Pneumonia Classification from X-ray Images

A Deep Learning Approach for Medical Image Analysis

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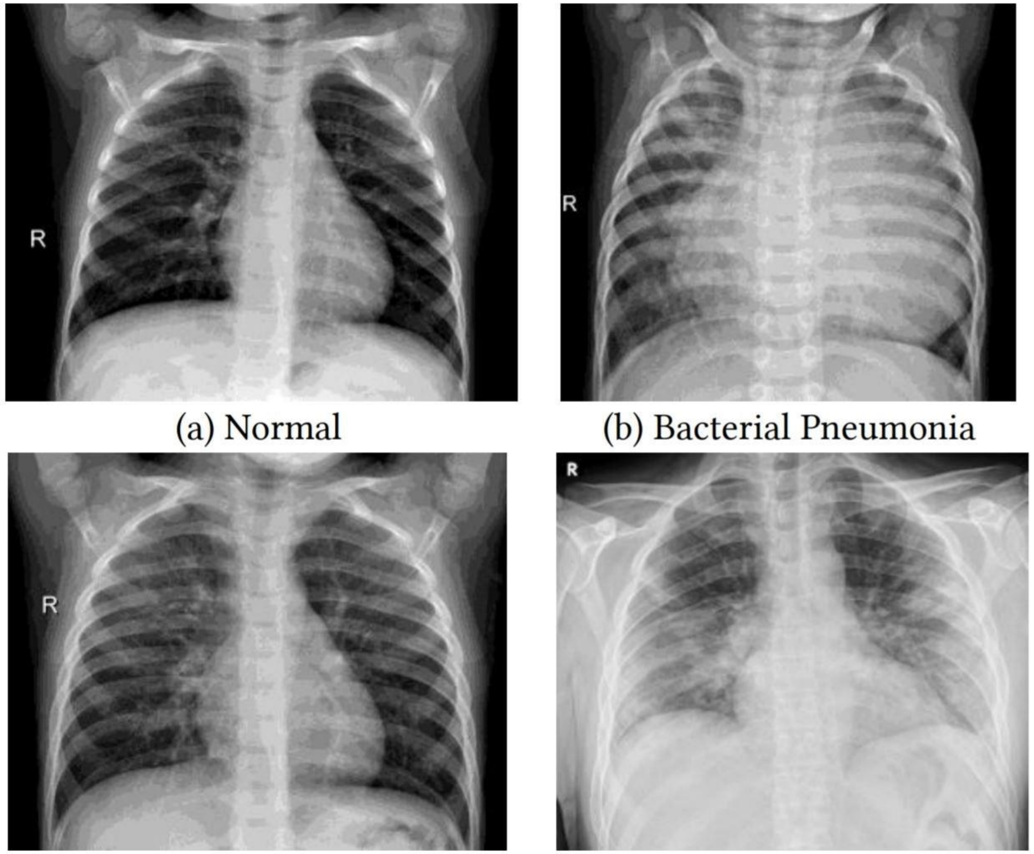
Project Overview

- **Objective:** Build a deep learning system to classify chest X-ray images as either pneumonia-positive or normal.
- **Motivation:** Pneumonia is one of the leading causes of death in children under five. Early AI-assisted diagnosis can save lives.
- **Approach:** Use CNNs and transfer learning (VGG16, Custom CNN) with ensemble modelling.
- **Outcome:** A web-based AI model capable of high-accuracy pneumonia detection.

Primary features to classify

- **Lung Opacities & Air Bronchograms** – White patches due to fluid-filled alveoli; visible bronchi.
- **Pleural Effusion & Increased Density** – Fluid buildup blunts lung bases; affected areas appear whiter.
- **Pattern Variations** – Bacterial: localized consolidation; Viral/atypical: patchy or interstitial patterns.

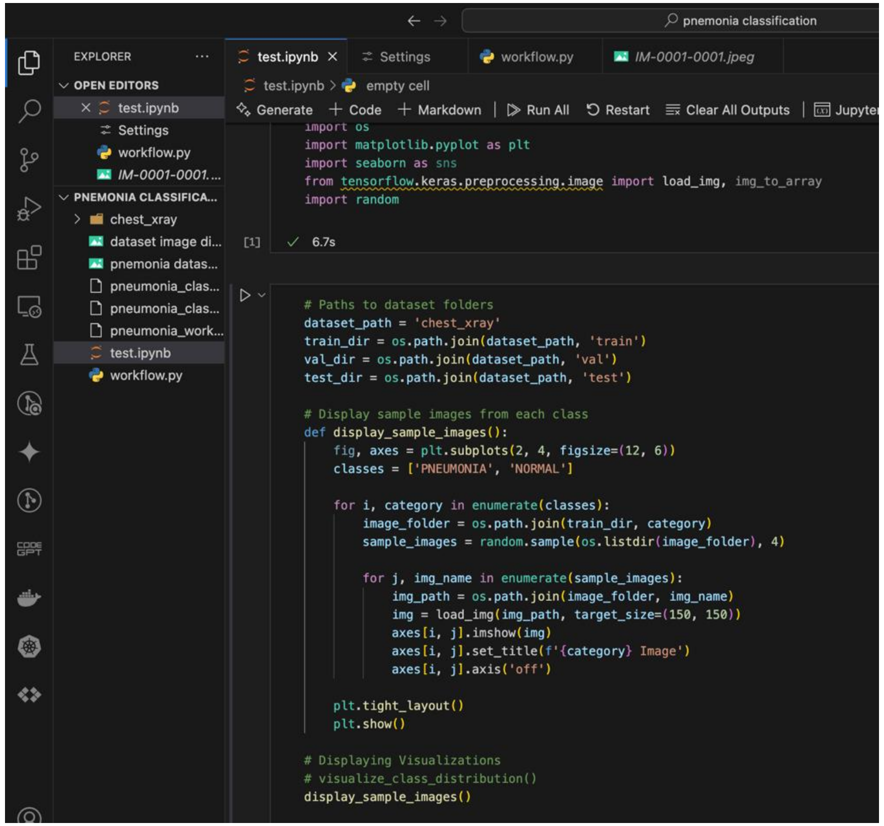


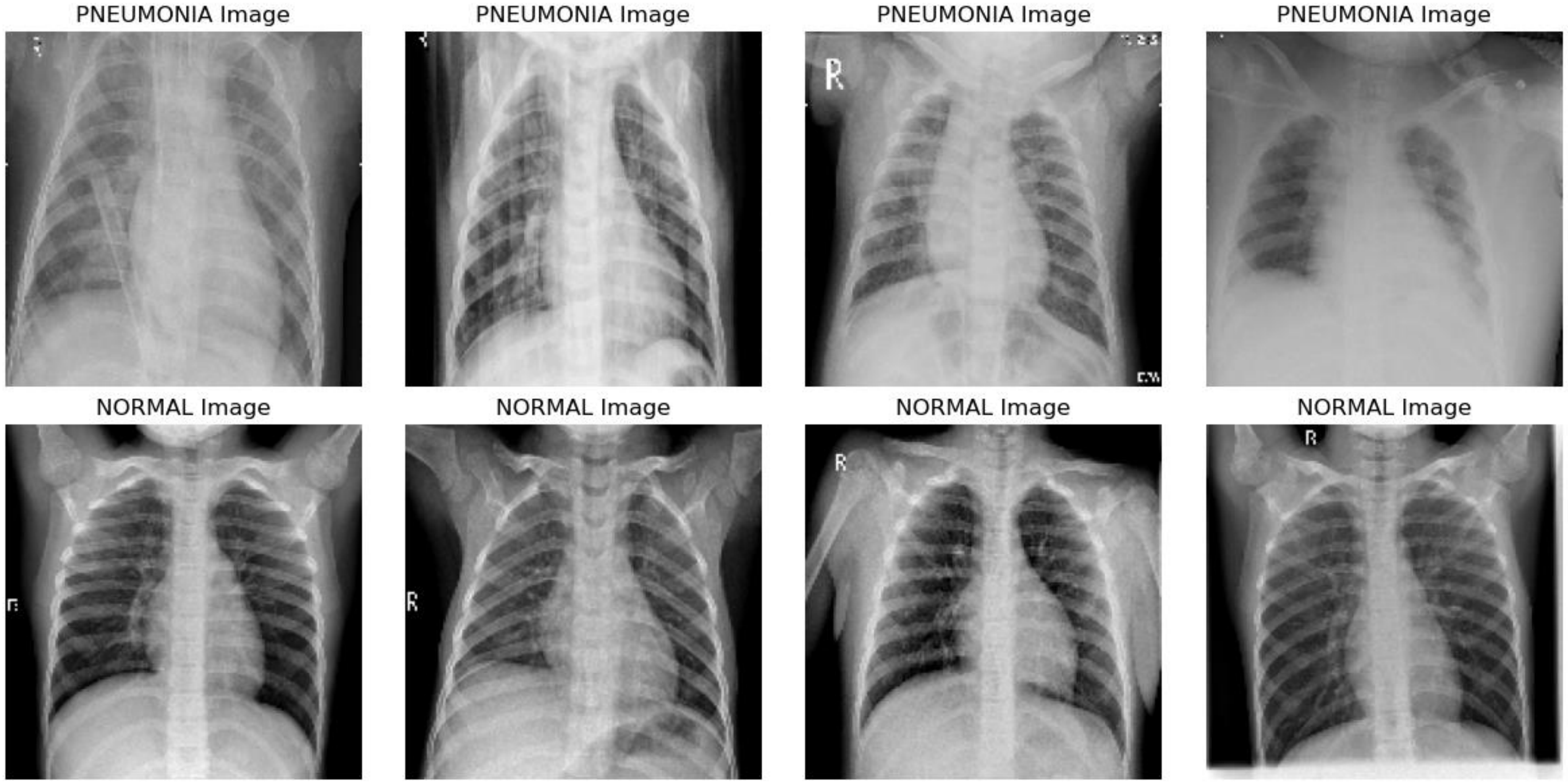
(a) Normal (b) Bacterial Pneumonia (c) Viral Pneumonia (d) COVID-19 Pneumonia

📊 Dataset Overview

- **Name:** Chest X-Ray Dataset
- **Source:** Guangzhou Women and Children's Medical Center
- **Type:** Pediatric Chest X-Ray Images (Ages 1-5)
- **Categories:** **Pneumonia** (Bacterial/Viral Infection), **Normal** (Healthy Lungs)
- **Pneumonia** (Bacterial/Viral Infection)
- **Normal** (Healthy Lungs)
- **Total Images:** 5,863 JPEG images
- **Data Split:** • **Training Set:** 5,216 images, **Validation Set:** 16 images, **Test Set:** 624 images
- **Training Set:** 5,216 images
- **Validation Set:** 798 images
- **Test Set:** 624 images
- **Source:** Taken from Kaggle [*Link*]

📊 Dataset Overview





Project Workflow: From Dataset to Web Interface

📁 Dataset Loading

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🧼 Data Preprocessing & Augmentation

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🧠 CNN & Transfer Learning

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⚙️ Ensemble Modeling

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📊 Evaluation & Metrics

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🌐 Web App Deployment

Data Preprocessing and Augmentation

1. **Image Standardization:**

All X-ray images are resized to a uniform size of **150x150 pixels**, and pixel values are **rescaled between 0 and 1** to normalize the input for the neural network.

2. **Data Augmentation Techniques:**

Applied **random zoom**, **horizontal flips**, and **shear transformations** to enhance dataset diversity without collecting new images. This simulates real-world variations in X-ray imaging.

3. **Class Balance & Benefits:**

Ensured a balanced representation of **normal and pneumonia cases** during training. These preprocessing steps **reduce overfitting**, **improve generalization**, and **enhance model robustness**.

Deep Learning Architectures Used (VGG-16)

1. **Pre-trained on ImageNet:**

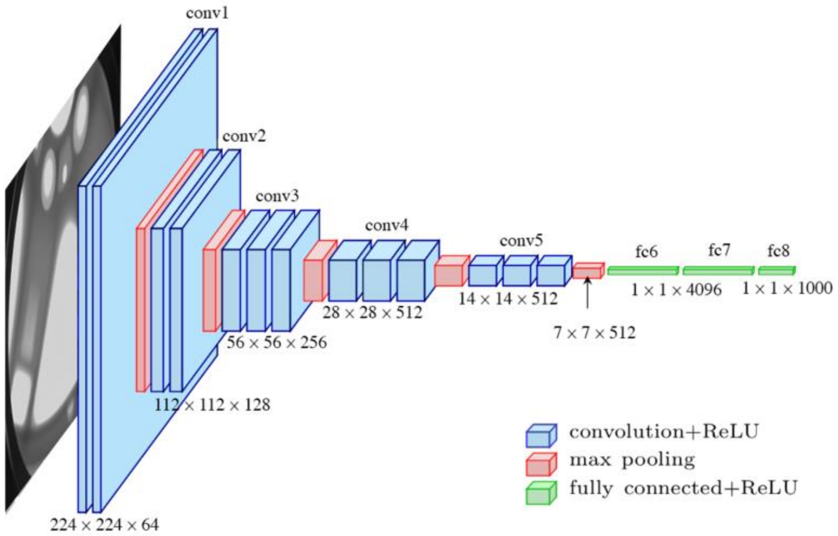
Leveraged VGG16, a deep CNN pre-trained on over 1 million images, to extract high-level features from chest X-rays.

2. **Custom Top Layers for Binary Classification:**

Replaced the original classification head with custom Dense, Dropout, and Sigmoid layers tailored for Pneumonia vs. Normal detection.

3. **Faster & Efficient Training:**

By freezing the convolutional base, the model trained quickly with strong performance even on a smaller medical dataset.



Deep Learning Architectures Used(Custom CNN)

1. Convolution + Pooling Blocks:

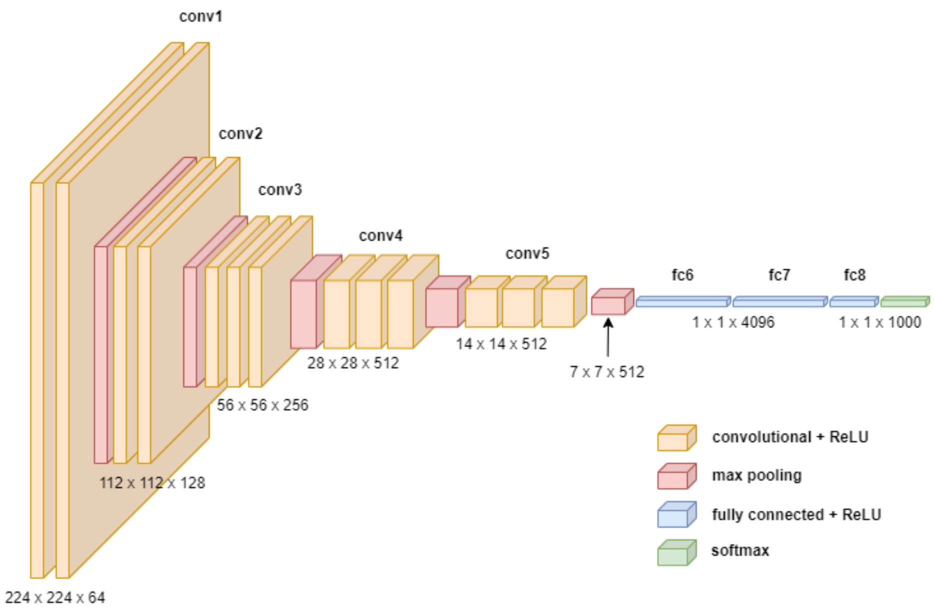
Designed a sequential CNN with increasing filter sizes (32 → 64 → 128) to learn progressively complex features from chest X-ray images.

2.Fully Connected Classifier:

The convolutional output was flattened and passed through dense layers with ReLU activation and dropout to prevent overfitting.

3.Task-Specific Learning:

Unlike VGG16, this model learned from scratch and was fine-tuned specifically for the pneumonia classification task using only the available dataset.



Ensemble Modeling

1.Model Combination Strategy:

Predictions from both **VGG-16 and Custom CNN** were combined by averaging their output probabilities, creating a simple yet effective **ensemble model**.

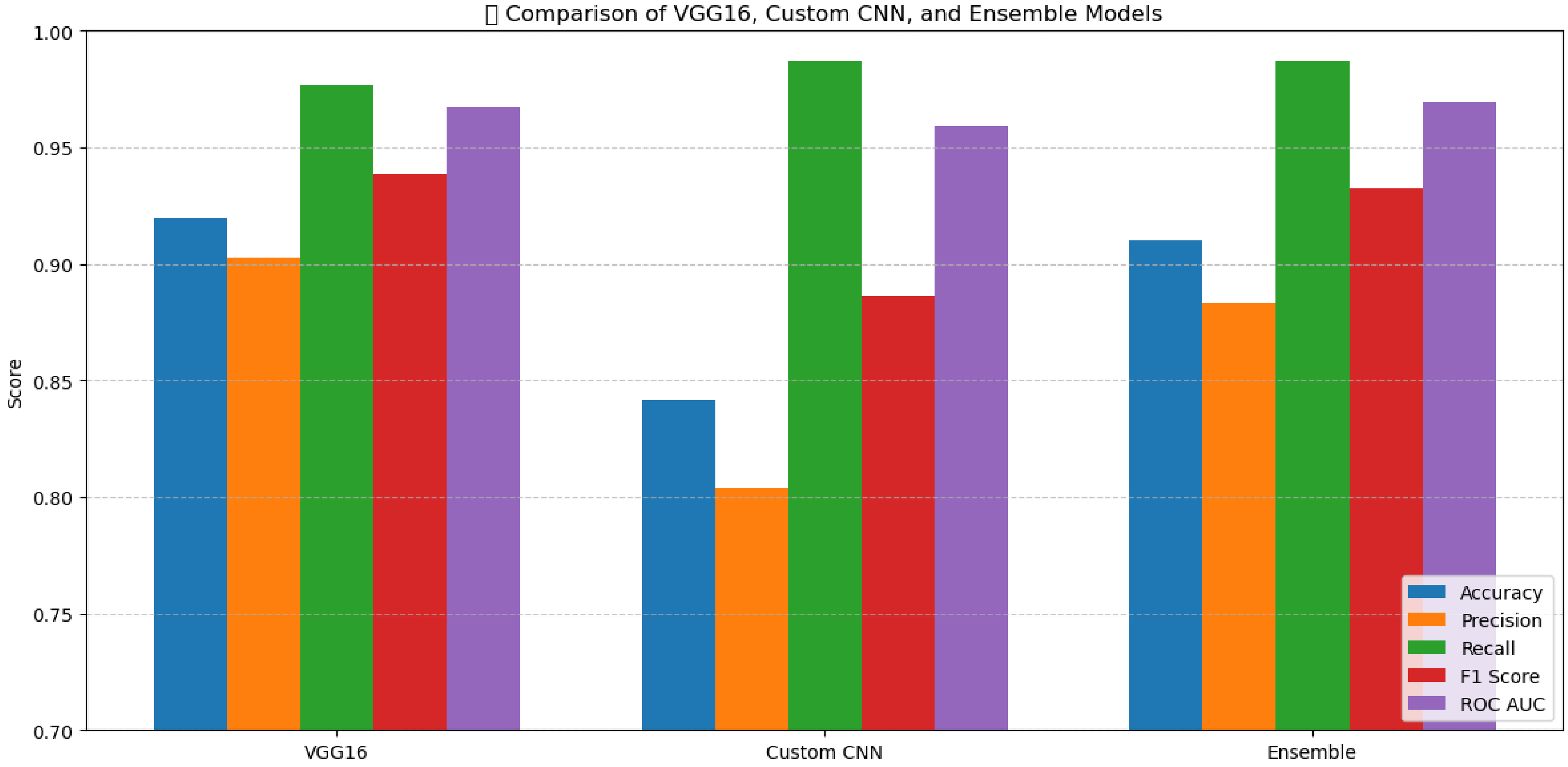
2.Improved Performance:

The ensemble approach leverages the strengths of both models, resulting in **better generalization** and **reduced prediction variance**, especially on unseen data.

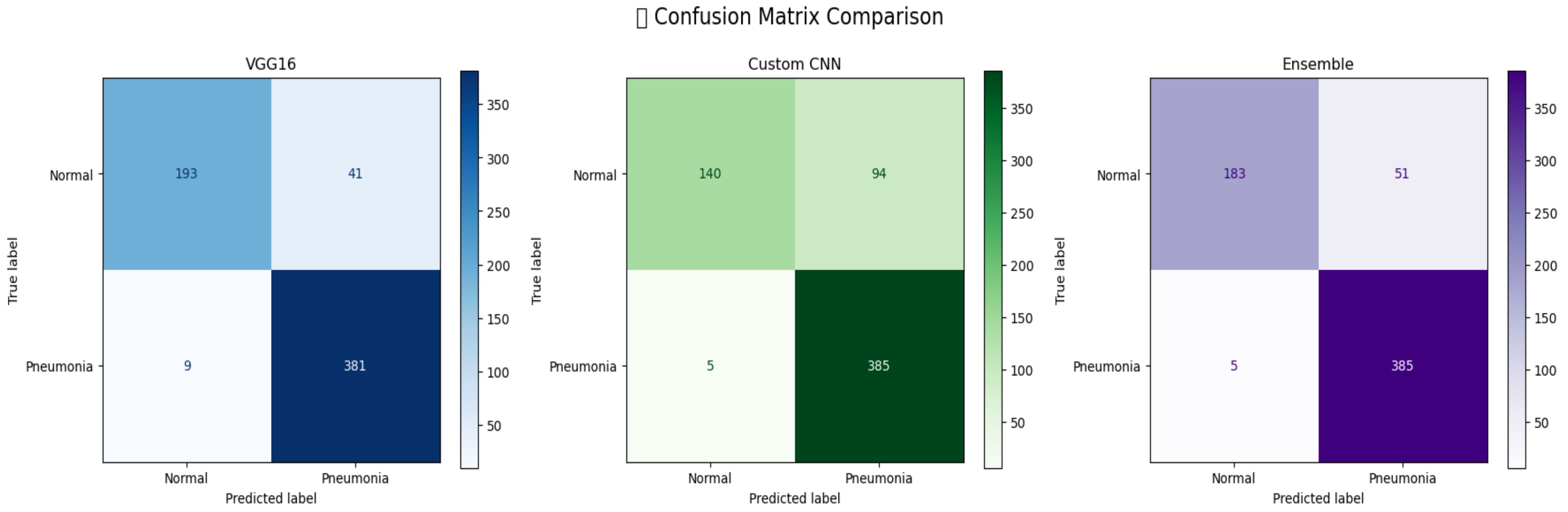
3.Final Output:

A prediction is considered **pneumonia** if the averaged confidence exceeds 0.5, ensuring a more balanced and reliable classification outcome.

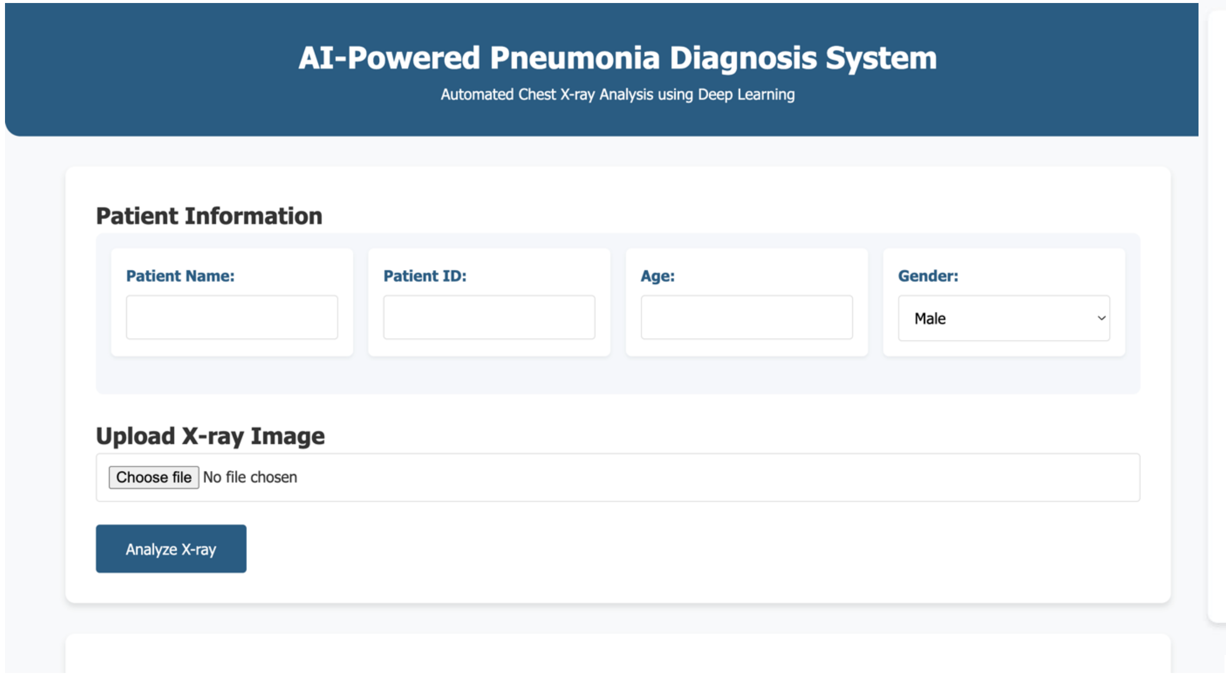
Performance Evaluation

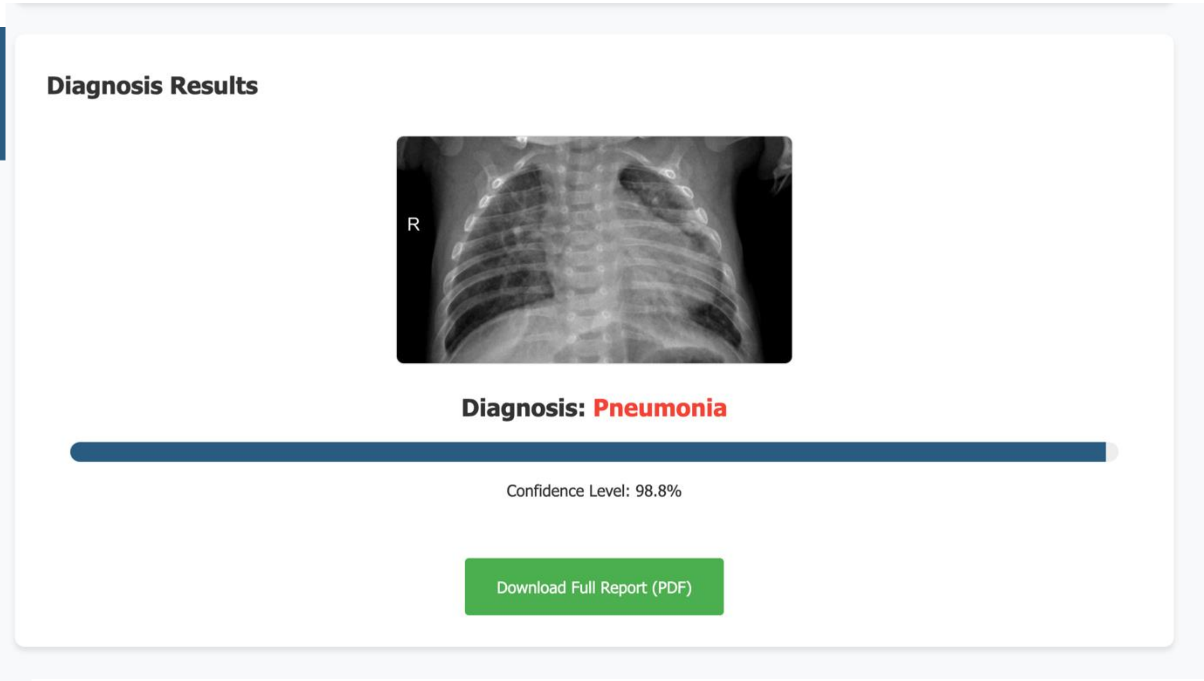


Confusion Matrix



Web Application Interface





Future Enhancements

1.Advanced Model Training & Classification:

Future versions will be trained on more diverse chest X-ray datasets, enabling the model to not only detect pneumonia but also differentiate between **bacterial and viral pneumonia**, improving diagnostic precision.

2.Explainable AI with Grad-CAM:

Integration of **Grad-CAM visualizations** will offer localized heatmaps on lung regions, enhancing interpretability and allowing radiologists to better trust and validate AI predictions.

3.Generative AI-Powered Instant Reporting:

A **GenAI system** will automatically generate personalized medical reports in real-time based on prediction results and image analysis — accelerating the diagnosis-to-treatment cycle and improving healthcare delivery.

Conclusion

1.Accurate and Reliable Classification:

The ensemble model combining VGG16 and Custom CNN delivered strong performance in classifying chest X-rays as pneumonia or normal, enhancing diagnostic accuracy.

2.Real-World Usability:

A functional **Flask-based web app** was developed for easy image upload and classification, enabling practical use in clinical or research settings.

3.Foundation for Future Upgrades:

This project lays the groundwork for enhancements like **Grad-CAM integration**, **pneumonia type classification**, and **automated report generation using Gen AI**.

References

- https://pmc.ncbi.nlm.nih.gov/articles/PMC9140837/pdf/diagnostics-12-01280.pdf
- https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia
- https://pmc.ncbi.nlm.nih.gov/articles/PMC9140837/

Thank You