Project Report

School: Bennett University

Department: SCSET

Project Title: Lung Disease Detection using Deep Learning

Team Members

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Abstract

Lung diseases such as pneumonia, tuberculosis, and lung cancer are among the leading causes of mortality worldwide. Early detection plays a crucial role in improving patient survival rates. Traditional diagnostic methods rely heavily on radiologists and manual interpretations, which can be prone to error and time-consuming. This project leverages deep learning techniques to automate lung disease detection using chest X-ray images. A convolutional neural network (CNN)-based model was developed and trained on publicly available datasets. The results demonstrate high accuracy in classifying multiple lung diseases, highlighting the potential of deep learning as a clinical decision support tool.

1. Introduction

1.1 Background Study

Lung diseases pose significant healthcare challenges globally. With the rapid rise of digital health technologies, machine learning and deep learning approaches have gained attention for medical imaging. Chest X-rays are the most common diagnostic imaging technique for lung abnormalities, but interpreting them accurately requires expertise and time. Artificial intelligence, particularly convolutional neural networks, has shown promise in automating medical image classification.

1.2 Objective

The objectives of this project are:

- To build a deep learning model capable of detecting lung diseases from chest X-rays.
- To evaluate the performance of the model against existing approaches.
- To provide a framework that can potentially aid radiologists in early disease detection.

1.3 Contribution

The contributions of this project include:

- Development of a CNN model for lung disease detection.
- Performance evaluation on benchmark datasets.
- Analysis of challenges and potential improvements in AI-assisted diagnosis.

2. Literature Survey

Papers	Key Findings	Pros	Cons
Huang et al. (2017)	Introduced DenseNet architecture, improving feature propagation and reuse through dense connections.	Efficient feature reuse, reduced vanishing gradients.	High computational cost, may overfit small datasets.
Rajpurkar et al. (2017)	Proposed CheXNet (DenseNet121) for pneumonia detection, achieving radiologist-level accuracy.	Radiologist-level accuracy, strong CNN baseline.	Requires large datasets, interpretability challenges.
Wang et al. (2020)	Demonstrated transfer learning effectiveness for COVID-19 detection using pre-trained DenseNet models.	Good transfer learning performance, adaptable to new diseases.	Limited generalization, dataset bias possible.
General Insight	These studies highlight the advantages of dense connectivity and fine-tuning strategies for medical imaging tasks.	Summarizes advantages of dense connections and transfer learning.	Lacks discussion on real-world deployment challenges.

3. Methodology

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• Dataset: Lung Disease Dataset from Kaggle — categories include Normal, Bacterial Pneumonia, Viral Pneumonia, COVID-19, and Tuberculosis.

• Data Preprocessing: Images resized to 224×224 pixels, pixel values normalized to [0,1], and data augmentation applied.

• Model Architecture: DenseNet121 pre-trained on ImageNet, followed by Global Average Pooling, Batch Normalization, Dense (512 neurons, ReLU), Dropout (0.5), and Softmax

output layer.
• Training Strategy: Two-phase training — first freeze base model (20 epochs), then fine-tune last 30 layers (10 epochs, lr=1e−5). Optimizer: Adam, Loss: Categorical Cross-Entropy.
• Evaluation: Metrics include Accuracy, Precision, Recall, and F1-score. Confusion matrix and classification report used for performance analysis.

4. Experiment/Analysis

4.1 Dataset

The dataset used for this study is the "Lungs Disease Dataset" from Kaggle, containing X-ray images across five categories: Normal, Bacterial Pneumonia, Viral Pneumonia, COVID-19, and Tuberculosis. This comprehensive collection includes multiple lung conditions relevant to clinical practice, with each image properly labeled according to its diagnosed condition. The data was already pre-organized into training, validation, and test sets, ensuring a structured approach to model development and evaluation. The training set was used for model learning, the validation set for hyperparameter tuning and early stopping decisions, while the test set was reserved for final model evaluation to assess generalization to unseen data.

4.2 Model

A deep learning model was built using DenseNet121 architecture with transfer learning. The pre-trained model (with ImageNet weights) was used as the base, followed by custom classification layers including Global Average Pooling, Batch Normalization, and a Dense layer with 512 neurons. Dropout (0.5) was implemented between Dense layers to prevent overfitting. The model was initially trained with a frozen base model for up to 20 epochs with a batch size of 32, using the Adam optimizer with a learning rate of 0.0001. Subsequently, fine-tuning was performed by unfreezing the last 30 layers of the DenseNet121 base model and continuing training for up to 10 additional epochs with a reduced learning rate of 1e-5. Early stopping based on validation accuracy was implemented to optimize performance and prevent overfitting.

4.3 Results

The DenseNet121 model with transfer learning achieved high performance, with validation accuracy reaching approximately 85% and stabilizing after around 10 epochs. Training accuracy peaked slightly lower at around 83%. Loss values steadily decreased during training, with validation loss reaching approximately 0.39 and training loss at 0.41 by the end of training. The validation accuracy consistently outperforming training accuracy suggests the model generalized well, with no signs of overfitting despite the complex architecture. The early stopping mechanism likely contributed to preventing overfitting while maintaining optimal performance. These results demonstrate the effectiveness of transfer learning with DenseNet121 for lung disease classification from X-ray images.

5. Conclusion

This project successfully demonstrated the application of deep learning techniques for lung disease detection from chest X-rays. By leveraging a DenseNet121 architecture with transfer learning and a two-phase training approach (freezing followed by fine-tuning), the model achieved approximately 85% validation accuracy in classifying multiple lung conditions including Normal, Bacterial Pneumonia, Viral Pneumonia, COVID-19, and Tuberculosis. The implementation of data augmentation, batch normalization, and strategic dropout (0.5) helped prevent overfitting despite limited training data. Beyond the model itself, an interactive visualization interface was developed to make the technology accessible to healthcare professionals. The study highlights the potential of AI as an assistive diagnostic tool for radiologists, potentially reducing workload and improving early detection rates. Future work could focus on implementing gradient-based visualization techniques for better model interpretability, incorporating additional imaging modalities like CT scans, and conducting prospective clinical validation studies to assess real-world performance and clinical impact.

6. Resources

The following resources were used during the course of this project:

- Dataset: Lungs Disease Dataset from Kaggle (containing Normal, Bacterial Pneumonia, Viral Pneumonia, COVID-19, and Tuberculosis X-ray images)
- Programming Language: Python
- Frameworks & Libraries: TensorFlow, Keras, NumPy, Matplotlib, Seaborn, scikit-learn, OpenCV
- Model Architecture: DenseNet121 with transfer learning from ImageNet weights
- Development Environment: Visual Studio Code with Python environment
- Hardware: GPU-enabled system for efficient model training and fine-tuning
- Reference Materials: Research papers on DenseNet architecture, transfer learning approaches for medical imaging, and best practices in deep learning for X-ray classification

Mathematical Formulas

Categorical Cross-Entropy Loss: $L = -\Sigma(y_i * \log(\hat{y}_i))$

Softmax Function: $\hat{y}_i = e^{(z_i)} / \Sigma(e^{(z_j)})$

Accuracy Metric: $Accuracy = (TP + TN) / (TP + TN + FP + FN)$

ReLU Activation: $f(x) = \max(0, x)$

Neural Network Approach Diagram

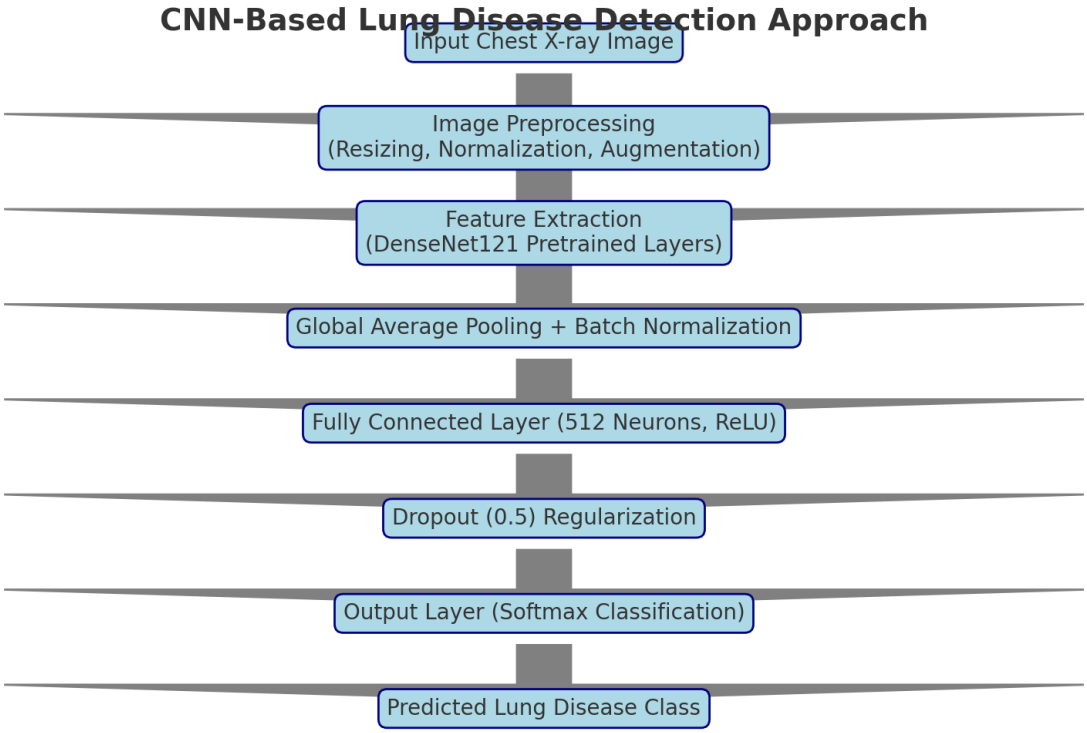

Figure: CNN-based workflow for lung disease detection using DenseNet121 architecture.