

An Interpretable EfficientNet-Based Lung Disease Detection and Risk Assessment System Using Chest X-ray Images

Dr. G. A. V. Ramachandra Rao¹; Kallepalli Mythri²; Kintali Meghana³; Korada Karthik⁴; Manepalli Bobby⁵

^{1;2;3;4;5}Department of Computer Science and Engineering Lendi Institute of Engineering and Technology
Vizianagaram, India

Publication Date: 2026/06/03

Abstract: Early detection of lung-related disorders is critical in providing timely treatment; however, detecting any minor anomalies in the lung region from the chest X-ray image is difficult, taking much time to process manually. As a result, it is required to have an automatic system that can analyze chest X-ray images. For this research, deep learning technology is employed in analyzing chest X-ray images, where the chosen deep learning model is called EfficientNetB0, capable of extracting important patterns and categorizing them as normal, lung Opacity, or viral pneumonia. In order to enhance the performance of the deep learning model, the chest X-ray images are preprocessed using Contrast Limited Adaptive Histogram Equalization (CLAHE). Once the images are preprocessed, the system produces predictions based on the category and provides an accuracy measure. It is also responsible for assigning a risk level, alongside highlighting important areas of the images using Grad-CAM.

Keywords: Deep Learning, Chest X-ray, Lung Disease Classification, EfficientNetB0, CLAHE, Grad-CAM, Medical Image Analysis.

How to Cite: Dr. G. A. V. Ramachandra Rao; Kallepalli Mythri; Kintali Meghana; Korada Karthik; Manepalli Bobby (2026) An Interpretable EfficientNet-Based Lung Disease Detection and Risk Assessment System Using Chest X-ray Images.

International Journal of Innovative Science and Research Technology, 11(5), 2960-2967.

<https://doi.org/10.38124/ijisrt/26may1510>

I. INTRODUCTION

It is difficult for individuals to detect lung diseases in their early stage owing to complicated and small changes in chest X-ray images that cannot be observed by the naked eye [1], [2]. In most cases, diagnosis requires experienced radiologists and involves manual observation, taking longer time and varying based on the level of knowledge [3], [4]. This creates a disparity between quick and efficient diagnosis and reliable medical decision-making processes. Deep learning algorithms have been widely applied in the field of medical imaging to detect lung diseases using chest X-ray images [5], [6]. Most systems utilize CNN algorithms and transfer learning to identify different types of lung diseases, including pneumonia [7], [8]. Datasets such as ChestX-ray8 contain labeled medical images, which are used to train these algorithms [9]. Nonetheless, these systems are not necessarily consistent in their accuracy when performing feature extraction [10]. EfficientNet is a new deep learning architecture that provides better results by reducing the number of parameters while improving accuracy and consistency through a balance of depth, width, and resolution [11]. Model types

based on EfficientNet can successfully extract the meaningful information contained in chest X-rays and are thus applicable to the task of medical image classification. One of the problems arising in the design of medical diagnostic systems is the problem of explainability. Many neural network models cannot provide a clear explanation about their working principles, and therefore, it can be hard for the doctor to rely fully on the results predicted by these models. To solve this problem, the method of Grad-CAM is utilized, as it highlights those parts of the picture that have the largest impact on the model's decision-making process [12]. Besides choosing the proper model type, preprocessing the images prior to the training stage is essential. One of the methods often applied for this purpose is Contrast Limited Adaptive Histogram Equalization (CLAHE) [13]. This way, better learning of the representations by the model can be achieved. Moreover, the importance of explainable AI techniques is growing for medical applications for more reliable and trusted predictions [14]. In order to address these problems, the proposed system introduces the implementation of an AI-based model for lung disease classification using EfficientNetB0. This system mainly aims at the

classification of chest X-rays into three different classes – lung opacity, normal and viral pneumonia. The image is preprocessed using CLAHE before being classified, and Grad-CAM is used for visualizing relevant regions of lungs. The introduced system performs all the operations required and outputs the result of classification with confidence scores and risk levels, which can help understand the results better. The developed model outputs stable results each time. The main goal of the project is to provide assistance in early detection of lung diseases through medical analysis, not to take the place of doctors.

➤ *The Main Contributions of this Work are Listed Below:*

- The system uses EfficientNetB0 with CLAHE preprocessing for improved feature extraction and classification of chest X-ray images.
- It provides prediction along with confidence score and risk level for better interpretation of results.
- Grad-CAM visualization is integrated to highlight important regions in the X-ray images.
- The model is designed to give stable and consistent outputs across multiple runs

The remainder of this paper is organized as follows: Section II discusses related work, Section III presents the motivation and problem statement, Section IV explains the methodology, Section V shows experimental results, and Section VI concludes the paper.

II. RELATED WORK

Recently, artificial intelligence has been applied extensively in the field of analyzing medical images, specifically for detecting any lung ailments from the chest X-ray images. There are several researchers who have been working on various methods based on deep learning to detect any cases of pneumonia or other lung anomalies [1], [2]. Such systems not only help in saving time while diagnosing but also assist the doctor during the decision-making process.

A common technique that has been employed by several researchers while classifying the medical images is convolutional neural networks (CNNs). This technique makes use of the neural networks to automatically detect the necessary features in the data [3], [4]. Researchers also use transfer learning to classify the images using pre-trained models [5], [6]. Apart from the above, there are researchers who made use of multiple models for improving accuracy [7]. Additionally, the researchers make use of large datasets such as ChestX-ray8 to train their models [8].

In an effort to further boost efficiency, the approaches considered the impact of incomplete or inaccurate input data due to employing external datasets along with enhanced training approaches [9]. However, conventional CNN architectures might prove insufficient when it comes to computational cost. Hence, novel approaches based on architecture redesigns are proposed, which provide high accuracy levels through reduced parameters and effective

scaling of the neural network [10]. Such architectures prove particularly useful in the field of medical image processing. A preprocessing step was also employed during image analysis in order to ensure a higher quality of the visual content. For example, the CLAHE technique helped enhance the visibility of certain details in the images, which made it possible for the model to recognize specific elements and improve its efficiency [11].

Along with accuracy and efficiency, explainability has become an essential aspect of medical solutions. Thus, methods such as Grad-CAM were used to reveal the specific areas of an input image that affected the model's output [12]. Furthermore, efforts have been made to analyze CNN results in an attempt to interpret their significance [13]. Explainable AI also proved to be relevant for medical applications [14].

Although many such research works have been done before, the majority of those are concerned mostly about the accuracy of classification. Only some systems attempt to integrate the process of preprocessing along with other components of efficiency, visualization, and auxiliary components such as confidence and risk level measures. Thus, there remains the requirement of developing an integrated system that can serve in a realistic environment of medicine. In addition, most of the current models are not much concerned about the consistency of their outputs after repeated usage. Hence, developing a system that provides consistency and interpretability is another requirement.

III. MOTIVATION AND PROBLEM STATEMENT

➤ *Motivation*

The motivation behind this project is to make a computer-based system for the detection of early stages of lung disease through chest X-ray images. It is quite challenging for us to differentiate between normal and affected images because there is no major difference between them. Due to this challenge, diagnosis of disease mostly relies on expert doctors. Another motivation behind using deep learning is the speed of analysis of X-ray images. If we have fewer experts in any region, then it will be quite hectic for them to analyze such a large amount of data. Deep learning can be really useful for us in this regard.

It must be kept in mind that almost all existing models provide only predictions as their output without going into details of them. Due to this, it gets a bit tough for us to fully rely on those models. We should work on a model that provides some extra outputs, such as probability score and visual output as well.

➤ *Problem Statement*

The detection of lung disease, including pneumonia, using chest X-ray images poses many challenges since the images may not be perfect and variations between the classes are minute. Though many deep learning-based models are available for detection, mostly the models focus on only improving accuracy.

Moreover, many of the models function as a black box. In such cases, it becomes difficult for the doctors to use the models since they do not know how the predictions are done. Therefore, there arises a necessity to design an application that will use the chest X-ray images as input, preprocess them, and categorize them based on normal, lung opacity, and viral pneumonia. Moreover, along with classification, it is necessary for the model to provide the risk level, confidence score, and visualization using Grad-CAM. The overall aim of the model would be assisting the analysis process and early detection, but without replacing the doctor.

IV. PRELIMINARIES

➤ *Use of Deep Learning for Detection of Diseases from Images*

Nowadays, deep learning plays an important role in the field of medical image analysis, as deep learning techniques are often employed in order to detect diseases based on images like chest x-rays. There is no need for hand-crafted features in medical image analysis using deep learning. Deep learning can easily capture fine details in images, even those that cannot be perceived by humans.

Chest X-ray images serve as the inputs in this study. Due to the presence of noise or low-contrast images, preprocessing of chest x-ray images is done before they are provided to the model. The role of deep learning is that it serves as the core part of the whole system by providing relevant features learned from the image inputs.

➤ *EfficientNet for Image Classification*

EfficientNet is an advanced machine learning technique that achieves high levels of precision while reducing the number of parameters in the model through the efficient trade-off between network depth, width, and resolution. As a result, it outperforms numerous other CNN-based systems.

In the proposed system, the task of classifying the chest X-ray images is performed by EfficientNetB0. This network is capable of identifying meaningful features in images, which improves its performance significantly.

➤ *Image Preprocessing by CLAHE*

The pre-processing stage is very crucial before feeding the data to the neural network architecture. Medical images such as X-rays tend to have poor contrasts, making it hard for us to be able to identify some significant areas within the image. For this reason, CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied.

CLAHE increases the contrast of the medical image. This will enable us to be able to identify small parts of the lung that we would have missed otherwise.

➤ *Data Augmentation*

The process of data augmentation is done in order to enhance the quantity of the data set and improve the performance of the model. Since medical data sets have a limited number of images, data augmentation methods are

employed.

In our project, various methods such as rotation, flipping, and zooming are employed in creating diverse images from the already existing images.

➤ *Visualization Using Grad-CAM*

Most deep learning algorithms can be considered black box algorithms since it is not easy to comprehend how the predictions are made by the algorithm. The use of visualization algorithms such as Grad-CAM solves this problem.

Grad-CAM picks out those parts of the image that affect the predictions made by the algorithm. Grad-CAM is used in this project to visualize the heatmaps of regions in chest x-ray images that have been identified.

➤ *Performance Metrics*

The following metrics are utilized to determine the performance of the model. The number of correct predictions can be determined using accuracy. Precision and recall will assist in finding the performance of the model for identifying positive instances.

These metrics will assist in determining the performance of the model rather than relying solely on the accuracy measure.

➤ *Output of System and Interpretation of Output*

The input of the system is an X-ray image of the chest, and the output of the system will be in the form of a class like Normal, Lung Opacity, or Viral Pneumonia. Other than that, it will also provide other information, like a confidence score and risk level.

This helps to make the user aware of the information provided by the system. This system can be used as an aid for any medical analysis, but it should not be used instead of doctors.

V. METHODS TO BE USED IN THE PROPOSED MODEL

In the proposed model, the system detects any lung diseases from chest x-ray images through deep learning algorithms. The major emphasis in the proposed model is laid on the preprocessing of the image, then efficient feature extraction via EfficientNetB0, and finally, giving interpretable output using visualization techniques.

➤ System Workflow

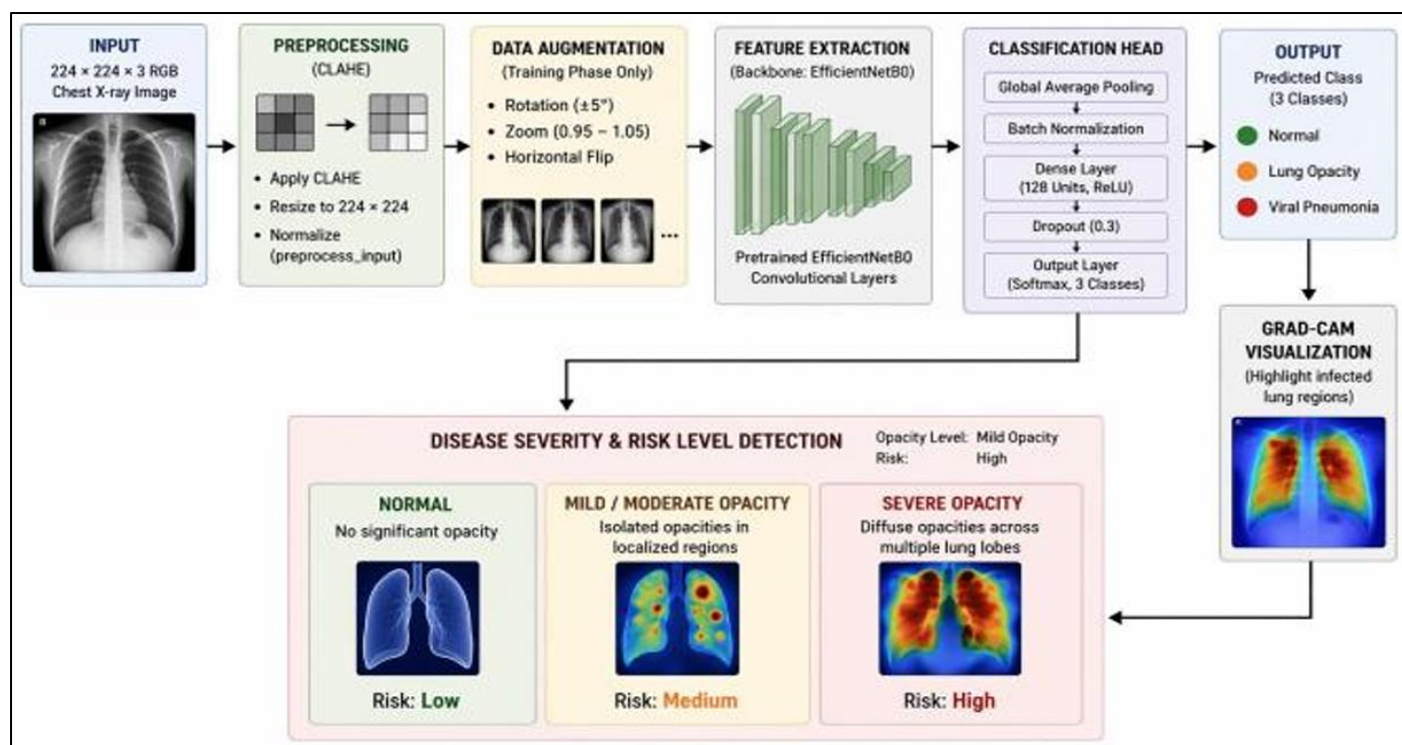


Fig 1 Overall System Workflow

The workflow of the system begins when the chest X-ray image is entered as an input to the model via the user interface. The input image then undergoes preprocessing, which includes contrast-limited adaptive histogram equalization. After preprocessing, normalization of EfficientNet is performed on the image.

While training the model, different methods like rotation, zoom, and horizontal flipping have been used to

augment the data and increase the size of the training set. Then, the input image is sent to EfficientNet B0 for feature extraction.

EfficientNetB0 then classifies the image into one of three classes viz., normal, lung opacity or viral pneumonia. Post classification, a heatmap is generated for the input image using the Grad-CAM technique.

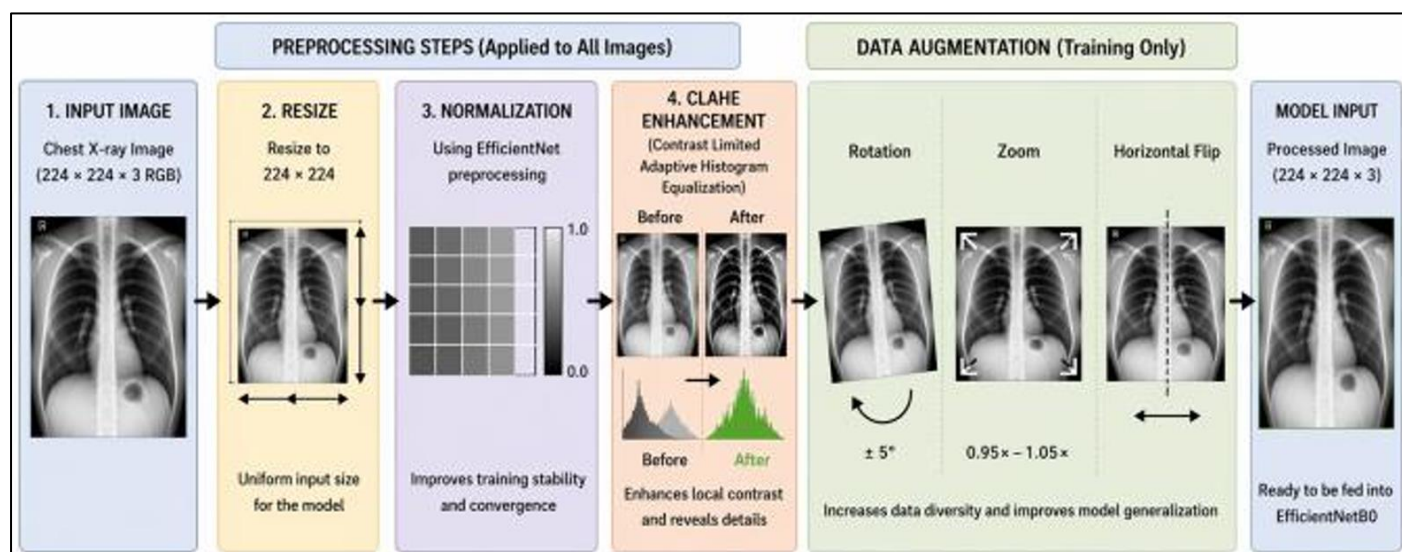


Fig 2 Image Processing Workflow of the Proposed System

➤ Image Processing Workflow

This section provides detailed information on the processing steps applied to the input chest x-ray image. In

this regard, the image undergoes resizing and normalization, followed by CLAHE to enhance contrast and increase visibility of lung areas.

Next, various forms of data augmentation are applied during training, thereby increasing the size of the dataset. The processed image is then fed into the EfficientNetB0 model to extract features.

Finally, the prediction step involves applying Grad-CAM to identify the salient regions in the image. The final output is provided together with the prediction and associated risk.

➤ *Image Preprocessing and Data Augmentation*

Initially, input images are preprocessed using CLAHE (Contrast Limited Adaptive Histogram Equalization) to enhance contrast. The image is transformed from RGB format to LAB, where the luminance channel is then subjected to histogram equalization to make lungs visible.

Once the images have been preprocessed, they are augmented using ImageDataGenerator. Methods like rotation, zooming, and flipping are applied. This ensures that the model will not be overfitted during training.

➤ *Model Architecture*

The EfficientNetB0 model is used as a base model for feature extraction with pre-trained weights from the ImageNet database. The layers of the network are truncated, and new classification layers are added to the base model.

A global average pooling step is applied to decrease feature dimensionality, then a batch normalization layer. Next, there is a dense layer with a ReLU activation function and dropout to overcome overfitting issues, and finally a softmax layer is used to classify the image into three classes.

The base model layers are not trained during the process; instead, they are frozen to preserve their learned features.

➤ *Training Approach*

For training the model, the Adam optimization algorithm together with categorical cross-entropy is used. Moreover, the early stopping technique is used to avoid overfitting.

In the training, the primary emphasis is laid on learning from the customized classification layers without changing the underlying layers of the EfficientNetB0 model. This way, the model benefits from pre-trained features, saves time, and attains generalization.

➤ *Performance Evaluation*

Performance of the model is measured based on accuracy, precision, recall, and F1-score. A confusion matrix is also calculated for analyzing the performance of

classification for each class.

The model is tested against the validation dataset, and predictions are compared to ground truth labels. This assists us in understanding the performance of the model and detecting any errors that might have occurred.

➤ *System Output and Deployment*

The last step is to save and deploy the model within a front-end interface that has been built using web programming languages. This allows the user to upload a chest X-ray image and receive the prediction result.

Output consists of prediction class, probability score, and associated risk level. Moreover, the Grad-CAM method is used to provide visualizations of areas in the lungs that are affected.

It is important to mention that the application serves as an auxiliary means for analysis purposes only.

VI. RESULTS AND DISCUSSION

➤ *Experimental Setup*

The experimental setup was conducted to measure the performance of the deep learning model that is developed to detect lung disease from chest X-ray images. Python was used to implement the model with TensorFlow and Keras packages. OpenCV was used for image preprocessing, while Matplotlib and Seaborn were employed for visualization.

In the experimental setup, the dataset was imported from Google Drive for training purposes. EfficientNetB0 with CLAHE and data augmentation was used to train the model in a GPU environment.

The dataset was partitioned into training, validation, and test datasets to facilitate appropriate testing and avoid overfitting issues during model training. Image resizing and normalization techniques were performed on images before being fed into the model.

Data augmentation techniques, including rotation, flip, and zoom, were utilized for improving the robustness of the model. Accuracy, precision, recall, F1-score, and confusion matrix were some of the metrics used to analyze the performance of the model.

Early stopping and learning rate reduction techniques were used during the training stage to enhance model convergence and classification performance. The final training process was performed with test images for validation purposes.

Table 1 System Configuration Details

System	Processor	RAM	Platform
Training System	Intel i7 / GPU	16 GB	Google Colab
Testing System	Intel i5	8 GB	Local Machine

➤ *Dataset Description*

The dataset contains chest X-ray images grouped into three classes: Normal, Lung Opacity, and Viral Pneumonia.

The images were preprocessed and augmented to improve model performance.

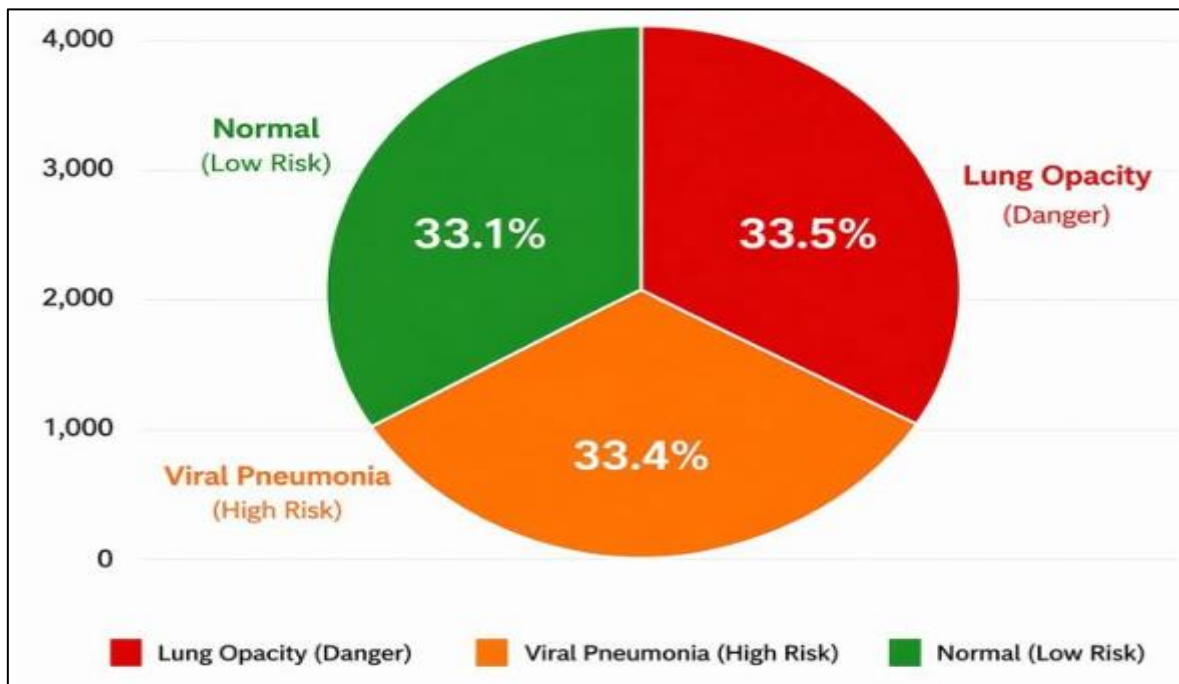


Fig 3 Dataset Distribution

Fig. 3 shows the class distribution. Variation in image quality helps the model learn generalized features.

custom model in order to avoid overfitting.

➤ *Model Training Performance*

Training was done using the pretrained EfficientNetB0 base layers with the classification layers updated for the

The model performed excellently on validation when classifying chest x-rays.

➤ *Performance Evaluation*

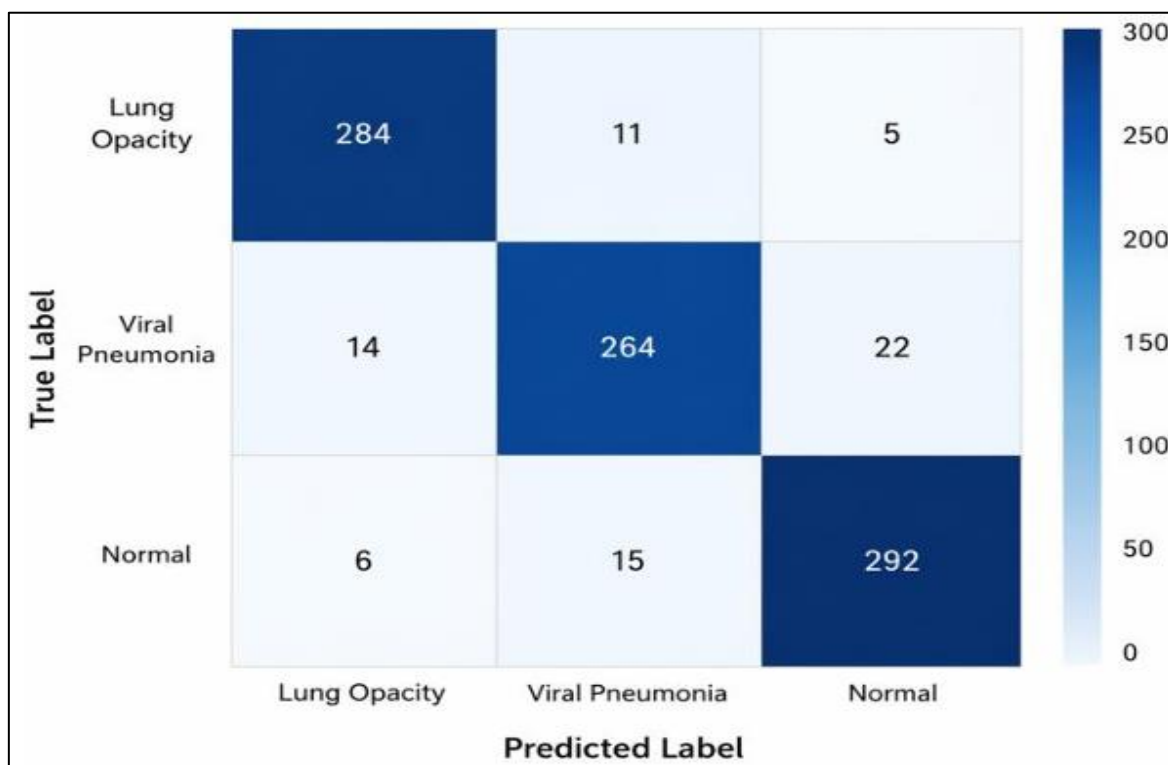


Fig 4 Confusion Matrix

Model performance was measured in terms of accuracy, precision, recall, and F1 Score. The confusion matrix in Fig. 4 depicts classification outputs by the classifier for each of the classes.

The model is able to classify the three classes with very little error.

➤ *Visualization Results using Grad-CAM*

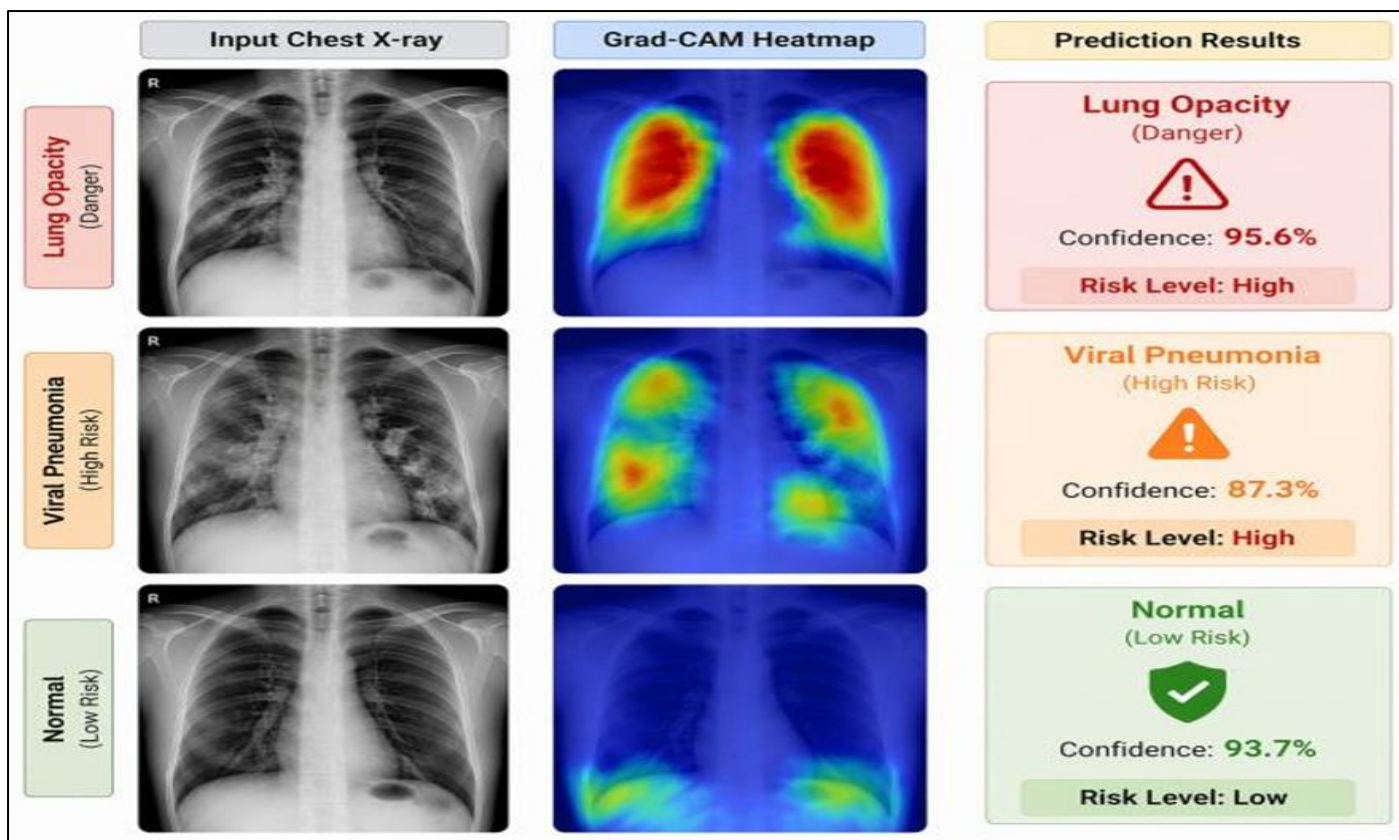


Fig 5 Grad-CAM Visualization Results

Grad-CAM highlights important regions in chest X-ray images. The heatmaps show where the model focuses while making predictions, helping to understand its behavior.

➤ *Sample Output Description*



Fig 6 Sample Output of the System

The system outputs predicted class, confidence score and risk level, making the results easier to interpret.

The new proposed system utilizes CLAHE preprocessing, EfficientNetB0, Grad-CAM visualization, and others to increase its practicality.

➤ *Comparing With Existing Literature*

Existing systems emphasize accuracy but lack the components such as preprocessing and visualization.

Table 2 Comparison with Existing Methods

Method	Preprocessing	Visualization	Extra Output
CNN Models	No	No	No
Transfer Learning Models	Partial	No Yes	No
Proposed System	Yes		Yes

➤ *Discussion*

The experimental results prove that the proposed system is an efficient one for the detection of diseases related to the lungs using chest X-ray images.

It is worth mentioning that the efficiency of the process relies on the quality of data utilized. Future scope could involve bigger datasets for more efficient performance.

To sum up, it should be mentioned that this system is highly useful for medical imaging purposes.

VII. CONCLUSION

This research work introduced a novel approach for identifying different lung ailments through the analysis of chest X-rays using an artificial intelligence-based model. The AI-based system consists of image preprocessing, the EfficientNetB0 model, data augmentation, and the Grad-CAM method.

As per the experimental results obtained, the integration of the CLAHE preprocessing method along with the efficient deep learning model performs better than basic CNN models in terms of feature extraction and identification of lung disease types. Data augmentation is a useful method that helps to improve the generalization capability of the model.

Furthermore, integrating Grad-CAM into the proposed model enhances interpretability by highlighting important regions in chest X-ray images. Additional features offered by the proposed model include confidence scores and risk levels. This system is a tool that can aid medical imaging in detecting any form of lung diseases. The system offers a user-friendly platform whereby users are able to upload images from chest X-rays to get predictions and visualizations at the same time.

In summary, this study presents a system that serves as a practical and efficient solution for the automated detection of lung diseases using images from chest X-rays. Some possible future work includes applying more data sets, optimizing the model, and expanding the detection to other lung diseases.

REFERENCES

- [1]. P. Rajpurkar et al., “CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning,” arXiv, 2017.
- [2]. A. Jacobi et al., “Portable chest X-ray in COVID-19: A pictorial review,” Clinical Imaging, 2020.
- [3]. D. S. Kermany et al., “Identifying medical diagnoses and treatable diseases by image-based deep learning,” Cell, 2018.
- [4]. Y. Bai et al., “Review on pneumonia image detection: A machine learning approach,” Human-Centric Intelligent Systems, 2022.
- [5]. A. K. Jaiswal et al., “Identifying pneumonia in chest X-rays: A deep learning approach,” Measurement, 2019.
- [6]. R. Kundu et al., “Pneumonia detection using an ensemble of deep learning models,” PLoS ONE, 2021.
- [7]. N. Dey et al., “Customized VGG19 architecture for pneumonia detection in chest X-rays,” Pattern Recognition Letters, 2021.
- [8]. L. Luo et al., “Deep mining external imperfect data for chest X-ray disease screening,” arXiv, 2020.
- [9]. X. Wang et al., “ChestX-ray8: Hospital-scale chest X-ray database and benchmarks,” IEEE CVPR, 2017.
- [10]. R. Tjoa and C. Guan, “A survey on explainable artificial intelligence (XAI): Toward medical applications,” Information, 2025.
- [11]. M. Tan and Q. V. Le, “EfficientNet: Rethinking model scaling for CNNs,” ICML, 2019.
- [12]. R. R. Selvaraju et al., “Grad-CAM: Visual explanations from deep networks,” ICCV, 2017.
- [13]. S. M. Pizer et al., “Adaptive histogram equalization and its variations,” CVGIP, 1987.
- [14]. S. Rajaraman et al., “Visualization and interpretation of CNN predictions in detecting pneumonia,” Applied Sciences, 2018.