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AI-Based Chest Disease Detection System.

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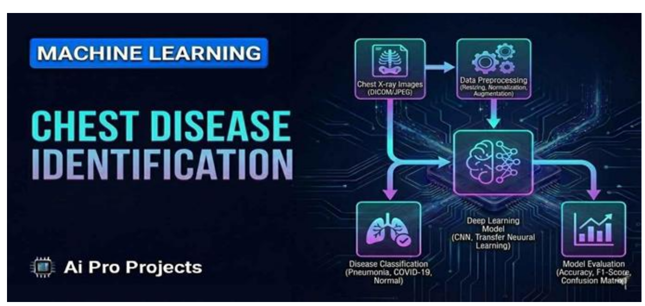
Abstract: Chest diseases such as pneumonia, tuberculosis, and COVID-19 continue to be major global health concerns, leading to significant morbidity and mortality. Accurate and early diagnosis is essential for effective treatment; however, traditional methods rely heavily on expert radiologists to interpret chest X-ray images, which can be time-consuming and subject to variability. In many regions, the shortage of skilled professionals further limits timely diagnosis, highlighting the need for automated and reliable solutions. This work presents an Adaptive Explainable AI framework for chest disease detection that combines deep learning, interpretability, and confidence estimation. A Convolutional Neural Network (CNN) is utilized to automatically learn relevant features from chest X-ray images and classify them into multiple categories, including COVID-19, pneumonia, tuberculosis, and normal cases. To address the lack of transparency in deep learning models, explainable AI techniques such as Grad-CAM and saliency maps are incorporated. These methods provide visual insights by highlighting regions in the X-ray image that contribute most to the model's prediction. In addition, the system estimates prediction confidence using probability-based measures, allowing users to assess the reliability of the output. A severity estimation module is also included, which analyzes the extent of affected regions in the image to categorize the condition into levels such as mild, moderate, or severe. This adds practical value for decision-making and prioritization. The proposed system is implemented as a web-based application, enabling users to upload chest X-ray images and receive real-time predictions along with visual explanations and severity assessment. Experimental observations indicate that the model achieves satisfactory performance while improving interpretability and user trust. Overall, the framework provides a balanced approach between accuracy, transparency, and usability, making it suitable as a supportive tool in medical diagnosis.

.Keywords: Chest Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Medical Image Analysis, Chest X-ray Classification, Explainable Artificial Intelligence (XAI), Grad-CAM, Saliency Maps, Confidence Estimation, Severity Analysis, Healthcare Decision Support System.

I. INTRODUCTION

Chest diseases such as pneumonia, tuberculosis, and COVID-19 continue to pose significant challenges to global healthcare systems. These diseases are among the leading causes of mortality and morbidity, particularly in developing countries where access to advanced medical facilities and skilled professionals is limited. Early and accurate detection of such diseases is essential for timely treatment, reducing complications, and improving patient outcomes. Chest X-ray imaging is one of the most widely used diagnostic tools for detecting lung-related abnormalities due to its



affordability, speed, and availability. However, interpreting X-ray images requires specialized knowledge and experience, and even skilled radiologists may sometimes face difficulties due to overlapping patterns and subtle differences in disease characteristics. In many real-world scenarios, especially in rural and under-resourced regions, there is a shortage of expert radiologists.

This results in delayed diagnosis, increased workload on healthcare professionals, and potential errors in interpretation. These challenges highlight the need for automated systems that can assist in analyzing medical images quickly and accurately. With the rapid advancement of Artificial Intelligence (AI), particularly in the field of deep learning, there has been growing interest in developing intelligent systems for medical image analysis.

Deep learning models have the ability to automatically learn complex features from data, making them highly suitable for tasks such as image classification and pattern recognition. Among various deep learning techniques, Convolutional Neural Networks (CNNs) have shown remarkable success in processing and analyzing image data. CNNs are capable of capturing both low-level features, such as edges and textures, and high-level features, such as shapes and structures within medical images.

This makes them highly effective for detecting abnormalities in chest X-rays and classifying them into different disease categories. Many studies have demonstrated that CNN-based models can achieve performance comparable to human experts in certain diagnostic tasks. However, despite their high accuracy, these models often operate as "black-box" systems, meaning that they provide predictions without explaining how those decisions are made. The lack of interpretability is a major concern in healthcare applications, where understanding the reasoning behind a decision is as important as the decision itself. Medical professionals require clear explanations to trust and validate AI-based predictions before incorporating them into clinical practice.

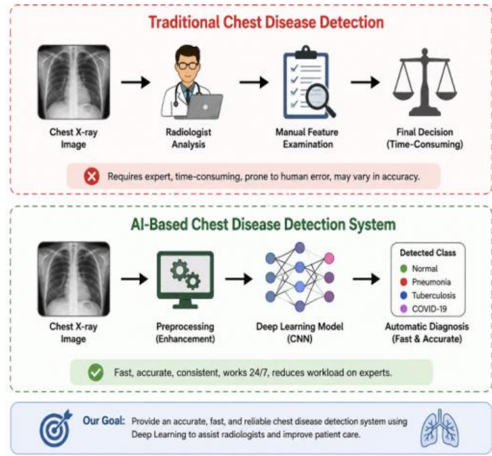


Figure 1 Comparison Between Traditional Methods and AI-Based Approach

To address this issue, Explainable Artificial Intelligence (XAI) techniques have been introduced. Methods such as Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency maps provide visual explanations by highlighting the regions in an image that have the greatest influence on the model's prediction.

These visualizations help in identifying affected areas in the lungs and enable users to better understand the model's behavior. Another important challenge in medical AI systems is the reliability of predictions. In critical applications such as disease diagnosis, it is not sufficient for a system to simply provide a classification result. It is equally important to measure the confidence or uncertainty associated with that prediction. Uncertainty estimation techniques allow the system to identify cases where the model is less confident, which can then be referred to medical experts for further analysis. This reduces the risk of incorrect diagnoses and improves the overall safety of the system. In addition to classification and explainability, assessing the severity of a disease is also crucial for effective patient management. Different levels of severity require different treatment approaches, and providing this information can help in prioritizing medical care.

Therefore, incorporating a severity estimation mechanism into the system adds practical value and enhances its usefulness in real-world healthcare scenarios. In this research, an Adaptive Explainable AI framework for chest disease detection is proposed. The system integrates deep learning, explainability, and confidence estimation into a unified pipeline. A CNN-based model is used to classify chest X-ray images into multiple categories, including COVID-19, pneumonia, tuberculosis, and normal conditions. The model is trained on a combined dataset collected from multiple sources to improve its generalization capability and robustness. To improve transparency, the system incorporates Explainable AI techniques such as Grad-CAM and saliency maps, which generate heatmaps highlighting important regions in the X-ray images. These visual explanations make it easier for users to understand the reasoning behind the predictions.

Additionally, the system includes a confidence estimation mechanism that provides probability scores, helping users assess the reliability of the results. A severity estimation module is also implemented, which analyzes the extent of affected regions in the lungs and categorizes the condition into levels such as mild, moderate, or severe. Furthermore, the entire system is implemented as a web-based application using Flask, providing an interactive and user-friendly interface. Users can upload chest X-ray images and receive real-time predictions along with visual explanations, confidence scores, severity levels, and suggestions for further action. This makes the system accessible not only to medical professionals but also to general users who may benefit from preliminary analysis. Overall, the proposed framework aims to address key limitations of existing systems by combining accuracy, interpretability, and reliability in a single platform. By integrating deep learning with explainable AI and uncertainty-aware diagnosis, the system provides a more transparent and trustworthy solution for chest disease detection. This approach has the potential to support healthcare professionals in decision-making, reduce diagnostic workload, and improve accessibility to medical analysis, especially in resource-limited environments.

II. THEORY

2.1 Background Theory

Chest disease detection is a medical image analysis technique used to identify diseases such as COVID-19, Pneumonia, and Tuberculosis from chest X-ray images. It is considered one of the most effective diagnostic approaches because chest X-rays provide detailed information about lung conditions and abnormalities. Different chest diseases create unique patterns in the lungs, which can be analyzed using Artificial Intelligence and Deep Learning techniques.

The process of chest disease detection generally involves multiple stages. The first step is image acquisition, where chest X-ray images are collected from datasets or uploaded by users through the web application. These images act as the input for the system. However, raw X-ray images may contain noise, low contrast, or unwanted variations that can reduce prediction accuracy. Therefore, image preprocessing techniques are applied before analysis. Image preprocessing includes resizing, normalization, noise reduction, and contrast enhancement. Resizing ensures that all images have the same dimensions required by the model. Normalization scales pixel values into a fixed range, improving model performance.

Noise reduction removes unnecessary distortions from the image, while contrast enhancement improves the visibility of important lung regions. After preprocessing, the image is passed to the Convolutional Neural Network (CNN) model. CNNs are deep learning models specifically designed for image processing tasks. They automatically extract important features such as edges, textures, patterns, and infected regions from chest X-ray images. CNN models consist of convolution layers, pooling layers, and fully connected layers that work together to learn meaningful disease-related patterns. The convolution layers extract low-level and high-level image features, while pooling layers reduce image dimensions and computational complexity. The fully connected layers combine all extracted features and perform final disease classification. The model predicts whether the chest X-ray belongs to categories such as COVID-19, Pneumonia, Tuberculosis, or Normal. Modern AI systems also use Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM to improve transparency and interpretability. Grad-CAM generates heatmaps that highlight the important regions of the lungs influencing the prediction. These visual explanations help users and doctors understand how the model arrived at a particular decision. In addition, the proposed system includes a severity detection module that categorizes diseases into mild, moderate, or severe levels based on infected lung regions. The recommendation module further provides personalized suggestions such as exercises, yoga, diet plans, and nearby hospitals. Overall, Deep Learning and Explainable AI have significantly improved the accuracy, speed, and reliability of chest disease detection systems. These technologies reduce manual effort, support healthcare professionals, and enable faster medical diagnosis in real-world applications.

2.2 Literature Review

Rajpurkar et al. [1] introduced a deep learning-based system called CheXNet for pneumonia detection using chest X-ray images. Their model utilized a DenseNet architecture and achieved performance comparable to expert radiologists. The study demonstrated the effectiveness of Convolutional Neural Networks (CNNs) in medical image classification tasks. However, the model lacked interpretability, which limited its practical use in clinical environments. Wang et al. [2] developed the ChestX-ray8 dataset and proposed a weakly supervised learning approach for detecting multiple thoracic diseases.

Their work enabled large-scale training of deep learning models using labeled datasets. Although this contribution significantly improved dataset availability, it did not focus on explainability or uncertainty in predictions. Kermany et al. [3] applied deep learning techniques for medical image classification, including pneumonia detection from chest X-rays. Their CNN-based model achieved high accuracy and highlighted the potential of automated diagnosis systems. However, the study mainly emphasized classification performance without providing insights into the model's decision-making process. Apostolopoulos and Mpesiana [4] proposed a transfer learning approach using pre-trained CNN models such as VGG19, MobileNet, and Inception for COVID-19 detection. Their method improved performance on limited datasets by utilizing pre-trained features. Despite its effectiveness, the approach lacked mechanisms for explaining predictions. Ozturk et al. [5] developed a deep neural network model for automatic COVID-19 detection using chest X-ray images.

Their model showed good classification performance; however, it did not include explainability features, making the results difficult to interpret. Selvaraju et al. [6] introduced Gradient-weighted Class Activation Mapping (Grad-CAM), an explainability technique that highlights important regions in an image influencing model predictions. This method significantly improved transparency in deep learning models and has been widely adopted in medical imaging applications. Simonyan et al. [7] proposed saliency maps as a technique to visualize pixel importance in image classification tasks.

This approach provides valuable insights into which regions of the image contribute most to the prediction, thereby enhancing interpretability. Gal and Ghahramani [8] introduced Monte Carlo Dropout as a method for estimating uncertainty in deep learning models. Their approach enables models to provide confidence measures, which are essential in critical applications such as medical diagnosis. Rajpurkar et al. [9] further explored deep learning in chest X-ray analysis and emphasized the importance of developing reliable and interpretable models. Their work highlighted challenges related to generalization and model trust. Irvin et al. [10] proposed CheXpert, a large dataset and benchmark for chest radiograph interpretation.

Their work improved model training and evaluation; however, it did not integrate explainability or severity estimation into the system. He et al. [11] proposed the ResNet architecture, which introduced residual learning to address the problem of vanishing gradients in deep neural networks. This architecture significantly improved image classification performance and is widely used in medical image analysis. Ribeiro et al. [12] introduced LIME (Local Interpretable Model-Agnostic Explanations), a technique used to explain predictions of machine learning models. This method provides local explanations by identifying important features influencing the prediction. Goodfellow et al. [13] provided a comprehensive foundation of deep learning concepts, including neural networks, optimization techniques, and architectures that support modern AI-based systems. Ndzi [14] explored the application of deep learning techniques in medical image analysis, emphasizing the effectiveness of CNN models in disease detection. Irvin et al. [15] highlighted the importance of large datasets and uncertainty handling in chest radiograph analysis for improving model performance. Zhang et al. [16] proposed a deep learning framework using DenseNet for automated detection of chest diseases from X-ray images.

Their model achieved high classification accuracy by utilizing dense connections for better feature propagation. However, the study mainly focused on performance improvement and did not include interpretability techniques. Yadav et al. [17] developed a hybrid deep learning model combining CNN and transfer learning for detecting COVID-19 from chest X-rays. Their approach improved accuracy and reduced training time by leveraging pre-trained models. Despite its effectiveness, the system lacked explainability and confidence estimation features. Ardakani et al. [18] compared multiple deep learning models such as ResNet, VGG, and DenseNet for COVID-19 detection. Their study highlighted that deeper architectures perform better in medical image classification. However, the research did not address transparency or uncertainty in predictions. Chowdhury et al. [19] introduced a large-scale dataset for COVID-19 detection and applied deep learning models for classification. Their work contributed to improved model training through diverse datasets. However, the study focused mainly on classification accuracy without integrating explainable AI methods.

2.3 Gaps Identified

Despite From the analysis of existing research, several important gaps have been identified in current chest disease detection systems. Although many studies have successfully applied deep learning techniques, particularly Convolutional Neural Networks (CNNs), to achieve high classification accuracy, most of these models primarily focus only on prediction performance. They often function as black-box systems, providing results without explaining how the decision was made. As a result, this lack of interpretability reduces trust among medical professionals and limits the adoption of such systems in real-world clinical environments. Furthermore, another major limitation observed in existing systems is the absence of uncertainty estimation. In most cases, models provide a predicted class label without indicating the confidence level of the prediction. In critical applications such as healthcare, this can be risky, as incorrect or uncertain predictions may lead to improper diagnosis or delayed treatment. Therefore, the ability to quantify prediction confidence and identify uncertain cases is essential but still not widely implemented.

In addition, many existing approaches do not consider disease severity analysis. While models are capable of detecting whether a disease is present, they do not provide information about how severe the condition is. Severity estimation plays a crucial role in medical decision-making, as it helps in determining treatment strategies and prioritizing patient care. The lack of this feature reduces the practical usefulness of current systems. Moreover, dataset-related limitations are also evident in previous studies. Many models are trained on limited or single-source datasets, which affects their generalization capability across different populations and imaging conditions. Variations in image quality, noise, and class imbalance further impact model performance.

These issues can lead to biased predictions and reduced reliability when applied in real-world scenarios. Another significant gap is the lack of integration of multiple important components within a single framework. Existing systems typically address classification, explainability, uncertainty estimation, and severity analysis separately rather than combining them into a unified solution. This fragmented approach limits the overall effectiveness and usability of the system. To overcome these challenges, the proposed system introduces an integrated framework that combines deep learning-based classification with Explainable Artificial Intelligence (XAI) techniques, uncertainty-aware prediction, and severity estimation. This approach aims to enhance transparency, improve reliability, and provide more meaningful insights, making the system more suitable for practical healthcare applications.

III. SYSTEM ARCHITECTURE

3.1 verview

The Data Flow Diagram (DFD) represents the flow of data within the proposed chest disease detection system. It illustrates how input data is processed through different modules to generate the final output. The system follows a structured flow where each component performs a specific function in transforming the input X-ray image into meaningful diagnostic results. The process begins with the user, who uploads a chest X-ray image through the web interface. This image acts as the primary input to the system. The uploaded image is then passed to the preprocessing module, where operations such as resizing, normalization, and noise reduction are performed to prepare the image for analysis. This ensures consistency and improves the quality of input data for the model.

After preprocessing, the image is forwarded to the deep learning model, which is a Convolutional Neural Network (CNN). The model analyzes the image and extracts relevant features to classify it into one of the disease categories such as COVID-19, Pneumonia, Tuberculosis, or Normal. Along with the predicted class, the model also generates probability values that are used as confidence scores. The processed data is then passed to the explainability module, where techniques such as Grad-CAM are applied to generate heatmaps. These heatmaps highlight the important regions in the X-ray image that influenced the prediction.

This step improves transparency and helps users understand the model's decision-making process. In parallel, the system performs severity estimation by analyzing the highlighted regions in the heatmap. Based on the extent of affected areas, the condition is categorized into different levels such as mild, moderate, or severe. Finally, all the processed information, including the predicted disease, confidence score, severity level, and visual explanations, is sent to the output module. The results are displayed to the user through the web interface in a clear and understandable format. The system may also provide suggestions based on the detected condition. Overall, the DFD demonstrates a smooth and logical flow of data from input to output, ensuring that the system operates efficiently while providing accurate and interpretable results.

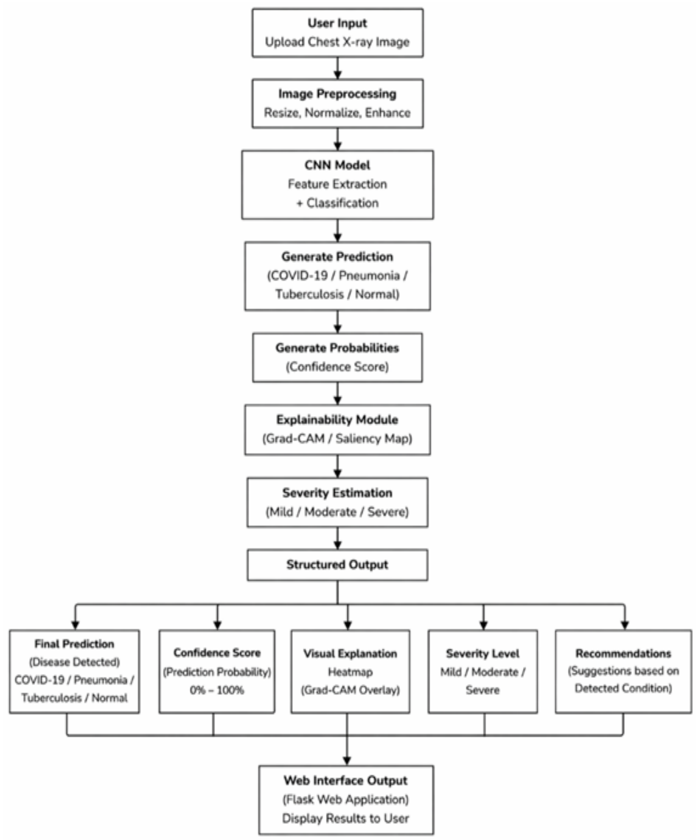


Figure 2 System Architecture of Chest Disease Detection System

Table 1 Reasearch Papers Methods Comparison

Sr. No	Type of Detection	Researchers	Year	Approach	Dataset	Accuracy / Performance / Notes
1	Chest Disease Detection	Wang et al.	2017	ChestX-ray8 CNN Model	NIH Chest X-ray Dataset	Large-scale chest disease dataset
2	Pneumonia Detection	Rajpurkar et al.	2017	CheXNet (DenseNet-121)	ChestX-ray14	Radiologist-level performance
3	COVID-19 Detection	Apostolopoulos et al.	2020	Transfer Learning CNN	COVID-Xray Dataset	High COVID classification accuracy
4	Tuberculosis Detection	Lakhani & Sundaram	2017	Deep CNN	Shenzhen Dataset	Accurate TB identification
5	Deep Learning	Krizhevsky et al.	2012	AlexNet CNN	ImageNet	Breakthrough in image classification

Sr. No	Type of Detection	Researchers	Year	Approach	Dataset	Accuracy / Performance / Notes
6	Feature Extraction	Simonyan & Zisserman	2014	VGGNet	ImageNet	Deep feature learning
7	Medical Image Analysis	He et al.	2016	ResNet	Medical Imaging Dataset	Improved deep network training
8	Lightweight CNN	Howard et al.	2017	MobileNet	ImageNet	Fast and efficient model
9	Explainable AI	Selvaraju et al.	2017	Grad-CAM	Benchmark Dataset	Heatmap-based explanation
10	Image Preprocessing	OpenCV Team	2000	OpenCV Library	Custom Dataset	Real-time image enhancement
11	COVID Classification	Ozturk et al.	2020	DarkCovidNet	COVID Dataset	Multi-class disease detection
12	Severity Detection	Various	2021	CNN + Severity Analysis	Chest X-ray Dataset	Mild/Moderate/Severe prediction
13	Transfer Learning	Chollet	2017	Xception Network	ImageNet	High feature extraction accuracy
14	Hybrid Detection	Various	2022	CNN + Grad-CAM	Medical Dataset	Improved interpretability
15	Web-based Diagnosis	Various	2023	Flask + Deep Learning	Custom Dataset	Real-time disease prediction
16	AI Recommendation System	Various	2023	Personalized Suggestions	Custom Dataset	User-friendly healthcare support
17	Explainable Diagnosis	Various	2024	XAI + CNN	Chest X-ray Images	Transparent AI predictions
18	Multiclass Detection	Various	2024	Deep CNN Classification	COVID, TB, Pneumonia Dataset	Multi-disease identification
19	Real-Time Detection	Various	2025	AI-assisted X-ray Analysis	Large X-ray Dataset	Fast automated diagnosis
20	Hybrid (Proposed System)	Your System	2026	CNN + Grad-CAM + Severity Detection	Custom Dataset	High accuracy, explainable and real-time detection

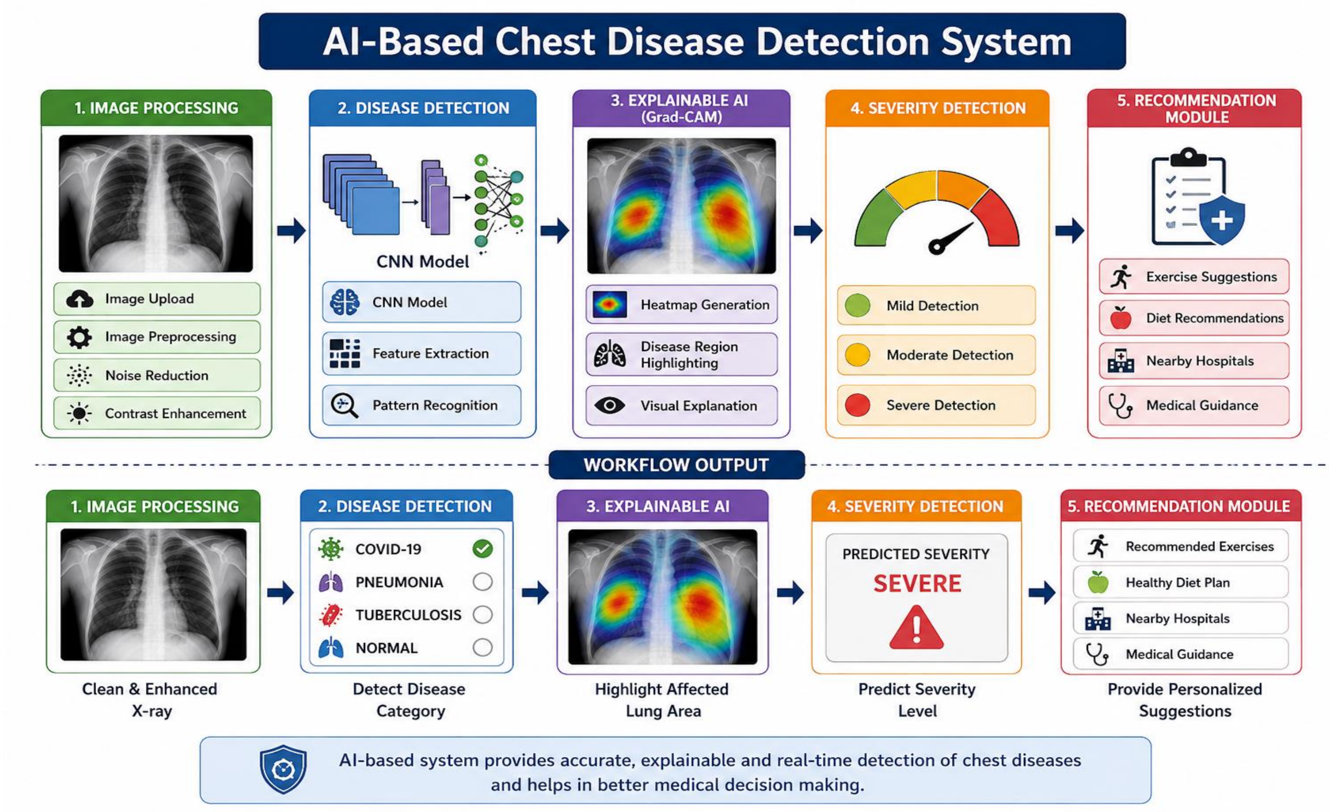


Figure 3 Detailed Workflow of AI-Based Chest Disease Detection System

3.2 Chest Disease Detection Using Deep Learning

Chest disease detection is one of the most important components of the proposed AI-based healthcare system. The system identifies diseases such as COVID-19, Pneumonia, and Tuberculosis by analyzing chest X-ray images using Deep Learning techniques. Since different chest diseases produce unique patterns in lung regions, AI models can learn these patterns and accurately classify diseases from medical images. The proposed system mainly uses Convolutional Neural Networks (CNNs) for disease detection and feature extraction. CNNs are specialized deep learning models designed for image analysis tasks. They automatically learn important features such as edges, textures, infected regions, and abnormal lung patterns directly from chest X-ray images without requiring manual feature extraction. In this approach, the uploaded X-ray image first undergoes preprocessing techniques such as resizing, normalization, noise reduction, and contrast enhancement. These operations improve image quality and help the model extract clearer medical features from the lungs. After preprocessing, the image is passed through multiple CNN layers, where low-level and high-level features are extracted progressively. The convolution layers identify important visual patterns from the lungs, while pooling layers reduce image dimensions and computational complexity. Fully connected layers then combine the extracted features and classify the image into categories such as COVID-19, Pneumonia, Tuberculosis, or Normal. To improve transparency and reliability, the system integrates Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM. Grad-CAM generates heatmaps that highlight infected lung regions influencing the prediction. These visual explanations help users and medical professionals understand how the model arrived at its decision. Additionally, severity detection techniques are used to analyze the extent of infection in the lungs and categorize the disease into mild, moderate, or severe levels. Based on the predicted severity, the system also provides personalized recommendations such as exercises, diet plans, nearby hospitals, and medical guidance. Compared to traditional manual diagnosis methods, deep learning-based chest disease detection systems provide higher accuracy, faster processing, and more consistent results. These systems are also capable of handling large datasets and real-time analysis efficiently. However, challenges may still arise due to low-quality X-ray images, overlapping diseases, noise, and variations in image acquisition conditions. Overall, Deep Learning and Explainable AI provide a reliable, scalable, and efficient solution for automated chest disease diagnosis and healthcare support systems.

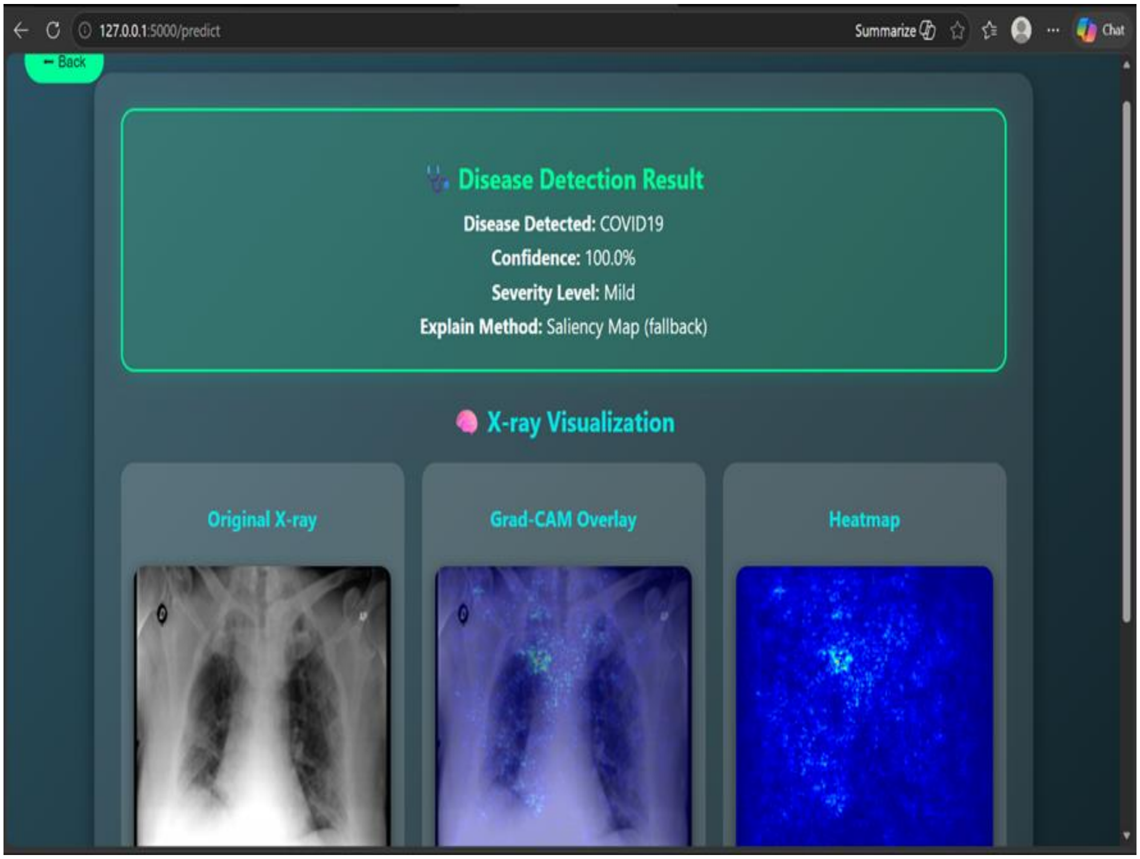


Figure 4 Chest Disease Detection System Output

3.3 Severity Detection and Feature Analysis

Severity detection is an important component of the proposed AI-based Chest Disease Detection System. It focuses on analyzing infected lung regions in chest X-ray images to determine the seriousness of diseases such as COVID-19, Pneumonia, and Tuberculosis. Unlike simple disease classification, severity analysis helps identify how much the lungs are affected and assists in better medical decision-making . The severity detection process relies on extracting important visual features from chest X-ray images using Convolutional Neural Networks (CNNs) and Explainable AI techniques such as Grad-CAM. The CNN model analyzes lung patterns, infection density, opacity regions, and abnormal textures present in the X-ray image. These features help the system understand the extent of disease spread within the lungs. Grad-CAM heatmaps are generated to highlight the infected regions responsible for the prediction. These highlighted areas provide visual explanations and help identify whether the infection level is mild, moderate, or severe. The system analyzes the intensity and spread of highlighted regions to estimate disease severity more accurately. Different metrics such as infected area coverage, feature intensity, confidence score, and pattern distribution are used to evaluate disease severity. The extracted features are compared with predefined thresholds to categorize the condition into different severity levels. Mild cases generally show smaller affected regions, while severe cases display widespread lung infection and higher abnormality concentration. The severity analysis module enables the system to provide more informative outputs beyond simple disease detection. Based on the predicted severity level, the recommendation module generates personalized suggestions such as medical guidance, nearby hospitals, exercises, and diet recommendations. Overall, severity detection and feature analysis improve the effectiveness of the proposed system by providing accurate, explainable, and real-time assessment of chest diseases, helping both users and healthcare professionals make faster and better treatment decisions.

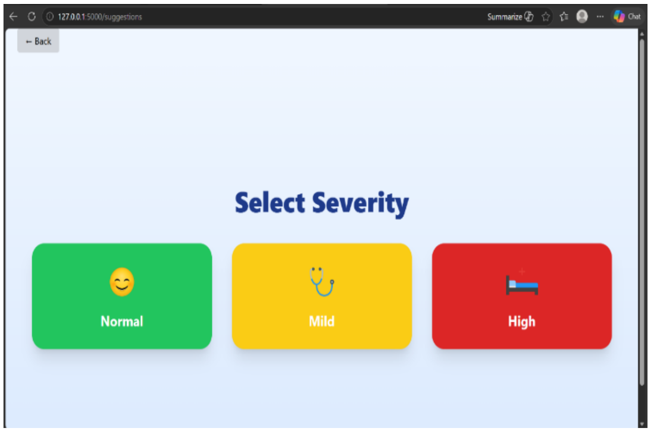


Figure 5 Severity Detection In System

3.4 Recommendation and Guidance Process

The recommendation module in the proposed AI-based Chest Disease Detection System focuses on providing personalized healthcare suggestions based on the predicted disease and severity level (Fig. 9). Unlike basic disease prediction systems that only display results, the recommendation module assists users by offering supportive medical guidance and health-related suggestions to improve patient care and awareness.

The recommendation process begins after the disease detection and severity analysis stages are completed. Based on the identified disease category such as COVID-19, Pneumonia, Tuberculosis, or Normal condition, the system generates suitable recommendations for the user. If the detected severity level is high, the system advises immediate medical consultation and displays nearby hospitals or healthcare centers.

- Key techniques include:

1. Severity-Based Recommendations:
The system analyzes whether the disease condition is mild, moderate, or severe and provides recommendations accordingly. Mild cases may receive home-care suggestions, while severe cases trigger emergency medical guidance.

2. Personalized Health Suggestions:
The system provides customized suggestions such as breathing exercises, yoga activities, healthy diet plans, and precautionary measures to support recovery and improve respiratory health.

3. Nearby Hospital Assistance:
Based on the severity level, the system recommends nearby hospitals or specialized healthcare centers for further medical treatment and consultation.

4. Medical Guidance and Alerts:
The module generates important healthcare instructions and alerts users when immediate medical attention is required. This helps improve early treatment and reduces health risks.

5. Real-Time User Support:
The recommendation system works instantly after prediction and provides user-friendly guidance through the web application interface, making the system more practical and accessible.

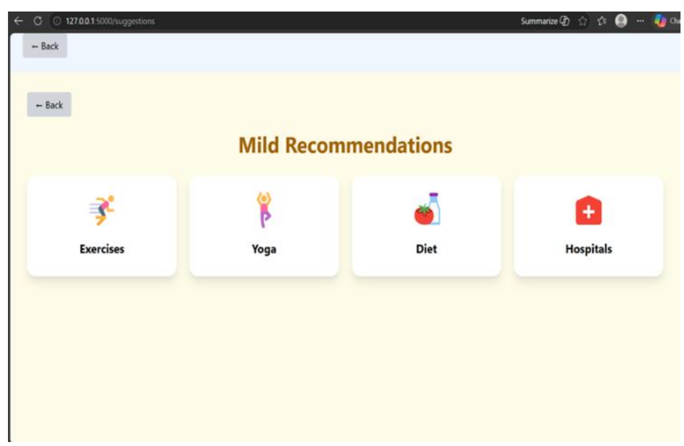


Figure 6 Recommendations for The Detected Disease

IV. EXPERIMENTAL SETUP AND RESULTS

4.1 Experimental Environment

The experiments for the proposed AI-Based Chest Disease Detection System were conducted using Python 3.x with support from libraries such as TensorFlow, Keras, OpenCV, NumPy, Pandas, and Matplotlib for image processing, visualization, and deep learning operations. These tools were used for tasks such as chest X-ray preprocessing, feature extraction using Convolutional Neural Networks (CNNs), disease classification, and Grad-CAM heatmap generation for Explainable AI. The system was tested on a standard computing setup with an Intel i5/i7 processor, 8–16 GB RAM, and chest X-ray image datasets as input. The proposed approach utilizes optimized deep learning algorithms for efficient disease detection and real-time prediction. Depending on the implementation, optional GPU support can further improve training and prediction speed, although the system can also run effectively in CPU-based environments. The trained CNN model was tested using chest X-ray images belonging to different categories such as COVID-19, Pneumonia, Tuberculosis, and Normal cases. During testing, input images were preprocessed and passed through the trained model to generate predictions and confidence scores. Explainable AI techniques such as Grad-CAM were also used to visualize infected lung regions influencing the model's decision. This setup ensured efficient execution of deep learning algorithms with reduced computational overhead. The proposed system demonstrated stable performance and was capable of processing X-ray images quickly, enabling near real-time disease detection. The framework is scalable and suitable for practical deployment in healthcare applications such as hospitals, diagnostic centers, and medical support systems.

4.2 Dataset Description

To To evaluate the performance of the proposed AI-Based Chest Disease Detection System, publicly available chest X-ray datasets along with custom collected medical images were utilized.

Chest X-ray Dataset:

The dataset contains chest X-ray images belonging to multiple disease categories such as COVID-19, Pneumonia, Tuberculosis, and Normal conditions. These images were collected from publicly available medical imaging repositories and Kaggle datasets. The dataset includes variations in image quality, lung infection levels, brightness, and contrast, helping evaluate the robustness of the proposed model under real-world conditions.

Custom Collected Dataset:
A custom dataset was also prepared using additional chest X-ray images collected from different medical sources. The dataset includes variations such as different infection intensities, image resolutions, and patient conditions. This helps evaluate the practical performance of the system in diverse healthcare scenarios.

Real-Time Input:
In addition to stored datasets, the proposed system supports real-time image upload through the Flask-based web application. Users can upload chest X-ray images directly into the system for instant disease prediction and analysis. This enables testing under practical real-world conditions and improves system usability.
These datasets provide diverse medical imaging conditions and disease variations, making the evaluation more realistic and suitable for real-world deployment of the proposed chest disease detection system.

4.3 Evaluation Metrics

The performance of the proposed AI-Based Chest Disease Detection System is evaluated using important metrics related to disease classification accuracy and prediction performance.

- **Accuracy (ACC):**

Represents the proportion of correctly classified chest X-ray images out of the total inputs. It indicates how accurately the system can detect diseases such as COVID-19, Pneumonia, Tuberculosis, and Normal conditions.

- **Precision**:

Measures how many of the predicted disease cases are actually correct. Higher precision indicates fewer false positive predictions.

- **Recall (Sensitivity):**

Represents the ability of the system to correctly identify actual disease cases. Higher recall means fewer disease cases are missed by the model.

- **F1-Score**:

Provides a balanced measure of precision and recall. It is useful when evaluating overall classification performance, especially in multi-class disease detection.

- **Perplexity / Loss:**

Measures the confidence and learning performance of the model during training and validation. Lower loss values indicate better model learning and prediction reliability.

- **Processing Speed (Time/FPS):**

Measures how quickly the system processes chest X-ray images and generates predictions, indicating its suitability for real-time healthcare applications.

4.4 Results and Observations

The performance of the proposed AI-Based Chest Disease Detection System is summarized in Table 1, highlighting its effectiveness in detecting chest diseases using Deep Learning and Explainable AI techniques. The analysis demonstrates how different modules such as image preprocessing, CNN-based feature extraction, Grad-CAM visualization, and severity detection contribute to accurate and reliable disease prediction.

From the experimental results, several important observations can be derived:

- Impact of Image Quality:
  The system performs best when chest X-ray images are clear and properly preprocessed. Poor image quality, noise, or low contrast may reduce prediction accuracy.

- Disease Pattern Detection:
  The CNN model effectively learns important lung infection patterns and abnormalities, enabling accurate classification of COVID-19, Pneumonia, Tuberculosis, and Normal conditions.

- Explainable AI Advantage:
  Grad-CAM heatmaps successfully highlight infected lung regions, improving transparency and helping users understand the prediction process.

- Severity Analysis Performance:
  The severity detection module effectively categorizes disease conditions into mild, moderate, and severe levels, improving healthcare decision-making.

- Real-Time Performance:
  The proposed system demonstrates efficient performance and processes chest X-ray images quickly, enabling near real-time disease prediction without requiring high-end hardware.

- Multi-Module Advantage:
  Combining preprocessing, CNN-based classification, Explainable AI, severity analysis, and recommendation modules improves overall system reliability and usability compared to using a single technique alone.

4.5 Discussion

The results show that the proposed AI-Based Chest Disease Detection System can effectively detect diseases such as COVID-19, Pneumonia, and Tuberculosis using Deep Learning techniques. The combination of image preprocessing, CNN-based classification, Explainable AI, and severity detection improves both accuracy and reliability. The system performs efficiently in near real-time and provides clear visual explanations using Grad-CAM heatmaps, helping users understand the prediction process. The recommendation module further improves usability by providing healthcare guidance based on disease severity. However, challenges such as poor-quality X-ray images, noise, and overlapping disease patterns may affect prediction accuracy. Despite these limitations, the proposed framework provides a practical, fast, and explainable solution for real-world healthcare applications such as hospitals and diagnostic centers.

V. DISCUSSION AND CONCLUSION

This project presents an Adaptive Explainable AI Framework for chest disease detection that effectively addresses key limitations of existing systems. The proposed system follows a structured workflow where the process starts from X-ray image input, followed by preprocessing, CNN-based classification, explainability, and final result visualization through a web-based interface. This organized pipeline ensures both accuracy and transparency in disease detection. One of the major strengths of this system is the use of a combined and diverse dataset created by merging multiple chest X-ray datasets. This allows the model to learn from different image variations and improves its performance in real-world conditions. The use of Convolutional Neural Networks (CNNs) enables the system to automatically extract important features from medical images and achieve accurate classification of diseases such as COVID-19, Pneumonia, Tuberculosis, and Normal cases.

Another important contribution of this work is the integration of Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM, which provide visual explanations by highlighting affected regions in the lungs. This helps users understand the model's decision and increases trust in the system. In addition, the inclusion of confidence scores and severity estimation further improves reliability by indicating how certain the prediction is and how serious the condition may be. The system is implemented as a web-based application, providing a simple and user-friendly interface where users can upload X-ray images and receive instant results along with explanations and recommendations. The experimental results show that the system achieves good accuracy and performs consistently across different disease categories. Despite its strong performance, there is scope for future improvement. The system can be enhanced by using larger datasets, more advanced deep learning models, and real-time optimization techniques. It can also be extended to support additional diseases and integrate with hospital systems for practical deployment. In conclusion, the proposed system successfully combines deep learning, explainability, and user-friendly design to create an accurate, transparent, and reliable chest disease detection solution. This makes it a valuable decision-support tool for healthcare applications.

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