Identifying Pneumonia in Chest X-rays Using Deep Learning

A Machine Learning Approach

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Business Problem & Stakeholders

Problem: Pneumonia is a leading cause of death, and timely diagnosis is crucial.

Stakeholders:

- **Hospitals & Clinics**: Improve diagnostic efficiency and reduce workload on radiologists.
- **Doctors & Radiologists**: Aid in early and accurate detection.
- **Patients**: Faster diagnosis leads to timely treatment and better outcomes.

Data Understanding

Overview

Data Source: NIH Chest X-ray dataset with labeled pneumonia cases.

Size: 5,856 X-ray images labeled as Normal, Pneumonia, and other conditions.

Classes:

- Normal: 1,583 images
- Pneumonia: 4,273 images

Data Understanding

Suitability

Why It's Suitable:

- Large dataset enables deep learning applications.
- Real-world hospital data improves generalizability.
- Labelled and pre-split by experts into training, validation, and testing sets.

Data Preparation

- **Images Resized: 150×150** pixels for deep learning models.
- Pixel Normalization: Values scaled to [0,1].
- **Augmentation Applied:** Rotation, zoom, horizontal flip (to generalize better).

Challenges:

- **Class Imbalance:** 75% Pneumonia vs. 25% Normal → Used **class weighting**.
- **Variability in Image Quality:** Different X-ray machines and noise levels.

Model Selection

Why Choose a CNN (Convolutional Neural Network)

- They are specifically designed for **Computer Vision** & **Image Processing** tasks.
- **Learns image features automatically** → No manual feature extraction or engineering.
- **Captures spatial relationships** → Can differentiate between healthy and infected lung patterns.
- **Performs well with large image datasets** → Reduces overfitting through pooling layers.

Key Metrics

Which metrics matter most

<u>Primary:</u>

- Recall — missing pneumonia cases is dangerous.
- ROC-AUC — ensures the model effectively separates normal vs. pneumonia cases.

<u>Secondary:</u>

- Precision — misclassifying normal cases would cause undue

Model Architecture

Baseline Model

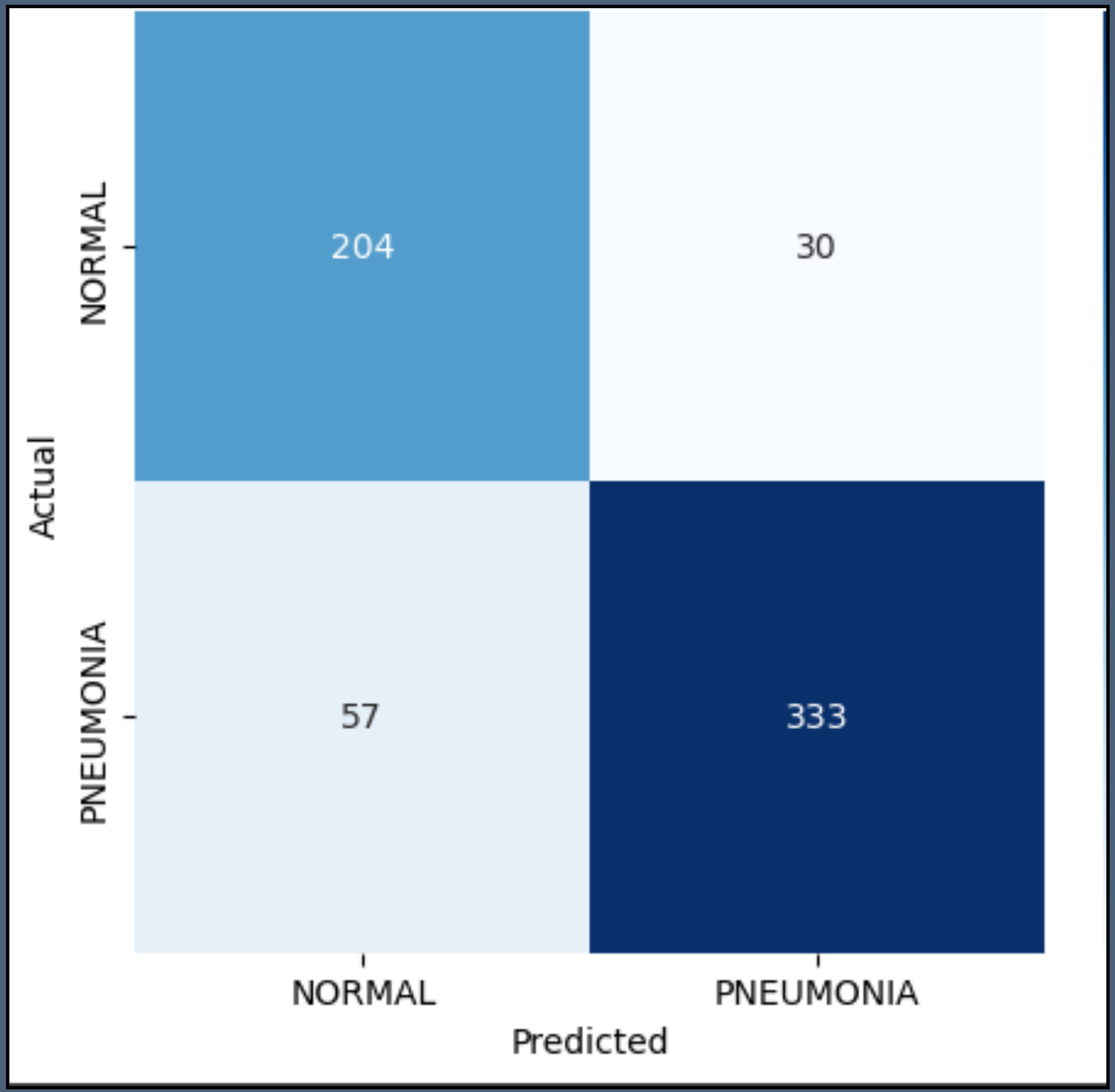
Architecture:

- **Conv2D Layers**: Extract spatial features from X-rays.
- **MaxPooling:** Reduces dimensionality.
- **Dense Layers:** Fully connected layers for classification.
- **Sigmoid Activation:** Single Neuron Layer for Binary Classification.

Baseline Model Evaluation

Performance:

- Recall: 85% — correctly identified Pneumonia cases.
- AUC: 0.90 — the model's confidence in distinguishing classes.
- Precision: 92% — Among all cases predicted as Pneumonia, 92% were correct.



Model Development

Tuned CNN

Tuned Enhancements:

Address class imbalance:

- Class weights.

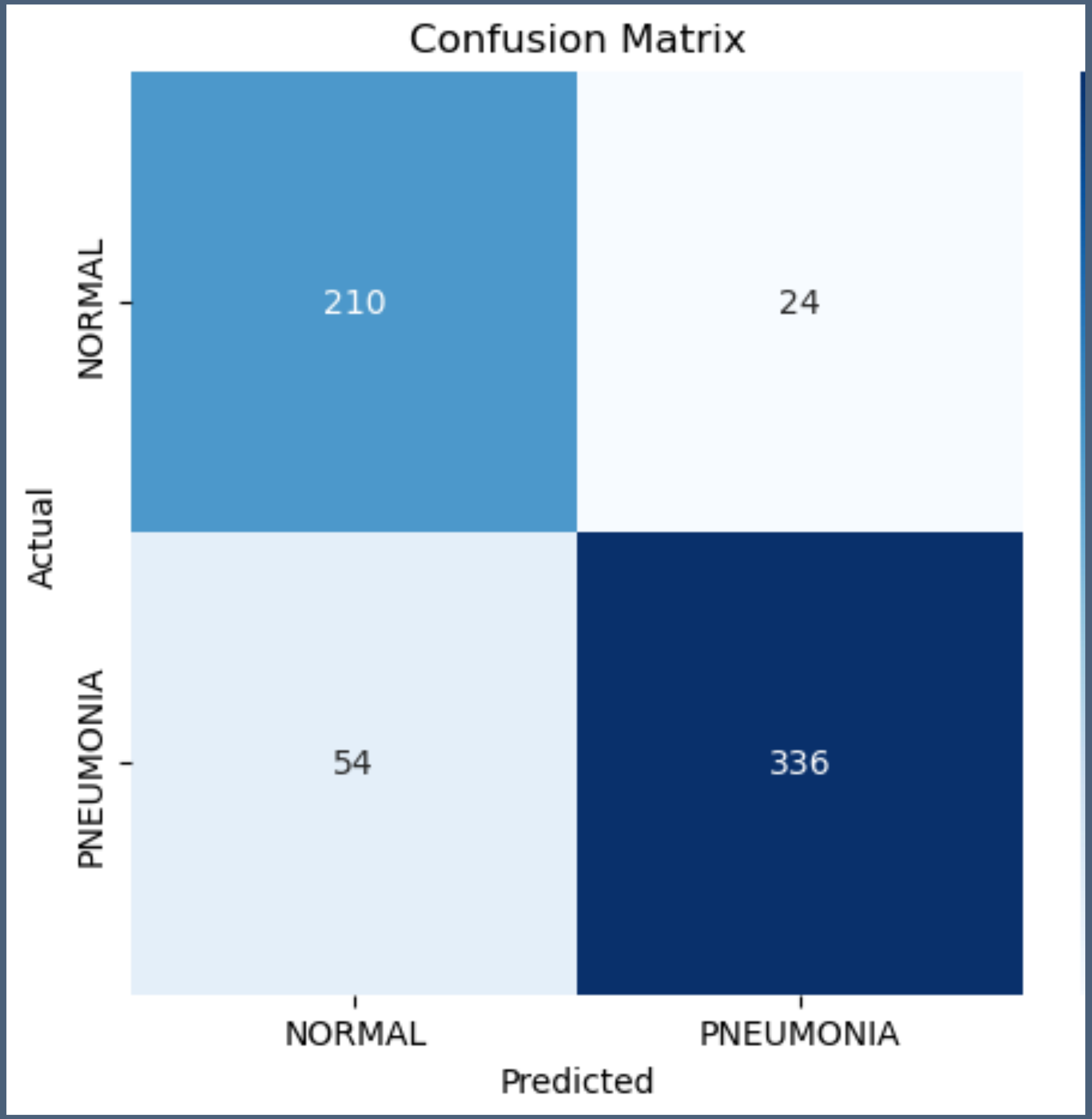
Address Overfitting:

- More noise via data augmentation to help the model generalize.
- Add dropout layers for more noise and better generalization.

Tuned Model Evaluation

<u>Performance:</u>

- Recall: 86% — 1% better.
- AUC: 0.94 — 4% better.
- Precision: 93% — 1% better.



Further Tuning

- Improve dataset diversity for better generalization.
- Increase input dimensionality to avoid down-sampling.
- Experiment with more layers and higher numbers of filters.
- Focus on maximizing Recall to minimize misclassified Pneumonia cases.

Use Cases (& Limitations)

Assuming further validation cycles:

- Recurring process running over database images to flag pneumonia cases (offline).
- Indicate high likelihood cases to radiologists (online, with human verification).
- Output common patterns in pneumonia positive cases for training purposes (offline, static).

Conclusion & Next Steps

- The evaluation metrics suggest the model is robust but requires refinement.
- Real-world deployment requires further validation.
- With a more tuned model we can begin exploring partnerships with hospitals for clinical trials.

Questions?