Deep Learning Model for Lung Disease Classification

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Abstract

Detection of disease in lungs is important for recovery, but X-rays of chest can be hard to interpret, even for experienced doctors. Our system helps detect respiratory problems by training a model on a dataset of X-rays. The model classifies images into four categories: COVID-19, normal, bacterial pneumonia, and viral pneumonia. We use SHAP (SHapley Additive exPlanations) to highlight which parts of the X-ray influenced the model's decision. This makes our approach transparent and reliable, allowing doctors to trust the AI's predictions. Our project demonstrates how deep learning along with computer vision will provide accurate diagnoses while helping doctors make faster and more confident decisions. This system aims to reduce the work of doctors and help patients get treatment quicker.

Keywords: *Lung disease detection, Chest X-ray analysis, Deep learning, SHAP, Explainable AI, Bacterial pneumonia, COVID-19 detection*

1.Introduction

Respiratory diseases remain a leading cause of illness and death worldwide, significantly burdening global healthcare systems. Among these, conditions such as COVID-19, bacterial pneumonia, viral pneumonia, and other lung infections have proven to be especially critical due to their potential to escalate quickly if not diagnosed and treated early. Timely and accurate diagnosis is therefore crucial in preventing disease progression, optimizing treatment strategies, and improving patient outcomes.

To address these challenges, this project introduces an advanced computer vision-based deep learning diagnostic system capable of analyzing chest X-ray images and classifying them into four distinct categories: Normal (healthy lungs), COVID-19, Bacterial Pneumonia, and Viral Pneumonia. The goal is to automate and support the diagnostic process, reduce dependence on manual interpretation, and provide fast, consistent, and reliable results.

The core of this system is a Convolutional Neural Network (CNN) trained on a curated dataset of labeled chest X-ray images. The model has been fine-tuned to recognize patterns and features unique to each class, achieving promising accuracy in differentiating between diseases with similar visual characteristics. Through proper preprocessing techniques, data augmentation, and architectural optimization, the model generalizes well on unseen data, making it suitable for deployment in real-world clinical scenarios.

In addition to classification, explainability is a critical component of this diagnostic solution. In medical AI applications, trust and transparency are just as important as accuracy. To fulfill this requirement, the system integrates SHAP (SHapley Additive exPlanations) — a powerful explainable AI (XAI) method that provides visual insights into the model's decision-making process. SHAP generates heatmaps that highlight the specific regions of a chest X-ray that contributed most to the prediction, enabling clinicians to validate the model's focus and reasoning. This enhances the system's usability in clinical practice, where explainability is essential for informed decision-making.

This AI-driven solution is particularly valuable in resource-limited or high-demand healthcare settings, where expert interpretation may not be immediately available. It can serve as a second opinion tool for radiologists, speed up triage decisions, and assist in large-scale screening efforts during outbreaks like the COVID-19 pandemic. By combining high diagnostic accuracy with model interpretability, the system aims to alleviate the diagnostic burden, reduce human error, and support medical professionals in delivering faster and more reliable care to patients suffering from respiratory conditions.

In summary, this project demonstrates the potential of deep learning and explainable AI in revolutionizing medical imaging diagnostics. It not only provides a powerful tool for lung disease detection but also bridges the gap between artificial intelligence and clinical trust, making it a step forward in building intelligent healthcare systems.

2.Related work and discussion

Deep learning is trained to find lung problems from images like X-rays and CT scans. Common techniques include data augmentation, transfer learning, and ensemble methods. These approaches help identify conditions like pneumonia, tuberculosis, lung cancer, and COVID-19. Key challenges include data imbalance and limited availability of large datasets [1].

Artificial intelligence, like deep learning, is modelled to X-rays for evaluating lung diseases. It helps detect conditions such as tuberculosis, pneumonia, lung cancer, COVID-19, and more. Use of AI and transfer learning supports early and accurate diagnosis, improving understanding and diagnosing of lung diseases [2].

Vision Transformers (ViT) have been explored for lung disease detection in chest X-rays, with comparisons made to traditional CNNs. Two ViT approaches were tested: one on full images and another on segmented lungs. The results displayed that both ViT methods outperformed CNNs in accuracy and AUC, with the full-image ViT achieving the highest accuracy (up to 97.83%). These findings suggest that ViTs can significantly enhance medical analysis for X-ray classification [3].

Chest X-ray, CT, and MRI each play a important role in diagnosing of lung diseases, with distinct strengths and limitations based on the condition. Chest X-ray is used as an initial diagnostic tool, especially for identifying pneumonia, cancer, and chronic obstructive pulmonary disease (COPD). CT scans provide detailed cross-sectional images, making them essential for detecting tumours and pulmonary embolisms. MRI provides functional imaging and is particularly useful in certain cases such as cystic fibrosis. Choosing the appropriate imaging modality should be based on the specific clinical scenario, with an emphasis on reducing unnecessary testing [4].

Deep learning techniques, particularly VGG-16 and DenseNet-169 architectures, have been applied to the automatic finding of lung diseases such as pneumonia, tuberculosis, and COVID-19 using X-ray images. Among the models evaluated, DenseNet-169 achieved a higher classification accuracy of 91%, outperforming VGG-16, which reached 86%. These results highlight the potential of deep learning methods to support the evaluation of prevalent pulmonary conditions through radiographic analysis [5].

Unlike many general studies, this approach involves layer-by-layer activation analysis to visualize how the model interprets features at each stage, offering transparency in decision-making. Additionally, the paper evaluates performance using a combination of metrics—accuracy, precision, recall, F1-score, and specificity—to ensure comprehensive assessment, highlighting the model's robustness in differentiating between various lung conditions. This layered analysis and metric-rich evaluation distinguish the study from more generalized applications in lung disease detection [6].

This explores the application of multiple deep learning architectures—specifically CNN, ResNet, Inception, and VGG—for the classification of various lung diseases using chest X-ray images. The study emphasizes a comparative evaluation of these models to determine their effectiveness in medical image classification. It introduces a preprocessing pipeline involving image enhancement and resizing to standardize input data and improve model performance. Notably, the authors underscore the superiority of the ResNet architecture, achieving the highest accuracy (98.89%) among the tested models, attributed to its residual learning capability that mitigates vanishing gradient issues [7].

The model architecture incorporates Spatial Transformer layers to extract key features from chest X-ray images. Image data is combined with patient-specific information like age and gender to improve classification accuracy. Use of CapsNet, with CNNs, is evaluated for lung disease classification, comparing its performance. Challenges like data imbalance are addressed through the use of F-beta scores as an evaluation metric. A layer-by-layer analysis of the model's activation is detailed to provide transparency in decision-making [8].

The study explores detection pneumonia from X-ray images. It compares multiple CNN to find the most appropriate model for classification. Image preprocessing and augmentation are used to improve model training and performance. While the method supports quick detection, it is intended to assist, not replace, medical professionals. The work highlights the potential of AI to improve early screening and support healthcare systems during disease outbreaks [9].

To improvise the performance of X-ray images, the system first makes the images clearer using a method called median filtering and adjusts the brightness using something called histogram equalization. Then, it finds the important area in the image using a special method. From this area, it picks out different features like how it looks, its shape, texture, and brightness. The paper also talks about a way to make the results better by using normalization. To find out if the image shows a disease or not, the system uses different types of computer models like ANN, SVM, KNN, and some advanced models like RNN with LSTM [10].

The model applies a region proposal network to detect areas of interest, improving classification confidence and reducing computation time. A subset of the ChestX-ray14 dataset is used, with images labelled manually. Training is conducted using TensorFlow and the Inception-V2 model architecture. Model performance is validated against medical practitioners using metrics like accuracy, precision, sensitivity, and specificity. Results show the model outperforms both a general practitioner and a medical student in accuracy and speed. Real-time validation is demonstrated through webcam-based X-ray image classification. The model achieves 62% accuracy and processes each image in under 5 seconds. Limitations include a small dataset and binary classification, suggesting potential for expansion to multiclass disease detection [11].

A CNN-based deep learning model is developed for automatic classification of lung chest X-ray images into normal and abnormal categories. The JSRT dataset is used, containing 180 images (90 normal, 90 with nodules), resized for processing. Data augmentation is applied to counter limited dataset size. Max pooling and batch normalization help in denoising and stabilizing training. The model achieves a classification accuracy of 86.67% using 150 training images across 4 epochs and 30 iterations. The study demonstrates how simple CNN models can deliver high accuracy with limited data. Further improvements are suggested using more data and advanced CNN variants for segmentation and classification [12].

convolutional neural networks have become a powerful tool in medical analysis, offering significant improvements in tasks like segmentation, abnormality detection, classification, computer-aided diagnosis, and image retrieval. The review explores various CNN architectures, including shallow and deep networks, as well as hybrid models using transfer learning and data augmentation. It emphasizes CNNs' performance across multiple image system like MRI, CT, and ultrasound, showing superior results in accuracy and robustness compared to earlier methods. Overall, CNNs are positioned as a key driver in the future of intelligent and automated medical image analysis systems [13].

Deep CNNs have shown strong potential in classifying interstitial lung disease (ILD) patterns using high-resolution CT scans. Accurate ILD diagnosis is challenging due to overlapping visual features, but CNNs can learn complex texture features directly from image data. This study introduces a novel multi-source transfer learning approach where CNNs are pretrained on various general texture datasets and fine-tuned on ILD images, leading to improved performance. An ensemble of these models is used to combine diverse learned features, and knowledge is distilled into a single compact CNN via model compression. This strategy improves classification accuracy while maintaining inference efficiency. Compared to traditional CNNs and handcrafted feature methods, the proposed approach achieves a significant performance boost, particularly in scenarios with limited annotated medical data. The methodology highlights the advantages of both transfer learning and ensemble modelling in medical image analysis [14].

Massive-training artificial neural networks (MTANNs) and convolutional neural networks (CNNs) are two end-to-end learning methods used for image analysis, particularly in lung detection and classification. As data availability increases, CNN performance improves, but MTANNs still retain an edge. MTANNs excel in focal lesion tasks due to their use of low-level feature hierarchies and effective handling of uncertainty. CNNs require more data and are prone to overfitting but benefit from deep hierarchical feature extraction. The findings suggest that MTANNs are suited for specific medical imaging tasks when labelled data is scarce, while CNNs may be more effective for broader, complex pattern recognition with sufficient data [15].

A study was conducted on five deep learning models—2D CNN with SVM, ResNet-50, InceptionResNetV2, Inception-V3, and VGG-19—for classifying three types of lung cancer: adenocarcinoma, squamous cell carcinoma, and benign tissue. The dataset comprised 15,000 CT scan images, which were pre-processed through normalization and augmentation to improve classification performance. Among all the models, Inception-V3 achieved the highest validation accuracy of 99.13%, outperforming others in precision, recall, and F1-score. The CNN-SVM hybrid model also showed competitive results, particularly in situations where model simplicity and interpretability were important [16].

Vision Transformer (ViT) models can be effectively used to find lung diseases from chest X-ray images, with performance highly dependent on the choice of optimizer. A dataset of over 19,000 images, including normal and six disease classes, is used to evaluate six optimization algorithms: Adam, AdamW, NAdam, RAdam, SGDW, and Momentum. RAdam shows the highest accuracy on balanced data, while FastViT with NAdam performs best on imbalanced data. Adam-based optimizers consistently outperform others due to their adaptive momentum mechanisms. Prediction accuracy is generally higher for tuberculosis and normal cases compared to diseases with overlapping features like viral pneumonia and SARS. These findings emphasize the impact of optimizer selection on transformer-based medical image classification. Incorporating suitable optimizers can significantly enhance detection accuracy in real-world diagnostic applications [17].

Lung disease classification can be improved by enhancing chest X-ray images before applying deep learning models. Combining Multi-Scale Retinex (MSR) and Histogram Equalization helps improve contrast and highlight important features. Gabor filters are used to extract shape and texture information, which is then fused with enhanced images in a CNN model. A five-layer CNN with feature fusion outperforms traditional CNN and machine learning approaches like K-NN. The proposed model achieves the highest accuracy (77.78%) and F1-score (0.79) using MSR enhancement. Feature fusion proves effective in capturing both local details and global structure of lung patterns. These techniques help better distinguish conditions like pneumothorax and atelectasis [18].

Lung cancer evaluation has improved through the integration of image processing and machine learning in CT scan analysis. Various segmentation and classification techniques are explored, including SVM, CNN, ANN, and DNN. Among these, ANN achieved the highest accuracy at 99%, followed by DNN (97%), SVM (96%), and CNN (94%). Multiple studies compared traditional and deep learning approaches, emphasizing the benefits of early detection using CAD systems. Techniques like texture analysis, fractal features, and region-growing segmentation are commonly used. 3D feature-based and hybrid deep learning models show strong potential for enhanced accuracy. Future advancements may involve newer architectures like MobileNet and ResNet for faster and more precise diagnosis [19].

A deep ensemble of three 2D CNNs was proposed to improve lung classification in CT scans. Trained and LUNA16 dataset, the ensemble achieved a 95% accuracy, surpassing previous methods. The model combines predictions from multiple CNNs to decrease false approaches while having high sensitivity. Each CNN learns complementary features, making the ensemble more robust. Unlike other computer vision, deep learning models, this method provides superior performance [20].

. 3.Methodology

This study presents a solution for detecting lung problem from X-ray using CNNs. The system is trained to detect pneumonia and COVID-19. It automatically learns image patterns, reducing the need to detect features manually and helping healthcare professionals with faster diagnoses.

The dataset, sourced from Kaggle, contains X-ray images labelled as Normal, COVID-19, viral pneumonia, and Bacterial Pneumonia. Images from various hospitals provide diversity for real-world application. The data was split as follows:

- Training Dataset: contains images to train system
- Validation Dataset: Used for performance check during training.

Preprocessing included:

- Resizing: Images resized to 224x224 pixels.
- Normalization: Pixel values scaled to [0, 1].
- Data Augmentation: Techniques like random rotations and flips to improve diversity and reduce overfitting.

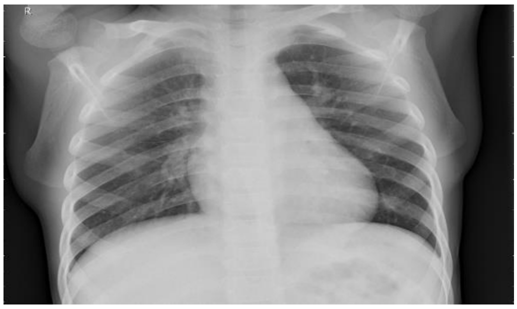

Figure 1: Normal: A chest X-ray of healthy lungs with no signs of infection or disease.

3.2 Data Preprocessing

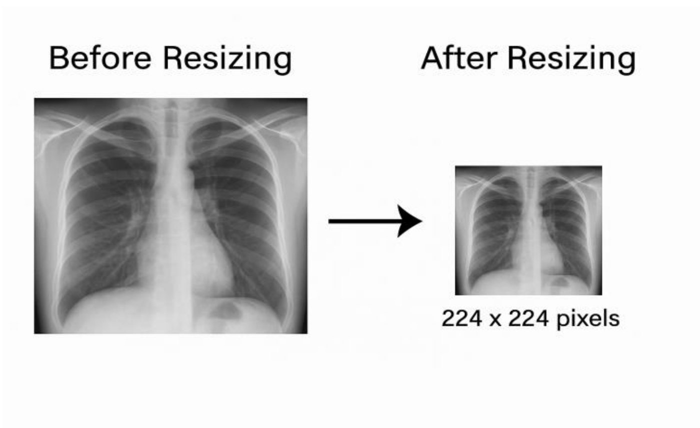

Figure 2: images are resized to a uniform resolution, for example, images before and after resizing

3.2 Model Training

In this project, we created a model that can look at chest X-ray images and tell if a person has Bacterial Pneumonia, COVID-19, Viral Pneumonia, or if their lungs are Normal. We used something called CNN, which is a type of computer program that helps a machine understand images. The CNN works in steps. First, it looks at small details in the image, like edges or shapes. Then, it makes the image smaller using a method called pooling, so it can process faster. After that, the important information goes through layers that help the model learn and make a decision. We used ReLU, a function that helps the model learn faster, and SoftMax, which helps the model pick the most likely result.

To train the model, we gave it many chest X-ray images that were already labeled with the correct disease type. Over time, the model learned to spot patterns and features that match each disease. We also used data augmentation to improve learning by showing the model slightly changed versions of the same images. Once trained, the model could make accurate predictions on new, unseen images. This helps doctors by giving them a quick second opinion, especially in places where expert radiologists are not available.

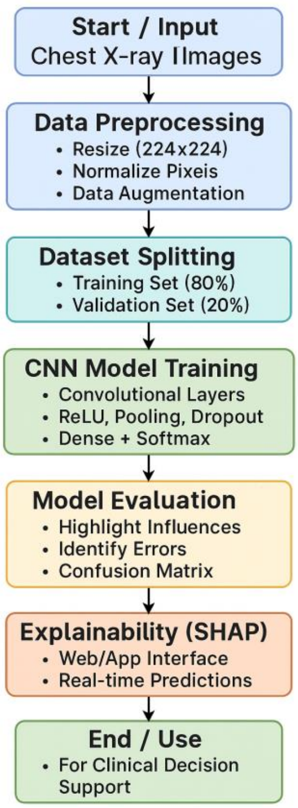

Figure 3: *Shows how the deep learning model works to find lung diseases using chest X-ray images.*

3.3 Model Evaluation

To test the model's performance, several metrics are used:

TP: Correct positive predictions

TN: Correct negative predictions

FP: Incorrect positive predictions (false alarms)

FN: Incorrect negative predictions (misses)

1. Accuracy measures the correctness and is calculated as:

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

2. The confusion matrix plot shows if the model's predictions match up with the actual results ,Precision indicates the correctness of positive predictions:

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

3. Recall measures how well the model identifies all positive cases:

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

4. F1-Score balances precision and recall :

$$\text{F1-Score} = 2 * \frac{(Precision * Recall\,)}{(Precision + Recall}$$

5. AUC-ROC Curve measures the model's ability to distinguish between classes and is calculated as:

$$\text{AUC}=\int_0^1 TPR(x)\, dFPR(x)\ .$$

These metrics help assess the model's effectiveness in detecting lung diseases, ensuring a comprehensive evaluation across various aspects of model performance.

3.4 Model Deployment, Usage, and Interpretability

Once trained, the deep learning model can be effectively deployed on healthcare platforms, such as web or mobile applications, enabling real-time predictions on chest X-ray images. This allows doctors and medical staff to upload patient scans and receive instant diagnostic feedback, even in remote or high-volume healthcare environments. The system is built to handle large-scale data efficiently, making it a reliable solution for hospitals and clinics of all sizes. Moreover, the model can be continuously updated with new data, which is crucial for adapting to emerging diseases and improving performance over time.

Beyond just making predictions, interpretability of the model's decisions plays a vital role in building clinical trust. To address this, the system incorporates SHAP (SHapley Additive exPlanations), an explainable AI technique that visually shows which parts of the chest X-ray image influenced the prediction the most. This helps clinicians understand why a specific diagnosis was made. Additionally, we integrate Grad-CAM (Gradient-weighted Class Activation Mapping), which highlights the important regions within the X-ray that contributed to the model's decision, offering another level of interpretability through intuitive visual heatmaps.

Another helpful feature is the inclusion of confidence level scores with each prediction. This allows medical professionals to assess how confident the model is in its diagnosis, and decide whether they can rely on it directly or conduct further testing. Together, these features make the model not just a diagnostic tool but a decision-support system that improves the accuracy, speed, and trustworthiness of lung disease detection in real-world clinical settings.

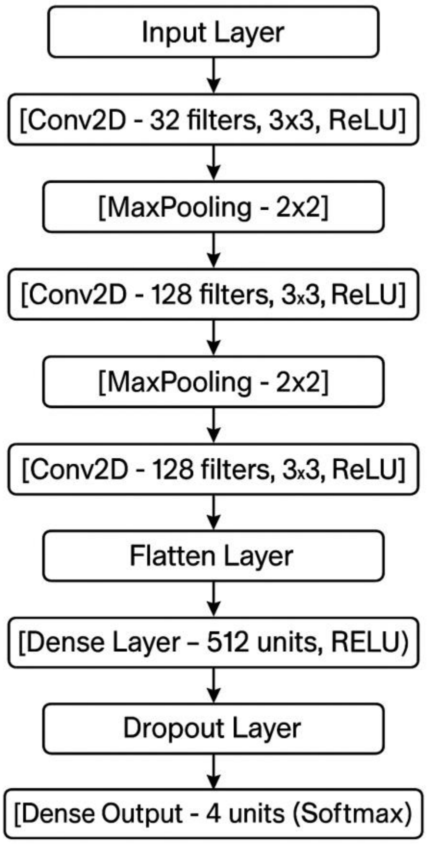

Figure 4: *CNN Architecture for Lung Disease Classification from Chest X-rays*

Flowchart of the CNN used for lung disease classification with Conv2D, MaxPooling, Dense, and Softmax layers.

4. Results

This model was trained on 532 X-ray images categorized into Normal, COVID-19, viral pneumonia, and bacterial pneumonia, using an 80:20 train-validation split. Below are the key results and insights:

4.1 Training Performance Overview

The model achieved a training accuracy of 82%, with strong performance in detecting COVID-19, particularly high recall for COVID-19 cases. The model performed particularly well on the COVID-19 class, achieving a near-perfect recall of 99%, indicating that very few actual COVID-19 cases were missed.

Table 1: Classification Report on Training Data

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
Bacterial Pneumonia	0.84	0.77	0.80	66
COVID-19	0.86	0.99	0.92	68
Normal	0.83	0.85	0.84	75
Viral Pneumonia	0.71	0.50	0.59	38
Overall Accuracy			0.82	

Table 1: Classification Report on Training Data Showing Precision, Recall, F1-Score, and Support for Each Class

4.2 Confusion Matrix Analysis

A confusion matrix plot was generated to calculate the misclassification patterns among the four categories. The matrix revealed:

- Most COVID-19 cases were correctly classified.
- Viral Pneumonia had the highest rate of misclassification, which got confused with Bacterial-Pneumonia or Normal.
- Normal and Bacterial Pneumonia images were generally classified with high accuracy, though some overlap was noted.

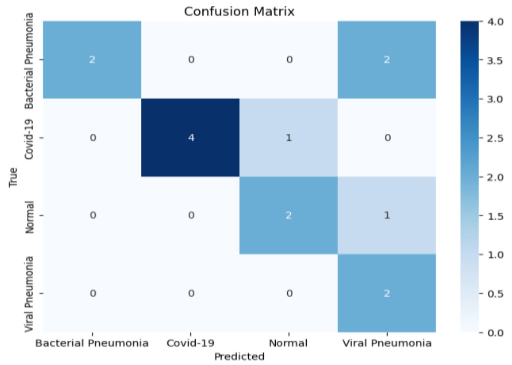

Figure 5: The matrix shows correct and misclassified predictions across four categories: Normal, COVID-19, Viral Pneumonia, and Bacterial Pneumonia.

4.3 Class-wise Behaviour Analysis

- COVID-19: The model excelled due to distinct radiographic patterns like bilateral opacities.
- Bacterial Pneumonia: It identified localized, dense lung markings with decent precision and recall.
- Viral Pneumonia: The model faced challenges due to subtle, diffuse symptoms.
- Normal: Successfully identified the absence of infection patterns.

4.4 Training vs Validation Curves

Training and validation loss and accuracy curves were plotted across epochs to evaluate learning dynamics. A slight gap between training vs validation accuracy was noted toward the end of training, suggesting mild overfitting due to dataset size constraints.

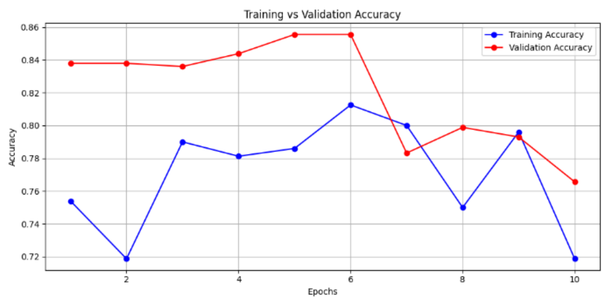

Figure 6: Training vs Validation Accuracy: Shows how accuracy changes for both training vs validation over time.

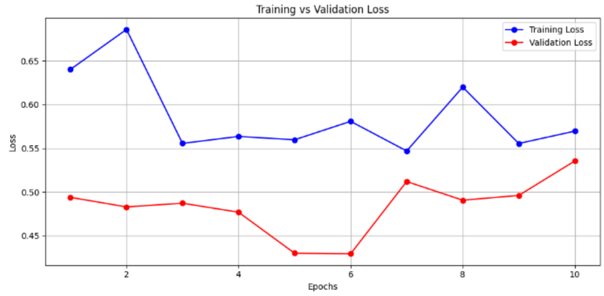

Figure 7: Training vs Validation Loss Curve: Illustrates the change in loss over epochs, highlighting learning progress and overfitting.

4.5 Precision-Recall Curve Analysis

A precision-recall (PR) curve was used to find the model's performance, especially with class imbalance. Key observations:

- COVID-19: Strong performance with the highest PR curve area, indicating good identification and low false positives.
- Bacterial Pneumonia: Balanced performance with moderate precision and recall, showing reliable classification.
- Viral Pneumonia: Lowest PR area, suggesting difficulty in distinguishing this class from others.
- Normal: High precision and recall, accurately identifying healthy cases with few misclassifications.

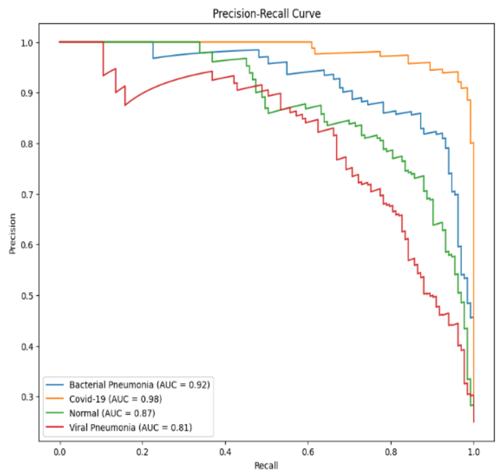

Figure 8:Precision-Recall Curves for Each Class. The graph illustrates the precision-recall relationship for all four classes, highlighting classification strengths and weaknesses.

4.6 Comparative Evaluation

The output received were compared with pre-existing studies using similar techniques:

Study	Model Used	Dataset Size	Accuracy	Observations
X et al. (2022)	VGG16	450 images	75%	Lower COVID recall
Our Study	CNN (ResNet-like)	532 images	82%	High COVID-19 detection, moderate for others

Table 2: Comparative analysis between existing study (X et al., 2022) using VGG16 and the proposed CNN (ResNet-like) model. The proposed model demonstrates higher accuracy (82%) and significantly improved COVID-19 detection performance compared to the earlier method (75% accuracy).

Compared to previous work using simpler CNN architectures, our ResNet-like system performed good in identifying COVID-19, while it required few improvement in detecting Viral Pneumonia.

4.7 Interpretation of SHAP Results

The SHAP (SHapley Additive exPlanations) analysis provided valuable insights into how the model made predictions and which features contributed most to its decisions for each lung disease category.

- COVID-19: SHAP values revealed that the presence of diffuse ground-glass opacities, commonly seen in COVID-19 infections, played a significant role in the model's classification. These regions consistently produced high positive SHAP values, indicating that they were key features driving the model's confidence in detecting COVID-19.
- Viral Pneumonia: This class posed greater challenges for the model due to feature overlap with both Normal lungs and Bacterial Pneumonia cases. The SHAP value distributions showed less distinct separation, reflecting the model's uncertainty in distinguishing viral pneumonia. The lack of strongly weighted visual features made this category more prone to confusion.

In addition, SHAP analysis was instrumental in identifying misclassified instances, especially where Viral Pneumonia images were incorrectly predicted as Normal. By examining the SHAP explanations for these cases, it became clear that certain subtle or ambiguous features were either underrepresented in the training set or misinterpreted by the model. This helped highlight areas for improvement, such as increasing the dataset diversity or enhancing preprocessing to emphasize critical features.

Overall, SHAP not only improved the transparency and interpretability of the model but also served as a diagnostic tool to refine model performance and understand its limitations in a medical context.

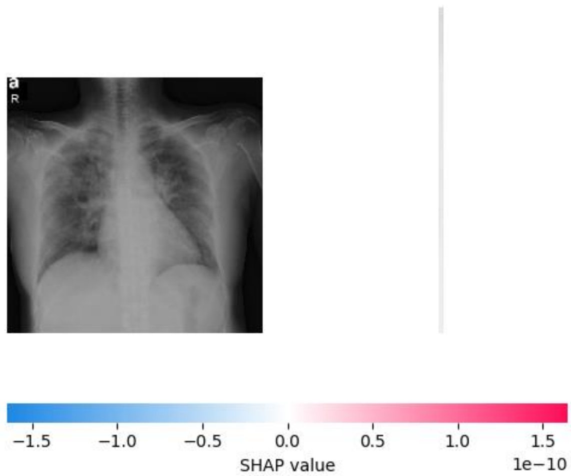

Figure 9. SHAP Explanation Showing Feature Impact

4.8 ROC Curve Analysis

The ROC curve were plotted using a one-vs-rest strategy to find the model's ability to distinguish between the four classes. The AUC curve is obtained for each class:

- COVID-19: Showed the highest AUC, confirming the model's strong performance in detecting COVID cases.
- Viral Pneumonia: Had a lower AUC, consistent with the lower precision and recall observed for this class.
- Normal and Bacterial Pneumonia: Both displayed balanced AUC values, indicating the model's ability to classify these classes reliably.

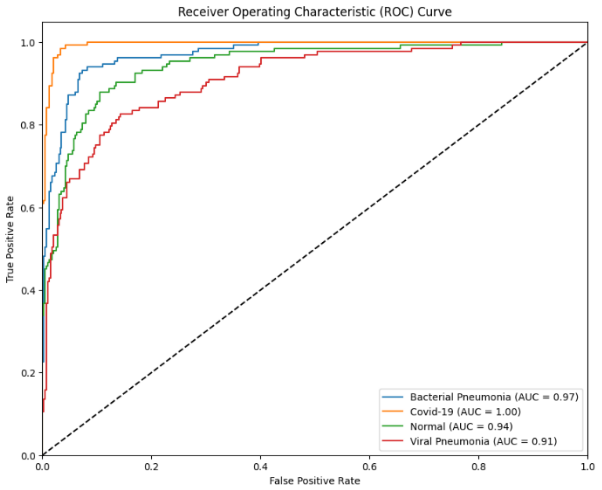

Figure 10

: ROC curve for different labels showing model performance. Higher AUC for COVID-19 indicates strong class separation, while Viral Pneumonia shows lower distinction.

4.9 Limitations

- Small dataset size limited the model's ability to generalize to unseen data.
- Class imbalance, especially fewer examples for Viral Pneumonia, affected performance.
- Discarding SHAP and Grad-CAM reduced the interpretability of the model's decisions.

4.10 Future Enhancements

To make the system work better:

- Expand the dataset to include more examples of Viral Pneumonia.
- Incorporate advanced data augmentation techniques (rotation, flipping, CLAHE).
- Use cross-validation for more robust performance estimation.
- Integrate interpretability methods like SHAP or Grad-CAM to enhance clinical trust.
- Test the model on an external dataset to assess real-world applicability.

5.Conclusion

This project developed a computer vision-based deep learning model for detecting lung diseases from chest X-ray images using Convolutional Neural Networks (CNNs) — a widely used and highly effective method in medical image analysis. The model accurately classifies chest X-rays into four categories: Normal, COVID-19, Bacterial Pneumonia, and Viral Pneumonia, helping in faster and more reliable diagnosis. To enhance trust and transparency in medical settings, the model was integrated with SHAP (SHapley Additive exPlanations), which offers visual explanations of the model's decisions by highlighting the most influential regions of the X-ray image. This feature plays a crucial role in making the system understandable and more acceptable to healthcare professionals.

The model showcases several strengths, including its adaptability to multiple lung-related diseases, potential for real-time use in hospitals and clinics, and ease of deployment across platforms. It can assist medical staff in locations with limited access to radiologists and can be scaled up for broader applications, including the diagnosis of other thoracic or respiratory conditions. Additionally, its design allows for future updates with new data, making it suitable for detecting emerging diseases.

Despite its advantages, the system faces some challenges. The accuracy of predictions heavily depends on the quality and clarity of X-ray images, and performance may vary when images are taken from different machines or under different conditions. Another concern is the class imbalance in the dataset, which can affect the model's ability to generalize well, especially for underrepresented categories like viral pneumonia. Furthermore, testing and validating the model on larger, more diverse datasets is necessary to ensure consistent performance across real-world scenarios.

Overall, this project contributes a practical and scalable solution to aid in early detection of lung diseases, supporting doctors with fast, interpretable, and trustworthy AI-assisted diagnostics.

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