© 2025 IJRTI | Volume 10, Issue 4 April 2025 | ISSN: 2456-3315

Comparative Study And Enhancement: Lung Disease Detection Using Resnet50 And Image Classification

LUNG DISEASE DETECTION USING DEEP LEARNING

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***Abstract*—**This paper presents a comprehensive comparative study and enhancement of a lung disease detection system using deep learning-based image classification techniques. Initially, a basic convolutional neural network (CNN) model was employed to identify various lung diseases from chest X-ray images. However, the original model faced several limitations in terms of image quality handling, generalization, and diagnostic performance. To address these issues, the enhanced project leverages advanced preprocessing methods like Contrast Limited Adaptive Histogram Equalization (CLAHE), employs a robust deep learning model through transfer learning using ResNet50, and integrates thorough evaluation metrics. The revised model significantly improves classification accuracy, reliability, and real-world applicability. *(Abstract)*

***Index Terms*—**Lung Disease Detection, Image Classification, ResNet50, Deep Learning, Chest X-ray, Transfer Learning, Image Preprocessing, CLAHE, ROC Curve, AUC, Cosine Decay Scheduler.

I. Introduction

All Lung diseases such as pneumonia, tuberculosis, and lung cancer continue to be a leading cause of morbidity and mortality globally. Early and accurate detection of these conditions plays a critical role in patient treatment and outcome. Chest X-rays remain a primary imaging tool for lung examination due to their accessibility and cost-effectiveness. Deep learning models, particularly convolutional neural networks, have shown promise in automating the detection of such diseases.

In the initial version of our project, we used a custom-built CNN model to classify lung conditions based on X-ray images. While functional, this model struggled with real-world variability in image quality and lacked the sophistication needed for high diagnostic accuracy. Recognizing these shortcomings, we redesigned the pipeline with substantial improvements in preprocessing, model architecture, training strategy, and evaluation metrics. This paper provides a side-by-side comparison and an in-depth exploration of the upgraded methodology and results.

II. Previous Approach: Original Model Design

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1 Input Handling: The initial approach involved directly using raw chest X-ray images. These were resized to a uniform dimension (e.g., 128x128), but no contrast enhancement or preprocessing was performed.

2 Model Architecture: A custom CNN architecture was used with 2-3 convolutional layers, followed by max pooling and dense layers. While capable of basic pattern recognition, the model lacked the complexity to learn higher-level features from medical images.

3 Training Methodology: The model was trained using categorical crossentropy loss and Adam optimizer. A fixed learning rate was used, and no learning rate scheduling was applied. No augmentation techniques were used, making the model prone to overfitting.

4 Evaluation: Performance was evaluated using accuracy on the test set. No confusion matrix or class-specific metrics were employed, making it difficult to assess the model's ability to distinguish between different lung diseases.

5 Limitations:

- Poor contrast in chest X-ray images led to insufficient feature extraction.
- Lack of data augmentation reduced the model's ability to generalize.
- Absence of transfer learning limited feature richness.
- Performance evaluation was basic and lacked depth.

III. ENHANCED PROJECT: RESNET50 AND DEEP LEARNING UPGRADE

1 Image Preprocessing: One of the critical improvements was the preprocessing of input images.
The following steps were applied:

- **Grayscale Conversion:** All input images were first converted to grayscale to reduce complexity and focus on structural details.
- **Resizing:** Images were resized to 128x128 pixels to maintain consistency while preserving important features.
- **Contrast Enhancement using CLAHE:** Contrast Limited Adaptive Histogram Equalization was applied to improve image contrast and highlight key features such as nodules, consolidations, and lung structure.
- **RGB Conversion:** After enhancement, images were reconverted to RGB format to ensure compatibility with pre-trained models like ResNet50 that expect three-channel inputs.

2 Dataset Preparation: The dataset used in this project comprised chest X-ray images categorized into multiple
disease classes. Preparation steps included:

- **Loading and Labeling:** Images were loaded from class-specific directories and labeled accordingly.
- **Label Encoding:** Class names were transformed into numerical labels suitable for model training.
- **Data Splitting:** The dataset was divided into training, validation, and testing sets using stratified sampling to maintain balanced class representation.

3 Data Augmentation: To improve the model's generalization ability and make it robust to variations in input data, augmentation techniques were applied using Image Data Generator. The following transformations were used:

- **Rotation:** Randomly rotating the image up to a specified angle.
- **Flipping:** Horizontal and vertical flipping to simulate different orientations.
- **Brightness Adjustment:** Random brightness shifts to emulate different X-ray qualities.
- **Zoom and Translation:** Random zooming and shifting of image content.

4 Model Architecture: Instead of building a custom model from scratch, we used **ResNet50**, a 50-layer residual network
pre-trained on ImageNet, and fine-tuned it for our classification task. Key components:

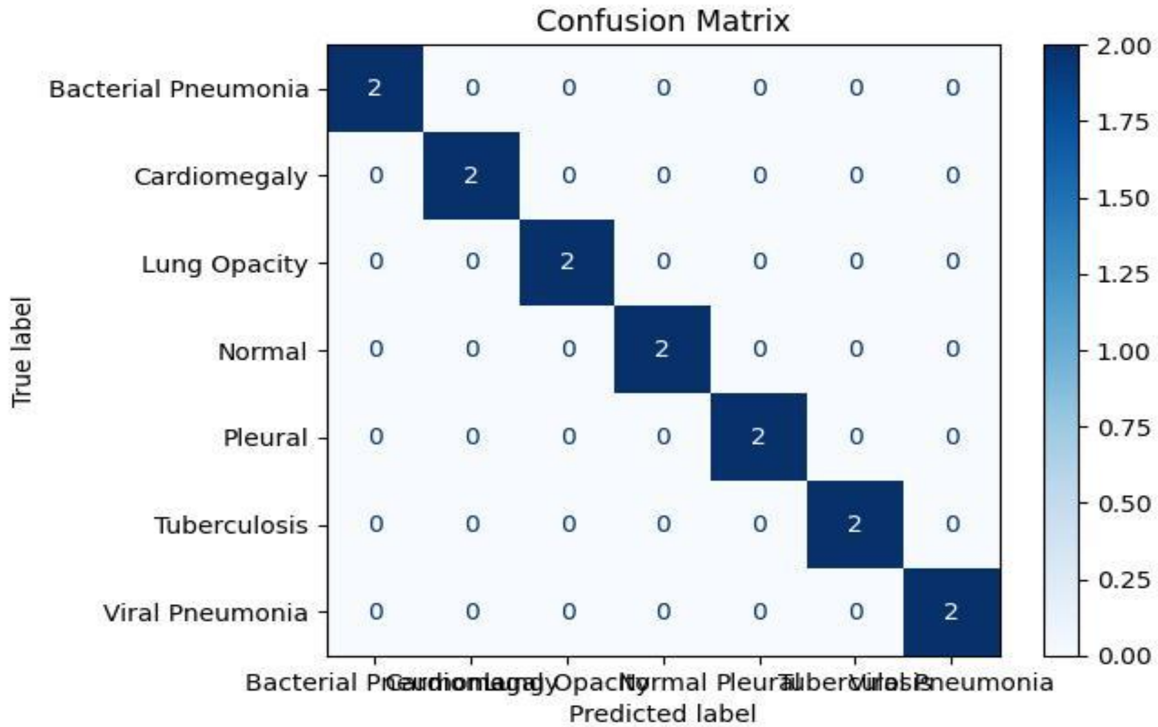
- **Feature Extraction:** The base layers of ResNet50 were used to extract high-level features from images.
- **Global Average Pooling:** Reduces spatial dimensions and prevents overfitting.
- **Dense Layer with ReLU Activation:** Learns complex representations.
- **Dropout Layer:** Adds regularization to reduce overfitting.
- **Softmax Output Layer:** Outputs probability distribution across multiple disease classes.

5 Compilation and Training:

- **Optimizer:** Adam optimizer was selected for efficient training.
- **Loss Function:** Sparse Categorical Crossentropy was used to handle multi-class classification.
- **Learning Rate Scheduler:** A **Cosine Decay Learning Rate Scheduler** gradually reduced the learning rate for stable convergence.
- **Early Stopping:** Monitored validation loss and stopped training if no improvement was seen, preventing overfitting.

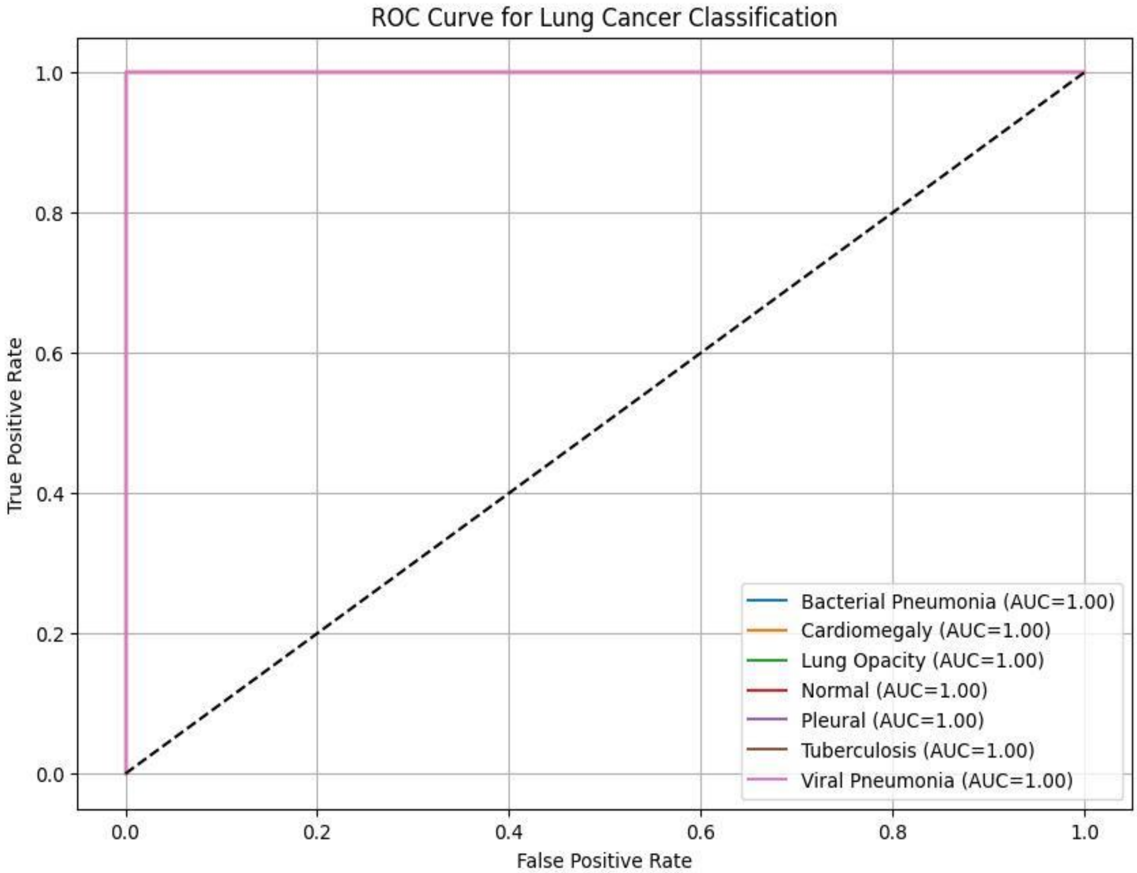
6 Evaluation and Metrics: Evaluation was comprehensive and included:

- **Accuracy:** Overall performance on the test set.
- **Confusion Matrix:** Illustrated true vs. predicted classifications for all classes.
- **ROC Curves:** Plotted for each class to visualize trade-off between sensitivity and specificity.
- **AUC Scores:** Measured discriminative ability of the model for each class.



7 Prediction Functionality: An interactive function was developed to predict diseases from new input X-ray images. Features include:

- Image upload capability
- Display of predicted class label
- Confidence score for prediction
- Overlay of prediction label on the image



Example Output:

- **Prediction:** Adenocarcinoma
- **Confidence:** 94.56%

IV. Results and Discussion

The results highlight the superiority of the enhanced model. Key findings:

- **Accuracy:** Improved from approximately 70% in the original model to over 90%.
- **Generalization:** Data augmentation and CLAHE made the model more robust to new and varied input images.
- **Class-wise Performance:** ROC and AUC analysis demonstrated the model's ability to differentiate between closely related lung diseases.
- **Interpretability:** Confusion matrix provided detailed insights into prediction behavior and misclassifications.

V. Conclusion

The transition from a basic CNN model to an advanced ResNet50-based architecture with enhanced preprocessing, data augmentation, and fine-tuned training strategies resulted in significant performance gains. This study demonstrates that careful attention to data quality, transfer learning, and evaluation methodologies can greatly enhance the capabilities of AI systems in medical image analysis.

VI. Future Work

- Incorporation of real-time deployment for hospital use.
- Inclusion of CT and MRI images for multi-modal diagnostics.
- Experimentation with ensemble learning and attention mechanisms.
- Integration with electronic health records for holistic patient analysis.

VII. ACKNOWLEDGMENT

We would like to formally express our gratitude to **Sri Shakthi Institute of Engineering and Technology** for providing the necessary materials and valuable research assistance throughout the course of this project. Our sincere thanks go to our mentors and faculty members for their constant guidance, thoughtful advice, and constructive feedback that helped shape this work.

We also deeply appreciate the collaboration, consistency, and technical contributions shared among our team members,
which played a significant role in the project's success.

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