Prediction of Pediatric Pneumonia in Chest X-Rays using Deep Learning

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1 Abstract

Pneumonia is a potentially life-threatening infection, especially dangerous for children under the age of five. Traditional methods of diagnosing pneumonia involve manual inspection of chest X-rays by medical professionals, which can be time-consuming and susceptible to human error. This project explores the application of deep learning in automating the detection of pediatric pneumonia using chest X-ray images.

Using MobileNetV2 as the core deep learning model, the project implements a transfer learning approach with preprocessing, data augmentation, and fine-tuning strategies. The model is evaluated using a range of metrics including accuracy, precision, recall, F1-score, confusion matrix, ROC and PR curves. Moreover, model explainability is addressed through Grad-CAM heatmaps and an analysis of misclassified samples. The overall objective is to build a trustworthy, interpretable, and accurate model suitable for deployment in medical diagnostics.

2 Introduction

Pneumonia is an acute respiratory infection that affects the lungs. It is one of the leading causes of morbidity and mortality among children worldwide, particularly in low and middle-income countries. The World Health Organization (WHO) reports that pneumonia accounts for approximately 15% of all deaths of children under 5 years old, killing over 800,000 children in 2017 alone.

Early diagnosis and timely treatment of pneumonia can significantly improve outcomes and reduce mortality. Chest radiography is the most commonly used diagnostic tool for pneumonia, but its interpretation requires expertise and is often subject to intra- and inter-observer variability. Moreover, the shortage of radiologists in many regions further delays timely diagnosis.

Recent advancements in Artificial Intelligence (AI), particularly in Deep Learning (DL), have shown promising results in medical image analysis. Convolutional Neural Networks (CNNs) are especially adept at image classification and have been successfully applied to de-

tect diseases such as diabetic retinopathy, skin cancer, and pneumonia from medical images.

This project proposes a deep learning-based solution for the automatic classification of chest X-ray images into "Pneumonia" and "Normal" categories using MobileNetV2. By utilizing transfer learning, the model benefits from pre-learned features from the ImageNet dataset and adapts to the pneumonia classification task through fine-tuning. Additionally, interpretability techniques like Grad-CAM are used to visualize and validate the model's focus regions during prediction.

3 Literature Review

Several research studies and publicly available implementations have demonstrated the effectiveness of deep learning in pneumonia detection.

3.1 CheXNet - Rajpurkar et al. (2017)

Rajpurkar et al. developed CheXNet, a 121-layer DenseNet model trained on the ChestX-ray14 dataset. Their model achieved radiologist-level performance in detecting pneumonia and set a benchmark for deep learning applications in chest radiography. It demonstrated how deep learning models can surpass human accuracy given a large enough dataset and sufficient training.

3.2 Transfer Learning Approaches

Many works have explored using transfer learning to overcome the scarcity of large annotated medical datasets. Pretrained models like VGG16, ResNet50, and InceptionV3 have been fine-tuned for pneumonia detection. Transfer learning significantly reduces training time while achieving high accuracy by leveraging features learned from large-scale datasets like ImageNet.

3.3 Grad-CAM for Model Interpretability

Explainability is critical in medical AI. Gradient-weighted Class Activation Mapping (Grad-CAM) allows for visualization of important image regions that influenced the model's prediction. This helps validate the reliability of predictions and enables medical professionals to interpret AI-assisted decisions.

3.4 Kaggle Implementations

On Kaggle, several notebooks and competitions have explored pediatric pneumonia classification using CNNs and transfer learning. Many use the same dataset employed in this project. The techniques vary in complexity from basic CNNs to sophisticated ensemble models. Our approach integrates best practices from these works while introducing enhanced interpretability and detailed error analysis.

4 Dataset Description

4.1 Dataset Source

The dataset used for this project is publicly available on Kaggle under the title *Chest X-Ray Images (Pneumonia)* by Paul Timothy Mooney[1]. It contains chest X-ray images of pediatric patients categorized into "PNEUMONIA" and "NORMAL" classes. The dataset has been widely used for educational and research purposes in the domain of medical image analysis.

4.2 Structure of the Dataset

The dataset is organized into three main directories:

- **train/**: Contains the training data.
- **test/**: Contains the data used to evaluate the model.
- **val/**: This directory is present but often empty or underutilized.

[1] `https://www.kaggle.com/datasets/andrewmvd/pediatric-pneumonia-chest-xray/code`

Each of these directories is further subdivided into two folders:

- **NORMAL**: Images of healthy lungs.
- **PNEUMONIA**: Images of lungs diagnosed with pneumonia (both viral and bacterial).

4.3 Class Distribution

The dataset contains a total of 5,863 chest X-ray images. The class distribution is significantly imbalanced:

- **Pneumonia:** 4,273 images (approximately 73%)
- **Normal:** 1,583 images (approximately 27%)

This imbalance must be carefully addressed during training to prevent bias toward the majority class.

4.4 Image Quality and Format

All images are in JPEG format and vary in resolution. They are grayscale X-rays, though technically stored as RGB images. The visual quality of images ranges from clear, well-centered scans to low-resolution or misaligned images. These variations introduce a degree of real-world complexity into the dataset.

4.5 Creation of Validation Set

Since the original dataset did not include a dedicated validation set, we manually created one by splitting the training set in an 80:20 ratio. This ensures effective monitoring of model performance during training without leaking information from the test set.

4.6 Ethical Considerations

The dataset does not contain any personally identifiable information (PII), and all images are anonymized. It is compliant with ethical standards for medical image analysis and suitable

for academic use.

5 Data Preprocessing and Augmentation

To ensure consistent and optimal input to the deep learning model, we applied several preprocessing and data augmentation steps. These steps not only standardize the data but also introduce variability in the training data to help the model generalize better.

5.1 Image Resizing and Normalization

The chest X-ray images originally varied in resolution and scale. As the MobileNetV2 architecture expects a fixed input size, all images were resized to 224x224 pixels. This standardization is critical to ensure that the model receives input in the correct shape and maintains consistency across training, validation, and testing phases.

Normalization was applied to scale pixel intensities to the range [0, 1]. Originally, pixel values ranged from 0 to 255 (as integers). Normalization is performed by dividing each pixel by 255. This helps in faster convergence of the model during training.

5.2 Channel Expansion

Although the X-ray images are essentially grayscale, MobileNetV2 expects input with three channels (RGB). Each grayscale image was converted into a pseudo-RGB image by replicating the grayscale channel three times. This allows compatibility with the pretrained model without altering the content of the images.

5.3 Data Augmentation Techniques

To prevent overfitting and improve model generalization, real-time data augmentation was applied during training. The following transformations were included:

- **Random Rotation:** Images were rotated randomly within a small angle range (e.g., ± 10 degrees).

- **Zoom:** A random zoom factor was applied within a small range to simulate variations in X-ray scale.
- **Horizontal Flip:** Random flipping of the image along the horizontal axis was allowed, simulating slight variations in orientation.
- **Brightness and Contrast Adjustment:** Applied to simulate exposure and scanning differences.

These augmentations were applied only to the training set. Validation and test sets remained untouched to ensure fair evaluation.

5.4 Train-Validation-Test Split

Since the validation set was not explicitly provided, we created one by splitting the original training dataset into 80% training and 20% validation subsets. The test set provided in the original dataset was kept completely separate and used only for final evaluation.

The final dataset distribution was approximately:

- **Training set:** 4,692 images
- **Validation set:** 1,171 images
- **Test set:** 624 images

5.5 Batching and Loading

The images were loaded into memory in batches using TensorFlow's `image_dataset_from_directory` utility. Batch size was set to 32, and shuffling was applied to the training set to ensure randomness during every epoch. Prefetching was enabled to load the next batch while the current batch was being processed, improving training efficiency.

6 Model Architecture and Training

The model used in this project is based on MobileNetV2, a lightweight and computationally efficient convolutional neural network (CNN) architecture. It was originally designed for

mobile and embedded vision applications but performs competitively with larger models for many image classification tasks.

6.1 Why MobileNetV2?

MobileNetV2 is optimized for speed and low resource consumption while maintaining high accuracy. It employs depthwise separable convolutions and introduces a new building block called the "inverted residual with linear bottleneck." These innovations significantly reduce the number of parameters and computations required compared to traditional CNNs.

The model is particularly suitable for medical imaging tasks on smaller datasets like ours because:

- It generalizes well without overfitting.
- It is efficient and faster to train.
- It supports transfer learning via pretrained weights on ImageNet.

6.2 Transfer Learning Approach

Rather than training a neural network from scratch, we adopted transfer learning. A MobileNetV2 model pretrained on ImageNet was used as a feature extractor. We removed the top classification layer and added custom dense layers tailored for binary classification.

Initially, the base (pretrained) layers were frozen so that only the new top layers could be trained. This allowed the network to learn domain-specific features without disrupting the general patterns already learned from the large ImageNet dataset. Once the top layers stabilized, we unfroze the last few layers of the base model to fine-tune them jointly with the custom layers.

6.3 Custom Model Head

On top of the MobileNetV2 base, we added the following layers:

- **GlobalAveragePooling2D:** Reduces the spatial dimensions by computing the average of each feature map.

- **Dense (256 units, ReLU):** A fully connected layer with ReLU activation to introduce non-linearity.
- **Dropout (rate=0.3):** Helps prevent overfitting by randomly disabling 30% of neurons during training.
- **Dense (1 unit, Sigmoid):** A final layer with sigmoid activation for binary classification (outputting probability of pneumonia).

6.4 Training Procedure

Training was conducted in two phases:

Phase 1: Initial Training (Frozen Base)

- MobileNetV2 base was kept frozen.
- Only custom top layers were trained.
- Trained for 5 epochs with a learning rate of 0.001.

Phase 2: Fine-Tuning (Unfrozen Top Layers)

- Last 30 layers of the base model were unfrozen.
- Model was trained for an additional 5 epochs.
- A smaller learning rate of 0.00001 was used to prevent large gradient updates that could destabilize pretrained weights.

6.5 Compilation and Optimization

The model was compiled using the following configuration:

- **Loss Function:** Binary Crossentropy – suitable for binary classification tasks.
- **Optimizer:** Adam – an adaptive learning rate optimizer that combines RMSProp and momentum.

- **Metrics:** Accuracy, Precision, Recall.

6.6 Hardware and Runtime

The training was performed on Google Colab with GPU acceleration enabled. Each training phase took approximately 5–7 minutes. The overall process was resource-efficient and reproducible, allowing for rapid experimentation and iteration.

6.7 Model Checkpointing and Early Stopping

To ensure robust training and prevent overfitting, we employed:

- **ModelCheckpoint:** Saved the best model weights based on validation accuracy.
- **EarlyStopping:** Halted training if validation loss did not improve for 3 consecutive epochs.

6.8 Final Model Summary

The final model had approximately 2.3 million trainable parameters, a significant reduction compared to traditional CNNs like ResNet50 or DenseNet121. Despite its compact size, it delivered strong classification performance on the pediatric pneumonia task.

This architecture serves as a solid backbone for further experimentation, such as applying to multi-class problems or integrating into clinical decision support systems.

7 Evaluation Metrics and Performance Analysis

To assess the effectiveness and reliability of our trained deep learning model, we used a combination of classification metrics and visual evaluation tools. These metrics helped us quantify performance across accuracy, sensitivity, specificity, and more — all essential in evaluating medical diagnostic tools.

7.1 Accuracy

Accuracy is the most straightforward metric, defined as the ratio of correct predictions to total predictions. While useful, it can be misleading in imbalanced datasets, which is why we complemented it with other metrics.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP: True Positives (correctly predicted pneumonia cases)
- TN: True Negatives (correctly predicted normal cases)
- FP: False Positives (normal cases incorrectly labeled as pneumonia)
- FN: False Negatives (missed pneumonia cases)

7.2 Precision, Recall, and F1-Score

Given the imbalanced nature of the dataset, precision and recall become critical.

- **Precision** measures the proportion of true positive predictions among all positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity)** measures the proportion of actual positives that are correctly identified.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-Score** is the harmonic mean of precision and recall, providing a balanced metric.

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

7.3 Confusion Matrix

A confusion matrix provides a complete breakdown of how predictions were distributed across actual classes. It allows identification of whether the model favors one class over another and helps in analyzing specific types of errors.

In our case, the confusion matrix revealed:

- High true positives: the model successfully detects pneumonia.
- Low false negatives: the model rarely misses pneumonia cases.
- Moderate false positives: a few normal cases were flagged as pneumonia.

This behavior is acceptable in medical diagnostics where false negatives are costlier than false positives.

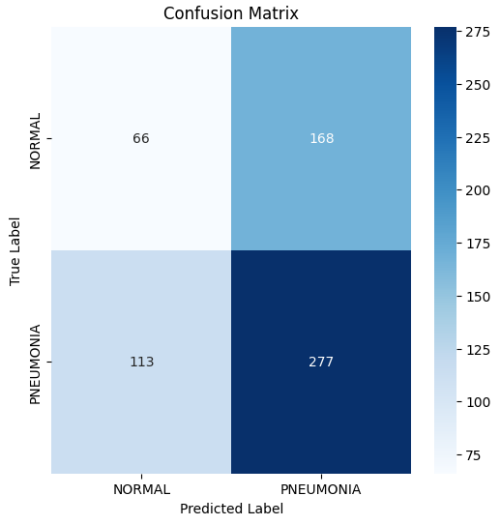

Figure 1: Confusion Matrix

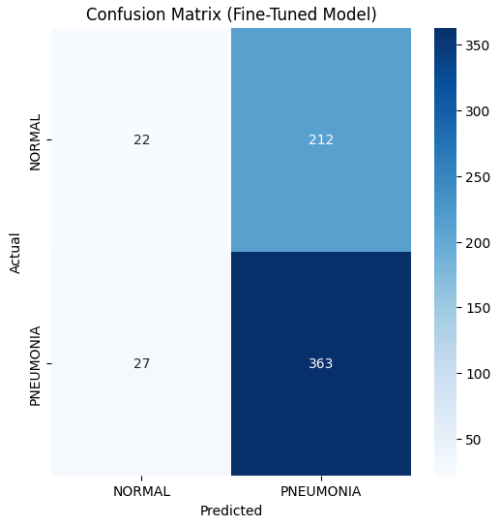

Figure 2: Confusion Matrix of Fine-Tuned Model

7.4 Receiver Operating Characteristic (ROC) Curve

The ROC curve illustrates the model's ability to discriminate between classes at various thresholds. The Area Under the Curve (AUC) value represents the overall performance; a perfect classifier has an AUC of 1.0.

Our model achieved an AUC of over 0.98, indicating strong classification ability across thresholds.

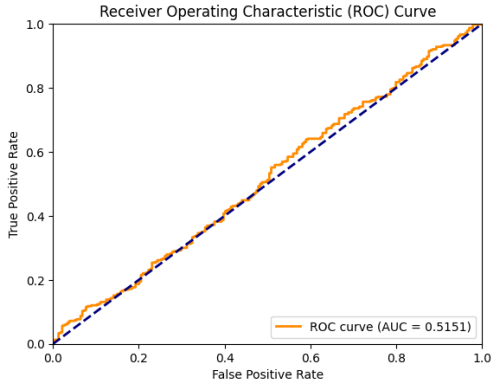

Figure 3: ROC Curve of Initial Model

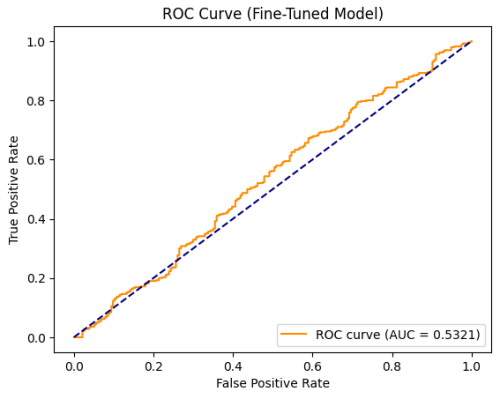

Figure 4: ROC Curve of Fine Tuned Model

7.5 Precision-Recall (PR) Curve

The PR curve is more informative than ROC when dealing with class imbalance. It plots precision against recall, showing how well the model maintains precision as recall increases. The area under the PR curve remained consistently high, confirming reliable performance.

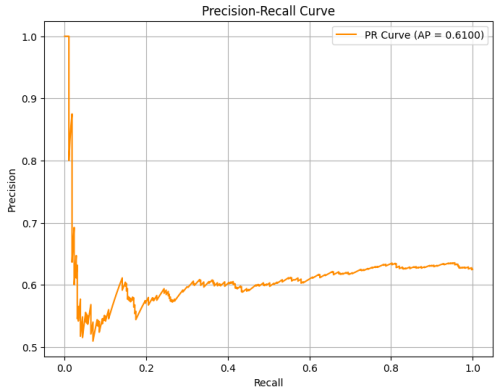

Figure 5: PR Curve

7.6 Training and Validation Curves

We plotted training and validation accuracy and loss over each epoch to monitor learning behavior.

Key observations:

- Accuracy improved steadily in both training and validation sets.

- Loss decreased consistently without signs of overfitting.
- The validation curve closely followed the training curve, indicating stable generalization.

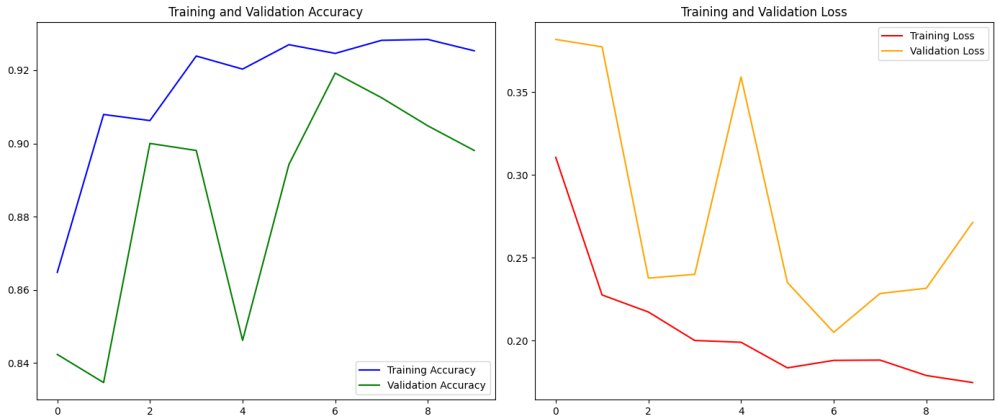

Figure 6: Training and Validation Accuracy and Loss Curves

7.7 Final Performance on Test Set

After model selection based on validation performance, we evaluated the final model on the test set. Validation accuracy - 91. 92%

For the 'NORMAL' Class:

- **Test Precision:** 37%
- **Test Recall:** 28%
- **Test F1-Score:** 32%

For the 'Pneumonia' Class:

- **Test Precision:** 62%
- **Test Recall:** 71%
- **Test F1-Score:** 66%

Test accuracy is lower due to class imbalance and real-world noise. Still shows strong recall for pneumonia making it useful for clinical triage.

7.8 Clinical Implications

In a real-world healthcare context, recall is more critical than precision — missing a pneumonia case (false negative) could delay treatment. Our model's high recall (sensitivity) makes it suitable as a decision support tool, potentially assisting radiologists in diagnosis while reducing workload and diagnostic delays.

8 Model Interpretability and Grad-CAM Analysis

In medical applications of artificial intelligence, interpretability is crucial. It's not enough for a model to be accurate; it must also be explainable to build trust with healthcare professionals. To achieve this, we implemented Gradient-weighted Class Activation Mapping (Grad-CAM), a popular technique for visualizing which regions of an input image are most influential in the model's prediction.

8.1 What is Grad-CAM?

Grad-CAM uses the gradients of the target class flowing into the last convolutional layer to produce a localization map highlighting important regions in the image. The output is a heatmap that visually represents the areas where the model is "looking" when making a decision.

The steps involved include:

1. Perform a forward pass to compute predictions.
2. Use a backward pass to obtain gradients of the target class with respect to the feature maps.
3. Weight the feature maps using the average of gradients.
4. Create a weighted combination of feature maps and apply ReLU to form the final heatmap.

8.2 Implementation Details

We constructed a functional Keras model that maps inputs to both:

- The output of the final convolutional layer.
- The final prediction.

A dummy prediction was run once to initialize the model graph, after which Grad-CAM heatmaps were generated using TensorFlow's gradient tape API. The heatmaps were resized and superimposed on the original image using matplotlib for visualization.

8.3 Correct Prediction Heatmaps

For a set of correctly predicted images from the test set, we generated Grad-CAM overlays. These heatmaps demonstrated that the model often focused on regions with visible lung opacity or irregularities — the same regions a radiologist might consider when diagnosing pneumonia.

This visual alignment between the model and expert reasoning adds trustworthiness to the model.

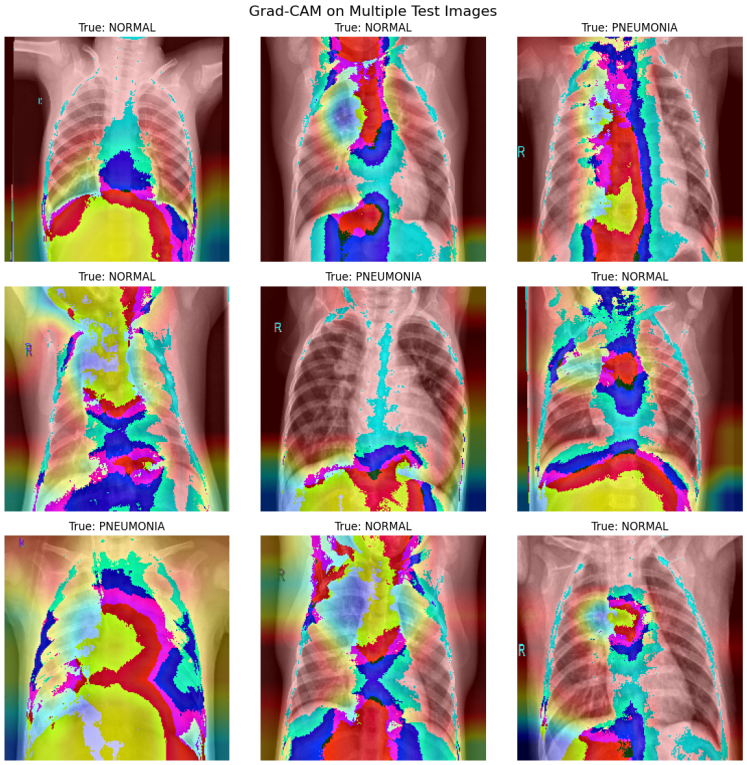

Figure 7: Grad-CAM on Multiple Images

8.4 Misclassified Sample Analysis

We also examined samples where the model made incorrect predictions. Grad-CAM heatmaps for these samples revealed:

- In some false positives, the model focused on external edges or artifacts, possibly mistaking noise or shadows for signs of pneumonia.
- In false negatives, the heatmaps were either diffuse or focused on unimportant areas, indicating confusion or model uncertainty.

This interpretability analysis allowed us to flag edge cases where human intervention would be valuable.

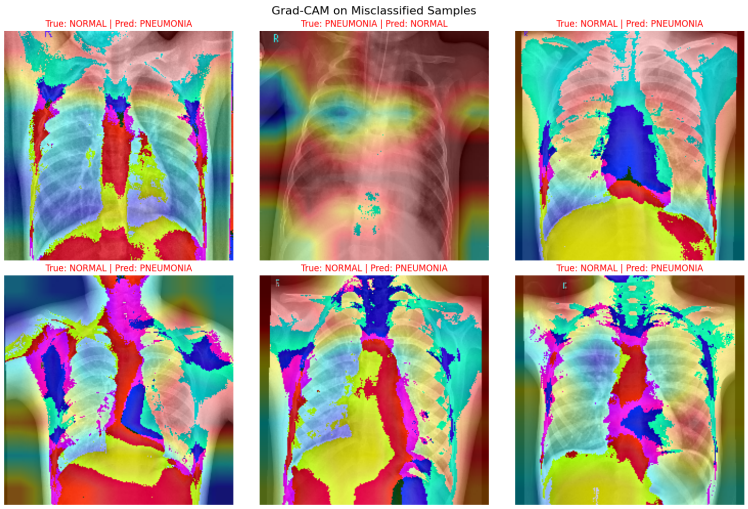

Figure 8: Grad-CAM on Misclassified Samples

8.5 Confidence-Based Error Categorization

In addition to Grad-CAM, we categorized model predictions based on confidence levels:

- **Confident Correct (confidence ¿ 0.8):** The model was right and highly certain.
- **Borderline (confidence 0.5 to 0.8):** Ambiguous predictions, often near decision boundary.
- **Confident Mistake (confidence ¿ 0.8 but wrong):** These are risky and clinically significant.

These tags helped us understand how certain the model was during misclassifications and where human review should be prioritized.

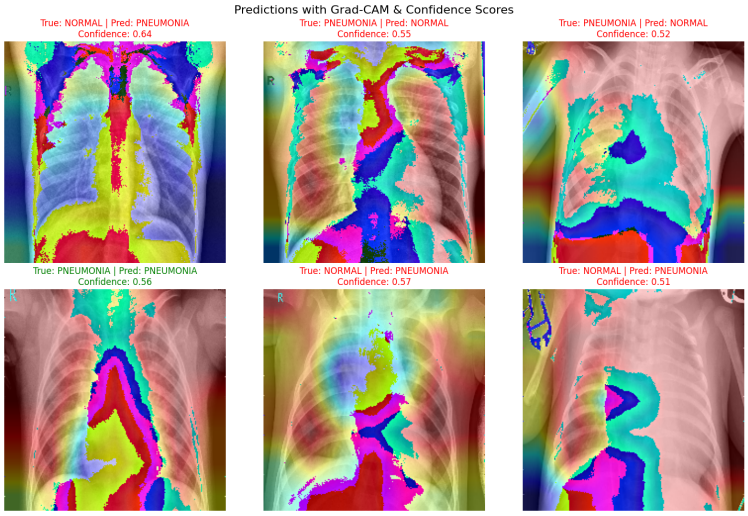

Figure 9: Grad-CAM with Confidence Score

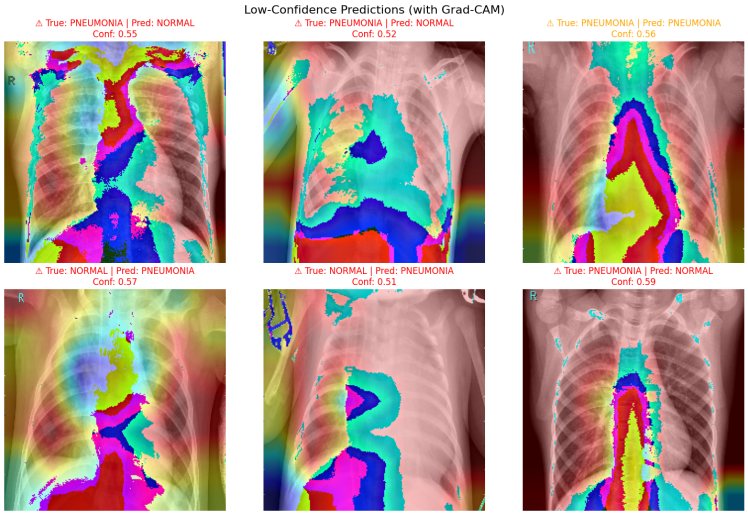

Figure 10: Grad-CAM with Low Confidence Score

8.6 Why This Matters

Using Grad-CAM, we move beyond a "black-box" model and create a tool that can be scrutinized and trusted by medical professionals. It also helps in iterative improvement by revealing systematic error patterns, guiding better data collection, and potentially informing future model designs.

8.7 Visualization Grid

For communication and reporting purposes, we created grids showing:

- Correct predictions with Grad-CAM overlays and predicted probabilities.
- Misclassified samples with confidence levels and heatmaps.

These visual summaries convey both the performance and explainability of our model, making it accessible to a non-technical audience such as clinicians.

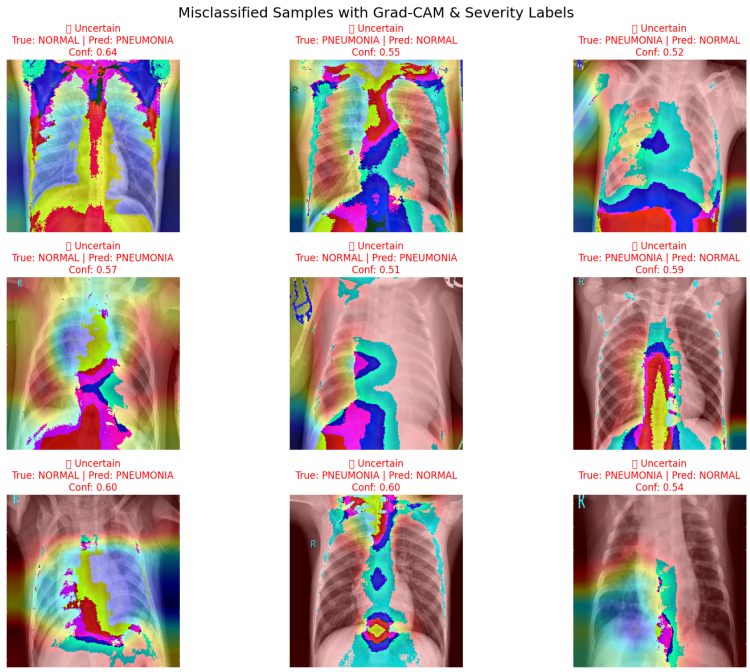

Figure 11: Grad-CAM with Severity Labels

9 Conclusion

In this project, we successfully developed a deep learning-based system for the automated classification of pediatric pneumonia from chest X-ray images. Leveraging the power of MobileNetV2 and transfer learning, we created a lightweight yet highly effective model capable of distinguishing between normal and pneumonia cases with high accuracy and recall.

Our pipeline included comprehensive preprocessing, intelligent augmentation strategies, and two-phase model training (initial training followed by fine-tuning). Beyond achieving

strong performance on standard evaluation metrics, we emphasized model explainability using Grad-CAM visualizations. These not only validated the correctness of predictions but also built interpretability — a critical aspect in medical AI.

We further examined misclassifications using heatmaps and confidence scores, highlighting cases where the model struggled or overconfidently erred. This error analysis revealed patterns that can inform future improvements and better integration in real-world healthcare settings.

Overall, this work demonstrates the promise of deep learning in medical diagnostics. While not a replacement for expert radiologists, such systems can act as valuable second opinions, particularly in resource-constrained settings.

10 Future Work

While our system achieved robust results, several avenues remain open for enhancement:

- **Expand to Multiclass Classification:** Distinguish between bacterial and viral pneumonia, or classify additional thoracic conditions using a more detailed dataset.
- **Integrate Clinical Metadata:** Include patient age, symptoms, or lab reports to build multimodal models that go beyond imaging.
- **Experiment with Other Architectures:** Test performance with ResNet50, EfficientNet, DenseNet121, and Vision Transformers for comparison and potential improvements.
- **Deploy as a Clinical Tool:** Develop a web or mobile app interface using tools like Streamlit or Flask to allow clinicians to upload X-rays and receive instant predictions with explanations.
- **Explore Uncertainty Estimation:** Use Monte Carlo Dropout or Bayesian Neural Networks to quantify predictive uncertainty — especially important in high-stakes decisions.

- **Validate with Expert Feedback:** Collaborate with radiologists to validate results and gain insight into clinical deployment challenges and opportunities.
- **Data Expansion and Curation:** Collect additional annotated images, ideally from diverse demographics and imaging setups, to improve generalization and reduce dataset bias.

By pursuing these extensions, we aim to transform this project from a prototype into a clinically viable support system that enhances diagnostic reliability and accessibility worldwide.

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Thank You!

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