

# PERFORMANCE EVALUATION OF DEEP LEARNING APPROACHES: LUNG DISEASE PERSPECTIVE

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## ABSTRACT

The early and accurate detection of pulmonary diseases is critical for effective treatment and improved patient outcomes. This project presents a deep learning-based system for multi-disease classification using chest radiographs. The proposed model is trained on the ChestX6 dataset, which contains six categories of chest X-ray images: Normal, Pneumonia-Bacterial, Pneumonia- Viral, COVID-19, Tuberculosis, and Emphysema. To achieve robust performance, multiple convolutional neural network (CNN) architectures such as CNN, MobileNet, VGG16 and DenseNet are employed and compared. The dataset is preprocessed to enhance image quality and ensure balanced class representation. The system is implemented using Python in Google Colab with T4 GPU support. Experimental results demonstrate that the proposed deep learning models can effectively distinguish between multiple lung diseases with high accuracy, supporting radiologists in diagnostic decision-making. This work highlights the potential of deep learning and medical imaging integration to advance automated healthcare diagnostics.

## KEYWORDS

Deep Learning, Chest X-ray, Lung Disease Classification, Multi-class Classification, Convolutional Neural Networks (CNN), Transfer Learning, MobileNet, VGG16, DenseNet, Medical Image Analysis, COVID-19, Pneumonia, Tuberculosis, Emphysema, Image Preprocessing.

## 1.INTRODUCTION

Respiratory diseases represent a significant global health challenge, with millions of cases reported annually. Conditions such as pneumonia, tuberculosis, COVID-19, and emphysema severely affect lung function and can lead to life-threatening complications if not diagnosed at an early stage. Early detection and accurate classification of these diseases are crucial for timely medical intervention and improved patient outcomes. Medical imaging techniques, particularly chest X-ray imaging, play a vital role in the diagnosis and treatment planning of pulmonary diseases due to their ability to provide essential anatomical information [1], [2].

Accurate classification of lung diseases is critical in clinical practice to determine appropriate treatment strategies. However, this task remains challenging due to the similarity in radiographic patterns among different diseases. For instance, viral and bacterial pneumonia often exhibit overlapping visual characteristics, making it difficult for radiologists to distinguish between them [3]. While medical experts play a crucial role in diagnosis, the availability of automated supportive tools for rapid and reliable assessment can significantly enhance diagnostic efficiency [4]. Currently, computer-aided diagnostic systems based on chest X-ray imaging offer a promising solution for lung disease detection, with X-rays being preferred due to their affordability, speed, and accessibility [5].

Artificial intelligence (AI), particularly deep learning models, has shown significant potential in improving the accuracy and efficiency of medical image analysis. Machine learning and deep learning techniques are increasingly being applied to lung disease detection and classification tasks. However, challenges such as limited dataset size, class imbalance, and lower accuracy in some existing models remain critical issues. Deep Convolutional Neural Networks (CNNs) have demonstrated strong performance in detecting and classifying lung diseases from chest X-ray images, although they often require substantial computational resources and training time.

To address these challenges, transfer learning using pre-trained deep learning models has emerged as an effective approach. Pre-trained architectures such as VGG, DenseNet, MobileNet, and EfficientNet have been widely adopted due to their ability to improve accuracy while reducing training time. These models have proven successful not only in medical imaging but also in various domains such as image recognition, speech processing, and pattern analysis.

This study focuses on the implementation and comparative analysis of multiple deep learning models, including a custom CNN, VGG16, and DenseNet121, for multi-class classification of lung diseases using chest X-ray images. The proposed system aims to classify six categories: Normal, Bacterial Pneumonia, Viral Pneumonia, COVID-19, Tuberculosis, and Emphysema. A transfer learning approach is utilized to enhance model

performance while minimizing computational complexity. Additionally, data preprocessing and augmentation techniques are applied to improve dataset quality and address class imbalance issues.

The objective of this work is to develop an efficient and accurate computer-aided diagnostic system that can assist healthcare professionals in the early detection and classification of lung diseases, thereby improving clinical decision-making and patient outcomes.

## II. LITERATURE REVIEW

A multi-class classification approach was proposed by Nahiduzzaman et al. [6] for identifying multiple lung diseases using chest X-ray images. The method combined convolutional neural networks with an extreme learning machine to improve classification performance, achieving high accuracy across multiple disease categories.

Gunraj et al. [7] developed COVIDNet-CT, a deep convolutional neural network tailored for detecting COVID-19 from CT images, demonstrating reliable performance in medical diagnosis. Cohen et al. [8] introduced a COVID-19 image dataset that has been widely used for training and evaluating deep learning models.

Gozes et al. [9] proposed an artificial intelligence-based system for automated detection and monitoring of COVID-19 using CT image analysis, highlighting the effectiveness of deep learning in real-time clinical applications. Narin et al. [10] applied deep convolutional neural networks for automatic detection of COVID-19 using chest X-ray images, achieving high classification accuracy.

Zhang et al. [11] introduced an anomaly detection-based deep learning approach for COVID-19 screening, improving efficiency in cases with limited labeled data. Panwar et al. [12] developed nCOVnet, a fast and efficient model for COVID-19 detection from X-ray images.

Minaee et al. [13] proposed Deep-COVID, a transfer learning-based framework that improved classification performance by leveraging pretrained models. Rajaraman and Antani [14] focused on tuberculosis detection using deep learning ensembles, enhancing robustness and accuracy.

Caliman Sturdza et al. [15] presented a comprehensive review of deep learning techniques for COVID-19 detection, discussing existing challenges and future directions. Foundational deep learning architectures such as ResNet [16], VGG [17], DenseNet [18], and AlexNet [19] have significantly contributed to advancements in image classification and are widely used in medical imaging applications.

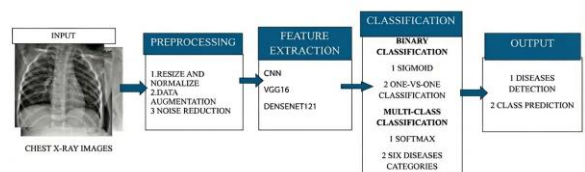
Rajpurkar et al. [20] introduced CheXNet, a deep learning model that achieved radiologist-level performance in

pneumonia detection, demonstrating the potential of AI in clinical diagnosis.

According to the literature review, several studies have already been conducted; however, the detection of lung diseases remains a highly challenging issue.

## III. METHODOLOGY

The methodology of the proposed work focuses on the automated classification of lung diseases from chest X-ray images using deep learning techniques. The system employs **Convolutional Neural Networks (CNN)**, **VGG16**, and **DenseNet121** models to perform **both binary and multi-class classification**. The overall methodology consists of data collection, preprocessing, feature extraction, classification, and performance evaluation. These approaches are widely supported by previous research in medical image analysis and deep learning applications.



**Fig. 1** presents the overall workflow of the proposed methodology for lung disease classification using deep learning techniques. Initially, chest X-ray images are collected and preprocessed to enhance image quality and ensure consistency in input size. The preprocessed images are then fed into deep learning models for feature extraction and classification. Based on the extracted features, the system predicts the corresponding lung disease category.

### A. Data Collection

Chest X-ray images were collected from publicly available medical imaging datasets. The dataset comprises six lung disease classes, including both normal and abnormal pulmonary conditions. All images were annotated according to their corresponding disease labels.

### B. Data Preprocessing

To ensure uniformity and improve learning efficiency, all X-ray images were resized to  $224 \times 224$  pixels. Image normalization was applied to scale pixel values, and data augmentation techniques such as rotation, horizontal flipping, and zooming were employed to reduce overfitting and enhance model generalization.

### C. Model Architecture

Deep features were extracted using three different architectures:

- CNN: A custom CNN model was designed to automatically learn hierarchical features from chest X-ray images.
- VGG16: A pretrained VGG16 model was fine-tuned using transfer learning to capture detailed lung disease patterns.
- DenseNet121: DenseNet121 was utilized for its dense connectivity, enabling effective feature reuse and improved gradient flow.

### D. Binary Classification Approach

Binary classification was performed using a one-vs-rest strategy for each lung disease class. In this approach, one disease category was treated as the positive class, while the remaining categories were considered negative. A sigmoid activation function was used in the output layer, and binary cross-entropy loss was employed to optimize the classification performance.

### E. Multi-Class Classification Approach

For multi-class classification, the extracted deep features were passed to a SoftMax classifier to categorize chest X-ray images into one of the six lung disease classes simultaneously. Categorical cross-entropy loss was used to train the models, enabling a unified framework for comprehensive lung disease diagnosis.

### F. Performance Evaluation

The performance of CNN, VGG16, and DenseNet121 models was evaluated using standard evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics provide a detailed assessment of the effectiveness of both binary and multi-class classification approaches.

## ADVANTAGES & APPLICATIONS

### ADVANTAGES

- Early Disease Detection
- Dual Classification Capability
- High Classification Accuracy
- Reduced Manual Effort
- Efficient Use of Medical Data
- Scalable Framework
- Cost-Effective Solution

### APPLICATIONS

- Hospital and Diagnostic Centers
- COVID-19 and Pneumonia Screening

- Telemedicine Platforms
- Medical Research
- Educational and Training Tools
- Public Health Monitoring
- Clinical Decision Support Systems

## IV. RESULTS AND DISCUSSIONS

The models were trained for multiple epochs using the prepared dataset of 15,000 chest X-ray images. After training, evaluation was performed on the test dataset to measure real performance.

Among the three models, DenseNet121 produced the best results with an accuracy of 90%. The validation accuracy improved steadily during training and became stable towards the final epochs. This indicates that the model was able to learn meaningful features from the dataset without significant overfitting.

The VGG16 model achieved 82% accuracy. It performed consistently but showed slightly higher validation loss compared to DenseNet121. Some fluctuations were noticed during early epochs, but performance stabilized after tuning the final layers.

The custom CNN model achieved 81% accuracy. While it was able to classify most images correctly, it showed difficulty in distinguishing between classes with similar radiographic patterns, especially bacterial and viral pneumonia.

During multi-class classification, most predictions were correct across all six categories. The confusion matrix showed that misclassification mainly occurred between pneumonia-related classes, which share similar visual features.

In binary classification experiments, the performance slightly improved because each model focused on identifying one disease at a time. DenseNet121 again showed more reliable and balanced predictions compared to the other models.

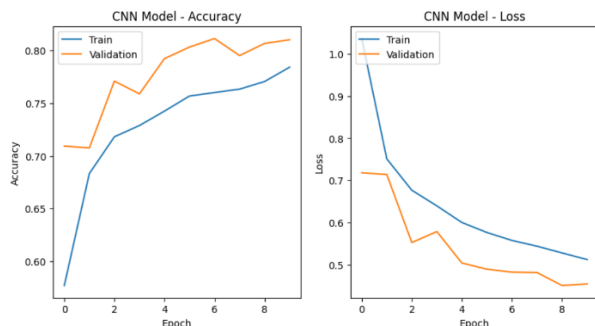
Overall, the results indicate that deeper pretrained models perform better for medical image classification compared to a basic CNN trained from scratch. Similar performance trends have been observed in previous studies on deep learning-based medical image classification



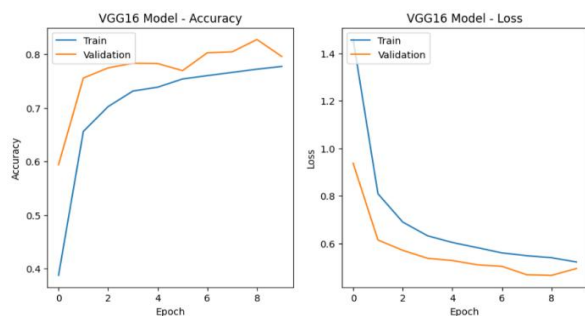
**Fig. 2** shows the input image used in the proposed system. The chest X-ray image is provided as the initial input to the model. It is then passed through preprocessing steps such as resizing and normalization before classification.

## RESULTS OF MULTI-CLASS CLASSIFICATION

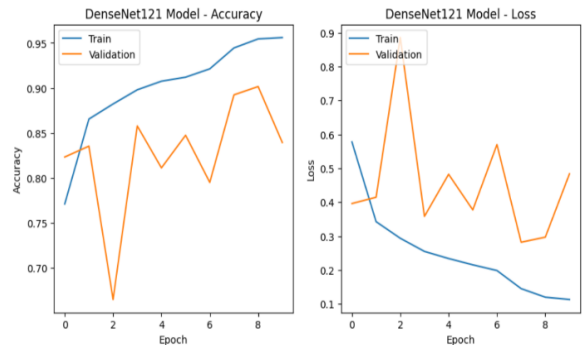
### TRAINING AND VALIDATION LOSS



**Fig. 3** shows the training and validation accuracy and loss curves of the CNN model. The increasing training accuracy and decreasing loss indicate effective learning, while the validation performance reflects the model's ability to generalize to unseen lung disease images.



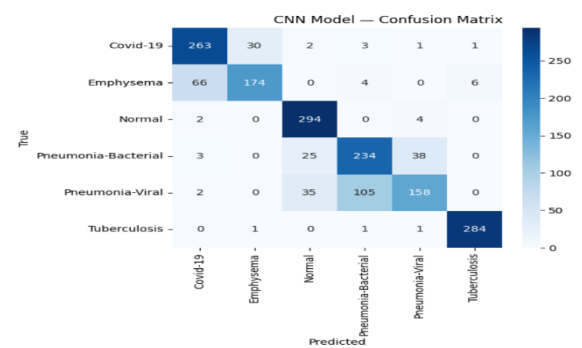
**Fig. 4** shows the training and validation accuracy and loss curves of the VGG16 model. The increasing accuracy and decreasing loss indicate effective learning, while the validation results demonstrate good generalization performance on lung disease images.



**Fig. 5** shows the training and validation accuracy and loss curves of the DenseNet121 model. The increasing accuracy and decreasing loss indicate effective learning, while the validation results reflect strong generalization performance for lung disease classification.

**Table 1** presents the comparative performance of CNN, VGG16, and DenseNet121 using standard evaluation metrics, including accuracy, precision, recall, and F1-score. The results demonstrate that DenseNet121 achieves superior performance in lung disease classification.

| Models      | Accuracy | Precision | Recall | F1 Score |
|-------------|----------|-----------|--------|----------|
| CNN         | 81%      | 81%       | 81%    | 80%      |
| VGG16       | 82%      | 80%       | 80%    | 79%      |
| DenseNet121 | 90%      | 90%       | 90%    | 89%      |



**Fig. 6** shows the confusion matrix of the CNN model for lung disease classification. The matrix compares actual class labels with predicted labels. The diagonal elements represent correctly classified samples, while off-diagonal elements indicate misclassifications. This visualization provides insight into the classification performance across different lung disease categories.

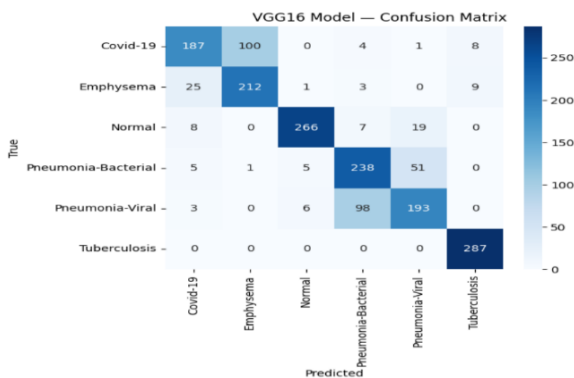


Fig. 7 illustrates the confusion matrix of the VGG16 model for lung disease classification. The matrix compares true and predicted class labels, where higher diagonal values indicate accurate predictions and off-diagonal values represent misclassifications.

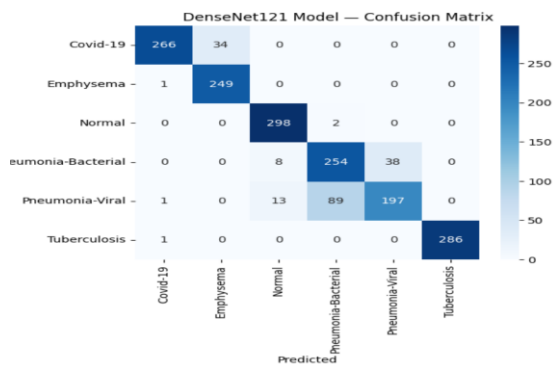


Fig. 8 presents the confusion matrix of the DenseNet121 model for lung disease classification. The matrix compares actual and predicted class labels, where strong diagonal values indicate accurate predictions. This suggests that DenseNet121 achieves superior classification performance compared to the other models.

**MODEL COMPARISON RESULTS**

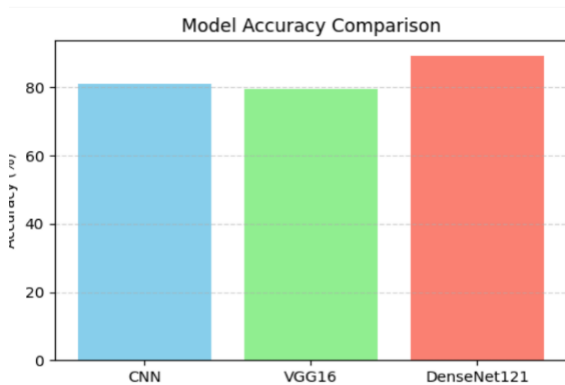


Fig. 9 shows the accuracy comparison of different deep learning models for lung disease classification. The results indicate that DenseNet121 achieves the highest accuracy, demonstrating superior performance compared to CNN and VGG16.

**BINARY CLASSIFICATION**

**(i) BINARY CLASSIFICATION PERFORMANCE OF CNN MODEL**

Table 2 presents the binary classification performance of the CNN model using the one-vs-rest strategy across six lung disease classes. Each class was considered independently as a binary problem. The results are evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

| Class-Pairs                            | Accuracy | Precision | Recall | F1-Score |
|--|----------|-----------|--------|----------|
| Covid-19 vs Emphasema                  | 76.5%    | 77%       | 76%    | 76%      |
| Normal vs Covid-19                     | 98%      | 98%       | 98%    | 98%      |
| Pneumonia-Bacterial vs Covid-19        | 98.1%    | 98%       | 98%    | 98%      |
| Pneumonia-Viral vs Covid-19            | 98.5%    | 99%       | 98%    | 98%      |
| Covid-19 vs Tuberculosis               | 98.4%    | 98%       | 98%    | 98%      |
| Normal vs Emphasema                    | 99.4%    | 99%       | 99%    | 99%      |
| Pneumonia-Bacterial vs Emphasema       | 96.9%    | 97%       | 97%    | 97%      |
| Pneumonia-Viral vs Emphasema           | 97.6%    | 98%       | 97%    | 98%      |
| Emphasema vs Tuberculosis              | 96%      | 96%       | 96%    | 96%      |
| Normal vs Pneumonia-Bacterial          | 95%      | 95%       | 95%    | 95%      |
| Normal vs Pneumonia-Viral              | 93.6%    | 94%       | 94%    | 94%      |
| Normal vs Tuberculosis                 | 98.9%    | 99%       | 99%    | 99%      |
| Pneumonia-Bacterial vs Pneumonia-Viral | 67.8%    | 68%       | 68%    | 68%      |
| Pneumonia-Bacterial vs Tuberculosis    | 99.1%    | 99%       | 99%    | 99%      |
| Pneumonia-Viral vs Tuberculosis        | 98.4%    | 98%       | 98%    | 98%      |

**(ii) BINARY CLASSIFICATION PERFORMANCE OF VGG16 MODEL**

| Class-Pairs           | Accuracy | Precision | Recall | F1-Score |
|-----------------------|----------|-----------|--------|----------|
| Covid-19 vs Emphasema | 100%     | 100%      | 100%   | 100%     |
| Normal vs Covid-19    | 97.7%    | 98%       | 98%    | 98%      |

|  |        |      |      |      |
|--|--------|------|------|------|
| Pneumonia-Bacterial vs Covid-19        | 97.9%  | 98%  | 98%  | 98%  |
| Pneumonia-Viral vs Covid-19            | 98.3%  | 98%  | 98%  | 98%  |
| Covid-19 vs Tuberculosis               | 96.6%  | 97%  | 97%  | 97%  |
| Normal vs Emphasema                    | 100%   | 100% | 100% | 100% |
| Pneumonia-Bacterial vs Emphasema       | 100%   | 100% | 100% | 100% |
| Pneumonia-Viral vs Emphasema           | 100%   | 100% | 100% | 100% |
| Emphasema vs Tuberculosis              | 100%   | 100% | 100% | 100% |
| Normal vs Pneumonia-Bacterial          | 90.4%  | 91%  | 90%  | 90%  |
| Normal vs Pneumonia-Viral              | 92.2%  | 93%  | 92%  | 92%  |
| Normal vs Tuberculosis                 | 99.6%  | 100% | 100% | 100% |
| Pneumonia-Bacterial vs Pneumonia-Viral | 66.79% | 67%  | 67%  | 67%  |
| Pneumonia-Bacterial vs Tuberculosis    | 98.7%  | 99%  | 99%  | 99%  |
| Pneumonia-Viral vs Tuberculosis        | 98.9%  | 99%  | 99%  | 99%  |

**Table 3** presents the binary classification results of the VGG16 model using the one-vs-rest strategy across six lung disease classes. Each class was considered independently as a binary problem. The performance is evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

**(iii) BINARY CLASSIFICATION PERFORMANCE OF DENSENET121 MODEL**

| Class-Pairs                      | Accuracy | Precision | Recall | F1-Score |
|----------------------------------|----------|-----------|--------|----------|
| Covid-19 vs Emphasema            | 100%     | 100%      | 100%   | 100%     |
| Normal vs Covid-19               | 98.9%    | 99%       | 99%    | 99%      |
| Pneumonia-Bacterial vs Covid-19  | 98.7%    | 99%       | 99%    | 99%      |
| Pneumonia-Viral vs Covid-19      | 99%      | 99%       | 99%    | 99%      |
| Covid-19 vs Tuberculosis         | 97.2%    | 97%       | 97%    | 97%      |
| Normal vs Emphasema              | 100%     | 100%      | 100%   | 100%     |
| Pneumonia-Bacterial vs Emphasema | 100%     | 100%      | 100%   | 100%     |

|  |       |      |      |      |
|--|-------|------|------|------|
| Pneumonia-Viral vs Emphasema           | 100%  | 100% | 100% | 100% |
| Emphasema vs Tuberculosis              | 100%  | 100% | 100% | 100% |
| Normal vs Pneumonia-Bacterial          | 92.1% | 92%  | 92%  | 92%  |
| Normal vs Pneumonia-Viral              | 92.9% | 93%  | 93%  | 93%  |
| Normal vs Tuberculosis                 | 100%  | 100% | 100% | 100% |
| Pneumonia-Bacterial vs Pneumonia-Viral | 76.3% | 77%  | 76%  | 76%  |
| Pneumonia-Bacterial vs Tuberculosis    | 99.6% | 100% | 100% | 100% |
| Pneumonia-Viral vs Tuberculosis        | 99.5% | 100% | 100% | 100% |

**Table 4** presents the binary classification results of the DenseNet121 model using the one-vs-rest strategy across six lung disease classes. Each class was considered independently as a binary problem. The performance is evaluated using standard metrics, including accuracy, precision, recall, and F1-score.

**V.CONCLUSION**

This study evaluated the performance of CNN, VGG16, and DenseNet121 models for lung disease detection using chest X-ray images. Both multiclass and binary classification approaches were implemented to analyze the effectiveness of the models. In multiclass classification, the models were trained to classify six lung disease categories. The results show that all models achieved good classification performance. For binary classification, a One-vs-One strategy was applied to evaluate each disease pair separately. Most class pairs achieved high accuracy, precision, recall, and F1-score. However, some pairs such as Pneumonia-Bacterial and Pneumonia-Viral were more challenging to distinguish. Among the three models, DenseNet121 demonstrated the best overall performance. It achieved higher accuracy and more consistent results across most disease pairs. Therefore, DenseNet121 is the most effective model for lung disease classification in this study.

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