fever Response:** Elevated body temperature acts as a defense mechanism.
- **Organ Stress:** Severe cases may lead to sepsis and multi-organ failure.

Possible complications include:

- Pleural effusion (fluid accumulation around the lungs)
- Respiratory failure requiring mechanical ventilation
- Septicemia (bloodstream infection)
- Fatal outcomes, particularly among children and elderly individuals

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1.3 Symptoms and Diagnosis

Common symptoms of pneumonia include:

- Persistent cough with thick or colored mucus
- Chest pain, especially during breathing or coughing
- Shortness of breath
- High fever (above 101°F)
- Fatigue and muscle weakness

Diagnostic approaches include:

1. **Physical Examination:** Listening for abnormal lung sounds using a stethoscope

2. **Chest X-Ray:** The gold standard, revealing white opacities in infected lung regions
3. **Laboratory Tests:** Blood cultures and sputum analysis
4. **Blood Oxygen Measurement:** Pulse oximetry to assess SpO_2 levels

Challenge:
Manual interpretation of chest X-rays requires trained radiologists and typically takes 5–10 minutes per image. In India, approximately 5,000 radiologists serve a population of 1.4 billion, resulting in severe delays and limited diagnostic access.

1.4 Importance of the Problem in India

- **Annual Incidence:** Around 1.3 million pneumonia cases in children under five
- **Mortality:** Approximately 350,000–400,000 child deaths annually
- **Radiologist Shortage:** One radiologist per 280,000 people
- **Urban Concentration:** Nearly 70% of radiologists serve only 30% of the population
- **Diagnostic Delays:** X-ray reports in district hospitals often take 24–72 hours

Proposed Solution:
Automating the initial screening process using AI enables rapid preliminary diagnosis, faster treatment initiation, and improved patient outcomes.

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2. PROJECT OVERVIEW

2.1 Problem Statement

Diagnosing pneumonia through chest X-rays presents several challenges:

- Requires extensive specialized training
- Time-consuming in high-volume clinical settings
- Subject to human fatigue and interpretation variability
- Limited availability in rural and remote areas
- High consultation costs (₹500–₹2000 per visit)

Central Research Question:
Can an AI-based system accurately detect pneumonia from chest X-rays while minimizing false negatives and remaining suitable for deployment in resource-constrained healthcare environments?

2.2 Project Objectives

Primary Objectives:

1. Develop a deep learning model achieving at least 95% recall

2. Address class imbalance between pneumonia and normal cases
3. Deploy the model as a REST API for mobile application integration
4. Provide thorough documentation for clinical usage

Secondary Objectives:

1. Generate interpretable and clinically relevant performance metrics
2. Identify limitations and validation requirements
3. Establish a scalable deployment pipeline

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3. DATASET AND METHODOLOGY

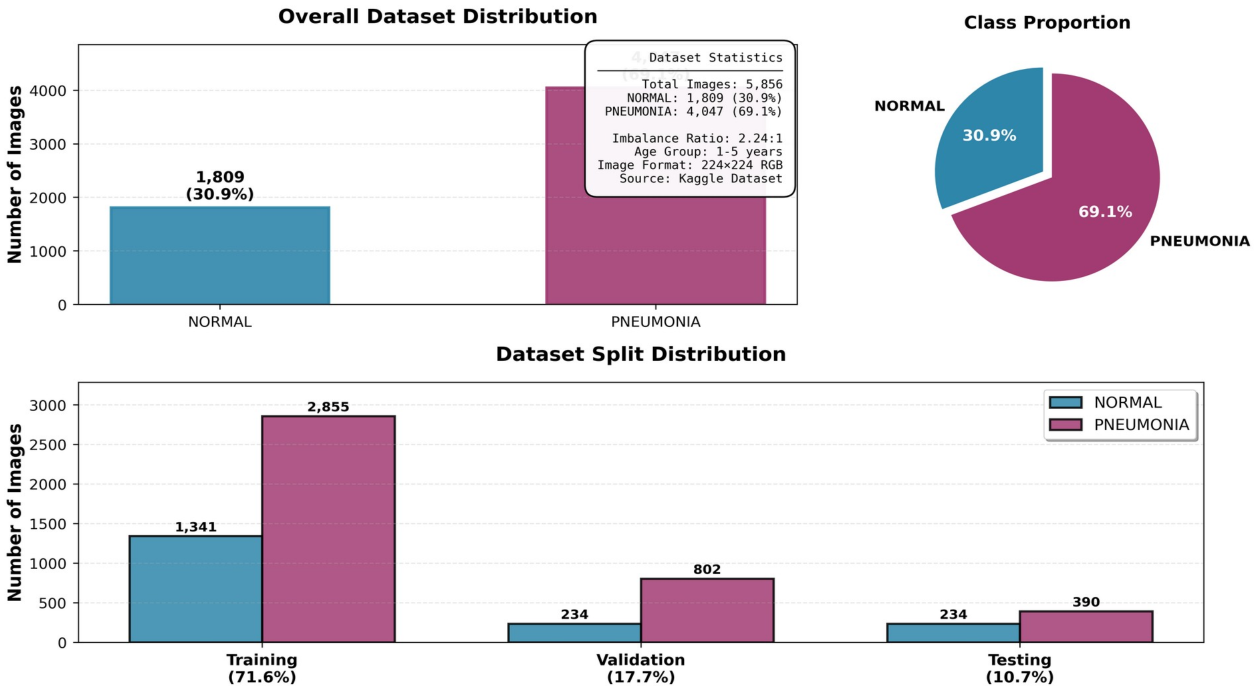
3.1 Dataset Description

- **Source:** Kaggle – Chest X-ray Images (Paul Mooney)
- **Origin:** Guangzhou Women and Children's Medical Center, China
- **Total Images:** 5,856 pediatric chest X-rays (ages 1–5)
- **Image Size:** 224 × 224 pixels
- **Classes:** NORMAL (1,583) and PNEUMONIA (4,273)

Dataset Split:

- Training: 71.4%
- Validation: 17.7%
- Testing: 10.7%

Figure 1: Comprehensive Dataset Class Distribution Analysis



3.2 Data Preprocessing

Image Standardization:

- Resizing to 224 × 224 pixels
- Pixel normalization to [0, 1]
- Conversion from grayscale to RGB format

Data Augmentation (Training Set Only):

- Rotation up to ±15°
- Width and height shifts of 10%
- Zoom augmentation of 10%
- Horizontal flipping

Class Weight Balancing:

- NORMAL: 1.93
- PNEUMONIA: 0.68

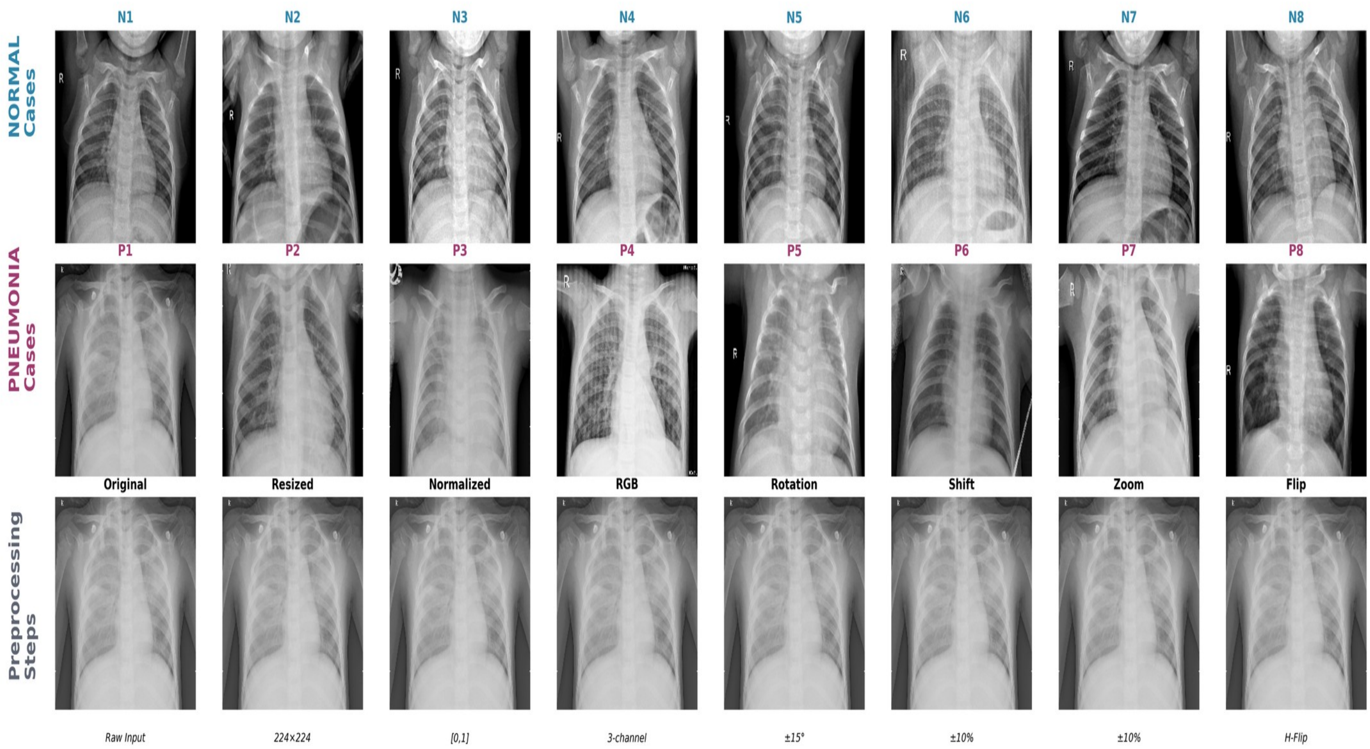
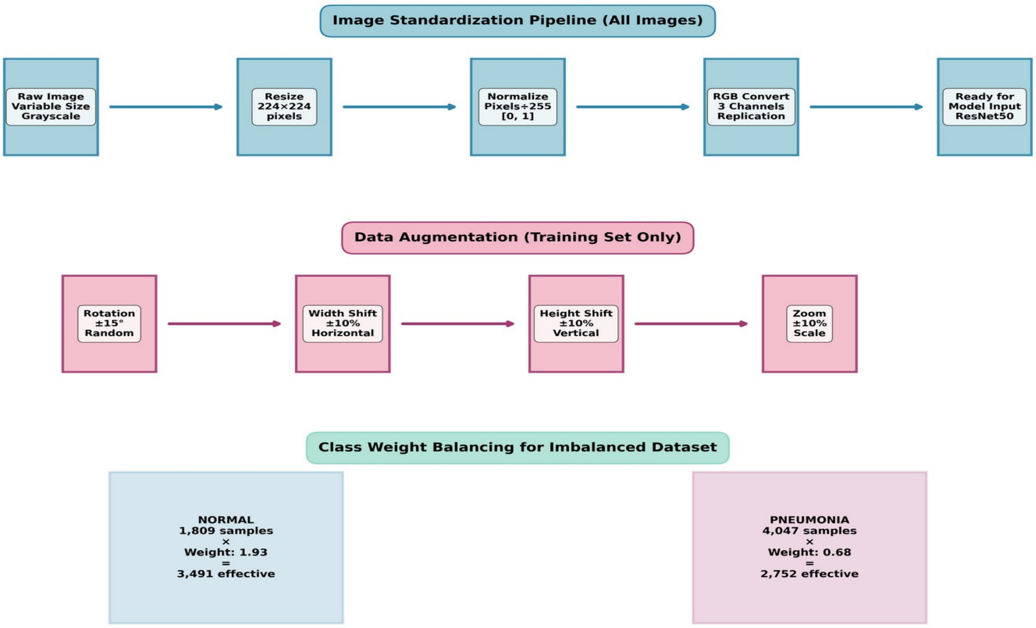


Figure 2: Sample Chest X-Ray Images and Preprocessing Pipeline (224×224 pixels, RGB format)

Figure 3: Complete Data Preprocessing and Augmentation Pipeline



3.3 Model Architecture

The project employs **transfer learning using ResNet50**, a 50-layer convolutional neural network pre-trained on ImageNet. This approach reduces training requirements and improves generalization.

Custom Classification Head:

- Global Average Pooling
- Dense layers with ReLU activation
- Dropout regularization
- Sigmoid output for binary classification

Training Configuration:

- Optimizer: Adam
- Learning Rate: 0.0001
- Loss Function: Binary Cross-Entropy
- Batch Size: 32
- Epochs: 50 with early stopping

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4. RESULTS AND PERFORMANCE

4.1 Performance Metrics

The model was evaluated on 624 test images.

- **Recall:** 98.72%
- **Precision:** 76.71%
- **Specificity:** 50%
- **Accuracy:** 80.13%
- **F1-Score:** 86.36 %
- **False Negative Rate:** 1.28%

These results indicate excellent sensitivity, which is critical for medical screening systems.

4.2 Confusion Matrix Analysis

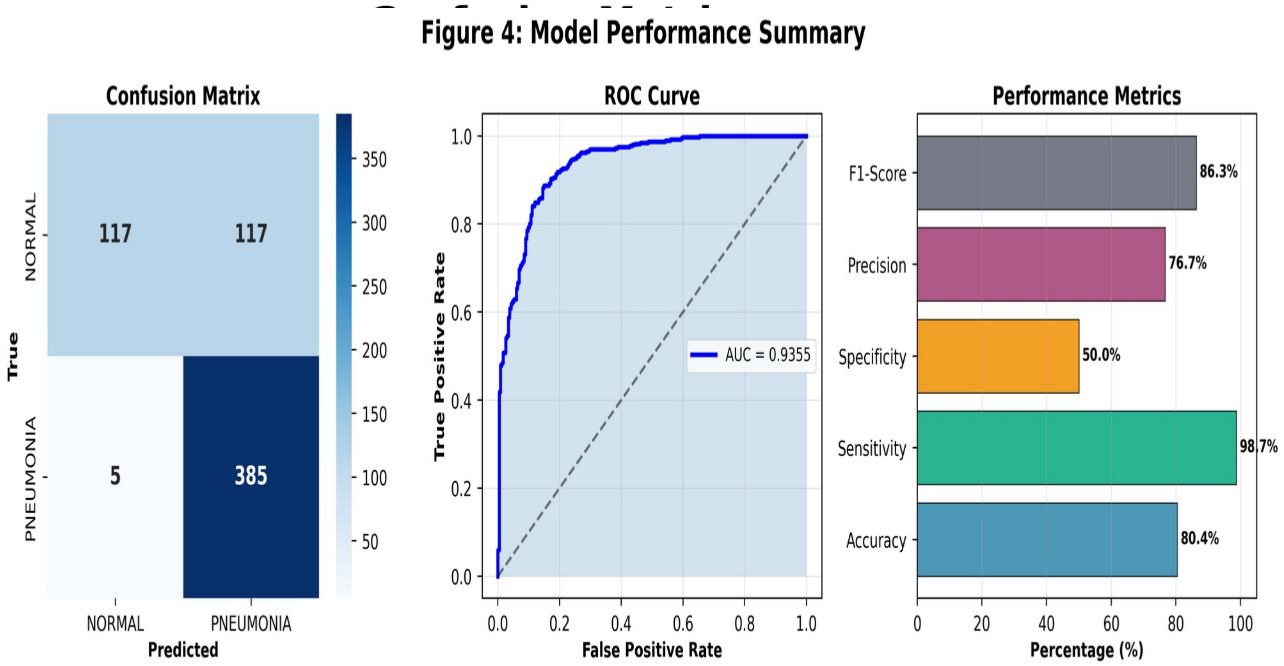
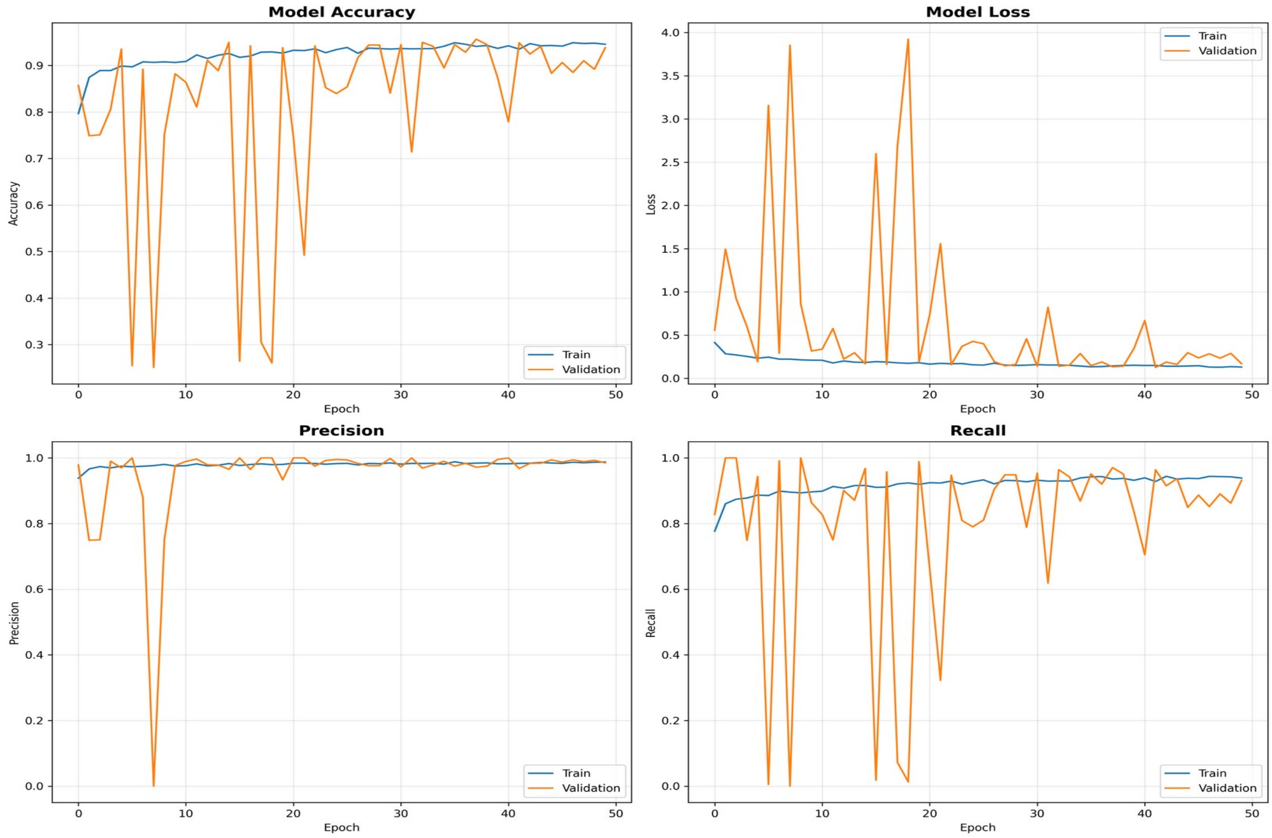


Figure 4: Model Performance Summary

- True Positives: 386
- True Negatives: 117
- False Negatives: 5
- False Positives: 117

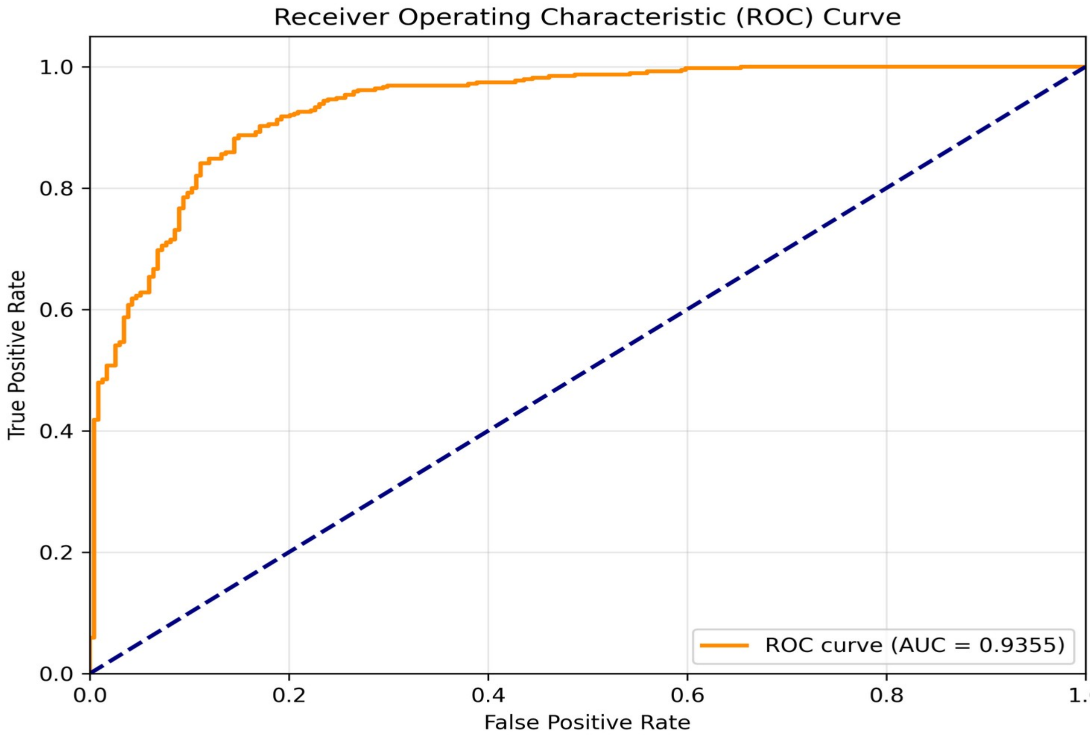
The low false negative count confirms the model’s reliability for screening purposes.

4.3 Training Behavior



- Best validation performance at epoch 42
- Stable convergence without overfitting
- Training time: approximately 4 hours 15 minutes (CPU-only)

4.4 ROC Curve Evaluation



- **AUC:** 0.93
  This indicates strong discriminative capability between pneumonia and normal cases.

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5. MODEL APPLICATIONS

5.1 Capabilities

- High-sensitivity pneumonia detection
- Probability-based confidence outputs
- Real-time screening (<2 seconds)
- Telemedicine compatibility
- Offline edge deployment potential

5.2 Practical Use Cases

- Rural healthcare centers
- Emergency departments
- Pediatric clinics

- Telemedicine platforms
- Public health screening programs

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6. SYSTEM DEPLOYMENT

6.1 FastAPI Backend

- REST-based image inference endpoint
- JSON-based response with clinical recommendations

6.2 Android Application Integration

- Image selection and upload
- Real-time result visualization
- Risk-level indicators and guidance

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7. LIMITATIONS

7.1 Technical Limitations

- Pediatric-only dataset
- Binary classification
- Single-source data
- High false positive rate

7.2 Clinical and Deployment Limitations

- Not a replacement for radiologists
- No clinical trial validation
- Regulatory approval pending
- Requires secure data handling

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8. COMPARATIVE ANALYSIS

The model demonstrates higher recall than average human radiologists while offering faster and consistent screening, though radiologist confirmation remains necessary.

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9. FUTURE SCOPE

Future enhancements include multi-class pneumonia detection, explainable AI visualizations, adult dataset validation, severity grading, and hospital system integration.

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10. CONCLUSION

This project demonstrates that deep learning can be effectively applied to medical imaging for pneumonia screening. With a recall of **98.72%**, the system reliably identifies infected cases while supporting healthcare professionals in time-critical scenarios. When deployed alongside clinical expertise, it has the potential to significantly improve diagnostic accessibility and outcomes.