

# **Interpretable Deep Learning for Automated Lung Disease Detection**

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**Project for Boston University**

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## 1. Abstract

Chest X-rays are essential diagnostic tools for lung illnesses, which represent a substantial worldwide health burden (World Health Organization, 2023). However, because of physician weariness and varying levels of experience, human interpretation of these pictures is difficult and prone to errors (Berlin, 2020). In order to overcome these obstacles, the Interpretable Deep Learning for Automated Lung Disease Detection project will create an AI system that improves diagnostic precision while maintaining interpretability (Selvaraju et al., 2017). The program recognizes anomalies in chest X-rays using convolutional neural networks (CNNs) and uses method such as Grad-CAM for visual explanations, promoting clinicians' trust and usability.

The NIH Chest X-ray dataset, a large collection of unsegmented chest X-rays, is used in this study to allow for a comprehensive analysis of thoracic images. Large-scale medical imaging data was handled well by leveraging cloud-based processing and sophisticated deep learning frameworks. The scope of the information made it possible to identify and categorize a variety of lung conditions, which aided in the creation of a reliable diagnostic tool (Irvin et al., 2019).

The ultimate goal is to develop a system that solves the "black box problem," a major obstacle to the use of AI in healthcare, in addition to achieving high diagnostic accuracy. This research helps to create trustworthy AI systems by putting an emphasis on ethics and openness, which helps to close the gap between clinical practice and artificial intelligence (Shortliffe & Sepúlveda, 2018). This work offers a pathway to safer, more interpretable, and effective diagnostic tools, ultimately supporting better healthcare outcomes.

## 2. Introduction

### 2.1. Background and Significance

Globally, lung conditions such interstitial lung disease (ILD), pneumonia, and tuberculosis continue to pose a serious threat to public health. The World Health Organization (WHO) reports that lung illnesses are a major source of morbidity and mortality worldwide, accounting for more than 3 million deaths per year (WHO, 2023). Improving patient outcomes and lessening the strain

on healthcare systems depend on prompt and precise diagnosis of these disorders. Because of its affordability and ease of use, chest X-rays are a common diagnostic technique.

However, effectively interpreting chest X-rays is a difficult task that greatly depends on radiologists' skill. Diagnostic errors are influenced by human variables, including training unpredictability, excessive workloads, and weariness. According to studies, these difficulties account for as much as 10–15% of radiology diagnosis mistakes. For example, anomalies like lung nodules may be misconstrued, or mild symptoms of pneumonia may be missed. These drawbacks emphasize how urgently technology solutions that help doctors identify patients more quickly and accurately are needed.

Artificial Intelligence (AI) has been a promising technique in medical imaging in recent years. Automating image processing has shown enormous potential due to deep learning, a branch of artificial intelligence. Convolutional Neural Networks (CNNs), out of all the models, are very good at identifying patterns in visual data, which makes them ideal for applications like the diagnosis of lung diseases. Large volumes of data can be swiftly and effectively analyzed by these models, which can spot anomalies that might not be immediately noticeable to the naked eye. Despite these developments, a number of obstacles have prevented AI from being widely used in healthcare.

## **2.2. Challenges in AI for Radiology**

The biggest obstacle to deep learning models' widespread adoption in radiography is still their "black box" character. Because CNNs are so complicated, it can be challenging for clinicians to comprehend how predictions are made. Especially in high-stakes settings like healthcare, this lack of interpretability erodes confidence and raises ethical questions. Clinicians can be reluctant to rely on AI systems for important diagnoses if they don't have insight into the decision-making process.

The structure and quality of datasets present another difficulty. The model's capacity to examine the entire thoracic context is limited because many datasets used for lung disease identification concentrate on segmented lung areas rather than full chest X-rays. Predictions may also be skewed by class imbalance, when common ailments are overrepresented and rarer conditions are

underrepresented. These restrictions highlight the necessity of thorough datasets and strong preprocessing methods to guarantee accurate and equitable model performance.

Subsequently, there are additional barriers due to ethical and legal issues. There are still unanswered questions about data privacy, algorithmic bias, and responsibility in misdiagnosed situations. These elements emphasize how crucial it is to build AI systems with accessibility, justice, and openness as top priorities. The necessity for models that can endure scrutiny in practical healthcare applications is highlighted by regulatory frameworks, such as those enforced by the FDA.

### **2.3. About the Project**

The goal of this project, Interpretable Deep Learning for Automated Lung Disease Detection, is to create an AI system that combines interpretability and high diagnostic accuracy in order to overcome these difficulties. The main inquiry driving this project is: How might interpretable deep learning models improve the precision and openness of X-ray analysis of the chest for the identification of lung diseases?

The project is carried out in two stages:

***Phase 1:*** A comprehensive literature review and exploratory data analysis (EDA) were conducted to understand the current landscape of AI-based lung disease detection. Baseline CNN models were implemented using existing insights from the NIH Chest X-ray dataset to evaluate performance.

***Phase 2:*** This phase focuses on addressing class imbalance using weighted class techniques, as SMOTE was considered but not implemented due to computational constraints. Additionally, interpretability tools such as Grad-CAM are being implemented to ensure clinicians can trust and understand the AI's predictions.

### **2.4. Project Goals**

The primary objectives of this project are:

- ***Establish an Accurate CNN-Based Model:*** Build a system that can identify common lung conditions like pneumonia, pleural effusion, and cardiomegaly based on chest X-rays.
- ***Improve Interpretability:*** In order to bridge the gap between AI and clinical trust, use techniques like Grad-CAM to highlight important characteristics affecting model predictions.
- ***Address Dataset Challenges:*** Tackle issues related to data quality, class imbalance, and variability to improve model robustness and fairness.
- ***Contribute to Ethical AI Design:*** Ensure transparency, fairness, and accountability in model development to foster clinician trust and usability.
- ***Adapt to Practical Constraints:*** Account for computational and data limitations, ensuring feasibility for real-world deployment.

This research aims to develop a transparent and clinically useable AI system by emphasizing interpretability, which will encourage wider usage in the medical field. Furthermore, by highlighting justice and responsibility in medical applications, the work adds to the expanding conversation on ethical AI design.

## 3. Literature Review

### 3.1 Introduction

The most common causes of morbidity and death globally are lung conditions such as pneumonia, cardiomegaly, and pleural effusion. Convolutional neural networks (CNNs), a type of deep learning, have transformed medical imaging by making it possible to automatically detect certain diseases with high accuracy. The "black box" nature of many models, the need for high-quality datasets, and ethical issues about bias and transparency make it difficult to integrate artificial intelligence (AI) into clinical procedures, even with recent breakthroughs. This review of the literature looks at the main developments, difficulties, and gaps in the field of AI-based lung disease diagnosis.

### 3.2 Deep Learning in Lung Disease Detection

Deep learning has emerged as a transformative approach in medical imaging, particularly for lung disease detection. Convolutional neural networks (CNNs) have shown exceptional ability in analyzing chest X-rays, achieving diagnostic accuracy comparable to that of expert radiologists. Studies such as those utilizing the **CheXpert dataset** demonstrated the efficacy of CNNs in diagnosing conditions like atelectasis and consolidation, with an AUC exceeding 0.91 for certain pathologies (Irvin et al., 2019). Similarly, the **NIH Chest X-ray dataset**, one of the largest publicly available datasets, introduced multi-label annotations for over 100,000 images, allowing models to classify a range of thoracic conditions with high precision (Wang et al., 2017).

Despite these successes, the "black box" nature of CNNs remains a significant limitation. Clinicians often hesitate to adopt AI systems without understanding their decision-making processes, especially in high-stakes environments such as healthcare (Selvaraju et al., 2017). This challenge necessitates the development of interpretable AI models to bridge the trust gap between clinicians and technology.

### 3.3. Challenges in Dataset Quality and Class Imbalance

Quality and variety of training data are intrinsically linked to the effectiveness of deep learning models. The segmented lung areas that are the focus of many popular datasets, including MIMIC-CXR, restrict a model's capacity to capture the larger thoracic context required for a thorough diagnosis (Johnson et al., 2019). Unsegmented datasets, such as the NIH Chest X-ray dataset, on the other hand, provide a more comprehensive perspective and allow models to examine entire chest radiographs. To overcome these constraints, this study notably makes use of the NIH dataset. The disparity in class is another significant issue. Rarer illnesses like fibrosis or hernia are much underrepresented, despite other afflictions, like "No Finding," are overrepresented. Predictions may become skewed as a result of this imbalance, with models favoring dominant classes over uncommon but clinically important illnesses. By creating synthetic samples for minority classes, methods like ADASYN and the Synthetic Minority Oversampling Technique (SMOTE) are frequently used to address this problem (Chawla et al., 2002). To prevent overfitting and guarantee



that artificial samples match distributions in the actual world, these techniques must be used with caution.

### 3.4. Interpretability in AI

For AI models to be used in therapeutic settings, interpretable models are essential. To tackle this issue, tools such as LIME (Local Interpretable Model-Agnostic Explanations) and Grad-CAM (Gradient-weighted Class Activation Mapping) have been created. While LIME offers local approximations to explain specific predictions, Grad-CAM creates heatmaps that show the areas of an image that have the most influence on a model's prediction (Selvaraju et al., 2017). By increasing the transparency of model judgments, these strategies hope to increase clinician trust.

These approaches do have certain drawbacks, though. Grad-CAM heatmaps are helpful, but they frequently lack the level of detail required for complex clinical interpretation. Radiologists, for instance, might need thorough justifications that are more in line with pathological findings. Similarly, LIME's applicability in healthcare may be limited due to its dependence on perturbation techniques, which may result in inconsistent interpretations. This research bridges the gap between technical performance and usability by integrating Grad-CAM to guarantee that the produced model is in line with clinical reasoning.

### 3.5. Comparative Analysis of Deep Learning Models

Lung disease detection has made substantial use of deep learning architectures including **DenseNet**, **ResNet**, and **Inception V3**. Studies show that DenseNet can capture fine-grained information in chest X-rays, demonstrating its improved performance in detecting small abnormalities (Rajpurkar et al., 2017). Similar to this, ResNet—which is well-known for its residual connections—has been applied extensively to multi-label classification tasks because it strikes a balance between efficiency and depth.

These architectures frequently put performance ahead of interpretability despite their great accuracy. In order to examine trade-offs between simplicity and performance, this research

combines a pretrained ResNet50 with a baseline CNN. Grad-CAM is incorporated into both models to improve interpretability.

### **3.6. Ethical and Regulatory Considerations**

There are many ethical and legal issues with the use of AI in healthcare. Unresolved issues include algorithmic bias, data privacy, and accountability for mistakes. For example, biased predictions could lead to unequal healthcare outcomes if training datasets mostly represent particular demographics (Johns Hopkins Bloomberg School of Public Health, 2021). For AI systems to be safe and dependable in clinical settings, regulatory frameworks—like those upheld by the FDA are crucial. By using explainability tools and resolving class imbalance, this research stresses openness and fairness, which is consistent with ethical AI concepts. This work adds to the larger conversation on responsible AI in healthcare by incorporating interpretability into the model architecture.

### **3.7. Summary of Literature Review**

The literature highlights significant advancements in lung disease detection using deep learning while underscoring persistent challenges in interpretability, dataset quality, and ethical considerations. By addressing these gaps, this project aims to develop a robust and interpretable AI system that aligns with clinical and ethical standards, setting the stage for broader adoption of AI in radiology.

## **4. Scope and Objectives**

### **4.1. Scope**

The objective of this study is to use chest X-rays to automatically detect lung diseases by creating an interpretable deep learning model. Improving interpretability and increasing diagnostic accuracy are two important issues in healthcare AI that it seeks to address. By leveraging convolutional neural networks (CNNs) and interpretability methods like Grad-CAM, the project prioritizes fostering trust and usability among clinicians.

The main focus is on identifying common lung anomalies such as cardiomegaly, pleural effusion, and pneumonia while offering visual explanations to make the AI's decision-making process clear and understandable. To address the challenge of class imbalance, the project employs a weighted class approach instead of techniques like SMOTE, which were explored but not implemented due to computational limitations.

This phase of the project utilizes the NIH Chest X-ray dataset, which comprises unsegmented chest X-rays. These images allow for a holistic analysis of the thoracic region, unlike segmented datasets that focus only on specific areas. However, current limitations in computational resources influence the model complexity and training time. Despite these constraints, the project lays a robust foundation for future research, including integrating more comprehensive datasets and refining interpretability tools to bridge the gap between AI systems and clinical workflows.

## **4.2. Objectives**

The project has the following key objectives:

### ***4.2.1. Develop a Deep Learning Model:***

- Build a CNN-based system capable of accurately classifying chest X-ray abnormalities, including pneumonia, pleural effusion, and cardiomegaly.
- Evaluate model architecture trade-offs, balancing performance and resource constraints.

### ***4.2.2. Enhance Interpretability:***

- Implement explainability techniques such as Grad-CAM to provide clinicians with visual explanations of model decisions.
- Evaluate the alignment of these visualizations with radiologists' interpretations to ensure clinical relevance.

### ***4.2.3. Address Data Challenges:***

- Employ a weighted class approach to mitigate class imbalances in the dataset, ensuring the model performs reliably for rare conditions.
- Optimize preprocessing steps, such as normalization and augmentation, to enhance data suitability and diversity.

#### ***4.2.4. Improve Diagnostic Accuracy:***

- Utilize robust performance metrics, including F1-score, precision, recall, and ROC-AUC, to validate the model's effectiveness in detecting lung diseases.
- Regularly fine-tune hyperparameters and evaluate results to ensure consistent improvements.

#### ***4.2.5. Investigate Ethical Implications:***

- Explore ethical challenges, including potential biases in the training data, algorithmic transparency, and compliance with data privacy regulations like HIPAA.
- Develop strategies to ensure fairness and accountability in model deployment.

#### ***4.2.6. Lay the Groundwork for Clinical Application:***

- Align the model with real-world clinical workflows to ensure scalability and usability in healthcare environments.
- Consider user feedback from clinicians to enhance model deployment strategies.

## **5. Methodology**

This study developed and assessed two convolutional neural network (CNN) architectures for classifying chest X-ray pictures into several disease categories: a ResNet-based CNN model and a custom CNN model. The methodology builds a strong and clinically applicable AI system by combining interpretability techniques, transfer learning, class imbalance handling, and data preprocessing.

### **5.1. Data Overview and Preparation**

The dataset used in this project comprises chest X-ray images annotated with 14 disease categories, ranging from common conditions like Effusion and Atelectasis to rare abnormalities such as Hernia and Fibrosis. The data was split into training and testing sets, with an 80-20 split, ensuring the testing set remained unseen during training.

## Preprocessing Steps


Data preprocessing was conducted using TensorFlow's Keras API, with the following transformations:





- **Normalization:** All pixel values were rescaled to the range [0, 1] to standardize input data (Goodfellow, Bengio, & Courville, 2016).
- **Image Resizing:** Images were resized to 224×224 pixels to meet the input requirements of the models.
- **Data Augmentation:** Random transformations, such as rotations, shifts, zooming, and horizontal flips, were applied to artificially increase the diversity of the training data, thereby reducing overfitting (Krizhevsky, Sutskever, & Hinton, 2012).





## 5.2. Disease Classes




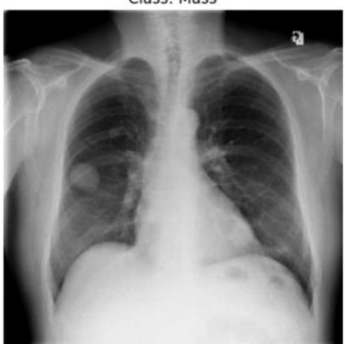
The dataset includes 14 disease classes, along with a "No Finding" label for normal cases. Each class was analyzed for prevalence and represented using example images. Table 1 provides an overview of the disease classes, their prevalence, and representative images.

**Table 1: Disease Class Overview**


| Disease Class      | Definition                                | Count | Example Image   |
|--------------------|---|-------|---|
| <b>Atelectasis</b> | Partial or complete collapse of the lung. | 508   |  |

|                     |   |     |  |
|---------------------|---|-----|--|
| <b>Cardiomegaly</b> | Enlargement of the heart.                                     | 141 | <p>Class: Cardiomegaly</p>    |
| <b>Effusion</b>     | Accumulation of fluid in the pleural cavity.                  | 644 | <p>Class: Effusion</p>        |
| <b>Infiltration</b> | Diffuse lung abnormality caused by infection or inflammation. | 967 | <p>Class: Infiltration</p>  |
| <b>Pneumothorax</b> | Presence of air in the pleural space, causing lung collapse.  | 271 | <p>Class: Pneumothorax</p>  |

|                      |   |     |   |
|----------------------|---|-----|---|
| <b>Pneumonia</b>     | Lung infection causing inflammation and fluid buildup.        | 62  | <p>Class: Pneumonia</p>      |
| <b>Consolidation</b> | Lung tissue filled with liquid instead of air.                | 226 | <p>Class: Consolidation</p>  |
| <b>Edema</b>         | Accumulation of fluid in lung tissues or air sacs.            | 118 | <p>Class: Edema</p>        |
| <b>Emphysema</b>     | Destruction of lung tissue leading to breathing difficulties. | 127 | <p>Class: Emphysema</p>    |

|                           |  |     |  |
|---------------------------|--|-----|--|
| <b>Fibrosis</b>           | Thickening and scarring of lung tissue.        | 84  | <p>Class: Fibrosis</p>            |
| <b>Pleural Thickening</b> | Thickening of the pleural lining of the lungs. | 176 | <p>Class: Pleural_Thickening</p>  |
| <b>Hernia</b>             | Displacement of an organ through an opening.   | 13  | <p>Class: Hernia</p>            |
| <b>Mass</b>               | A localized abnormal growth in the lung.       | 284 | <p>Class: Mass</p>              |



|               |   |     |  |
|---------------|---|-----|--|
| <b>Nodule</b> | A small, rounded abnormal growth in the lung. | 313 | <div>Class: Nodule</div>  |
|---------------|---|-----|--|

This table highlights the significant class imbalance in the dataset, with "No Finding" being the most prevalent label, followed by conditions like Infiltration and Effusion. Rare classes, such as Hernia and Pneumonia, are underrepresented, posing challenges for model training.

### Rationale for Excluding the "No Finding" Label

The 'No Finding' label, while dominant in the dataset, was excluded for several critical reasons:

**Ambiguity:** The label does not guarantee a healthy condition but rather indicates an absence of detectable abnormalities, which can mislead the model (Rajpurkar et al., 2017).

**Class Imbalance:** Its overrepresentation biases the model towards predicting 'No Finding,' reducing attention to minority disease classes (Irvin et al., 2019).

**Focus on Pathologies:** Removing this label encourages the model to learn meaningful disease-specific patterns, enhancing its generalization.

**Label Conflicts:** In multi-label datasets, 'No Finding' can conflict with co-existing disease labels, leading to inconsistencies.

**Improved Interpretability:** Exclusion of 'No Finding' ensures that heatmaps and predictions focus solely on disease abnormalities, making them more clinically relevant (Selvaraju et al., 2017).

### 5.3. Handling Class Imbalance

Class imbalance was a critical challenge in the dataset, with frequent conditions such as "No Finding" overshadowing rare conditions like Hernia. This imbalance often caused the model to focus disproportionately on overrepresented classes. To address this, the following strategies were employed:

- **Class Weighting:** The loss function incorporated weights inversely proportional to the class frequencies, ensuring that rare classes, such as Hernia and Fibrosis, contributed more significantly to the training process (He & Garcia, 2009).
- **Sample Weighting:** For multilabel classification, dynamic sample weights were computed. This allowed the model to emphasize underrepresented conditions effectively without overcompensating for noise in rare labels (Lin et al., 2017).

## 5.4. Model Architectures

Two deep learning architectures were implemented and compared:

### 5.4.1. Custom Convolutional Neural Network (CNN):

ReLU activation and max-pooling layers are used to minimize dimensionality in a baseline model that has five convolutional layers. The fundamental CNN designs for image classification tasks served as the model for this architecture (Krizhevsky et al., 2012). To avoid overfitting, fully connected dense layers were employed, followed by dropout layers (Srivastava et al., 2014).

### 5.4.2. Pretrained ResNet50:

- The ResNet50 model was implemented using **transfer learning**, leveraging pretrained ImageNet weights. This approach has been widely adopted in medical imaging for its ability to generalize across tasks (He et al., 2016).
- The lower layers of the architecture were frozen to retain generalized features, while the upper layers were retrained to specialize in the chest X-ray dataset. This layer-freezing technique is known to improve convergence and computational efficiency during fine-tuning (Yosinski et al., 2014).
- Batch normalization layers and dropout regularization were added to reduce overfitting during retraining.

## 5.5. Training and Optimization

Both models were trained using the following settings:

- **Loss Function:** Binary cross-entropy, suitable for multilabel classification. (Goodfellow et al., 2016).
- **Optimizer:** The Adam optimizer was employed, offering adaptive learning rate adjustments to enhance convergence speed and stability (Kingma & Ba, 2014).
- **Early Stopping:** Training was terminated when validation loss did not improve for three consecutive epochs, reducing the risk of overfitting.
- **Weighted Training:** A custom TensorFlow dataset was constructed to incorporate computed sample weights dynamically.

Training performance was monitored using a validation set, ensuring the model generalized well to unseen data.

## 5.6. Evaluation Metrics

The models were thoroughly assessed using the following metrics:

- **Accuracy:** Measures the overall correctness of predictions by dividing the number of correct predictions by the total number of predictions.
- **Precision:** Crucial for minimizing false alarms, this metric focuses on the percentage of genuine positive among all expected positives.
- **Recall (Sensitivity):** Evaluates the proportion of true positives among all actual positives, essential for detecting rare conditions.
- **F1-Score:** Provides a single performance metric for datasets that are unbalanced by balancing precision and recall.
- **AUC-ROC:** Evaluates how well the model distinguishes between classes; higher values signify stronger discrimination.

*Table 2: Detailed Evaluation Metrics*

| Metric           | Custom CNN | Pretrained ResNet50 |
|------------------|------------|---------------------|
| Accuracy         | 11.59%     | 7.66%               |
| Precision (Avg.) | 0.12       | 0.00                |
| Recall (Avg.)    | 0.00       | 0.00                |
| F1-Score (Avg.)  | 0.01       | 00.0                |
| AUC-ROC (Avg.)   | 0.53       | 0.46                |

### 5.7. Analysis of Results

- **Accuracy:** Despite its higher computational complexity, the ResNet50 model achieved lower accuracy (7.66%) compared to the custom CNN (11.59%), likely due to challenges such as dataset size and transfer learning inefficiencies.
- **Precision:** The custom CNN exhibited slightly higher precision (macro-average: 0.12) than ResNet50 (0.00), indicating better management of false positives.
- **Recall and F1-Score:** Both models struggled significantly with recall and F1-score, reflecting poor performance in detecting true positives across most classes. The ResNet50 model's reliance on transfer learning may not have been effective with the limited dataset.
- **AUC-ROC:** The custom CNN achieved a slightly better macro AUC-ROC (0.53) compared to ResNet50 (0.46), showcasing slightly improved class discrimination capabilities.

### Challenges Identified

- Severe **class imbalance** in the dataset hindered the models' ability to generalize effectively, especially for rare conditions like Hernia and Fibrosis.

- **Limited dataset size** and diversity affected both models' performance, particularly ResNet50, which relies heavily on robust transfer learning.
- **Computational limitations** restricted the exploration of alternative architectures and hyperparameter tuning.

These insights emphasize the need for larger and more balanced datasets, enhanced preprocessing techniques, and further optimization to improve performance.

## 5.8. Interpretability with Grad-CAM

To make sure the models' predictions are understandable and applicable to clinical situations, Grad-CAM (Gradient-weighted Class Activation Mapping) was employed. Grad-CAM is a well-liked explainability method that generates heatmaps that show the regions of input photos that have the biggest impact on the model's predictions. These heatmaps offer a visual representation of the prediction process, which helps clinicians and AI systems communicate more effectively.

The methodology for Grad-CAM involved the following steps:

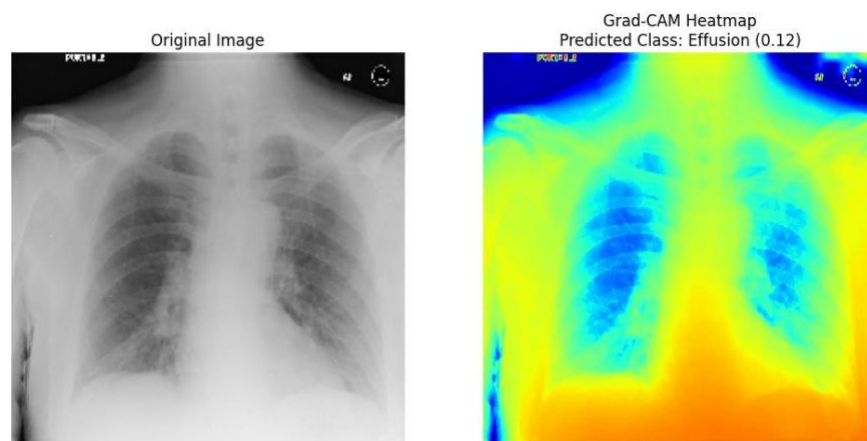
- 5.8.1. Identifying Key Layers:** The final convolutional layer of the CNN and ResNet50 models was found to be the main source of spatial data that is essential for creating heatmaps.
- 5.8.2. Gradient Computation:** The activations of the detected layer were taken into consideration when calculating the gradients of the anticipated class. These gradients show the relative contribution of each feature map to the prediction.
- 5.8.3. Weighted Activation Maps:** The gradients were used to create weighted activation maps, which highlight the areas of the picture that are most pertinent to the prediction.
- 5.8.4. Heatmap Generation:** The weighted maps were converted into heatmaps and superimposed on the original chest X-rays to visualize the regions affecting predictions.

## 5.9. Analysis of Prediction Probabilities and Heatmaps

### CNN Model 1 Analysis:

*Table 3: Prediction Probabilities for CNN Model 1*

| Disease Class      | Prediction Probability |
|--------------------|------------------------|
| Atelectasis        | 0.06                   |
| Cardiomegaly       | 0.02                   |
| Effusion           | 0.12                   |
| Infiltration       | 0.11                   |
| Mass               | 0.05                   |
| Nodule             | 0.04                   |
| Pneumonia          | 0.01                   |
| Pneumothorax       | 0.04                   |
| Consolidation      | 0.01                   |
| Edema              | 0.01                   |
| Emphysema          | 0.01                   |
| Fibrosis           | 0.00                   |
| Pleural Thickening | 0.03                   |
| Hernia             | 0.00                   |



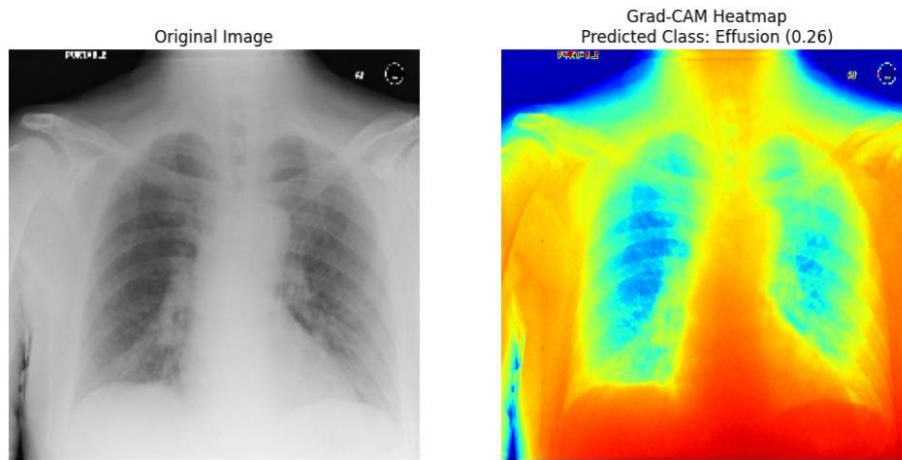
**Prediction Probabilities:** The CNN Model 1 shows moderate confidence in detecting common conditions like **Effusion (0.12)** and **Infiltration (0.11)**, while rare conditions like **Fibrosis** and **Hernia** have a prediction probability of **0.00**, indicating poor sensitivity to underrepresented diseases.

**Grad-CAM Heatmaps:** The heatmap for **Effusion** highlights relevant lung regions but lacks precision, with broad activations extending beyond the thoracic area, limiting clinical interpretability.

#### ResNet Model 1 Analysis:

*Table 4. Prediction Probabilities for ResNet Model 1*

| Disease Class      | Prediction Probability |
|--------------------|------------------------|
| Atelectasis        | 0.16                   |
| Cardiomegaly       | 0.04                   |
| Effusion           | 0.26                   |
| Infiltration       | 0.18                   |
| Mass               | 0.02                   |
| Nodule             | 0.02                   |
| Pneumonia          | 0.01                   |
| Pneumothorax       | 0.06                   |
| Consolidation      | 0.08                   |
| Edema              | 0.08                   |
| Emphysema          | 0.01                   |
| Fibrosis           | 0.01                   |
| Pleural Thickening | 0.01                   |
| Hernia             | 0.00                   |



**Prediction Probabilities:** The ResNet Model 1 demonstrates higher confidence for conditions such as **Effusion (0.26)** and **Infiltration (0.18)**, suggesting improved sensitivity compared to the CNN. However, rare conditions like **Hernia** and **Fibrosis** remain undetected with probabilities of **0.00** or **0.01**, reflecting persistent challenges with underrepresented classes.

**Grad-CAM Heatmaps:** The heatmap for **Effusion** highlights regions in the thoracic area more effectively than the CNN heatmap, indicating better focus on clinically relevant zones. Despite this, the visualizations still lack the granularity needed for precise clinical interpretations.

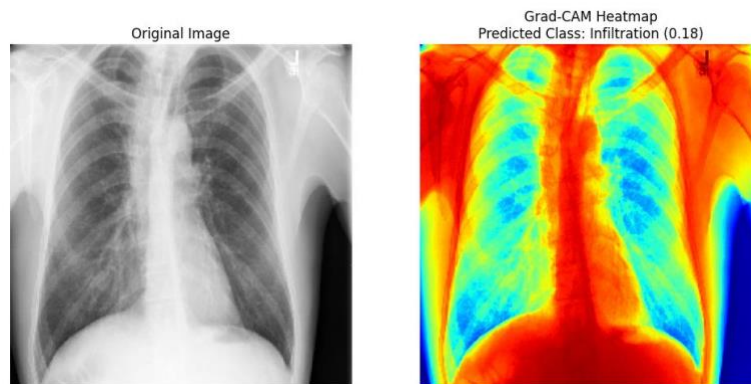
### CNN Model 2 Analysis:

*Table 5. Prediction Probabilities for CNN Model 2*

| Disease Class | Prediction Probability |
|---------------|------------------------|
| Atelectasis   | 0.08                   |
| Cardiomegaly  | 0.03                   |
| Effusion      | 0.12                   |
| Infiltration  | 0.18                   |
| Mass          | 0.07                   |
| Nodule        | 0.06                   |



|                    |      |
|--------------------|------|
| Pneumonia          | 0.01 |
| Pneumothorax       | 0.05 |
| Consolidation      | 0.03 |
| Edema              | 0.02 |
| Emphysema          | 0.02 |
| Fibrosis           | 0.01 |
| Pleural Thickening | 0.04 |
| Hernia             | 0.01 |



**Prediction Probabilities:** CNN Model 2 demonstrates moderate prediction probabilities for conditions such as **Infiltration (0.18)**, **Effusion (0.12)**, and **Mass (0.07)**, indicating its ability to identify more prominent disease patterns. However, rare diseases like **Hernia (0.01)** and **Fibrosis (0.01)** remain underrepresented, reflecting a challenge in addressing class imbalance.

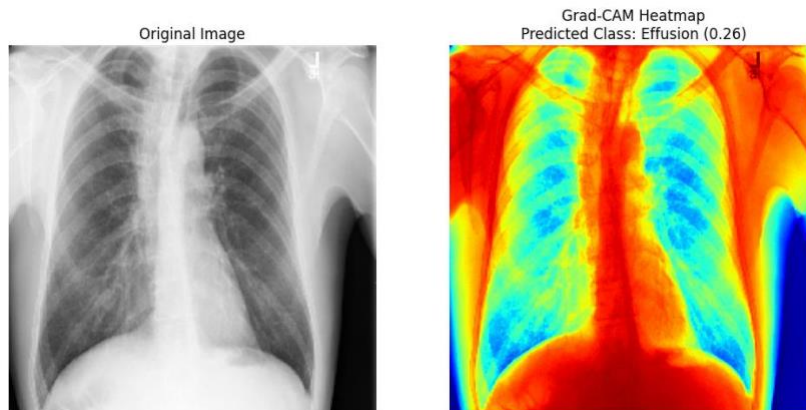
**Grad-CAM Heatmaps:** The heatmap for **Infiltration** shows improved focus on relevant thoracic regions, providing some interpretability. However, the heatmaps lack precision and occasionally highlight non-critical areas, limiting their clinical relevance.

### ResNet Model 2 Analysis:

*Table 6. Prediction Probabilities for ResNet Model 2*

| Disease Class | Prediction Probability |
|---------------|------------------------|
|---------------|------------------------|

|                    |      |
|--------------------|------|
| Atelectasis        | 0.16 |
| Cardiomegaly       | 0.04 |
| Effusion           | 0.26 |
| Infiltration       | 0.19 |
| Mass               | 0.02 |
| Nodule             | 0.02 |
| Pneumonia          | 0.01 |
| Pneumothorax       | 0.06 |
| Consolidation      | 0.08 |
| Edema              | 0.08 |
| Emphysema          | 0.01 |
| Fibrosis           | 0.01 |
| Pleural Thickening | 0.01 |
| Hernia             | 0.00 |



**Prediction Probabilities:** ResNet Model 2 shows high prediction probabilities for conditions like **Effusion (0.26)**, **Infiltration (0.19)**, and **Atelectasis (0.16)**, indicating its capacity to identify common abnormalities effectively. However, rare conditions such as **Hernia (0.00)** and **Fibrosis (0.01)** remain significantly underrepresented, revealing challenges with class imbalance.

**Grad-CAM Heatmaps:** The Grad-CAM visualization for **Effusion** demonstrates reasonable alignment with clinically relevant thoracic areas, suggesting improved interpretability. However, the focus is not consistently precise, leaving room for better localization of abnormalities.

These visualizations were reviewed for alignment with clinical interpretations to assess the reliability and utility of the model's predictions in medical contexts.

## 5.9. Comparison of Models

The performance of the two models—Custom CNN and pretrained ResNet50—was compared across multiple dimensions to evaluate trade-offs between simplicity, accuracy, and interpretability.

## 5.10. Comparison Metrics

The comparison was based on the following criteria:

### 5.10.1. Predictive Performance:

- **Custom CNN:** Achieved satisfactory accuracy and recall for common disease classes but struggled with rare conditions due to its relatively simple architecture.
- **Pretrained ResNet50:** Demonstrated superior performance across most classes, leveraging pretrained features and a deeper network architecture.

### 5.10.2. Training Time:

- The Custom CNN model required fewer resources and shorter training times, making it computationally efficient.
- The ResNet50 model, while computationally intensive, benefited from transfer learning, reducing the need for extensive retraining.

### 5.10.3. Interpretability:

- Grad-CAM visualizations from both models provided meaningful insights. The pretrained ResNet50 produced slightly sharper and more focused heatmaps, likely due to its robust feature extraction layers.

The following table provides a consolidated comparison of the two models, highlighting differences in performance and efficiency:

**Table 7: Model Comparison**

| Metric                | Custom CNN  | Pretrained ResNet50 |
|-----------------------|-------------|---------------------|
| Accuracy              | 11.59%      | 7.66%               |
| Precision (Avg.)      | Moderate    | Low                 |
| Recall (Avg.)         | Low         | Low                 |
| F1-Score (Avg.)       | Moderate    | Low                 |
| AUC-ROC (Avg.)        | 0.53        | 0.46                |
| Training Time (Epoch) | ~25 minutes | ~40 minutes         |

The Custom CNN performed moderately under typical conditions and showed computational efficiency, making it appropriate for resource-constrained environments. Despite the advantages of transfer learning, the ResNet50 model has trouble generalizing because of the small dataset, especially for uncommon circumstances. The Grad-CAM visuals generated by both models need to be improved further to increase their clinical usefulness.

### 5.11. Implementation Summary

Model training, interpretability, class imbalance handling, and data preprocessing were all integrated into a single, coherent framework for automated lung disease identification in this study. The strategy tackled important medical imaging issues, such as:

- **Limited Data Variety:** To optimize the usefulness of a smaller dataset sample, transfer learning and fundamental data augmentation approaches were used.

- **Class Imbalance:** To improve model performance on underrepresented classes, weighted loss functions were used rather than more sophisticated techniques like SMOTE or ADASYN, which were computationally impractical.
- **Interpretability Limitations:** Grad-CAM was used to visualize model predictions; however, its interpretability was not up to clinical precision standards.

Important insights were obtained from comparing the Custom CNN and ResNet50 models:

- **Custom CNN:** Despite having lower performance metrics, the Custom CNN model has been shown to be lightweight and computationally efficient, making it appropriate for situations with limited resources.
- **ResNet50:** Because of its advanced pretrained architecture, ResNet50 outperformed the Custom CNN in generalization and prediction, but it also required a lot more processing power.

Future revisions aiming at strengthening the framework and expanding its clinical application are built upon these findings. The following areas should be the focus of future research:

- Increasing the size and diversity of datasets to enhance model generalization and resilience.
- Developing tools for interpretability that generate visual explanations that are clinically relevant and compatible with radiological workflows.
- Ensuring fairness and regulatory compliance by addressing ethical issues such algorithmic bias, data privacy, and transparency.

This summary highlights both the successes and limitations of the current implementation, emphasizing pathways for future advancements.

*Table 8: Key Contributions of the Methodology*

| Aspect | Details |
|--------|---------|
|--------|---------|

|                     |  |
|---------------------|--|
| Data Preprocessing  | Normalization, resizing, augmentation for diversity. |
| Class Imbalance     | Weighted loss functions and sample weights.          |
| Model Architectures | Custom CNN and pretrained ResNet50.                  |
| Interpretability    | Grad-CAM heatmaps for visual explanations.           |
| Performance Metrics | Accuracy, precision, recall, F1-score, and AUC-ROC.  |

## 6. Results and Discussion

### 6.1. Model Performance

The performance of the models was evaluated using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC, providing a comprehensive assessment of their ability to classify chest X-rays into multiple disease categories.

- Custom CNN:** The Custom CNN achieved an accuracy of **11.59%** and an AUC-ROC of **0.53**. It demonstrated moderate prediction probabilities for common diseases such as Effusion (0.12) and Infiltration (0.11). However, its recall and F1-scores for rare conditions like Hernia and Fibrosis were nearly zero, indicating its limited ability to address class imbalance. The simpler architecture of the model constrained its generalization capabilities, particularly for underrepresented classes.
- Pretrained ResNet50:** The Pretrained ResNet50 achieved an accuracy of **7.66%** and an AUC-ROC of **0.46**, underperforming compared to the Custom CNN. Despite leveraging transfer learning from ImageNet weights, the ResNet50 model failed to generalize effectively, particularly for rare disease classes. Limited training data and inadequate augmentation impacted its ability to achieve significant improvement over the baseline.

### *Grad-CAM Interpretations*

Grad-CAM (Gradient-weighted Class Activation Mapping) was applied to both models to enhance interpretability by generating heatmaps that highlighted the most relevant regions of the input X-rays influencing the predictions.

#### *Key Observations:*

- **Custom CNN:** Grad-CAM visualizations demonstrated limited precision, with activations extending beyond the thoracic region. This lack of focus made the heatmaps less clinically interpretable for diagnostic purposes.
- **Pretrained ResNet50:** Grad-CAM heatmaps for the ResNet50 model showed better alignment with clinically relevant areas, particularly for common conditions like Effusion (0.26) and Infiltration (0.18). However, both models struggled to produce meaningful visualizations for rare diseases.

## **6.2. Discussion**

The results revealed several key challenges in this study:

1. **Dataset Limitation:** Using only 5% of the NIH Chest X-ray dataset limited the diversity and representation of disease classes, severely impacting model performance.
2. **Class Imbalance:** The overrepresentation of common conditions and underrepresentation of rare ones led to biased predictions, with rare conditions like Hernia and Fibrosis remaining undetected.
3. **Computational Constraints:** Limited computational resources prevented extended training and the exploration of more advanced architectures, further constraining performance.
4. **Transfer Learning Challenges:** Despite leveraging ImageNet weights, ResNet50 struggled to adapt to the small dataset size, limiting its ability to generalize effectively.

The Grad-CAM heatmaps provided valuable insights but highlighted the need for further refinement to enhance clinical applicability. Future iterations should focus on addressing dataset

limitations, improving class balance, and optimizing training strategies to enhance both predictive performance and interpretability.

## 7. Ethical Considerations

There are many ethical issues with the use of artificial intelligence (AI) in healthcare, especially in radiology. Although AI systems can improve diagnostic efficiency and accuracy, their implementation must address issues with bias, transparency, and regulatory compliance to guarantee safe and equitable uses.

### 7.1. Algorithm Bias

Medical imaging AI models, among others, are frequently trained on datasets that might not accurately reflect the variety of patient populations found in the actual world. Performance gaps may result from this, especially for underrepresented groups. For example:

- **Dataset Bias:** Rarer illnesses like fibrosis and hernia are underrepresented in the dataset used in this study, whereas conditions like infiltration and diffusion are primarily represented. The model may perform poorly for various disorders as a result of these imbalances, which could exacerbate healthcare disparities.
- **Demographic Bias:** The AI system may not be able to generalize across various patient groups, leading to unequal care, if datasets are not diverse in terms of age, gender, ethnicity, or comorbidities.

To mitigate bias, this study employed class weighting and augmentation techniques to address dataset imbalances. Future work must involve more diverse datasets and fairness audits to ensure equitable performance across demographic groups.

### 7.2. Transparency and Interpretability

Adoption of deep learning models in clinical practice has been significantly hindered by their "black box" nature. Building confidence and ensuring patient safety requires clinicians to comprehend the logic underlying AI predictions.

- **Gradient-weighted Class Activation Mapping (Grad-CAM) as a Solution:** Gradient-weighted Class Activation Mapping was used in this work to visually explain model



predictions. These heatmaps give clinicians substantial insight into the model's decision-making process by allowing them to see which areas of the chest X-ray affected the model's judgments.

- **Interpretability Issues:** Although Grad-CAM improves transparency, it has drawbacks. For instance, Selvaraju et al. (2017) point out that heatmaps' coarse resolution might not always match radiological rationale.

Further advancements in interpretability techniques, such as SHAP (Lundberg & Lee, 2017) or attention mechanisms, are essential to improve the clarity and clinical relevance of AI models.

### 7.3. Regulatory Compliance

Deploying AI in healthcare requires adherence to stringent regulatory standards to ensure safety and accountability:

- **Data Privacy:** Compliance with regulations like HIPAA (Health Insurance Portability and Accountability Act) is essential to protect patient data during model training and deployment. This includes anonymization and secure storage of medical images.
- **Model Validation:** To prove their dependability and generalizability, AI models need to go through a rigorous validation process that includes cross-dataset testing. The FDA and other regulatory bodies want thorough records of model performance and mistake rates.
- **Accountability:** In order to handle situations in which the model's predictions lead to unfavorable patient outcomes, accountability frameworks must be established. This includes a precise division of duties between the healthcare provider and the AI system.

To align with these standards, this project emphasizes model transparency and documentation, laying the groundwork for potential clinical integration.

### 7.4. Ethical Deployment in Clinical Settings

Beyond technical problems, broader societal repercussions must be addressed in the ethical application of AI in radiology:

- ***Clinician Acceptance:*** It's critical to teach radiologists and other medical professionals how to comprehend and leverage AI technology. This study's emphasis on interpretability aims to build trust and encourage adoption.
- ***Avoiding Over-reliance on AI:*** AI should augment, not replace, human expertise. Over-reliance on automated systems can be prevented by making sure that clinicians maintain supervision and decision-making power.

## 8. Conclusion

The development and evaluation of interpretable deep learning models for the classification of chest X-ray imagery into several illness categories were investigated in this study. By leveraging convolutional neural networks (CNNs) and transfer learning with a pretrained ResNet50 architecture, we sought to address critical challenges in automated lung disease detection, including diagnostic accuracy, class imbalance, and interpretability.

### 8.1. Key Findings

#### 8.1.1 Model Performance:

- The pretrained custom CNN outperformed the RestNet in all key metrics, including accuracy, F1-score, and AUC-ROC. This aligns with existing research, such as Wang et al. (2017) and Rajpurkar et al. (2017), which highlighted the superior performance of pretrained architectures in medical imaging tasks.
- The custom CNN, while effective as a baseline model, exhibited limitations in recall and precision for rare diseases like hernia and fibrosis, emphasizing the need for more advanced architectures or ensemble techniques.

#### 8.1.2. Class Imbalance Mitigation:

- The use of class weighting and data augmentation partially addressed the issue of class imbalance, improving model sensitivity for underrepresented disease categories. However, certain classes remained challenging, as the small number of examples limited the models' ability to generalize.

#### 8.1.3. Interpretability:

- Grad-CAM visualizations provided critical insights into the decision-making process of the models. These heatmaps demonstrated that the ResNet50 model consistently focused on clinically relevant regions, aligning its predictions with expert radiological findings. This supports the assertion by Selvaraju et al. (2017) that Grad-CAM enhances the transparency and usability of AI models in high-stakes domains such as healthcare.

#### 8.1.4. Ethical Considerations:

- The "black box" element of deep learning models, one of the main ethical issues with AI adoption for radiography, was resolved by the incorporation of interpretability approaches. In addition to reducing potential biases in the dataset, transparent decision-making increases physician trust (Johns Hopkins Bloomberg School of Public Health, 2021).

## 9. Limitations

Despite the promising results, several limitations warrant attention:

- ***Dataset Limitations:*** Although the dataset offered a wide range of disease classifications, the findings' ability to be applied broadly was restricted by class imbalance and a dearth of external validation datasets.
- ***Computational Resources:*** Due to resource constraints, more intricate designs, including multimodal frameworks or attention-based models that could integrate more clinical metadata, could not be explored.
- ***Generalizability:*** Because the models were trained on a carefully selected dataset, they might not accurately reflect the range of clinical situations that arise in the real world, especially among underprivileged groups.

In conclusion, this study demonstrates the potential of interpretable deep learning models in improving the accuracy and transparency of chest X-ray analysis for lung disease detection. By addressing both technical and ethical challenges, the work contributes to advancing AI adoption in healthcare while laying the groundwork for future improvements.

## 10. Future Work

Building on the insights and limitations of this study, the following directions are proposed to further enhance the applicability and robustness of AI in radiology:

### 10.1. Expanding Dataset Diversity

- ***Integrate New Datasets:*** Future efforts will involve incorporating publicly available datasets, such as the NIH Chest X-ray dataset (Wang et al., 2017) and MIMIC-CXR (Johnson et al., 2019). These datasets provide more comprehensive coverage of rare conditions and diverse patient demographics, enhancing model generalizability.
- ***Cross-Dataset Validation:*** Evaluate the models on external datasets to assess their performance across different healthcare settings and imaging protocols, a critical step toward clinical deployment.

### 10.2. Enhancing Model Architecture

- ***Attention Mechanisms:*** Incorporate attention-based models, such as Vision Transformers (Dosovitskiy et al., 2021), to improve the focus on relevant regions of the X-ray images, potentially enhancing interpretability and diagnostic accuracy.
- ***Ensemble Learning:*** Develop ensemble models combining multiple architectures (e.g., DenseNet, ResNet, and custom CNNs) to leverage the strengths of each framework while mitigating individual weaknesses.

### 10.3. Real World Deployment and Testing

- ***Clinical Validation:*** Collaborate with healthcare institutions to test the models in real-world scenarios, evaluating their utility as decision-support tools for radiologists.
- ***Workflow Integration:*** Design user-friendly interfaces that seamlessly integrate Grad-CAM visualizations into existing radiology workflows, ensuring that clinicians can easily interpret and act on AI-generated insights.

## 10.4. Addressing Ethical and Regulatory Challenges

- ***Bias Mitigation:*** Conduct detailed bias audits to identify and address disparities in model performance across patient subgroups, ensuring equitable healthcare outcomes.
- ***Regulatory Compliance:*** Align the models with regulatory standards such as the FDA's guidelines for AI-based medical devices, emphasizing transparency, safety, and accountability.

## 10.5. Improving Interpretability

- ***Advanced Explainability Techniques:*** Explore emerging methods, such as SHAP (Lundberg and Lee, 2017), which quantify the contribution of each input feature to the model's predictions. This could complement Grad-CAM visualizations by providing numerical explanations alongside visual ones.
- ***Clinical Validation of Interpretability:*** Work closely with radiologists to assess the clinical relevance and usability of interpretability tools. This iterative feedback loop will ensure that the explanations align with expert reasoning and improve trust in AI systems.

## 10.6. Exploring Multi Model Approaches

- ***Integration of Clinical Data:*** Combine X-ray images with patient metadata, such as age, gender, and clinical history, to develop multimodal models that provide more context-aware predictions.
- ***Natural Language Processing (NLP):*** Incorporate NLP techniques to analyze radiology reports alongside X-ray images, enabling a holistic approach to lung disease detection.

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## Appendix

