World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

Check for updates

Multi label classification of lung diseases using deep learning

C. Pabitha *

Associate Professor, Department of Computer Science and engineering, SRM Valliammai Engineering College, Kattankulathur Chengalpattu, India.

Rohith S, Sanjay M and Shivsharan A
SRM Valliammai Engineering college. Kattankulaathur, Chengalpattu, India.

World Journal of Advanced Engineering Technology and Sciences, 2025, 17(02), 155-162

Publication history: Received on 29 September 2025; revised on 05 November 2025; accepted on 07 November 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.17.2.1472

Abstract

This project aims to address the pressing need for reliable and early detection of lung-related illnesses, including COPD, COVID-19, pneumonia, and lung cancer. A Region-based Convolutional Neural Network (RCNN) model was designed using MATLAB, utilizing chest X-ray images to classify these conditions. One of the standout features of this study is the incorporation of RCNN for generating synthetic images, which effectively tackles data imbalance issues and enhances model stability. This innovative approach significantly improved classification accuracy when compared to traditional methods. The system leverages MATLAB's deep learning toolboxes for model training, validation, and performance analysis. Experimental outcomes reveal the model's strong capability in distinguishing between different lung conditions, demonstrating the potential of AI-powered medical imaging to support clinical decision-making. By facilitating early and precise diagnosis, this research highlights how RCNN can enhance diagnostic accuracy, ultimately contributing to improved patient care and medical advancements.

Keywords: RCNN; Chest X-Ray Classification; Deep Learning; Lung Disease Detection; Synthetic Image Augmentation; Medical Image Processing

1. Introduction

This system integrates medical image analysis with deep learning techniques, specifically Region-based Convolutional Neural Networks (RCNNs). Chest X- ray images serve as the primary input data source, offering a non-invasive and efficient method for assessing lung conditions. To enhance image quality and ensure consistency in the input, the system employs a series of preprocessing steps before analysis.

The RCNN model is designed to identify and highlight regions of interest within the images, particularly areas that may indicate pathological concerns. A key feature of this system is the inclusion of RCNN-driven synthetic image generation, which effectively addresses data imbalance issues common in medical datasets. This imbalance often arises in cases involving rare diseases or less common conditions, where certain categories may be significantly underrepresented. Without this correction, the model's performance could be compromised due to biased training data. The classification module, built using the RCNN framework, extracts key features and classifies the input images into specific categories such as pneumonia, lung cancer, COPD, COVID-19, or normal cases. Implemented in MATLAB, the system leverages its advanced deep learning toolboxes for training, validation, and performance assessment. The system's output provides diagnostic predictions, assisting healthcare professionals in making well-informed clinical decisions.

* Corresponding author: C. Pabitha

2. Literature review

2.1. Enhanced BI-ResNet Model for Lung Sound Classification and Recognition

The enhanced Bi-ResNet model proposed by C. Wu, N. Ye, and J. Jiang significantly improves lung sound classification accuracy by incorporating skip connections and additional direct links within the network. This enhancement boosts feature extraction, resulting in a notable classification accuracy of 77.81%, marking a 25.02% improvement over the baseline Bi-ResNet model. The model also achieved an F1 score of 71.05%, demonstrating its effectiveness in distinguishing various lung sound types

Limitations

- The model's performance may vary with different datasets due to variations in recording conditions and equipment.
- Limited real-world testing in clinical environments may affect its practical applicability.
- The model may require significant computational resources for training and deployment.

2.2. Classifying Lung Patterns Using a Deep Convolutional Neural Network for Interstitial Lung Diseases.

In their 2016 study, Marios Anthimopoulos et al. introduced a CNN for classifying ILD patterns with 85.5% accuracy. The model features five convolutional layers, LeakyReLU activations, and classifies seven lung conditions. Trained on 14,696 image patches, it aids CAD systems, with future plans for 3D CT scan integration.

Limitations

- The model's performance may vary across different imaging protocols and scanner types due to dataset variability...
- Limited testing on real-time clinical cases may restrict its immediate adoption in healthcare settings.
- The proposed method focuses solely on 2D image patches, limiting its ability to analyze complete 3D lung structures, which are often crucial for accurate ILD diagnosis.

2.3. Deep Learning-Based Multi-Label Lung Disease Classification

In their 2024 study, Muhammad Irtaza et al. applied deep learning models like MobileNet, DenseNet, and VGG-16 to classify lung diseases using the NIH Chest X-ray dataset.

Mobile Net achieved the best results. To address class imbalance, they used a GAN, improving the F1-score from 0.553 to 0.582.

Limitations

- The model's recall score of 57% suggests potential challenges in correctly identifying positive cases, which may impact early diagnosis reliability.
- The study's focus on the NIH Chest X-ray dataset limits generalization to other datasets with varying imaging conditions or demographics.

2.4. Classifying Lung Sounds Through Co-Tuning and Stochastic Normalization

In their 2022 study, Tho Nguyen and Franz Pernkopf proposed using ResNet models with lung sound co-tuning and stochastic normalization classification. Their methods, combined with time- frequency data augmentation and spectrum

correction, effectively addressed class imbalance and device variability, outperforming most cutting- edge methods for classifying lung sounds.

Limitations

- The model's performance may vary when applied to unseen datasets with significantly different recording conditions.
- Dependence on pre-trained models may limit adaptability to rare or unconventional lung sound patterns.

- Improving the Classification of Lung Acoustic Signals Using Conventional and Eigenvector- Based Augmentation Techniques.

In their 2024 study, Nithin Babu et al. proposed an automated lung sound classification system using eigenvector-based data augmentation to improve detection rates. By extracting key features from spectrograms and applying machine learning classifiers, the system effectively reduces noise and enhances diagnostic accuracy in low-resource healthcare settings.

Limitations

- The eigenvector-based method may struggle with highly complex or rare lung sound patterns.
- Performance may vary with unseen data from different recording devices or environments

3. Methodology

3.1. Data Collection and Preprocessing:

The proposed multi-label lung disease classification system processes chest X-ray images from datasets like NIH Chest X-ray and CheXpert. Using CNN architectures such as ResNet and EfficientNet, the model applies preprocessing techniques like resizing, normalization, and augmentation to enhance generalization. Transfer learning improves feature extraction, while binary cross-entropy loss optimizes classification accuracy. Grad-CAM visualizations provide interpretability, helping radiologists understand model predictions. The model is integrated into a web or mobile interface for real-world deployment, supporting healthcare professionals in accurate and efficient diagnosis.

3.2. Multi-LabelEncoding:

The proposed lung disease classification model effectively identifies multiple conditions using chest X-ray datasets such as CheXpert and NIH Chest X- ray. Leveraging CNN architectures such as ResNet and EfficientNet, the system enhances performance through data augmentation and transfer learning. Binary cross-entropy loss ensures precise multi- label classification, while Grad-CAM visualizations improve interpretability. Integrated into a web or mobile platform, the model assists healthcare professionals in delivering accurate and timely diagnoses

- Data tilization: Uses NIH Chest X-ray and CheXpert datasets.
- Model Architecture: Employs ResNet and EfficientNet with transfer learning.
- Data Enhancement: Includes resizing, normalization, and augmentation.
- Performance Optimization: Uses binary cross- entropy loss to improve accuracy.
- Deployment: Integrated into web and mobile platforms for real-time diagnosis.

3.3. Model Selection and Architecture Design:

The proposed system efficiently classifies multiple lung diseases using deep learning models like ResNet and EfficientNet. Data preprocessing steps such as resizing, normalization, and augmentation improve model generalization. Binary cross-entropy loss is applied to enhance multi-label classification accuracy. Grad-CAM visualizations ensure interpretability by highlighting key image regions. Integrated into web and mobile platforms, the system aids healthcare professionals in providing faster, more accurate lung disease diagnosis.

3.4. Preprocessing Module

Preprocessing is a crucial step in getting data ready for deep learning models with the goal of enhancing image quality and ensuring data uniformity.

3.4.1. Normalization

Normalization adjusts pixel intensity values to a fixed range, such as [0, 1] or [-1, 1]. This step By maintaining a consistent intensity distribution, the model can focus more effectively on key patterns while minimizing distractions from noise or irrelevant variations.

3.4.2. Image Enhancement

Image enhancement techniques improve the visual quality of chest X-ray images by increasing contrast, reducing noise, and sharpening critical details. Methods such as histogram equalization, contrast stretching, and adaptive contrast enhancement are commonly employed. These enhancements improve the model's ability to detect important lung structures, enhancing feature extraction.

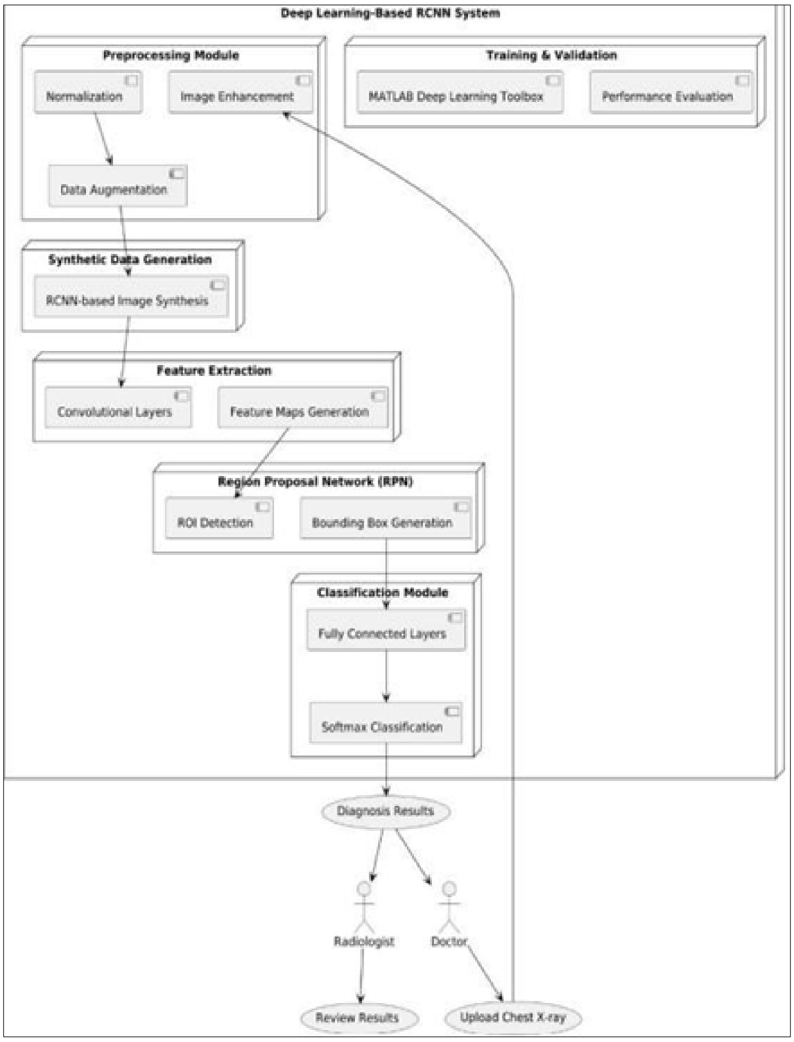

Figure 1 Architecture Diagram II Synthetic Data Generation

Since medical imaging datasets are often imbalanced or insufficient, synthetic data generation techniques are crucial for improving model robustness.

3.5. RCNN-based Image Synthesis:

Using an RCNN framework, synthetic chest X-ray images are generated to augment the dataset. This helps mitigate class imbalance issues, especially for rare lung conditions.

The synthetic data mimics real-world conditions by preserving key anatomical structures whilediversifying visual patterns.

3.5.1. Feature Extraction

Feature extraction is the core of the RCNN system, where critical visual patterns from X-ray images are identified for accurate diagnosis.

- Convolutional Layers: These layers automatically extract important image features such as edges, textures, and shapes.
- Each layer progressively identifies more complex patterns, enhancing the model's ability to detect lung conditions.
- Visual depictions of extracted features are called feature maps. They draw attention to important areas that influence the model's judgment. These maps aid in the detection of anomalous lung patterns such consolidations, nodules, or opacities.

3.5.2. Region Proposal Network (RPN)

The RPN module is responsible for identifying the most relevant areas in an X-ray image that may contain abnormalities.

- ROI (Region of Interest) Detection:
- The system scans the entire X-ray image and identifies potential regions that could indicate disease.
- By focusing on key areas such as lung fields, the model reduces irrelevant data processing.

3.5.3. Bounding Box Generation

After identifying ROIs, the system generates bounding boxes to localize suspected abnormalities. Each bounding box highlights regions where the model predicts disease presence, allowing healthcare professionals to focus on specific areas

3.5.4. Classification Module

Once features are extracted and ROIs are identified, the system classifies the detected abnormalities.

- Fully Connected Layers
  - These layers aggregate extracted features to produce meaningful predictions.
  - By combining information from different convolutional layers, the network refines its understanding of disease patterns.
- Softmax Classification
  - The final classification layer uses each class is given a probability using a softmax function..This step outputs the likelihood of specific lung diseases, ensuring multi-class classification capability.

3.6. Diagnosis and Results

The system's final stage delivers results to medical professionals for evaluation and decision- making.

3.6.1. Diagnosis Results

The system provides detailed diagnostic reports indicating potential lung conditions with corresponding confidence scores.

3.6.2. Review Results

Radiologists and doctors can assess the system's predictions to confirm accuracy and provide expert insights.

Interpretability tools that illustrate the regions that impacted the model's conclusions include Grad- CAM (Gradient-weighted Class Activation Mapping).

3.6.3. Upload Chest X-ray

By enabling real-time diagnostic predictions and guaranteeing ongoing use in clinical practice, the technology enables medical personnel to upload new chest X-ray images.

3.6.4. Training and Optimization

The model is trained using binary cross-entropy loss (suitable for multi-label tasks), the Adam optimizer, and dropout techniques to prevent overfitting. Class imbalance is tackled through weighted loss functions and oversampling strategies

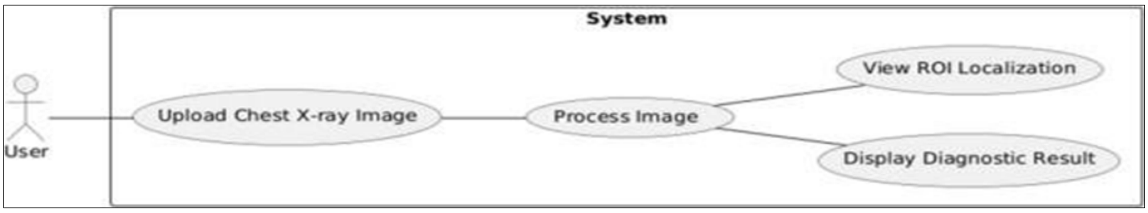

Figure 2 Use case Diagram

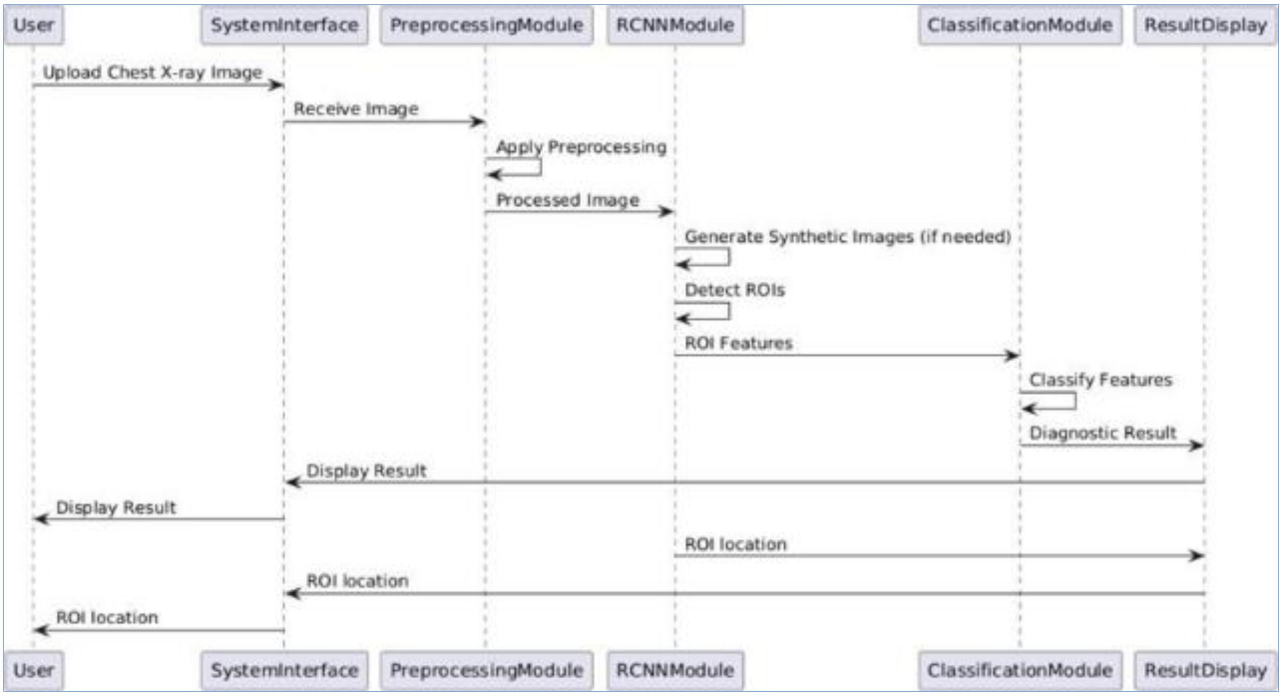

Figure 3 Sequence Diagram

4. Future enhancements

4.1. Dataset Expansion for Improved Accuracy

Expanding the dataset to include a broader range of patient demographics is essential for enhancing the model's reliability. By incorporating data from various age groups, ethnicities, and medical conditions, the model can better generalize across different clinical scenarios. This approach reduces bias and improves diagnostic accuracy in real-world applications. Additionally, increasing the dataset's diversity by including images captured from different devices and imaging conditions can further improve the model's robustness and ensure consistent performance in healthcare settings.

4.2. Integration with Clinical Systems

Developing a Clinical Decision Support System (CDSS) that integrates seamlessly with Hospital Information Systems (HIS) and Picture Archiving and Communication Systems (PACS) can greatly enhance diagnostic efficiency. By providing automated AI-assisted diagnosis, such systems can support radiologists and healthcare professionals in making accurate decisions. Incorporating patient history, lab results, and other clinical information alongside chest X-ray images further improves diagnostic precision. This integration ensures timely insights, helping medical practitioners provide improved care and reducing the chances of diagnostic errors.

4.3. Enhancing Model Interpretability and Multimodal Learning:

To ensure the clinical usability of AI models, improving interpretability is crucial. Techniques such as visual explanations using Grad-CAM or saliency maps can help radiologists understand model decisions. Additionally, combining multimodal learning by integrating chest X-rays with other imaging modalities like CT scans and clinical data can improve diagnostic accuracy. Incorporating Natural Language Processing (NLP) to analyze radiology reports can further enhance insights, ensuring the model effectively supports healthcare professionals in accurate disease identification and decision-making.

4.4. Advancing Lung Disease Detection with RCNN and Synthetic Image Generation

This study demonstrates the effectiveness of a Region-Based Convolutional Neural Network (RCNN) in diagnosing lung conditions including COPD, COVID-19, lung cancer, and pneumonia using chest X-ray images. To address class imbalance issues, the study employed synthetic image generation, which improved data diversity and enhanced model performance.The RCNN model excels in detecting and localizing affected lung regions, enabling precise identification of abnormal patterns. This improved diagnostic accuracy is reflected in The model's excellent performance in terms of AUC-ROC, recall, accuracy, and precision.The research highlights the transformative potential of AI-driven medical imaging in enhancing early disease detection and clinical decision-making. By introducing an automated diagnostic system, this approach can assist healthcare professionals in delivering faster, more accurate diagnoses, ultimately improving patient care and outcomes.

5. Conclusion

This study emphasizes the efficiency of a Region- Based Convolutional Neural Network (RCNN) in detecting various lung illnesses using chest X-ray pictures, including COVID-19, lung cancer, pneumonia, and Chronic Obstructive Pulmonary Disease (COPD).The research introduces innovative techniques to address common challenges in medical imaging, particularly class imbalance issues, which are prevalent in datasets containing rare conditions.To overcome this imbalance, the study incorporated synthetic image generation methods, enhancing data diversity and ensuring the model received adequate training across all disease classes. This improved the RCNN’s performance, allowing it to achieve reliable and consistent predictions. By expanding the dataset with synthetic samples, the model effectively minimized bias toward more dominant classes and improved its ability to recognize fewer common conditions. The RCNN model's key strength lies in its precise detection and localization of lung regions affected by various diseases.

Unlike traditional classification models that only identify the presence of a disease, RCNN accurately pinpoints the affected areas within the chest X-ray. This ability to analyze intricate patterns and distinguish abnormalities enhances diagnostic accuracy. Consequently, the model delivered impressive results across several performance indicators, such as AUC-ROC, recall, accuracy, and precision, confirming its robustness in distinguishing between different lung conditions.

In addition to improving detection rates, this research highlights the transformative potential of AI-driven medical imaging in advancing early disease diagnosis. By integrating an automated diagnostic tool, the system empowers healthcare professionals to make making better judgments more quickly, cutting down on diagnostic delays, and enhancing patient outcomes. Such tools are especially valuable in resource-limited environments, where access to experienced radiologists may be limited

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] IEEE Access, vol. 12, pp. 73079-73094, 2024, doi:10.1109/ACCESS.2024.3404657, "Classification and Recognition of Lung Sounds Based on Improved BiResNet Model," by C. Wu, N. Ye, and J. Jiang.

[2] M. Anthimopoulos, S. Christodoulidis, L. Ebner, A. Christe, and S. Mougiakakou's paper, "Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network," was published in IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1207-1216, May 2016, doi:10.1109/TMI.2016.2535865. In

IEEE Transactions on Industrial Cyber- Physical Systems, vol. 1, pp. 1–20, 2023, Y. Liu, X. Tao, X. Li, A. W. Colombo, and S. Hu, "Artificial Intelligence in Smart Logistics Cyber-Physical Systems: State-of- The-Arts and Potential Applications," doi: 10.1109/TICPS.2023.3283230

[3] M. Irtaza, A. Ali, M. Gulzar, and A. Wali's paper, "Multi-Label Classification of Lung Diseases Using Deep Learning," was published in IEEE Access, vol. 12, pp. 124062-124080, 2024, doi: 10.1109/ACCESS.2024.3454537.

[4] T. Nguyen and F. Pernkopf, "Lung Sound Classification Using Co-Tuning and Stochastic Normalization," IEEE Transactions on Biomedical Engineering, vol. 69, no. 9, Sept. 2022, pp. 2872-2882, doi: 10.1109/TBME.2022.3156293

[5] N. Babu, D. Pruthviraja, and J. Mathew's paper, "Enhancing Lung Acoustic Signals Classification With EigenvectorsBased and Traditional Augmentation Methods," was published in IEEE Access, vol. 12, pp. 87691–87700, 2024, doi:10.1109/ACCESS.2024.3417183. In IEEE Access, vol. 10, pp. 4441344445,2022, M. Elsanhoury et al., "Precision Positioning for Smart Logistics Using Ultra-Wideband Technology-Based Indoor Navigation: AReview,"doi:10.1109/ACCESS.2 022.3 169267.

[6] T. Wanasinghe, S. Bandara, S. Madusanka, D. Meedeniya, M. Bandara, and I. D. L. T. Díez, "Lung Sound Classification With Multi- Feature Integration Utilizing Lightweight CNN Model," IEEE Access, vol. 12, pp. 21262-21276, 2024, doi: 10.1109/ACCESS.2024.3361943. (doi:10.1109/ ACCESS.2024.3444282) Y. Lu, "Advancing Logistics Management: E3L-Net for Predictive Demand Analytics," IEEE Access, vol. 12, pp. 114809114819, 2024.

[7] S. R. Vinta, B. Lakshmi, 54 M. A. Safali, and G. S. C. Kumar, "Segmentation and Classification of Interstitial Lung Diseases Based on Hybrid Deep Learning Network Model," IEEE Access, vol. 12, pp.5044450458,2024, doi:10.1109/ACCESS.20

[8] 24.3383144 "Enabling Technologies to Support Supply Chain Logistics 5.0," by B. Andres, M. Diaz- Madroñero, A. L. Soares, and R. Poler, in IEEE Access, vol. 12, pp. 43889-43906, 2024, doi:10.1109/ACCESS.2024.3374194. S. Z. Y. Zaidi, M. U. Akram, A. Jameel, and N. S. Alghamdi's paper, "Lung Segmentation- Based Pulmonary Disease Classification Using Deep Neural Networks," appeared in IEEE Access, vol. 9, pp.125202125214,2021, doi:10.1109/ACCESS. 2021. 3110904

[9] In IEEE Access, vol. 12, pp. 185078-185102, 2024, M. S. Devi and S. Priya's paper, "Defending Data Poisoning Attack Through Watermarked Friendly Noise Luminosity Activated Dense Layered UNet for Classification of Lung Disease," doi: 10.1109/ACCESS.2024.3513485