Pneumonia Detection from chest X-Rays

B.Tech (AIDS)
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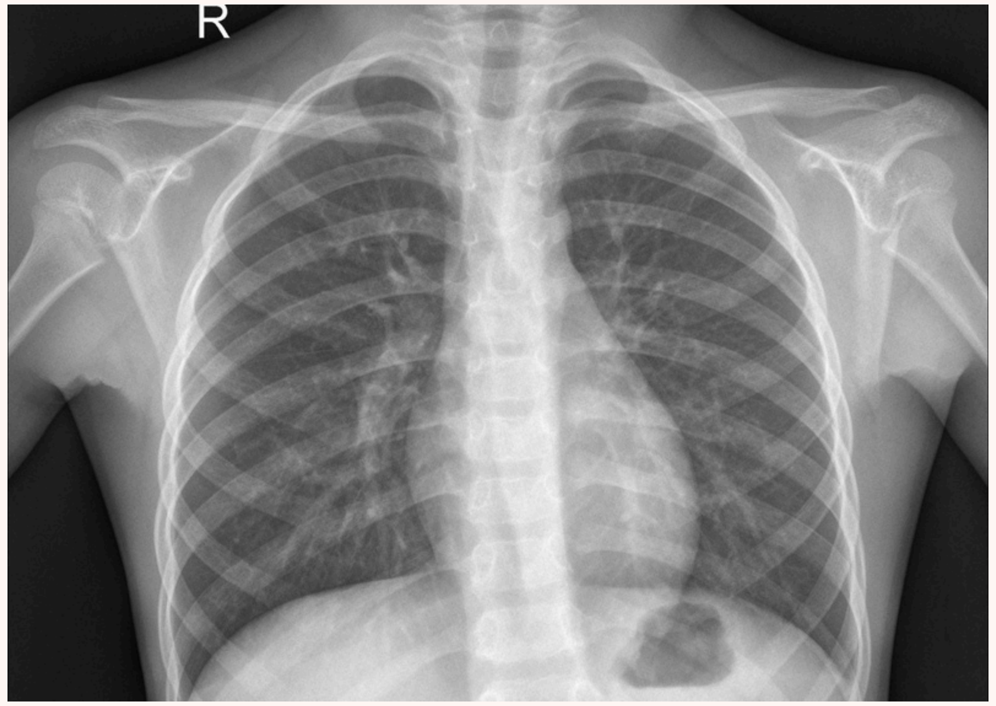
CONTENT

Introduction

- This project focuses on automated detection of pneumonia from chest X-ray images using artificial intelligence.
- Manual interpretation of chest X-rays can be time-consuming and prone to variability, especially in high patient-load settings.
- To address this, the project applies deep learning and machine learning techniques for accurate and consistent classification.
- In addition to detection, the system estimates disease severity and provides visual explanations to support clinical decision-making.

Introduction- What is pneumonia?

- Pneumonia is an infection of the lungs that causes inflammation in the air sacs (alveoli)
- The alveoli may fill with fluid or pus, reducing oxygen exchange
- Can affect one lung or both lungs
- Severity ranges from mild to life-threatening, especially in children and elderly
- Leads to reduced blood oxygen levels, affecting overall organ function
- Appears as opacities on chest X-rays, enabling image-based AI diagnosis



Pneumonia – Clinical Overview

Causes

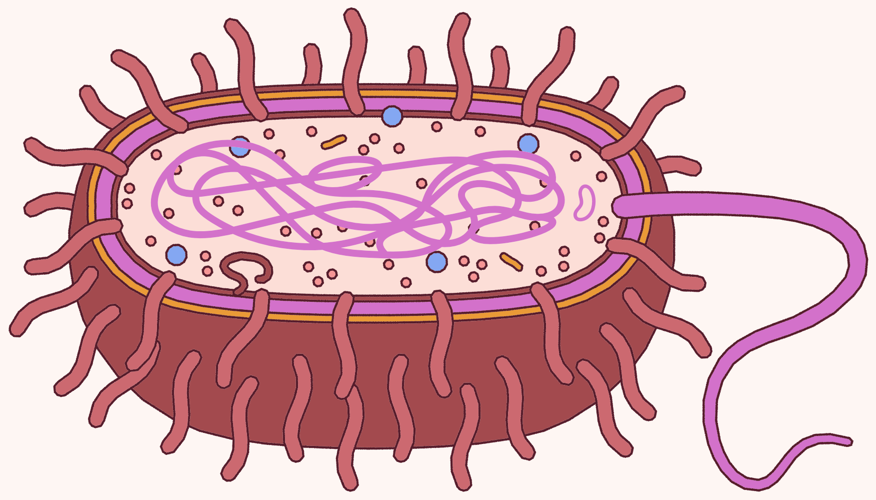
- Bacterial, viral, or fungal infections affecting the lungs
- Aspiration of food, liquids, or gastric contents into the airways

Symptoms

- Persistent cough, fever, and chest pain
- Shortness of breath and reduced oxygen levels

Diagnosis

- Chest X-ray imaging to identify lung opacities
- Blood tests and oxygen saturation assessment
- Antibiotics or antivirals based on the cause
- Oxygen therapy, vaccination, and early medical intervention



Pneumonia – Need for AI

Limitations of Manual Diagnosis

- interpretation is time-consuming and depends heavily on radiologist expertise
- Earlier stages show subtle opacities that can be easily overlooked

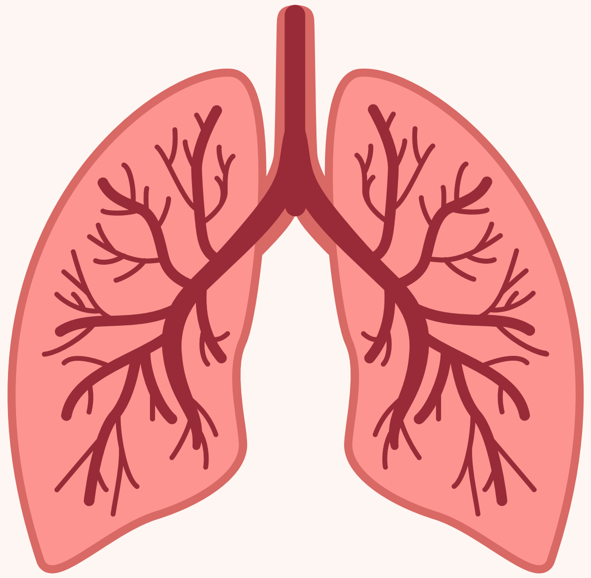
Clinical Challenges

- Similar visual patterns across different lung diseases increase misclassification risk
- Severity assessment is often qualitative, making patient triage difficult

Role of Artificial Intelligence

- AI enables fast and consistent analysis of chest X-ray images
- Supports early detection and severity-based risk stratification
- Explainable AI highlights relevant lung regions, improving clinical trust and decision suppor

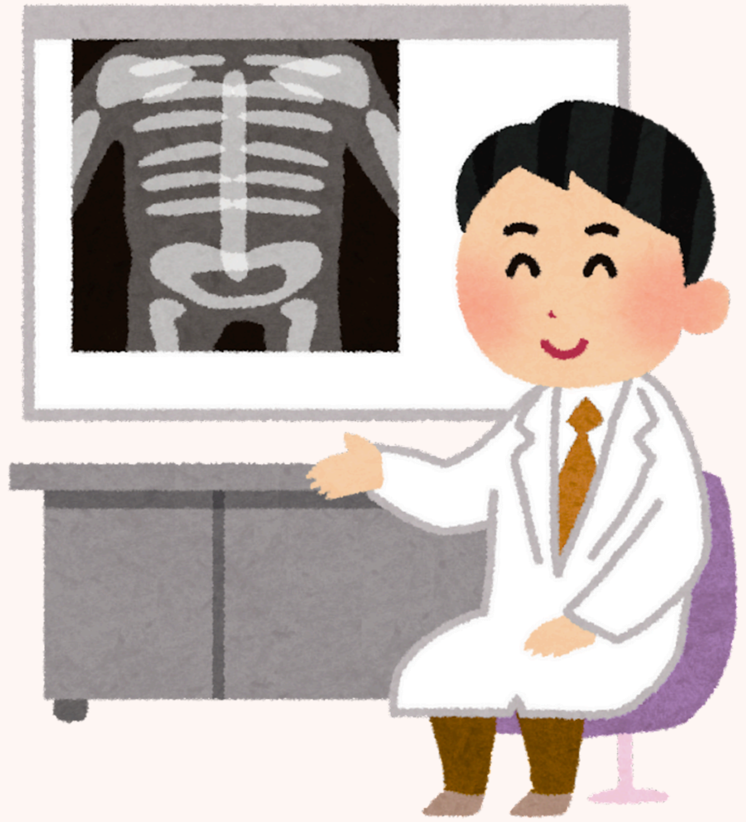
Objectives of the Project



- To develop an automated pneumonia detection system using chest X-ray images by combining deep learning feature extraction with machine learning classification.
- To use DenseNet-121 as a feature extractor for capturing meaningful lung texture patterns and subtle radiographic details.
- To train, compare, and optimize machine learning classifiers such as SVM, Random Forest, and Logistic Regression using hyperparameter tuning.
- To design and evaluate a custom CNN model for end-to-end pneumonia classification and compare its performance with feature-based ML models.
- To perform lung segmentation using a pretrained U-Net model and estimate the percentage of pneumonia-affected lung region for severity assessment.
- To analyze trade-offs between classical ML and deep learning in terms of accuracy, efficiency, interpretability, and clinical relevance.

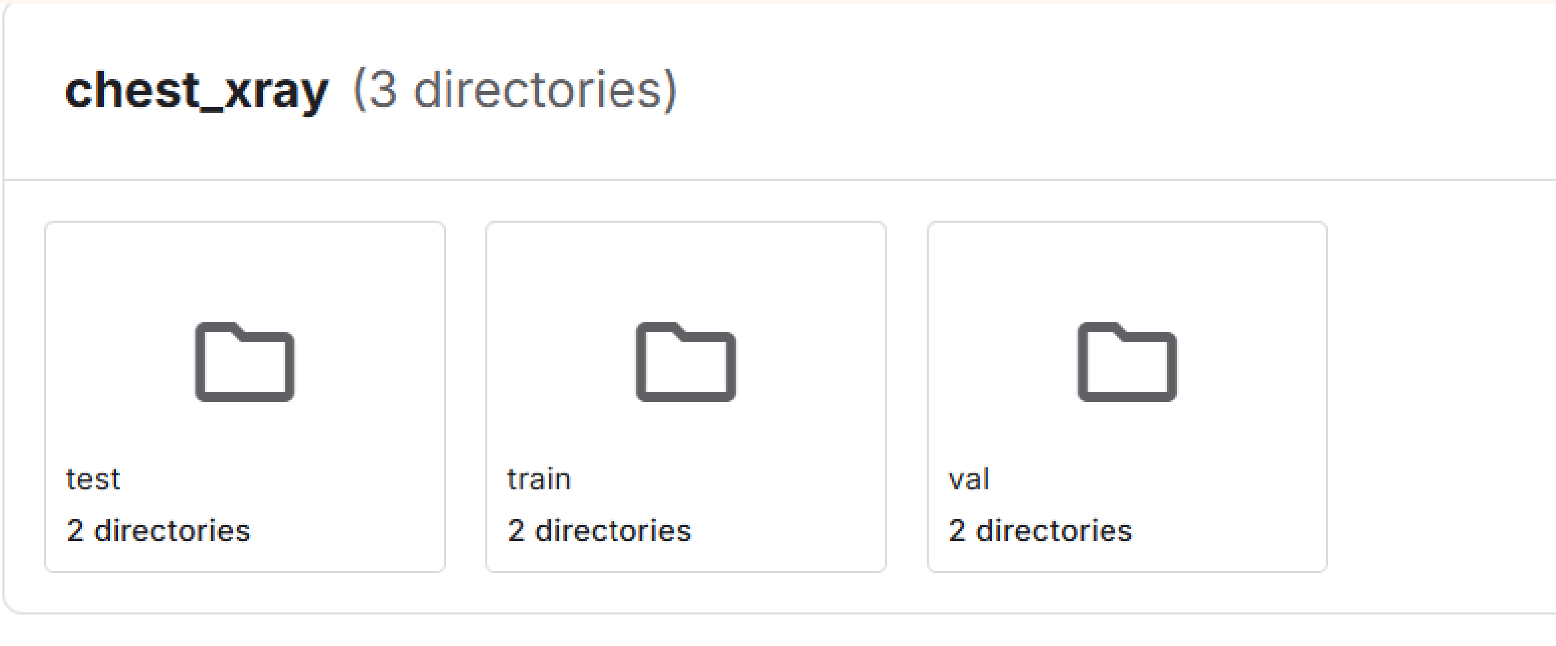
Literature Review

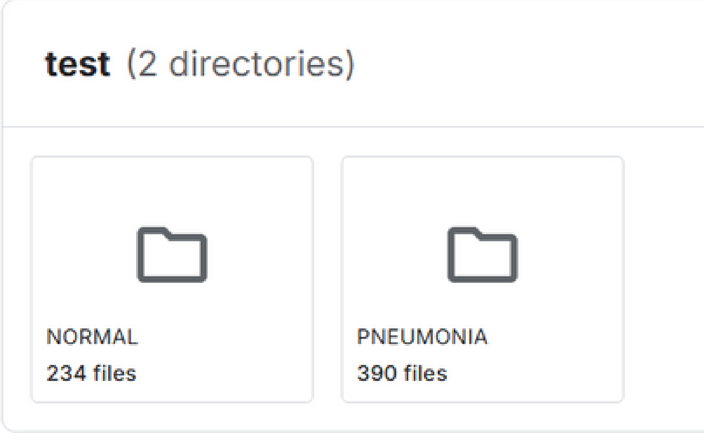
- Recent studies show that deep learning models perform better than traditional methods for pneumonia detection from chest X-rays.
- Transfer learning using pretrained CNNs such as DenseNet improves accuracy and reduces training time.
- Research also highlights the role of image preprocessing techniques like CLAHE to enhance lung opacities.
- Additionally, lung segmentation and explainable AI methods such as Grad-CAM help improve severity analysis and clinical trust.

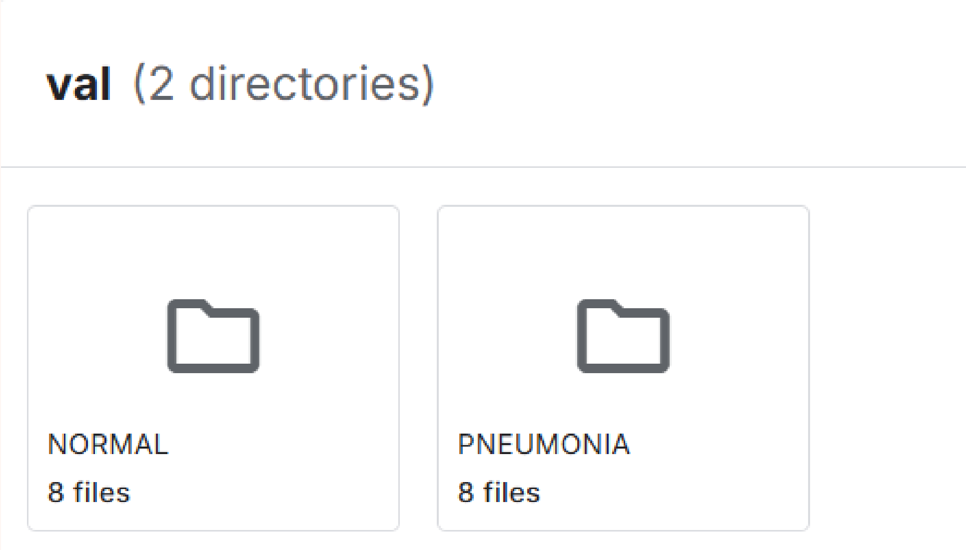


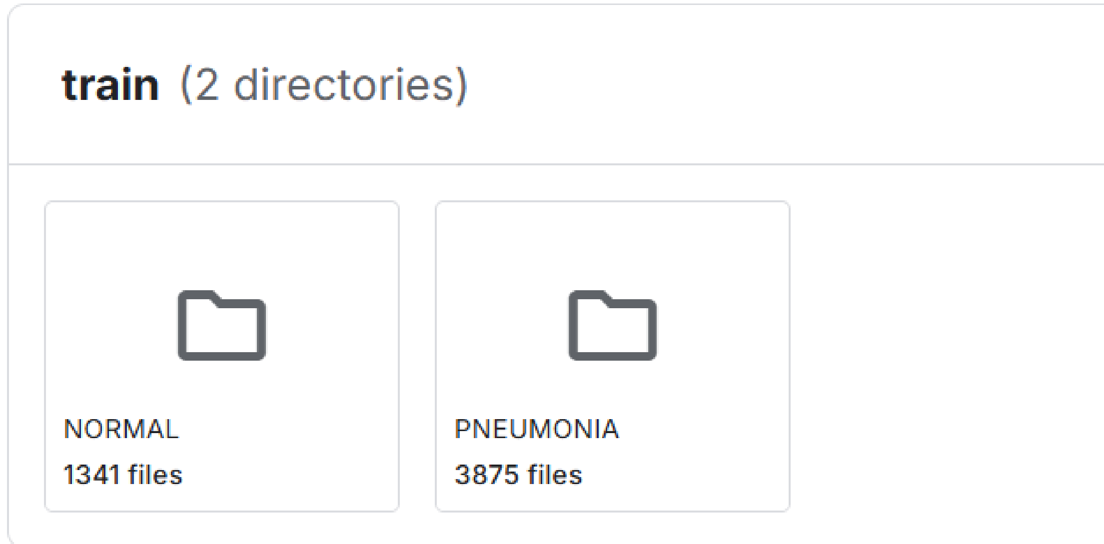
Dataset Description

- Total Images: 5,863 frontal chest X-ray images in JPEG format
- Normal Cases-1,583 images; Pneumonia Cases-4,273 images
- Image Resolution- Variable (widths: 384–2916 pixels, heights: 127–2713 pixels)
- Data Splits-Train, Validation, Test folders with Normal and Pneumonia subfolders









Proposed Methodology – Classification Pipeline

Dataset Acquisition – Chest X-ray images of normal and pneumonia cases are collected from a publicly available dataset

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Image Preprocessing (CLAHE) – Contrast Limited Adaptive Histogram Equalization is applied to enhance lung details and improve visibility

↓

Feature Extraction (DenseNet121) – A pretrained DenseNet121 model is used to extract deep, high-level features from X-ray images

↓

Feature Scaling (StandardScaler) – Extracted features are normalized to ensure uniform feature distribution and stable model training

↓

Classification (ML Models) – Machine learning classifiers including SVM, Random Forest, Logistic Regression, KNN, and Naive Bayes are trained using the extracted features

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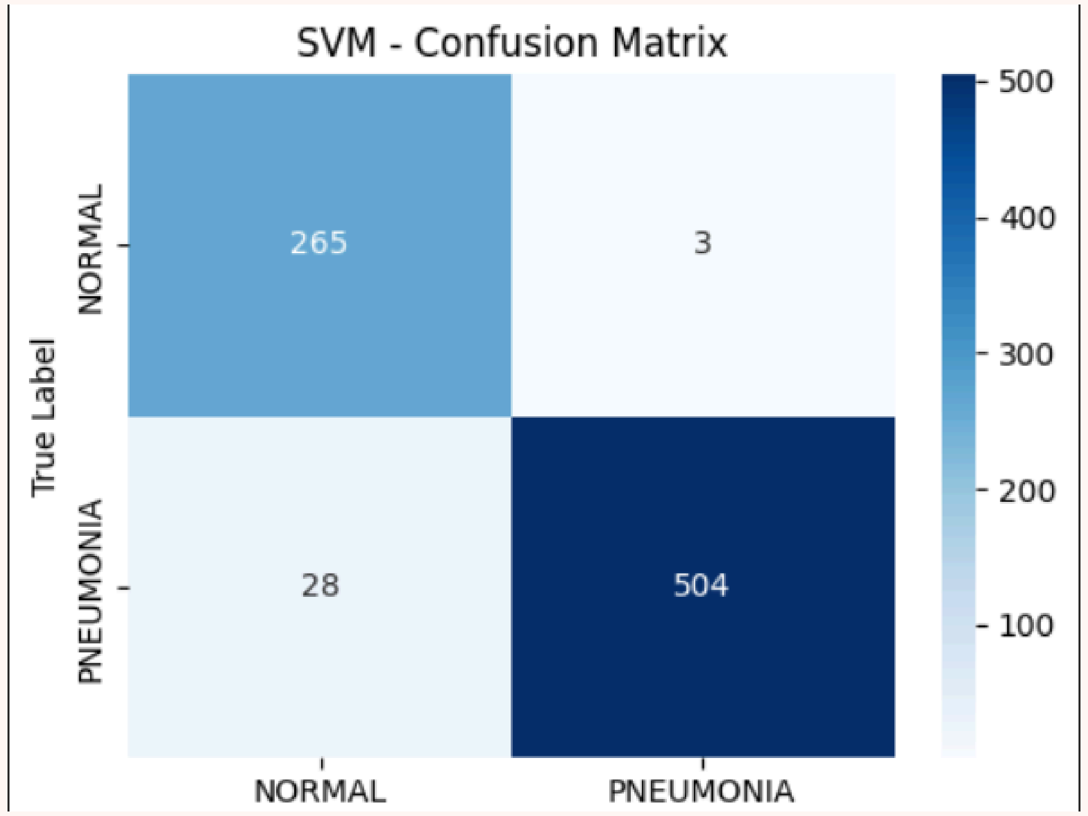
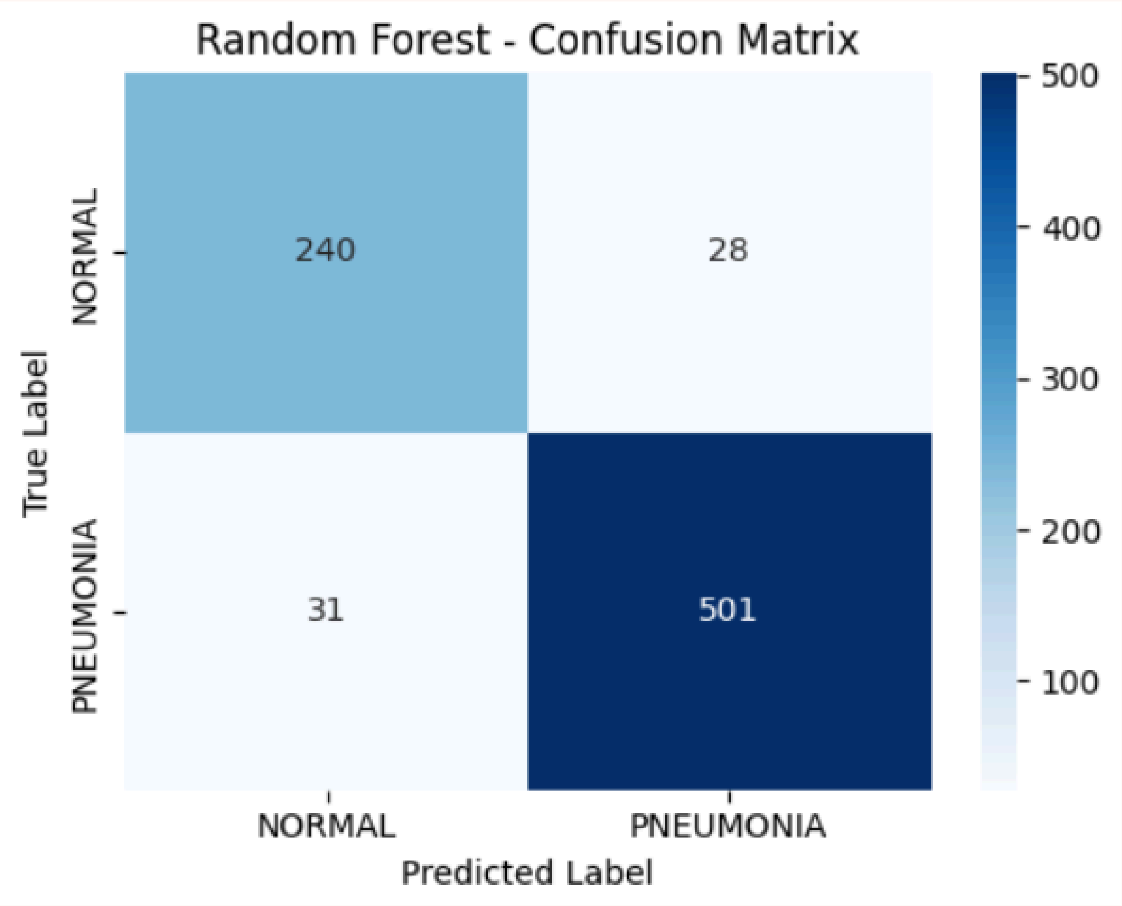
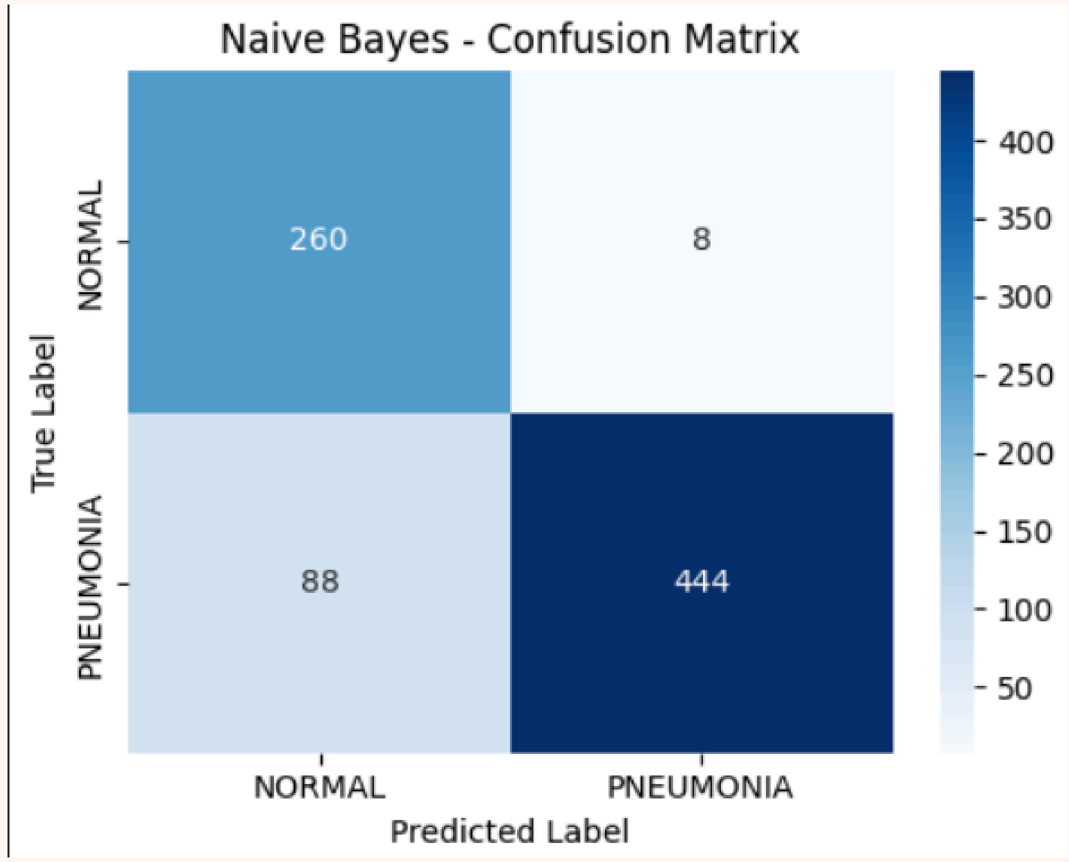
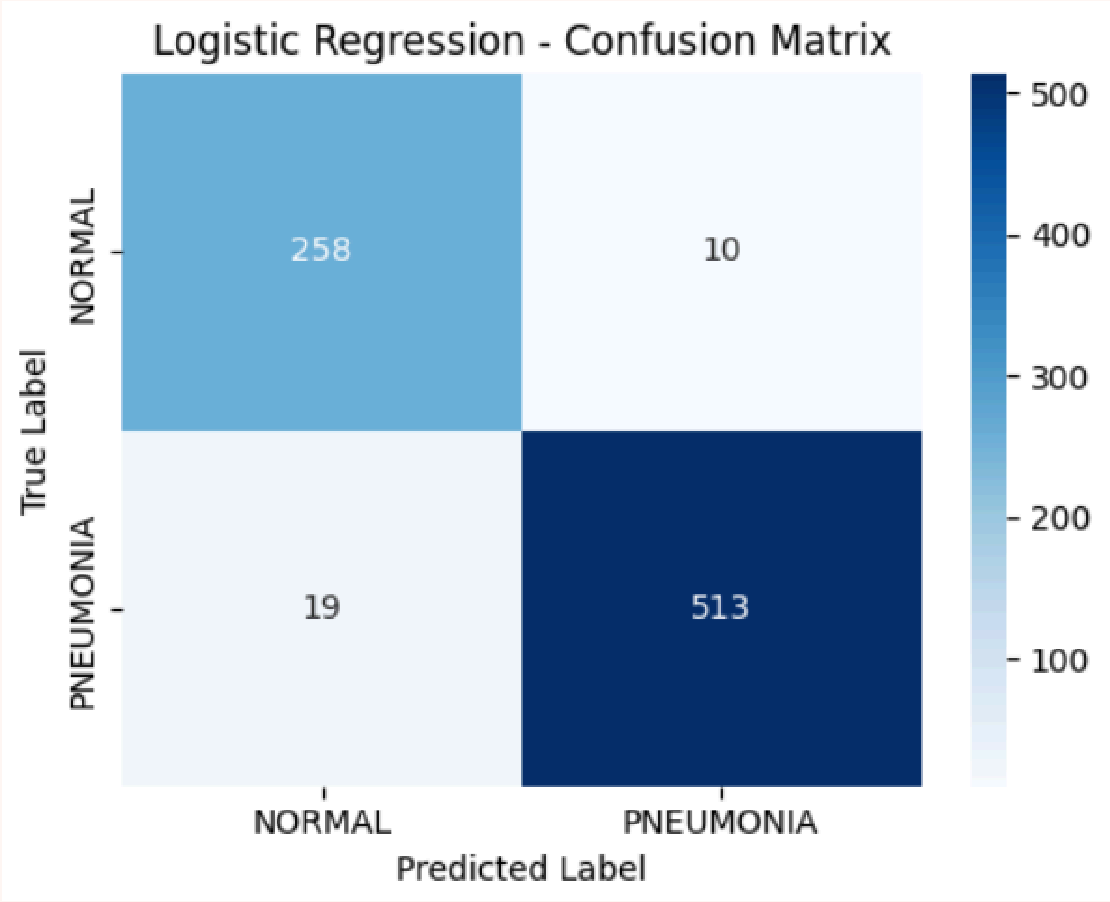
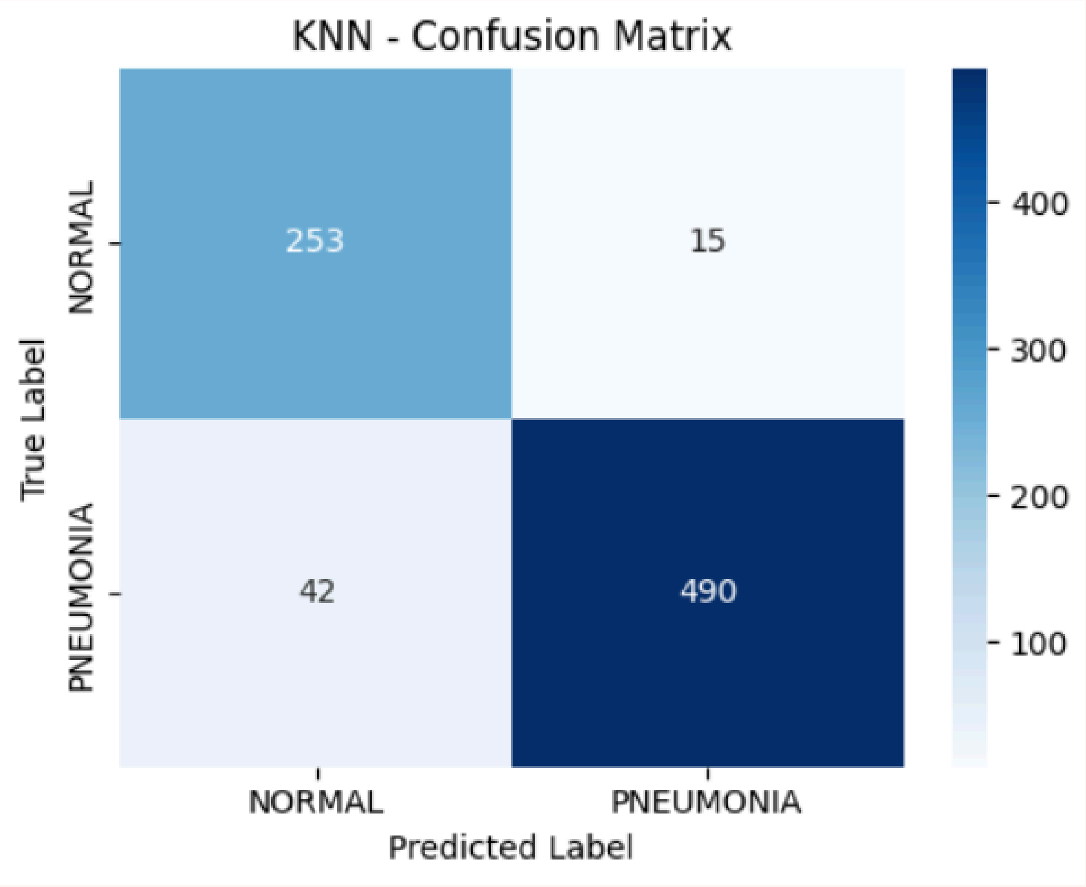
Performance Evaluation – Model performance is evaluated using accuracy scores and confusion matrices


SVM - Confusion Matrix
True Label
NORMAL
PNEUMONIA
265
3
28
504
NORMAL
PNEUMONIA
500
400
300
200
100


Random Forest - Confusion Matrix
True Label
NORMAL
PNEUMONIA
240
28
31
501
NORMAL
PNEUMONIA
Predicted Label
500
400
300
200
100


Naive Bayes - Confusion Matrix
True Label
NORMAL
PNEUMONIA
260
8
88
444
NORMAL
PNEUMONIA
Predicted Label
400
350
300
250
200
150
100
50


Logistic Regression - Confusion Matrix
True Label
NORMAL
PNEUMONIA
258
10
19
513
NORMAL
PNEUMONIA
Predicted Label
500
400
300
200
100

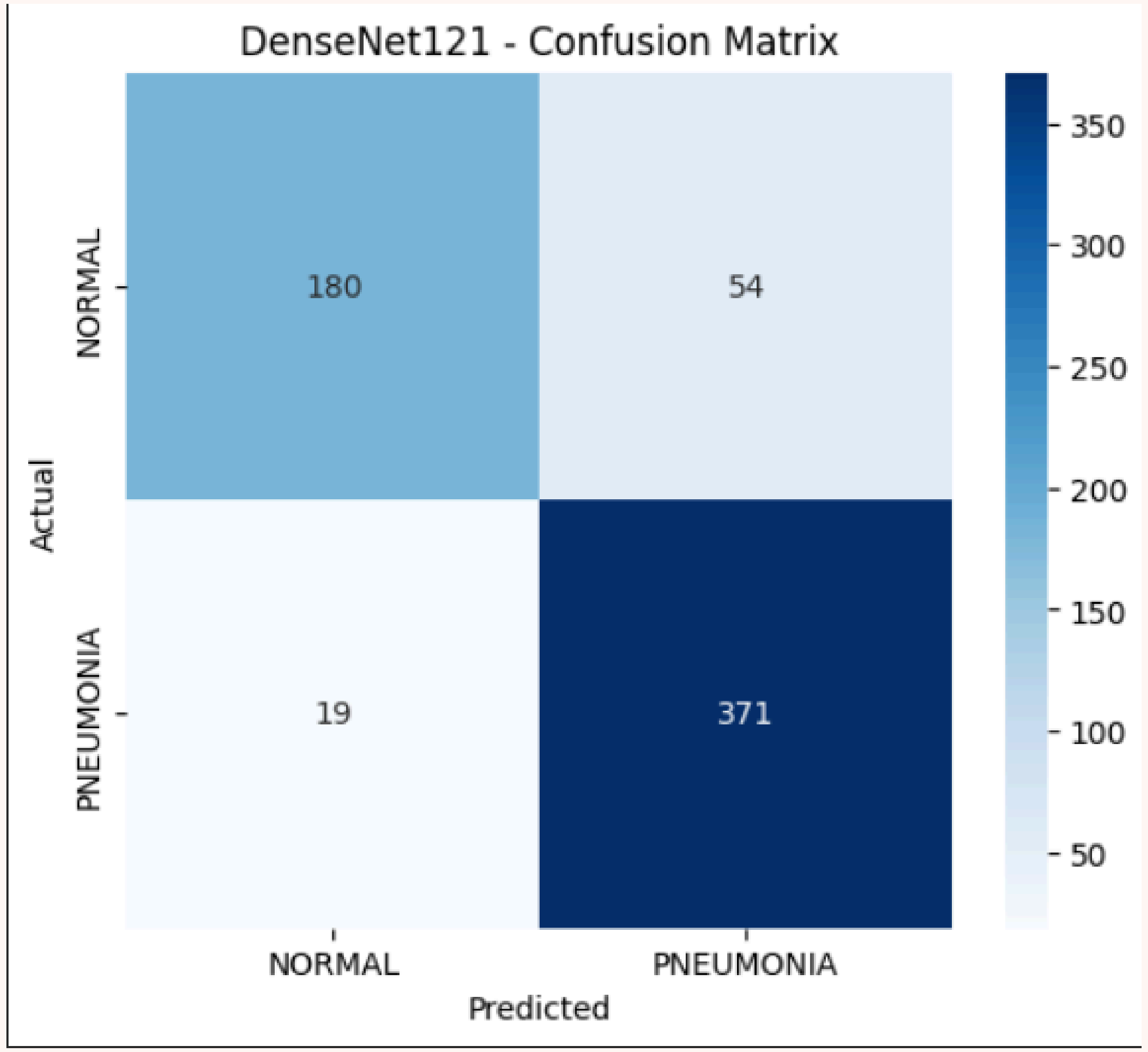

KNN - Confusion Matrix
True Label
NORMAL
PNEUMONIA
253
15
42
490
NORMAL
PNEUMONIA
Predicted Label
400
300
200
100

Proposed Methodology – CNN Pipeline

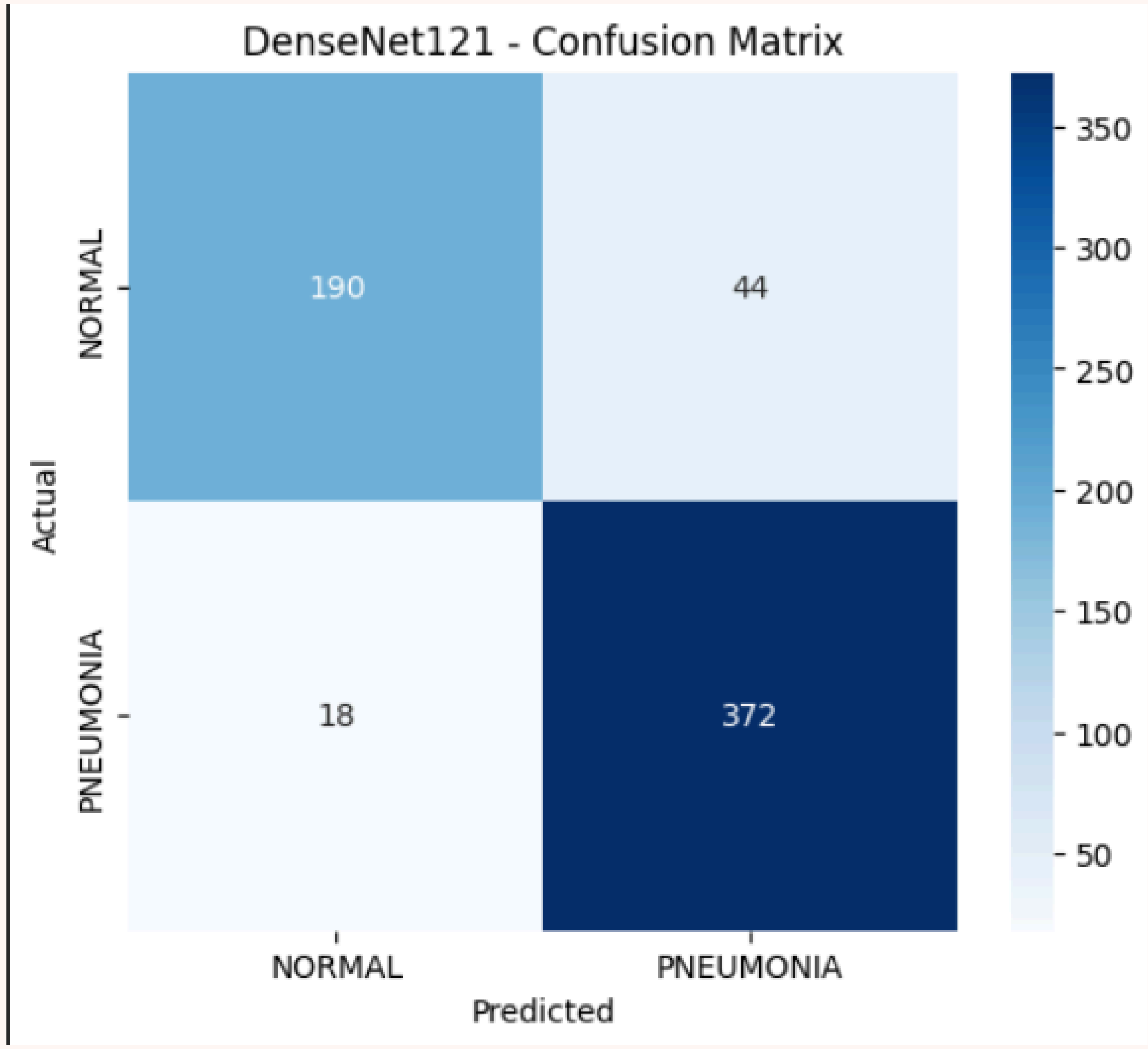
- **Backbone Feature Extraction-**Pretrained CNN features
- **X-ray Contrast Enhancement-** CLAHE-based enhancement
- **Balanced Data Loading**- Class-weighted training
- **Feature Dimension Reduction-** Global average pooling
- **Frozen Layer Training-** Stable initial learning
- **Regularization & Stability-** BatchNorm and Dropout
- **Binary Classification Output-** Sigmoid-based prediction
- **Performance Visual Analysis-** Confusion matrix visualization

Proposed Methodology – CNN Pipeline (finetune)

- **Pre-trained Backbone:** DenseNet121 feature extraction.
- **Image Enhancement:** CLAHE contrast adjustment.
- **Initial Training:** Frozen backbone, classifier only.
- **Model Fine-Tuning:** Unfreeze last 20 layers.
- **Class Balancing:** Balanced weights for pneumonia.
- **Dimensionality Reduction:** Global Average Pooling.
- **Overfit Prevention:** Dropout and Early Stopping.
- **Binary Output:** Sigmoid probability classification.



Before fine tuning



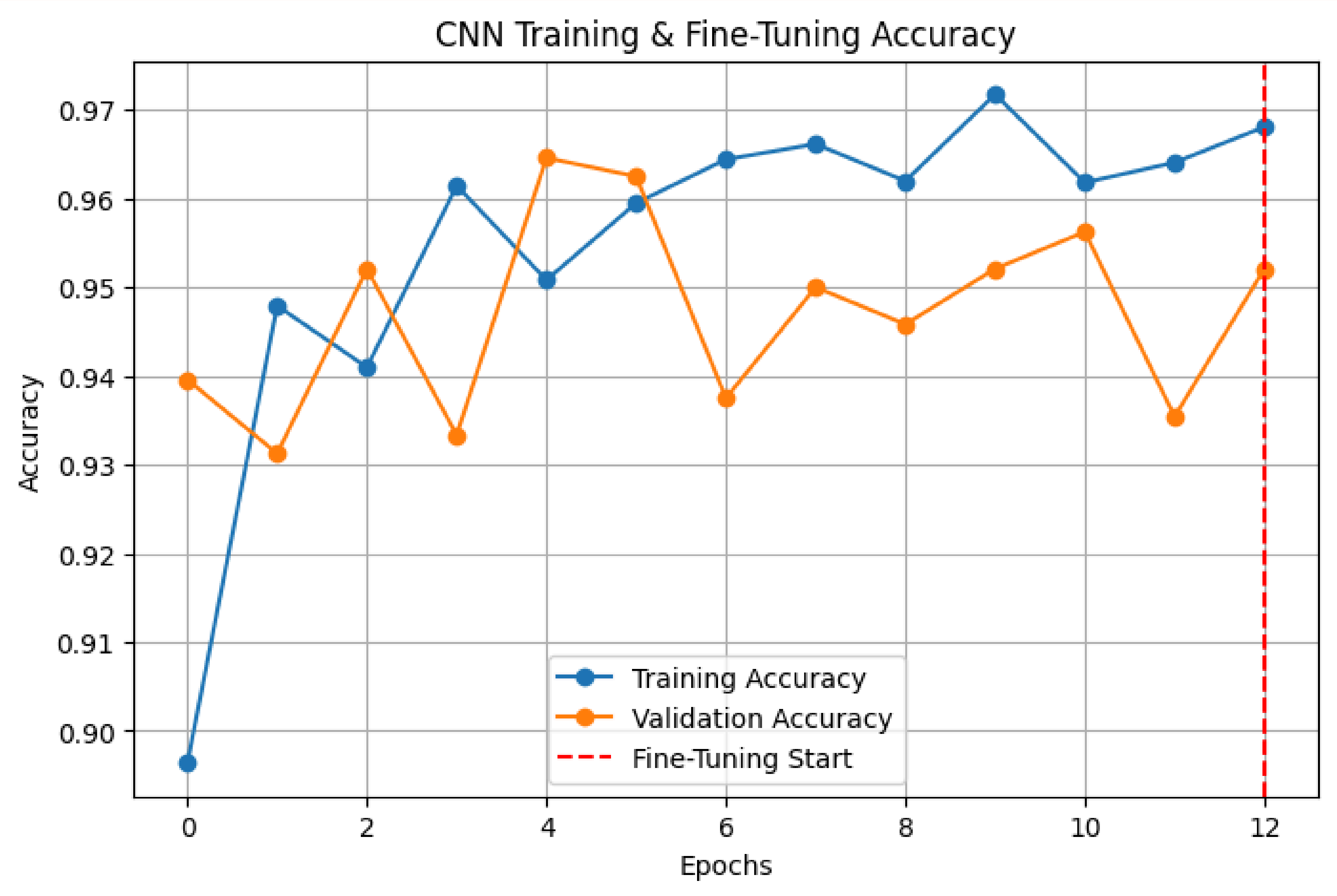
After fine tuning

Model Learning Curve: Training vs. Validation

- The Trend: The graph tracks our model's accuracy over 12 epochs. The Blue Line (Training) shows consistent learning, while the Orange Line (Validation) fluctuates but generally trends upward, reaching a peak of ~96%.
- The vertical red line marks the start of Fine-Tuning.
- Before this line, we trained only the new layers (feature adaptation).
- After this line, we "unfroze" the top layers of DenseNet121, allowing the model to make subtle adjustments specifically for X-ray textures.
- Conclusion: The convergence of training and validation accuracy confirms the model is learning generalized patterns, not just memorizing the training data.

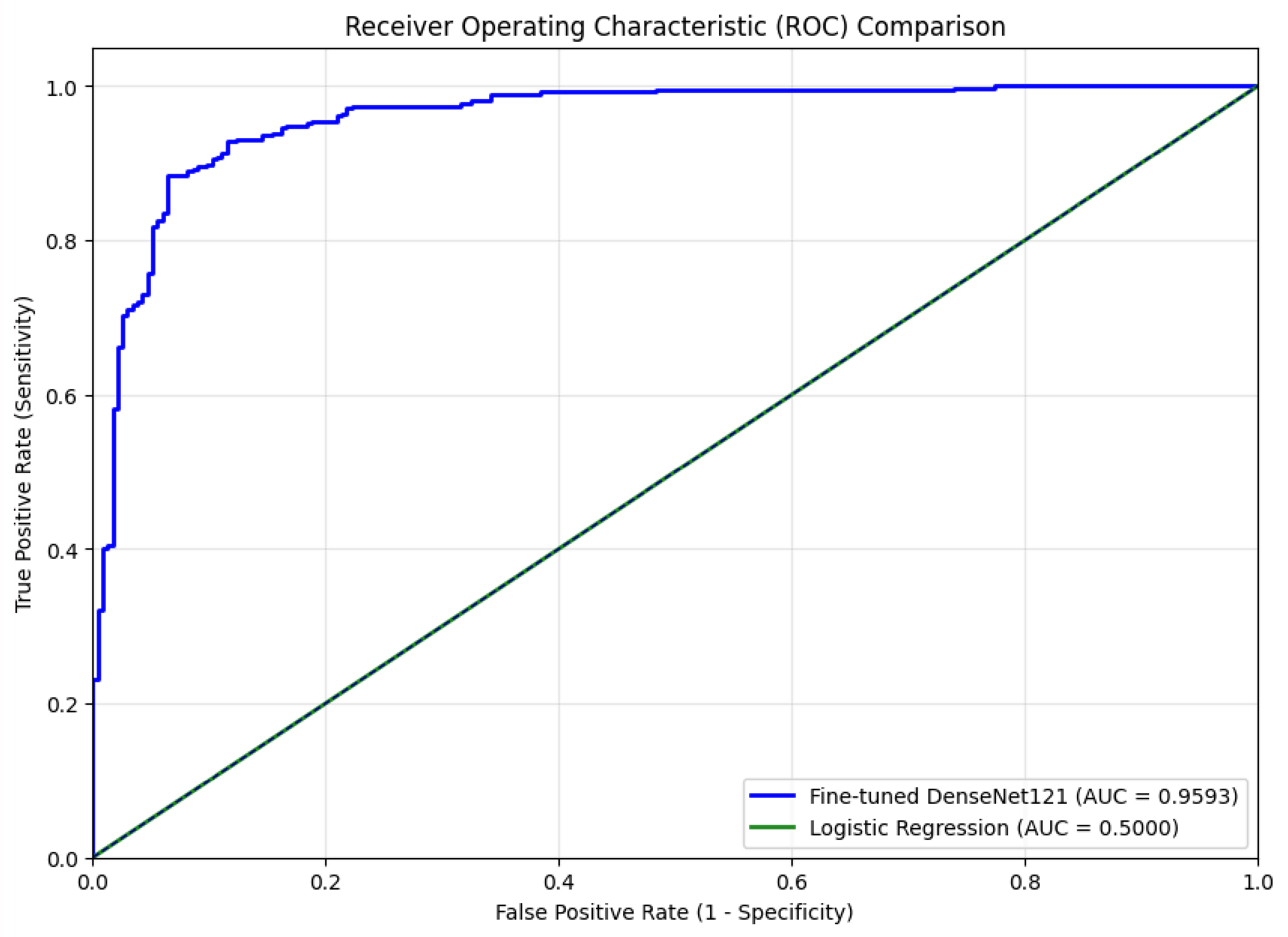
Diagnostic Reliability: Precision vs. Recall

- Recall: catch all the pneumonia cases (Minimizing False Negatives).
- Precision: When we said it was pneumonia, (Minimizing False Positives).
- Visual Analysis: The curve reaches the top-right corner (area near 1.0).
- Interpretation: This "perfect L-shape" indicates our model achieves high recall without sacrificing precision. It successfully identifies nearly all positive cases without generating excessive false alarms.



Deep Learning vs. Traditional Machine Learning

- Comparison: This plot compares our Fine-tuned DenseNet121 (Blue) against a standard Logistic Regression (Green) baseline.
- Result: DenseNet121 (Blue): Achieved an AUC of 0.9593. The curve shoots up immediately, showing excellent sensitivity.
- Logistic Regression (Green): Flatlined at the diagonal (AUC = 0.5000). This represents "random guessing."
- Takeaway: This visual proof justifies our choice of Deep Learning. Traditional methods (Logistic Regression) failed to capture the complex patterns in X-ray pixels, whereas the CNN successfully extracted the deep features needed for accurate diagnosis.



Automated Lung Severity Analysis

Methodology: Computer Vision & Image Processing

- Region of Interest (ROI) Extraction:
  - Isolates the lung area using the generated binary mask (cv2.bitwise_and), ensuring analysis is restricted strictly to lung tissue.
- Opacity Detection (Consolidation Mapping):
  - Identifies potential pneumonia opacities using Adaptive Gaussian Thresholding, which adjusts to varying lighting conditions in the X-ray.
  - Refines detection using Morphological Opening (5x5 kernel) to eliminate small noise artifacts.
- Visual Diagnostics:
- Overlay: Highlights detected opacities in Red on the original image for easy verification.
- Annotation: Automatically stamps the image with the specific severity percentage and risk classification

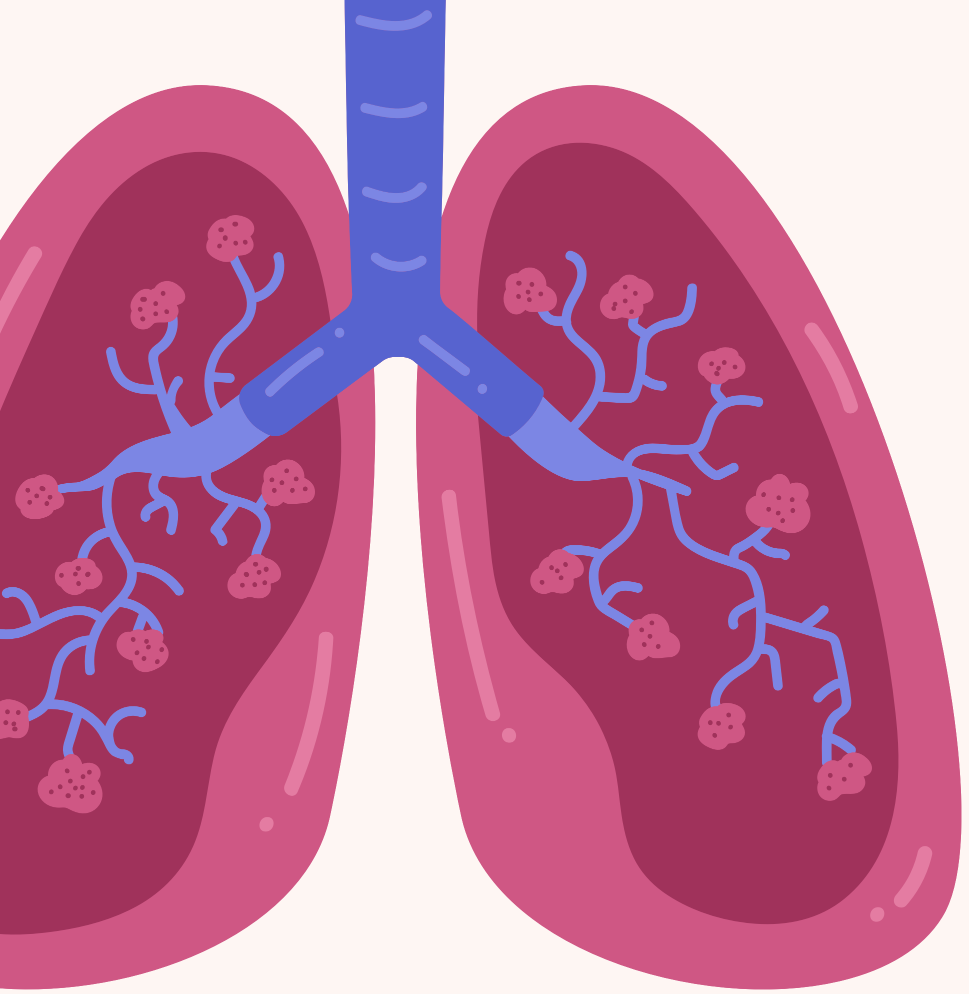
Applications and Future Scope

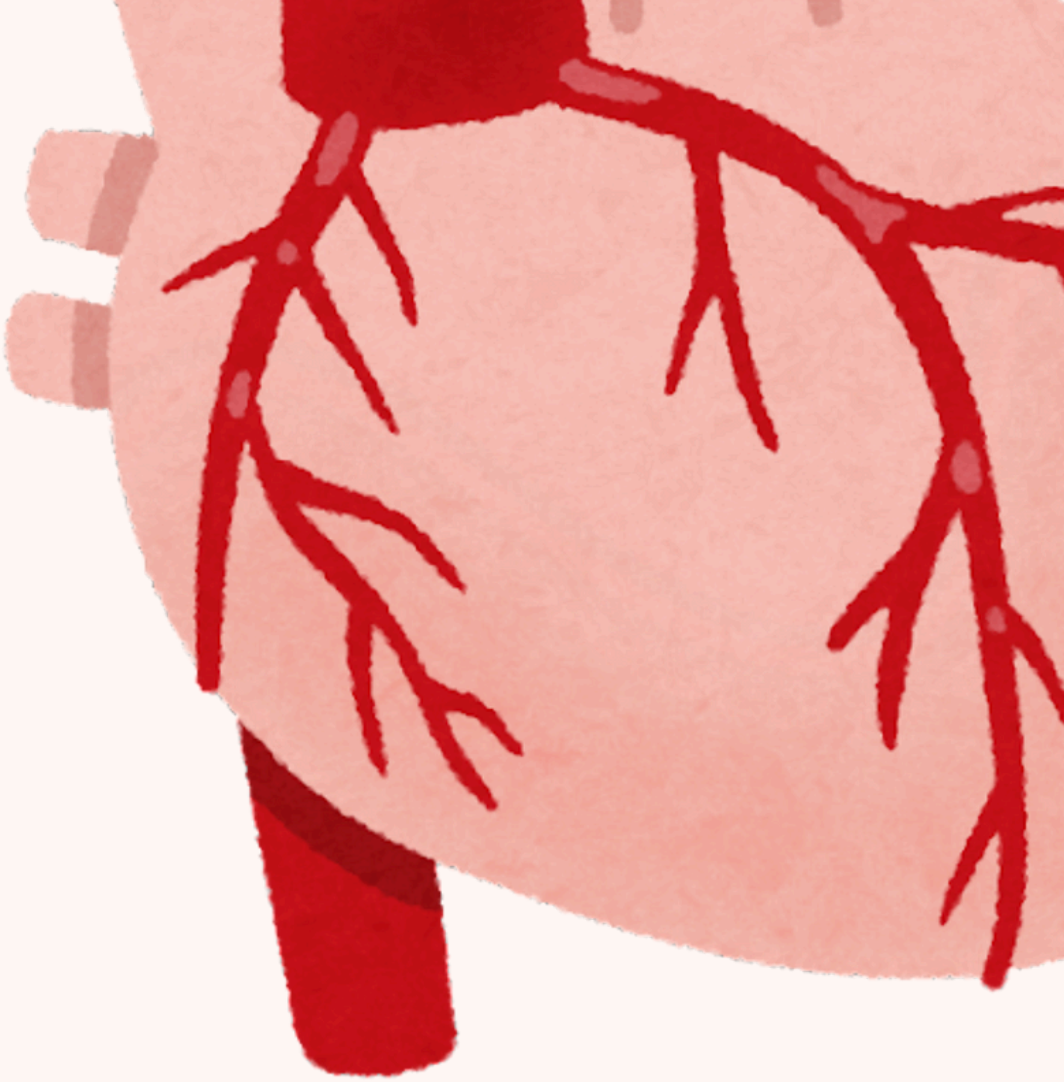
Applications:

- Automated pneumonia screening in hospitals
- Clinical decision support for radiologists
- Severity-based patient triage
- Remote screening in telemedicine settings
- Assistance during high patient-load situations

Future Scope:

- Training with larger and multi-center datasets
- Extension to other lung diseases (TB, COVID-19, fibrosis)
- Real-time web or mobile application deployment
- Integration with hospital PACS and EHR systems
- Multi-modal analysis combining imaging and clinical data





Thank You